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Air Pollution and Mortality Impacts of Coal Mining: Evidence from Coalmine Accidents in China *

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Abstract

We leverage the timing of coalmine accidents to examine the effect of coal mining on air pollution. Safety regulations mandate that coal mining be suspended if a mine experiences an accident with 10 or more fatalities. We use a stacked difference-in-differences approach to compare counties with an accident to those experiencing an accident more than two years earlier or later. We provide evidence that the timing of accidents cannot be predicted. Next, we combine satellite-based air pollution data at the county-day level with the dates of accidents to show that on average, suspending coal mining reduces local air pollution by 8%. Changes in the level of coal consumption do not drive this reduction. We also find significant decreases in respiratory mortality after suspending coal mining with particularly large effects on vulnerable populations.

Keywords: air pollution, coal mining, coalmine accidents, health impacts

JEL Codes: I10, Q40, Q53, R11

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1 Introduction

Coal is a major source of air pollution and harms public health. Many studies have examined the impact of burning coal (Cesur et al., 2017; Clay et al., 2016; Beach and Hanlon, 2018; Johnsen et al., 2019), but few address the fact that producing coal also generates pollution. Coal mining generates pollution in three ways. The first is wind erosion of uncovered coal stockpiles and *gangue* (the waste products of mining) that generates pollution laden dust. Second, the oxidation of coal and *gangue* causes the formation of pollutants. Third, handling coal, moving it from the mine-mouth to stockpiles; crushing it; and loading it onto trucks, trains, or barges for delivery creates pollution as well.

We estimate the casual effect of coal mining on air quality and mortality in China, which has long been the global leader in coal production. Our identification strategy exploits an orthogonal determinant of coal mining: the timing of accidents. Between 2003-2015, the Chinese central government required coalmines that experienced an accident with 10 or more deaths to suspend underground mining until inspectors certified their operations as safe.¹ We use a stacked difference-in-differences approach (Deshpande and Li, 2019; Fadlon and Nielsen, 2021; Baker et al., 2022) with a staggered treatment rollout and construct multiple counterfactual groups to parse the sources of identification.

Combining satellite measures of particulate matter (aerosol optical depth, referred to as AOD) with dates and locations of severe accidents between 2003-2015 allows us to map suspensions of coal mining to nearby air pollution levels. We restrict our event window to 90 days before and after the accident to minimize the effects of confounding factors that are correlated with both coal mining and air quality. One threat to identification is that unobserved differences between mines that experience severe accidents and those that do not may also be correlated with pollution associated with coal mining. To address this concern, we exploit the timing of accidents. We use a stacked difference-in-differences approach to compare counties currently experiencing a severe accident with those experiencing one but over two years in the future (or over two years in the past). Our identification only requires that the timing of accidents with suspensions of coal mining is random for which we provide evidence. Our research design is similar to several studies that

¹We use the term “severe accident” to refer to a coal mine accident with 10 or more fatalities throughout the remainder of the paper.

exploit the potential randomness of the timing of shocks within a short period of time (Guryan, 2004; Deshpande and Li, 2019; Fadlon and Nielsen, 2021). We also test the external validity of our estimation results by comparing counties that experience an accident to a comparison group of counties that experienced no accidents during our sample period.

Our results indicate that suspensions of coal mining lead to a lagged reduction in the levels of ambient air pollution. In the first month after a suspension, our results, albeit imprecisely estimated, show that AOD levels decrease. In the second month of suspension, AOD levels fall significantly by 8% of the sample mean. Our findings are robust across the three sets of comparison groups. We show that the lagged effect on AOD levels can be explained by the continued operation of non-mining activities during a suspension of mining. During a suspension, regulators do allow moving, handling, and shipping the coal inventory. The amount of inventory held by coal companies influences the length of the lag before the decrease in the levels of ambient air pollution. We show that coal companies hold inventory equivalent to a month of sales on average that is consistent with the lag we observe in the decrease in air pollution. We also provide evidence that the observed improvement in ambient air quality is not driven by changes in the level of economic activities or coal consumption in counties that experience an accident. As a placebo test, we estimate the effect of suspending coal mining on the level of SO_2 , which is associated with coal combustion but not with its production. We do not find a significant reduction in SO_2 levels.

We provide evidence that suspensions of coal mining are associated with reduced all-age mortality in the mine’s county. For a subset of counties in our sample we are able to collect daily mortality information. We combine the mortality data with the dates and locations of severe accidents from 2003-2015, obtaining a matched sample of 16 counties with 18 accidents. We then compare the daily cause-specific all-age mortality rates between the treated and the comparison groups shortly before and after a suspension using a Poisson event-study framework. Our results show that the average all-age mortality rate due to respiratory (RES) diseases significantly decreases by 12.9% in the third month following a suspension relative to the comparison group. Additionally, women are more affected than men. Consistent with the literature (Tanaka, 2015; Anderson, 2020), we also find that populations vulnerable to air pollution experience much larger decreases in mortality rates following a suspension: the elderly see a significant drop in the RES mortality rate. Our back-of-envelope calculation indicates that the annual cost to health imposed by coal mining in

China is 51.2 billion USD.

This paper contributes to the literature in three ways. First, there is a burgeoning literature about the effects from coal combustion on pollution and health (Clay et al., 2016; Cesur et al., 2017; Beach and Hanlon, 2018; Johnsen et al., 2019). Beach and Hanlon (2018) estimate the mortality effects of British industrial coal use in the period from 1851 to 1860 using wind patterns for identification. Clay et al. (2016) demonstrate that a sizeable increase in infant mortality could be attributed to the historical expansion of US coal-fired power plants in the early and mid-1900s. Leveraging variation in the intensity of natural gas use, Cesur et al. (2017) find that the expansion of natural gas infrastructure in Turkey significantly reduced the rate of infant mortality. Johnsen et al. (2019) find that the recent displacement of coal by cheap natural gas in the U.S. electricity sector significantly lowers $PM_{2.5}$ levels.

In the Chinese context, several studies have investigated the effects of air pollution from coal combustion on health during winter heating. Chen et al. (2013a) and Ebenstein et al. (2017) use a regression discontinuity design that is based on a policy that only areas to the north of the Huai River received free or highly subsidized coal for indoor heating and find significant reductions in life expectancy. Fan et al. (2020) also use a regression discontinuity design that is based on the exact starting dates of winter heating across different cities and find that turning on the heating system leads to a significant increase in mortality rates. Chen et al. (2018) find that coal-fired power generation increases the SO_2 levels nearby, which increases respiratory and lung cancer deaths. In our paper, we add to this literature by extending the analysis to the upstream of the coal industry and investigating the pollution and health effects of coal mining.

Second, there has been some evidence in the literature that a negative correlation exists between coal mining and local air quality or public health. In this early literature, causal identification has been elusive. Several scientific studies have shown that a rise in the level of particulate matter during coal mining by sampling a few sites (Onder and Yigit, 2009; Aneja et al., 2012; Knuckles et al., 2013). Fitzpatrick (2018) finds that increased exposure to surface coal mining is associated with significantly more asthma hospitalizations in West Virginia. Although the study controls for time-invariant confounding factors with panel regressions, their findings are subject to contamination from time-varying unobservables that are correlated with both mining and health outcomes. In a review article, Greenstone et al. (2021) suggest that the decrease in $PM_{2.5}$ levels in China during

the period from 2015 to 2018 after it declared war against air pollution were less likely to decrease in cities with coal mining. Our study contributes to the literature by estimating the causal effect of coal mining on both air quality and mortality based on a comprehensive, county-level dataset in the largest coal-producing country in the world. In addition, while most studies have focused on the environmental effects of surface mining, we investigate a setting where almost all coal mining is conducted underground.

To the best of our knowledge, there is only one paper that attempts to estimate the causal effect of coal inventories on air pollution. Jha and Muller (2018) find that a 10% increase in $PM_{2.5}$ causes a 1.1% increase in average adult mortality in the US by instrumenting for the exposure to $PM_{2.5}$ with coal stored at power plants. We study the same mechanism - pollution emissions from coal storage – using a different identification strategy (coal mining accidents vs coal inventory levels) in a different country. We find a slightly larger air pollution elasticity of all-age mortality, perhaps because coal mining generates more particulate matter than coal storage at power plants. In addition, the levels of environmental regulation and health care differ significantly between China and the US. Because China is the world’s largest producer of coal, we argue that these results provide important additional context to those presented in Jha and Muller (2018).

Third, several studies have pointed out greater pollution emissions and negative health effects that are associated with natural gas production (Litovitz et al., 2013; Rasmussen et al., 2016; Hill, 2018; Banan and Gernand, 2020). Our paper complements these studies and highlights the importance of conducting a comprehensive life-cycle evaluation of fossil fuels for an accurate calculation of their social costs.

Fourth, our paper adds to a growing literature that demonstrates the potential negative effects of mining and extractive industries on women’s health in developing countries. Baum and Benshaul-Tolonen (2021) note that the effect of mining on health in general and women’s health in particular is not obvious. Mining typically is associated with increased economic activities that in turn leads to better access to medical care. On the other hand, mining is associated with increased pollution which has negative health effects. The literature refers to this as the health-wealth trade off. This tradeoff has been documented in the context of gold mining (Von der Goltz and Barnwal, 2019), oil fields (Hurtig and San Sebastián, 2002) and coal mining (Hendryx and Ahern, 2008). Different from (Hendryx and Ahern, 2008) who study the tradeoff in the US, our paper identifies the tradeoff

for women from coal mining in a developing country: exposure to air pollution from mining leads to significant increases in mortality for women in mining regions that tend to have lower incomes.

There are several clear policy implications of this work. First, previous estimates of the external costs that are associated with coal are understated. We find relatively large human health effects from coal mining that are, to our knowledge, new to the literature. A future cost-benefit analysis of environmental regulation should incorporate these external costs. Second, some regions will continue to rely on coal for the foreseeable future, so it is important to reduce the local air pollution and health effects of its production. These effects we find suggest that regulations on the air pollution from coal mining could be justified. Better handling of coal and *gangue* could reduce pollution exposure at modest costs.

2 Background

China is the world’s largest producer and consumer of coal. Large flows of capital have entered the coal mining and processing industry since the mid-2000s that led to an approximately 50% increase in production capacity between 2005 and 2017. Domestically, coal has played a dominant role in the energy sector by providing 70% of the energy consumed in China.

In China, the vast majority of the mining is underground. Open pit mines only account for 13% of the total production among the key state-owned coal mines in China (National Coalmine Safety Administration, 2009). All the accidents in our sample occurred in underground coal mines.² The Chinese coal mining industry has experienced a large number of accidents. In 2004, China’s fatalities amounted to 80% of the world’s total, while producing 40% of the world’s coal (Nie et al., 2013). The fatality rate for coal mining in China is significantly higher than other countries, even other developing ones.³

Surging coal mine deaths have attracted public attention and posed a threat to social stability. In response, the central government has comprehensively overhauled regulations to substantially improve the safety of coal mines. One of them is the “Measures for Administrative Punishment of Coal Mine Security Supervision” issued by the State Administration of Work Safety and the

²There were a handful of accidents in open pit mines, but they were all during the construction of the mine so there was no suspension of mining. We exclude these accidents from the analysis.

³As of 2000, the fatality rate for coal mining in China was 140 times that of the US; and 14 times higher than India (Wright, 2004).

National Coal Mine Safety Administration in 2003. The regulation focused on a standard set of punishments for coal mines that experienced accidents or did not follow health and safety regulations. We focus on a provision that states that any coal mine experiencing an accident with “material incidence of over 10 deaths” would suffer a suspension.

The regulatory agencies categorize accidents with 10 or more fatalities as “very serious”, and the media covers them extensively. The State Council of China has categorized workplace accidents based on the number of fatalities. An accident with 3 or fewer fatalities is classified as “general”, 3–9 is classified as “relatively serious”, and 10 and above is classified as “very serious”. “Very serious” (severe) accidents must be reported to the State Administration of Work Safety and the State Council immediately. Mine officials and local bureaucrats that delay reporting or under-report accidents are subject to administrative penalties (e.g., demotion or dismissal) and criminal charges.⁴ After a coalmine reports a severe accident, a suspension of mining occurs that is strictly enforced by state officials until the workplace can be certified as safe.

In practice, this regulation means that coalmines are required to stop all underground mining activities after an accident with 10 or more deaths. The safety risks in our case all come from underground activities but not above-ground activities. The safety regulation that requires a suspension upon the occurrence of a severe accident only mentions suspensions of mining, where the risk lies. Suspensions do not apply to above-ground activities such as transporting, handling, or shipping coal stored above ground, which are critical for coal companies during a suspension since they can mitigate cash-flow problems. We have confirmed the ban only applies to underground activities.⁵ Once the coal company ships the limited coal stocks, local air pollution should begin to drop.

We identify the date of each severe accident from the website of State Administration of Work Safety of China. We collect online media articles about each accident and confirm that the regulator enforced the “Measures for Administrative Punishment of Coal Mine Security Supervision” and that each mine experienced a suspension immediately after the accident. Local governments have the discretion on whether to extend a suspension to nearby coal mines. We manually collect data on the range of suspensions (e.g., single mine, county-wide, city-wide, or province-wide) after each

⁴See Articles 91 and 92 in “The Production Safety Law” issued in 2002.

⁵We met with private mine owners and confirmed that coalmines can still operate above ground while under suspension.

accident that we use in alternative empirical model specifications for robustness checks. For the few accidents that the media reported its length, the suspensions lasted for up to three months. The length of suspension varies across coal mines but we are not able to obtain this information from online media coverage for all accidents. We choose a 90-day event window to estimate the effect of suspensions on ambient air pollution and all-age mortality. We also perform robustness checks on whether the lagged effect lasts more than 90 days after a suspension.

