NBER WORKING PAPER SERIES

ABANDONED BY COAL, SWALLOWED BY OPIOIDS?

Gilbert E. Metcalf
Qitong Wang

Working Paper 26551
http://www.nber.org/papers/w26551

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
December 2019

We thank Melissa McInerney and Jeff Zabel for helpful comments and the National Center for Health Statistics for access to county level mortality data. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Abandoned by Coal, Swallowed by Opioids?
Gilbert E. Metcalf and Qitong Wang
NBER Working Paper No. 26551
December 2019
JEL No. I1,Q32,Q35

ABSTRACT

Opioid addiction and mortality skyrocketed over the past decade. A casual look at the geographic incidence of opioid mortality shows sharply higher mortality rates in the Appalachian region, especially in coal-mining areas. This has led observers to make a link that was characterized by one newspaper as "abandoned by coal, swallowed by opioids." We test that theory using restricted death data and mine level coal production data. Specifically, we examine whether higher reliance on coal mining in a county's economy leads to higher or lower opioid mortality. We find a positive relationship between the share of coal miners among total local labor force and county-level opioid mortality rates. This contradicts the "abandoned by coal, swallowed by opioids" story. Rather our results suggest that the higher rates of injury in underground coal mining (in particular) lead to greater amounts of opioid consumption and mortality. An implication is that the decline in coal mining in the United States may have a positive spillover in the form of reduced mortality from opioid use.

Gilbert E. Metcalf
Department of Economics
Tufts University
Medford, MA 02155
and NBER
gilbert.metcalf@tufts.edu

Qitong Wang
Department of Economics
3620 South Vermont Ave. Kaprielian (KAP) Hall, 300
Los Angeles, CA 90089-0253
USA
qitongwa@usc.edu

I. Introduction

Opioid use has become a major health crisis in the United States affecting all sectors of society. Deaths from drug overdoses have increased more than fourfold since 1999, rising from just under 17,000 in 1999 to over 70,000 in 2017 (Hedegaard et al., 2018). Death rates from opioid overdoses have risen especially rapidly as shown in Figure 1. Recently, synthetic opioid drugs (like Fentanyl) have become especially lethal. These artificial drugs are designed to mimic the effect of natural opioid-like codeine or morphine and to provide additional solutions to pain issues. These substances are normally highly potent and can achieve the same effect at low doses, which means they are also much more dangerous when misused. For example, Fentanyl, one of the most common synthetic opioids, has been mixed with heroin when sold in black market and caused many deaths in the United States.

Opioid mortality is geographically concentrated in certain regions of the country including the East coast, Rust Belt regions, and the Southwest (figure 2). Within the East, the Appalachian region, has been especially hard hit. This is a region whose economies, coincidently or not, are heavily dependent on coal mining.

At the same time that opioid death rates have been sharply rising, the U.S. energy market has been undergoing a massive transformation. Coal, once the dominant fuel source for electricity generation, has been replaced by natural gas as the largest fuel source for electricity production. This is the result of major technological advances in natural gas production. Hydraulic fracking and advances in horizontal drilling technology have led to an explosion in domestic natural gas production. Domestic natural gas production has risen by over fifty percent since 2006, according to data from the U.S. Energy Information Administration. The result has been a sharp fall in the price of natural gas. EIA data tell the story: the price of natural gas supplied to electric power plants fell by fifty percent over this period while coal prices were essentially unchanged. Figure 3 shows the transition away from coal towards natural gas in electricity generation with the share of coal among electricity sector fuel usage dropping from 51% in 2000 to 30% in 2017. Since over 90% of the coal produced in the United States has been used in electricity generation, this fall in demand has contributed to a 28% decrease in total production and a 34% decline in coal-related employment.

The fall in employment is due to more than the overall decline in demand. Coal production in the United States has been shifting from Eastern coal mines, e.g. mines in the Appalachian regions to Western regions, like the Powder River Basin, in part because of the lower sulfur content of Western coal and in part due to higher productivity of Western coal mines. Because Western coal is primarily surface mined coal as opposed to underground mined coal, the productivity of Western coal miners is much higher. In 2016, for example, the mean productivity of workers in mines in the Powder River basin was 27.5 tons per worker hour versus 3.4 tons per hour in Appalachian coal mines.

Figure 4 shows the decline in coal mining employment since 2000. While both surface mines and underground mines have shed workers, the job loss in underground mines is much larger. Moreover, there are more layoffs of coal miners from both surface and underground mines in the Appalachian regions relative to other areas.

It is widely believed that the opioid epidemic is associated with a worsening economic environment. Research suggests that people facing stressful economic and social conditions are more likely to abuse drugs (Sinha, 2008). Or, in the coal mining context as an article in *The Guardian* put it, Eastern coal miners have been "abandoned by coal, swallowed by opioids." If it is true that decreasing coal mining activity has contributed to the drug crisis, then this is a factor that policy makers should take into consideration when designing climate policies and any transitional assistance associated with those policies.

On the other hand, coal mining is extremely difficult work with a high injury rate. Perhaps the correlation between opioid use and coal mining is due more to opioid use in response to the arduous work. In that case, policies to reduce reliance on coal could indirectly help reduce opioid addiction and mortality.

This paper examines the relationship between the decline of the coal industry and the death rate from opioid overdose. We combine county-level death record data from the National Center for Health

Statistics with mine-level coal production data from Energy Information Administration (EIA) to conduct a county-level empirical analysis on the relationship between opioid death rates and county coal mining activity.

We estimate models with the opioid overdose death rate as the dependent variable and the share of coal miners in the county labor force as the key independent variable while controlling for other factors. We also consider potential endogeneity in the labor share by constructing a Bartik-style variable to instrument for coal mining employment.

Our results indicate that a lower dependency of the local economy on coal mining is associated with lower opioid death rates. Specifically, a one percent increase among the coal-producing counties in the share of coal miners in the workforce increases the opioid mortality by 0.192 percent. To better understand the magnitude of the impact, if coal mining activity in 2016 were at its 2011 peak level, the opioid death rate would have been fifteen percent higher. The impact is stronger among underground than surface coal mines. Impacts are also larger when instrumenting for the labor share variable. Based on these results, we argue that the shift from coal to natural gas not only has produced environmental benefits but also has helped to blunt damages from the opioid epidemic. We explore several possible mechanisms. One possible channel is that increasing coal mining activity leads to more workplace injuries and more opioid prescriptions in the community; the increased access to drugs leads to higher opioid death rates, according to this theory.

II. Background

As noted at the outset, overdose death rates have risen dramatically over the past two decades. The increase in opioid related deaths is even more striking, rising from 8,407 in 2000 to 47,600 in 2017 (Hedegaard et al., 2018). A strong driver in the sharply rising opioid death rate is the substantial increase of opioid prescribing rates (Dart et al., 2015). This was driven, in part, by a heightened focus on pain management beginning in the 1990s (Levy et al., 2015). But it is also clear that aggressive marketing by drug companies also contributed to the crisis (Van Zee, 2009). Compounding the problem is the proliferation of powerful synthetic opioids including Fentanyl that can be prescribed legally but also have shown up in street heroin. The Centers for Disease Control and Prevention estimates that prescription opioid misuse cost the United States nearly $80 billion annually in costs of treatment, lost productivity, and criminal justice costs in 2013 (Florence et al., 2016). Efforts to control the use of opioid or overdose with laws to date have not been effective (Meara et al, 2016).

At the same time that the opioid crisis was taking off, the coal industry has experienced the most severe decline in the history of mining in the United States. Driving the decline, among other factors, is the sharp drop of natural gas price resulting from the fracking revolution that has brought large quantities of natural gas into the market and made the United States the largest producer of natural gas in the world. Natural gas has driven out a considerable amount of coal-fired electricity and is one of the most important factors that caused coal mine closures (Coglianese, 2017). Other factors are the rise of wind generation (Fell and Kaffine, 2018) and the decline of electricity consumption (Linn and McCormack, 2017). Jordan et al. (2018) also argue that the increasing costs of production contributed the most for the closure of Appalachian coal mines.

We are interested in the question of how changes in coal mining rates may affect opioid mortality as opposed to a simple correlation between coal mining activity and mortality. One possible response to a decline in Eastern coal mining and the resulting economic decline is an increase in opioid addiction and mortality as suggested by the work of Case and Deaton (2015) and their idea of "deaths of despair." They argued that poor economic conditions for less-educated middle-aged white Americans have induced an increase in the prevalence of death due to suicide, alcohol, and drug addiction. Deaths of despair suggests that sharply rising unemployment and declining economic conditions in Appalachian coal mining communities could lead to higher rates of opioid addiction and death.

In a subsequent paper, Case and Deaton (2017) argued that "deaths of despair" cannot be solely explained by declining economic conditions. They noted that the death rate for less-educated middle-aged white Americans actually started to rise in the early 2000s prior to the financial crisis; moreover, the death rate for this group continued to rise as the economy began to recover from the Great Recession. Case and

Deaton attributed the rising death rate for this group to more general social problems including stagnating real wages. Focusing more specifically on drug overdoses, Ruhm (2018) examined whether the increase in drug mortality is due more to stagnating economic opportunities ("death by despair") or just one of the consequences of a worsening "drug environment." He concludes that it is inappropriate to attribute the rise in drug overdose to the "deaths of despair" framing but rather more a function of the drug environment.

Case and Deaton's work builds on earlier work on the relationship between general macroeconomic conditions and personal health. Results in that literature are mixed. Smith (1999) found that declining economic conditions are bad for the health of the elderly. Ruhm (2000) found total mortality to be strongly procyclical to macroeconomic conditions. He argued that a strong economy contributed to unhealthy diets and more cardiovascular disease and transport accidents. Ruhm (2015) revisited this idea and found that the procyclical pattern of total mortality have been weaken recently. Although cardiovascular disease and transport accident continue to be procyclical, cancer has shown a strong countercyclical pattern. It is worth noticing that Lindo (2015) found different results when the analysis is done at a lower level of aggregation. Specifically, when aggregated at county level, he found smaller results comparing to state-level analysis.

Focusing on pain killers, recent research has found that declining economic conditions, especially the decline of manufacturing, will increase the prescription of pain killers, such as opioids, and lead to more opioid deaths (Carpenter et al. 2017, Charles et al. 2018). These effects are more concentrated on working white-males with low educational attainment. Hollingsworth et al. (2017) analyzed the relationship between a worsening economic situation and opioid death rates, as well as Emergency Department (ED) visits with a 16-year panel and county fixed effect regression. They also considered the impacts of state-specific policies, such as Prescription Drug Monitoring Program (PDMP) and reached the conclusion that opioid-related deaths and ED visits increase during an economic downturn. Precisely, a one percent point increase in local unemployment rate leads to 3.6% increase in opioid deaths. Results are stronger when regressions are run at the state rather than county level, a result attributed by Lindo (2015) to spillover effects across counties within a state.

Betz and Jones (2018) examined the heterogeneous effect of employment growth and wage changes on opioid overdoses in different industries. They used average earnings as a proxy for working skills and divided industries into four skill-level tiers. The results implied that wage and employment growth in low-skill industries can decrease opioid overdose of rural, white males. The same improvement is also helpful for black and female population. On the other hand, higher employment was associated with more opioid overdose in population within high-paying industries. These results suggest that the mechanism driving opioid overdoes can be different depending on the natural of the occupation.

While increased opioid use may be driven in part by worsening economic conditions, it is also possible that work related injuries could also drive increased opioid use. Underground coal mining is an especially hazardous occupation requiring workers to spend long periods of time in cramped working conditions. In Figure 5, we rank industries at the same NAICS level according to their incident rate of non-fatal injuries and illnesses.

Coal mining activity is above the 60th percentile in the ranking of incident rate of non-fatal workplace injuries and illness among all the industries at the same NAICS level recorded by Bureau of Labor Statistics in 2017, while underground coal mining is above the 90th percentile whereas surface coal mining is at the 20th percentile. Coal mining, especially underground coal mining, is one of the most dangerous professions in the United States. Thus, these coal miners may experience injuries leading to a higher rate of use of painkillers. This conjecture is supported by the abnormally high prescription rate of opioid drugs in Appalachian regions. From Figure 6, we can see that the prescription rate of opioid in the Appalachian region is almost double the prescription rate in other regions. Starting from 2013, the prescription rate of opioids has been decreasing dramatically. This is because states began to review Prescription Drug Monitoring Program (PDMP) data and implement pain clinic regulation (Guy Jr et al., 2017).

Coal mining has never been a safe profession. Coleman and Kerkering (2007), Margolis (2010) and Komljenovic et al. (2008) used several estimation methods to measure the risk of injury in coal mining activity. They reached the conclusion that even though the risk of injury has decreased compared to past years, coal mining is still one of the most dangerous occupations in the United States. Margolis (2007) also found that the risk of injury may increase with an increase in workers' age.

Thumula et al. (2017) used 26 workers' compensation jurisdictions covering data from October 2009 through March 2015 to study the trends in the use of opioids and prescribing patterns of pain medication. They found that in the 2013 - 2015 period, over half of the injured workers with pain medications were prescribed with opioids. These conclusions echo with the observation of Havens et al. (2007) and McDonald et al. (2012) that Appalachian region had abnormally high opioid death rates.

The difficult working environment may contribute to injuries or chronic pain that leads to increased reliance on painkillers, including opioids. In addition, the culture of coal mining may make it difficult for injured coal miners to take time off from work, especially as jobs are being cut back due to reduced demand for Appalachian coal. According to a documentary done by PBS (Public Broadcasting Service), miners are reluctant to take time off from work from a fear of being replaced by other miners. These facts make coal miners more exposed to opioids than other occupations.

The relationship between opioid use and labor force participation is complex. Using American Time Use Survey (ATUS), Krueger (2017) estimates that over 40 percent of the decline in male labor force participation may be attributed to increases in opioid use. His research is the first to consider the reverse relationship - from opioids to unemployment. Currie et al. (2018) further investigated this topic by allowing mutual effects between employment and opioid usage. Their research employed opioid prescription rate data from 2006 to 2014 and county-level employment data to regress employment to population ratio on opioid prescription to population ratio and vice versa. The authors find a positive relationship between opioid prescribing and employment. Specifically, a 100% increase in opioid prescribing would result in increases in employment of 3.8% for women with education levels higher than mean, and 5.2% for women with education lower than mean. This effect was, however, not significant for men. These results indicated that although dangerous and addictive, opioids may help women stay in the labor force. For the other direction, they found that higher employment can reduce opioid prescription among young workers in counties with education levels above the median.

