Cancer Death Disparities and Uranium Mine Waste on Indian Reservations

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Abstract

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The United States experienced a uranium mining boom during the Nuclear Arms Race, with much of the mining activity occurring in and around Indian Reservations. Abandoned uranium mines (AUMs) and tailings dumps are spread throughout the territory of Indian reservations, and many have not been environmentally remediated. Mine waste and drainage pose an ongoing environmental and public health threat. This type of mining releases carcinogens into the natural environment. Although there is existing literature on the topic of uranium mining waste, a sociological analysis of the problem has not yet been performed. In this paper, I evaluate the impact of mining on public health throughout the contiguous US since uranium mining occurred elsewhere in the US. I used a fixed effects regression model to determine whether people living in Indian reservations with AUMs are more likely to experience negative health outcomes. I explore the relationship between deaths from kidney and stomach cancers compared to non-native communities with abandoned uranium mines. The dependent measure is the age adjusted death rate per 100,000 people from stomach cancer or kidney and renal-pelvis cancer. The key findings in my models demonstrate that the effects of the dependent variable are most strongly influenced by health behaviors, whether or not the county contains reservation land, and median household income.

0.1 Introduction

What is the relationship between exposure to uranium mine waste and cancer death rates when controlling for health behaviors, income, and other variables? I plan to address this question through a sociological lens in which I use sociological theories to establish a backdrop of why this is an important issue in terms of contribution to existing literature and its policy implications.

The significance of this research program is to outline a specific context in which unequal exposure to environmental contaminants may be a contributing factor to cancer death disparities. I plan to use the findings of this research program to highlight the fact that resources need to be allocated towards environmental remediation and federal health expenditures for the Indian Health Service. The literary contributions of this project are primarily empirical.

In the context of environmental justice on Indian reservations, there is a lack of empirical sociological literature that discusses this specific problem. The existing literature that has tracked the negative environmental and public health impacts of exposure to mine waste has been disseminated primarily outside of the social science fields. Scholars in the fields of environmental science and public health research have focused on the physical scientific component of how the uncontained pollution is distributed and what some of the negative health outcomes are. However, I am making the case that there is an environmental justice story in this research program. In the subfield of environmental sociology, this problem has not been explored as a potential mechanism in which distributive and participatory environmental justice is particularly important.

This work will draw upon numerous theories. I argue that fundamental cause theory is applicable in this case because it is an example of a health disparity that exists despite the availability of resources to treat complex diseases. I also draw upon the treadmill of production and the treadmill of destruction theories. The treadmill of production is relevant because uranium mining was part of post-World War II economic development in the United States that resulted in environmental degradation. The treadmill of destruction is applicable here because that development was part of the broader military industrial complex since much of the extracted uranium was used in nuclear weapons. It also touches upon the aspect of this being a problem on Indian Reservations.

I use a fixed effects linear regression model to address my research question. This method enables me to create additive models that include one, both, or no health behaviors to see how the outcome variable is influenced by health behaviors. I also use models for each health outcome that contain both health behaviors and models with no health behaviors included. The data I use comes from federal government agencies including the Centers for Disease Control, the Environmental Protection Agency, the US Census Bureau, and the Bureau of Indian Affairs. These sources give me data for health outcomes, health behaviors, locations of pollution sources, locations of Indian Reservations, and county-level population and geographic data.

Key findings show a pattern that if there is an increase in the number of pollution sources per county by 1 standard deviation, then there is a decrease in the effect of the dependent variable. This effect ranges from 0.52 to 1.31 standard deviation decreases across all models. In the models with both health behaviors included, there is a stronger effect from the rate of smoking compared to rate of binge drinking.

0.2 Background and Theory

The theoretical perspectives which I am drawing upon for this project include Fundamental Cause Theory, Treadmill of Production Theory, and The Treadmill of Destruction Theory. Fundamental Cause Theory, developed by Jo C. Phelan and Bruce G. Link, posits that despite advances in medical technology, health disparities persist due to differences in socioeconomic status (Phelan et al. 2010). In this case, the fundamental cause to which I am referring is the Indian Health Service being underfunded at the per capita level compared to the national US health expenditure. The Treadmill of Production theory refers to the process in which developed economies sustain their development through resource extraction that is unsustainable and contributes to environmental degradation (Curran 2017), (Gould et al. 2004). In this case, uranium was mined to produce nuclear weapons and later for use in nuclear energy.

