Drug Overdose Related Deaths and Their Relationship with Blue-collar Jobs

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Abstract:

Over the years, drug overdose deaths have steadily increased in the Appalachian region, which is known for having a high blue-collar job composition. This study examines drug overdose related deaths and their relationship with blue-collar jobs. Annual county level data which describes 13 U.S. states in the Appalachian region was collected to investigate the relationship between the drug overdose mortality rate and blue-collar jobs. In-order to measure blue-collar job composition, the total employment percentage of mining, quarrying, oil and gas extraction, construction, and manufacturing were used. Ultimately, the results show that counties with a higher employment percentage in mining, quarrying, oil and gas extraction have a higher drug overdose mortality rate. Conversely, counties with a higher employment percentage in construction or manufacturing have a lower drug overdose mortality rate.

Introduction:

Drug overdoses are an important, yet an inadequately understood public health problem. Over the years, the drug overdose mortality rate has substantially increased in the United States. The drug overdose mortality rate or DOMR is defined as the number of drug overdose related deaths per 100,000 people. The number of these types of deaths has increased by nearly 5% from 2018 to 2019 and has quadrupled since 1999 (CDC). Much is discussed on the causes that increase or decrease these types of deaths. One factor many point to is the type of occupations that may be causal to this crisis. Many believe because of the intense manual labor, high risk of work-related injury, and high mental stress blue-collar jobs tend to have in comparison to other occupations, leads to more drug overdose related deaths. A particular region in the U.S. which is known for having a high composition of blue-collar jobs is the Appalachian region. Unfortunately, this region has been plagued with high drug overdose related deaths and drug use in general compared to other areas of the U.S (Ahmad, 2021). Considering factors like this, along with the writer's personal interest on the subject of the impact drugs have on society, there is interest in learning if counties with a large employment percentage in blue-collar jobs do, in fact, experience a high drug overdose mortality rate. A collection of annual county level data from states (all of which are in the Appalachian region) was done. The main variables of interest are the total employment percentages in three blue-collar occupations that are high risk, in addition to a collection of other variables that may have significance to this research. The results of this research partially explains that counties with high blue-collar job compositions have higher DOMR. Although only partially, the results still provide an important story as to why certain counties experience a higher DOMR compared to others.

Literature Review:

Much research has been done on the DOMR to determine factors contributing to increases or decreases. Researchers tend to look at factors such as regional, cultural, financial and employment based to gain an understanding of the potential factors that cause an increase or decrease in this measure.

Typically, a common measurement used when testing the DOMR is region based. Specifically, there tend to be regions in the United States that have a higher DOMR than others. For instance, Blake-Gonzalez et al. (2021) found that the DOMR was higher in rural locations compared to urban locations. Specific rural regions such as the Appalachian belt, which involves states like Pennsylvania, West Virginia, and Ohio, experience a high DOMR. Additionally, western states such as New Mexico and Arizona also experience a high DOMR due to their ruralness in much of these states. The underlying question one may ask is, why do rural areas experience a higher DOMR compared to urban regions? Additional research from Monnet (2018) found that regions lacking socialization, less educational opportunity, and manually labor-intensive jobs tended to have a higher DOMR. Based on the results of this study, the regions that had high levels of these variables were mostly rural.

Specifically, it is the types of drugs that these rural regions are getting access to that is causing such a high DOMR. Opioids such as OxyContin, Fentanyl, Percocet, and a plethora of other opiates and synthetic opiates tend to be the main drivers of drug overdose deaths in the United States and in these rural regions (CDC). One study from Jonas et al. (2012) found that Oxycontin use was higher in regions such as rural Appalachia. Being that the travel distance for emergency responders and emergency departments is greater in rural than urban regions results in a much higher DOMR. These types of deaths can often be prevented if patients obtain life support and naloxone (a medicine that rapidly reverses an opioid overdose). Unfortunately, due to ruralness, providing treatment for these individuals is difficult. However, ruralness is not the defining factor when looking at drug overdose related deaths.