III. Conceptual Framework

The total number of underground coal miners dropped from 50,312 in 2011 to 27,604 in 2016, a decline of 45 percent. In the same period, the number of surface coal miners dropped from 34,585 to 20,345, a decline of 41 percent. This negative employment shock was predominantly concentrated on male workers with educational outcomes of high school degree or less. Data from the Current Population Survey (CPS) indicate that over 90% of coal miners are male. Roughly 10% of miners in the sample have a college degree and 70% of the coal miners are between 25 and 50 years old (Figure 7).

Moreover, the decline of the local coal mining industry may have spillover effects on people other than coal miners. As one of the main industries of the Appalachian region, the coal mining industry provides support for various local businesses and declining coal production has spillover economic impacts. Following Bowen et al. (2018), we show the trend of employment in the Appalachian region, with or without coal production and the rest of the U.S. (Figure 8). After 2010, employment has been trending up across the whole country expect for those Appalachian counties where coal is no longer produced (or was never produced).[1] The research concluded and we quote: "This evidence suggests that the loss in coal employment has led to broader spillover effects which have suppressed overall economic growth in the relevant regions". The "deaths of despair" hypothesis suggests that declining coal production could lead to higher rates of opioid use and mortality.

[1] In Figure 8, coal producing counties are counties with positive coal output in the given year. The number of coal producing counties is changing over time and a county that stops producing coal will be moved from the graph of mining counties to the graph of non-mining counties The sharp drop in employment in Appalachian non-mining counties reflects the loss of jobs as coal mining declines in the region.

As discussed above, however, a competing hypothesis states that if opioid use is driven, in part, by the prevalence of coal mining activity, the decline of coal employment may decrease the demand for pain killers and so mitigate the impact of the opioid epidemic.[2] According to the same documentary by PBS, the Appalachian region is suffering from the problem that doctors often prescribe more opioid than patients actually need. This increases the prevalence of opioids in the illegal market since these patients (no matter real or not) can sell their exceeded prescription to addicts. When former coal miners no longer need to take opioid painkillers to stay in their position, the prevalence of opioid in the local community is going to decrease, hence, lead to less opioid death. These results combined should induce a positive relationship between coal mining activity and opioid death.

Whether the steep decline in coal mining exacerbated or mitigated the opioid crisis is an empirical question. We turn to the data in the next section.

IV. Empirical Methods

1. Baseline Model

This paper employs a simple fixed-effect model to examine the relationship between coal mining activity and opioid death at the county level.[3] We regress the opioid mortality rate on measures of coal mining activity along with other covariates. To account both for variation in the size of individual mines in counties as well as the size of counties themselves, our measure of coal mining activity is the share of coal miners among the local total workforce. A higher share indicates coal mining plays a bigger role in the local economy. We include lagged employment share terms in the model to allow for gradual responses of opioid mortality arising from changes in employment patterns. These elements suggest a regression model with the following form:

---

[2] This assumes, of course, that new jobs that replace the lost coal mining jobs are not equally or more dangerous. Given how dangerous underground coal mining is, as illustrated in Figure 5, this seems a reasonable assumption.
[3] Using the county rather than state as the unit of observation will likely lead to conservative estimates assuming spillover effects across counties as suggested by Lindo (2015).

$$(1) \qquad y_{it} = \beta_0 + \beta_1 S_{it} + \beta_2 S_{it-1} + \cdots + AX_{it} + \delta_t + \lambda_i + \theta_{st} + \varepsilon_{it}$$

where y_{it} is the death rate of opioid (death per 100,000 residents) in county i in year t, S_{it} is the share of coal miners among total local employment, X_{it} is a vector of covariates, δ_t are time fixed effects, λ_i are county fixed effects, and θ_{st} are state-by-year fixed effects. We include as covariates the county unemployment rate and median household income to account for local economic conditions, and population density as a proxy for urbanization. We also include country demographic variables for gender and age distribution as well as educational attainment.

Hollingsworth et al. (2017) discuss how local policies that influence the death rate of opioid over time are possibly correlated with the economic condition. These policies, e.g. Prescription Drug Monitoring Program (PDMP) and Medicaid policies, often are set at the state-level. We include state-by-year fixed effect to capture these policies. Although PDMP is conducted at the state-level, there are variations among states as the detailed progresses of implementing PDMP can be different for different counties. A more detailed approach, such as county-specific time trend, may be helpful when considering the different relationship between coal mining and opioid death on county-level, but it dramatically reduces the degree of freedom and so affects the ability to obtain precisely estimated coefficients.

Krueger (2017) and Currie et al. (2018) considered the effect of pain and opioid usage on local employment. This suggests a possible bias with OLS estimation due to correlation between the error term and coal mining employment shares. We argue that any effect of shocks to opioid death rates are likely to affect the overall labor market rather than coal mining in particular. If true, the coal mining employment share should be uncorrelated with the error term in the regression. But since we have no a priori evidence to support this argument, we also run IV regressions using Bartik-style instruments as we discuss below.

2. Subgroup Analysis

In order to further investigate the mechanism of how changes in coal mining activity affect opioid mortality, we will present regression results for subgroups to explore heterogeneous effects that can be used to reveal more information on the channels of such relationship.

Men have predominated in the coal mining business. This may be caused by the high demand for physical strength in the mining operation or historical reasons. We don't want to limit our analysis to male death rates, however, since increased access to opioids could have indirect effects on female death rates in the county. Therefore, we estimate the effect of coal mining activity on male and female death rate separately to investigate the heterogeneous effects by gender. Since most coal miners are men, we expect opioid mortality rates for men to be more sensitive to changes in coal mining activity than female death rates.

We also estimate the heterogeneous relationships across different age groups. More specifically, we allow for differential impacts for these age groups: population under 20 years old, between 20 and 39, between 40 and 59, and above 60 years old. Since coal miners are mostly prime-age workers, we expect to see a larger impact on the death rate of the population between 20 and 59 years old than other age groups.

If coal mining only contributes to opioid mortality directly, we would not expect to see a relationship between coal mining and mortality for females and the elderly. Any relationship for these two groups could suggests an indirect effect, perhaps through increased prescriptions in the community contributing to greater availability of opioids in general in the community.

We also explore differential impacts between underground coal mining and surface mining. According to our conceptual model, the relationship between coal mining activity and opioid death comes from the dangerous working environment in the mines. Since underground miners generally face harsher conditions than their colleagues on the surface, they are more likely to get injured, thus more exposed to opioid painkillers. Following this conjecture, underground coal mining should have a stronger relationship with opioid death than surface coal mining. More specifically, more underground coal mining will induce more workplace injuries, and more opioid prescriptions, thereby increasing opioid access in the community.

V. Data

We merge restricted mortality data from the Centers for Disease Control and Prevention (CDC) with coal production data from Energy Information Administration (EIA) to produce a data set covering over 3,100 counties in the United States over the time period 2000 to 2016. To these data, we add various socioeconomic and demographic information.

1. Mortality Data

The mortality data used in our analysis are the Mortality – All County Micro data compiled by the National Center for Health Statistics from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program based on data reported on death certificates for U.S. residents. The death certificate in the United States asks the medical practitioner or the registrar to fill out basic demographic information, one underlying cause of death (UCOD), as well as up to 20 multiple causes of death (MCOD).[4] Public use mortality data can be found on CDC Wide-ranging Online Data for Epidemiologic Research (WONDER). Public use data, however, have results suppressed if there are fewer than ten records at one location in a year. Because the public data withhold data when there are fewer than ten deaths in a county, there can be significant underreporting. In 2016, for example, there were 42,249 opioid related deaths in the United States. When aggregating up from the public dataset, however, there are only 37,526 deaths reported. In that year, there were opioid deaths reported in 2,773 counties in the United States. The public use data set only reports deaths in 701 counties. The data

[4] The underlying cause of death is "(a) the disease or injury which initiated the train of events leading directly to death, or (b) the circumstances of the accident or violence which produced the fatal injury" (U.S. Department of Health and Human Services, 2004, p. 12). The multiple causes of death are based on coroner entries on the death certificate.

withholding problem is more severe when looking at finer cuts of the data. If a county experienced eleven deaths, for example, with five being male and six female, the public use data would report the county statistic for overall deaths. But when pulling data on deaths among males (or females), deaths from this county would be withheld. All of our statistical results are based on the restricted data.

Over the time period from 2000 to 2016, there were 615,070 overdose deaths recorded, with 343,339 of those deaths attributed to opioids. For each county, we aggregate death data to annual rates. Figure 9 shows the increase in deaths due to overdoses over this period and the sharp increase in the proportion due to opioids. Opioid deaths include overdose deaths from heroin, natural and semisynthetic opioids (e.g. oxycodone and hydrocodone), methadone, and other synthetic drugs (e.g. fentanyl and tramadol). These categories aren't mutually exclusive. Following the approach of Hedegaard et al. (2018), we use the following codes to extract records of death by overdose and death by opioid: for death by overdose, select records with UCOD as X40-X44, X60-X64, X85, and Y10-Y14. Among records with UCOD as overdose, the following MCOD codes indicate the drug type(s): T40.0-T40.4, T40.6. Detailed definition of these codes can be found in the appendix. If the only cause of death is opioid overdose, then both the direct cause and underlying cause will be opioid overdose.

From Figure 10, we can see that there are two waves of dramatic increase of opioid death, one was led by heroin from 2010, and the other was synthetic opioids other than methadone since 2013. Death rates from natural and semi-synthetic opioids have experienced a consistent increase over the last decade. Methadone was once a fatal opioid drug, but recently it has been used to treat heroin addiction.

The rich information in CDC's death dataset provides an opportunity to break down national total death records into different subgroups to understand how this opioid epidemic affects people with different gender and age differently. Table 1 breaks out opioid deaths and death rates by gender and illustrates higher mortality rates for men than women. The death rate, however, for women has been growing at a more rapid pace than for men. Between 2000 and 2016, the rate grew at an annual rate of

9.3 percent for men and 10.6 percent for women. Figure 11 shows the opioid death rate broken down by age groups and shows the rapid increase in the death rate since 2010 for adults in the 20 to 59 age range.

2. Coal Production Data

Individual coal mine production and employment data covering the years 2000-2016 are taken form the Energy Information Administration (EIA) form 7A. There are six coal-producing regions in the United States: Appalachia, Illinois Basin, Interior, Powder River Basin, Uinta Basin, and Western Region. Detailed definition of these regions can be found in the appendix. Among these regions, the Appalachian region covers between 80 and 90 percent of the producing coal mines in the United States for any given year.

Although Powder River Basin (PRB) has fewer coal mines than other regions (two percent of the total number of operating coal mines), the surface mines there are highly productive and account for over 40 percent of annual coal production. Coal mines in the Powder River Basin produced 27.6 short tons of coal per labor hour in 2016. In contrast Appalachian coal mines produced 3.1 tons per hour. The higher productivity of PRB mines follows from the ability to use large mechanized machinery to remove coal from very thick veins of coal just under the soil surface (Metcalf, 2019).

Coal is predominantly produced from surface and underground mines.[5] Table 2 shows output and employment for surface and underground mines over the period of our sample. In 2016, surface mines were more than 2.5 as productive as underground mines (23.4 tons per hour versus 9.1 tons per hour). Production from surface mines is nearly double that of underground mines despite their hiring fewer workers.

3. Other Data Sources

[5] EIA also records production from auger mines separately from the other two categories. Auger mining activity is done by portable augers that drill into the overburden of previously worked mines. Auger mining production is less than one percent of surface mining production and we exclude these mines from our analysis. We also exclude refuse mines, mines where coal is extracted from the waste material from previously mined sites. These too account for a trivial share of U.S. coal production (less than one percent).

We augment data on opioid mortality and coal production with county level data on household median income and educational attainment from the American Community Survey (ACS). Annual data are not available at the county level between 2001 and 2005 and data from 2006 to 2008 cover only around half of the counties in the United States. To fill in missing data, we linearly interpolate using county data on income and educational attainment from the 2000 Census. We also include data on population from the Census Bureau and employment data from the Bureau of Labor Statistics (BLS).

Table 3 provides summary statistics for variables in the regressions. We separate counties into coal and non-coal producing counties. Coal producing counties are defined as counties in our dataset that produced coal in any of the years of our sample. The mean opioid death rate in coal-producing counties is nearly twice that of non-coal-producing counties. Opioid prescription rates are also substantially higher. Coal producing counties have a higher unemployment rate, lower population density, and lower income, on average. Educational attainment rates are slightly lower as well.

VI. Results

Table 4 presents results from OLS regressions of opioid death rates on various regressors including the share of coal miners in the county labor force. To allow for gradual impacts of changes in coal mining activity on the death rate, we include the contemporary labor share and three lags. We report the cumulative impact (sum of coefficient estimates) in this and subsequent tables. (Full regression results are reported in the Appendix to the paper.) In addition to reporting the estimated coefficient, we report the elasticity of the death rate with respect to the labor share and the interquartile range impact (IQR Impact) measured as follows:

$$IQR\ Impact = \frac{(\sum_{s=0}^{3} \beta_s) \times IQR}{y_{median}} \qquad (2)$$

The IQR Impact shows the percentage change in the median death rate across counties (y_{median}) when moving from the 25th percentile of labor share for coal mining to the 75th percentile (for the subset of counties with coal production). For regression sub-samples where the median opioid death rate is zero, the IQR Impact is not defined.