Mines that experienced less severe accidents are our alternative comparison group, but regulators occasionally suspend these mines due to accidents as well. However, these suspensions are not mandated by the National Coal Mine Safety Administration, but provincial and local officials have the discretion to order suspensions. Because the decision rule is unclear regarding these suspensions, we exclude them from the analysis.

3 Empirical Strategy

In this section, we discuss how we use accidents and the subsequent suspensions of underground mining to identify the effect of coal mining on the ambient air pollution and the mortality of nearby residents. Since the most granular data available for many of our key variables are at the county level, we conduct most of our analyses at this level.

3.1 Estimation of the Air Pollution Effects

To choose the proper empirical strategy, we start by testing whether accidents are correlated with county characteristics. We find that some variables consistently predict the occurrence of a severe accident. However, we find no observable characteristic or interaction of characteristics that consistently predicts the timing of an accident conditional on an accident taking place during the sample period. This evidence means none of the factors that predict the existence of severe accidents are effective at predicting their timing.⁶ We therefore only use the timing of accidents in designing our empirical strategy.⁷ The key identifying assumption is that the timing of coalmine accidents is as good as random.

⁶A description of this analysis and the empirical results are reported in Appendix A1.

⁷Our approach is similar to a host of studies that exploit the variation in the timing of program roll-outs to estimate the causal effects of those programs (Guryan, 2004; Deshpande and Li, 2019; Fadlon and Nielsen, 2021).

Accidents happen at different times in different counties. Goodman-Bacon (2021) has shown that the source of identification can be non-intuitive in a two-way fixed effects, difference-in-differences estimation where treatment timing varies across units. This pooled specification produces an estimator that is a weighted average of the differences between various groups, including the early treated units versus the untreated units, the late treated units versus the untreated units, and groups that receive treatments at different times (e.g., using earlier treated units as the control after their treatment begins or later treated units as the control before their treatment begins). To avoid this confusion, we set counties that are currently experiencing an accident as the treated ones and construct two samples: one that exploits the earlier treated counties as the control and a second that exploits the later treated counties as the control. We do not use the set of counties that never experience an accident for comparison, except in a robustness check. This approach allows us to parse the source of identification. Importantly, we also show that the estimated effects of suspensions are similar across our two samples.

We compare pollution in counties that have a coalmine that experiences an accident to other counties whose coalmines experience an accident during a different part of the sample period. Counties with coalmines that experience a suspension at time t are defined as treated in that period. We compare the treated and control counties within a short time window (day -90 to day 90) around time t . We choose two sets of comparison groups: (a) counties that did not experience an accident for at least two years after time t ; and (b) counties that experienced an accident more than two years prior to time t .

We call comparison group (a) the later treated, because they had an accident resulting in suspension after the treated group. To deal with the fact that a county may experience multiple accidents, for the later treated comparison group we drop counties that also experienced an accident in the 180 days before time t because the lingering effects of previous mining suspensions could contaminate the comparison group. We call comparison group (b) the earlier treated, because they experienced an accident before the treated group. For the earlier treated comparison group we drop counties that also experienced an accident within 180 days of the treatment date t for similar reasons. To shield our estimates from a potential spillover effect, we also drop the counties that are in the same province as the treated county from the control group.

We build our sample using the following procedure. First, we identify each of the 315 severe

coalmine accidents. For an accident j , we mark the timing of occurrence, date t_j . We define as treated the county where accident j occurred and select as controls the counties that experienced an accident but after date $t_j + \Delta$ (or those that experienced an accident but before date $t_j - \Delta$). We set Δ to be 730 days or equivalently 2 years. This approach means that for each event, we have one treated county but multiple control counties. We then confine our sample period to a short time window (day -90 to day 90) around date t_j for both the treated and control groups for accident j . How we select the treated and comparison counties and construct our sample for each time window of an accident is illustrated in Figure 1. A narrow event window avoids biases from potential confounding factors correlated with coal mining.⁸ We label event months (30 days) relative to the accident date. Next, we append the panels of all 315 accidents into a single dataset. Eventually, we have 199 counties in our sample.⁹

To estimate the causal effect of a suspension in coal mining on the ambient air quality, we estimate the following equation using a stacked difference-in-differences framework:

$$Y_{ict} = \delta_0 \cdot Treated_{ict} + \sum_{\tau} \alpha_{\tau} M_{ict}^{\tau} + \sum_{\tau} \delta_{\tau} (Treated_{ict} \cdot M_{ict}^{\tau}) + \bar{\beta} \cdot \bar{X}_{ict} + \epsilon_{ict} \quad (1)$$

where Y_{ict} is the ambient air pollution (AOD) level for county i affected by accident c on day t . $Treated_{ic}$ is an indicator equal to one for the county that experienced accident c . M_{ict}^{τ} is an indicator equal to one if day t is τ month (defined as 30 days) after (or before, if τ is negative) the accident date and zero otherwise. Specifically, M_{ict}^1 is the indicator for the days from Day 1 to Day 30 following the date of accident c , M_{ict}^{-1} is the indicator for the days from Day -30 to Day -1 prior to the date of accident c and so on. We use a narrow window around each accident date such that $|\tau| \leq 3$. The difference-in-differences estimator, δ_{τ} , is our primary coefficient of interest, and we use it to measure the relative difference in the AOD levels between the treated and comparison counties τ months after (or before) an accident. Day -90 to -60 ($\tau=-3$) is the reference category

⁸There is another reason for focusing on the current time window after the accident. Anecdotal evidence suggests that a coal mine suspension after a severe accident could last for three months.

⁹In our sample period, some counties experience multiple accidents. We treat consecutive accidents that occur in the same county as two separate events if they are sufficiently distant away from each other (more than 180 days). If the timing difference between two accidents is less than 180 days, there is an overlap of the (day -90 to day 90) event windows around the two accidents. Under such scenarios, for the first accident, we drop the post-treatment observations that overlap with the window of the following accident; for the second accident, we drop the pre-treatment observations that overlap with the window of the prior accident. If the dates of the two accidents are too close, we drop both events from our sample. More detailed explanations of how we deal with overlapping observations between two accidents within the same county can be found in the Appendix A2.

and is omitted from the regressions.

\overline{X}_{ict} is a vector of control variables: the linear and quadratic weather characteristics (average temperature, sunshine duration, average relative humidity, average wind speed, precipitation, and average air pressure); day-of-week dummies; Chinese holiday dummies; and a set of fixed effects at the county, province-by-year, and province-by-month levels.¹⁰ In some specifications, we also control for county-specific trends and county-level annual industrial activities by using the lagged total value of coal-related sectors (electricity, coal, metallic minerals, and nonmetallic minerals) and total industrial output.

Our identifying assumption is that in the absence of suspensions caused by accidents, the ambient air pollution in counties that experience a current accident will evolve in a parallel fashion to counties that will experience an accident in the future or counties that experienced an accident in the past. We test the validity of our identifying assumption by estimating the following empirical model:

$$Treated_{ict} = \beta \cdot \overline{X}_{ict} + \mu_{ict} \quad (2)$$

which is a modified version of equation (1). We construct the sample as discussed above except that we drop all post-accident observations (i.e., day 0 to day 90) for each accident. The dependent variable is $Treated_{ict}$ that is an indicator for the county that experienced an accident. The DID terms are dropped from equation (1). In this manner, we test whether key observable characteristics, \overline{X}_{ict} , are able to predict the timing of an accident conditional on an accident taking place during the sample period. Shown in Table 1, we find that none of the factors, even those predicting the existence of severe accidents (reported in Table 13 in Appendix A1), are effective at predicting their timing. This finding holds regardless of whether we choose the later treated comparison group (shown in panel A of Table 1) or the earlier treated comparison group (shown in panel B of Table 1). This congruence indicates the timing of accidents is essentially random.

Selecting a comparison group based on the timing of accidents has the advantage of alleviating endogeneity, but it may raise concerns about the external validity of our results since we restrict our sample to only counties that have experienced a coal mine accident. We then explore the external validity of our results using an additional comparison group that consisting of counties

¹⁰Treatment status varies within county over time so we can include county-level fixed effects to control for time invariant unobserved county-level variables.

that have never experienced an accident with a death during our sample period. We follow the same procedure as explained earlier to construct the estimation sample.

3.2 Estimation of the All-age Mortality Effects

Next we describe the econometric model for estimating the all-age mortality effect of suspensions of coal mining on nearby residents. We use mortality to illustrate the part of the economic costs of air pollution caused by coal mining. We focus on mortality because the nationally representative data of other health outcomes are not available or reliably measured at the county level during our sample period. Data on the number of deaths and their causes are available at the county-day level. Because the dependent variable is count data, we use a Poisson model. Due to data availability, we are only able to match the mortality information to 16 counties with 18 accidents that had resulted in the suspension of coal mining. Therefore, our identification strategy for estimating the effect of mining suspensions on air quality will not work with such a small number of accidents. Instead, we estimate the following Poisson regression:

$$E(Mortality_{it}|X_{it}, \alpha) = \alpha \cdot \exp[\gamma \cdot M_{it}^{|\tau|>3} + \sum_{\tau=1}^3 \delta_{\tau}(Treated_{it} \cdot M_{it}^{\tau}) + \bar{\beta} \cdot \bar{K}_{it} + \varphi_{it}] \quad (3)$$

where $Mortality_{it}$ is the number of all-age deaths in county i on day t , $Treated_{ict}$ is an indicator that equals one if a county experienced an accident, and M_{ict}^{τ} is an indicator for the τ th month after an accident had resulted in a suspension. Rather than assembling observations from different time windows around each accident as specified in equation (1), we use the entire sample period (2004-2015). We add an indicator, $M_{it}^{|\tau|>3}$, for the periods outside the window of (Day -90 to Day 90) around each accident. This indicator helps us to focus on the comparison between the treated and the comparison groups shortly before and after a suspension. The coefficient of the interaction between $Treated_{ict}$ and M_{ict}^{τ} , δ_{τ} , is the coefficient of primary interest, and it captures the relative change in all-age mortality in the treated counties in the τ th month following the suspension of coal mining compared to the comparison group. Note that $Treated_{ict}$ is co-linear with the county fixed effects and therefore are left out from the model. We include all counties covered by our mortality data as our controls.¹¹

¹¹We check for robustness of our health results by confining the control counties to be those that have coal mining. Our results hold. These results are available on request.

\overline{K}_{ict} is a vector of control variables that comprise daily weather characteristics (average temperature, sunshine duration, average relative humidity, average wind speed, precipitation, and average air pressure) and their quadratic terms for Chinese holiday dummies, day-of-week dummies, and annual county-level industrial activities (i.e., lagged total value of coal-related sectors and lagged total industrial output). We also add county, year, and calendar month fixed effects.

The results from the above model may reflect not only the pollution effect but also the socioeconomic effect from a suspension of coal mining. Testing the fall in employment or controlling for county-level socioeconomic variables before and after a suspension may help to probe the severity of bias due to the latter effect. Unfortunately, mine-level data for China are not available, so we do not have information on the employment at mines with accidents.¹² Neither do we have monthly county-level socioeconomic data, so we cannot control for these variables in our model.¹³ Yet, even if suspensions did affect a population’s health through socioeconomic factors such as income or employment, then the marginal effect would be negative and would be opposite to the health effect induced by a lower level of air pollution. Thus, our estimate would be a lower bound of the true pollution effect.

4 Data and Summary Statistics

In this section, we describe the data sources used to estimate the air pollution and the all-age mortality effects of coal mining. First, we collect the location (county), date, number of deaths, and cause of all the coal mine accidents in China from January 2003 to December 2015 from the State Administration of Work Safety of China.

Second, we collect the daily AOD at a pixel size of 3 km \times 3 km during 2003 to 2015 from the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA’s Terra and Aqua

¹²However, we are able to exploit annual data sets to check the mean share of employment of the coal-mining industry in our treated counties. We use the employment information from the Annual Survey of Industrial Enterprises of China that provides information on all state-owned enterprises and other types of enterprises with annual sales above the threshold of five million RMB. We aggregate the data at the county level to calculate the total employment of the coal-mining industry in the treated counties. Combining this variable with data on annual county-level total employment, we find that the mean share of employment in the coal-mining industry in our treated counties is 4.5% (the median is 1.2%). Therefore, a suspension of coal mining is unlikely to drastically affect the entire labor market in our treated counties. We thus argue that the potential bias arising from labor market disruptions in our health analyses is likely to be small.

¹³We conduct sensitivity tests where county-specific trends are added to our regression model. The results remain robust. The results are available on request.

satellites. AOD is a remotely sensed measure of particulate matter, which is calculated based on the fraction of incoming light reflected by the air column before reaching the ground.¹⁴ The literature has used AOD as a proxy for air pollution to estimate the effects of a voluntary program to reduce pollution in Mexico, Indonesian wildfires, and subway system openings worldwide (Foster et al., 2009; Jayachandran, 2009; Gendron-Carrier et al., 2018). Approximately 30% of days have missing AOD values, usually due to thick clouds. To calculate the daily county-level AOD, we keep only the pixels with valid AOD values for at least 30 days in each year. We then calculate the daily county-level AOD by averaging its values for all pixels within the geographic boundary of each county. In addition, as a falsification test, we collect daily SO₂ at a spatial resolution of 0.25°×0.25° from the Level-3 Aura/OMI Global OMSO₂e Data Products from NASA. This variable is calculated using the vertical column density of SO₂ in Dobson Units (1 DU = 2.69×10¹⁶ molecules/cm²), which is suitable for analyzing near-surface pollution.¹⁵ The SO₂ data dates back to 2004.