Drug use over the years in the United States has also been impacted by certain social and cultural backgrounds. Studies such as Kaestner (1998) suggest that drug use is correlated with certain values and behaviors that may be thought of as constituting a particular form of culture. What are the elements defined as cultural that may have an impact on drug use? Culture can encompass any set of beliefs, moral values, traditions, language, and laws held in common by a community, or a group of people (IGI GLOBE). Factors such as education, demographic background, and family background may help illustrate a correlation to drug overdoses and drug use in general.

A typical cultural measurement used by researchers when studying the DOMR is education. The general thinking is that more knowledge of the ill effects of drug abuse can prevent individuals from participating in this type of activity. For instance, Ho (2017) found that drug overdoses accounted for 20% of all high school graduates' deaths and 10% to 16% for all college graduates' deaths. As one can see from this study, more education significantly decreases the DOMR. Reasons for these high levels of drug overdose mortalities among the less educated are explained by Galea et al. (2007), concluding that they may be driven by peers with the similar education attainment, less employment opportunities, increased risk at workplace injuries leading to prescribed painkillers, and fewer resources to combat drug addiction. Although education has a significant impact on whether individuals participate in drug use, it is not the defining cultural factor when measuring the DOMR.

Demographic characteristics such as ethnicity, age, and sex also seem to have a correlation with drug abuse and the DOMR. Hansen and Netherland (2016) suggested that drug overdoses leading to deaths are predominantly a white male problem, due to this type of group having better access to prescription pain medication than other groups. However, other racial/ethnic groups such as Blacks, Hispanics, Asians, American Indian or Alaska Native, are also heavily affected. From 2015 to 2017, nearly all racial/ethnic groups experienced significant increases in overdose death rates (CDC). According to Lippold et al. (2017), opioid-involved overdose deaths in large metro areas from 2015-2017 increased for Blacks by 38.6%, 29.9% for non-Hispanic Whites, and 35.5% for Hispanics. Clearly, drug overdoses are not discriminatory and continue to affect many racial/ethnic groups in the United States. Overall, each group seems to have its own unique factors which are increasing the DOMR.

Another consideration to take into account when looking at the DOMR and drug use is family background. Drug addiction is heavily shaped by environmental factors and genetics. The environment a person grows up in affects their mental health making them more prone to drug addiction. In addition, one can simply be born with a family history of addiction, which genetically predisposes one to drug addiction. A study from Blake-Gonzalez et al. (2021) tested this by observing incarceration rates and observing if the drug-overdose death rate increased, since incarceration has a disruptive impact on families and communities. What was discovered was that a 5% absolute increase in the jail population increased the DOMR by 7.11% of the population that is incarcerated. Not only do those who have been incarcerated exhibit higher levels of drug abuse, but so do their friends and family. Additional research from Monnat (2018) used U.S. Census data from 2000 to test social factors such as family distress to determine if it correlated with its age-adjusted drug-mortality rate (AAMR). The data showed that family distress was associated with a 13.6% increase in the AAMR. It is evident when looking at these studies that family background has a significant impact on drug use and the DOMR. The ultimate issue is how significant family background is compared to other factors when correlating it to DOMR.

Drug addiction does seem to significantly impact individuals among the lower economic status. For many years, drug addiction and the DOMR has plagued people who cannot cover their basic needs, those who struggle to make ends meet, and those that are living in a low-income household or in poverty. In contrast, citizens who are financially stable and employed tend to have low drug use participation and DOMR (Lesser, 2021). One study from Blake-Gonzalez et al. (2021) tested this by taking median annual household income (MEDHHINC) and percentage unemployment rate (UNEMPL) in 84 Virginia counties to determine any correlation with the DOMR. The DOMR increased drastically in regions with a high unemployment rate, while the DOMR decreased drastically in regions with a high median annual household income, hypothesizing that income and economic status do have a significant impact on the DOMR, but for what reasons? Research from Altekruse et al. 2020 concluded that individuals who have lower education and live in rural areas tend to have lower incomes which increases the likelihood of drug use. An additional study from Ho (2017) explained that areas that experience a higher unemployment, high levels of poverty, and slower recovery after the 2008 financial crisis, may have an increased vulnerability to drug use. As far as the types of drugs that are to blame for this increase in death among low income individuals, heroin (a highly addictive analgesic drug derived from morphine) and crack (a highly addictive stimulant derived from a chemical) compared to other illicit drugs are mostly responsible (Kerr).