The top panel of Table 4 provides results focusing on the share of all coal miners in the labor force. We find that a higher share of coal miners in the labor force leads to more opioid deaths, after controlling for various socioeconomic variables, county and year fixed effects, as well as state-by-year fixed effects. Specifically, a one percentage point increase in the share of coal miners is associated with an increase in the mortality rate of 0.52 per 100,000. This corresponds to an elasticity of 0.192 and is statistically significant at one percent level. This effect is comparable between men and women, as shown in the next two columns though the elasticity of the response is higher among women than men. The impact is estimated more precisely for women than for men. Moving from the 25th to the 75th percentile in labor force share increases the opioid mortality rate by one-third for men and four-fifths for women, or roughly two-fifths for the population as a whole.

The next panel focuses on the share of underground miners in the labor force. The estimated effect is now larger and statistically significant for both men and for women (and the population as a whole). The elasticities and IQR impacts, however, are smaller for underground miners than for miners as a group.[6] The final panel shows results for surface miners. The estimates are only precisely estimated for women and the whole population.

That increased mining activity increases the female opioid death rate suggests an indirect impact of coal mining on mortality given the very small number of women coal miners.[7] We conjecture that coal

---

[6] It is not surprising that the elasticities are lower since the share of miners in the population is the sum of the shares of underground and surface miners. The elasticities for the overall mining share regressions equals, to an approximation, $\left(\frac{\widehat{\beta_T}}{\widehat{\beta_U}}\right)\varepsilon_U + \left(\frac{\widehat{\beta_T}}{\widehat{\beta_S}}\right)\varepsilon_S$, where T indicates a regression on all mines, s indicates a surface mine regression and u, a underground mine regression and $\hat{\beta}$ is an estimated coefficient and ε an elasticity.

[7] According to the National Institute for Occupational Safety and Health (2012), less than 4 percent of employees in the coal mining sector were female.

mining induces more workplace injuries, which, in turn, increases opioid usage. The increased usage could lead to higher rates of access in the community thereby driving up opioid usage more generally.

In Figure 5 above, we documented higher rates of injuries in underground than surface mines. The larger impacts of a one percentage point increase in the share of underground coal miners on opioid mortality relative to surface miners combined with the higher injury rates for underground miners suggests the role of workplace injuries as the mechanism linking higher coal mining labor shares in a county to higher opioid mortality rates.

We next estimate the effects of the share of coal miners on the opioid death rate by various age groups. As shown in Table 5, the change in coal mining activity has heterogeneous effects on population with different ages, as expected. Generally speaking, the effect on population between 20 and 39 is the largest among all four. Specifically, the estimated elasticity when focusing on all mines for death rates of the population in the 20-39 age bracket is 0.190 and is statistically significant at the ten percent level. The impact is large as well. Moving from the 25th to the 75th percentile in coal mining labor shares among counties with positive shares is associated with a roughly one-half increase in mortality. We also see a large and statistically significant effect for the age group 40 to 59. The death rate among other age groups is not materially affected by changes in the labor share. Results are slightly larger when focused on underground mines (and statistically significant for the age 20 to 39 group) but smaller and not statistically significant within the same group for surface mines. For the age 40 – 59 population group, surface coal mining activity has a statistically significant effect on opioid death rates.

VII. Further Results

1. Instrumental Variable Approach with a Bartik Instrument

A concern with the OLS regressions is that the local opioid epidemic may have negative impacts on the labor pool of coal mines in the region and so affect the employment of local coal miners. For this to be a problem, it would have to be the case that shocks to opioid mortality differentially affect coal mining employment, as opposed to general employment. We address this potential problem by employing a Bartik instrument for employment. Following Currie et al. (2018), we construct the Bartik-style variable for coal employment as:

$$B_{jt} = \frac{1}{P_{jt}} \sum_{k} (L_{jkt_0} \times \frac{\sum_{i \in \{counties \setminus j\}} L_{ikt}}{\sum_{i \in \{counties \setminus j\}} L_{ikt_0}})$$

where B_{jt} is the instrumental variable for county j, in year t and k indexes the type of coal mine (surface or underground). L_{kt} is the national employment level of type k coal mines in year t, P_{jt} is the population of county j in year t, and L_{jkt_0} is coal mining employment in county j of type k mine in year t_0, our base year (2006).[8] The instrument captures changes in local employment correlated with national employment changes but uncorrelated with local shocks. This assumes that the national coal mining employment level is not affected by the local shocks in opioid mortality. This Bartik-style instrumental variable provides an exogenous demand shock to local coal mining employment. Instead of using the share among total local workforce, we use the ratio between constructed employment level and local population to avoid endogeneity between employment and opioid crisis. This variable gives an analogous representation of the county's dependence on coal mining activity scaled by the size of the county.

Table 6 shows the results with IV estimation. The pattern of results is similar to the OLS regressions with more significant impact among men than women. If anything, the impact is now larger suggesting a negative correlation between local opioid mortality shocks and coal mining labor shares and suggests a negative correlation between the error term in the OLS regressions and coal mining labor shares. This would be consistent with shocks to opioid death rates in a county disproportionately impacting coal miners and leading to lower coal mining activity in the country. That we get statistically significant coefficient estimates in the OLS regressions despite this negative correlation also suggest that

[8] Counties vary in mining activity over time so some counties with active mines in some years that are not active in 2006 are dropped from the analysis. Our results are robust to different choices of the base year for constructing the Bartik variable.

the OLS regressions provide a conservative estimate of the impact of coal mining on opioid death rates. Detailed regression results can be found in Appendix Table A1.

Table 7 shows IV regressions across age groups as in Table 5. As in Table 6, the estimated effects are uniformly larger with the exception of the under 20 age group. The estimated coefficients for this group are now uniformly negative in contrast to the OLS results, and they are statistically significant.

2. Underlying Mechanism

Our results so far suggest that higher death rates from opioid use may be caused by higher rates of usage by coal miners due to job-related injuries. We explore that potential mechanism here by regressing opioid prescription rates on our measure of coal mining activity. A positive coefficient on the coal mining labor share is consistent with our hypothesis that job-related injuries are increasing the prevalence of opioid use in the county. Results are shown in Table 8 (and full regression results in the Appendix). The results are suggestive. In all regressions, whether OLS or IV, the estimated total impact of coal mining activity (cumulated over three lags) is positive. In the IV regressions, the IQR impact is on the order of 5 to 6 percent of the median prescription rate. The estimated coefficients, however, are not statistically significant for the most part. While suggestive, we would not want to argue that we have found a smoking gun mechanism.

3. Contrasting Coal Mining with Retailing

To ensure we're not picking up a spurious correlation between coal mining activity and opioid mortality, we run similar regressions substituting the labor share in retailing for the labor share in coal mining. To the extent that the mechanism for opioid mortality is greater use of these drugs in response to the stressful and injury-prone nature of coal mining, we'd expect to see a smaller marginal impact of retailing labor share on opioid mortality rates. We focus on retailing since it has a similar wage scale but is less physically demanding work.

Results are reported in Table 9. We see that there is a negative correlation among male population between the retail worker share in the county labor force and opioid deaths with more precisely estimated results for males than females. The negative correlation also shows up in age group regressions (Table 10) with the strongest result for deaths in the 20 to 39 age group. To the extent that a stronger retailing sector (as evidenced by a higher labor force share) is a proxy for a stronger economy, the negative correlation suggests an underlying "Death by Despair" relationship with lower economic activity associated with higher opioid mortality rates. If so, the positive relationship between coal mining activity and opioid mortality indicates an even stronger health and employment relationship in the coal mining industry, given the need to overcome any underlying economic driver of opioid use.

VIII. Discussion

This paper focuses on the relationship between coal mining activity and opioid mortality. Using restricted death records and coal production data, we are able to construct a county-level panel data and carry out fixed effect regressions to estimate the impact of changes in coal mining activity on local opioid death. Because of the rich information of both datasets, we are able to explore the extent to which results differ for men and women, underground coal mining and surface coal mining, and different age groups.

The estimated effects of share of coal miners among total local labor force are consistent with different subgroups and suggest that there are positive relationships for both men and women, underground mining and surface mining after controlling for various socioeconomic variables, county and year fixed effect, as well as state-by-year fixed effect. More specifically, a one percent increase in the share of coal miners will result in a 0.192 percent increase in local opioid death rates, based on the OLS regression in Table 4 while the IV regression suggests a 0.42 percent increase (Table 6). The impacts are similar when focusing on underground mines only and suggest that the decline of underground coal mining could help alleviate the opioid epidemic in this region.

Recall the two competing hypotheses mentioned in the conceptual framework section. The positive relationship between coal mining activity and opioid death supports the hypothesis that more coal mining activity leads to more workplace injuries. More injuries lead to the prevalence of opioid painkillers in the community, then results in more opioid overdose. The comparison between underground coal mining and surface coal mining also supports this conjecture. Since we control other socioeconomic factors, county fixed effect and year fixed effect, the gap between the impact of underground coal mining and surface coal mining can be traced to the difference in the natures of these two kinds of mining. Because underground miners suffer from more severe working conditions than surface miners, they are more likely to get injured and be prescribed with opioids. The greater impact from underground mining on male mortality rates suggests that when considering the consequences of dangerous mining activity, men are more likely to be affected because of the higher participation rate. However, we are not able to further examine this claim due to data limitations. It is also worth noticing that a higher share of coal miners among the total workforce also increases the opioid death rate of women, who seldom participate in mining activity. This could be explained as a spillover effect with higher prescription rates among men leading to greater amounts of opioids in the county some of which are used by women.

Since this study analyzes the relationship between coal mining activity and opioid mortality, one reasonable concern is that a severe opioid epidemic may affect local labor market and so affect coal mine employment. This is a reasonable concern and suggests a negative bias in OLS regressions of mortality on coal mining labor force shares. That we still estimate positive and statistically significant coefficients on the labor force share variable in the OLS regressions suggests that the positive correlation is real and that increased coal mining activity (especially underground coal mining) leads to higher opioid mortality rates. We test that directly by running IV regressions using a Bartik instrument. That the estimated coefficients are more positive supports the conjecture of a positive feedback from mortality to labor force participation in coal mining.

We want to be cautious in this conclusion for a couple of reasons. First, Currie et al. (2018) directly examined the impact of opioid usage on employment and fail to identify any significant correlation between employment and opioid prescription, except for low-educated women. Second, even if there were a negative effect of opioid mortality on the local labor market, a decrease in the local workforce will not necessarily change the *share* of coal miners among local workforce. In order to cause endogeneity in the model, opioid epidemic has to impact the coal mining industry disproportionately more than other sectors (to affect the share). There is no a priori reason to believe this would be the case though the change in results from the IV regressions suggest some underlying relation causing bias in the OLS regressions.

Another source of endogeneity is the presence of local opioid policies. With state-by-year fixed effect in the model, we are able to capture the state-specific policies, such as the Prescription Drug Monitoring Program. However, the implementation of some policies may vary within the state. Then, the state-by-year fixed effect is not adequately accounted for these variations. Moreover, the coal mining activity may have increased (or decreased) in locations that were on different trajectories in terms of drug mortality because of unknown reason (Hollingsworth et al., 2017). In these cases, the model presented above could still incorrectly attribute a pre-existing trend in mortality to changes in coal mining activity. Ideally, a model with county-by-year fixed effect should be constructed. However, it is infeasible since there is no much variation in the model once we specify all three types of fixed effects: county-year fixed effect, county fixed effect, and year fixed effect.

As a check on our results, we also estimate the relationship between retailing activity and opioid mortality. The results are the opposite to what we find with coal mining. Both coal mining and retailing are industries dominated by low-educated workers. The difference is that coal mining is generally more physically demanding and has higher injury rates. The difference in the results supports the conjecture of workplace injury being the main driving factor behind the positive relationship between coal mining and opioid mortality. Moreover, the negative relationship between retailing and opioid mortality backs the idea of "Deaths of Despair," with a worsening economic environment leading to more opioid abuse.

Even if the results here do not align with the "Deaths of Despair" hypothesis, our results do not necessarily contradict the idea. "Deaths of Despair" idea attributes the increase in opioid death rate in the twenty-first century to the worsening social and economic situation of older and less-educated workers in the United States. This can still be true for coal miners since most of these workers don't have a college degree. However, because of the dangerous nature of mining activity, the positive relationship between coal mining and opioid mortality may simply outweigh the benefits of better economic condition and stable employment.

IX. Conclusion

Overall, this study uses restricted mortality data and coal production data to investigate the relationship between coal mining and opioid mortality. The results suggest that a higher share of coal miners among the local total workforce is associated with a higher opioid death rate. This conclusion is the opposite of what mainstream media would claim. Results are strongest for underground coal mining activity and for miners in the 20 to 39 age group. We also use a Bartik-style instrumental variable to control for potential endogeneity between employment and opioid abuse. Estimates from the IV regressions are larger and more statistically significant than those of OLS for men.

What explains this positive relationship? One possible channel is that increasing coal mining activity leads to more workplace injuries, higher opioid prescription rates, and a consequent greater prevalence of opioids in the community. This in turn leads to more opioid deaths. The larger estimation with physically prime-age population supports this explanation. Results from prescription rate regressions are consistent with this hypothesized channel but are not statistically significant.

This study does not further investigate the mechanism behind this positive relationship between coal mining activity and opioid mortality due to data limitation. More thorough analysis can be carried out in the future if individual level data is available. Louie and Pearce (2016) conjecture that laid-off coal miners have been absorbed by other industries. It would be interesting to see if regions with more substitute industries for coal miners exhibit different relationship between coal mining activity and opioid morality.

Reference

Betz, M. R., & Jones, L. E. (2018). Wage and Employment Growth in America's Drug Epidemic: Is All Growth Created Equal? *American Journal of Agricultural Economics*, *16*(1), 19. http://doi.org/10.1093/ajae/aay069

Brett Jordan, I. L. A. J. L. (2018). Coal Demand, Market Forces, and US Coal Mine Closures, 1–65.

Bowen, E., Christiadi, J. Deskins, and B. Lego. (2018) *An Overview of the Coal Economy in Appalachia*, Appalachian Regional Commission.

