Death of Coal and Breath of Life: The Effect of Power Plant Closure on Local Air Quality

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Abstract

The number of U.S. coal-fired power plants declined by nearly 250 between 2001 and 2018. Given that burning coal generates large amounts of particulate matter known to have adverse health effects, closure of coal-fired power plants should improve local air quality. Using spatial panel data from air quality monitor stations and coal-fired power plants, we estimate the relationship between plant closure and local air quality. We find that on average, the local levels of particulate matter within 25 and 50 mile buffers declined between 26 and 39 percent in the immediate months after closure and by 3 percent longer-term. We estimate that the event of closure is associated with a 0.6 percent decline in local mortality probabilities. On a value of statistical life basis, the median local benefit of coal power plant closure ranged between \$1 and \$4 billion since the early 2000s.

Keywords: air quality; coal; plant closure

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*The views here are those of the author and are not attributable to the Federal Reserve Bank of Kansas City or the Federal Reserve System.

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1 Introduction

The confluence of abundant natural gas, rising concerns over reducing greenhouse gas emissions, and a mix of state and federal policies are leading to shifts in the energy composition of the United States. Nowhere is this confluence more on display than in the power-utility sector. Coal was approximately 50 percent of the fuel source used in power generation for many decades. However, in the mid-2000s coal's share began to decline and by 2018 represented only 27 percent of fuel used in electricity generation. Natural gas is already displacing coal in power generation because of the shale revolution in the United States. Between 2007 and 2012 it is estimated that abundant natural gas displaced 28 percent of coal-generated electricity (Johnsen et al., 2019). In 2018 over 60 percent of electric generating capacity installed was fueled by natural gas, while nearly 70 percent of retired capacity was fueled by coal (Energy Information Administration, 2019b). With coals steady decline and renewable energy steady increase, total U.S. consumption of coal and renewable energy have reached parity (Figure 1).

Due to these shifts in power generation, the number of coal-fired power plants has declined across the country. Coal-fired units have shut down because of sluggish growth in electricity demand and increased competition from natural gas and renewable sources (Energy Information Administration, 2019a). Between 2001 and 2018, over 250 coal power plants closed (Figure 2). Previous research has shown higher levels of local air pollution near coal power plants (Kahn, 2009). As a result, there could be improvements in local air quality following closures. Burning of coal is known to emit substantially more particulate matter relative to natural gas (Energy Information Administration, 1999). As a result, the decline in coal-fired power plants is expected to reduce emissions in the local area where closures occur.

A general air pollutant of concern is particulate matter ($PM_{2.5}$), where 2.5 references the size of air particles measured in micrometers. Researchers have focused on $PM_{2.5}$ because of its diffuse and harmful nature, especially due to its association with higher risks of respiratory and cardiovascular issues (Jha and Muller, 2018; Giaccherini et al., 2019). For example, prior research has found higher mortality risk from exposure to $PM_{2.5}$ (National Research Council, 2010; Muller et al., 2011; Muller, 2014). While others have investigated effects of the rise of natural gas via hydraulic fracturing (Johnsen et al., 2019) and stockpiles of coal (Jha and Muller, 2018) on local particulate matter, no research that we are aware of, has directly estimated the effect of coal power plant closure.

We help fill this gap in the literature by estimating the effect of coal power plant closure on local air quality. To do so, we combine spatial data on air quality monitor stations, power plant emissions and closures, as well as local economic conditions. Using monthly data from air monitor stations and power plants from the Environmental Protection Agency, we estimate the effect of coal power plant closure on local air quality within 25 and 50 mile buffers of each monitoring station between 2001 and 2018 using a difference-in-difference identification strategy. Controlling for total power production, local economic conditions, location-by-year and monthly fixed effects, we find that the average effect is a 16 to 21 percent reduction in the level of particulate matter ($PM_{2.5}$) three months after the power plant closure and 3 percent reduction longer-term. As a result, an improvement in local air quality from coal-fired power plant closures may also provide additional health benefits in these areas. We estimate that the event of closure is associated with a 0.6 percent decline in local mortality probabilities. On a value of statistical life basis, the median local benefit of coal power plant closure ranged between \$1 and \$4 billion since the early 2000s. Thus, one positive local externality from the closure of coal-fired power plants is less emissions and lower risk of adverse health effects.

2 Previous Literature

Previous research has shown that the utility sector is the largest polluter in the U.S. economy, accounting for one-third of air pollution damages (Muller et al., 2011). More specifically, Muller et al. find that coal-fired electric generation is the single largest industrial contributor with gross external damages of $53 billion annually, which exceed the estimated value added of the sector by a factor of two. The majority of these external costs are related to higher mortality on a value of statistical life basis. Although not explicitly looking at coal power plants, Deryugina et al. (2019) investigate the relationship between daily changes in pollution exposure and population health among Medicare recipients. They use Medicare claims data to look at how spikes in $PM_{2.5}$ affect life expectancy and mortality. They find a reduction in concentrations of 4 $\mu g/m^3$ led to a gain of a little over a month of life per elderly person.

Our paper builds on a growing literature that uses quasi-experimental research designs to estimate how regulations, production, and transportation affect air quality (Currie and Neidell, 2005; Currie et al., 2015; Schlenker and Walker, 2015; Isen et al., 2017). With respect to regulation, Currie et al. (2019) summarizes a large body of work that has evaluated the impact of the Clean Air Act over the past 50 years. One of their distilled conclusions is that there has been a reduction in concentrations of regulated pollutions, even though not all of the reduction can be directly attributed to the Clean Air Act. Other outcomes of interest have been how changes in air quality affect housing values (Chay and Greenstone, 2005; Davis, 2011) and infant or childhood mortality (Chay and Greenstone, 2003; Almond et al., 2018). Graff Zivin and Neidell (2013) summarize another strand of the literature that has evaluated links between pollution effects on labor productivity, educational attainment, and crime.

Our research follows more closely to recent papers by Jha and Muller (2018) and Johnsen et al. (2019). Jha and Muller consider the local air pollution cost of coal storage and handling by U.S. power plants. They find that a 10 percent increase in coal stock piles held by power plants was linked to a 0.09 percent increase in average $PM_{2.5}$ levels within 25 miles of the power plants. Jha and Muller estimate that the 10 percent increase in coal stock piles causes a 1.1 percent increase in adult mortality rates. Using a value of statistical life approach, they find that a one ton increase in coal stock piles results in about $200 more in local pollution costs. Johnsen et al. (2019) estimate the indirect benefits of improved air quality caused by fuel switching of power plants from coal to natural gas due to the rise of U.S. natural gas production from hydraulic fracturing. They identify a 4 percent decline int average $PM_{2.5}$ levels due to decreased coal-fired generation. Also using a value of statistical life approach, they estimate accumulated health benefits of reduced air pollution from coal electricity generation at approximately $17 billion annually.