In addition to affecting those who are unemployed, drug overdose deaths are prevalent among the blue-collar working class. Ho (2017) found that a high prevalence of overdose deaths in those with physically demanding jobs, unreliable workers, and those with limited health care benefits. Research from this study explains that those who work in blue-collar jobs, such as mining and manufacturing, may incur more work-related injuries and disabilities, leading them to suffer from chronic pain conditions. What this ultimately leads to is an increased likelihood of these workers being prescribed opioid painkillers, which is associated with greater risk for drug addiction and subsequently drug overdoses. One study by Blake-Gonzalez et al. (2021) tested this by taking the percentage of miners in a county (out of 84 Virginia counties) to determine its correlation with the DOMR. What was discovered was a 5% absolute increase in median workers in mining increased the DOMR by 9.05%.

Additionally, not only are these blue-collar jobs physically demanding, but also mentally demanding, which may result in individuals looking to substance use in order to relieve themselves from their mentally strenuous jobs. Maclean et al. (2015) examines how workplace problems may influence mental health and substance abuse (MHSU) by taking three variables involving workplace problems (co-workers, job changes and perceived financial strain) and three variables involving mental health and substance abuse (mood, anxiety, and substance abuse/dependence) to see if there is a correlation. Research discovered that experiencing workplace problems is strongly associated with an increased risk for substance use disorder. Specifically, problems with co-workers, job changes and perceived financial strain are associated with a 4.1%, 2.6%- and 5.9%-point increase in the probability of a substance use disorder, respectively. Interestingly, occupations that experience high workplace problems are typically blue-collar jobs like mining, manufacturing, construction, and many others.

Overall, there are a plethora of factors that either increase or decrease the DOMR in the United States. Factors such as financial and employment, regional, and cultural seem to be the foundational ones, however, these factors are just scratching the surface when it comes to looking at the DOMR. It is crucial to incorporate all factors in order to understand the full picture of the DOMR and what it affects, which is why combining financial and employment, regional, and cultural factors together are crucial. Simply if only a few of these factors are tested one can only understand half of the reasons why the DOMR is increasing or decreasing in the United States.

Data and Methodology:

Based on the pieces of literature mentioned in the previous section, this writer is interested in discovering how the Drug Overdose Mortality Rate is affected by the blue-collar job composition of a county in Appalachian states. To determine this, a single regression using the DOMR as the dependent variable, which is measured by the number of drug poisoning deaths per 100,000 population (see Equation 1 for regression equation) will be used.

Equation 1

$$\textit{Drug Overdose Mortality Rate} = \beta_0 + \beta_1(\text{Mining}) + \beta_2(\text{Construction}) + \beta_3(\text{Manufacturing}) + \beta_i(\text{Education}) + \beta_j(\text{Race/Ethnicity}) + \beta_u(\text{Sex/Age}) + \beta_r(\text{Region Classification}) + \beta_4(\text{HIV Prevalence Rate}) + \beta_5(\text{Unemployment Rate}) + \beta_6(\text{Median Household Income}) + \beta 7(\text{Opioid Dispense Rate}) + u_i$$

This data was taken from County Health Rankings and Roadmaps. With this data and tests, it will look to conclude that in addition to educational attainment, social factors and employment having a significant impact on the DOMR, blue-collar jobs, and ruralness of an area are just as significant.