The air quality data from monitoring stations released by China’s Ministry of Ecology and Environment (referred to as MEE) are not ideal for this analysis for several reasons. First, air quality data based on records from monitoring stations were only available at the prefecture-city level and covered only 113 cities prior to 2013.¹⁶ The network of monitoring stations was greatly expanded in 2013, but many counties still do not have a station. Second, the MEE changed the computing formula for the air quality data in 2013 so that the data are incompatible across time.¹⁷ Third, even though the concentration of PM₁₀ is available before and after 2013, the data quality is very likely to differ. This is because the MEE launched the real-time pollution monitoring and disclosure programs in 2013, which significantly improve the data quality of air pollution (Greenstone et al., 2022). In fact, researchers have found evidence that the air quality

¹⁴See Remer et al. (2013) for the details of how to construct AOD.

¹⁵Since the spatial resolution of remote-sensed SO₂ data are a little coarse, we construct SO₂ at the county by day level using an inverse-distance weighting method. For each county, we draw a circle with a radius of 100 km from the county’s center and calculate the weighted average daily SO₂ using all grids within that circle. The weight we use is the inverse of the distance between the center of the county and that of each grid.

¹⁶The prefecture-level city is a Chinese administrative unit between the county (our level of analysis) and the province.

¹⁷The data were termed as the Air Pollution Index (API) before 2013 and the Air Quality Index (AQI) afterwards. Besides PM₁₀, SO₂, and NO₂, the AQI also incorporates PM_{2.5}, CO, and O₃, all of which are not included in the calculation of API. The weight of the concentration of NO₂ is also different between the API and AQI. See Ghanem and Zhang (2014) and <https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/jcffbz/201203/W020120410332725219541.pdf> for more information.

data before 2013 suffered from manipulation in many Chinese cities (Andrews, 2008; Chen et al., 2012; Ghanem and Zhang, 2014; Stoerk, 2016; Greenstone et al., 2022).¹⁸ The geographic and time series limitations as well as the credibility issue of station-level data on air quality reduce our ability to identify the effects of coal mining on air quality. In contrast, as an object measure, AOD does not suffer from the flaw of data manipulation due to gaming incentives of Chinese officials (Chen et al., 2013b; Stoerk, 2016; Greenstone et al., 2022). The literature has also found a high correlation between AOD and the ground-level monitoring data of particular matter in China (Guo et al., 2009; Chen et al., 2012; Xin et al., 2016; Guo et al., 2017). Therefore, we rely on the AOD data provided by NASA for the relevant empirical analysis.

Weather plays a role in influencing air pollution levels. Therefore, we collect weather data from the China Meteorological Data Sharing Service System that provides the daily average temperature, relative humidity, wind speed, precipitation, and atmospheric pressure for approximately 700 weather stations in China. Since many counties do not have any weather station, we construct daily county-level weather variables from station-level weather records using an inverse-distance weighting method.¹⁹ Specifically, for each county, we draw a circle with a radius of 100 km from its center and calculate the weighted average daily weather variables using all stations within the circle. We use the inverse of the distance between the county’s center and each station as the weight.

In certain model specifications, we also control for the one-year lagged annual industrial activities: the total industrial output value and the output values of the electricity, coal, metallic minerals and nonmetallic minerals sectors. These variables are collected from the Annual Survey of Industrial Enterprises of China that is a large-scale enterprise survey conducted by the Chinese National Bureau of Statistics. It covers all state-owned enterprises and other types of enterprises with annual sales above the threshold of five million RMB. Leveraging the input-output table available from the Chinese National Bureau of Statistics, we also compute the value of coal consumption for enterprises in major coal-consuming sectors which we define as the electricity, metallic minerals and nonmetallic minerals sectors. We aggregate the enterprise-level industrial activity and coal

¹⁸For instance, Chen et al. (2012) show that there exists a significant discontinuity for the API (used before 2013) data at the threshold for "Blue Sky" days (API=100). Ghanem and Zhang (2014) report similar findings for the the PM₁₀ data. These evidences indicate the air quality data before 2013 suffered from manipulation in some Chinese cities.

¹⁹There are 2844 county-level administrative districts in China.

consumption variables at the county level.

We collect cause-specific daily mortality data for a subset of Chinese counties from the Disease Surveillance Point System (referred to as DSPS) of the Chinese Center for Disease Control and Prevention. The data span from 2004 to 2015. A series of studies have used these data to explore the effects of air pollution on health in China (Chen et al., 2013a; He et al., 2016; Ebenstein et al., 2017; Fan et al., 2020; He et al., 2020). Launched in the 1990s, the DSPS collects the most comprehensive mortality information in China via reports from community or hospital doctors at representative survey locations. Before 2013, the DSPS covered 161 distinct counties in China. From 2013, the coverage increased to 605 counties. The sampled locations eventually encompassed approximately a quarter of China’s total population. In the end, we are able to match 16 counties where severe accidents occurred (with a total number of 18 accidents) with the DSPS data. Additionally, we have 72 matched coal-producing counties with no accident in the sample period. We focus on the deaths caused by cardio-respiratory illness (i.e., cardiovascular diseases and respiratory diseases) that according to the public health literature are closely associated with air pollution.

Our sample comprises 315 severe coal mine accidents from 2003 to 2015. This corresponds to 199 coal-producing counties, some of which experienced multiple accidents during the sample period. Our sample also includes 379 coal-producing counties that experienced no accidents with fatalities in the sample period, which we explore in certain empirical specifications as an additional comparison group. By identifying the date of each accident from 2003 to 2015 and the locations of the treated and comparison counties, we match the information on suspensions to our air pollution and weather data at the county-day level. Figure 2 displays the number of severe accidents across different years. The Chinese central government made mining safety a policy priority in the late 2000s so that the number of accidents has decreased since that time.

Table 2 has a summary of the data. The AOD and weather characteristics are at the county-day level. Production values in coal-consuming sectors are at the county-year level. From 2003 to 2015, we have a balanced panel of 578 coal-producing counties comprising 2,744,344 county-day level observations. AOD can be missing when cloud cover is thick or the level of air pollution is extremely high, so there are fewer observations with valid AOD values than weather characteristics.

Column 5 of Panel A in Table 3 presents the mean differences in AOD and weather variables between counties that experience severe accidents that lead to the suspension of coal mining and

those that experience no accidents with a fatality. The t-statistics indicate that the AOD level is higher in counties without an accident and that several weather variables such as the average temperature, sunshine duration, relative humidity, wind speed, and the air pressure also differ between the two subsamples. We therefore directly control for these weather characteristics when estimating the effects of coal mine accidents on AOD. Column 5 of Panel B in Table 3 presents the mean differences in production values in coal-consuming sectors between the two subsamples. Counties experiencing severe accidents have higher production values in coal and electricity sectors but lower production values in the metallic mineral sector and lower total industrial output.

5 Results

In this section, we discuss our empirical findings. We first describe the effect of suspending coal mining after a severe accident on air quality. We demonstrate that our results are not contaminated by potential threats to identification, particularly not by variations in the levels of coal combustion. Next, we present the effect of an accident on all-age mortality. Finally, we calculate the health costs of air pollution induced by coal mining in China.

5.1 The Effects of Coal Mining on Ambient Air Pollution

As discussed in Section 3.1, we identify the causal effect of coal mining on the ambient air quality based on a difference-in-differences framework by comparing counties with a current severe accident to other comparison counties.

Table 4 presents the estimation results of our baseline model (equation (1)). The dependent variable is the AOD on a specific day. We restrict our event window to ± 90 days around each accident date. Each row in the table gives the relative difference in AOD between the treated and comparison groups in a given month (30 days) prior to or following an accident, with the first month chosen as the reference group. Regressions in Panels A and B exploit the timing of accidents for identification. We exploit the later treated counties as the control group in Panel A, whereas we exploit the earlier treated counties as the control group in Panel B. More details of how we build our sample is explained in Section 3.1. They serve as robustness checks for the internal validity of our estimation results. In Panel C, we use all coal-producing counties that experienced no accidents

during the sample period as the comparison group. By doing so, we investigate the external validity of the estimation results. In all specifications, we control for the linear and quadratic terms for weather variables, Chinese holiday dummies, day-of-week dummies and for the fixed effects at the county, province-by-year, and province-by-calendar month levels.

Overall, we find a lagged effect of suspending coal mining on the ambient air quality. Panel A shows that compared with the comparison group, AOD in the treated group is 0.02-0.022 units (though imprecisely estimated), 0.038-0.043 units, and 0.033-0.034 units lower in the first, second, and third months after an accident, respectively. Panel B shows that the AOD in the treated group is 0.024-0.025 units, 0.046-0.047 units, and 0.022-0.023 units (though imprecisely estimated) lower in the first, second, and third months following an accident. In Panel C, we find significant decreases in AOD in the treated group in the second month after an accident. This panel also shows significant decreases in treated-group AOD in the first and third months after an accident, with coefficients having similar magnitudes relative to those in Panels A and B. Within each panel, our results are also robust across various model specifications in which we alternate between county characteristics and county-specific trends. In sum, we find robust evidence that the suspension of coal mining after accidents leads to a significant decrease in the level of AOD in the second month.²⁰

The length of the lag before air pollution levels start to decline is likely a function of inventory held by coal companies. As mentioned in Section 2, the suspension under the current analysis only applies to underground mining, where the risk lies, but not to above-ground activities. If coal companies stock a significant level of inventory, the wind erosion and oxidation of onsite coal stockpiles or their handling will continue generating particulate matter after the suspension of coal mining. With no mining activities, coal inventory and waste stored above ground are not replenished. Over time, emissions from them dissipate.²¹

We probe the inventory explanation for our findings by comparing the end-of-year inventory with monthly sales for coal companies in the treated counties during our sample period (2003 to 2015). Specifically, we calculate the ratio of inventory to monthly sales for the coal mining industry

²⁰We also check whether the impact lasts beyond 3 months by extending our event window to 120 days before and after each accident. The results are reported in Figure 3. We do not find statistically significant lagged impacts in the fourth month following a coalmine accident.

²¹Jha and Muller (2018) find that coal storage in U.S. power plants significantly increases the concentration of PM_{2.5} pollution nearby. The authors argue that the major source of air pollution is wind erosion and oxidation of coal stock and handling of coal stock. We think a similar mechanism applies to coal storage at coalmines.

in the treated counties by using the ASIEC data described in Section 4. Figure 4 displays the distribution of this ratio and the kernel density estimates. The mean is 1.1, and the median is 0.7. These values indicate that the air pollution associated with the coal inventory above ground at our sampled mines may last for approximately one month after an accident, even though regulators have suspended the underground coal mine. This is consistent with our findings of a lagged reduction in the AOD level in the second month after an accident.

In addition to being statistically significant, the estimated improvement in air quality is economically significant. Table 4 shows that suspensions decrease AOD by 0.032-0.06 units in their second month.²² These figures amount to 5.88%-11.03% of the average AOD (0.544 units) in the sample of counties that experience a severe accident.

5.2 Potential Threats to Identification

In this subsection, we discuss possible threats to identification such as different trends in air pollution and the effects of suspensions on local coal users and spillovers to coal consumers in nearby counties. We also conduct a placebo test to examine the effects of accidents on SO_2 levels. SO_2 is not associated with coal mining or storage and therefore should not be influenced by suspensions of mining.

The first potential threat to identification is the existence of any different trends in air pollution between treated and comparison counties prior to accidents. Our baseline results in Table 4 already provide some evidence that this is unlikely to be true. In all specifications across the three panels, we find no significant differences in AOD in the first and second months before an accident between the treated and comparison groups. This finding indicates that the parallel trend assumption holds. To further check the robustness of this assumption, we implement an event-study analysis following Jacobson et al. (1993) in which we expand the pre-treatment period to six months (180 days) prior to an accident. Setting the month immediately before the accident date as the reference point, we examine the relative change in the treated-group AOD in the second to the sixth months before an accident date and in the first to third months after the accident date in one regression.

Table 5 and Figure 5 display the DID coefficients. Panels A to C refer to the results from using

²²We use the point estimate in column (4) of Panel B. We add to (subtract from) it one standard error to calculate the upper (lower) bound.

comparison group A, B and C as in Table 4, respectively. Table 5 and Figure 5 further confirm the parallel trend assumption since the change in AOD for the treated group is not significantly different from that for the comparison group in the second to sixth months before the accident date. As a comparison, we still find significant decreases in treated-group AOD in the second month after the accident date regardless of the comparison group used.

The second identification concern is whether a suspension decreases coal stocks in local coal-burning facilities and in turn reduces air pollution due to less intensive coal combustion. This reduction would bias our estimation results downward. We perform several robustness checks to demonstrate that our results are not driven by changes in the level of coal combustion. First, we regress the first log difference of the production values of electric power and coal production companies on a series of dummy variables that represent coal mine accidents in different years. Table 6 presents these results. D_1 indicates a dummy for the occurrence of an accident in the current year but not the previous year. D_2 indicates the occurrence of an accident in the previous year but not in the current year. D_3 indicates the occurrence of accidents in the current and previous years. The reference group is no accident for two consecutive years. Columns (1)-(3) give the effects on production values of the electric power companies. Columns (4)-(6) show the effects on coal companies. Columns (2) and (5) further control for a vector of time-varying firm characteristics which comprises age, a dummy for state ownership, a dummy for export firms, employment, and the capital-labor ratio. Columns (3) and (6) further control for a vector of time-varying county variables which consists of the lagged production values of coal, nonmetallic minerals, metallic, and electricity industries and lagged total industrial output values. Across all specifications, we find that the occurrence of an accident in the current or previous year significantly decreases the production values of coal companies but has no influence on companies in the electric power sector. These results indicate that coal mine accidents are unlikely to lead to less coal burning by electric power companies that then reduces $PM_{2.5}$.