Our contribution differs from Jha and Muller (2018) and Johnsen et al. (2019) in some important ways. First, we are considering the actual event of coal-fired power plant closure. Implicit in operating and closure is coal storage. Our purpose is not to separate out the effect of coal storage versus the burning of coal. We consider both to the extent that the coal is stored at the power plant or within the same buffers we consider. Second, our goal is not to use a dispatch model as Johnsen et al. to predict local differences in coal-fired generation. We take the closures as exogenous locally because of the structural forces pushing down on coal-fired generation. Rather than going through the effect of fuel switching via abundant natural gas on coal-fired generation at the margin, we use discrete changes in coal-fired power plants shutting down. Coal-fired power plant closures effect on local air quality has not been studied extensively. We are only aware of one previous study. Russell et al. (2017) investigate the impact of three coal-fired power plant closures in Pittsburgh, PA and find a nine percent reduction in average $PM_{2.5}$ levels. Relative to Russel et al., we consider coal-fired closures over a much wider geographical area and over a longer time frame.

3 Empirical Framework & Data

3.1 Empirical Model

Previous research most often utilizes local variation in air quality over space and time alongside high dimensional fixed effects or discrete changes in policies alongside differences-in-differences to estimate subsequent changes in local air quality. We utilize a differences-in-differences strategy and fixed effects panel model in order to estimate local air quality response to power plant closure. Specifically, we estimate the following:

$$PM_{i,t} = \alpha_{i,y} + \delta_t + \beta_j \sum_{j=-1}^{4} CPC_{i,t-j} + \lambda HI_{i,t-1} + \gamma UER_{i,t-1} + \varepsilon_{i,t}, \tag{1}$$

where i indexes air quality monitor in month t. Controls included in the equation are monitor-by-year ($\alpha_{i,y}$) fixed effects, monthly fixed effects (δ_t), the total level of heat input used in generation from all plants intersecting the 25 or 50 mile buffer around the monitor station ($\lambda HI_{i,t-1}$), the local unemployment rate of the county that the air monitor is located in ($\gamma UER_{i,t-1}$) and an error term $\varepsilon_{i,t}$ clustered at the site-by-year level. The fixed effects are used to control for unobserved factors which may influence particulate matter in each location over time and seasonal factors which can temporarily influence air quality. The total heat input used to generate electricity within an area controls for electricity generation, which would increase particulate matter as generation increases. The local unemployment rate captures labor market conditions, with higher unemployment rates expected to be negatively associated with emissions. This follows as emissions of particulate matter are expected to increase with greater economic activity holding other factors constant.

The key coefficients of interest are β_j, which measure the average differences in $PM_{2.5}$ one month before a plant closure, the month of closure, and the following four months after closure. By looking at this window around plant closure, the coefficients measure the differences in particulate matter at air quality monitor stations that had a coal power plant closure relative to the monitor stations that did not have a closure around the same event time frame. In this setting, power plant closure acts as a treatment effect on the level of particulate matter. One would expect that the farther in time away from the event (before or after) of a closure, CPC_t, the less precision there would be in estimating the response of air quality because other unobserved factors that are likely to influence local air quality.

It is possible that power plants reduce electricity production prior to actually closing and therefore lower emissions. To account for this, we include a time indicator one month before closure (CPC_{t+1}). We expect this coefficient to be positive due higher emissions before closure, but realize that it may be negative if particulate matter is already declining due to lower electricity production just prior to closure. However, our control for total heat input from electricity generation in the area should also take this into account. Each coefficient on the month of closure and subsequent months measures the average response in each period. As a result, the sum of the coefficients on CPC at and following closure measure the near-term average effect of closure on local particulate matter.

Given that coal power plant closures are likely permanent, we estimate the longer-term effect of closure on local air quality using:

$$PM_{i,t} = \alpha_{i,y} + \delta_t + \beta CPC_{i,t} + \lambda HI_{i,t-1} + \gamma UER_{i,t-1} + \varepsilon_{i,t}, \tag{2}$$

where CPC is an indicator of post-closure. The indicator takes and maintains a value of one once closure occurs. The coefficient (β) measures the average longer-term change to local air quality within each buffer from coal power plant closure. We expect that the longer-term effect may be smaller and/or less precisely estimated compared to immediately around the time of closure. The most likely reason for this is because of any other local changes in industrial activity related or unrelated to the power plant closure. Similar to the previous specification, equation 2 controls for heat input from all other plants, local economic conditions, buffer-by-year and month of year fixed effects, with standard errors clustered at the buffer-by-year level.

3.2 Data Sources

Emissions data from power plants were collected from the Air Markets Program Data (AMPD) provided the U.S. Environmental Protection Agency (EPA). AMPD include monthly emissions and generation data on generators at power plants that are subject to certain regulatory programs. The regulatory programs do not cover the full universe of power plants, however, they are our only source of emissions data coming directly from power plants. These data include the emissions of CO_2, SO_2, and NO_x in addition to the gross load (generation) and heat input for each generator. We select all generators that use coal as its fuel source then aggregate this generator-level data to the plant-level by taking the total amount of CO_2, SO_2, and NO_x emissions, the total generation, and the total heat input for each plant in each month over the sample period 1995-2018. We proxy closures of coal plants by identifying the first month in which the plant is no longer in the sample. This closure proxy can be the result of an actual closure of the whole plant, or a switch of fuel sources in which coal is no longer used.

Local air quality data comes from the Air Quality System (AQS) provided by the EPA, which has daily average readings of ambient $PM_{2.5}$ concentration levels measured in micrograms per cubic meter ($\mu g/m^3$), at monitor stations across the U.S. The data capture each type of $PM_{2.5}$ measured, i.e., lead $PM_{2.5}$, mercury $PM_{2.5}$, etc. To measure the total ambient $PM_{2.5}$ levels, we first sum the individual particulate matters to get the total daily value for each air monitor station. We then calculate the monthly average $PM_{2.5}$ level at each monitor over the period 1995-2018.

Additionally, both the AMPD and the AQS provide latitude and longitude coordinates for each power plant and monitor site, respectively. We use this location information in order to match power plants to monitor sites by capturing power plants within a certain radius of monitor sites.

Finally, our unemployment data comes from the Local Area Unemployment Statistics produced by the Bureau of Labor Statistics, which provide monthly estimates of unemployment rates for each county in the U.S.[1]

[1] https://www.bls.gov/lau/.

3.3 Data Merge

For each air quality monitor site we merge the emissions from coal fired-plants in the surrounding area as follows:

1. We create two sets of buffers, one of 25 miles and one of 50 miles, around all 2,096 $PM_{2.5}$ monitor sites from our sample period and match all 331 coal power plants from the AMPD that fall within each of the buffers. This results in some plants being accounted for more than once, when they fall into more than one buffer. However, it is impossible to know just how diffuse emissions of each plant would be.

2. The plant-monitor match is then merged against the panel of plant-month emissions data, allowing us to aggregate the emissions data to the monitor-level by month.

3. The potential issue with the above merge is if there are monitors that were not measuring at the same time that there were emissions from power plants. To correct for this, we merge the above data set against the ambient $PM_{2.5}$ panel by monitor-month and drop anywhere there was emissions data with no corresponding air quality data.

4. Finally, using the county location of each monitor, we merge in county-level unemployment rates to control for local economic activity occurring near a monitor.

5. The final dataset contains 442 $PM_{2.5}$ monitor sites with at least one coal plant within 25 miles of the monitor and 539 $PM_{2.5}$ monitor sites with at least one coal plant within 50 miles of the monitor.