To test the question of how the DOMR is affected by the blue-collar job composition of a county in Appalachian states, county level annual data describing 13 states in the U.S. which are located on the Appalachian belt from 2017-2019 will be utilized. Based on Appalachia's history of mining, manufacturing, and construction, along with its variance in ruralness and urban areas, makes it an ideal region from which to test. The reason for collecting data by county is based on Blake-Gonzalez et al. (2021) research which looked at the effects on the DOMR by county level using 84 Virginia counties. In addition, simply collecting data over an entire state may mislead the true nature of a state's characteristics. Therefore, using county level data will likely show more variation. In order to measure the blue-collar job composition of a county, the total employment in a county and the total employment of one of my blue-collar job variables' in a county was divided then multiplied by 100 to get a percentage. This resulted in the total employment percentage in that blue-collar job. Below in Equation 2 is an example of this calculation.

Equation 2

$$Employment\ Percentage\ in\ Manufacturing = \frac{\text{Number of Employed in Manufacturing}}{\text{Total Employment in County}} * 100$$

The main independent variables of interest which include total employment percentage in mining, quarrying, and oil and gas extraction, manufacturing, and construction were collected from Emsi. The reason for choosing these specific occupations was based on Monnat et al. (2018) research which used a similar technique by taking the labor market dependency of these occupations from a region. In addition, these specific blue-collar occupations are known for having high workplace related injuries, along with being more mentally and physically demanding compared to other blue-collar jobs.

Historically, Appalachian communities gained development and population due to blue-collar jobs like mining. From the 1800s through the 1970s this region was America's primary coal-producing region (Zipper et al. 2021). Unfortunately, some blue-collar jobs have been steadily decreasing over the years, leaving the people who live in this region jobless. Ultimately, when people lose their jobs, it may contribute to them engaging in activities like drug use. Additionally, as far as hazards to worker health and providing a safe working environment, jobs like mining, quarrying, oil and gas extraction and construction are physically and manually intensive occupations which have been associated with an increase in mental health problems, injuries, and chronic pain (Monnat et al. 2018). Ultimately, the working conditions these occupations provide lead to higher rates of substance abuse, whether medications/substances have been prescribed by a doctor or obtained through illegal means. Based on this information, I hypothesize that counties with a higher composition in mining, quarrying, and oil and gas extraction, manufacturing, and construction will have a higher drug overdose mortality rate.

An additional factor of these blue-collar jobs is location. These occupations (primarily mining and manufacturing) tend to be located in rural regions. Due to Appalachia's vast amount of ruralness, it is no surprise that the blue-collar job make-up of this region is large. Unfortunately, drug use (specifically with opioids) has often been a rural phenomenon (Rural Health Info Hub). These regions tend to have high poverty rates, high unemployment, lack of mental healthcare, and isolation, causing the population to be at an increased risk of death from drug overdose. Based on this information, rural-urban continuum codes from the U.S. department of agriculture that classify counties as more urban or rural was used to determine if it will increase or decrease the DOMR. Dummy variables omitting counties classified as rural were utilized.

Using a one to nine scale, one being a county classified as metro (an area of 1 million population or more) and nine being a county classified as non-metro (completely rural or less than 2,500 urban population, not adjacent to a metro area) three groups were created. Counties that are classified as one, two or three will be labeled as metro. Counties classified as four, six, or eight will be labeled as non-metro adjacent. Lastly, counties classified as five, seven or nine will be labeled as rural. With interest in counties that are classified as more rural, rural will be the omitted variable since it is the group which is being referenced. I hypothesize that counties that are classified as metro or non-metro adjacent will have a lower DOMR in relation to counties classified as rural.

Although blue-collar job composition is the main variable of interest, it is important to consider other variables that are significant when looking at the DOMR. Many pieces of literature focused on the topic of drug overdoses find that educational attainment has a significant impact on drug use. For instance, Ho (2017) tested this by creating two groups of education levels. One was individuals aged 25-29 that were high school graduates and the other was individuals aged 25-29 that were college graduates to estimate the burden of drug overdose mortality. Ho concluded that in 1992, drug overdoses accounted for more deaths among high school students than it did for college graduates. To clarify, this provides evidence that drug overdose related deaths are positively correlated with low educational attainment.