We also conduct a placebo test to examine the effects of accidents on SO_2 levels. We replace SO_2 as the dependent variable and re-estimate the baseline model (equation (1)). We also define the treated group based on the intensity of coal combustion and match the valid comparison group to further investigate whether our results are contaminated by changes in the level of coal combus-

tion.²³ Table 7 presents these results. Column (1) uses the full sample. In Column (2), we restrict the treated group to counties with electric power generation. In Column (3), we restrict the treated group to counties with both electric power generation and steel production. In addition, we divide all the treated counties into four subsamples based on the quartiles of consumption as a share of coal production. Columns (4)-(7) present the estimated effects of an accident on SO_2 for these four subsamples. We find that compared with the comparison group, SO_2 in the treated group is not significantly different after an accident in most cases. This finding indicates that the suspension generally does not lead to a drop in coal usage in corresponding counties. Our best guess is that given the large production capacity of the coal mining industry, plants can find alternative sources of coal relatively easily in China. The only exception is column (7), where we find SO_2 in the treated group is 0.046 and 0.058 units lower in the second and third months after an accident. Therefore, as another robustness check, we drop the treated counties in the highest quartile of the consumption to production ratio and reestimate the effect of an accident on AOD. Our main results are almost unchanged.²⁴

Third, suspensions may also reduce coal consumption and improve air quality in nearby counties. This improvement in turn may cause a reduction in particulate matter in the counties experiencing accidents due to spatial spillovers of air pollution. To probe whether this channel biases our results, we implement another placebo test in which we examine the spillover effects of coal mine accidents on the daily average SO_2 of nearby counties that burn coal. Our sample consists of Chinese counties with coal-consuming industries. The results are displayed in Table 8. The treated group comprises counties located within a certain distance (50 km for Panel A, 100 km for Panel B, and 200 km for Panel C) from the center of a county that experienced a severe accident. The comparison group comprises counties located within the respective radius around the center of a county that did not experience a severe accident within six months before the accident date but would experience one two years later. In columns (1) - (3) of each panel, we further restrict the comparison group

²³Reduction in coal combustion may be more likely to occur under geographically wider suspension. Based on manually collected information on the geographical range of suspensions, we also examine this concern by dividing our sample into accidents that lead to suspensions of different geographical ranges. We separately focus on treated counties with accidents that result in a suspension for a single mine or that result in suspensions that apply to all or some of the coal mines in the related county, city, or province. Estimating the baseline model with matched controls, we fail to find a significant decrease in SO_2 levels in any of the subsamples, even in treated counties that experienced province-level suspensions. The results are available on request.

²⁴This result is available on request.

to counties that are 200-500 km, 500-700 km, and 700-1000 km away from the treated counties, respectively. Table 8 shows that there are no significant spillover effects on SO_2 from accidents. This evidence suggests that suspending coal mining does not result in less coal combustion in nearby counties.

5.3 The Effects of Coal Mining on All-age Mortality

In this section, we describe the estimated effects of coal mining on all-age mortality that are a part of the economic costs imposed by air pollution. The empirical model we use in the health regressions, shown in equation (3), differs from the one used in the air pollution analyses due to a major difference in the sample size: we are only able to match 16 counties (versus 199 counties in the air pollution regressions) that both have mortality information and that experienced a severe accident.²⁵ The dependent variable is the number of deaths caused by different diseases at the county-day level. We use the Poisson model because it uses count data. More details of the model can be found in subsection 3.2.

Columns (1)-(3) of Table 9 display the event-study estimates of the effect of suspensions on the overall, respiratory (RES), and cardiovascular (CVD) mortality rates for the entire population of a county. Column (2) shows that the RES mortality rate significantly decreases in the third month following an accident (and a suspension) compared with the comparison group. Column (3) shows that the CVD mortality rate also decreases in the third month after an accident, although the coefficient is imprecisely estimated. In subsection 5.1, we find significant decreases in air pollution in the second and third months after a coal mine accident which is consistent with the result that an accident leads to a significant decrease in RES mortality three months later.

This is consistent with the epidemiological literature that finds that the cumulative effects of air pollution on RES mortality are larger than the contemporaneous effects (Braga et al., 2001; Costa et al., 2017). We check the parallel trend assumption for RES mortality. As shown in Figure 6, there is no discernible difference before an accident. We also examine the effect of suspending

²⁵For this reason, we are not able to estimate the causal effect of air pollution on mortality by leveraging coal mine accidents as an instrument for endogenous ambient air pollution. Instead, we check the effect of suspending coal mining on air pollution based on the matched balanced counties and the same econometric model as the health analyses. We find that for the same treated counties that we match with the mortality data, there is a significant drop in the level of AOD in the second month following an accident. This is consistent with the reduction in air pollution as an underlying channel for our mortality results.

coal mining on non-cardiovascular and non-respiratory (non-CVR) mortality as a placebo test. The results in Column (4) show that the estimated coefficients for the effect on non-CVR mortality are not statistically different from zero.

The literature has shown gender may play a role in the effect of air pollution on health, but the findings are not consistent (Clougherty, 2010). We examine the heterogeneous effects of coal mining on all-age mortality rates across genders. The results are displayed in Table 10. In the male subsample, the only significant result is the decrease in the RES mortality rate in the third month after a coalmine accident. For the female subsample, both the RES and CVD mortality rates decrease significantly in the third month following an accident. The estimated effects on RES and CVD mortality rates in the third month for the females have larger magnitudes than those for the males.

These results are consistent with findings in the epidemiology literature that females are more vulnerable to damages from air pollution than males (Chen et al., 2005; Kan et al., 2008). For instance, Chen et al. (2005) find a significant long-term association between the exposure to ambient particular matters and the risk of fatal coronary heart disease for females but not for males. Kan et al. (2008) show that PM10 has a larger impact on daily mortality among females than males. The physiological literature finds greater lung deposition fractions of air pollution particles for females (Kim and Hu, 1998; Jaques and Kim, 2000). The deposition of particular matters in the lung could elicit inflammatory responses (Tamagawa et al., 2008). In addition, Sørensen et al. (2003) find positive associations between PM2.5 exposure and the level of the red blood cell (RBC) only for females, the increase of which could raise the risk for cardiovascular diseases (Lowe et al., 1997). Differences in socioeconomic characteristics such as education levels may contribute to the gender difference in our mortality results as well. Nevertheless, it is an open question beyond the current study.

Examining the mortality of the entire population may hide the effect of changes in air quality associated with coal mining. The literature consistently finds that the elderly are more susceptible to air pollution than healthy adults (Ostro et al., 2006; Tanaka, 2015; Anderson, 2020). We examine the effects of coal mine accidents on the mortality rates of the elderly (aged over 60-years-old).²⁶

²⁶Another vulnerable group typically investigated by the literature is infants. However, our sample size for the health analyses is small and infant mortality is very rare at the daily level. These factors combine to give us a small number of cases for the less frequent outcome when we focus on infants. The statistics literature has long noted that

Table 11 presents the results. The elderly experience a significant drop in RES-related deaths in the third month after an accident.

As we have discussed in subsection 3.2, our results here indicate not only the pollution effect but also the socioeconomic effect. Since our estimate presents a lower bound of the former effect, suspensions may negatively affect population health through socioeconomic factors such as income or employment that is opposite to the effect caused by a lower level of air pollution on health. Our health results present a lower bound of the pollution effect.

5.4 Estimation of the Health Benefits from Coalmine Suspensions

In this subsection, we calculate the health benefits of improved air quality from the suspensions of coal mining by using the estimated effects of coal mine accidents on all-age RES mortality rates obtained in Table 9.²⁷ We calculate the health benefits in 2015 that is the most recent year for which we have the DSP data. The calculation procedures are as follows: first, we calculate the sample average of all-age RES mortality rate for each county in 2015 after excluding the three-month window following an accident. We denote the average daily all-age RES mortality rate in county i as $MortExclAcc_i$ and its population as Pop_i .²⁸ We then calculate the population-weighted average daily all-age RES mortality rate across all counties:

$$AvgMort = \frac{\sum_i MortExclAcc_i \times Pop_i}{\sum_i Pop_i} \quad (4)$$

Second, we compute the annual health benefits from improved air quality due to suspensions of coal mining by using the following formula:

$$Overall\ Health\ Benefit = AvgMort \times (1 - Irr) \times Pop \times 365 \times VSL \quad (5)$$

Irr refers to the estimated incident rate ratio of the all-age RES mortality rate after an accident to the rate before an accident obtained from Table 9 (87.1%). Pop refers to the sample population.

this is a recipe for overestimating the magnitude of an effect, which they term as a “type-M” error. Therefore, we chose not to conduct analyses on infants.

²⁷The underlying assumption is that the estimated reduction in mortality based on the subset of counties in the health analyses can be applied to other coalmining counties.

²⁸We use the 2010 census data for the county-level population that is the most recent census available.

VSL refers to the value of statistical life. Using the 2005 Census data of China, Qin et al. (2013) estimate that the *VSL* was 1.81 million RMB in 2005. Based on this study, Fan et al. (2020) finds that the average *VSL* of in China was around 7.46 million RMB (1.15 million USD) in 2015, which we use for our calculation.

Table 12 presents the estimated health benefits for three different samples. Sample 1 comprises all coal-producing counties in China, sample 2 comprises coal-producing counties that had a severe accident, and sample 3 comprises coal-producing counties that have mortality data from the DSP system.

The upper panel of Table 12 shows that suspending coal mining results in a health benefit that spans 109 to 129 million USD per million people and is consistent across different samples. This consistency indicates that extrapolating our estimated effect of coal mine accidents on all-age mortality to all coal-producing counties may not result in large biases in total health benefits. Suspensions of coal mining led to a total health benefit worth 51 billion USD across all coal-producing counties in 2015. This number is similar in magnitude to the short-term health benefits from replacing coal with natural gas for winter heating (72 billion USD in Fan et al. (2020)) but smaller than the long-term health costs from winter heating in China (266 billion USD in Ebenstein et al. (2017)). We note that the sample size used in the mortality analysis is quite a bit smaller than the air pollution analysis, so the estimates are less precise. Still, given the consistent result that particulate matter is associated with mortality, it is not surprising to find reductions in mortality associated with suspending coal mining.

6 Conclusion

The environmental and health consequences of burning coal are well known and widely studied. To date the air quality effects of coal mining have not received the same attention. We fill this gap by estimating the causal effects of coal mining on ambient air pollution and all-age mortality based on a sample of underground coal mines in China. Our identification strategy leverages the timing of severe accidents that trigger suspensions of mining due to the safety regulations of the Chinese central government. We use a stacked difference-in-differences framework to compare the ambient air pollution and all-age mortality in counties experiencing a coal mine accident with counties that

experience an accident before or after a current accident.

Our results demonstrate a consistent decrease in ambient air pollution in the second month after a suspension. Numerous robustness checks bolster our conclusion that the decrease in air pollution is attributed to a decrease in coal-producing but not coal-burning activities nearby. Our Poisson regression model shows that all-age respiratory mortality decreases in the third month following a coal mine accident. We also find that the females benefit more from the reduction in the air pollution associated with coal mining. Focusing on vulnerable age groups, our results show that mining suspensions are associated with a decrease in respiratory mortality among the elderly. Based on our calculation, coal mining in China generates an annual cost of around 51 billion USD due to premature death.

By showing that there are pollution costs and mortality effects from coal mining, our results quantify a new negative externality associated with coal use. Future calculations of environmental costs of coal use should include these damages. The air pollution benefits of suspensions of underground coal mining are likely from reduced pollution from wind erosion and the handling of coal inventory and the mining waste, *gangue*. This inventory is stored outside the mine on the ground. Enhanced regulation on the storage and management of coal stockpiles and gangue could help reduce the pollution of particulate matter and decrease the health costs from coal mining for local communities.

Given that in the foreseeable future coal will continue to be an important source of energy worldwide, our study has important policy implications for both China and other major coal-producing countries. First, our results indicate that analysis of the social cost of coal should be expanded to include the evaluation of the pollution damages from coal mining. The extant analysis of these damages likely understates the magnitude of the problem. Regulations that manage the handling of coal and the storage of *gangue* to minimize emissions are worth exploring. Second, pollution from coal mining has important equity implications. In China, coal mines are mainly located in the less developed central and western provinces. Worldwide coal is generally mined in locations with lower per-capita incomes as well. Since coal is generally produced in less economically developed regions, the negative external costs of coal mining are primarily imposed on economically disadvantaged groups. Additionally, our result that women experience larger health effects from air pollution caused by coal mining indicates gender inequality in human health capital, which deserves

attention from policymakers.