Our constructed data set is a panel by monitor-month that includes information on the ambient $PM_{2.5}$ level, and the total emissions from coal power plants that are within either 25 or 50 miles of the monitor, and the unemployment rate of the county of the monitor. Table 1 reports the summary statics from the two samples. Comparing 25- versus 50-mile buffers, the number of observations increases with the 50-mile buffer because with the larger distance more air monitor buffers have at least one power plant. The average number of observed plant closures is similar between the two buffers. In general, the larger buffer has more power plants that intersect it, which explains the higher levels of heat input and other emissions produced by the plants. However, there is no significant difference in average unemployment rates between the two at 6.5 percent. Average concentration levels of particulate matter are higher in the 25-mile buffer. This is consistent with concentration levels being lower the further away from potential sources of pollution. Over the period 2001-2018, we identify 296 coal plant closures. Figure 3 shows the locations of air monitor stations with at least one coal-fired power plant closures in 25 and 50 mile buffers. A majority of the closures have occurred in the eastern half of the country.

4 Local Air Quality Findings

We estimate our empirical model at the monthly frequency between 1995 and 2018 for 397 and 489 monitor stations at 25 and 50 mile buffers, respectively.[2] In order to help put our estimates of the reduction in $PM_{2.5}$ into context, Figure 4 shows the distribution of monthly average $PM_{2.5}$ levels six months prior to power plant closures. The dashed vertical line represents the concentration level most often monitored by the World Health Organization at 10 μg/m^3. The solid vertical line at 15 μg/m^3 represents the federal standard for compliance with the Clean Air Act. A large portion of the histogram indicates that particulate matter concentrations were outside of compliance prior to power plant closure. Table 2 reports the average of particulate matter concentrations six months before each closure. Average readings prior to closure were between 16 an 17 μg/m^3.

Table 3 reports results from estimating the near-term local air quality response to coal power plant closures within 25 and 50 mile buffers of air quality monitors. As expected, we find that heat input is positively and significantly correlated with higher $PM_{2.5}$ emissions. Higher unemployment rates are negatively associated with particulate matter emissions, but

[2]The number of monitor stations increases with the larger distance because more buffers have at least one power plant.

only significant in the 50 mile buffer sample. Average $PM_{2.5}$ levels where higher prior to closure, but only statistically significant for the 50 mile buffer sample.

At the month of a coal power plant closure, we find a 0.7 μg/m^3 reduction in $PM_{2.5}$, which corresponds to a 4.1 and 5.1 percent reduction at sample averages for the 25 and 50 mile buffers six months before closure. Focusing on the 25 mile buffer results, additional reductions of 0.7 to 0.8 μg/m^3 occur in each of the first three months following a coal power plant closure. The total estimated near-term reduction in $PM_{2.5}$ is 3.2 μg/m^3, representing a 19 percent reduction at average concentration levels before closure. We obtain similar but slightly smaller estimates for the 50 mile buffer sample. At months one through three following a coal plant closure, the average estimated reduction in particulate matter ranges between 0.4 and 0.6 μg/m^3. The slightly smaller coefficients on coal power plant closure in the 50 mile buffer sample are somewhat expected as the observed plant closure is typically further away from the air monitor station. The total near-term estimated reduction in $PM_{2.5}$ for the 50 mile buffer sample is 2.2 μg/m^3, or 14 percent. For both the 25 and 50 mile buffer samples, the average effect of a coal power plant closure is still negative, but no longer statistically significant.

Turning to the longer-term response from closure, Table 4 reports the post-closure air quality results for both the 25 and 50 mile buffers. The coefficient on post coal plant closure indicates a longer-term reduction in $PM_{2.5}$ of 0.6 μg/m^3 and 0.5 μg/m^3 for the 25 and 50 mile buffers. The average response corresponds to a little over a 3 percent reduction in $PM_{2.5}$, relative to pre-closure levels. The smaller and less-precisely estimated longer-term effect size relative to near-term is not surprising. Reduction in particulate matter would likely be highest around the time of the event of closure and immediate following months. Over time, subsequent activity could cause particulate matter levels to increase. While we attempt to control for this with location-by-year fixed effects and local labor market conditions, the post-closure coefficient likely averages out the more permanent reduction from closure and other changes in particulate matter not directly linked to the event of closure.

One feature of coal power closures is that some occurred in within the same 12-month period for a given air quality monitor station. As a result, our initial results could be influenced by subsequent closures that are close in time. For example, if an additional closure occurs one or two months after the initial closure, it would likely influence our estimates of closure. To account for this, we drop observations that had more than one power plant closure within a 12-month period and re-estimate our model. Table 5 reports the near-term results for the 25 and 50 mile buffers using the same set of fixed effects and local controls. The coefficients on average $PM_{2.5}$ one month prior to a coal power plant closure remain positive and statistically insignificant. However, isolating a single treatment effect in a 12-month period increases the estimated average responses for the month of closure and subsequent months. For the 25 mile buffer sample, the estimated reduction of $PM_{2.5}$ at closure is 1.8 $\mu g/m^3$. The average effect is negative and significant in each of the four following months.[3] The total estimated reduction in particulate matter in this subsample is 6.6 $\mu g/m^3$, or a 39 percent decline four months after a coal power plant closure compared to average pre-closure levels. Similar results were obtained for the 50 mile buffer, but with declines only significant through three months following a closure. The total estimated decline in $PM_{2.5}$ is 4.1 $\mu g/m^3$, or 26 percent (4.139/16.08). Thus, isolating single closure events within a 12-month period suggest that local particulate matter declines between 26 and 39 percent within the first few months after a coal power plant closure. Similarly, the longer-term results when omitting sites with multiple closures produces a slightly larger point estimate, but with less statistical precision for the 50 mile buffer sample (Table 6).

Our results are consistent with previous findings, with somewhat larger estimates in the near-term but smaller longer-term. Johnsen et al. (2019) estimate shutting down all US coal-fired power plants would on average decrease $PM_{2.5}$ by 16 percent. While our near-term results suggest a 14 to 19 percent reduction in local $PM_{2.5}$ levels following closure, our longer-term results indicate reductions of around 3 percent. The main reason for the differences in

[3] We estimated models that included additional lags for five and six months following closure, but the coefficients were not statistically significant.

our estimates compared to Johnson et al., is research design. There estimates were derived from estimating fracking's effect of natural gas displacement of coal-fired power plants and thus more or less estimates of a switching effect of the fuel source on local $PM_{2.5}$ levels. In our framework, we are only concerned about isolating the effect of the actual coal-fired power plant closure and not the potential switching of fuels between coal to natural gas, which could occur at the same plant. Power plants often have multiple generators, where it is possible that conversion process would allow one generator burning coal to remain functional while other generators are switched over to natural gas. In such a setting, one would expect to estimate lower reduction levels in particulate matter versus in a setting that attempts to isolate the effects of plant closure directly.

5 Health Implications of Power Plant Closures

At least two primary channels exist by which power plant closures may have local health implications through changes in air quality. First, the actual closure of the power plant by definition eliminates the air pollution emitted by the plant. Second, additional pollution from coal storage, rail car and truck traffic would also likely be reduced, if not eliminated, once closure occurs. Compared to the previous literature, we do not attempt to disentangle the health implications from changes in air quality from reduced output from coal power plants or coal storage (Jha and Muller, 2018; Johnsen et al., 2019). Instead, we investigate how the overall closure effects local mortality rates.