Native Americans are known to be disproportionately affected by health problems due to exposure to environmental contaminants (Brook 1998), high rates of alcoholism and drug use (French 2004), and poor access to healthcare (Warne et al. 2012). The health effects on former uranium miners in the Navajo Nation and other reservations with uranium mines are now well documented, with high rates of lung cancer deaths as a result (Gilliland et al., 2000). However, the focus of this project is on health outcomes in a modern context. One possible source of health disparities for Native Americans is unequal funding. 'When comparing per capita personal health care expenditures in the user population, the IHS expenditure is $2,741 while the total US population expenditure is $7,239' (Moore-Nall 2015). In addition, hospitals and healthcare facilities in the Indian Health Service often lack the proper infrastructure to treat more complex diseases. A study on access and quality of care within the IHS revealed that physicians practicing within the IHS reported generally poor access to adequate healthcare among American Indian/Alaska Natives (AI/AN). "Physicians reported relatively low rates of adequate access to high quality specialists (29%), non-emergent hospital admission (37%), high quality diagnostic imaging (32%), and high-quality outpatient mental health services (16%)." (Sequist et al. 2011). Other studies have outlined disparities in access and quality of care for AIANs. One study revealed that AIANs had more problems accessing healthcare services, higher levels of unmet needs, and were less likely to use basic medical care, including doctor and dental visits compared to whites (Zuckerman et al., 2004).

When the IHS was established in 1955, it did drastically increase the general quality of health among Native Americans, numerous disparities are still present. Prior to the establishment of the IHS, tuberculosis was a common problem among Native Americans and the infant mortality rate was about 4 times higher than the national average at the time (Jones 2005). While agencies like this and the Bureau of Indian affairs are imperfect, they play a vital role in continuing to improve the quality of life of people living on reservation land. Therefore, I find it important to highligp that this issue of uranium mine waste and cancer death disparities are issues that require attention.

Another perspective of Native American health disparities is through other dimensions of population health. According to a study using the CDC's Behavioral Risk Factor Surveillance System (BRFSS), Native Americans surveyed in the state of Arizona, which contains

22 federally recognized tribes, are more likely to have diabetes, be overweigp or obese, have high blood pressure, report fair or poor health status, and have higher levels of physical inactivity compared to the rest of the American population (Adakai et. al. 2018). This could be attributed to several factors such as food deserts and lack of social network components that encourage physical activity. Additionally, it highligps how a better healthcare system can help mitigate these issues and perhaps even promote more positive health behaviors.

The mining of uranium for the production of nuclear weapons is a function of the 'treadmill of production', which in turn harms a marginalized group, in this case Native Americans. The prevalence of uranium mining is a circumstance in which tribal lands are home to subterranean resources that became desirable after the lands had been allotted. This problem serves as an example of an ongoing problem which disproportionately affects indigenous people in the global north (Faber et al., 2021). Furthermore, the exploitation can be attributed to institutional frameworks in addition to the natural resource and human capital explanations (Anderson et al., 2008).

To build more of a theoretical foundation, I also draw upon the treadmill of destruction theory. This theory is a critique of the treadmill of production theory that puts emphasis on the role of the military industrial complex in contributing to environmental degradation (Clark, Jorgenson, 2012). This theory is applicable because the type of resource extraction that I am describing was primarily used for manufacturing weapons of mass destruction (Hooks et al., 2021). Gregory Hooks and Chad L. Smith successfully apply this theory to environmental degradation that was committed by the US military that disproportionately impacts Native Americans (Hooks et al., 2004). The mining of uranium on tribal lands is an example in which the treadmill of production theory is applicable since there is environmental destruction that came as a result of the development and expansion of the US military's nuclear arsenal.

Underfunding in the IHS has influenced rates of cancer and cancer deaths. This can be attributed to the inability of the IHS to prevent cancer-causing behaviors such as smoking, and the underfunding results in poor access to more complex cancer and end-of-life care (Warne et al., 2012). When assessing disparities in Native American cancer patients, other studies have revealed that Native Americans had higher rates of terminal cancer that can be detected by screening, less knowledge about cancer screening, and poorer attitudes toward cancer treatment (Guadagnolo et al., 2009).

The EPA has enacted a long-term project to seal and clean up numerous abandoned uranium mines on tribal lands. While the EPA currently has $1.7 billion in funds for cleaning and sealing the mines in the Navajo Nation, hundreds of other abandoned uranium mines (AUMs) within the Navajo Nation and other native communities remain unsealed (Environmental Protection Agency, n.d.). The Spokane Reservation in Washington is another example of a native community that has been negatively affected by the presence of uranium mines. A 1999 study conducted by the EPA on water quality and surface materials in the Spokane Reservation revealed that there was a high level of uranium contaminants, as well as other heavy metals (Flett et al., 2021).