Carpenter, C. S., McClellan, C. B., & Rees, D. I. (2017). Economic conditions, illicit drug use, and substance use disorders in the United States. *Journal of Health Economics*, *52*, 63–73. http://doi.org/10.1016/j.jhealeco.2016.12.009

Case, A., & Deaton, A. (2015). Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century. *Proceedings of the National Academy of Sciences*, *112*(49), 15078–15083. http://doi.org/10.1073/pnas.1518393112

Case, A., & Deaton, A. (2017). Mortality and Morbidity in the 21st Century. *Brookings Papers on Economic Activity*, *2017*(1), 397–476. http://doi.org/10.1353/eca.2017.0005

Charles, K. K., Hurst, E., & Schwartz, M. (2018). The Transformation of Manufacturing and the Decline in U.S. Employment. NBER Working Paper No. 24468. Cambridge, MA: National Bureau of Economic Research.

Coglianese, J., Gerarden, T., & Stock, J. H. (2017). *The Effects of Fuel Prices, Regulations, and Other Factors on U.S. Coal Production, 2008-2016* (pp. 1–24).

Coleman, P. J., & Kerkering, J. C. (2007). Measuring mining safety with injury statistics: Lost workdays as indicators of risk. *Journal of Safety Research*, *38*(5), 523–533. http://doi.org/10.1016/j.jsr.2007.06.005

Currie, J., Jin, J. Y., & Schnell, M. (2018). US employment and opioids: Is there a connection? NBER Working Paper No. 24440. Cambridge, MA: National Bureau of Economic Research. http://doi.org/10.3386/w24440

Dart, R. C., Surratt, H. L., Cicero, T. J., Parrino, M. W., Severtson, S. G., Bucher-Bartelson, B., & Green, J. L. (2015). Trends in Opioid Analgesic Abuse and Mortality in the United States. *New England Journal of Medicine*, *372*(3), 241–248. http://doi.org/10.1056/NEJMsa1406143

Fell, H., & Kaffine, D. T. (2018). The Fall of Coal: Joint Impacts of Fuel Prices and Renewables on Generation and Emissions. *American Economic Journal: Economic Policy*, *10*(2), 90–116. http://doi.org/10.1257/pol.20150321

Florence, C. F. Luo, L Xu, and C Zhou (2016). The Economic Burden of Prescription Opioid Overdose, Abuse and Dependence in the United States, 2013. *Med Care* 54(10): 901-06. http://doi:10.1097/MLR.0000000000000625.

Guy, G. P., Jr, Zhang, K., Bohm, M. K., and, J. L. M. M., & Hoffmann, T. (2017). Vital signs: changes in opioid prescribing in the United States, 2006–2015. *Ncbi.Nlm.Nih.Gov*, *66*(26), 697–704. http://doi.org/10.15585/mmwr.mm6626a4

Havens, J. R., Walker, R., & Leukefeld, C. G. (2007). Prevalence of opioid analgesic injection among rural nonmedical opioid analgesic users. *Drug and Alcohol Dependence*, *87*(1), 98–102. http://doi.org/10.1016/j.drugalcdep.2006.07.008

Hedegaard, H., Miniño, A. M., & Warner, M. (2018). Drug Overdose Deaths in the United States, 1999–2017. *NCHS Data Brief*, *329*(5152), 1–8. http://doi.org/10.15585/mmwr.mm675152e1

Hollingsworth, A., Ruhm, C. J., & Simon, K. (2017). Macroeconomic conditions and opioid abuse. *Journal of Health Economics*, *56*, 222–233. http://doi.org/10.1016/j.jhealeco.2017.07.009

Katherine A. Margolis. (2010). Underground coal mining injury: A look at how age and experience relate to days lost from work following an injury. *Safety Science*, *48*(4), 417–421. http://doi.org/10.1016/j.ssci.2009.12.015

Komljenovic, D., Groves, W. A., & Kecojevic, V. J. (2008). Injuries in U.S. mining operations – A preliminary risk analysis. *Safety Science*, *46*(5), 792–801. http://doi.org/10.1016/j.ssci.2007.01.012

Krueger, A. B. (2017). Where Have All the Workers Gone?: An Inquiry into the Decline of the U.S. Labor Force Participation Rate. *Brookings Papers on Economic Activity*, *2017*(2), 1–87. http://doi.org/10.1353/eca.2017.0012

Levy, B., Paulozzi, L., Mack, K. A., & Jones, C. M. (2015). Trends in Opioid Analgesic–Prescribing Rates by Specialty, U.S., 2007–2012. *American Journal of Preventive Medicine*, *49*(3), 409–413. http://doi.org/10.1016/j.amepre.2015.02.020

Lindo, J. M. (2015). Aggregation and the estimated effects of economic conditions on health. *Journal of Health Economics*, *40*, 83–96. http://doi.org/10.1016/j.jhealeco.2014.11.009

Louie, E. P., & Pearce, J. M. (2016). Retraining investment for U.S. transition from coal to solar photovoltaic employment. *Energy Economics*, *57*(C), 295–302. http://doi.org/10.1016/j.eneco.2016.05.016

McCormack, J. L. A. K. (2017). The Roles of Energy Markets and Environmental Regulation in Reducing Coal-Fired Plant Profits and Electricity Sector Emissions, 1–44.

McDonald, D. C., Carlson, K., & Izrael, D. (2012). Geographic Variation in Opioid Prescribing in the U.S. *The Journal of Pain*, *13*(10), 988–996. http://doi.org/10.1016/j.jpain.2012.07.007

Meara, E., Horwitz, J. R., Powell, W., McClelland, L., Zhou, W., O'Malley, A. J., & Morden, N. E. (2016). State Legal Restrictions and Prescription-Opioid Use among Disabled Adults. *New England Journal of Medicine*, *375*(1), 44–53. http://doi.org/10.1056/NEJMsa1514387

Metcalf, G. (2019) *Paying for Pollution: Why a Carbon Tax is Good for America*. New York: Oxford University Press.

National Center for Health Statistics. *Mortality Data – All County Micro Data, 1999 – 2016.*

National Institute for Occupational Safety and Health. (2012), *National Survey of the Mining Population, Part I: Employees*, Washington, DC: NIOSH, IC 9527.

Ruhm, C. J. (2000). Are Recessions Good for Your Health? *The Quarterly Journal of Economics*, *115*(2), 617–650. http://doi.org/10.2307/2587005?refreqid=search-gateway:d2525ec045cbeb4bc80098d490bae93c

Ruhm, C. J. (2015). Recessions, healthy no more? *Journal of Health Economics*, *42*, 17–28. http://doi.org/10.1016/j.jhealeco.2015.03.004

Ruhm, C. J. (2018). Drivers of the Fatal Drug Epidemic. *Journal of Health Economics, 64:25-42*
http://doi.org/10.1162/ajhe_a_00113

Sinha, R. (2008). Chronic Stress, Drug Use, and Vulnerability to Addiction. *Annals of the New York Academy of Sciences*, *1141*(1), 105–130. http://doi.org/10.1196/annals.1441.030

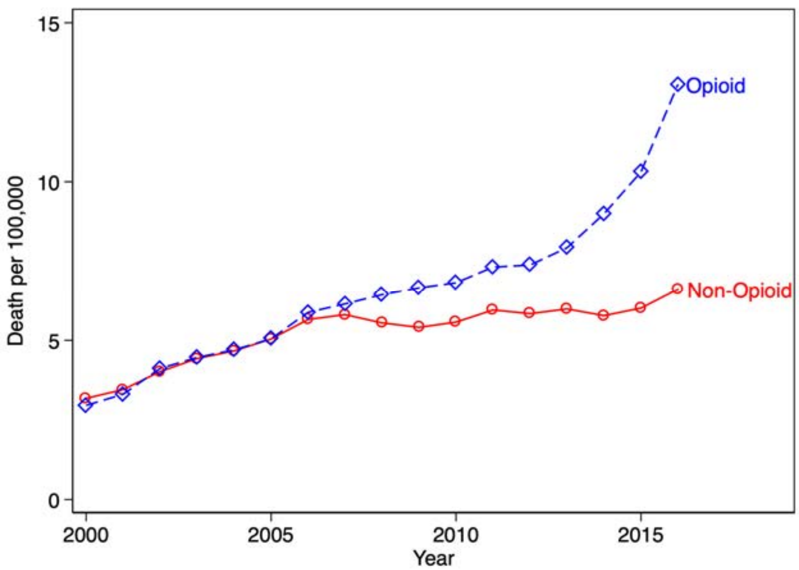
Smith, J. P. (1999). Healthy Bodies and Thick Wallets: The Dual Relation Between Health and Economic Status. *Journal of Economic Perspectives*, *13*(2), 145–166. http://doi.org/10.1257/jep.13.2.145

Thumula, V., Wang, D., & Liu, T.-C. (2017). Interstate Variation In Use of Opioids. *Workers Compensation Research Institute*, 1–129.

U.S. Department of Health and Human Services. (2004) *Technical Appendix from Vital Statistics of United States 1999 Mortality*, Centers for Disease Control and Prevention, National Center for Health Statistics, Hyattsville, MD.

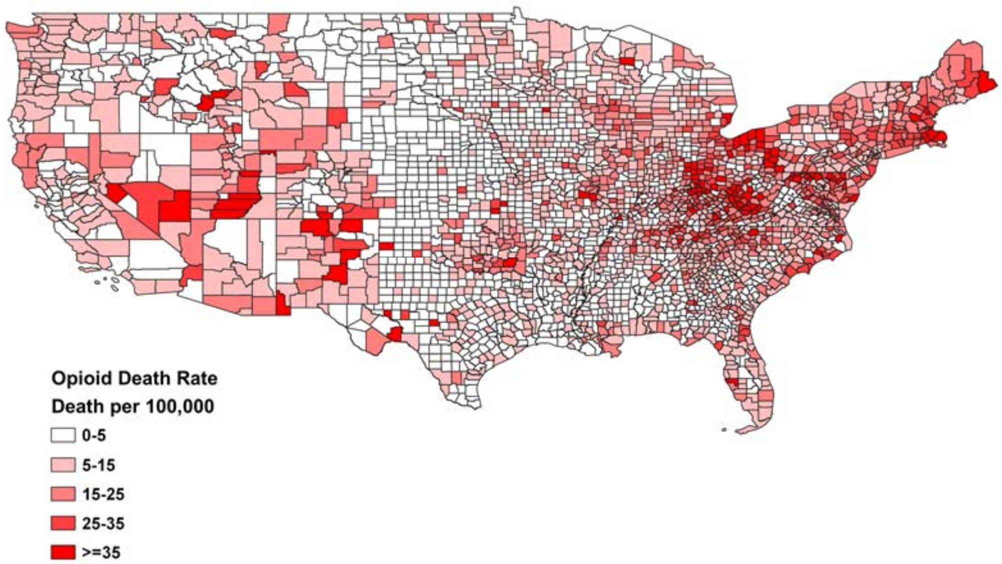
Van Zee, A. (2009). The Promotion and Marketing of OxyContin: Commercial Triumph, Public Health Tragedy. *American Journal of Public Health*, 99(2): 221-227.

Figure 1: Death Rate by Opioid Types



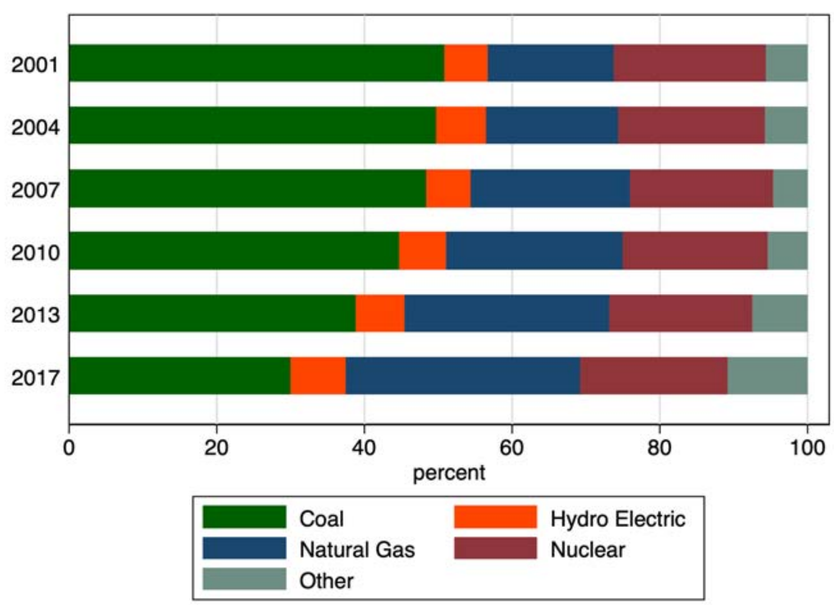
Data Source: Center of Disease Control Mean weighted by population
Death Code: Any opioid (T40.0-T40.4, T40.6), opium (T40.0), heroin (T40.1), natural and semisynthetic opioids (T40.2), methadone (T40.3), and synthetic opioids other than methadone (T40.4)
Non-Opioid: Include other records with underlying cause of death being identified as overdose death, e.g. Cocaine (T40.5)

Figure 2: Geographical Distribution of Opioid Mortality



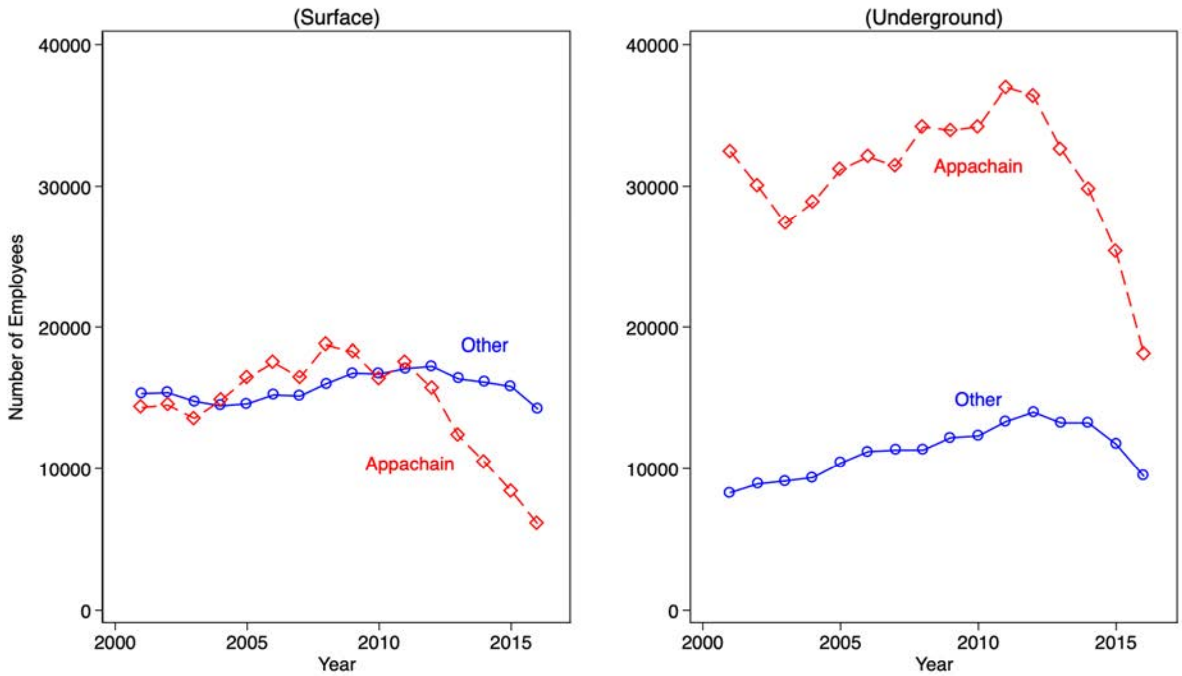
Data Source: Center of Disease Control
County level data taken in year 2016. Map created by authors.