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Tables

Table 1: Factors that Predict the Timing of Coalmine Accidents

	Panel A: Two years Afterward		Panel B: Two Years Beforehand	
	(1)	(2)	(1)	(2)
Temperature	-8.976*	-8.662	0.008	-0.489
	(5.330)	(5.305)	(4.079)	(4.011)
Sunshine Duration	-1.612	-1.345	2.985	3.237
	(3.729)	(3.755)	(3.205)	(3.186)
Relative Humidity	0.066	-0.450	1.086	0.908
	(2.655)	(2.670)	(2.425)	(2.420)
Wind Speed	-9.851	-8.773	2.408	4.009
	(18.568)	(18.451)	(16.110)	(16.315)
Precipitation	-0.342	-0.479	-0.246	-0.305
	(0.942)	(0.944)	(0.702)	(0.698)
Air Pressure	3.556	3.700	-0.147	-0.011
	(4.235)	(4.205)	(3.759)	(3.733)
Temperature Sq	-0.103	-0.103	0.052	0.052
	(0.116)	(0.115)	(0.107)	(0.106)
Sunshine Duration Sq	0.125	0.119	-0.192	-0.216
	(0.302)	(0.298)	(0.277)	(0.275)
Relative Humidity Sq	-0.013	-0.008	-0.001	0.000
	(0.022)	(0.022)	(0.019)	(0.019)
Wind Speed Sq	0.331	0.329	-0.354	-0.596
	(2.513)	(2.511)	(2.732)	(2.752)
Precipitation Sq	-0.005	-0.002	0.003	0.004
	(0.011)	(0.011)	(0.008)	(0.008)
Air Pressure Sq	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Coal		59.227		-0.706
		(39.986)		(12.217)
Non-metallic		63.936		20.380
		(43.000)		(12.711)
Metallic		-22.998		3.462
		(15.866)		(11.857)
Electricity		-46.678*		-16.766
		(27.157)		(11.163)
Industrial		-22.125		-9.694
		(171.246)		(92.584)
Holiday	-5.997	-6.044	7.615	7.839
	(7.040)	(6.992)	(5.061)	(5.037)
Monday	-0.133	-0.135	-0.310	-0.314
	(0.941)	(0.932)	(0.740)	(0.740)
Tuesday	-0.943	-0.879	-0.407	-0.432
	(0.847)	(0.845)	(0.714)	(0.716)
Wednesday	-0.969	-0.944	-0.581	-0.649
	(0.985)	(0.974)	(0.881)	(0.881)
Thursday	0.096	0.118	-0.191	-0.233
	(0.944)	(0.930)	(0.760)	(0.761)
Friday	1.279	1.313	-1.338*	-1.362*
	(1.048)	(1.035)	(0.766)	(0.761)
Saturday	-1.199	-1.139	-0.266	-0.326
	(0.871)	(0.855)	(0.749)	(0.744)
# of Counties	214	214	219	219
Observations	641127	641127	663951	663951
R squared	0.481	0.486	0.504	0.505

Note: This table reports regression results of equation (2), where we test whether key observable characteristics predict the timing of a coal mine accident with ten or more fatalities among counties that experienced an accident during our sample. We use “later treated counties”, that experience a 10+ fatality accident two or more years after our treated county as the comparison in panel A. “Earlier treated counties”, that experience a 10+ fatality accident two or more years before our treated county are the comparison group in panel B. Key control variables include linear and quadratic climatic variables, annual county-level industrial activities (one-year lagged total value of different sectors and total industrial output), Chinese holiday FE and day-of-week FEs. We also control for the county, province by year, province by calendar month FEs. To make the coefficients easier to read we divide all explanatory variables in this table by 10,000.

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors are reported in the parenthesis.

Table 2: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N	Unit of Obs
Panel A: Counties with coalmine accidents (over 10 deaths)						
Air quality and climatic variables						
AOD	0.544	0.491	-0.05	4.997	320075	County \times Day
SO ₂ (Dobson Units)	0.243	0.727	-4.881	21.121	660951	County \times Day
Temperature (°C)	12.495	11.365	-32.2	36.307	944852	County \times Day
Sunshine Duration (Hours)	5.418	3.999	0	14.7	944852	County \times Day
Relative Humidity (%)	66.282	17.883	7.107	100	944852	County \times Day
Wind Speed (m/s)	2.043	1.082	0	15.24	944852	County \times Day
Precipitation (mm)	2.189	6.634	0	341.567	944852	County \times Day
Air Pressure (hPa)	940.205	58.131	699.205	1042.165	944852	County \times Day
Production values in coal-consuming sectors						
Coal (Billion RMB)	3.603	7.639	0	86.857	2566	County \times Year
Electricity Production (Billion RMB)	0.594	2.094	0	62.991	2566	County \times Year
Metallic (Billion RMB)	2.12	9.255	0	277.852	2566	County \times Year
Non-metallic (Billion RMB)	1.203	4.577	0	119.77	2566	County \times Year
Total Industrial (Billion RMB)	13.946	22.493	0.005	296.355	2566	County \times Year
Panel B: Counties without any coalmine accidents with fatalities						
Air quality and climatic variables						
AOD	0.606	0.559	-0.05	5	664068	County \times Day
SO ₂ (Dobson Units)	0.244	0.772	-9.505	21.121	1290026	County \times Day
Temperature (°C)	12.809	11.385	-41.5	35.644	1799492	County \times Day
Sunshine Duration (Hours)	5.89	3.935	0	15.9	1799492	County \times Day
Relative Humidity (%)	65	18.157	4	100	1799492	County \times Day
Wind Speed (m/s)	2.107	1.056	0	14.9	1799492	County \times Day
Precipitation (mm)	2.173	7.168	0	416.208	1799492	County \times Day
Air Pressure (hPa)	944.529	71.341	638.800	1046.01	1799492	County \times Day
Production values in coal-consuming sectors						
Coal (Billion RMB)	1.057	6.482	0	145.983	4814	County \times Year
Electricity Production (Billion RMB)	0.38	1.232	0	18.855	4814	County \times Year
Metallic (Billion RMB)	2.763	10.782	0	301.675	4814	County \times Year
Non-metallic (Billion RMB)	1.344	4.419	0	91.558	4814	County \times Year
Total Industrial (Billion RMB)	21.761	62.365	0	1785.473	4814	County \times Year

Note: This table summarizes our county-by-day data set. We have a balanced panel of 578 coal-producing counties observed between 2003-2015 for a total sample size of 2,744,344. Among the sample counties, 379 ones experienced no coalmine accidents with fatalities; 199 counties experienced coalmine accidents with 10 or more deaths (resulting in coalmine suspension by mandates). The data for air quality and climatic variables is at the county-day level. Production data for coal-consuming sectors is at the county-year level. Some counties do not have production data in some years in the Annual Survey of Industrial Enterprises of China (ASIEC).

Table 3: Summary Statistics

Variable	Unit	No Incidence	Incidence	No Incidence - Incidence
Panel A: Air quality and climatic variables				
AOD	-	0.606 (0.559)	0.544 (0.491)	0.061*** (0.001)
SO ₂	Dobson Units	0.244 (0.772)	0.243 (0.727)	0.001 (0.001)
Temperature	°C	12.81 (11.39)	12.50 (11.37)	0.313*** (0.014)
Sunshine Duration	Hours	5.890 (3.935)	5.418 (3.999)	0.472*** (0.005)
Relative Humidity	%	65.00 (18.16)	66.28 (17.88)	-1.282*** (0.023)
Wind Speed	m/s	2.107 (1.056)	2.043 (1.082)	0.065*** (0.001)
Precipitation	mm	2.173 (7.168)	2.189 (6.634)	-0.015 (0.009)
Air Pressure	hPa	944.5 (71.34)	940.2 (58.13)	4.324*** (0.085)
Panel B: Production values in coal-consuming sectors				
Coal	Billion RMB	1.057 (6.482)	3.603 (7.639)	-2.546*** (0.169)
Electricity	Billion RMB	0.380 (1.232)	0.594 (2.094)	-0.214*** (0.039)
Metallic	Billion RMB	2.763 (10.78)	2.120 (9.255)	0.643* (0.251)
Non-metallic	Billion RMB	1.344 (4.419)	1.203 (4.577)	0.141 (0.109)
Total Industrial	Billion RMB	21.76 (62.36)	13.95 (22.49)	7.815*** (1.273)

Note: This table summarizes our county-by-day data set. We have a balanced panel of 578 coal-producing counties observed between 2003-2015 for a total sample size of 2,744,344. Among the sample counties, 379 experienced no coalmine accidents with fatalities; 199 counties experienced coalmine accidents with 10 or more deaths resulting in coalmine suspension by mandates. The air quality and climatic data is at the daily level. Production data for coal-consuming sectors is measured annually. Column 4 reports the mean differences between the two groups, and the standard errors from the t-test that the means are equal in the comparison and treatment groups. Stars indicate the significance levels from the t-tests. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Baseline Estimation: AOD Levels

	Panel A: Two Years Afterward				Panel B: Two Years Beforehand				Panel C: Counties with no accidents			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Treated	0.012 (0.011)	0.011 (0.011)	0.021* (0.012)	0.021* (0.012)	0.009 (0.010)	0.010 (0.010)	0.005 (0.011)	0.005 (0.011)	-0.012 (0.013)	-0.012 (0.013)	-0.006 (0.013)	-0.006 (0.013)
Treated $\times (-60, -30]$	-0.010 (0.012)	-0.010 (0.012)	-0.007 (0.012)	-0.007 (0.012)	-0.013 (0.013)	-0.013 (0.013)	-0.012 (0.013)	-0.012 (0.013)	-0.020 (0.013)	-0.020 (0.013)	-0.014 (0.014)	-0.014 (0.014)
Treated $\times (-30, -0]$	-0.014 (0.013)	-0.014 (0.013)	-0.013 (0.013)	-0.013 (0.013)	-0.017 (0.014)	-0.017 (0.014)	-0.019 (0.014)	-0.019 (0.014)	-0.023* (0.012)	-0.023* (0.012)	-0.012 (0.013)	-0.012 (0.013)
Treated $\times (0, 30]$	-0.020 (0.013)	-0.021 (0.013)	-0.022 (0.014)	-0.022 (0.014)	-0.025* (0.014)	-0.025* (0.014)	-0.024* (0.014)	-0.024* (0.014)	-0.045*** (0.013)	-0.045*** (0.013)	-0.032** (0.014)	-0.032** (0.014)
Treated $\times (30, 60]$	-0.038*** (0.013)	-0.038*** (0.013)	-0.043*** (0.014)	-0.043*** (0.014)	-0.047*** (0.014)	-0.047*** (0.014)	-0.046*** (0.014)	-0.046*** (0.014)	-0.045*** (0.013)	-0.045*** (0.013)	-0.032** (0.015)	-0.032** (0.015)
Treated $\times (60, 90]$	-0.033** (0.014)	-0.033** (0.014)	-0.034** (0.015)	-0.034** (0.015)	-0.023 (0.015)	-0.023 (0.015)	-0.022 (0.015)	-0.022 (0.015)	-0.037*** (0.014)	-0.037*** (0.014)	-0.016 (0.017)	-0.016 (0.017)
(-90, -60]	0.008 (0.015)	0.008 (0.015)	0.008 (0.015)	0.008 (0.015)	0.019 (0.020)	0.019 (0.020)	0.018 (0.019)	0.018 (0.019)	0.010 (0.019)	0.010 (0.019)	0.010 (0.019)	0.010 (0.019)
(-60, -30]	0.002 (0.015)	0.002 (0.015)	0.001 (0.014)	0.001 (0.014)	0.017 (0.017)	0.017 (0.017)	0.016 (0.017)	0.016 (0.017)	0.008 (0.018)	0.008 (0.018)	0.007 (0.018)	0.007 (0.018)
(-30, -0]	-0.009 (0.014)	-0.008 (0.014)	-0.009 (0.014)	-0.008 (0.014)	0.009 (0.015)	0.009 (0.015)	0.009 (0.015)	0.009 (0.015)	0.001 (0.018)	0.001 (0.018)	0.001 (0.018)	0.001 (0.018)
(0, 30]	-0.007 (0.015)	-0.007 (0.015)	-0.006 (0.015)	-0.006 (0.015)	0.018 (0.016)	0.018 (0.016)	0.017 (0.016)	0.017 (0.016)	0.002 (0.017)	0.002 (0.017)	0.002 (0.017)	0.002 (0.017)
(30, 60]	-0.005 (0.015)	-0.005 (0.015)	-0.005 (0.015)	-0.005 (0.015)	0.024 (0.017)	0.024 (0.017)	0.023 (0.017)	0.023 (0.017)	0.004 (0.019)	0.004 (0.019)	0.004 (0.019)	0.004 (0.019)
(60, 90]	-0.005 (0.015)	-0.005 (0.015)	-0.005 (0.014)	-0.005 (0.014)	0.002 (0.017)	0.002 (0.017)	0.002 (0.016)	0.002 (0.016)	-0.001 (0.019)	-0.001 (0.019)	-0.002 (0.019)	-0.002 (0.019)
Weather variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province \times year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Province \times month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County characteristics	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
County specific trends	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
# of counties	214	214	214	214	219	219	219	219	542	542	542	542
Observations	387,938	387,938	387,938	387,938	431,081	431,081	431,081	431,081	1,179,933	1,179,933	1,179,933	1,179,933
R-squared	0.409	0.409	0.412	0.412	0.399	0.399	0.401	0.401	0.414	0.414	0.417	0.417

Note: The dependent variable is daily mean AOD in a Chinese county. In panel A and B, we confine our sample to coal-producing counties which experience with accidents of 10 or more fatalities (we call it a severe accident). For an accident j that occurred at date t_j , we define as treated the county where accident j occurred. We select as controls the counties that experienced an accident but after date $t_j + \Delta$ in panel A, or those that experienced an accident but before date $t_j - \Delta$ in panel B. We set Δ to be 2 years. In panel C, we choose coal-producing counties that experienced no severe accidents as the comparison group. We confine our sample period to a short time window (day -90 to day 90) around date t_j for both the treated and comparison groups for accident j . Our estimating sample consists of observations of all accidents pooled together. The window of days (-90 to -60) relative to the accident date is the reference category and omitted from regressions. In all specifications, we control for level and quadratic terms of daily weather conditions (average temperature, sunshine duration, average relative humidity, average wind speed, precipitation, and average air pressure), dummies for Chinese holidays and days of the calendar week, and the county, province-by-year and province-by-calendar-month fixed effects. The columns show the results of specifications that alternate in terms of the inclusion of county characteristics and county-specific trends. County characteristics include the log of 1 plus one-year lagged coal/nonmetallic minerals/steel/electricity/industrial production values at the county level. For panel A and B, a county may switch treatment status across different accidents, so the treated dummy is not absorbed by the county fixed effects. However, for panel C, the treated dummy, is absorbed by the county fixed effects since neither the treated nor the control counties switch treatment status across time. Standard errors clustered at the accident level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Examining Pre-trends in AOD

