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Federal Reserve Bank of Kansas City

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 is 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 levels of particulate matter within 25 and 50 mile buffers around air quality monitors declined between 7 and 14 percent with each closure. 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 or 5 to 15 percent of local GDP since the early 2000s.

Keywords: air quality; coal; plant closure

JEL Classification Numbers: Q35, Q53, R11

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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). Over 250 coal power plants closed between 2001 and 2018 (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 and mortality. 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 1995 and 2018 using a difference-in-difference identification strategy. Controlling for total power production, power plant emissions, wind direction, local economic conditions, location-by-year and monthly fixed effects, we find that the average effect is a 7 to 14 percent reduction in the level of particulate matter ($PM_{2.5}$). 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 or 5 to 15 percent of local GDP since the early 2000s. Thus, one positive local externality from the closure of coal-fired power plants is less emissions and consequently lower risk of adverse health effects for nearby residents.

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 μg/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 in 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:

$$PM_{i,t} = \alpha_{i,y} + \delta_t + \beta_0 Pre_{i,t} + \beta_1 CPC_{i,t} + \beta_2 MSC_{i,t} + \lambda HI_{i,t-1} + \phi_k X^k_{i,t-1} + \psi WD_{i,t-1} + \gamma UER_{i,t-1} + \varepsilon_{i,t}, \tag{1}$$

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 ($HI_{i,t-1}$), total pollutant output ($X^k_{i,t-1}$) from all coal power plants in the buffer including carbon dioxide, nitrous oxide, and sulfur dioxide, wind direction ($WD_{i,t-1}$), 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 monitor-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 and pollutants control for electricity generation in the area, which would increase particulate matter as generation increases. Measures of air pollution can be impacted by wind, especially wind direction relative to the point source and monitor station (Hanna and Oliva, 2015; Sullivan, 2017; Deryugina et al., 2019). For example, if monitors are downwind of power plant they are much more likely to capture air pollution from the plant. To account for this we construct a measure similar to (Schlenker and Walker, 2015) using the cosine of the difference between the wind direction and the direction of the air monitors. The local unemployment rate captures labor market conditions, with higher unemployment rates expected to be negatively associated with emissions. Emissions of particulate matter are expected to increase with greater economic activity holding other factors constant.

The key variables of interest are Pre, CPC and MSC, which measure the average differences in $PM_{2.5}$ in the pre-closure period, month of closure, and months since closure.

The post-closure period is the reference category, but including months since closure allows us to capture the trend in particulate matter after closure. The coefficients β_0 and β_1 measure the average 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 and the post-closure period for those that had a closure.

We apply a restriction for locations that had multiple closures over time. Instead of throwing out the entire monitor-site, we keep those observations in the sample until the month before the subsequent closure. This restriction helps reduce measurement error in estimating the average pre-closure and closure effects from additional closures at the same location that occur later in the sample period.

3.2 Data Sources

Emissions data from power plants were collected from the Air Markets Program Data (AMPD) provided by 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. Our wind data comes the National Oceanic Atmospheric Administration/National Centers for Environmental Information s (NOAA/NCEI) Local Climatological Data (LCD), which provides hourly weather-related data for stations across the world. We aggregate this hourly wind data to get the median wind direction for a station from 1995 to 2018. Each weather stations includes latitude and longitude coordinates, which we use to find the nearest weather to station to each air quality monitor.

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]

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.

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

2. The plant-monitor match is then merged against the panel of plant-month emissions data.

3. We then merge in the median wind direction by monitor and calculate the bearing direction from each monitor to each plant within its buffer.

4. 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.

5. Following this, we aggregate the emissions data to the monitor-level by month, including the median bearing direction of plants for a monitor.

6. The cosine difference between the median wind direction and the average bearing direction is calculated, which tells us how downwind the monitor is from the average plant.

7. 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.

8. 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 142 and 248 monitor stations at 25 and 50 mile buffers, respectively.[2] In order to help put our estimates of the reduction in $\mathrm{PM}_{2.5}$ into context, Figure 4 shows the distribution of monthly average $\mathrm{PM}_{2.5}$ 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 14 an 15 μg/m^3.

Table 3 reports results from the local air quality response to coal power plant closures within 25 and 50 mile buffers of air quality monitors. The key coefficients of interest are shown in Figure 6. At the month of a coal power plant closure, we find a 1.1 to 1.4 μg/m^3 reduction in $PM_{2.5}$, which corresponds to a 7.3 and 10 percent reduction at pre-closure sample averages for the 25 and 50 mile buffers. The coefficients on the pre-closure period where

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

not significant in either sample, indicating the pre-closure $PM_{2.5}$ levels were not significantly different compared to post-closure. Although not significant, the positive coefficients on months since closure correspond to gradual increases in $PM_{2.5}$ levels following closure.

As expected, we find that power plant heat input is positively and significantly correlated with higher $\mathrm{PM}_{2.5}$ emissions. Higher unemployment rates are negatively correlated with particulate matter emissions, indicating that less economic output is associated with less local air pollution. Monitors more downwind of coal power plants have higher levels of particulate matter.

As a robustness check, we restrict our sample to only include air monitor stations that are downwind of the power plants. Our definition of downwind is if the cosine of the difference between wind direction and location is greater than zero. Full and key results of the subsamples are reported in Table 4 and Figure 7. In general, the estimated effect of closure is slightly stronger in the downwind sample. At the month of a coal power plant closure, we find a 1.5 to 2.0 μg/m^3 reduction in $PM_{2.5}$, which corresponds to a 9.5 and 13.9 percent reduction at pre-closure, downwind sample averages for the 25 and 50 mile buffers. Similar to the full sample, the post-closure trend in $PM_{2.5}$ is positive but not statistically significant.

As an additional robustness check, we consider the potential endogeneity of which areas experience closure. Prior research on shutdown decisions at the plant level by Davis et al. (2018) indicates the age of power plants is likely a stronger predictor. We report IV-2SLS results in Tables A1 and A2. While we find a larger post-closure reduction in particulate matter when we instrument for closure with plant age and its quadratic, the instruments are not sufficiently strong. As a result, we prefer to focus on our initial difference-in-difference estimates, but we recognize that our findings on the magnitude of $PM_{2.5}$ reduction may not extend to future closures.

Overall, our results suggest a 7 to 14 percent reduction in local $\mathrm{PM}_{2.5}$ levels following a coal plant closure. Our findings are consistent with previous estimates. Johnsen et al. (2019) estimate shutting down all US coal-fired power plants would on average decrease $\mathrm{PM}_{2.5}$ by

16 percent. There estimates were derived from estimating 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.

It is important to note that our model does not directly capture the long-term response of air quality to coal power plant closure. The biggest empirical challenge is not being able to observe other changes in industrial activity around the monitor station after closure which may be related or unrelated to the power plant closure. Despite this limitation, we can approximate when the affect of the closure is no longer detectable using the simple test:

$$\beta_1 + \beta_2 \cdot MSC_{i,t} \cdot t = 0, \tag{2}$$

where MSC increases with each month t. If β_2 is positive/negative, it indicates that the particulate matter is increasing/decreasing over time following closure. When β_2 is positive and β_1 is negative, one can solve for t to determine the number of months after closure when the effect of closure is zeroed out. Moreover, a t-test of equation 2 over time can also show when the effect is no longer statistically significant. Using the downwind sample, Figure 8 shows a 40 month time horizon post-closure. Because our estimates of β_2 were positive the estimated level of $PM_{2.5}$ gradually increases over time. However, the farther in time away from closure the 95 percent confidence interval, shown by the grey shading gets, much larger. For the 25 mile buffer sample (Figure 8a), the implied time to zero out the initial reduction in $PM_{2.5}$ is 39 months. However, the reduction is no longer statistically significant after 8 months. In the 50 mile buffer sample, the reduction remains significant out to 20 months (Figure 8b). Because of this limitation, we focus on the month of closure effects when considering potential health implications.

5 Health Implications of Power Plant Closures

Previous research has established a clear link between air pollution and mortality in a variety of settings. For example, Knittel et al. (2016) show that particulate matter has large marginal effects on infant mortality rates. Luechinger (2014) uses changes in desulfurization of power plants to estimate the effect of sulfur dioxide pollution on infant mortality. Deryugina et al. (2019) find that mortality effects from changes in local air pollution are concentrated in about 25 percent of the elderly population. Schlenker and Walker (2015) show that hospitalization rates increase from higher local exposure to carbon monoxide from airplane idling and taxiing.