Existing literature has outlined that Native Americans exist on a front of environmental justice in a way that differs from other forms of environmental inequality that occur (Darian-Smith, 2010). Tribal sovereignty creates further complications due to their status as semi-autonomous entities (Ranco & Suagee, 2007). Land quality and use should be considered when viewing environmental racism on reservations. The Dawes Act, also known as the General Allotment Act of 1887, was meant to ensure that Native families would receive approximately 160 acres of land. However, by the 1920s, the policy had come under extreme criticism because of its inability to reduce poverty and prevent non-Native people from settling the land (Leonard, 2018). This was somewhat reversed by the Indian Reorganization Act of 1934 which rerouted lands to the Bureau of Indian Affairs. This circumstance creates complications in self-governance and the way decisions associated with land use and economic development are made. The argument can be made that environmental problems and exploitation occurring on tribal lands are an extension or continuation of the genocide that has already occurred against Native Americans. Numerous examples of toxic waste dumping on tribal land are similar to the fact that most uranium mines, at least in the Navajo Nation, remain uncontained. These environmental problems are compounded by the fact that tribal sovereignty often provides only limited agency of the tribes to decide what is done with their land (Brook, 1998). This indicates a failure in participatory justice in which there is a lack of agency for people living on Indian Reservations. This creates difficulties in decision making regarding land use.

Despite the controversial nature of nuclear energy, there is a sustained demand for nuclear energy in countries that have access to nuclear power (Pravalie & Bandoc, 2017). Although newer uranium mining methods have been developed to be less harmful to both miners and the natural environment, it is still important to consider the environmental and public health impacts of uranium extraction. Specifically, a method known as in situ leaching is found to be more cost effective and tends to generate less waste rock. Other methods such as milling, open pit mining, and underground mining are still in use ; however they tend to be more expensive and difficult to remediate (Osmanlioglu, 2022). Furthermore, public opinion on nuclear energy is dynamic as there is concern about nuclear accidents and how waste products are disposed of. There are existing arguments that nuclear energy could play a critical role in mitigating the effects of climate change as an energy source that does not produce carbon emissions.

Although there is not a large body of literature linking uranium mine waste exposure to stomach cancer and kidney cancer specifically, I chose death rates from these cancers as dependent variables because I wanted to see how this type of pollution exposure combined with other structural variables influenced this association. Uranium exposure has been linked to various documented health issues such as kidney failure (Vinken, 2022) and occupation-related cancers such as lung cancer, specifically through radon exposure (Richardson et al. 2022). Furthermore, an increase in the rate of stomach cancer deaths have been documented in uranium miners (Kelly-Reif et al. 2021) With these documented health outcomes, I am interested in exploring if there is a link between living in the presence of these pollution sources and stomach and kidney cancer death rates. The rationale behind using these specific health outcomes is also partially influenced by availability of reliable data, as well as increased importance at the policy level when using deaths as the outcome variable. Another reason why I use these outcomes as dependent variables is because I am interested in the role of carcinogenic health behaviors that exist in impoverished communities. These behaviors include binge drinking and cigarette smoking. The focal independent variable, number of pollution sources per county, was chosen because it is the best measure I have for the intensity of pollution by county. This is where I connect my analysis to the treadmill theories. The presence of these pollution sources by county is connected to the treadmill of production because they represent scars of past economic activity that continue to release pollution into the natural environment.

To fully integrate fundamental cause theory as a theoretical mechanism, I use median household income by county to establish the upstream effects described in the theory. Median household income provides a sense of how poverty is related to these health outcomes under the assumption that a higher poverty rate could be related to inability to access treatment for rare types of cancer. As mentioned previously, there are documented healthcare access disparities on Indian reservation land, which serves as an upstream mechanism. There is also an argument to be made that the treadmill theories discussed previously can serve as the upstream effects as well. The treadmill of production and treadmill of destruction's function in this case has led to there being pollution sources present that pose a public health threat to marginalized communities.

In terms of connecting the treadmill of production and treadmill of destruction theories to my analysis, I argue that the number of pollution sources represents the treadmill of production. In this case, the presence of abandoned mines and processing facilities represents the past economic activity that led to environmental degradation. When it comes to the treadmill of destruction, the presence of Indian reservation land is included as a variable since that theory focuses on the effect of environmental degradation on indigenous populations (Hooks et al. 2004). To summarize my theoretical framework, fundamental cause theory is captured through the inclusion of median household income as a co-variate. The treadmill of production theory is captured through the number of pollution sources. Finally, the treadmill of destruction theory is captured through the use of reservation status as an independent variable.

0.3 Data and Methods

My current research design intends to compare Indian reservation land with non-Indian Reservation land that has had uranium mining. However, I will include all US counties in this study to compare the effect in reservation and non-reservation land without uranium mines as well. I also used reservation and non-reservation counties under the assumption that people living in that county are more likely to be covered under the Indian Health Service. Cigarette smoking and binge drinking will be used as control and mediating variables to observe the effect on the outcome variables. To get a measure of the locations and intensity of pollution sources, I am using a variable that indicates how many pollution sources there are per county. As controls, I am also using total county population and total land area in square miles. In order to get a sense of quality of healthcare access, I included median household income by county as a co-variate. Finally, I am using age adjusted rates of stomach and kidney cancer deaths per 100,000 people as the dependent outcome variable. Measuring this variable as deaths provides a higher level of importance at the policy level when talking about deaths as an outcome. I use a fixed-effects regression model in order to view the associations between all of the variables. There are two models for each health outcome and for each health behavior. I also include models that contain no health behaviors and a model that includes both health behaviors. In the regression models, I standardized the variables so that they are measured on the same scale. Further, since this is a fixed effects approach, the regression coefficients are giving the means across all counties within states. Additionally, I am using states as fixed effects estimators so that I can control for unobserved characteristics that may influence population health across counties such as state level policies.