	Panel A: Two Years Afterward		Panel B: Two Years Beforehand		Panel C: No Accidents	
	(1)	(2)	(1)	(2)	(1)	(2)
Treated \times (-180, -150]	-0.005 (0.013)	-0.005 (0.013)	-0.002 (0.015)	-0.002 (0.015)	-0.002 (0.013)	-0.002 (0.013)
Treated \times (-150, -120]	-0.004 (0.014)	-0.004 (0.014)	-0.009 (0.015)	-0.009 (0.015)	-0.006 (0.014)	-0.006 (0.014)
Treated \times (-120, -90]	0.007 (0.014)	0.007 (0.014)	0.000 (0.016)	0.000 (0.016)	0.001 (0.014)	0.001 (0.014)
Treated \times (-90, -60]	0.013 (0.013)	0.013 (0.013)	0.011 (0.014)	0.011 (0.014)	0.011 (0.012)	0.011 (0.012)
Treated \times (-60, -30]	0.003 (0.012)	0.003 (0.012)	0.003 (0.012)	0.003 (0.012)	0.004 (0.012)	0.004 (0.012)
Treated \times (0, 30]	-0.007 (0.012)	-0.007 (0.012)	-0.007 (0.014)	-0.007 (0.014)	-0.007 (0.012)	-0.007 (0.012)
Treated \times (30, 60]	-0.024** (0.012)	-0.024** (0.012)	-0.029** (0.015)	-0.029** (0.015)	-0.027** (0.012)	-0.027** (0.012)
Treated \times (60, 90]	-0.017 (0.013)	-0.017 (0.013)	-0.003 (0.014)	-0.003 (0.014)	-0.015 (0.014)	-0.015 (0.014)
Weather variables	Yes	Yes	Yes	Yes	Yes	Yes
Holiday FE	Yes	Yes	Yes	Yes	Yes	Yes
Day-of-week FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Province \times year FE	Yes	Yes	Yes	Yes	Yes	Yes
Province \times month FE	Yes	Yes	Yes	Yes	Yes	Yes
County characteristics	No	Yes	No	Yes	No	Yes
# of counties	214	214	219	219	542	542
Observations	586,484	586,484	654,379	654,379	3,625,318	3,625,318
R-squared	0.405	0.405	0.397	0.397	0.402	0.402

Note: This table reports regression results for the effects of coal mining suspensions on the level of AOD based on an event-study analysis following the methods of Jacobson et al. (1993). Our method of constructing the sample in panels A, B and C are the same as in Table 4. The month before the accident is the reference category and omitted from the regressions. All specifications include daily climatic variables and their quadratic terms, Chinese holiday FE, day-of-week FE, county FE, province-by-year FE, and province-by-calendar-month FE. The specifications alternate the inclusion of county characteristics (i.e., the log of 1 plus one-year lagged coal/nonmetallic minerals/steel/electricity/industrial production values at the county level) as controls. The coefficients for the indicators for the τ th month relative to the accident date, M_{ict}^τ , are not reported to conserve space. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Event Study: Production Values of the Electricity and Coal-mining Firms

	Electric Power				Coal	
	(1)	(2)	(3)	(4)	(5)	(6)
D ₁	-0.077 (0.062)	-0.074 (0.062)	-0.073 (0.061)	-0.144*** (0.042)	-0.145*** (0.042)	-0.127*** (0.040)
D ₂	-0.005 (0.056)	-0.002 (0.056)	-0.002 (0.055)	-0.089** (0.040)	-0.089** (0.039)	-0.097** (0.038)
D ₃	0.006 (0.190)	0.016 (0.185)	-0.005 (0.187)	0.187 (0.158)	0.187 (0.158)	0.154 (0.149)
Firm characteristics	No	Yes	Yes	No	Yes	Yes
County characteristics	No	No	Yes	No	No	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Province×year FE	Yes	Yes	Yes	Yes	Yes	Yes
# of firms	1,622	1,622	1,622	8,865	8,865	8,865
Observations	8,769	8,769	8,769	39,322	39,322	39,322
R-squared	0.000	0.003	0.018	0.003	0.003	0.017

Note: This table reports results of a regression of log-first-differences of firm-level annual production values of electric power and coal firms against a set of dummy variables indicating the occurrence of coalmine accidents. The production data comes from the Annual Surveys of Industrial Enterprises in China (ASIEC). D₁ is a dummy for the occurrence of a coalmine accident in the current year but not the prior year in the respective county; D₂ represents a dummy for the occurrence of a coalmine accident in the prior year but not the current year in the respective county; D₃ represents a dummy for the occurrence of a coalmine accident in two consecutive years. The scenario of no accidents in two consecutive years is the reference and omitted from the regression. Specifications alternate in terms of whether firm characteristics (age, dummy for state ownership, dummy for exporters, employment, capital-labor ratio) and county characteristics (the lagged production values of coal/nonmetallic minerals/metallic/electricity industries and the lagged total industrial output values) are included. Firm fixed effects and province-by-year fixed effects are included in all specifications. The standard errors are clustered at the county level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Placebo Tests using SO₂: Local Coal Consumption

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Consumption-Production Ratio (Coal)						
	Full	Power	Power+Steel	<25%	[25%, 50%)	[50%, 75%)	>75%
Treated	0.005 (0.017)	-0.005 (0.030)	0.010 (0.037)	0.052 (0.063)	-0.034 (0.065)	-0.074* (0.040)	0.041 (0.048)
Treated × (0, 30]	-0.002 (0.014)	0.025 (0.022)	0.016 (0.027)	0.026 (0.025)	-0.040 (0.033)	-0.037 (0.024)	-0.002 (0.033)
Treated × (30, 60]	-0.007 (0.015)	0.030 (0.022)	-0.015 (0.028)	0.020 (0.029)	0.006 (0.038)	-0.042 (0.028)	-0.046* (0.026)
Treated × (60, 90]	-0.006 (0.017)	0.011 (0.026)	-0.048 (0.036)	-0.004 (0.040)	-0.007 (0.034)	0.008 (0.039)	-0.058** (0.027)
# of counties	180	93	72	132	124	123	138
Observations	508663	221479	155218	113772	112624	101943	180324
R squared	0.019	0.022	0.022	0.022	0.022	0.019	0.021

Note: The dependent variable is daily mean SO₂ in a Chinese county. *Treated* is a dummy variable for the county where a severe accident occurred. Our way of creating the comparison group is the same as that in Panel A of Table 4. We include as controls daily climatic variables (average temperature, sunshine duration, average relative humidity, average wind speed, precipitation, and average air pressure) and their quadratic terms, Chinese holiday dummies, day-of-week dummies, county characteristics (i.e., the log of 1 plus coal/nonmetallic minerals/steel/electricity/industrial production values at the county level) and county-specific trends. We also control for the county, province-by-year, province-by-calendar-month fixed effects. The first column represent the full sample result. Columns (2)-(7) alternate in the way that we restrict the treated counties based on the intensity of local coal consumption. In column (2), we restrict the treated counties to the ones with electric power generation. In column (3), we select among treated counties the ones with both electric power generation and steel production. We also rank the treated counties based on coal consumption as a share of coal production, and then separate them into quartiles. Columns (3)-(7) present the results based on subsamples of the 1st to 4th quartiles. The coefficients for the indicators of the τ th month relative to the accident date, M_{ict}^τ , are not reported to conserve space. Standard errors clustered at the accident level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Placebo Tests using SO₂: Spillover Effects

	Panel A: Radius of 50 km			Panel B: Radius of 100 km			Panel C: Radius of 200 km		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Treated	0.007 (0.010)	0.013 (0.009)	0.008 (0.012)	0.003 (0.007)	0.008 (0.007)	0.000 (0.009)	0.005 (0.005)	0.007 (0.005)	-0.002 (0.008)
Treated × (0, 30]	-0.006 (0.014)	-0.021 (0.017)	-0.007 (0.016)	-0.01 (0.010)	-0.018 (0.012)	-0.009 (0.013)	-0.007 (0.008)	-0.013 (0.010)	-0.007 (0.011)
Treated × (30, 60]	-0.005 (0.015)	-0.001 (0.018)	0.013 (0.016)	0.008 (0.011)	0.006 (0.014)	0.019 (0.013)	0.007 (0.008)	0.006 (0.011)	0.019 (0.011)
Treated × (60, 90]	0.022 (0.017)	0.021 (0.023)	0.012 (0.022)	0.011 (0.012)	0.004 (0.018)	-0.002 (0.018)	0.008 (0.009)	0.002 (0.014)	-0.002 (0.015)
# of counties	484	481	481	1101	1103	1103	1902	1903	1902
Observations	2426249	1328088	2471148	5984769	3895379	6403553	10941403	8777569	12376875
R squared	0.022	0.015	0.016	0.019	0.014	0.015	0.019	0.015	0.014

Note: The dependent variable is daily average SO₂ concentration in a Chinese county with coal-consuming industries. For a severe coalmine accident j occurring at date t_j , we select as the treated group the counties that are located within a particular radius (50 km for panel A, 100 km for panel B, and 200 km for panel C) around the center of the county that experienced accident j ; we select the comparison group from counties located within the respective radius around the center of counties that would have a severe accident two years after t_j . In columns (1) - (3) of each panel, we further restrict the comparison counties to those that are 200-500 km, 500-700 km and 700-1000 km away from the treated counties, respectively. *Treated* is a dummy variable for the treated group. Besides the treated dummy and the relative-time-window dummy variables, we also include the interactions of the two, daily weather variables (average temperature, sunshine duration, average relative humidity, average wind speed, precipitation, and average air pressure) and their quadratic terms, Chinese holiday dummies, day-of-week dummies, county characteristics (i.e., the log of 1 plus coal/nonmetallic minerals/steel/electricity/industrial production values at the county level) and province-specific trends. We also control for the county, the province-by-year, and the province-by-calendar-month fixed effects. The coefficients of the indicators for the τ th month relative to the accident date, M_{ict}^τ , are not reported to conserve space. Standard errors clustered at the accident level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: The Effects of Coalmine Suspension on Disease-Specific All-age Mortality

	All-cause (1)	RES (2)	CVD (3)	Non-CVR (4)
Day (0, 30]	0.008 (0.038)	-0.062 (0.070)	0.017 (0.044)	0.030 (0.036)
Day (30, 60]	-0.038 (0.079)	-0.010 (0.104)	-0.077 (0.103)	-0.009 (0.071)
Day (60, 90]	-0.093 (0.078)	-0.138** (0.061)	-0.156 (0.108)	-0.016 (0.069)
# of Counties	605	605	605	605
Observations	1150942	1150942	1150942	1150942

Note: This table reports the estimated effects of coal mining suspension on disease-specific mortality in an event study analysis. The dependent variable is mortality in a Chinese coal-producing county on a specific day. Each column reports a Poisson model for a specific type of mortality: all-cause (excluding injury), respiratory (RES) diseases, cardiovascular (CVD) diseases, and non-cardiovascular and non-respiratory (Non-CVR) deaths (excluding injury). Other control variables include daily climatic variables (average temperature, sunshine duration, average relative humidity, average wind speed, precipitation, average air pressure) and their quadratic terms, Chinese holiday dummies, day-of-week dummies, county characteristics (i.e., the log of 1 plus coal/nonmetallic minerals/steel/electricity/industrial production values at the county level). We also control for the county FEs, year FEs and calendar month FEs. Standard errors clustered at the accident level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: The Effects of Coalmine Suspension on Disease-Specific All-age Mortality: by Gender

	Male				Female			
	All-cause (1)	RES (2)	CVD (3)	Non-CVR (4)	All-cause (5)	RES (6)	CVD (7)	Non-CVR (8)
Day (0, 30]	0.042 (0.044)	0.006 (0.085)	0.057 (0.058)	0.044 (0.041)	-0.043 (0.037)	-0.162 (0.103)	-0.035 (0.041)	0.005 (0.075)
Day (30, 60]	-0.020 (0.078)	0.047 (0.127)	-0.056 (0.104)	-0.010 (0.068)	-0.066 (0.089)	-0.095 (0.112)	-0.104 (0.107)	-0.006 (0.087)
Day (60, 90]	-0.064 (0.072)	-0.113* (0.062)	-0.110 (0.107)	-0.006 (0.062)	-0.139 (0.090)	-0.176** (0.071)	-0.215* (0.117)	-0.033 (0.093)
# of Counties	605	605	605	605	605	605	605	605
Observations	1150942	1150942	1150942	1150942	1150942	1150942	1150942	1150942

Note: This table reports the estimated effects of coal mining suspension on disease-specific mortality by gender using an event study analysis. The dependent variable is mortality in a Chinese coal-producing county on a specific day. Each column reports results from a Poisson model for a specific type of mortality: all-cause (excluding injury), respiratory (RES) diseases, cardiovascular (CVD) diseases, and non-cardiovascular and non-respiratory (Non-CVR) deaths (excluding injury) for a single gender. Other control variables include daily weather variables (average temperature, sunshine duration, average relative humidity, average wind speed, precipitation, average air pressure) and their quadratic terms, Chinese holiday dummies, day-of-week dummies, county characteristics (i.e., the log of 1 plus coal/nonmetallic minerals/steel/electricity/industrial production values at the county level). We also control for the county FEs, year FEs and calendar month FEs. Standard errors clustered at the accident level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: The Effects of Coalmine Suspension on Disease-Specific Mortality: the elderly

	All-cause (1)	RES (2)	CVD (3)	Non-CVR (4)
Day (0, 30]	0.001 (0.037)	-0.085 (0.072)	0.016 (0.041)	0.032 (0.035)
Day (30, 60]	-0.034 (0.078)	-0.033 (0.113)	-0.080 (0.097)	0.028 (0.075)
Day (60, 90]	-0.103 (0.073)	-0.128** (0.063)	-0.161 (0.101)	-0.015 (0.067)
# of Counties	605	605	605	605
Observations	1150942	1150942	1150942	1150942

Note: This table reports the estimated effect of coal mining suspension on disease-specific mortality for the elderly (age>60) using an event study analysis. The dependent variable is mortality at a Chinese coal-producing county on a specific day. The dependent variable is mortality in a Chinese coal-producing county on a specific day. Each column reports results from a Poisson model for a specific type of mortality: all-cause (excluding injury), respiratory (RES) diseases, cardiovascular (CVD) diseases, and non-cardiovascular and non-respiratory (Non-CVR) deaths (excluding injury). Other control variables include daily weather variables (average temperature, sunshine duration, average relative humidity, average wind speed, precipitation, average air pressure) and their quadratic terms, Chinese holiday dummies, day-of-week dummies, and county characteristics (i.e., the log of 1 plus coal/nonmetallic minerals/steel/electricity/industrial production values at the county level). All specifications include county FEs, year FEs and calendar month FEs. Standard errors clustered at the accident level are shown in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Imputed health benefits for coal mining counties from improved air quality (unit: billion USD)

Health benefit per million people	
Sample 1: all coal mining counties	0.110
Sample 2: counties with coalmine accidents with 10+ deaths	0.129
Sample 3: coal mining counties with DSP data	0.110
Total health benefit	
Sample 1: all coal mining counties	51.234
Sample 2: counties with coalmine accidents with 10+ deaths	10.914
Sample 3: coal mining counties with DSP data	11.720

Note: This table presents the estimated health benefits from coalmine production suspension for three samples of counties. Sample 1 includes all coal mining counties in China. Sample 2 includes coal producing counties with coalmine accidents with ten deaths or more. Sample 3 includes coal mining counties covered by the Disease Surveillance Point (DSP) system.