In our analysis, at least two primary channels exist by which power plant closures may have local health implications via 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 5). The probability of heart-related deaths or lung cancer increases between 13 and 24 percent. Using an average of our estimates, a 1.5 $\mu g/m^3$ reduction in $PM_{2.5}$ from coal power plant closure is around 15 percent of the exposure threshold in Krewski et al. (2009). The second and third columns of Table 5 report an approximation of the decline in mortality from coal-fired power plant closures by rescaling the previous estimates. A back of the envelope calculation suggests a 0.8 reduction in the probability of death from a coal power plant closure.

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)[3] 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 9 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:

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

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 ($X^k_{i,t}$) 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 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 6 reports

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

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 7 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 5 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:

$$PHB_{i,t} = population_i * r^m_{i,t} * 0.004 * \$7.4 \text{ million},$$

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, 0.004, in Table 5 to capture the reduction in mortality from reduced particulate matter via coal power plant closure. Figure 10 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 \$0.9 to \$4.3 billion. Similarly, the estimated median benefit ranged from between \$0.4 and \$2.0 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 11 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. Using county-level data from Bureau of Economic Analysis, Figure 12 reports the potential health benefit as a share of real gross domestic product. We fine that average (median) local benefit ranged from 4 to 14 (2.5 to 11) percent of GDP.

To give a sense of the aggregate benefit, we sum up the potential health benefit across all counties with closures. Figure 13 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 1995 and 2018, we find reductions in local particulate matter of 7 to 14 percent. The reduction in the level of $PM_{2.5}$ concentrations is about 15 percent of previously estimated mortality hazard ratios. The reductions we estimate represent approximate reductions of 0.8 percentage points 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 or 5 to 15 percent of local GDP 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.

References

Almond, Douglas, Janet Currie, and Valentina Duque. 2018. "Childhood circumstances and adult outcomes: Act II." *Journal of Economic Literature*, 56(4): 1360–1446.

Case, Anne, and Angus Deaton. 2017. "Mortality and morbidity in the 21st century." *Brookings Papers on Economic Activity*, 2017(1): 397–476.

Case, Anne, and Angus Deaton. 2020. *Deaths of Despair and the Future of Capitalism.*: Princeton University Press.

Chay, Kenneth Y, and Michael Greenstone. 2003. "The impact of air pollution on infant mortality: evidence from geographic variation in pollution shocks induced by a recession." *The Quarterly Journal of Economics*, 118(3): 1121–1167.

Chay, Kenneth Y, and Michael Greenstone. 2005. "Does air quality matter? Evidence from the housing market." *Journal of Political Economy*, 113(2): 376–424.

Currie, Janet, Lucas Davis, Michael Greenstone, and Reed Walker. 2015. "Environmental health risks and housing values: evidence from 1,600 toxic plant openings and closings." *American Economic Review*, 105(2): 678–709.

Currie, Janet, and Matthew Neidell. 2005. "Air pollution and infant health: what can we learn from California's recent experience?" *The Quarterly Journal of Economics*, 120(3): 1003–1030.

Currie, Janet, Reed Walker et al. 2019. "What Do Economists Have to Say about the Clean Air Act 50 Years after the Establishment of the Environmental Protection Agency?" *Journal of Economic Perspectives*, 33(4): 3–26.

Davis, Lucas W. 2011. "The effect of power plants on local housing values and rents." *Review of Economics and Statistics*, 93(4): 1391–1402.

Davis, Rebecca J, J Scott Holladay, and Charles Sims. 2018. "Drivers of Coal Generator Retirements and their Impact on the Shifting Electricity Generation Portfolio in the US." Technical report, Working Paper.

Deryugina, Tatyana, Garth Heutel, Nolan H Miller, David Molitor, and Julian Reif. 2019. "The mortality and medical costs of air pollution: Evidence from changes in wind direction." *American Economic Review*, 109(12): 4178–4219.

Energy Information Administration. 1999. "Natural Gas 1998 Issues and Trends." `https://www.eia.gov/naturalgas/archive/056098.pdf`.

Energy Information Administration. 2019a. "More U.S. coal-fired power plants are decommissioning as retirements continue." `https://www.eia.gov/todayinenergy/detail.php?id=40212`, Accessed: November 7, 2019.

Energy Information Administration. 2019b. "U.S. electricity generation from renewables surpassed coal in April." `https://www.eia.gov/todayinenergy/detail.php?id=39992`, Accessed: June 26, 2019.

Giaccherini, Matilde, Joanna Kopinska, Alessandro Palma et al. 2019. "When Particulate Matter Strikes Cities. Social Disparities and Health Costs of Air Pollution." Working Paper No. 467, Tor Vergata University, CEIS.

Graff Zivin, Joshua, and Matthew Neidell. 2013. "Environment, health, and human capital." *Journal of Economic Literature*, 51(3): 689–730.

Hanna, Rema, and Paulina Oliva. 2015. "The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City." *Journal of Public Economics*, 122 68–79.

Isen, Adam, Maya Rossin-Slater, and W Reed Walker. 2017. "Every breath you take—every dollar you'll make: The long-term consequences of the clean air act of 1970." *Journal of Political Economy*, 125(3): 848–902.

Jha, Akshaya, and Nicholas Z Muller. 2018. "The local air pollution cost of coal storage and handling: Evidence from US power plants." *Journal of Environmental Economics and Management*, 92 360–396.

Johnsen, Reid, Jacob LaRiviere, and Hendrik Wolff. 2019. "Fracking, Coal, and Air Quality." *Journal of the Association of Environmental and Resource Economists*, 6(5): 1001–1037.

Kahn, Matthew E. 2009. "Regional growth and exposure to nearby coal fired power plant emissions." *Regional Science and Urban Economics*, 39(1): 15–22.

Knittel, Christopher R, Douglas L Miller, and Nicholas J Sanders. 2016. "Caution, drivers! Children present: Traffic, pollution, and infant health." *Review of Economics and Statistics*, 98(2): 350–366.

Krewski, Daniel, Michael Jerrett, Richard T Burnett, Renjun Ma, Edward Hughes, Yuanli Shi, Michelle C Turner, C Arden Pope III, George Thurston, Eugenia E Calle et al. 2009. "Extended follow-up and spatial analysis of the American Cancer Society study linking particulate air pollution and mortality." Research Report 140, Health Effects Institute.

Luechinger, Simon. 2014. "Air pollution and infant mortality: a natural experiment from power plant desulfurization." *Journal of Health Economics*, 37 219–231.

Muller, Nicholas Z. 2014. "Boosting GDP growth by accounting for the environment." *Science*, 345(6199): 873–874.

Muller, Nicholas Z, Robert Mendelsohn, and William Nordhaus. 2011. "Environmental accounting for pollution in the United States economy." *American Economic Review*, 101(5): 1649–75.