The data I have used includes the Centers for Disease Control's Cancer Statistics Data tool which provides cancer death outcomes at the county level. The CDC's Behavioral Risk Factor Surveillance System (BRFSS) gives me rates of smoking and drinking as health behaviors. The CDC's Social Determinants of Health and Places dataset is a processed form of BRFSS data that gives me health behaviors at the county level. I will also use the Environmental Protection Agency uranium location database (ULD) to determine where abandoned uranium mines, processing locations, and associated pollution sources are located throughout the US. I also used this variable to determine how many pollution sources there are in each county. The median household income data was obtained through the US Census Bureau's Small Area Income & Poverty Estimates (SAIPE) dataset. Finally, I used total county population and total county area in square miles to get a sense of the intensity and level of exposure from the pollution sources.

The descriptive statistics tables show both the raw, un-standardized versions of the variables and the standardized versions of the variables. In the standardized descriptive statistics tables, the means are close to 0. They depict the measures of central tendency and inter-quartile ranges of the variables for each health outcome. The correlation matrices for each health outcome variable show the correlation coefficients between each variable.

0.4 Analytic Strategy

As mentioned before, I use the age-adjusted rate of deaths from stomach cancer and kidney cancer as the dependent variable. I am using these outcomes to see if and how there is a relationship between uranium waste exposure and deaths from these types of cancers. My focal independent variable is the number of pollution sources by county. This variable is connected to the treadmill of production theory that I have integrated into this project. This variable also captures the frequency and intensity of pollution sources by county, under the assumption that a greater number of pollution sources means a higher intensity of pollution. Median household income is used as the upstream effect within fundamental cause theory. Reservation status establishes the connection to the treadmill of destruction component. The rates of health behaviors are included as mediator variables for the relationship between the dependent and focal independent variable. I am using a fixed effects regression model with states as the fixed effects in order to view how the health outcomes are affected by the presence of pollution sources, as well as numerous other co-variates.

To tie the analysis to the three theories I am integrating, I present the following connections between theory and analysis. Fundamental cause theory is being tested through the median household income variable as this is the upstream effect that represents a disparity in healthcare access. The number of pollution sources represents the treadmill of production theory as the pollution sources are connected to past economic activity that resulted in environmental degradation. The treadmill of destruction theory is captured through the reservation status variable, as this theory has an emphasis on the role of indigenous lands and people in the context of environmental destruction.

0.5 Results and Discussion

Table 7 depicts model 1 which is looking at stomach cancer deaths as the outcome variable and neither of the health behaviors are included. If the number of pollution sources increases by 1 standard deviation, then the rate of cancer deaths decreases by 0.52 standard deviations. If median household income increases by 1 standard deviation, then the rate of cancer deaths decreases by 0.21 standard deviations. If the county contains reservation land, then the rate of cancer deaths increases by 0.14 standard deviations. If total county population increases by 1 standard deviation, then the rate of cancer deaths decreases by 0.06 standard deviations. If total county area in square miles increases by 1 standard deviation, then there is a 0.45 standard deviation increase in the rate of cancer deaths. All of these effects are found to be statistically significant.

Table 8 shows model 2 which looks at stomach cancer death rates and cigarette smoking as the health behavior. If the number of pollution sources increases by 1 standard deviation, then there is a 1.31 standard deviation decrease in the rate of cancer deaths. If median household income increases by 1 standard deviation, then there is a 0.31 standard deviation increase in the rate of cancer deaths. If the rate of smoking increases by 1 standard deviation, then there is a 1.10 standard deviation increase in the rate of cancer deaths. If the county contains reservation land, then there is a 0.06 standard deviation decrease in the rate of cancer deaths. If the total county population increases by 1 standard deviation, then there is a 0.03 increase in the rate of cancer deaths. If the total county area increases by 1 standard deviation, then there is a 0.17 standard deviation increase in the rate of cancer deaths. All of these effects are found to be statistically significant.

Table 9 shows model 3, which looks at stomach cancer death rates and binge drinking as the health behavior variable. If the number of pollution sources increases by 1 standard deviation, then there is a 0.57 standard deviation decrease in the rate of cancer deaths. If median household income increases by 1 standard deviation, then there is a 0.19 standard deviation decrease in the rate of cancer deaths. If the rate of binge drinking increases by 1 standard deviation, then there is a 0.08 standard deviation decrease in the rate of cancer deaths. However, this effect is not found to be statistically significant. If the county contains reservation land, then there is a 0.13 standard deviation increase in the rate of cancer deaths. If the total county population increases by 1 standard deviation, then there is a 0.06 standard deviation decrease in the rate of cancer deaths. If the total county area in square miles increases by 1 standard deviation, then there is a 0.44 increase in rate of cancer deaths.