Previous estimates of particulate matter exposure and mortality rates may shed light on potential health and economic implications of the reduction in local air pollution from coal-fired power plant closures. Looking at particulate matter exposure across metropolitan areas, Krewski et al. (2009) estimate hazard ratios of various causes of death from a 10 $\mu g/m^3$ exposure. They find that at that level of exposure, the overall mortality probability increases by 5.6 percent (Column 1 of Table 7). The probability of heart-related deaths or lung cancer increases between 13 and 24 percent. Using our longer-term estimate of a 0.6 $\mu g/m^3$ reduction in $PM_{2.5}$ from coal power plant closure is around 6 percent of the exposure threshold in Krewski et al. (2009). The second and third columns of Table 7 report an approximation of the decline in mortality from coal-fired power plant closures by rescaling the previous estimates to our near- and longer-term estimates. A back of the envelope calculation suggests a 0.3 to 4 reduction in the probability of death from a coal power plant closure is a reasonable range to expect.

The Centers for Disease Control and Prevention (CDC) tracks the underlying causes of death for crude mortality and age-adjusted mortality rates in their Wide-Ranging Online Data for Epidemiologic Research (WONDER)[4] for each year since 1999. We use the age-adjusted rate, which is weighted by the population of all age groups the CDC covers, because this controls for differences in the age distribution of the population over time. Previous research has shown there are regional differences in mortality rates (Case and Deaton, 2017). Similarly, Figure **??** shows that there has been large geographic disparity in the change in mortality rates from 2000 to 2018. However, there is no consistent pattern of the mortality rate dropping more in counties with coal power plant closures.

In order to test the link between coal power plant closures and mortality, we use an approach similar to Jha and Muller (2018). We estimate the relationship between mortality and coal power plant closure by:

$$ln(MR_{i,t}) = \alpha_{i,y} + \delta_t + \beta CPC_{i,t} + \lambda HI_{i,t-1} + \phi_k X_{i,t}^k + \gamma UER_{i,t} + \varepsilon_{i,t}, \tag{3}$$

where the log of age-adjusted mortality in county i in month t is a function of coal power plant closures ($CPC_{i,t}$), total pollutant output in logs ($X_{i,t}^k$) from all coal power plants in the county including carbon dioxide, nitrous oxide, and sulfur dioxide, total heat input used in generation from all power plants in the county ($HI_{i,t-1}$), the local unemployment rate ($UER_{i,t-1}$) and an error term $\varepsilon_{i,t}$ clustered at the county-by-year level. County-by-year

[4]https://wonder.cdc.gov

fixed effects ($\alpha_{i,y}$) help control for unobservables specific to each county that might change over time that impact mortality. Month fixed effects (δ_t) control for any seasonality in mortality.

We consider three measures of closure: single event closure, multiple closures in the same month, and the cumulative number of coal power plant closures over time. Table 8 reports the results from these three specifications. Overall, these models can explain approximately 88 percent of the variation in local mortality rates. The first column reports results from the specification using a closure dummy variable. A single closure is associated with a 1.1 percent reduction in the mortality rate. Measuring closure with the number closures in a county in a given month resulted in a slightly smaller coefficient with each closure associated with a reduction in the mortality rate by 0.6 percent. Similarly, in the third column of the table, the coefficient on the running total of closures also suggests a 0.06 percent reduction in the mortality rate per coal power plant closure. Across the specifications, higher nitrous oxide emissions were correlated with higher mortality, while higher unemployment rates were negatively correlated with mortality; consistent with previous work on deaths and despair (Case and Deaton, 2017, 2020).

Recognizing the possibility of a lag between coal plant closure and mortality, we re-estimate equation 3 at the annual frequency. We include county and year fixed effects in the regression and cluster standard errors at the county-level. The remaining control variables are the same. Table 9 reports the results across three specifications with the same three measures of closure. At the annual frequency, a coal power plant closure is associated with a 0.2 to 0.8 percent reduction in county mortality rates. Because the annual frequency cannot control for time varying factors across counties, the monthly results are the preferred specification.

5.1 Value of Statistical Life Estimates

We next use our county-monthly estimates of changes in mortality from change in particulate matter from coal power plant closure as well as the actual plant closure to calculate the potential economic impact from a value of statistical life perspective. Starting with the air quality results, we must estimate the population at risk within the 25 and 50 mile buffers. We dissolve the 25 and 50 mile buffers into larger "buffer regions," thereby creating distinct areas with no overlapping population. Within each of these buffer regions we capture all Census tracts that are completely contained within the border of the region. This restriction does mean that we may underestimate the true population at risk. However, we find that the smaller tracts that are contained within the buffer regions represent the larger population cores of these areas and thus the majority of population. Figure **??** shows the buffer regions and tracts that are contained within each region. The western portion of the country has more sparsely populated areas, which do not fit within a buffer region, but the tracts that do fall into these regions are densely populated.

The Environmental Protection Agency suggests using an estimate of \$7.4 million (in 2006 dollars) to quantify mortality risk reduction benefits, which is approximately the middle of the range of available estimates summarized by Viscusi and Aldy (2003). We calculate the potential health benefit (PHB) for a single closure for each buffer region as follows:

$$PHB_{i,t} = population_i * r^m_{i,t} * 0.003 * \$7.4 \text{ million},$$

where $population_i$ is the total population of the buffer region, calculated as the sum of tract populations that are within the region and r^m_i is the population-weighted age-adjusted mortality rate in region i. We calculate the population-weighted, age-adjusted rate by weighting the county-level age-adjusted mortality rate from the CDC by the share of buffer region population that is made up by Census tracts that fall within a given county and buffer region. We use the adjusted hazard ratio for all mortalities using the longer-term estimate, 0.003, in Table 7 to capture the reduction in mortality from reduced particulate matter via coal power plant closure. Figure 5 presents the mean and median value of potential health benefits across all buffer regions in each year. Between 2002 and 2018, the average estimated potential health benefit from coal power plant closure ranged from \$0.6 to \$3.2 billion. Similarly, the estimated median benefit ranged from between \$0.3 and \$1.5 billion.

While these potential health benefits were based on previous research linking reductions in particulate matter and mortality, we also estimate the potential health benefits from coal plant closure and mortality. To do this, we our estimate of each closure associated with a 0.6 percent reduction in county mortality rates. We calculated the PHB for each county as:

$$PHB_{i,t} = population_{i,t} * r_{i,t}^{m} * 0.006 * CPC_{i,t} * \$7.4 \text{ million},$$

where $population_{i,t}$ is the total population, $r_{i,t}^{m}$ is the population-weighted, age-adjusted mortality rate, and $CPC_{i,t}$ is the number of coal power plant closures in county i in month t. Using those county-month observations with closures, Figure 6 shows the estimated county mean and median benefit. Between 2002 and 2018, the average potential health benefit ranged from \$1-7 billion, while the median benefit ranged from \$1-4 billion. To give a sense of the aggregate benefit, we sum up the potential health benefit across all counties with closures. Figure 7 shows the estimated annual benefit. The year to year differences are driven by the number coal power plant closures. The estimated aggregate annual benefit ranged from a low of \$3.9 billion in 2003 to a high of \$156 billion in 2013. At peak years in 2008 and 2013, the annual estimated benefit was equivalent to 1 percent of U.S. GDP. Thus, the positive externality of coal-fired power plant closures is quite substantial and economically meaningful.