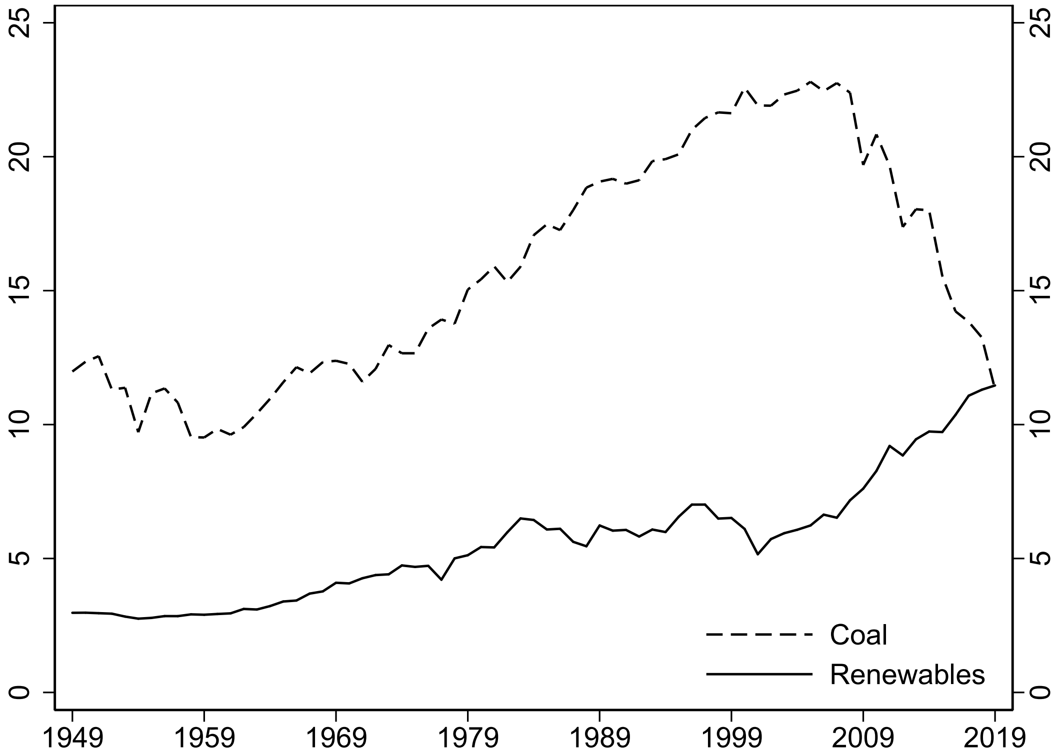
National Research Council. 2010. *Hidden costs of energy: unpriced consequences of energy production and use.*: National Academies Press.

Russell, Marie C, Jessica H Belle, and Yang Liu. 2017. "The impact of three recent coal-fired power plant closings on Pittsburgh air quality: A natural experiment." *Journal of the Air & Waste Management Association*, 67(1): 3–16.

Schlenker, Wolfram, and W Reed Walker. 2015. "Airports, air pollution, and contemporaneous health." *The Review of Economic Studies*, 83(2): 768–809.

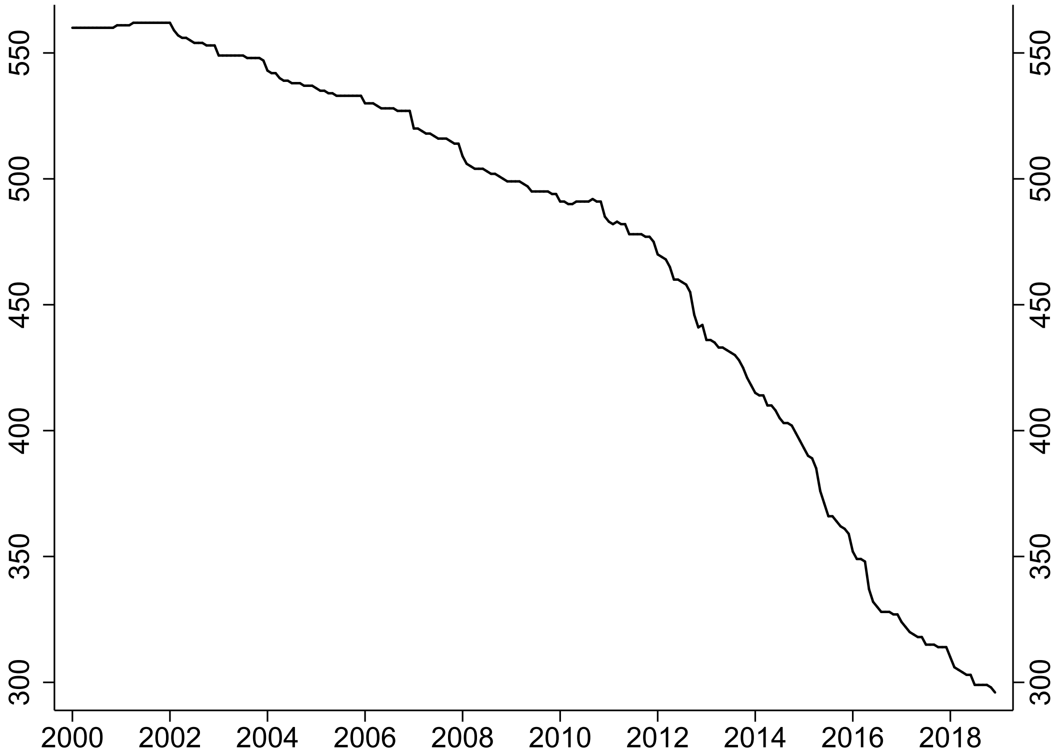
Sullivan, Daniel M. 2017. "The true cost of air pollution: Evidence from the housing market."Technical report, Working Paper.

Viscusi, W Kip, and Joseph E Aldy. 2003. "The value of a statistical life: a critical review of market estimates throughout the world." *Journal of Risk and Uncertainty*, 27(1): 5–76.