To test the effect educational attainment has on the DOMR, a collection of variables form the U.S. Census was extracted. These include individuals aged 25 or older with less than 9th grade and less than a high school diploma, high school diploma, some college or associate degree, bachelor's degree, and graduate or professional degree. To determine how higher educational attainment affects the DOMR, individuals aged 25 or older with less than 9th grade and less than a high school diploma were omitted. All of the educational attainment variables are total percentages for each county in the 13 Appalachian states. I hypothesize that individuals aged 25 or older with less than 9th grade and less than a high school diploma will have a higher DOMR. Conversely, individuals aged 25 or older with a high school diploma or anything higher will experience a lower DOMR in relation to those with less than 9th grade and less than a high school diploma.

An additional factor that must be considered when discussing drug use are demographic factors such as age, sex, and ethnicity. Scholarly studies from Hansen and Netherland (2016) suggested drug overdoses, specifically involving opioids or synthetic opioids leading to death is predominately a non-Hispanic Caucasian problem. Individuals among this ethnicity simply have better access to prescription pain medication than do Hispanics, Blacks, and Asians (Addison). Another study from Blake-Gonzalez et al (2021) captured this by taking the percentage of Caucasians aged 15 years and above from 84 Virginia counties to determine if the drug overdose death rate was an increasing function. Based on these two studies, similar variables were added that would focus on ethnicity and its relationship with the DOMR. The percentage population of Black, Asian, Hispanic, and Non-Hispanic White from each county in the 13 Appalachian states were taken. This data was extracted from County Health Rankings and Roadmaps. Based on the literature, I hypothesize that counties with higher percentages of Non-Hispanic White will result in a high DOMR. Conversely, counties with higher percentages of Asian will have a lower DOMR. Due to an imbalance of results from articles comparing ethnicities with drug overdose rates, it is uncertain which counties that have high percentages of both Black and Hispanic populations.

Besides demographic factors such as ethnicity, both sex and age are also significant factors to consider with relationship to drug usage. A study from Ho (2017) included age and sex in their data to estimate the burden of drug overdose mortality by education. For each educational group in this study (less than high school, high school completion, some college, and college or more) age and sex were also included in the estimate. Age ranges from 25-29 male, 25-29 female and 30-34 male, 30-34 female were included. Spanning all age groups, males in each educational group experienced drug overdose rates that were twice as high. Similarly, a method was adopted to capture the age and sex makeup of a county by taking the percentage of the male population ages 25 to 29 years, percentage of the female population ages 25 to 29 years, percentage of the male population ages 30 to 34 years, and percentage of the female population percent ages 30 to 34 years. These independent variables were collected from the U.S. Census. My hypothesis for these variables is that counties with a higher percentage of the male population in both age ranges will have a higher DOMR. While counties with a higher percentage of females aged 30 to 34 will have a lower DOMR.

To establish a causal relationship between the main variables of interest and its relationship with the DOMR, added control variables were added that could influence the outcomes. The control variables are the HIV prevalence rate (Number of people aged 13 years and older living with a diagnosis of human immunodeficiency virus infection per 100,000 population), unemployment rate (percentage of population ages 16 and older unemployment but seeking work), log of median household income, and U.S. County opioid dispensing rate (opioid dispensing rate per 100 persons). The U.S. county opioid dispensing rate data was retrieved from the CDC. All other control variables were obtained from County Health Rankings and Roadmaps. My hypothesis for these control variables is that counties with a high HIV prevalence rate, high percentage of unemployment, and a high U.S. County opioid dispensing rate will have a high DOMR. However, counties with a high median household income will likely have a low DOMR. Based on Blake-Gonzalez et al (2021) study which included median household income, unemployment rate, and average opioid prescribing rate to find the factors that have contributed to the appearance of increased drug abuse and mortality, similar variables were adopted for the project.