6 Conclusion

The on-going transition in the power-utility sector is not only changing the fuel sources from coal to natural gas and renewables, but it is also changing local air quality along the way. While prior research has analyzed the air quality response of fuel-switching and coal storage, we focus on the event of coal power plant closure. Our contribution is estimating the effect of coal-fired power plant closures on local air quality, especially in concentrations of particulate matter $PM_{2.5}$, and on mortality.

Using monthly panel data of air monitor stations between 2001 and 2018, we find reductions in local particulate matter of 25 to nearly 40 percent. The reduction in the level of $PM_{2.5}$ concentrations is about 66 percent of previously estimated mortality hazard ratios. The reductions we estimate represent approximate reductions of 3.7 percent in the probability of total deaths. When we estimate the effect of coal power plant closure on local mortality we find a 0.6 percent reduction in the mortality rate with each closure. We estimate that on a value of statistical life basis, the median local benefit of coal plant closure ranged between \$1 and \$4 billion since the early 2000s. In aggregate, we estimate that the annual benefit ranged from a low of \$3.9 billion in 2003 to a high of \$156 billion in 2013. At peak years in 2008 and 2013, the annual estimated benefit was equivalent to 1 percent of U.S. GDP. Thus, the positive externality of coal-fired power plant closures is quite substantial and economically meaningful.

It is important to note that our estimates do not capture the net effect of coal power plant closure and the opening of natural gas-fired power plants. Previous research has shown that hydraulic fracturing, which led to cheap, abundant natural gas, is a main contributor to the decline in coal-fired generating electricity. However, it is unknown how new natural gas-fired power plants or the extraction of natural gas might effect local air quality. Both represent possible future areas of research.

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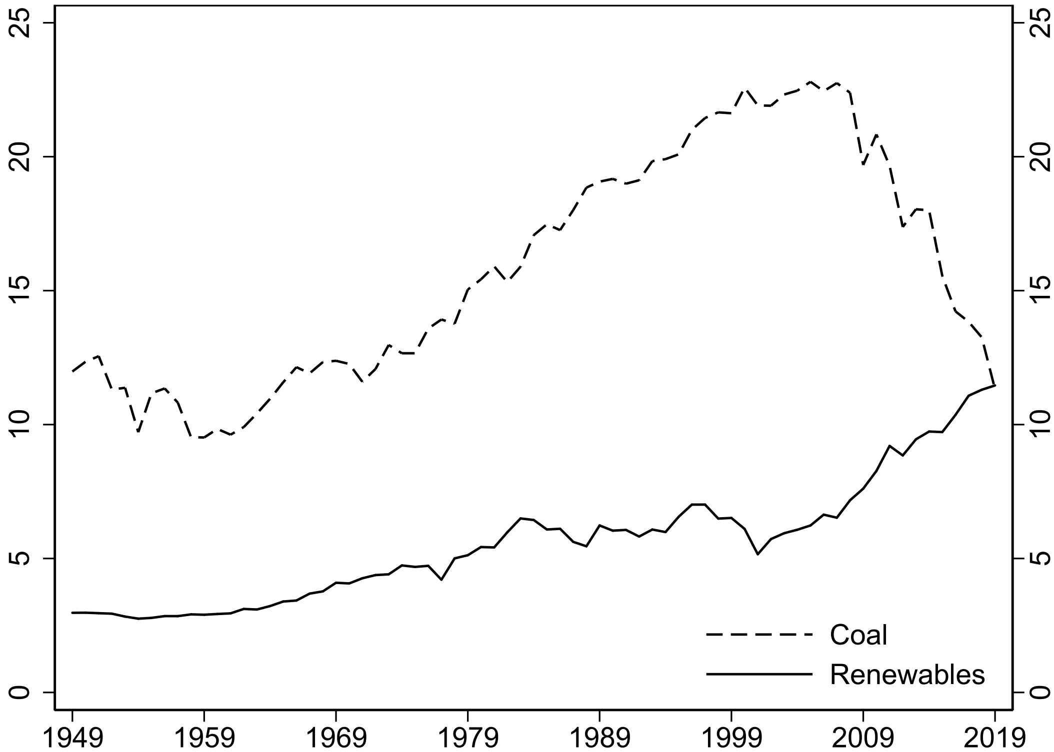
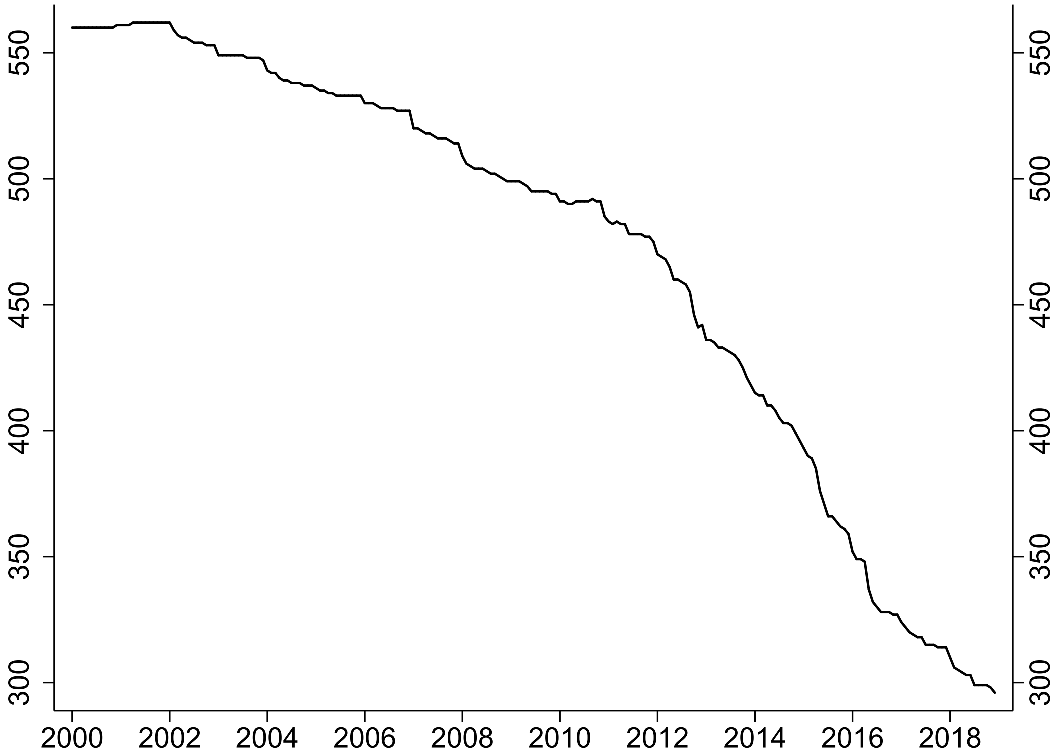