Figure 3: Energy Consumption In Electricity Sector, by Energy Source



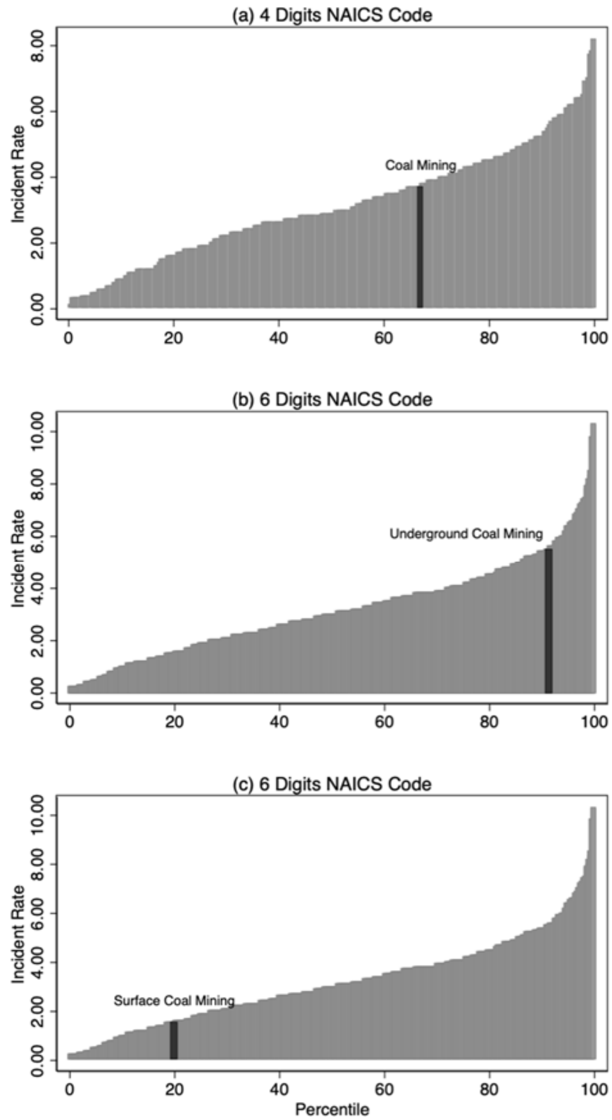
Data Source: U.S. Energy Information Administration

Figure 4: Employment Change by Regions and Mine Types



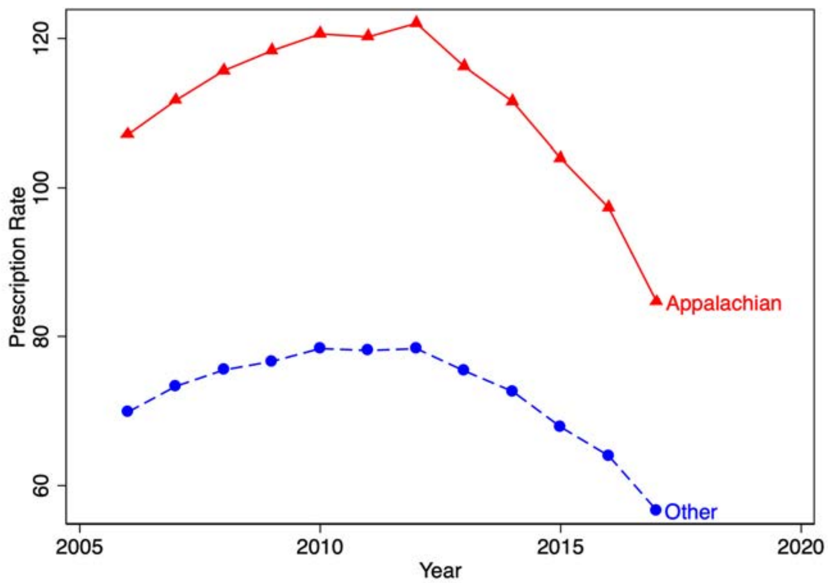
Data Source: U.S. Energy Information Administration

Figure 5: Incident Rate Non-fatal Injuries and Illness of Coal Industry in 2017



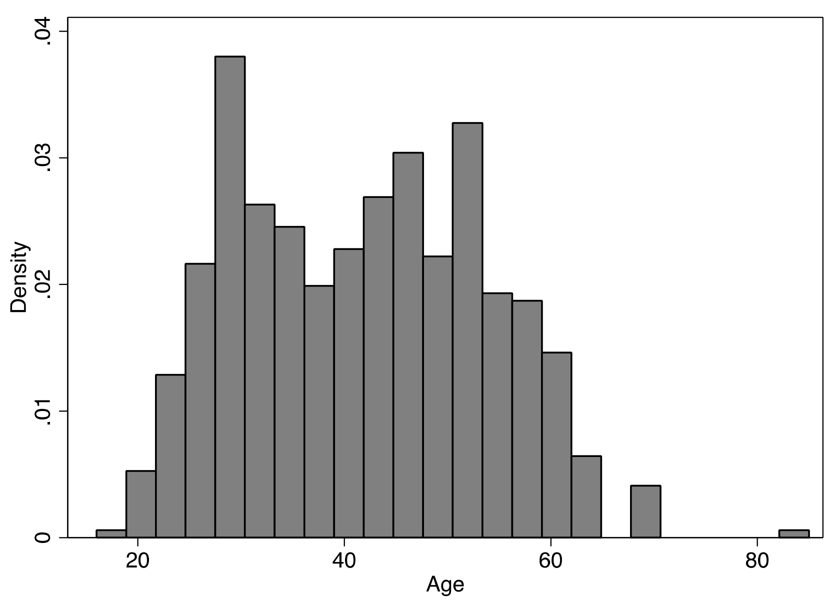
Data Source: Bureau of Labor Statistics, U.S. Department of Labor, Survey of Occupational Injuries and Illnesses, in cooperation with participating state agencies.
NAICS Code: Coal mining, 2121, Underground coal mining, 212112, Surface coal mining 212111.
All comparison between same NAICS level.
The incidence rates represent the number of injuries and illnesses per 100 full-time workers and were calculated as: (N/EH)x200,000 where :
N : number of injuries and illnesses.
EH : total hours worked by all employees during the calendar year.
200,000: base for 100 equivalent full-time workers (working 40 hours per week, 50 weeks per year).

Figure 6: Prescription Rate in Appalachian and Other Regions



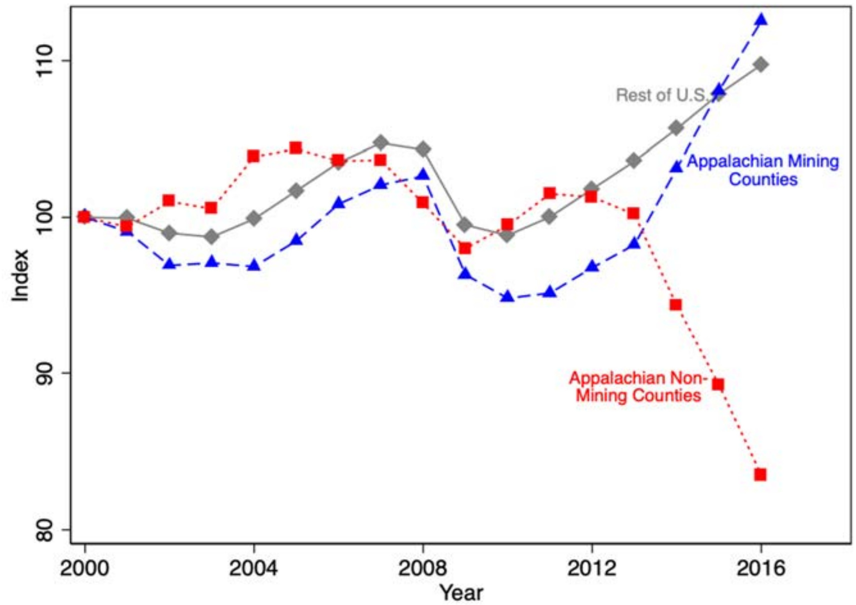
Data Source: CDC Opioid Prescription Map.
Prescription Rate: Opioid prescriptions written for every 100 Americans

Figure 7: Age Distribution of Coal Miners



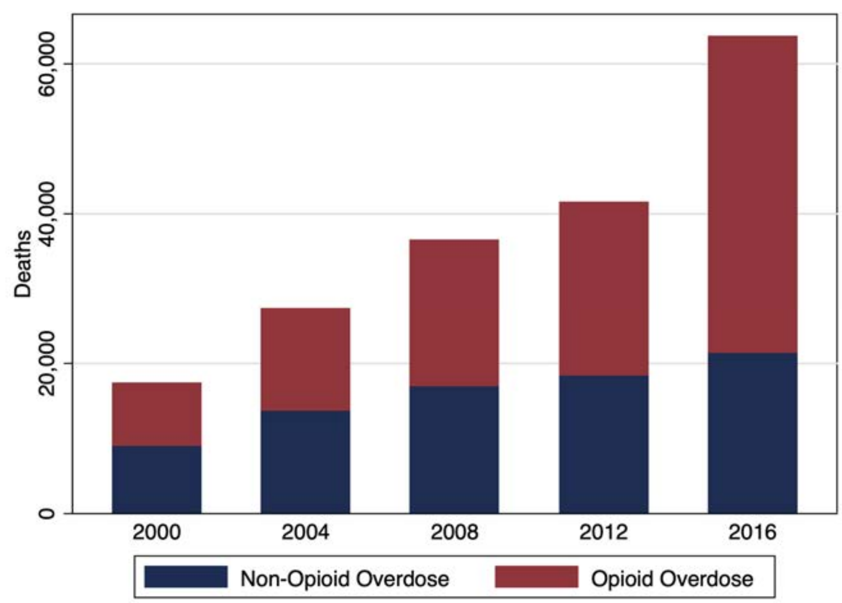
Data Source: Current Population Survey.

Figure 8: Employment Level Change In the United States



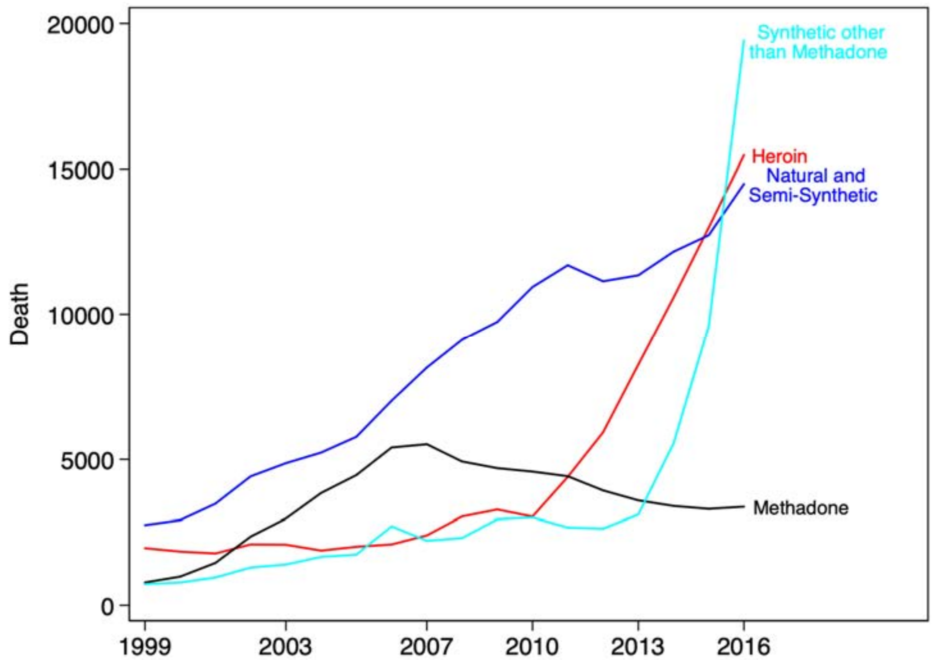
Data Source: Quarterly Census of Employment and Wages (QCEW)
Index shows the employment level relative to year 2000.