Figures

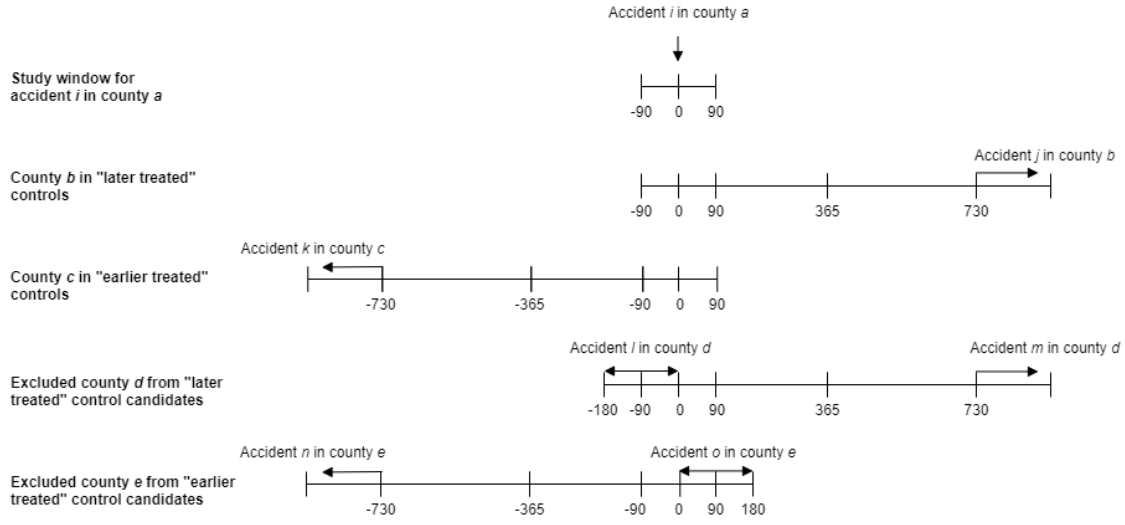


Figure 1: Data Construction for the Environmental Effect Analysis

Note: Our estimating sample for the empirical analysis shown in equation (1) consists of panels of all accidents (± 90 days around an accident for the treated and controls) pooled together. This figure shows how we construct our sample for a particular accident, accident i , occurring at county a . The first row shows the event window for accident i . County a is the treated county. The second row illustrates an example of "later treated" counties, county b , which experiences an accident two years after the date of accident i . The third row shows an example of "earlier treated" counties, county c , which experiences an accident two years before the date of accident i . Given that a county may experience a severe accident multiple times during our sample period, if a "later treated" ("earlier treated") control county also experiences an accident shortly before (after) the date of accident i , it will not be used as a control. Row 4 and 5 shows how we exclude those inappropriate controls from our estimation sample.

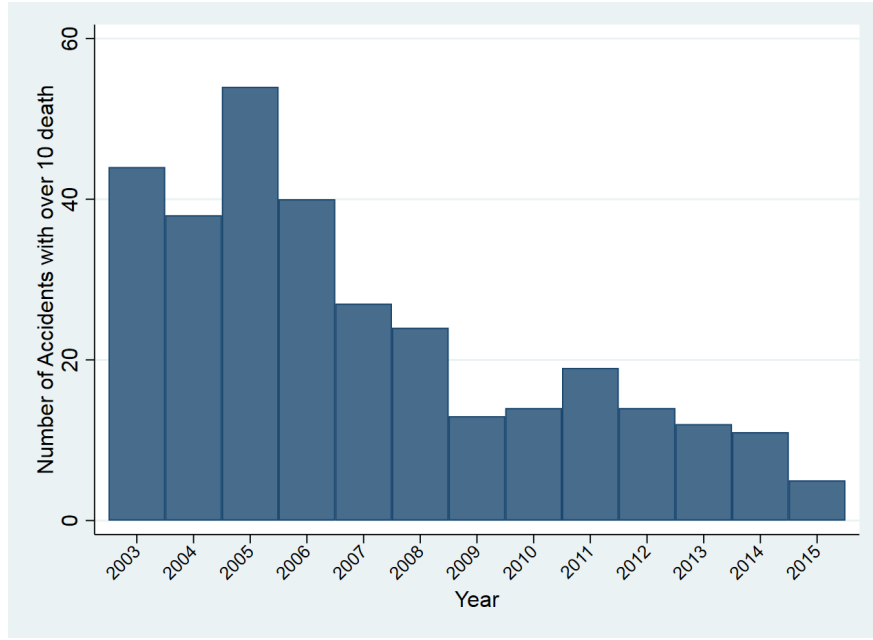


Figure 2: Distribution of Coalmine Accidents across Years (2003-2015) in China

Note: This figure reports the frequency of accidents with 10 or more deaths that result in coal mining activity suspensions by year.

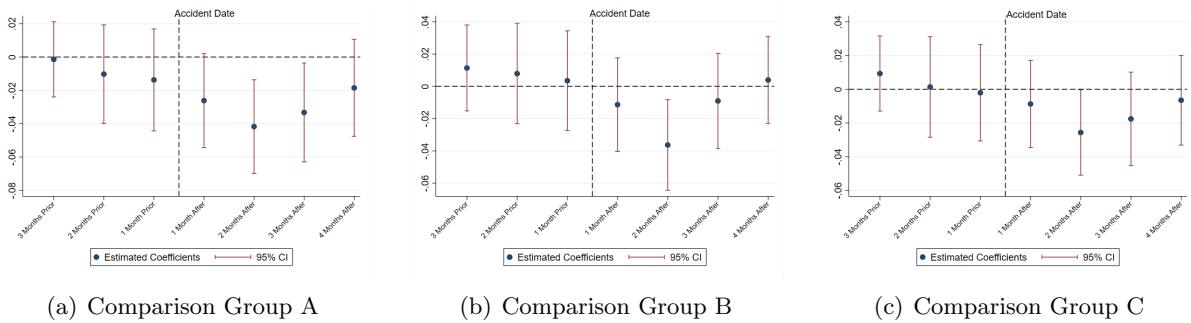


Figure 3: Robustness Checks on the Event Window: Day -120 to Day 120

Note: The figures here plot the effect of coal mining suspensions on the level of AOD based on equation 1 with an extended event window (day -120 to day 120). In panel A, counties that experienced no 10+ fatality coalmine accidents within the six months before the accident date, but would have 10+ fatality accidents two years afterwards are set as the comparison group. In panel B, counties that experienced no 10+ fatality coalmine accidents within the six months after the accident date, but had 10+ fatality accidents two years before are set as the comparison group. In panel C, we choose coal-producing counties that experienced no coalmine accidents as the comparison group. The x -axis represents the relative month (30 days) to the treatment date. Day -120 to day -90 is the reference category and omitted from regressions.

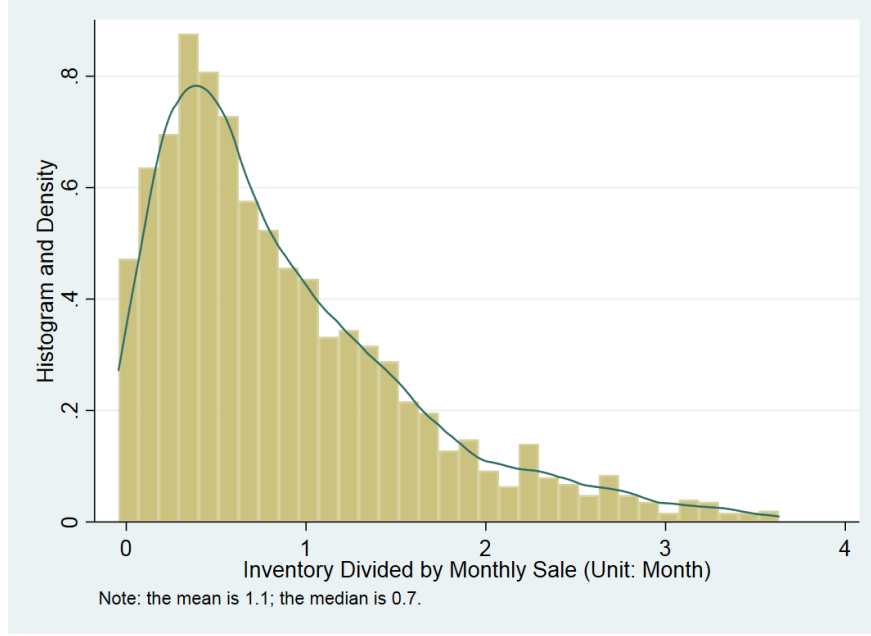


Figure 4: Inventory of Coal Firms in Treated Counties

Note: We compare end-of-year coal inventory with monthly sale of coal in the treated counties of our sample during 2003-2015. The data comes from the ASIEC, a large-scale enterprise survey conducted by the Chinese National Bureau of Statistics (NBS) which covers all state-owned enterprises and other types of enterprises with annual sales above the threshold of five million RMB. Focusing on the coal mining industry, we aggregate both the inventory and sale data to the county level and calculate the statistics of inventory as a share of monthly sale. The figure shows the distribution of the statistics and the kernel density estimates. The mean is 1.1 and the median is 0.7. For scaling, observations above the 95th percentile are dropped.

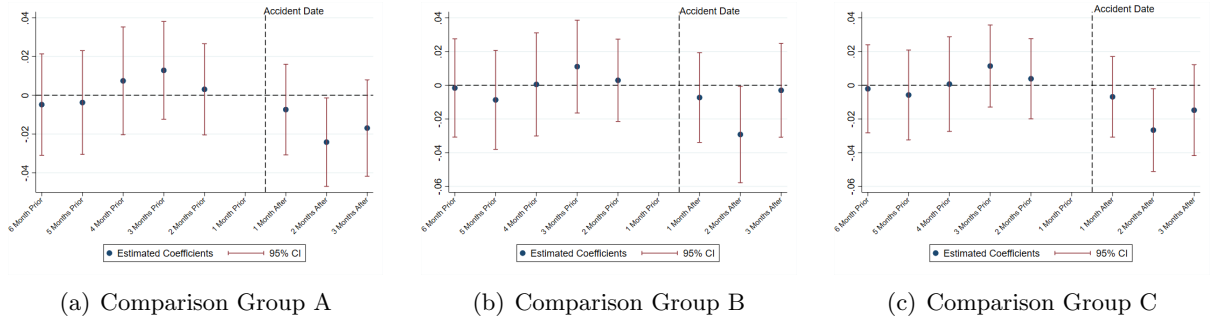


Figure 5: Tests for Parallel Pre-trends in AOD

Note: The figures plot the effect of coal mining suspensions on the level of AOD based on an event-study analysis following the methods of Jacobson et al. (1993). Compared to the baseline model in Table 4, we extended the pre-treatment periods to 180 days before the date of the accident. In panel A, counties that experienced no 10+ fatality coalmine accidents within the six months before the accident date, but would have 10+ fatality accidents two years afterwards are set as the comparison group. In panel B, counties that experienced no 10+ fatality coalmine accidents within the six months after the accident date, but had 10+ fatality accidents two years before are set as the comparison group. In panel C, we choose coal-producing counties that experienced no coalmine accidents as the comparison group. The x -axis presents the month relative to the date of the accident. The first month prior to the accident date is set as the reference category and omitted. We also control for daily climatic variables and their quadratic terms, county characteristics, Chinese holiday FE, day-of-week FE, county FE, province by year FE, and province by calendar month FE.