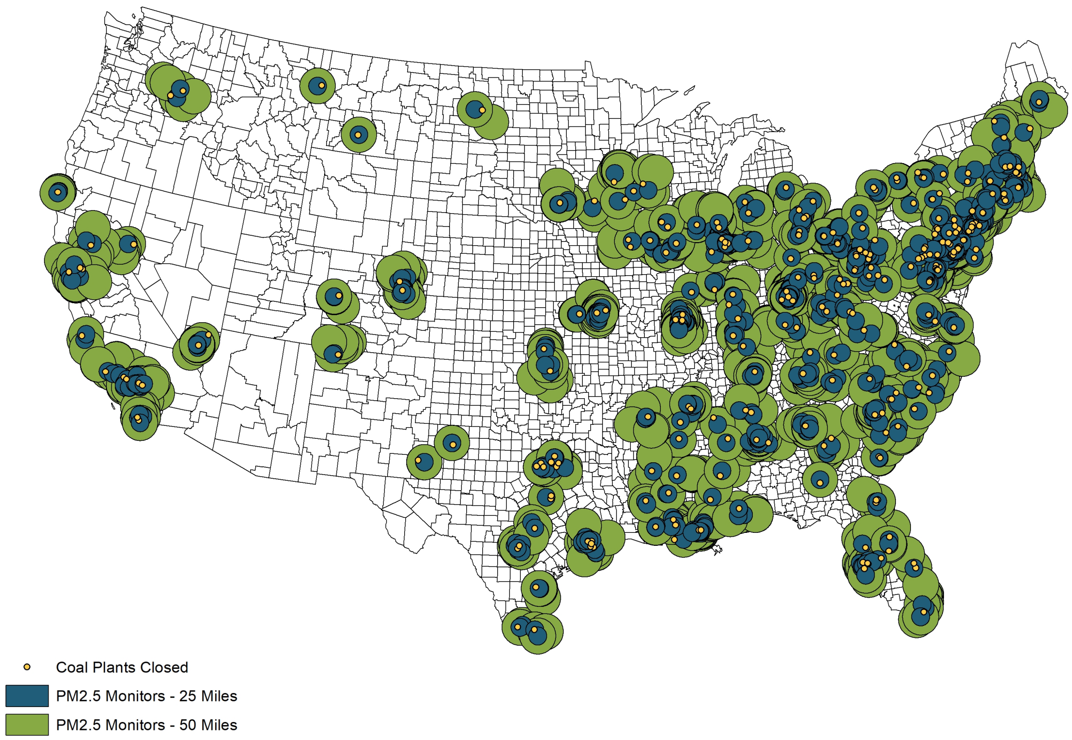
Source: EIA

Figure 1: U.S. Coal and Renewable Energy Consumption (Quad BTU)