Figure 9: Death By Overdose In The United States



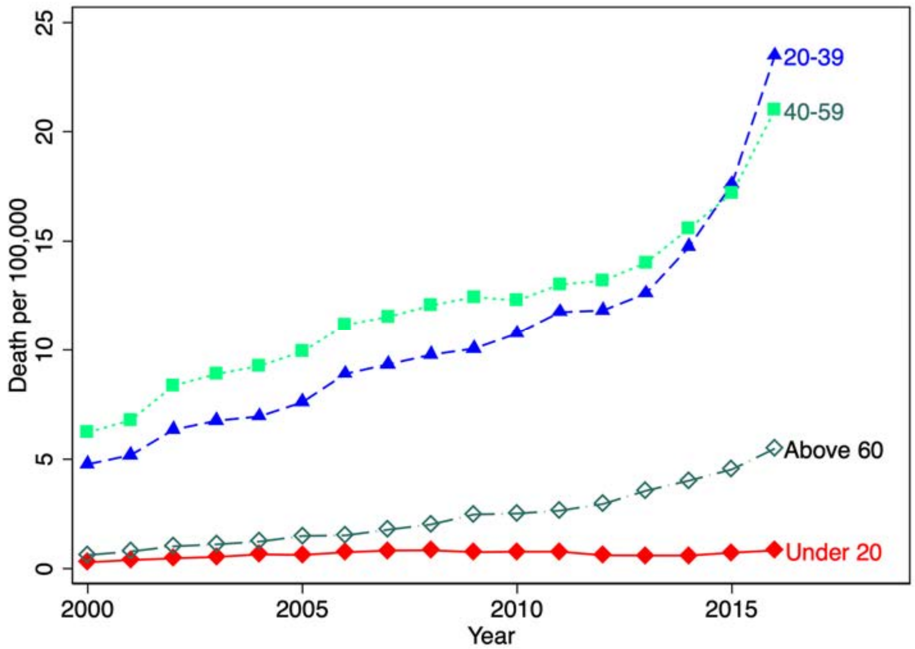
Data Source: Center of Disease Control.

Figure 10: Drug Overdose Death, by Opioid Category



Data Source: CDC Mortality data.
Death Code: Any opioid (T40.0-T40.4, T40.6), heroin (T40.1), natural and semisynthetic opioids (T40.2), methadone (T40.3), and synthetic opioids other than methadone (T40.4).

Figure 11: Opioid Overdose Death Rate, by Age Group



Data Source: CDC Mortality data.
Death Code: Any opioid (T40.0-T40.4, T40.6), heroin (T40.1), natural and semisynthetic opioids (T40.2), methadone (T40.3), and synthetic opioids other than methadone (T40.4).

Table 1: Summary Statistics of Opioid Death by Gender

	Total		Male		Female	
Year	Number	Deaths per 100,000	Number	Deaths per 100,000	Number	Deaths per 100,000
2000	8342	1.60	6092	2.39	2250	0.85
2001	9420	1.77	6677	2.56	2743	1.01
2002	11842	2.19	8103	3.05	3739	1.36
2003	12938	2.33	8801	3.24	4137	1.47
2004	13756	2.44	9113	3.30	4643	1.62
2005	14918	2.65	9757	3.53	5161	1.80
2006	17545	3.02	11600	4.06	5945	2.01
2007	18516	3.15	11935	4.13	6581	2.20
2008	19580	3.30	12761	4.37	6819	2.26
2009	20421	3.41	13134	4.46	7287	2.39
2010	21086	3.48	13355	4.49	7731	2.51
2011	22782	3.73	14459	4.81	8323	2.68
2012	23166	3.77	14734	4.87	8432	2.70
2013	25051	4.04	15997	5.24	9054	2.87
2014	28647	4.57	18420	5.98	10227	3.21
2015	33089	5.24	21671	6.97	11418	3.56
2016	42249	6.63	28498	9.09	13751	4.25

Data Source: Center of Disease Control (CDC) Mortality data.
Deaths per 100,000: average county opioid death rate weighted by total population.

Table 2: Output and Employment by Mine Type

	Total		Surface		Underground	
Year	Output	Employees	Output	Employees	Output	Employees
2001	1125.9	70.4	745.3	29.7	380.6	40.7
2002	1093.3	68.8	735.9	29.9	357.4	38.9
2003	1070.8	64.8	718.0	28.3	352.8	36.4
2004	1111.1	67.5	743.5	29.3	367.6	38.2
2005	1130.8	72.6	762.2	31.0	368.6	41.5
2006	1162.0	76.0	803.0	32.7	359.0	43.3
2007	1145.5	74.3	793.7	31.6	351.8	42.7
2008	1170.4	80.3	813.3	34.8	357.1	45.5
2009	1072.2	81.2	740.2	35.0	332.1	46.2
2010	1082.5	79.6	745.4	33.1	337.2	46.5
2011	1094.0	84.9	748.4	34.6	345.6	50.3
2012	1015.1	83.3	672.7	32.9	342.4	50.4
2013	982.9	74.6	641.2	28.7	341.7	45.9
2014	998.4	69.6	643.7	26.6	354.7	43.0
2015	895.6	61.3	588.7	24.2	306.8	37.1
2016	727.5	47.9	475.4	20.3	252.1	27.6

Data Source: EIA-7A.
Output is in million short tons; Employees is in thousand people.

Table 3: Summary Statistics

	National	Coal Producing	Non-Coal Producing
Death Rate(Opioid) per 100k	6.903	12.607	6.540
	(9.283)	(15.882)	(8.570)
Death Rate(Any) per 100k	12.590	20.820	12.068
	(12.289)	(17.960)	(11.643)
Share Of Coal Miners	0.003	0.047	0.000
	(0.020)	(0.066)	(0.000)
Output(Million Tons)	0.328	5.493	0.000
	(6.729)	(27.020)	(0.000)
Unemployment Rate	6.820	7.530	6.775
	(2.956)	(2.694)	(2.966)
Median Household Income	44.786	40.474	45.059
	(11.886)	(9.621)	(11.964)
Population Density	262.135	98.517	272.527
	(1755.237)	(159.247)	(1809.180)
Male Population Ratio	0.500	0.499	0.500
	(0.022)	(0.016)	(0.023)
Age Group 20-39 Ratio	0.237	0.241	0.237
	(0.044)	(0.033)	(0.044)
Age Group 40-59 Ratio	0.277	0.282	0.277
	(0.027)	(0.022)	(0.027)
High School Diploma Rate	83.547	81.359	83.686
	(7.364)	(8.204)	(7.285)
Bachelor's Degree Rate	19.336	15.798	19.561
	(8.762)	(7.263)	(8.801)
Observations	34509	2061	32448

Year Range: 2006-2016. Standard Errors in Parentheses. Coal mining counties are counties that produced coal in any year of our sample

Table 4: OLS Results by Gender Groups

	Opioid Death Rate		
	Whole Population	**Male**	**Female**
Share of Coal Miners			
Effect	51.886***	43.905*	59.357***
S.E.	(16.608)	(25.988)	(17.667)
IQR Impact	0.427	0.299	0.801
Elasticity	0.192	0.129	0.296
Lags	3	3	3
Share of Underground Miners			
Effect	73.476***	89.600**	54.663*
S.E.	(25.416)	(43.784)	(29.621)
IQR Impact	0.212	0.214	0.258
Elasticity	0.115	0.111	0.115
Lags	3	3	3
Share of Surface Miners			
Effect	55.490**	34.912	76.155***
S.E.	(23.435)	(36.628)	(22.174)
IQR Impact	0.233	0.121	0.525
Elasticity	0.119	0.06	0.22
Lags	3	3	3

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Effect is the linear combination of all lagged terms.
*Standard errors clustered at county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1 .*

Table 5: OLS Results by Age Groups

	Opioid Death Rate			
	Under 20	**20-39**	**40-59**	**Above 60**
Share of Coal Miners				
Effect	5.993	93.515*	73.714**	18.847
S.E.	(5.431)	(50.670)	(35.377)	(18.358)
IQR Impact	.	0.460	0.415	.
Elasticity	0.308	0.190	0.156	0.326
Lags	3	3	3	3
Share of Underground Miners				
Effect	0.463	277.19***	5.795	17.27
S.E.	(6.809)	(91.307)	(62.969)	(27.598)
IQR Impact	.	0.477	0.011	.
Elasticity	0.01	0.237	0.005	0.126
Lags	3	3	3	3
Share of Surface Miners				
Effect	11.472	52.941	109.024**	21.638
S.E.	(8.044)	(63.441)	(51.011)	(25.546)
IQR Impact	.	0.133	0.313	.
Elasticity	0.342	0.062	0.134	0.217
Lags	3	3	3	3

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Effect is the linear combination of all lagged terms.
*Standard errors clustered at county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1 .*

Table 6: IV Results with Bartik Instrument, by Gender Groups

	Opioid Death Rate		
	Whole Population	**Male**	**Female**
Share of Coal Miners			
Effect	113.153***	125.802**	103.839*
S.E.	(22.765)	(36.625)	(62.059)
IQR Impact	0.931	0.857	1.401
Elasticity	0.420	0.371	0.517
Lags	3	3	3
Share of Underground Miners			
Effect	260.813***	298.114***	230.268
S.E.	(51.391)	(78.990)	(140.589)
IQR Impact	0.751	0.711	1.088
Elasticity	0.407	0.370	0.483
Lags	3	3	3
Share of Surface Miners			
Effect	199.517***	216.698***	188.765*
S.E.	(40.822)	(67.604)	(110.546)
IQR Impact	0.838	0.753	1.301
Elasticity	0.429	0.37	0.545
Lags	3	3	3

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Effect is the linear combination of all lagged terms.
*Standard Errors are obtained by bootstrap in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Table 7: IV Results with Bartik Instrument, by Age Groups

	Opioid Death Rate			
	Under 20	**20-39**	**40-59**	**Above 60**
Share of Coal Miners				
Effect	-37.359***	82.255	339.212***	62.435*
S.E.	(13.372)	(83.743)	(120.588)	(37.270)
IQR Impact	.	0.405	1.910	.
Elasticity	-1.920	0.167	0.719	1.080
Lags	3	3	3	3
Share of Underground Miners				
Effect	-79.780***	193.289	781.863***	144.297*
S.E.	(30.793)	(182.159)	(275.736)	(81.676)
IQR Impact	.	0.333	1.541	.
Elasticity	-1.726	0.165	0.698	1.05
Lags	3	3	3	3
Share of Surface Miners				
Effect	-69.558***	145.289	595.799***	109.337
S.E.	(23.770)	(153.857)	(213.968)	(68.320)
IQR Impact	.	0.365	1.713	.
Elasticity	-2.071	0.171	0.732	1.095
Lags	3	3	3	3

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Effect is the linear combination of all lagged terms.
*Standard Errors are obtained by bootstrap in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Table 8: Opioid Prescription Rates

	Opioid Prescription Rate	
	OLS	**IV**
Share of Coal Miners		
Effect	66.363	132.069
S.E.	(72.562)	(94.346)
IQR Impact	0.039	0.077
Elasticity	0.026	0.052
Lags	3	3
Share of Underground Miners		
Effect	222.919*	273.461
S.E.	(122.590)	(204.869)
IQR Impact	0.046	0.056
Elasticity	0.037	0.046
Lags	3	3
Share of Surface Miners		
Effect	9.433	253.447
S.E.	(83.191)	(175.554)
IQR Impact	0.003	0.076
Elasticity	0.002	0.058
Lags	3	3

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Effect is the linear combination of all lagged terms.
For OLS, standard errors clustered at county level in parentheses.
*For IV, standard errors obtained by bootstrap in parentheses *** p<0.01, ** p<0.05, * p<0.1 .*

Table 9: Retailing Sector Regressions, by Gender Groups

	Opioid Death Rate		
	Whole Population	**Male**	**Female**
Share of Retail			
Effect	-5.146	-16.067**	6.541
S.E.	(5.650)	(7.301)	(7.891)
IQR Impact	-0.025	-0.066	0.053
Elasticity	-0.049	-0.122	0.084
Lags	3	3	3

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Effect is the linear combination of all lagged terms.
*Standard errors clustered at county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1 .*

Table 10: Retailing Sector Regressions, by Age Groups

	Opioid Death Rate			
	Under 20	**20-39**	**40-59**	**Above 60**
Share of Retail				
Effect	-4.462	-22.854*	-1.273	7.644
S.E.	(3.630)	(13.607)	(12.405)	(8.658)
IQR Impact	.	-0.068	-0.004	.
Elasticity	-0.590	-0.119	-0.007	0.340
Lags	3	3	3	3

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Effect is the linear combination of all lagged terms.
*Standard errors clustered at county level in parentheses, *** p<0.01, ** p<0.05, * p<0.1 .*

Appendix - Not for Publication

1. Detailed Definition of Death Codes

For Drug Overdose Data:

To use these codes listed below, input these codes as underlying cause of death in CDC WONDER underlying cause of death data extractor.

X40: Accidental poisoning by and exposure to nonopioid analgesics, antipyretics and antirheumatics
X41: Accidental poisoning by and exposure to antiepileptic, sedative-hypnotic, antiparkinsonism and psychotropic drugs, not elsewhere classified
X42: Accidental poisoning by and exposure to narcotics and psychodysleptics [hallucinogens], not elsewhere classified
X43: Accidental poisoning by and exposure to other drugs acting on the autonomic nervous system
X44: Accidental poisoning by and exposure to other and unspecified drugs, medicaments and biological substances
X60: Intentional self-poisoning by and exposure to nonopioid analgesics, antipyretics and antirheumatics
X61: Intentional self-poisoning by and exposure to antiepileptic, sedative-hypnotic, antiparkinsonism and psychotropic drugs, not elsewhere classified
X62: Intentional self-poisoning by and exposure to narcotics and psychodysleptics [hallucinogens], not elsewhere classified
X63: Intentional self-poisoning by and exposure to other drugs acting on the autonomic nervous system
X64: Intentional self-poisoning by and exposure to other and unspecified drugs, medicaments and biological substances
X85: Assault by drugs, medicaments and biological substances
Y10: Poisoning by and exposure to nonopioid analgesics, antipyretics and antirheumatics, undetermined intent
Y11: Poisoning by and exposure to antiepileptic, sedative-hypnotic, antiparkinsonism and psychotropic drugs, not elsewhere classified, undetermined intent
Y12: Poisoning by and exposure to narcotics and psychodysleptics [hallucinogens], not elsewhere classified, undetermined intent
Y13: Poisoning by and exposure to other drugs acting on the autonomic nervous system, undetermined intent
Y14: Poisoning by and exposure to other and unspecified drugs, medicaments and biological substances, undetermined intent

For Opioid Drug Overdose Data:

To use these codes listed below, input the drug overdose codes listed above in the underlying cause of death section in the CDC WONDER multiple cause of death data extractor then input the codes listed below into the multiple cause of death section.