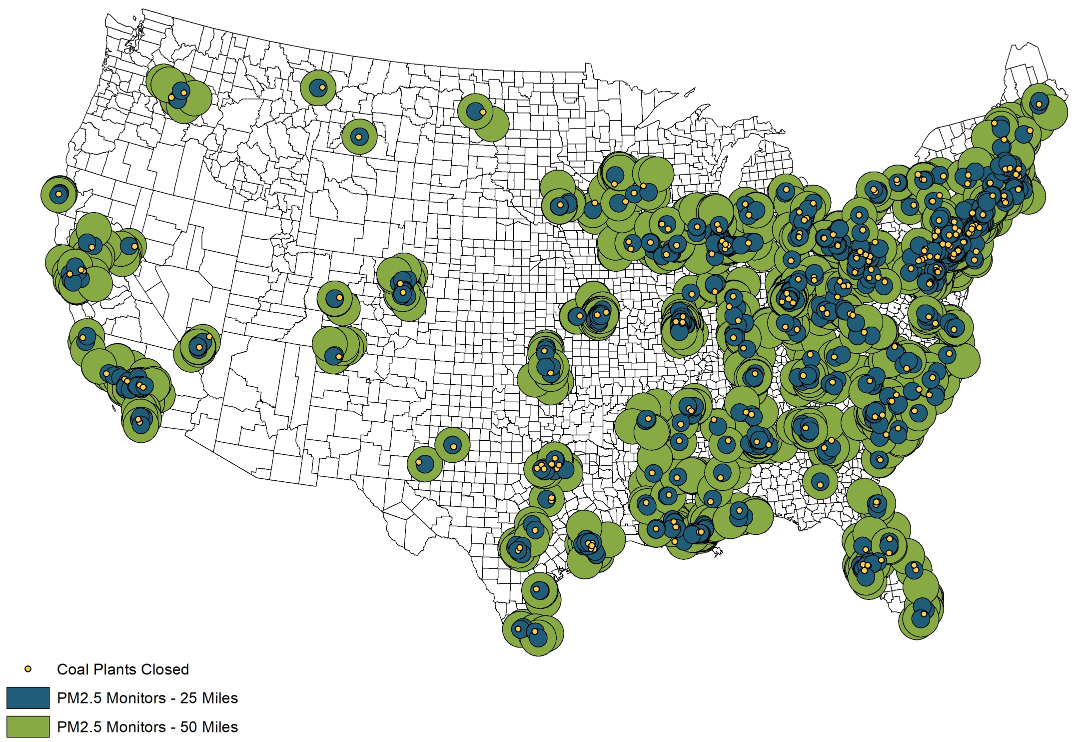
Source: EIA

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



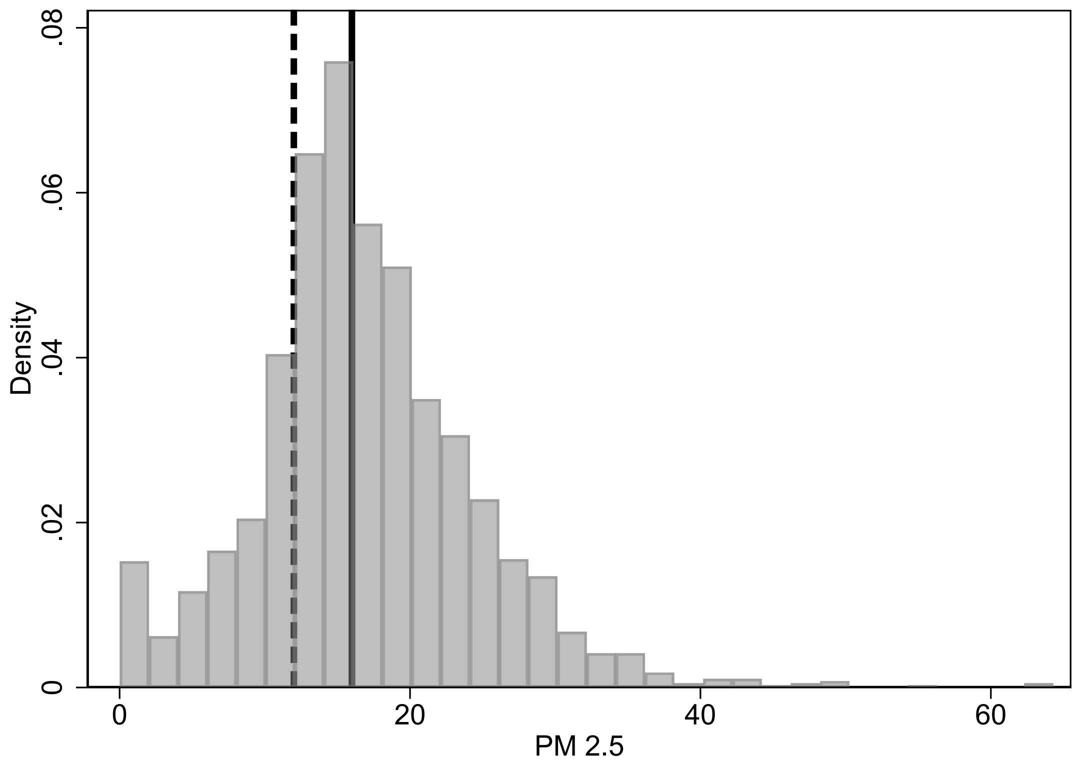
Source: EIA

Figure 2: Coal Power Plants



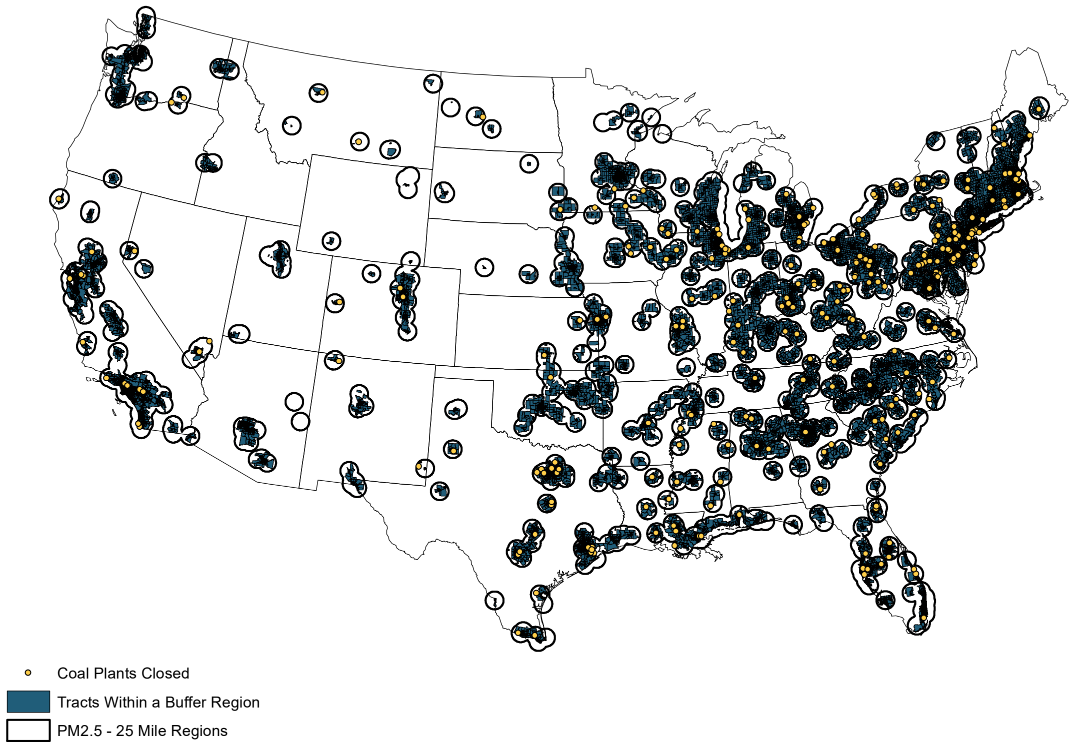
Source: EPA

Figure 3: Coal Power Plant Closures, 2001 to 2018



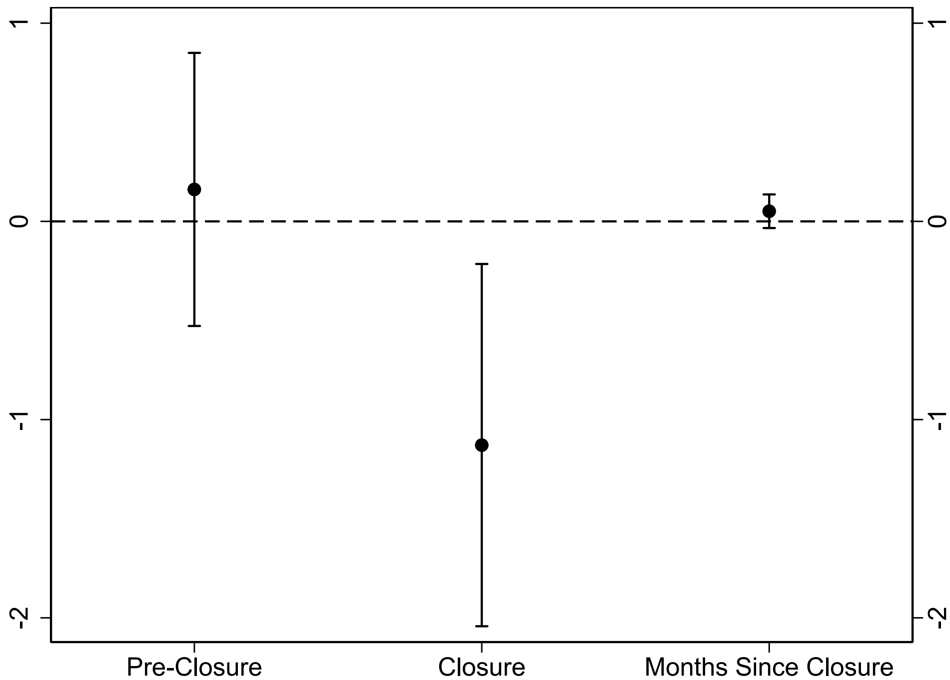
Source: EPA

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

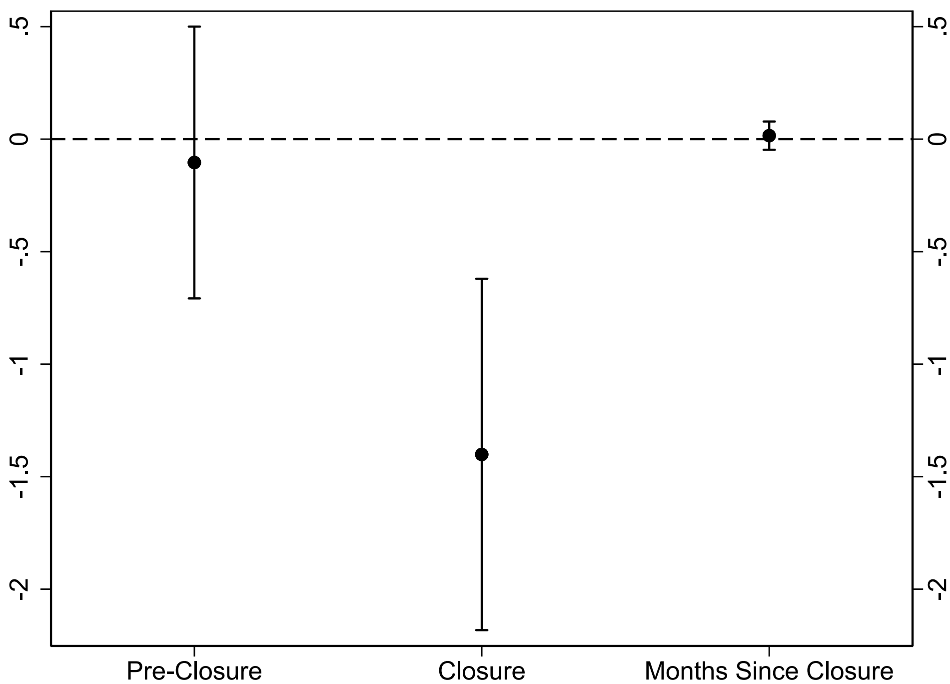


Source: Census, EPA

Figure 5: $PM_{2.5}$ Buffer Regions and Census Tracts



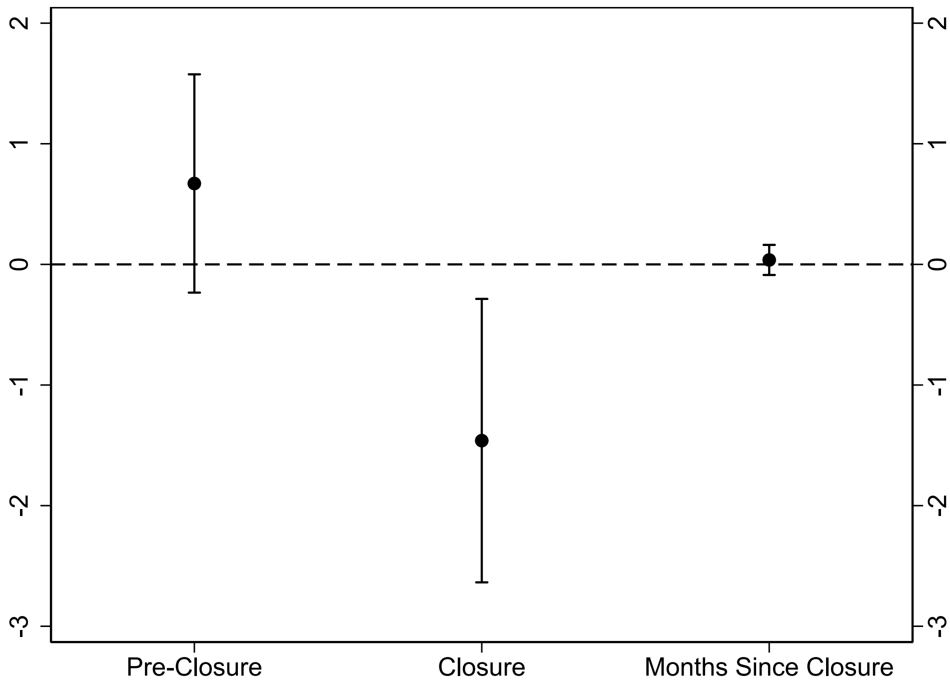