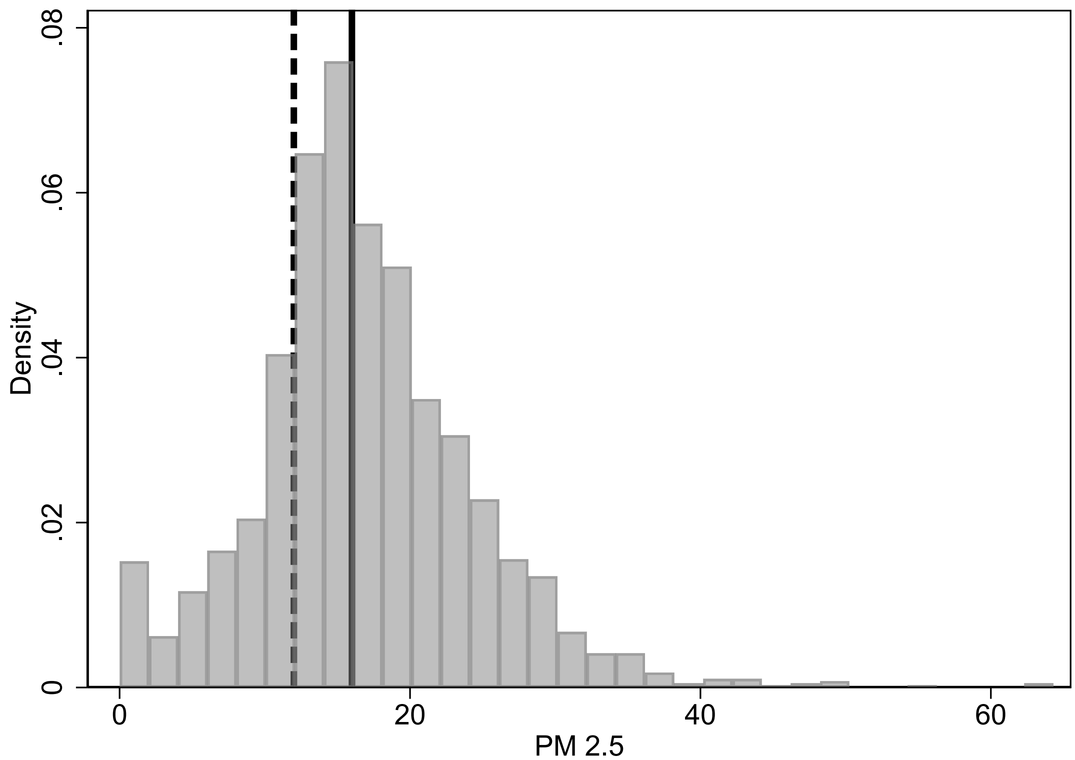
Source: EIA

Figure 2: Coal Power Plants



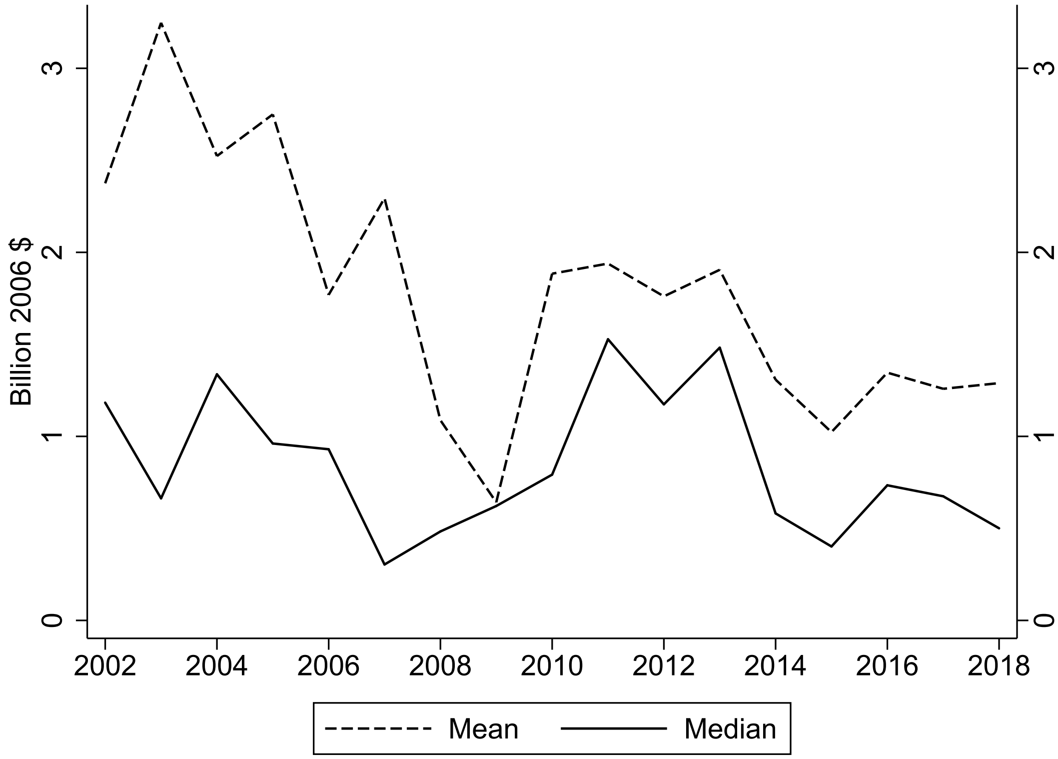
Source: EPA

Figure 3: Coal Power Plant Closures, 2001 to 2018



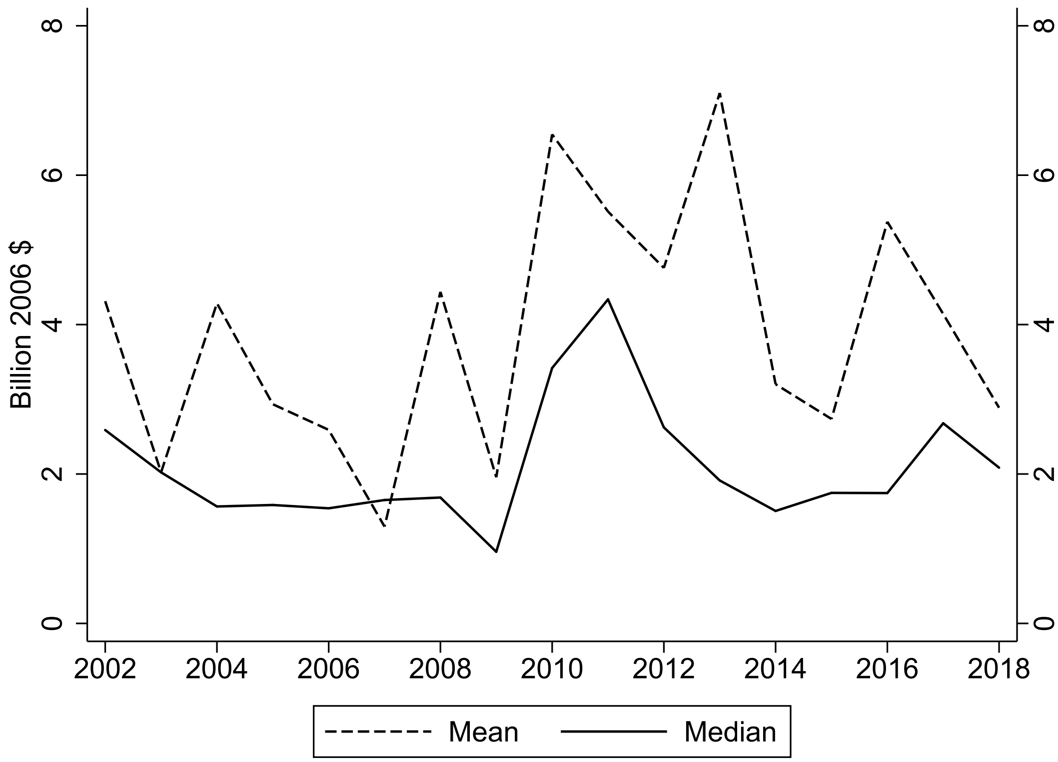
Source: EPA

Figure 4: Histogram of Average Monthly $PM_{2.5}$ Levels Six Months Pre-Coal Plant Closure



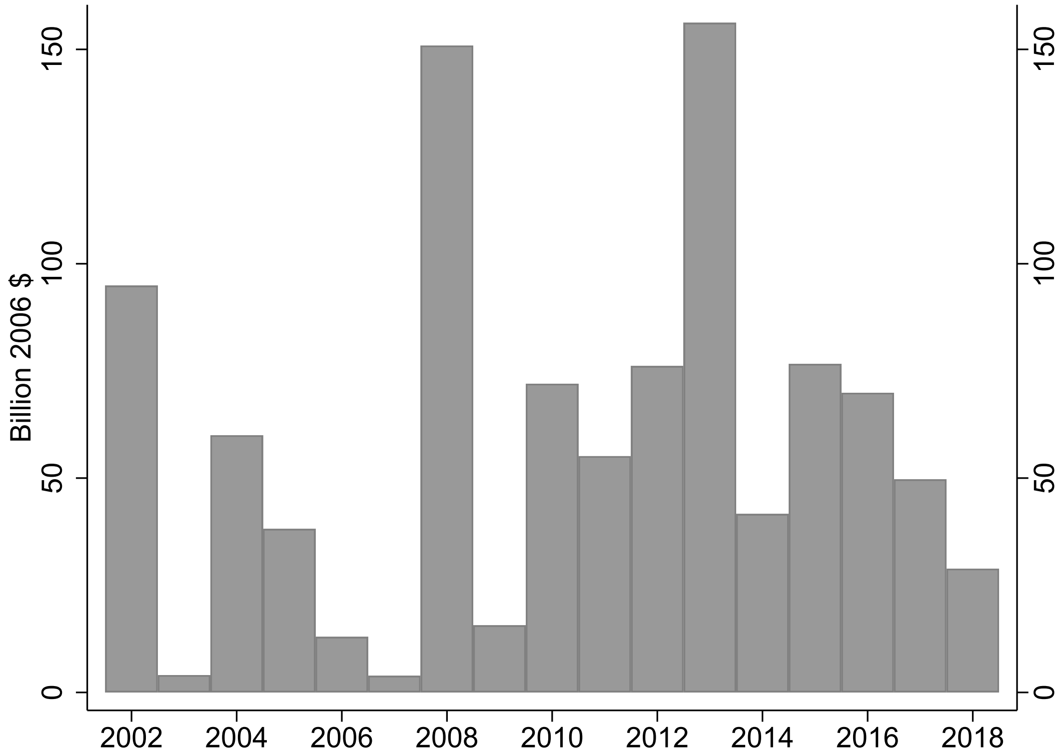
Source: Census, CDC, EPA

Figure 5: Potential Local Health Benefit of Reduced $PM_2.5$ from Coal Plant Closure



Source: Census, CDC, EPA

Figure 6: Potential Local Health Benefit of Coal Plant Closure



Source: Census, CDC, EPA

Figure 7: Potential Aggregate Health Benefit of Coal Plant Closure

Table 1: Descriptive Statistics

(a) 25 Mile Buffer

	Mean	SD	Min	Max
$PM_{2.5}$	14.64	8.50	0.02	289.72
Coal Plant Closure	0.01	0.09	0.00	3.00
Heat Input (QBTU)	0.71	0.85	0.00	6.15
CO2 (Thous. Tons)	572.06	701.25	0.00	4,329.42
SO2 (Thous. Tons)	1.53	3.07	0.00	29.60
NO (Thous. Tons)	0.61	1.01	0.00	13.05
Unemployment Rate (%)	6.51	2.85	1.60	31.90
N	43257			

(b) 50 Mile Buffer

	Mean	SD	Min	Max
$PM_{2.5}$	13.09	8.50	0.02	289.72
Coal Plant Closure	0.01	0.14	0.00	6.00
Heat Input (QBTU)	1.45	1.62	0.00	11.13
CO2 (Thous. Tons)	1,234.73	1,481.81	0.00	10,891.02
SO2 (Thous. Tons)	3.65	7.50	0.00	91.65
NO (Thous. Tons)	1.37	2.21	0.00	22.57
Unemployment Rate (%)	6.48	2.88	1.30	31.90
N	57326			

Notes: The unit of observation is the air quality monitor-month level.