Results:

As noted in the previous section, a single regression using the drug overdose mortality rate as the dependent variable (DOMR) was used to determine if counties with a higher blue-collar job composition in mining, quarrying, oil and gas extraction, construction, and manufacturing have a higher DOMR. For the rest of this section, an in-depth explanation of the models results and how they are interpreted will be provided. Pictured in Table 1 are the results from the regression. Robust standard errors were used in the results due to heteroskedasticity being a concern. There was a total of 2,900 observations in the model. The R-squared value was 0.3081, meaning that the regression model accounts for 30.81% of the variation in the drug overdose mortality rate.

Table 1

Independent Variable(s)	Drug Overdose Mortality Rate (Dependent Variable)
Constant	1.48 (20.61)
% Mine	100.76*** (21.67)
% Construction	-81.34*** (9.41)
% Manufacturing	-11.82*** (2.41)
% Black	-0.40*** (0.02)
% Asian	0.08 (0.11)
% Hispanic	-0.29*** (0.05)
% High School	0.12 (0.08)
% Some College	0.11 (0.11)
% Bachelors	0.42*** (0.11)
% Grad/Professional	-0.61*** (0.11)
% Male 25-29	-0.10 (0.23)
% Male 30-34	0.77*** (0.25)
% Female 25-29	-0.66** (0.28)
% Female 30-34	0.26 (0.31)
HIV Prevalence Rate	0.008*** (0.002)
% Unemployed	0.95*** (0.24)
Log of Median Household Income	0.47 (0.007)
Opioid Dispensing Rate	0.04*** (0.007)
Metro	8.05*** (0.77)
Non-Metro Adjacent	3.48*** (0.70)
Observations R-Squared (R^2) F-Statistic	2,900 0.3081 72.85***
Dependent Variable Drug Overdose Mortality Rate (DOMR): The number of drug related deaths per 100,000 total population.	

Note: Robust standard errors for independent variables are shown in parentheses. ***, **, * indicate statistical significance at the .01, .05, and .10 levels.

The first set of variables discussed are the main variables of interest which are the total employment percentage in mining, quarrying, oil and gas extraction, construction, and manufacturing by county. All three of the variables were statistically significant at the one percent level. However, the only variable out of these three that fit the hypothesis was the total employment percentage in mining, quarrying, oil and gas extraction. Therefore, a one percentage point increase in the total employment percentage in mining, quarrying, oil and gas extraction would lead to around 1.01 more drug overdose related deaths per 100,000 people. Conversely, the other two variables of interest, total employment percentage in manufacturing and construction did not fit the hypothesis. Both of the coefficients for these variables were negative. Therefore, a one percentage point increase in total employment percentage in construction would lead to 0.81 less drug overdose related deaths per 100,000 people. In addition, a one percentage point increase in total employment percentage in manufacturing would lead to 0.12 less drug overdose related deaths per 100,000 people. Although these two variables did not give the expected results, they helped put in perspective how bad drug overdose related deaths are in mining, quarrying, oil and gas extraction jobs.

Out of all the blue-collar jobs chosen, the mining industry seems to be the occupation with the highest pressure on employees, with its heavy workloads and hazardous conditions. This can cause workers to turn to substances for coping with high levels of physical pain, emotional turmoil, and mental stress. In addition, when considering where mining operations are geographically located, these results seem obvious. A study in 2019 from the OECD indicated the negative externalities around and in close proximity to mining operations, that included:

- Income inequalities between population groups
- Limited job opportunities for local workforce and skills mismatches

- Pressures on public services and infrastructures
- Volatility in housing prices, limited affordability or abandonment
- Weakened social cohesion and limited civic engagement

Areas with a high mining composition tend to be located in communities with low development economically and structurally. Ultimately, these are strong factors that can lead to a high DOMR.