(a) Reduction in $PM_{2.5}$ - 25 Mile Buffer Sample



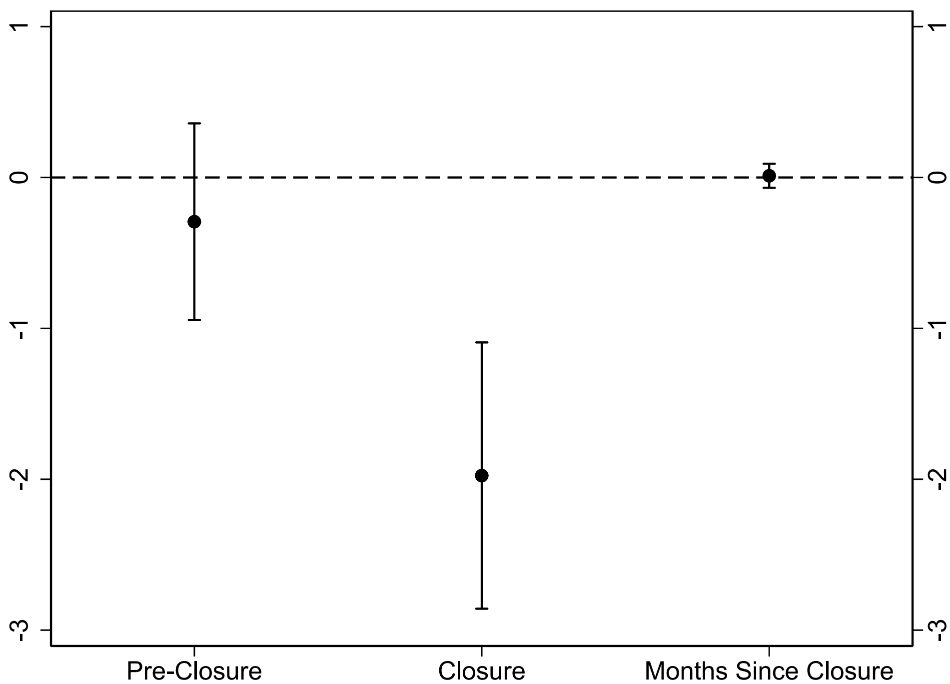
(b) Reduction in $PM_{2.5}$ - 50 Mile Buffer Sample

Notes: Point estimates and 95 percent confidence intervals are represented by dots and whiskers.

Figure 6: Air Quality Response to Coal Plant Closure



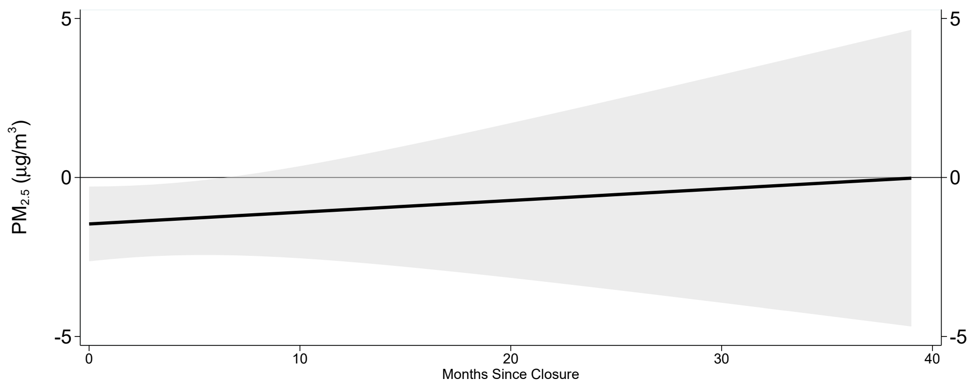
(a) Reduction in $PM_{2.5}$ - 25 Mile Buffer Sample



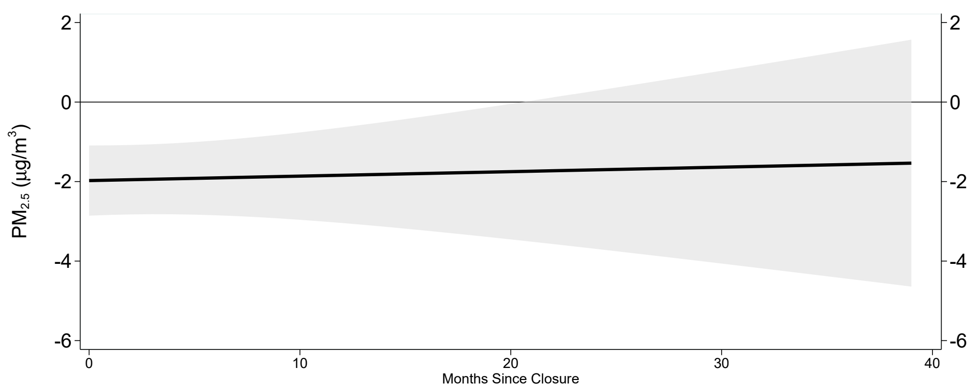
(b) Reduction in $PM_{2.5}$ - 50 Mile Buffer Sample

Notes: Point estimates and 95 percent confidence intervals are represented by dots and whiskers.