Table 2: Descriptive Statistics of Air Quality 6-Months Pre-Closure

	Mean	SD	Min	Max
$PM_{2.5}$ 25 Miles	16.88	7.68	0.03	64.31
$PM_{2.5}$ 50 Miles	16.08	7.85	0.03	95.95

Notes: The statistics include only air quality monitors with a closure.

Table 3: Estimated Near-Term Air Quality Response to Coal Power Plant Closure

	25 mile	50 mile
Coal Plant Closure$_{t+1}$	0.189	0.315*
	(0.305)	(0.189)
Coal Plant Closure$_{t}$	-0.762**	-0.678***
	(0.355)	(0.168)
Coal Plant Closure$_{t-1}$	-0.735**	-0.366**
	(0.374)	(0.173)
Coal Plant Closure$_{t-2}$	-0.823**	-0.558***
	(0.345)	(0.150)
Coal Plant Closure$_{t-3}$	-0.863**	-0.602***
	(0.378)	(0.167)
Coal Plant Closure$_{t-4}$	-0.158	-0.019
	(0.365)	(0.181)
Heat Input$_{t-1}$	0.305**	0.332***
	(0.139)	(0.085)
Unemployment Rate$_{t-1}$	-0.075	-0.083**
	(0.068)	(0.039)
Adj. R-squared	0.601	0.652
N	40,322	53,875

Notes: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered by air monitor site-year are in parentheses. All regressions include air monitor site by year and month fixed effects.

Table 4: Estimated Longer-Term Air Quality Response to Coal Power Plant Closure

	25 mile	50 mile
Coal Plant Closure$_{t+1}$	0.119	0.206
	(0.290)	(0.173)
Post Coal Plant Closure$_t$	-0.630*	-0.524**
	(0.324)	(0.257)
Heat Input$_{t-1}$	0.336**	0.350***
	(0.136)	(0.083)
Unemployment Rate$_{t-1}$	-0.084	-0.079**
	(0.064)	(0.038)
Adj. R-squared	0.603	0.653
N	42,047	55,879

Notes: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered by air monitor site-year are in parentheses. All regressions include air monitor site by year and month fixed effects.

Table 5: Estimated Near-Term Air Quality Response: Excluding Multiple Closure Sites in 12-Month Window

	25 mile	50 mile
Coal Plant Closure$_{t+1}$	0.144	0.313
	(0.439)	(0.348)
Coal Plant Closure$_{t}$	-1.760***	-1.195***
	(0.520)	(0.281)
Coal Plant Closure$_{t-1}$	-0.995*	-1.069***
	(0.583)	(0.353)
Coal Plant Closure$_{t-2}$	-1.322**	-0.869***
	(0.545)	(0.320)
Coal Plant Closure$_{t-3}$	-1.338**	-1.006***
	(0.619)	(0.348)
Coal Plant Closure$_{t-4}$	-1.158**	-0.355
	(0.542)	(0.331)
Heat Input$_{t-1}$	0.830***	0.767***
	(0.209)	(0.123)
Unemployment Rate$_{t-1}$	-0.109	-0.100**
	(0.073)	(0.042)
Adj. R-squared	0.596	0.638
N	34,836	44,286

Notes: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered by air monitor site-year are in parentheses. All regressions include air monitor site by year and month fixed effects.

Table 6: Estimated Longer-Term Air Quality Response: Excluding Multiple Closure Sites

	25 mile	50 mile
Coal Plant Closure$_{t+1}$	0.026	0.285
	(0.401)	(0.337)
Post Coal Plant Closure	-0.760*	-0.304
	(0.392)	(0.321)
heat input$_{t-1}$	0.869***	0.791***
	(0.203)	(0.119)
unemployment rate$_{t-1}$	-0.123*	-0.098**
	(0.069)	(0.040)
Adj. R-squared	0.598	0.639
N	36,407	45,997

Notes: * p<0.10, ** p<0.05, *** p<0.01. Robust standard errors clustered by air monitor site-year are in parentheses. All regressions include air monitor site by year and month fixed effects.

Table 7: Mortality Hazard Ratios of $PM_{2.5}$ Exposure

Cause of Death	Hazard Ratio (10 $\mu g/m^3$)	Adjusted Hazard Ratio (Near-Term 6 $\mu g/m^3$)	Adjusted Hazard Ratio (Longer-Term 0.6 $\mu g/m^3$)
All Causes	1.056	1.037	1.003
Cardiopulmonary	1.129	1.085	1.008
Ischemic Heart Disease	1.240	1.158	1.014
Lung Cancer	1.137	1.094	1.008

Source: Estimated hazard ratios of a 10 $\mu g/m^3$ exposure by Krewski et al. (2009) reported in the first column were adjusted to 66 percent of that exposure to approximate magnitude of near-term exposure reduction from coal closure and 6 percent for longer-term.

Table 8: Estimated Mortality Rate Response to Coal Power Plant Closure

	Mortality Rate	Mortality Rate	Mortality Rate
Coal Plant Closure	-0.011**		
	(0.005)		
Coal Plant Closure(s)		-0.006**	
		(0.003)	
Cum. Coal Plant Closures			-0.006**
			(0.003)
Heat Input	-0.005	-0.005	-0.005
	(0.004)	(0.004)	(0.004)
Carbon Dioxide	0.001	0.001	0.001
	(0.003)	(0.003)	(0.003)
Nitrous Oxide	0.005***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)
Sulfur Dioxide	0.000	0.000	0.000
	(0.001)	(0.001)	(0.001)
Unemployment Rate	-0.002*	-0.002*	-0.002*
	(0.001)	(0.001)	(0.001)
Adj. R-squared	0.876	0.876	0.876
N	33,697	33,697	33,697

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Robust standard errors clustered by county-year are in parentheses. All regressions include year, county by year and month fixed effects.

Table 9: Estimated Mortality Rate Response to Coal Power Plant Closure - Yearly

	Mortality Rate	Mortality Rate	Mortality Rate
Coal Plant Closure	-0.004		
	(0.003)		
Coal Plant Closure(s)		-0.002*	
		(0.001)	
Cum. Coal Plant Closures			-0.008***
			(0.002)
Heat Input	0.005	0.006	0.007
	(0.006)	(0.006)	(0.006)
Carbon Dioxide	-0.011**	-0.011**	-0.010**
	(0.005)	(0.005)	(0.005)
Nitrous Oxide	0.002	0.002	0.000
	(0.003)	(0.003)	(0.003)
Sulfur Dioxide	0.001	0.001	0.001
	(0.002)	(0.002)	(0.001)
Unemployment Rate	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.002)
Adj. R-squared	0.921	0.921	0.923
N	3,105	3,105	3,105

Notes: * $p<0.10$, ** $p<0.05$, *** $p<0.01$. Robust standard errors clustered by county are in parentheses. All regressions include year and county fixed effects.