The second set of variables are the race/ethnicity-based variables which are the total population percentage of Black, Asian, Hispanic, and non-Hispanic White in a county. Non-Hispanic White is the dropped variable meaning the results of all other races are in relation to non-Hispanic White. The only variable that was not significant out of the three was total population percentage of Asian. However, percentage of Black and Hispanic were statistically significant at the one percent level. Therefore, a one percentage point increase in percentage Black would lead to 0.40 less drug overdose related deaths per 100,000 people. Similarly, a one percentage point increase in percent Hispanic would lead to 0.29 less drug overdose related deaths per 100,000 people. Overall, counties that have a higher percentage of Black and Hispanics experience a lower drug overdose mortality rate in comparison to counties with high population percentages of non-Hispanic Whites, which follows the original hypothesis. The likely reason for this is that individuals among Non-Hispanic Whites race/ethnicity group simply have better access to prescription pain medication than do Hispanics, Blacks, and Asians (Addison). Prescription pain medications such as Oxycodone, Hydrocodone, Fentanyl and other related medications are huge drivers of drug overdose related deaths and being that non-Hispanic Whites gain easier access to them, it is no surprise that they have a higher DOMR.

Next are the variables regarding age and sex. These variables include total population percentage of male ages 25-29, female 25-29, male 30-34, and female 30-34. The only variable that was significant at the one percent level was males 30-34. Therefore, a one percentage point increase in total population percentage of males 30-34 would lead to 0.79 more drug overdose related deaths per 100,000 people. Although I hypothesized that drug overdose related deaths would be more prevalent among males aged 25-29, it is not all that surprising to see a higher DOMR in males 30-34. Interestingly, when looking at the employed persons by industry and age in each of the blue-collard jobs (mining, oil and gas extraction, manufacturing, and construction) males aged 30-34 have the highest employment in each occupation (BLS). With such a high composition of males in this age range in these types of jobs it makes sense that there is such a high amount of drug overdose related deaths.

Additional variables that are important to mention are the education variables included in the regression. The variables that were statistically significant include percentage of people with a bachelor's degree, and percentage of people with a graduate or professional degree. Both of these variables are in relation to percentage of people with less than a high school degree. When interpreting the percent with a bachelor's degree, a one percentage point increase in the percentage of people with a bachelor's degree would lead to 0.42 more drug overdose related deaths per 100,000 people. On the other hand, a one percentage point increase in the percentage of people with a graduate or professional degree would lead to 0.61 less drug overdose related deaths per 100,000 people. Surprisingly, my hypothesis that counties with a higher percentage of people with a bachelor's degree will have a lower DOMR was false. However, my hypothesis regarding the percent with a graduate or professional degree will have a lower DOMR was correct. To better understand why counties with a high percentage of those with bachelor's degrees experience a higher DOMR, research from Arria et al (2013) which suggests that reduced occupational expectations, occupational attainment and stability, decreased wage earnings and job satisfaction are all factors that lead to drug involvement.

Other statistically significant variables are the regional classification dummy variables. These include counties classified as metropolitan (metro), non-metropolitan but adjacent to a metropolitan area (non-metro adjacent), and non-metropolitan not adjacent to a metropolitan area (rural). With interest in mind of counties that are classified as more rural, rural is the omitted variable. Interestingly, the previous hypothesis that rural counties will experience a higher DOMR did not match up with my results. In fact, counties that are classified as metro have 8 more drug overdose related deaths per 100,00 people, relative to counties classified as rural. In addition, counties classified as non-metro adjacent have 3.48 more drug overdose related deaths per 100,000 people relative to counties classified as rural. A likely reason for this may be due to individuals having easier access to drugs such as heroin, fentanyl, and other drugs notorious for having a high probability of overdosing from.

The last set of statistically significant variables are the control variables, which include unemployment percentage, opioid dispensing rate, HIV prevalence rate, and the log of median household income. First, when looking at the results of the percent unemployed, a one percentage point increase in percent unemployment would lead to 0.95 more drug overdose related deaths per 100,000 people. Next, the results of the opioid dispensing rate showed that a one percentage point increase in opioids dispensed per 100 people would lead to 0.04 more drug overdose related deaths per 100,000 people. Lastly, the results of the HIV prevalence rate showed that a one percentage point increase in the HIV prevalence rate would lead to 0.008 more drug overdose related deaths per 100,000 people. Overall, other than the log of medium household income not being significant, all the other control levels followed by original hypothesis.