Table 10 shows model 4, which looks at the rate of stomach cancer deaths and includes both health behaviors. If the number of pollution sources increases by 1 standard deviation, then there is a 1.22 standard deviation decrease in rate of cancer deaths. If median household income increases by 1 standard deviation, then there is a 0.27 standard deviation increase in the rate of cancer deaths. If the rate of binge drinking increases by 1 standard deviation, then there is a 0.17 standard deviation increase in the rate of cancer deaths. If the rate of smoking increases by 1 standard deviation, then there is a 1.13 increase in the rate of cancer deaths. If the county contains reservation land, then there is a 0.05 decrease in the rate of cancer deaths. If the total county population increases by 1 standard deviation, then there is a 0.03 increase in the rate of cancer deaths. All of these effects are found to be significant. If the total county area increases by 1 standard deviation, then there is a 0.18 standard deviation increase in the rate of cancer deaths. All of these effects were found to be significant.

Table 11 shows model 5, which is the first model that uses the rate of kidney cancer deaths as the outcome variable. If the number of pollution sources increases by 1 standard deviation, then there is a 0.51 decrease in the rate of cancer deaths. If median household income increases by 1 standard deviation, then there is a 0.21 standard deviation decrease in the rate of cancer deaths. If the county contains reservation land, then there is a 0.13 standard deviation increase in the rate of cancer deaths. If total county population increases by 1 standard deviation then there is a 0.06 standard deviation decrease in the rate of cancer deaths. If the total county area increases by 1 standard deviation, then there is a 0.44 standard deviation increase in the rate of cancer deaths. All of these effects were found to be significant.

Table 12 depicts model 6, which uses kidney cancer death rate as the outcome variable and cigarette smoking as the health behavior variable. If the number of pollution sources increases by 1 standard deviation, then there is a 1.28 standard deviation decrease in the rate of cancer deaths. If median household income increases by 1 standard deviation, then there is a 0.30 standard deviation increase in the rate of cancer deaths. If the rate of smoking increases by 1 standard deviation, then there is a 1.08 standard deviation increase in the rate of cancer deaths. If the county has reservation land, then there is a 0.06 standard deviation decrease in the rate of cancer deaths. If total county population increases by 1 standard deviation, then there is a 0.03 standard deviation increase in the rate of cancer deaths. If total county area increases by 1 standard deviation, then there is a 0.16 standard deviation increase in the rate of cancer deaths. All of these effects were also found to be significant.

Table 13 shows model 7 which uses binge drinking as the health behavior variable and kidney cancer death rates as the outcome variable. If the number of pollution sources increases by 1 standard deviation, then there is a 0.56 standard deviation decrease in the rate of cancer deaths. If median household income increases by 1 standard deviation, then there is a 0.19 standard deviation decrease in rate of cancer deaths. If the rate of binge drinking increases by 1 standard deviation then there is a 0.08 standard deviation decrease in rate of cancer deaths although this effect is not found to be significant. If the county contains reservation land then there is a 0.13 standard deviation increase in rate of cancer deaths. If the total county population increases by 1 standard deviation, then there is a 0.06 standard deviation decrease in the rate of cancer deaths. If total county area increases by 1 standard deviation, then there is a 0.43 increase in rate of cancer deaths.

Table 14 depicts model 8 which is the model that uses both health behavior variables and the rate of kidney cancer deaths as the outcome variable. If the number of pollution sources increases by 1 standard deviation, then there is a 1.20 standard deviation decrease in the rate of cancer deaths. If median household income increases by 1 standard deviation, then there is a 0.27 standard deviation decrease in rate of cancer deaths. If the rate of binge drinking increases by 1 standard deviation, then there is a 0.17 standard deviation increase in rate of cancer deaths. If the rate of smoking increases by 1 standard deviation, then there is a 1.10 standard deviation increase in the rate of cancer deaths. If the county contains reservation land, then there is a 0.05 standard deviation decrease in the rate of cancer deaths. If total county population increases by 1 standard deviation, then there is a 0.03 standard deviation increase in the rate of cancer deaths. If there is a 1 standard deviation increase in total county area then there is a 0.18 standard deviation increase in rate of cancer deaths. All of these effects were found to be statistically significant.

Across all of these models, there is a tendency for health behaviors, particularly the rate of smoking to be strong predictors of the rate of cancer deaths. This mirrors existing literature. In the models without health behaviors, reservation land has a small yet positive relationship between the county containing reservation land and the rate of cancer deaths increasing. These results also appear in models where binge drinking is the health behavior. The relationship between median household income and rate of cancer deaths is less clear. In the models that include no health behaviors and the models where binge drinking is the health behavior, there is a negative relationship as the rate of cancer deaths decreases if median household income increases. These models would align most with the fundamental cause perspective.