T40.0: Opium
T40.1: Heroin
T40.2: Other opioids (Codeine) (Morphine)
T40.3: Methadone
T40.4: Other synthetic narcotics (Pethidine)
T40.5: Cocaine
T40.6: Other and unspecified narcotics

2. Definition of Coal Mining Regions:

The following regions and their definitions are from Energy Information Administration.

Coal-producing regions: A geographic classification of areas where coal is produced.

- **Appalachian region**: Consists of Alabama, Eastern Kentucky, Maryland, Ohio, Pennsylvania, Tennessee, Virginia, and West Virginia.
- **Northern Appalachian region**: Consists of Maryland, Ohio, Pennsylvania, and Northern West Virginia.
- **Central Appalachian region**: Consists of Eastern Kentucky, Virginia, Southern West Virginia, and the Tennessee counties of: Anderson, Campbell, Claiborne, Cumberland, Fentress, Morgan, Overton, Pickett, Putnam, Roane, and Scott.
- **Southern Appalachian region**: Consists of Alabama, and the Tennessee counties of: Bledsoe, Coffee, Franklin, Grundy, Hamilton, Marion, Rhea, Sequatchie, Van Buren, Warren, and White.
- **Interior region (with Gulf Coast)**: Consists of Arkansas, Illinois, Indiana, Kansas, Louisiana, Mississippi, Missouri, Oklahoma, Texas, and Western Kentucky.
- **Illinois Basin**: Consists of Illinois, Indiana, and Western Kentucky.
- **Western region**: Consists of Alaska, Arizona, Colorado, Montana, New Mexico, North Dakota, Utah, Washington, and Wyoming.
- **Powder River Basin**: Consists of the Montana counties of Big Horn, Custer, Powder River, Rosebud, and Treasure and the Wyoming counties of Campbell, Converse, Crook, Johnson, Natrona, Niobrara, Sheridan, and Weston.
- **Uinta Basin**: Consists of the Colorado counties of Delta, Garfield, Gunnison, Mesa, Moffat, Pitkin, Rio Blanco, Routt and the Utah counties of Carbon, Duchesne, Emery, Grand, Sanpete, Sevier, Uintah, Utah, and Wasatch.

3. Data Interpolation

We obtained the educational attainment and median household income data from American Community Survey (ACS). For year 2005 to 2007, ACS only covered 1/3 of the counties in the United States. Such data was not available from 2001 to 2004. Since educational attainment and income level may have profound effects on one's drug abuse, we interpolate these variables to match our regression period. We assume that the growth rates of median household income and educational attainment are constant from 2000 to 2016 within the county. Since there is not much fluctuation in these variables, this assumption should be reasonable.

Full Regression Results

Table A1: Gender Group Results with All Types of Coal Mining

	OLS			Bartik Instrument		
	Whole	Male	Female	Whole	Male	Female
Share of Coal Miners	46.503*	66.613	23.893	76.210	80.215	70.752*
	(25.525)	(43.671)	(21.970)	(73.237)	(116.151)	(37.991)
1 Lag	-64.430**	-120.124**	-6.114	-88.653	-71.110	-105.369*
	(31.527)	(53.658)	(24.192)	(96.812)	(165.834)	(54.220)
2 Lag	37.546	66.788*	6.333	198.189***	209.732	188.211**
	(22.945)	(36.725)	(28.434)	(61.963)	(132.600)	(76.420)
3 Lag	32.267	30.628	35.246	-72.592**	-93.035	-49.755
	(26.209)	(36.320)	(27.495)	(30.132)	(77.931)	(67.148)
Unemployment Rate	0.011	-0.006	0.038	0.033	0.026	0.050
	(0.061)	(0.088)	(0.071)	(0.082)	(0.134)	(0.060)
Median Household Income	-0.002	-0.026	0.038	-0.006	-0.034	0.035
	(0.041)	(0.039)	(0.076)	(0.045)	(0.054)	(0.044)
Population Density	-0.002***	-0.001	-0.002***	-0.002***	-0.001**	-0.002***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Male Population Ratio	-51.755***	-81.257***	-18.937	-55.363***	-85.550***	-21.958
	(19.170)	(22.398)	(29.906)	(16.612)	(19.100)	(30.706)
Age Group 20-39 Ratio	14.436	43.494***	-17.161	15.321***	45.759***	-17.790
	(10.661)	(13.519)	(16.542)	(4.578)	(9.570)	(16.358)
Age Group 40-59 Ratio	5.745	24.942*	-15.494	6.192	25.164	-14.901
	(8.867)	(12.901)	(12.402)	(12.828)	(25.446)	(10.537)
Highschool Diploma Rate	-0.125***	-0.223***	-0.016	-0.109**	-0.203**	-0.004
	(0.047)	(0.058)	(0.072)	(0.045)	(0.084)	(0.015)
Bachalor Degree Rate	0.022	0.139**	-0.109	0.026	0.149**	-0.111
	(0.048)	(0.059)	(0.079)	(0.049)	(0.063)	(0.097)
Constant	39.266***	50.613***	26.243	39.519***	50.703***	26.763**
	(10.654)	(11.357)	(17.645)	(5.924)	(7.981)	(11.581)
Cumulative Effect	51.886***	43.905*	59.357***	113.153***	125.802**	103.839*
S.E.	(16.608)	(25.988)	(17.667)	(22.765)	(36.625)	(62.059)
IQR Impact	0.427	0.299	0.801	0.931	0.857	1.401
Elasticity	0.192	0.129	0.296	0.420	0.371	0.517
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
State Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.12	0.10	0.06	0.12	0.10	0.06
N. of Counties	3139	3139	3139	3091	3091	3091
N. of Observations	34487	34487	34487	33938	33938	33938

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Cumulative Effect is the linear combination of all lagged terms.
For OLS, standard Errors are clustered at county level.
*For IV, standard Errors are obtained by bootstrap in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Table A2: Gender Group Results with Underground Coal Mining

	OLS			Bartik Instrument		
	Whole	Male	Female	Whole	Male	Female
Share of Underground Coal Miners	82.541**	114.553*	45.631	169.108	176.115	158.663*
	(41.441)	(67.509)	(49.329)	(167.389)	(261.570)	(89.896)
1 Lag	-94.354*	-167.371**	-18.402	-207.212	-185.347	-227.579*
	(48.472)	(71.644)	(57.032)	(224.394)	(369.282)	(125.421)
2 Lag	58.379	85.221	31.466	460.176***	523.611*	402.115***
	(46.855)	(72.530)	(49.391)	(143.089)	(295.897)	(151.966)
3 Lag	26.911	57.196	-4.031	-161.260**	-216.265	-102.930
	(54.241)	(73.649)	(50.996)	(66.897)	(181.115)	(140.241)
Unemployment Rate	0.008	-0.007	0.032	0.027	0.018	0.047
	(0.062)	(0.090)	(0.071)	(0.081)	(0.134)	(0.059)
Median Household Income	0.000	-0.025	0.040	-0.004	-0.031	0.037
	(0.041)	(0.039)	(0.077)	(0.045)	(0.054)	(0.045)
Population Density	-0.002***	-0.001	-0.002***	-0.002***	-0.001**	-0.002***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Male Population Ratio	-50.681***	-80.387***	-17.658	-53.625***	-83.595***	-20.418
	(19.184)	(22.390)	(29.919)	(16.396)	(19.185)	(30.877)
Age Group 20-39 Ratio	13.844	42.776***	-17.616	13.846***	44.034***	-19.035
	(10.696)	(13.493)	(16.607)	(4.766)	(9.907)	(16.833)
Age Group 40-59 Ratio	5.295	24.514*	-15.974	5.093	23.915	-15.872
	(8.909)	(12.900)	(12.478)	(12.627)	(25.355)	(10.843)
Highschool Diploma Rate	-0.123***	-0.222***	-0.013	-0.106**	-0.200**	-0.001
	(0.047)	(0.058)	(0.072)	(0.045)	(0.084)	(0.014)
Bachalor Degree Rate	0.021	0.139**	-0.111	0.023	0.145**	-0.114
	(0.048)	(0.059)	(0.079)	(0.049)	(0.063)	(0.097)
Constant	38.856***	50.374***	25.666	39.057***	50.174***	26.373**
	(10.665)	(11.364)	(17.652)	(5.800)	(8.077)	(11.511)
Cumulative Effect	73.476***	89.600**	54.663*	260.813***	298.114***	230.268
S.E.	(25.416)	(43.784)	(29.621)	(51.391)	(78.990)	(140.589)
IQR Impact	0.212	0.214	0.258	0.751	0.711	1.088
Elasticity	0.115	0.111	0.115	0.407	0.370	0.483
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
State Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.12	0.10	0.06	0.12	0.10	0.06
N. of Counties	3139	3139	3139	3091	3091	3091
N. of Observations	34487	34487	34487	33938	33938	33938

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Cumulative Effect is the linear combination of all lagged terms.
For OLS, standard Errors are clustered at county level.
*For IV, standard Errors are obtained by bootstrap in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Table A3: Gender Group Results with Surface Coal Mining

	OLS			Bartik Instrument		
	Whole	Male	Female	Whole	Male	Female
Share of Surface Coal Miners	42.259	57.071	25.433	138.544	147.285	127.327*
	(30.139)	(50.442)	(24.970)	(129.183)	(207.156)	(65.257)
1 Lag	-57.129	-110.398*	-1.109	-151.746	-109.203	-192.590**
	(37.756)	(64.368)	(25.890)	(167.767)	(297.015)	(95.762)
2 Lag	32.078	65.611	-4.491	342.344***	338.885	347.417**
	(25.304)	(39.955)	(37.848)	(108.147)	(236.585)	(148.982)
3 Lag	38.282	22.628	56.322*	-129.625**	-160.269	-93.389
	(25.449)	(35.447)	(33.081)	(54.980)	(135.122)	(126.190)
Unemployment Rate	0.004	-0.013	0.030	0.038	0.033	0.053
	(0.061)	(0.089)	(0.071)	(0.083)	(0.135)	(0.062)
Median Household Income	-0.002	-0.026	0.037	-0.008	-0.036	0.033
	(0.041)	(0.039)	(0.076)	(0.045)	(0.054)	(0.044)
Population Density	-0.002***	-0.001	-0.002***	-0.002***	-0.001*	-0.002***
	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)
Male Population Ratio	-51.987***	-81.054***	-19.603	-56.744***	-87.085***	-23.204
	(19.162)	(22.414)	(29.894)	(16.797)	(19.038)	(30.591)
Age Group 20-39 Ratio	15.054	43.754***	-16.210	16.491***	47.101***	-16.775
	(10.659)	(13.554)	(16.506)	(4.443)	(9.307)	(15.993)
Age Group 40-59 Ratio	5.883	24.881*	-15.153	7.056	26.118	-14.108
	(8.867)	(12.911)	(12.387)	(12.994)	(25.530)	(10.305)
Highschool Diploma Rate	-0.126***	-0.225***	-0.017	-0.111**	-0.206**	-0.006
	(0.047)	(0.058)	(0.072)	(0.045)	(0.084)	(0.016)
Bachalor Degree Rate	0.023	0.139**	-0.108	0.028	0.151**	-0.109
	(0.048)	(0.059)	(0.079)	(0.050)	(0.064)	(0.097)
Constant	39.371***	50.668***	26.391	39.904***	51.161***	27.072**
	(10.648)	(11.359)	(17.634)	(6.026)	(7.916)	(11.635)
Cumulative Effect	55.490**	34.912	76.155***	199.517***	216.698***	188.765*
S.E.	(23.435)	(36.628)	(22.174)	(40.822)	(67.604)	(110.546)
IQR Impact	0.233	0.121	0.525	0.838	0.753	1.301
Elasticity	0.119	0.060	0.220	0.429	0.370	0.545
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
State Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.12	0.10	0.06	0.12	0.10	0.06
N. of Counties	3139	3139	3139	3091	3091	3091
N. of Observations	34487	34487	34487	33938	33938	33938

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Cumulative Effect is the linear combination of all lagged terms.
For OLS, standard Errors are clustered at county level.
*For IV, standard Errors are obtained by bootstrap in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Table A4: Age Group Results with All Types of Coal Mining

	OLS				Bartik Instrument			
	Under 20	20-39	40-59	Over 60	Under 20	20-39	40-59	Over 60
Share of Coal Miners	11.094**	158.419***	7.917	4.417	10.573	268.079	4.156	-28.008
	(5.108)	(56.339)	(53.574)	(20.515)	(23.492)	(190.272)	(146.557)	(27.871)
1 Lag	-1.052	-189.033**	-51.200	-28.847	27.347	76.729	-322.668	-16.082
	(9.221)	(75.797)	(91.964)	(32.384)	(30.839)	(341.602)	(271.065)	(42.141)
2 Lag	5.303	166.919**	-9.756	20.510	-11.991	313.070	390.799**	71.312
	(11.415)	(81.391)	(79.700)	(41.057)	(9.821)	(220.568)	(154.128)	(64.975)
3 Lag	-9.352	-42.791	126.752**	22.767	-63.289***	-575.622***	266.925***	35.214
	(8.570)	(78.128)	(63.621)	(24.973)	(22.496)	(98.611)	(98.581)	(34.636)
Unemployment Rate	0.031	-0.081	0.112	0.030	0.044	0.119	0.023	0.007
	(0.044)	(0.166)	(0.143)	(0.059)	(0.029)	(0.220)	(0.111)	(0.056)
Median Household Income	0.003	0.030	0.057	-0.067	0.004	0.029	0.043	-0.072
	(0.012)	(0.084)	(0.130)	(0.049)	(0.018)	(0.118)	(0.124)	(0.045)
Population Density	-0.000	-0.005***	-0.003**	0.001**	-0.000	-0.005***	-0.003**	0.001**
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Male Population Ratio	5.946	-143.034***	-40.743	-1.041	6.611	-151.261***	-43.180	-3.892
	(6.560)	(40.465)	(48.594)	(22.795)	(7.237)	(38.636)	(64.081)	(27.418)
Highschool Diploma Rate	-0.014	-0.486***	0.109	-0.064	-0.014	-0.433***	0.122	-0.065
	(0.020)	(0.111)	(0.138)	(0.043)	(0.017)	(0.064)	(0.085)	(0.051)
Bachalor Degree Rate	0.049**	0.197	-0.204	0.049	0.050***	0.191	-0.195	0.057**
	(0.022)	(0.132)	(0.142)	(0.048)	(0.010)	(0.152)	(0.203)	(0.023)
Constant	-2.087	123.265***	26.976	10.856	-2.487	122.949***	27.467	12.385
	(3.933)	(23.439)	(32.417)	(14.289)	(4.250)	(17.716)	(31.999)	(17.662)
Cumulative Effect	5.993	93.515*	73.714**	18.847	-37.359***	82.255	339.212***	62.435*
S.E.	(5.431)	(50.670)	(35.377)	(18.358)	(13.372)	(83.743)	(120.588)	(37.270)
IQR Impact	.	0.460	0.415	.	.	0.405	1.910	.
Elasticity	0.308	0.190	0.156	0.326	-1.920	0.167	0.719	1.080
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.02	0.08	0.07	0.04	0.02	0.08	0.07	0.04
N. of Counties	3139	3139	3139	3139	3091	3091	3091	3091
N. of Observations	34487	34487	34487	34487	33938	33938	33938	33938