Conclusion:

In conclusion, since the results of the regression had only one of three blue-collar job variables fitting my hypothesis, I can only partially accept my hypothesis that counties with a higher blue-collar job composition have a higher DOMR. Although this is not the expected result, there is still an important takeaway from these results. First, the results can conclude that mining compared to construction and manufacturing has specific characteristics that are causing this increase in drug overdose related deaths. These characteristics are mostly based on the lack of opportunity available to these mining sectors, causing workers to turn to drugs because of boredom, stress and pain from work, and copious amounts of income with nothing to spend it on but illicit drugs. In addition, unlike construction and manufacturing, mining workers tend to only work in an area for a short period of time, therefore, workers are not looking toward buying a house, car, creating a stable life, or other social norms that societies' occupations create. Looking towards the future, I would like to examine other blue-collar occupations such as welding, pipefitting, electrical maintenance and other occupations related to the ones chosen for this project. In addition, adding variables such as workplace risk may provide an interesting relationship with higher amounts of drug overdose deaths.

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Appendix: Description and Sources of Variables

Table 2: *Description and Source of Variables*

Variable (source)	Description	Mean	Standard Dev.	Minimum	Maximum
Population Asian (1)	Percent of population that is Asian	1.32	2.09	0.04	27.12
Population Black (1)	Percent of population that is Black	16.95	18.62	0.15	85.33
Population Hispanic (1)	Percent of population that is Hispanic	4.57	4.72	0.42	56.16
Population Non-Hispanic White (1)	Percent of population that is Non-Hispanic White	75.21	20.04	9.23	98.06
Less than a high school degree (2)	Total percentage of population 25 years and over with less than a high school degree	16.07	5.86	1.8	41.8
High school degree (2)	Total percentage of population 25 years and over with a high school degree or equivalent	35.99	7.40	7.3	54.9
Some college no degree (2)	Total percentage of population 25 years and over with some college with no degree	19.78	3.19	8.4	31.6
Bachelor's degree (2)	Total percentage of population 25 years and over with bachelor's degree	12.24	5.57	2.4	36.7
Graduate or professional degree (2)	Total percentage of population 25 years and over with a graduate or professional degree	7.79	4.61	1.1	42.5
Female aged 25-29 (2)	Total percentage of female population aged 25-29	5.77	1.18	1.3	14.1
Female aged 30-34 (2)	Total percentage of female population aged 30-34	5.64	1.01	1.4	12.4
Male aged 25-29 (2)	Total percentage of male population aged 25-29	6.28	1.52	1.4	16.1
Male aged 30-34 (2)	Total percentage of male population aged 30-34	5.98	1.28	1.3	20.5
Employment in mining, quarrying, oil & gas extraction (3)	Total employment percentage in mining, quarrying, oil & gas extraction	0.007	0.02	0	0.27
Employment in manufacturing	Total employment percentage in manufacturing	0.16	0.11	0	0.72
Employment in construction (3)	Total employment percentage in construction	0.06	0.03	0.005	0.35
Metro (4)	Counties in metropolitan areas ranked 1-3	0.46	0.50	0	1
Non-metro adjacent (4)	Counties in non-metropolitan adjacent areas ranked 4-6	0.36	0.48	0	1
Rural (4)	Counties in rural areas ranked 7-9	0.17	0.38	0	1
Medium household income (1)	The income where half of households in a county earn more and half of households earn less	$4,7041.93	$14,112.64	$22,045	$136,191
Log medium household income (1)	Logarithm of the income where half of households in a county earn more and half of households earn less	10.72	0.26	10.00	11.82
U.S. opioid dispensing rate (1)	Total percentage of opioid prescriptions dispensed in the United Sates per 100 persons	66.52	42.09	0	567.9
HIV prevalence rate (1)	Number of people aged 13 years and older living with a diagnosis of human immunodeficiency virus (HIV) infection per 100,00 population	223.44	221.43	17	2414

Sources: (1) County Health Rankings, (2) U.S. Census Bureau, (3) Emsi, (4) U.S. Department of Agriculture