I ran a variance inflation factor (VIF) analysis on each of the models and found that in the generalized VIF, there is moderate to high multicollinearity across the variables. However, with the generalized VIF that is adjusted for degrees of freedom, there is low to moderate multicollinearity. Specifically, there is moderate to high multicollinearity with the rate of smoking variable. This indicates that there could be some inflation in the coefficients for the rate of smoking. However, across the remaining variables there is not a particularly high value for any of the other variables indicating that there is generally not high multicollinearity among the variables.

0.6 Conclusion

To summarize the results of this study, there is a negative and statistically significant association between presence of uranium pollution sources and rate of cancer deaths from stomach cancer and kidney cancer when running models with numerous independent variables. In other words, these models predict that the rate of cancer deaths actually decreases if there are more pollution sources present. These results are mediated through the inclusion of health behaviors and structural-level variables. Throughout the models, there tends to be a positive relationship between health behaviors and rate of cancer deaths, which is consistent with existing literature. Furthermore, the argument could be made that structural-level variables such as median household income and reservation status have a stronger effect on the health outcomes rather than the pollution sources. I would argue that there is a stronger association between the health behavior variables that influence the effects on the dependent variable. However, there are still useful and meaningful results from this study. Based on the results of this study, health behaviors, particularly smoking, are found to be a strong predictor of increasing the rate of cancer deaths. The results of some of the models align with the inclusion of fundamental cause theory in this research, since there is a clear upstream effect, as shown in the models and the associated literature.

In terms of other practical applications of this research, the argument can still be made that uranium mine waste continues to pose an environmental threat. One form of future analysis that would be useful would be to see if and how there are ongoing health effects from diseases such as lung cancer or other forms of kidney disease. This is also important because of renewed interest in uranium extraction globally as nuclear energy continues to be in demand, especially as a non-carbon producing energy source. Therefore, the environmental and public health impacts of uranium mining need to be known.

There are some limitations in this study. The dependent measure does not account for in-migration in counties where cancer death data were collected. This means that a person could have developed cancer in a different county than the one they died in. Additionally, there was not a more accurate measure to get a sense of the intensity of pollution exposure. However, getting the number of pollution sources by county as well as county population and area still gave a sufficient idea of what the levels of pollution exposure look like. This study is also not longitudinal, and it only measures the effects of each variable at a single point in time. Data taken from the CDC at the county level (cancer deaths, health behaviors) often has missing cases for counties, so the measurements are done to the level at which data is available. The dataset I used to locate pollution sources contained locations of uranium mines and processing facilities that were known to exist up to and including the year 2004. This database contains points for abandoned pollution sources. Therefore, this dataset and analysis does not account for active uranium mining and processing locations.

To address the issue of ecological fallacy, I argue that these results only address the relationship between reservation land, pollution sources, and income. This analysis does not answer the question of the relationship between pollution sources and other variables with respect to how indigenous populations and non-indigenous populations are differentially affected.

I aim to rectify some of these limitations with more in-depth analysis of this issue. An important step would be to run the same analysis using data from previous years. This would enable a longitudinal study that can capture if and how the effect of cancer deaths changes over time. It would also be useful to get an idea of if and how the different pollution sources are being remediated and whether this varies across space.

0.7 Figures

Table 1: Descriptive Statistics for Stomach Cancer Raw Numbers

Variable	**Min**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max**	**NA's**
Age-Adjusted Rate	1.00	100.00	415.00	721.30	1407.00	1453.00	2314
Pollution Count	1.00	100.00	415.00	721.30	1407.00	1453.00	–
Median HH Income	-2.13	-0.69	0.15	0.11	0.36	6.49	126
Rate of Binge Drinking	9.10	12.40	16.50	15.56	17.90	26.00	61
Rate of Smoking	5.30	12.70	14.40	14.79	15.90	37.30	61
Reservation	–	–	–	–	–	–	–
Total Population	51	9769	15371	64863	43811	9721138	61
Total Area	-1.15	-0.85	-0.27	0.00	0.42	6.73	65

Table 2: Descriptive Statistics for Stomach Cancer Standardized Variables

Variable	**Min**	**1st Qu.**	**Median**	**Mean**	**3rd Qu.**	**Max**	**NA's**
Age-Adjusted Rate	-1.402	-0.458	-0.270	0.000	0.202	8.128	7717
Pollution Count	-1.175	-1.014	-0.500	0.000	1.119	1.194	2314
Median HH Income	-2.133	-0.690	0.153	0.108	0.362	6.490	126
Rate of Binge Drinking	-2.151	-1.052	0.313	0.000	0.780	3.477	61
Rate of Smoking	-2.885	-0.636	-0.119	0.000	0.337	6.840	61
Reservation	-0.803	-0.803	-0.803	0.000	1.244	1.244	–
Total Population	-0.309	-0.263	-0.236	0.000	-0.100	46.058	61
Total Area	-1.154	-0.849	-0.272	0.000	0.421	6.732	65