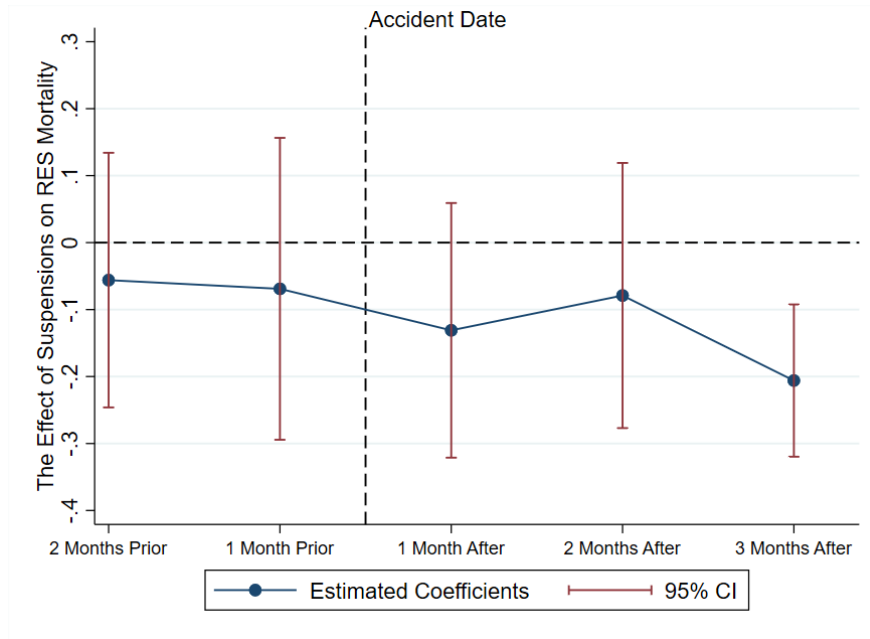


Figure 6: Test for Parallel Trends in All-age RES Mortality

Note: The figures plot the effect of coal mining suspensions on all-age mortality due to RES diseases based on an event-study analysis following the methods of Jacobson et al. (1993). The x -axis presents the month (30 days) relative to the accident date. Day -90 to day -60 is set as the reference category and omitted from the regression. We also control for daily climatic variables and their quadratic terms, county characteristics, Chinese holiday FE, day-of-week FE, year FE, calendar month FE and county FE.

Appendix A1: Extra Tests for the Exogeneity of Accident Timing

To choose the proper empirical strategy, we first examine whether coalmine accidents are correlated with county characteristics. We test whether county characteristics predict the likelihood of an accident with 10 or more deaths for each year between 2003-2015. We conduct a series of cross-sectional analyses for all coal producing counties in China by estimating the following equation:

$$Accident_i = \alpha + \gamma \cdot Controls_i + \eta_i \quad (6)$$

where $Accident_i$ is an indicator that county i experienced an accident with at least 10 fatalities in a given year. $Controls_i$ is a vector of annual county characteristics in the previous year, such as the log value of total industrial output, the log production values for coal-related sectors (coal mining, electricity, metallic minerals, and nonmetallic minerals), climatic conditions (the median values of temperature, wind speed and precipitation) and ambient air pollution (the median, minimum and maximum of AOD). Panel A of Table 13 shows that some variables consistently predict the probability of an accident across different sample years.

$$Timing_i = \alpha + \gamma \cdot Controls_i + \varepsilon_i \quad (7)$$

Next, we investigate whether local characteristics predict the timing of an accident conditional on the occurrence. One approach is to estimate the equation (2) shown in Section 4 in the main text. Additionally, following Deshpande and Li (2019), we also test whether local characteristics predict the year in which an accident will take place. We restrict our sample to counties that experienced at least one coalmine accident with 10+ deaths and estimate equation (7). The dependent variable, $Timing_i$, is the year in which county i experienced an accident. The results are documented in Panel B of Table 13. We can see that no observable characteristic consistently predicts the timing of an accident conditional on an accident taking place during the sample period. This evidence indicates that none of the factors that predict the existence of major accidents are effective at predicting their timing. We take it as suggestive that the timing of accidents is essentially random.

Table 13: Factors that Predict the Occurrence or Timing of Coalmine Accidents

	Panel A: Probability of Accident			Panel B: the Year of Accident		
	(1)	(2)	(3)	(1)	(2)	(3)
	2003	2008	2013	2003	2008	2013
Area	-0.013 (0.012)	-0.011 (0.008)	-0.004* (0.002)	-0.223 (0.167)	2.226* (1.160)	-1.478 (0.906)
Coal	0.020*** (0.002)	0.011*** (0.001)	0.003*** (0.001)	0.016 (0.063)	0.069 (0.073)	-0.136 (0.136)
Electricity	0.006** (0.003)	0.002 (0.002)	-0.000 (0.001)	-0.008 (0.042)	-0.046 (0.037)	-0.016 (0.043)
Industrial	0.001 (0.008)	0.003 (0.006)	0.002 (0.004)	-0.194 (0.204)	0.083 (0.206)	-0.022 (0.274)
Temperature	-0.004 (0.004)	0.003 (0.002)	-0.000 (0.001)	0.141 (0.098)	0.045 (0.089)	0.050 (0.063)
Wind	-0.010 (0.020)	0.033* (0.018)	0.021** (0.010)	0.282 (0.543)	0.446 (0.507)	0.049 (0.735)
Precipitation	0.235*** (0.090)	0.456*** (0.130)	0.050** (0.024)	-0.403 (1.589)	2.029 (1.860)	-1.129 (1.772)
Median AOD	0.032 (0.128)	-0.109* (0.063)	-0.063 (0.039)	-5.157* (2.876)	0.583 (2.976)	0.392 (1.847)
Max AOD	-0.019 (0.017)	-0.006 (0.010)	0.003 (0.007)	-0.054 (0.363)	-0.491 (0.419)	-0.403 (0.302)
Min AOD	-0.348 (0.292)	0.056 (0.173)	0.140 (0.093)	4.123 (6.198)	1.982 (5.294)	-0.818 (5.421)
N	967	1032	950	182	90	21
R squared	0.101	0.084	0.024	0.059	0.140	0.525

Note: Panel A presents the regression results from equation (6) where we test whether a set of county characteristics can predict the occurrence of a coalmine accident. The sample is all coal-producing counties in China and the dependent variable is whether a county experienced a coalmine accident with ten or more fatalities in or after the year shown in the column heading. Panel B presents the regression results from (7) where the timing of an accident is regressed against a set of potential predictive county characteristics. The sample is counties that ever experienced an accident in or after the year shown in the column heading. The dependent variable in panel B is the year of an accident. For counties that experienced multiple accidents, we select the timing of the first accident. ***, **, and * represent 1%, 5%, and 10% significance levels, respectively. Robust standard errors are reported in parentheses.

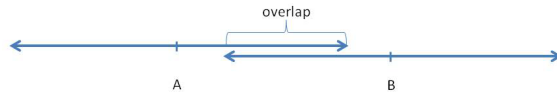
Appendix A2: Overlap of Accidents

A2.1 Overlap of Event Windows between Multiple Accidents

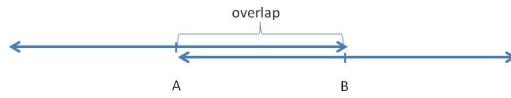
A2.1.1 Multiple Accidents within a County

Some counties experience multiple accidents at coal mines that involve over 10 deaths in our sample. These multiple accidents may lead to overlaps of event windows (day -90 to day 90) within which we compare air quality between the comparison and treated counties before and after suspensions as shown by equation (1). If two accidents are sufficiently distant away from each other (more than 180 days), we keep both accidents as separate events around which we build data with matched controls. If the timing difference between two accidents is close enough (less than 180 days), the issue of overlapping event windows arises. Here we discuss in detail how we handle the overlapping windows of multiple accidents.

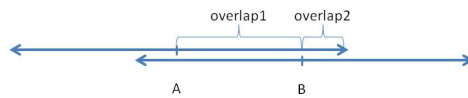
There might be three possible scenarios as shown in Figure 7. In each panel, there are two events that occur on day A and day B. Around each event, there is a window with a bandwidth of 90 days. In scenario 1, the difference in the accident dates is in the range of (90, 180). Then the overlap period shown in Figure 7(a) is invalid to serve as a pre-treatment counterfactual for event B, while it can still serve as a valid post-treatment observation for event A. Therefore, we only drop the overlap period observation shown in Figure 7(a) from event B under scenario 1. In scenario 2, event B occurs exactly 90 days after A. The post-treatment period of event A coincides with the pre-treatment period of event B that leads to no valid pre-treatment observations at all for event B. This absence means we need to drop the entire window of event B. However, in our sample no counties experienced two accidents that are exactly 90 days apart. Figure 7(c) shows the third possible scenario where the difference in the accident dates is less than 90 days. In this case, different segments of the overlapping period matter differently for events A and B: for event A, observations in the period labeled by “*overlap2*” are not valid post-treatment samples; for event B, observations in the period labeled by “*overlap1*” are not valid pre-treatment samples. Thus, we drop them from events A and B respectively when constructing the data. If two accidents are too close to each other (less than 45 days), we drop both events from our sample. Our results are also robust when we drop all events categorized by scenario 3.



(a) Scenario 1



(b) Scenario 2



(c) Scenario 3

Figure 7: Overlaps of Event Windows

Note: Here we show three possible scenarios where two event windows may overlap each other. In each panel, there are two events that occur on day A and day B. Around each event, there is a window with a bandwidth of 90 days.

A2.1.2 Overlapping due to Large-range Suspension

Facing coal mine accidents with severe casualties and economic losses, local Chinese governments may order a large-scale suspension such that all or some of the coal mining are affected within a county, a city, or even a province. This ability means the air quality may be temporarily ameliorated if coal mines are affected by a suspension due to accidents in nearby counties. Accordingly, observations in periods around the extended suspension may be contaminated.

We tackle this concern by manually collecting information on the geographical range of a suspension associated with each accident in our sample based on news coverage on the internet.²⁹ Given that our analysis is conducted at the county level, we construct windows of geographically extended suspensions for the counties involved in city-wide or province-wide suspensions and check whether they overlap with windows of suspensions due to accidents in the original county. This construction can apply to both treated and comparison counties. We exploit variations in coal mining only due to mandated suspensions after severe accidents out of the concern that local enforcement may be weak and very short-lived for geographically extended suspensions. We then drop overlapping observations that are affected by the expanded suspension window as described in Section A2.1.1.

²⁹We input key words such as “suspension” or “ratification”, and the locality and date of accidents in internet search engines (Baidu, Google, or Bing) to collect the information on geographical range of a suspension.

Appendix A3: Data documentation

The data used in this study come from seven sources. First, we collect the location (county), date, number of deaths, and cause of all the coal mining accidents in China from January 2003 to December 2015 from the website of the State Administration of Work Safety of China. Second, we collect daily aerosol optical depth (AOD) at a pixel size of $3 \text{ km} \times 3 \text{ km}$ from the Moderate Resolution Imaging Spectroradiometer (MODIS) aboard NASA’s Terra and Aqua satellites. AOD is a remotely sensed measure of particulate matter that reflects the fraction of incoming light from the air column before reaching the ground. To calculate the daily county-level AOD, we keep only the pixels with valid AOD values for at least 30 days in each year. We then calculate the daily average AOD for each county using all pixels within the geographic boundary of each county.

Third, we collect daily SO_2 at a spatial resolution of $0.25^\circ \times 0.25^\circ$ from the Level-3 Aura/OMI Global OMSO2e Data Products from NASA. This variable measures vertical column density of SO_2 in Dobson Units ($1 \text{ DU} = 2.69 \times 10^{16} \text{ molecules/cm}^2$), which is suitable for analyzing near-surface pollution. Since the spatial resolution of remote-sensed SO_2 data is a little coarse, we construct SO_2 at the county by day levels using an inverse-distance weighting method. For each county, we draw a circle with a radius of 100 km from the county’s center and calculate the weighted average daily SO_2 using all grids within that circle. The weight we use is the inverse of the distance between the center of the county and that of each grid.

Fourth, we collect weather data from the China Meteorological Data Sharing Service System (CMDSSS) that provides the daily average temperature, relative humidity, wind speed, precipitation, and atmospheric pressure for around 700 weather stations in China. Since many counties do not have any weather stations, we construct daily county-level weather variables from station-level weather records using an inverse-distance weighting method. Specifically, for each county, we draw a circle with a radius of 100 km from its center and calculate the weighted average daily weather variables using all stations within the circle. We use the inverse of the distance between the county’s center and each station as the weight.

Fifth, we collect the total industrial output value and the output values of sectors including the electricity, coal, metallic minerals, and nonmetallic minerals from the Annual Survey of Industrial Enterprises of China (ASIEC) that is a large-scale enterprise survey conducted by the Chinese

National Bureau of Statistics (NBS). Leveraging the input-output table available from the Chinese NBS, We also compute the value of coal consumption for enterprises in major coal-consuming sectors which we define as the sectors of electricity, metallic minerals, and nonmetallic minerals. We aggregate the enterprise-level industrial activity data and coal consumption data at the county level.

Sixth, we calculate the county-level population using the 2010 census data for China, which is a 0.35% random sample of the whole census. We calculate the population for each county and divide it by 0.35% to get the estimated county-level population. All the relevant variables in the six data sources mentioned above are open access in our online appendix.

Seventh, we access cause-specific daily mortality data for each Chinese county via an online data platform constructed by the Disease Surveillance Point (DSP) System of the Chinese Center for Disease Control and Prevention (CCDC). CCDC collects records of individual deaths through the DSP System and validates the data quality including the cause of death. For this research purpose, they then calculate the numbers of deaths due to cardiovascular (CVD) diseases, respiratory (RES) diseases, and non-CVD non-RES diseases. Interested individuals should submit an application for accessing the relevant data for replication to CCDC and access these variables on the online data platform of CCDC. All the other variables in the other five data sources can also be found on the online data platform of CCDC.