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Cumulative Effect is the linear combination of all lagged terms.
For OLS, standard Errors are clustered at county level.
*For IV, standard Errors are obtained by bootstrap in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Table A5: Age Group Results with Underground Coal Mining

	OLS				Bartik Instrument			
	Under 20	20-39	40-59	Over 60	Under 20	20-39	40-59	Over 60
Share of Underground Coal Miners	11.127	219.180**	57.259	38.637	18.556	585.348	-2.581	-56.396
	(14.644)	(110.763)	(93.942)	(39.362)	(54.250)	(425.454)	(341.627)	(67.554)
1 Lag	9.851	-237.475	-87.445	-92.179	66.461	164.622	-721.165	-45.063
	(16.632)	(146.144)	(122.742)	(84.580)	(74.456)	(742.277)	(632.590)	(105.445)
2 Lag	4.585	282.665	-38.154	61.692	-22.470	746.151*	906.156**	153.739
	(22.595)	(190.549)	(112.934)	(73.845)	(23.631)	(423.465)	(361.613)	(149.770)
3 Lag	-25.100	12.820	74.136	9.121	-142.327***	-1302.832***	599.453***	92.017
	(17.219)	(192.855)	(93.395)	(34.061)	(51.961)	(205.068)	(222.153)	(78.843)
Unemployment Rate	0.027	-0.100	0.121	0.034	0.042	0.091	0.029	0.008
	(0.044)	(0.165)	(0.144)	(0.060)	(0.028)	(0.216)	(0.111)	(0.056)
Median Household Income	0.004	0.033	0.059	-0.067	0.004	0.037	0.044	-0.072
	(0.012)	(0.083)	(0.130)	(0.049)	(0.018)	(0.117)	(0.124)	(0.045)
Population Density	-0.000	-0.005***	-0.003**	0.001**	-0.000	-0.005***	-0.003**	0.001**
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Male Population Ratio	6.068	-141.874***	-39.589	-0.760	6.507	-149.055***	-41.920	-3.693
	(6.562)	(40.536)	(48.603)	(22.808)	(7.197)	(39.153)	(64.048)	(27.224)
Highschool Diploma Rate	-0.014	-0.488***	0.115	-0.062	-0.013	-0.420***	0.121	-0.066
	(0.020)	(0.112)	(0.138)	(0.043)	(0.017)	(0.066)	(0.085)	(0.051)
Bachalor Degree Rate	0.048**	0.199	-0.208	0.048	0.050***	0.179	-0.195	0.057**
	(0.022)	(0.132)	(0.142)	(0.047)	(0.010)	(0.151)	(0.203)	(0.023)
Constant	-2.149	122.706***	26.022	10.575	-2.531	120.372***	27.275	12.387
	(3.937)	(23.501)	(32.408)	(14.295)	(4.217)	(18.169)	(31.904)	(17.534)
Cumulative Effect	0.463	277.190***	5.795	17.270	-79.780***	193.289	781.863***	144.297*
S.E.	(6.809)	(91.307)	(62.969)	(27.598)	(30.793)	(182.159)	(275.736)	(81.676)
IQR Impact	.	0.477	0.011	.	.	0.333	1.541	.
Elasticity	0.010	0.237	0.005	0.126	-1.726	0.165	0.698	1.050
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.02	0.08	0.07	0.04	0.02	0.08	0.07	0.04
N. of Counties	3139	3139	3139	3139	3091	3091	3091	3091
N. of Observations	34487	34487	34487	34487	33938	33938	33938	33938

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Cumulative Effect is the linear combination of all lagged terms.
For OLS, standard Errors are clustered at county level.
*For IV, standard Errors are obtained by bootstrap in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Table A6: Age Group Results with Surface Coal Mining

	OLS				Bartik Instrument			
	Under 20	20-39	40-59	Over 60	Under 20	20-39	40-59	Over 60
Share of Surface Coal Miners	14.320**	162.334**	-6.824	-7.707	22.512	495.231	14.229	-54.466
	(6.208)	(64.338)	(66.990)	(23.268)	(41.072)	(341.818)	(254.131)	(47.149)
1 Lag	-4.851	-179.563**	-42.306	-6.914	45.695	143.369	-578.624	-22.944
	(10.217)	(84.995)	(113.053)	(21.703)	(51.715)	(625.697)	(469.405)	(68.741)
2 Lag	5.442	138.733	-3.183	3.963	-24.377	530.896	680.207**	131.659
	(12.888)	(89.893)	(93.219)	(38.300)	(17.470)	(439.713)	(265.782)	(113.838)
3 Lag	-3.438	-68.563	161.337**	32.297	-113.388***	-1024.206***	479.987***	55.088
	(9.006)	(61.849)	(75.389)	(31.827)	(39.510)	(190.337)	(176.600)	(61.354)
Unemployment Rate	0.029	-0.106	0.110	0.029	0.046	0.142	0.019	0.006
	(0.044)	(0.165)	(0.144)	(0.059)	(0.029)	(0.223)	(0.112)	(0.055)
Median Household Income	0.003	0.032	0.056	-0.067	0.004	0.023	0.043	-0.072
	(0.012)	(0.084)	(0.129)	(0.049)	(0.018)	(0.118)	(0.123)	(0.045)
Population Density	-0.000	-0.005***	-0.003**	0.001**	-0.000	-0.005***	-0.003**	0.001**
	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)
Male Population Ratio	5.885	-141.913***	-41.110	-1.065	6.697	-153.061***	-44.102	-4.030
	(6.555)	(40.428)	(48.558)	(22.792)	(7.269)	(38.213)	(64.126)	(27.585)
Highschool Diploma Rate	-0.015	-0.492***	0.110	-0.064	-0.014	-0.444***	0.123	-0.065
	(0.020)	(0.112)	(0.138)	(0.043)	(0.017)	(0.063)	(0.086)	(0.052)
Bachalor Degree Rate	0.049**	0.199	-0.205	0.049	0.051***	0.200	-0.195	0.056**
	(0.022)	(0.132)	(0.142)	(0.048)	(0.010)	(0.153)	(0.204)	(0.023)
Constant	-1.991	123.278***	27.168	10.887	-2.449	125.066***	27.598	12.372
	(3.930)	(23.415)	(32.387)	(14.288)	(4.276)	(17.343)	(32.079)	(17.770)
Cumulative Effect	11.472	52.941	109.024**	21.638	-69.558***	145.289	595.799***	109.337
S.E.	(8.044)	(63.441)	(51.011)	(25.546)	(23.770)	(153.857)	(213.968)	(68.320)
IQR Impact	.	0.133	0.313	.	.	0.365	1.713	.
Elasticity	0.342	0.062	0.134	0.217	-2.071	0.171	0.732	1.095
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.02	0.08	0.07	0.04	0.02	0.08	0.07	0.04
N. of Counties	3139	3139	3139	3139	3091	3091	3091	3091
N. of Observations	34487	34487	34487	34487	33938	33938	33938	33938

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Cumulative Effect is the linear combination of all lagged terms.
For OLS, standard Errors are clustered at county level.
*For IV, standard Errors are obtained by bootstrap in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*

Table A7: IV First Stage Regressions

	Gender Groups			Age Groups		
	All	Underground	Surface	All	Underground	Surface
Predicted Share	2586.794***	1159.866***	1426.928***	2585.331***	1160.605***	1424.726***
	(377.031)	(235.731)	(326.357)	(378.030)	(236.061)	(326.365)
Unemployment Rate	-0.360**	-0.132***	-0.229**	-0.355**	-0.131***	-0.224**
	(0.140)	(0.044)	(0.108)	(0.140)	(0.044)	(0.108)
Median Household Income	0.022	-0.003	0.024	0.023	-0.001	0.025
	(0.025)	(0.012)	(0.021)	(0.024)	(0.012)	(0.020)
Population Density	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Male Population Ratio	6.392	-6.044	12.437	5.386	-1.997	7.383
	(13.683)	(5.791)	(11.651)	(9.704)	(4.931)	(7.432)
Age Group 20-39 Ratio	-2.363	5.974	-8.338			
	(14.116)	(3.777)	(13.395)			
Age Group 40-59 Ratio	-14.585	-1.485	-13.101			
	(12.272)	(3.323)	(11.255)			
Highschool Diploma Rate	-0.041	-0.037	-0.004	-0.045	-0.038	-0.007
	(0.053)	(0.030)	(0.036)	(0.052)	(0.030)	(0.035)
Bachalor Degree Rate	-0.008	0.014	-0.022	-0.009	0.012	-0.021
	(0.052)	(0.019)	(0.043)	(0.050)	(0.019)	(0.042)
Constant	6.001	5.544	0.457	2.167	4.650	-2.483
	(7.138)	(3.798)	(4.606)	(7.277)	(3.705)	(4.924)
F Statistic	47.073	24.209	19.117	46.771	24.173	19.057
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
State Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.23	0.19	0.14	0.23	0.19	0.13
N. of Counties	3091	3091	3091	3091	3091	3091
N. of Observations	43225	43225	43225	43225	43225	43225

Year Range: 2006-2016.

Includes year fixed effect, county fixed effect, state-by-year fixed effect. F statistic is the test of null hypothesis that excluded instrument coefficient in first stage regression equals zero.

**** p<0.01, ** p<0.05, * p<0.1.*

Table A8: Prescription Rate Regressions

	Opioid Prescription Rate					
	OLS			IV		
	Whole	Underground	Surface	Whole	Underground	Surface
Share	27.568	134.404	-5.458	274.097**	625.778**	486.268**
	(46.348)	(116.717)	(52.638)	(135.592)	(305.189)	(243.389)
1 Lag	14.143	106.495	-15.788	-95.949	-220.657	-168.410
	(36.625)	(99.016)	(45.511)	(82.810)	(184.412)	(149.125)
2 Lag	-49.778	-124.750	-27.643	-128.463***	-313.544***	-213.593**
	(31.016)	(83.584)	(32.483)	(48.390)	(108.223)	(87.153)
3 Lag	74.430	106.769	58.322	82.383	181.885	149.181
	(62.927)	(94.204)	(69.797)	(80.724)	(189.403)	(139.958)
Unemployment Rate	-0.287	-0.247	-0.323	-0.106	-0.116	-0.098
	(0.237)	(0.234)	(0.241)	(0.228)	(0.229)	(0.227)
Median Household Income	-0.178**	-0.177**	-0.175**	-0.159***	-0.153**	-0.163***
	(0.086)	(0.086)	(0.086)	(0.060)	(0.060)	(0.061)
Population Density	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***	-0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Male Population Ratio	-118.206	-113.645	-118.156	-110.777***	-107.367***	-113.646***
	(79.841)	(79.774)	(79.860)	(32.450)	(31.266)	(33.481)
Age Group 20-39 Ratio	54.678	50.610	57.169	55.850	53.428	57.918
	(39.636)	(39.433)	(39.693)	(40.711)	(40.158)	(41.201)
Age Group 40-59 Ratio	-2.274	-3.357	-1.429	-1.502	-3.315	0.051
	(41.214)	(41.147)	(41.237)	(27.309)	(26.619)	(27.903)
Highschool Diploma Rate	0.467***	0.474***	0.464***	0.435***	0.443***	0.428***
	(0.151)	(0.151)	(0.151)	(0.063)	(0.064)	(0.062)
Bachalor Degree Rate	-0.139	-0.146	-0.136	-0.158	-0.165	-0.151
	(0.147)	(0.147)	(0.147)	(0.171)	(0.168)	(0.173)
Constant	88.553**	86.807**	87.992**	86.194***	84.740***	87.363***
	(37.486)	(37.471)	(37.492)	(16.091)	(16.091)	(16.121)
Cumulative Effect	66.363	222.919*	9.433	132.069	273.461	253.447
S.E.	(72.562)	(122.590)	(83.191)	(94.346)	(204.869)	(175.554)
IQR Impact	0.039	0.046	0.003	0.077	0.056	0.076
Elasticity	0.026	0.037	0.002	0.052	0.046	0.058
Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes	Yes
State Year Fixed Effect	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.19	0.19	0.19	0.19	0.19	0.19
N. of Counties	2983	2983	2983	2936	2936	2936
N. of Observations	30850	30850	30850	30332	30332	30332

Year Range: 2006-2016.
Includes year fixed effect, county fixed effect, state-by-year fixed effect.
Cumulative Effect is the linear combination of all lagged terms.
For OLS, standard Errors are clustered at county level.
*For IV, standard Errors obtained by bootstrap in parentheses, *** p<0.01, ** p<0.05, * p<0.1.*