Table 3: Descriptive Statistics for Kidney Cancer Raw Numbers

Variable	Min	1st Qu.	Median	Mean	3rd Qu.	Max	NA's
Age-Adjusted Rate	1.0	100.0	415.0	721.3	1407.0	1453.0	2314
Pollution Count	1.0	100.0	415.0	721.3	1407.0	1453.0	–
Median HH Income	-2.13	-0.69	0.15	0.11	0.36	6.49	126
Rate of Binge Drinking	9.10	12.40	16.50	15.56	17.90	26.00	61
Rate of Smoking	5.30	12.70	14.40	14.79	15.90	37.30	61
Reservation	–	–	–	–	–	–	–
Total Population	51	9769	15371	64863	43811	9721138	61
Total Area	-1.15	-0.85	-0.27	0.00	0.42	6.73	65

Table 4: Descriptive Statistics for Kidney Cancer Standardized Variables

Variable	Min	1st Qu.	Median	Mean	3rd Qu.	Max	NA's
Age-Adjusted Rate	-1.412	-0.451	-0.258	0.000	0.222	8.299	7724
Pollution Count	-1.175	-1.014	-0.500	0.000	1.119	1.194	2314
Median HH Income	-2.133	-0.690	0.153	0.108	0.362	6.490	126
Rate of Binge Drinking	-2.151	-1.052	0.313	0.000	0.780	3.477	61
Rate of Smoking	-2.885	-0.636	-0.119	0.000	0.337	6.840	61
Reservation	-0.803	-0.803	-0.803	0.000	1.244	1.244	–
Total Population	-0.309	-0.263	-0.236	0.000	-0.100	46.058	61
Total Area	-1.154	-0.849	-0.272	0.000	0.421	6.732	65

Table 5: Kidney Cancer Correlation Matrix

	Age-Adjusted Rate	Pollution Count	Median HH Income	Rate of Smoking	Rate of Binge Drinking	County Has Res	Total Population	Total Area
Age-Adjusted Rate	1.000	-0.091	-0.522	0.798	-0.097	0.261	-0.109	0.647
Pollution Count	-0.091	1.000	-0.348	0.252	0.077	-0.553	-0.380	0.152
Median HH Income	-0.522	-0.348	1.000	-0.770	0.430	0.011	0.358	-0.576
Rate of Smoking	0.798	0.252	-0.770	1.000	-0.098	0.049	-0.279	0.617
Rate of Binge Drinking	-0.097	0.077	0.430	-0.098	1.000	-0.371	0.148	-0.168
Reservation	0.261	-0.553	0.011	0.049	-0.371	1.000	0.281	0.135
Total Population	-0.109	-0.380	0.358	-0.279	0.148	0.281	1.000	-0.099
Total Area	0.647	0.152	-0.576	0.617	-0.168	0.135	-0.099	1.000

Table 6: Stomach Cancer Correlation Matrix

	Age-Adjusted Rate	Pollution Count	Median HH Income	Rate of Smoking	Rate of Binge Drinking	County Has Res	Total Population	Total Area
Age-Adjusted Rate	1.000	-0.087	-0.521	0.798	-0.093	0.258	-0.106	0.654
Pollution Count	-0.087	1.000	-0.350	0.254	0.076	-0.552	-0.381	0.151
Median HH Income	-0.521	-0.350	1.000	-0.769	0.428	0.014	0.357	-0.579
Rate of Smoking	0.798	0.254	-0.769	1.000	-0.096	0.046	-0.278	0.621
Rate of Binge Drinking	-0.093	0.076	0.428	-0.096	1.000	-0.369	0.147	-0.170
County Has Res	0.258	-0.552	0.014	0.046	-0.369	1.000	0.283	0.137
Total Population	-0.106	-0.381	0.357	-0.278	0.147	0.283	1.000	-0.100
Total Area	0.654	0.151	-0.579	0.621	-0.170	0.137	-0.100	1.000

Table 7: Model 1: Stomach Cancer and No Health Behaviors

Variable	Estimate	Std. Error	p-value
Intercept	0.27454	0.32488	0.3984
Pollution Count	-0.52122	0.13468	1.18e-4 ***
Median HH Income	-0.21740	0.04458	1.33e-6 ***
Reservation	0.14146	0.03861	2.66e-4 ***
Total Population	-0.06722	0.01989	7.66e-4 ***
Total Area	0.45875	0.05819	1.15e-11 ***