Figure 7: Air Quality Response to Coal Plant Closure: Downwind Sample



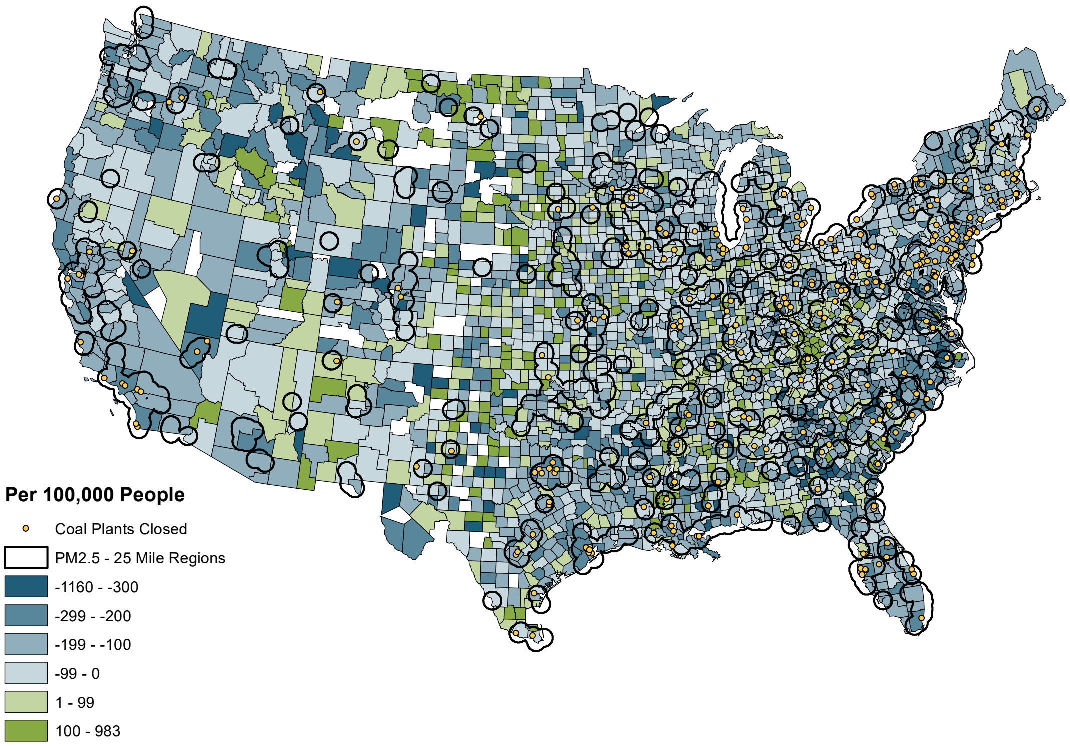
(a) Reduction in $PM_{2.5}$ Over Time - 25 Mile Buffer Sample



(b) Reduction in $PM_{2.5}$ Over Time - 50 Mile Buffer Sample

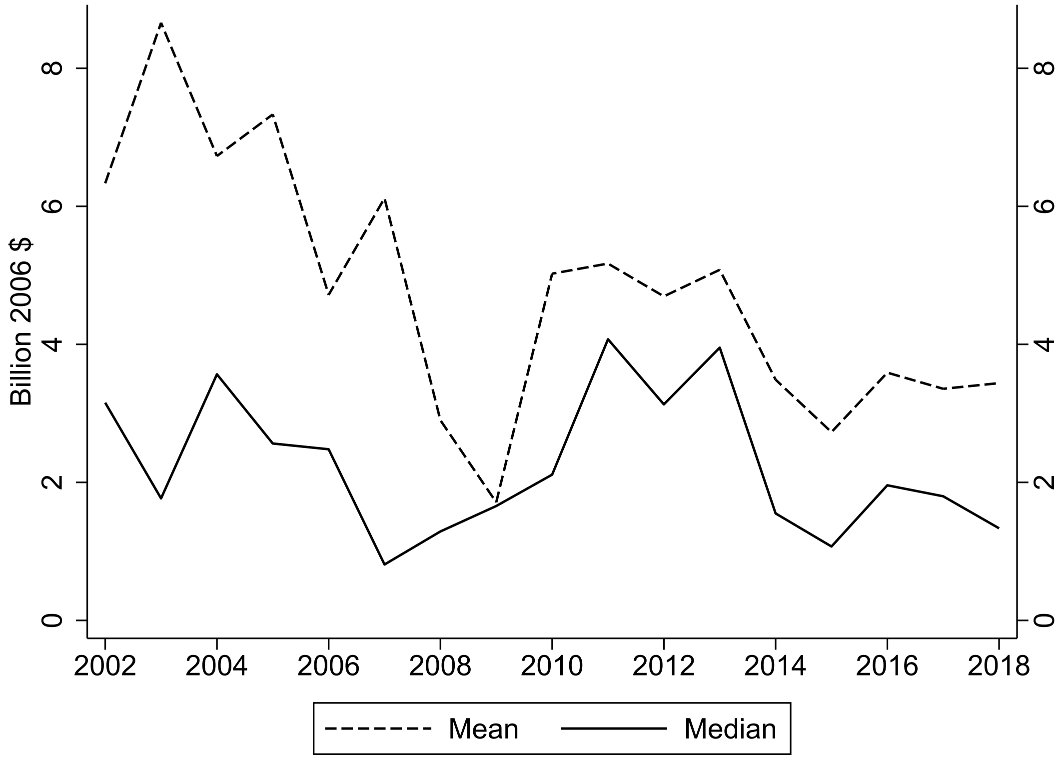
Notes: Point estimates and 95 percent confidence intervals are represented by solid line and shaded area.