Significance levels: *** p ¡ 0.001, ** p ¡ 0.01, * p ¡ 0.05, . p ¡ 0.1

Table 8: Model 2: Stomach Cancer and Cigarette Smoking

Variable	Estimate	Std. Error	p-value
Intercept	-1.15301	0.22776	5.24e-7 ***
Pollution Count	-1.31181	0.09614	2.00e-16 ***
Median HH Income	0.31163	0.03559	2.00e-16 ***
Rate of Smoking	1.10399	0.03822	2.00e-16 ***
Reservation	-0.06475	0.02737	1.82e-2 *
Total Population	0.03789	0.01409	7.33e-3 **
Total Area	0.17253	0.04104	2.94e-5 ***

Significance levels: *** p ¡ 0.001, ** p ¡ 0.01, * p ¡ 0.05, . p ¡ 0.1

Table 9: Model 3: Stomach Cancer and Binge Drinking

Variable	Estimate	Std. Error	p-value
Intercept	0.18147	0.33302	0.586
Pollution Count	-0.57235	0.14059	5.19e-5 ***
Median HH Income	-0.19518	0.04792	5.15e-5 ***
Rate of Binge Drinking	-0.08845	0.07011	0.207
Reservation	0.13423	0.03901	6.13e-4 ***
Total Population	-0.06484	0.01998	1.22e-3 **
Total Area	0.44801	0.05879	7.80e-12 ***

Significance levels: *** p ¡ 0.001, ** p ¡ 0.01, * p ¡ 0.05, . p ¡ 0.1

Table 10: Model 4: Stomach Cancer and Both Health Behaviors

Variable	**Estimate**	**Std. Error**	**p-value**
Intercept	-1.00093	0.22968	1.50e-5 ***
Pollution Count	-1.22842	0.09804	2.00e-16 ***
Median HH Income	0.27981	0.03635	4.51e-12 ***
Rate of Binge Drinking	0.17687	0.04845	2.81e-4 ***
Rate of Smoking	1.13032	0.03858	2.00e-16 ***
Reservation	-0.05523	0.02727	4.32e-2 *
Total Population	0.03564	0.01399	1.11e-2 *
Total Area	0.18719	0.04089	5.53e-6 ***

Significance levels: *** p ¡ 0.001, ** p ¡ 0.01, * p ¡ 0.05, . p ¡ 0.1

Table 11: Model 5: Kidney Cancer and No Health Behaviors

Variable	**Estimate**	**Std. Error**	**p-value**
Intercept	0.71187	0.29547	1.62e-2 *
Pollution Count	-0.51771	0.13247	1.02e-4 ***
Median HH Income	-0.21292	0.04381	1.43e-6 ***
Reservation	0.13772	0.03796	3.05e-4 ***
Total Population	-0.06801	0.01958	5.42e-4 ***
Total Area	0.44969	0.05728	1.47e-14 ***

Significance levels: *** p ¡ 0.001, ** p ¡ 0.01, * p ¡ 0.05, . p ¡ 0.1

Table 12: Model 6: Kidney Cancer and Smoking

Variable	**Estimate**	**Std. Error**	**p-value**
Intercept	-0.84252	0.20981	6.54e-5 ***
Pollution Count	-1.28648	0.09474	2.00e-16 ***
Median HH Income	0.30928	0.03512	2.00e-16 ***
Rate of Smoking	1.08281	0.03765	2.00e-16 ***
Reservation	-0.06691	0.02700	1.34e-2 *
Total Population	0.03580	0.01391	1.03e-2 *
Total Area	0.16910	0.04050	3.33e-5 ***

Significance levels: *** p ¡ 0.001, ** p ¡ 0.01, * p ¡ 0.05, . p ¡ 0.1

Table 13: Model 7: Kidney Cancer and Binge Drinking

Variable	**Estimate**	**Std. Error**	**p-value**
Intercept	0.62635	0.30359	3.94e-2 *
Pollution Count	-0.56650	0.13834	4.69e-5 ***
Median HH Income	-0.19184	0.04708	5.11e-5 ***
Rate of Binge Drinking	-0.08416	0.06901	0.223
Reservation	0.13089	0.03836	6.79e-4 ***
Total Population	-0.06576	0.01966	8.63e-4 ***
Total Area	0.43946	0.05787	9.49e-14 ***

Significance levels: *** p ¡ 0.001, ** p ¡ 0.01, * p ¡ 0.05, . p ¡ 0.1

Table 14: Model 8: Kidney Cancer and Both Health Behaviors

Variable	**Estimate**	**Std. Error**	**p-value**
Intercept	-0.70238	0.21161	9.47e-4 ***
Pollution Count	-1.20375	0.09666	2.00e-16 ***
Median HH Income	0.27803	0.03587	3.04e-11 ***
Rate of Binge Drinking	0.17411	0.04780	2.89e-4 ***
Rate of Smoking	1.10844	0.03799	2.00e-16 ***
Reservation	-0.05764	0.02690	3.24e-2 *
Total Population	0.03359	0.01381	1.52e-2 *
Total Area	0.18361	0.04036	6.29e-6 ***

Significance levels: *** p ¡ 0.001, ** p ¡ 0.01, * p ¡ 0.05, . p ¡ 0.1

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