Figure 8: Air Quality Response to Coal Plant Closure Over Time



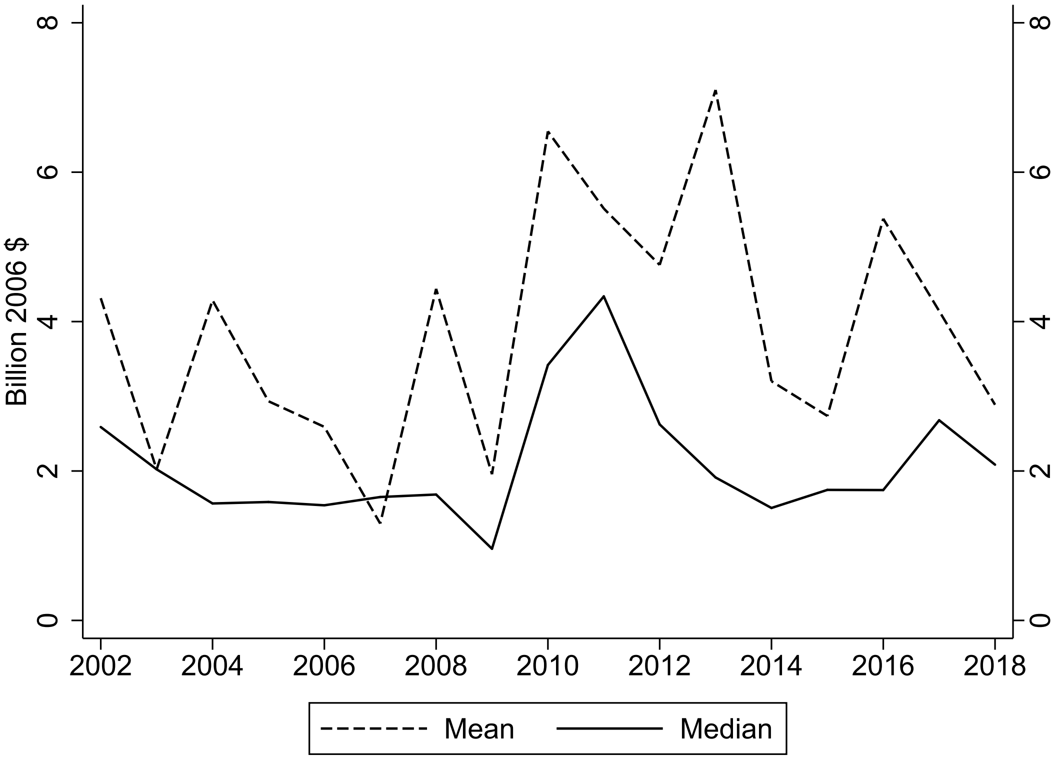
Source: CDC, EPA

Figure 9: Change in Mortality Rates for All Causes of Death, 2000-2018



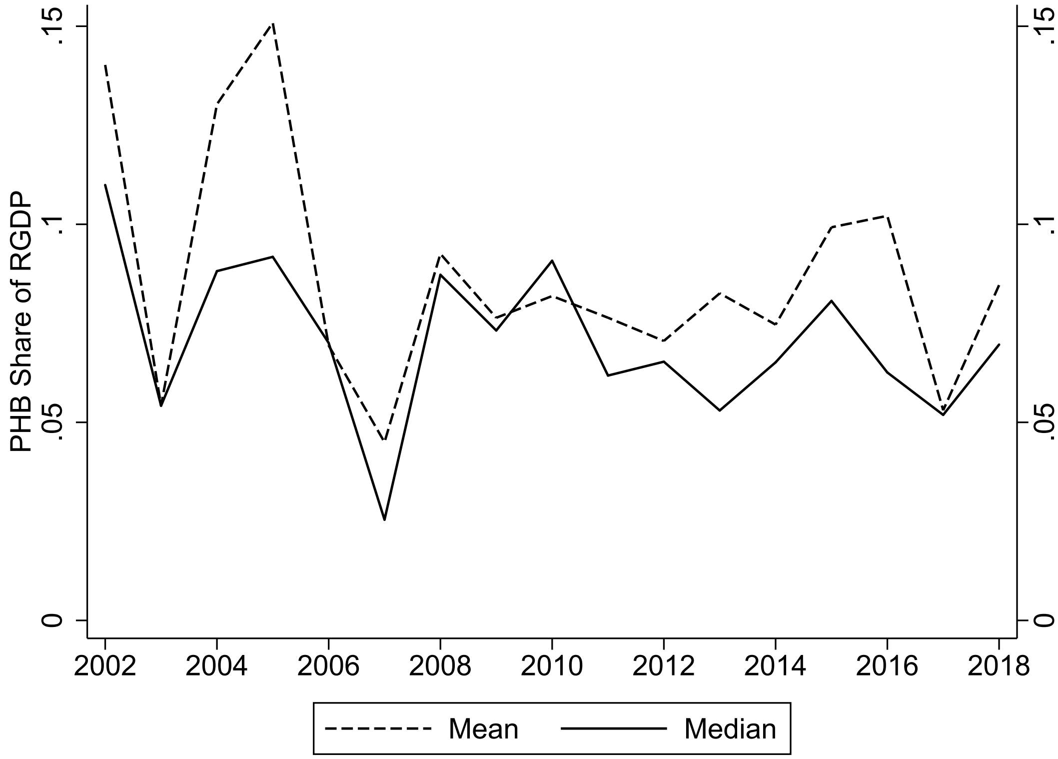
Source: Census, CDC, EPA

Figure 10: Potential Local Health Benefit of Reduced $PM_{2.5}$ from Coal Plant Closure



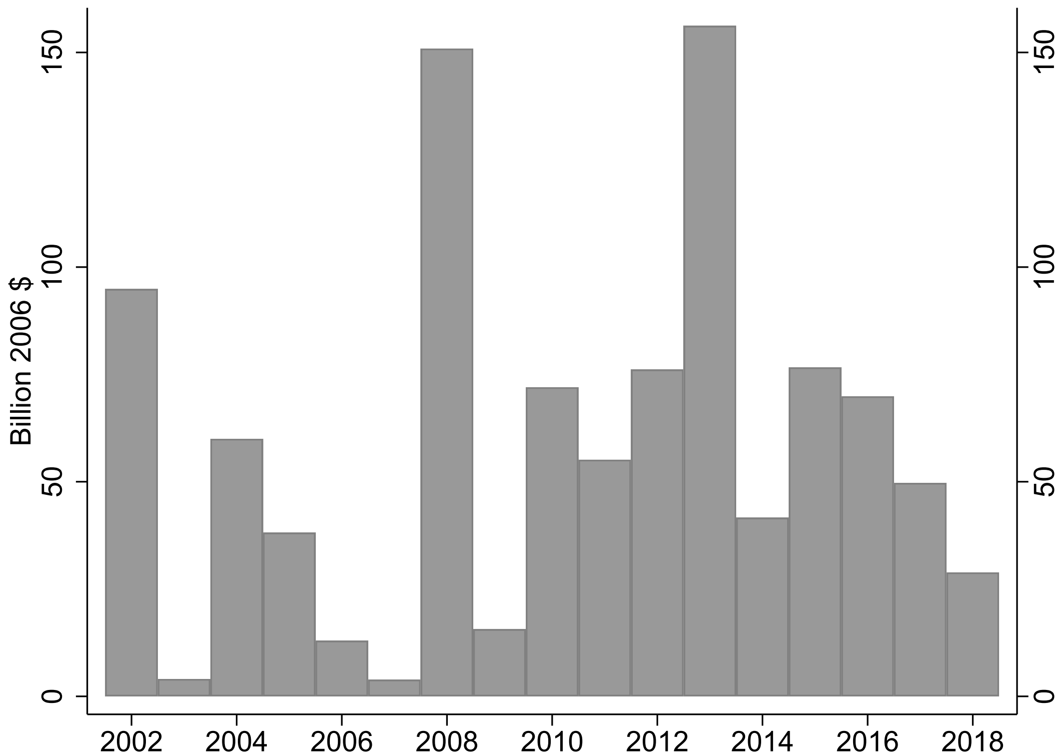
Source: Census, CDC, EPA

Figure 11: Potential Local Health Benefit of Coal Plant Closure



Source: Census, CDC, EPA, BEA

Figure 12: Potential Local Health Benefit as Share of County Real GDP



Source: Census, CDC, EPA

Figure 13: Potential Aggregate Health Benefit of Coal Plant Closure

Table 1: Descriptive Statistics

(a) 25 Mile Buffer

	Mean	SD	Min	Max
$PM_{2.5}$	15.91	8.42	0.02	289.72
Coal Plant Closure	0.01	0.09	0.00	1.00
Heat Input (QBTU)	0.90	0.88	0.00	5.77
CO2 (Thous. Tons)	751.70	761.92	0.00	4,329.42
SO2 (Thous. Tons)	2.41	3.67	0.00	29.60
NO (Thous. Tons)	0.92	1.20	0.00	10.44
Unemployment Rate (%)	6.45	2.48	1.60	19.70
Wind Direction	0.33	0.64	-1.00	1.00
N	15788			

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

(b) 50 Mile Buffer

	Mean	SD	Min	Max
$PM_{2.5}$	14.16	8.74	0.02	289.72
Coal Plant Closure	0.01	0.10	0.00	1.00
Heat Input (QBTU)	1.68	1.69	0.00	11.13
CO2 (Thous. Tons)	1,495.15	1,638.12	0.00	10,891.02
SO2 (Thous. Tons)	5.33	9.60	0.00	91.65
NO (Thous. Tons)	1.85	2.68	0.00	22.57
Unemployment Rate (%)	6.51	2.73	1.50	20.60
Wind Direction	0.36	0.65	-1.00	1.00
N	25082			

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

Table 2: Descriptive Statistics of Air Quality Pre-Closure

	Mean	SD	Min	Max
$PM_{2.5}$ 25 Miles	15.55	7.21	0.02	108.97
$PM_{2.5}$ 50 Miles	14.01	7.77	0.02	108.97

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

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

	25 mile	50 mile
Pre-Closure$_t$	0.161	-0.104
	(0.351)	(0.308)
Coal Plant Closure$_t$	-1.129**	-1.401***
	(0.466)	(0.398)
Months Since Closure$_t$	0.051	0.016
	(0.043)	(0.032)
Heat Input$_{t-1}$	0.664	1.033***
	(0.547)	(0.355)
Unemployment Rate$_{t-1}$	-0.016	-0.020
	(0.104)	(0.060)
Wind Direction$_{t-1}$	0.583	0.884**
	(0.478)	(0.438)
Carbon Dioxide$_{t-1}$	-0.001	-0.000
	(0.001)	(0.000)
Nitrous Oxide$_{t-1}$	-0.985***	-0.620***
	(0.122)	(0.046)
Sulfur Dioxide$_{t-1}$	0.293***	0.143***
	(0.066)	(0.028)
Adj. R-squared	0.621	0.615
N	15,569	24,757

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 Air Quality Response to Coal Power Plant Closure - Downwind Sample

	25 mile	50 mile
Pre-Closure$_t$	0.671	-0.293
	(0.461)	(0.332)
Coal Plant Closure$_t$	-1.461**	-1.976***
	(0.599)	(0.450)
Months Since Closure$_t$	0.037	0.011
	(0.064)	(0.041)
Heat Input$_{t-1}$	0.132	1.049***
	(0.573)	(0.371)
Unemployment Rate$_{t-1}$	-0.006	-0.055
	(0.132)	(0.068)
Wind Direction$_{t-1}$	1.454**	1.121**
	(0.624)	(0.543)
Carbon Dioxide$_{t-1}$	0.001	-0.000
	(0.001)	(0.000)
Nitrous Oxide$_{t-1}$	-1.133***	-0.697***
	(0.145)	(0.061)
Sulfur Dioxide$_{t-1}$	0.115	0.142***
	(0.079)	(0.032)
Adj. R-squared	0.577	0.585
N	10,717	17,956

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

Cause of Death	Hazard Ratio (10 $\mu g/m^3$)	Adjusted Hazard Ratio (1.5 $\mu g/m^3$)
All Causes	1.056	1.008
Cardiopulmonary	1.129	1.019
Ischemic Heart Disease	1.240	1.024
Lung Cancer	1.137	1.021

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 15 percent of that exposure to approximate magnitude of exposure reduction from coal closure.

Table 6: Estimated Mortality Rate Response to Coal Power Plant Closure

	Mortality Rate (All Deaths)	Mortality Rate (Circulatory Deaths)	Mortality Rate (Respiratory Deaths)
Coal Plant Closure(s)	-0.006**	-0.010**	-0.009
	(0.003)	(0.005)	(0.009)
Heat Input	-0.005	-0.005	-0.012
	(0.004)	(0.005)	(0.009)
Carbon Dioxide	0.001	-0.000	0.006
	(0.003)	(0.005)	(0.008)
Nitrous Oxide	0.005***	0.005**	0.003
	(0.002)	(0.003)	(0.004)
Sulfur Dioxide	0.000	0.001	-0.000
	(0.001)	(0.001)	(0.002)
Unemployment Rate	-0.002*	-0.001	0.005
	(0.001)	(0.002)	(0.004)
Adj. R-squared	0.876	0.830	0.753
N	33,697	32,052	26,305

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

Table 7: 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.

Appendix: Additional Empirical Results

Endogeneity of Closure

As an additional robustness check, we consider the potential endogeneity of which areas experience closure. Prior research on shutdown decisions at the plant level by Davis et al. (2018) indicates the age of power plants is likely a stronger predictor. To address this we use a 2SLS-IV approach where in the first stage we estimate:

$$CPC_{i,t} = \alpha_{i,y} + \delta_t + \sigma Age_{i,t} + \beta Age^2_{i,t} + \lambda HI_{i,t-1} + \phi_k X^k_{i,t-1} + \psi WD_{i,t-1} + \gamma UER_{i,t-1} + \mu_{i,t}, \quad (4)$$

where $Age_{i,t-1}$ is average power plant age of all the plants that intersect each 25 and 50 mile buffer. The second stage is estimated using:

$$PM_{i,t} = \alpha_{i,y} + \delta_t + \beta CPC_{i,t} + \lambda HI_{i,t-1} + \phi_k X^k_{i,t-1} + \psi WD_{i,t-1} + \gamma UER_{i,t-1} + \varepsilon_{i,t}. \quad (5)$$

First stage results are reported in Table A1. Age is negatively and significantly correlated with closure, while the quadratic term was near zero and insignificant. The F-statistic for the instruments is 7 and 16 in the 25 and 50 mile buffer samples, respectively. The instrumental variables are not sufficiently strong in either buffer sample. The endogeneity test was only significant in the 25 mile buffer sample. Overidentifaction tests indicated that the instruments were uncorrelated with second stage residuals. The second stage results suggest that coal power plant closure in the 25 mile buffer sample reduced longer-term $PM_{2.5}$ by 13.3 $\mu g/m^3$ or 85 percent (13.3/15.5) of the average pre-closure level (Table A2).

Table A1: First Stage Results of Coal Power Plant Closure

	25 mile	50 mile
Plant Age_t	-0.011*	-0.018**
	(0.006)	(0.008)
Plant Age_t^2	0.000	0.000
	(0.000)	(0.000)
Heat Input_{t-1}	0.005	0.021
	(0.027)	(0.017)
Unemployment Rate_{t-1}	0.008**	0.004**
	(0.003)	(0.002)
Wind Direction_{t-1}	0.002	0.034**
	(0.011)	(0.013)
Carbon Dioxide_{t-1}	-0.000	-0.000
	(0.000)	(0.000)
Nitrous Oxide_{t-1}	0.001	0.002***
	(0.002)	(0.001)
Sulfur Dioxide_{t-1}	-0.005**	-0.003***
	(0.002)	(0.001)
IV-F	7.01***	16.13***
Adj. R-squared	0.951	0.951
N	15,565	24,754

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 A2: IV-2SLS Estimates of Local Air Quality Response Post Closure

	25 mile	50 mile
Post Plant Closure$_t$	-13.319**	-4.288
	(5.707)	(3.227)
Heat Input$_{t-1}$	0.499	1.095***
	(0.616)	(0.362)
Unemployment Rate$_{t-1}$	0.088	-0.002
	(0.121)	(0.063)
Wind Direction$_{t-1}$	0.525	0.958**
	(0.488)	(0.441)
Carbon Dioxide$_{t-1}$	-0.000	-0.000
	(0.001)	(0.000)
Nitrous Oxide$_{t-1}$	-0.901***	-0.608***
	(0.127)	(0.045)
Sulfur Dioxide$_{t-1}$	0.211***	0.129***
	(0.076)	(0.029)
Endogeneity test	7.96***	1.34
Overidentification test	0.117	0.414
Adj. R-squared	0.593	0.612
N	15,565	24,754

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.

Mortality Response: Alternative Closure Measures

Table A3: Estimated Mortality Rate Response to Coal Power Plant Closure - Single Closure

	Mortality Rate (All Deaths)	Mortality Rate (Circulatory Deaths)	Mortality Rate (Respiratory Deaths)
Coal Plant Closure	-0.011**	-0.017**	-0.018
	(0.005)	(0.009)	(0.013)
Heat Input	-0.005	-0.005	-0.012
	(0.004)	(0.005)	(0.009)
Carbon Dioxide	0.001	-0.000	0.006
	(0.003)	(0.005)	(0.008)
Nitrous Oxide	0.005***	0.005**	0.003
	(0.002)	(0.003)	(0.004)
Sulfur Dioxide	0.000	0.001	-0.000
	(0.001)	(0.001)	(0.002)
Unemployment Rate	-0.002*	-0.001	0.005
	(0.001)	(0.002)	(0.004)
Adj. R-squared	0.876	0.830	0.753
N	33,697	32,052	26,305

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

Table A4: Estimated Mortality Rate Response to Coal Power Plant Closure - Cumulative Closures

	Mortality Rate (All Deaths)	Mortality Rate (Circulatory Deaths)	Mortality Rate (Respiratory Deaths)
Cum. Coal Plant Closures	-0.008***	-0.010***	-0.017**
	(0.003)	(0.004)	(0.008)
Heat Input	-0.005	-0.005	-0.012
	(0.004)	(0.005)	(0.009)
Carbon Dioxide	0.001	-0.000	0.006
	(0.003)	(0.005)	(0.008)
Nitrous Oxide	0.005***	0.005**	0.003
	(0.002)	(0.003)	(0.004)
Sulfur Dioxide	0.000	0.001	-0.000
	(0.001)	(0.001)	(0.002)
Unemployment Rate	-0.002*	-0.001	0.005
	(0.001)	(0.002)	(0.004)
Adj. R-squared	0.876	0.830	0.753
N	33,697	32,052	26,305

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