

Do Doctors Save Lives?

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INTRODUCTION

Health and medicine are arguably one of the vastest and thoroughly researched fields there is. It is such an important service to us that the United States national healthcare expenditure has grown to \$4.3 trillion in 2021 accounting for 18.3% of Gross Domestic Product (Centers for Medicare & Medicaid Services, 2023). Given that it plays such a large role both economically but also into our daily lives, it is of wonder as to why its effects are not more studied. Not specifically the medical treatments but rather the medical industry on America, and more specifically on rural America. As of 2023, 15% of the U.S. population lives in rural America facing many health disparities and are at higher risk of dying from heart disease, cancer, unintentional injury, chronic lower respiratory disease, and stroke (Public Health Infrastructure, 2023). Recent literature shows that there is a “Rural Mortality Penalty”. That is, there is a greater mortality disparity in rural America (Cosby, et al., 2019)

This begs the question, “Why are rural communities more at risk and why is there a greater mortality disparity in these areas?”. There are many arguments for the mechanism of these rural health disparities. Barriers that prevent patients from receiving care include Resource Limitations, Confidentiality Limitations, Overlapping Roles, Provider Travel, Service Access, and Training Constraints (Brems et al., 2006). One major health disparities found in rural communities is the access to healthcare. According to Health Resources and Services Administration as of September 30, 2023, there is a 65% shortage of health professionals in rural areas. This can be compared to their Non-Rural counterparts with a shortage of 29%. The shortage of doctors is prevalent across the nation, however as noted above plays a larger role in rural America.

This study specifically attempts to answer the question, “Does access to healthcare have a significant effect on mortality rates in rural America in comparison to urban areas?”. This paper aims to use the number of doctors per capita as a proxy for access to healthcare. The data needed to answer this question is the number of physicians per county, mortalities per capita, and rural-urban continuum classification. These values will ensure that different levels of urbanicity are compared with varying number of physicians in each county accompanied with the varying number of mortalities. It is my belief that rural health communities will be found to have higher mortality rates due to the lack of access to healthcare in comparison to more urban communities.

DATA

The data used in this study comes from two sources. The first being the 2018-2020: Underlying Cause of Death by Single-Race Categories from the Centers for Disease Control and Prevention (CDC) WONDER. This data is produced by the National Center for Health Statistics (NCHS) at the CDC. The data is collected by state registries and provided to the National Vital Statistics System. The data is based on the death certificates for U.S. residents only. The data collected for this study cover the years 2018-2020 and is covering 3,100 counties of the United States. The second set of data comes from the Health Resources & Services Administration (HRSA) from 2018-2020. This data provides the number of active physicians per county in each state. The source of this data comes from the AMA Physician Masterfile, from the years 2018-2020. The AMA Physician Masterfile includes current and historical data for over 1.4 million physicians, residents, and medical students in the United States (AMA, 2023). It records all the physicians, both M.D. and D.O., in the United States, barring any physician that chooses to opt out.

When an individual enters medical school that is accredited by the United States a record is made into this database. When that individual moves onto a residency program it is noted and any other certification or training a doctor receives is made record here.

In this study we are interested in the number of mortalities per county. This is measured in a whole number year after year. The death is recorded from the deceased place of residence. There are slight limitations to this data the first being small data values are suppressed. To protect personal privacy of the deceased small data values are not available in certain situations. If the number of deaths or population in the county represents less than 10 people. Also, any number of deaths under 20 are deemed unreliable and therefore will need to be taken out of the data set.

The key independent variable of interest is the number of doctors per capita people in each county. This will be measured from the HRSA data as the number of physicians per county divided by that county's population. There is random assignment due to the number of respondents and having varying occupations in which people might have.

Other key important co-variate variables are the 2013 NCHS Urban-Rural Classification given to each of the counties. There are 6 categories from which each county will be assigned. The 6 categories are in order from most urban to least (or least rural to most rural): (1) Large Central Metro, (2) Large Fringe Metro, (3) Medium Metro, (4) Small Metro, (5) Micropolitan, (6) Non-Core. The categories are decided on the following metrics. Large central metro counties are counties in Metropolitan statistical areas (MSA) of a population of 1 million that: contain the entire population of the largest principal city of the MSA or are completely contained within the largest principal city of the MSA or contain at least 250,000 residents of any principal city in the MSA.

Large fringe metro counties are counties in MSA of a population of 1 million or more but do not qualify as large central metro. Medium metro counties are in MSA of a population ranging

| County | State | CountyFip | Urbanization | UrbanizationCode | Year | Deaths | Population | ID | Doctors | Deaths | Mortalities per Capita | Doctors per Capita |
|-----------------------------------|-------|-----------|--------------------|------------------|--------|--------|------------|------|---------|--------|------------------------|--------------------|
| Matanuska-Susitna Borough | AK | 2170 | Medium Metro | | 3 2019 | 651 | 108317 | 2170 | 117 | 651 | 0.0176611 | 0.0010802 |
| Southeast Fairbanks Census Area | AK | 2240 | NonCore (Nonmetro) | | 6 2018 | 42 | 6918 | 2240 | 3 | 42 | 0.2110437 | 0.0004337 |
| North Slope Borough | AK | 2185 | NonCore (Nonmetro) | | 6 2020 | 54 | 9294 | 2185 | 4 | 54 | 0.1843125 | 0.0004304 |
| Hoonah-Angoon Census Area | AK | 2105 | NonCore (Nonmetro) | | 6 2018 | 15 | 2151 | 2105 | 0 | 15 | 0.2040911 | 0 |
| Fairbanks North Star Borough | AK | 2090 | Small Metro | | 4 2018 | 471 | 98971 | 2090 | 189 | 471 | 0.0158834 | 0.0019097 |
| Prince of Wales-Hyder Census Area | AK | 2198 | NonCore (Nonmetro) | | 6 2020 | 61 | 6147 | 2198 | 7 | 61 | 0.2990077 | 0.0011388 |
| Nome Census Area | AK | 2180 | NonCore (Nonmetro) | | 6 2019 | 84 | 10004 | 2180 | 9 | 84 | 0.2189124 | 0.0008996 |

from 250,000-999,999 population. Small metro counties are counties in MSAs of less than a population of 250,000. The last two categories do not belong to an MSA and are considered nonmetropolitan counties. Micropolitan counties are in micropolitan statistical area; Noncore counties are not in a micropolitan statistical area. We will also consider county and year fixed effects. The table below summarizes the data and gives the first few rows of data.

The summary statistics of the six different urbanization categories are provided below.

Table 1: Summary Statistics of Data

| Urbanization Class | Observations | Mean | Std. Dev | Min | Max | p-value |
|-------------------------|--------------|---------|----------|-----|------|---------|
| Large Central Metro | 204 | 1308.97 | 756.7874 | 5 | 2382 | 0.0000 |
| Large Fringe Metro | 1,104 | 1196.53 | 661.7934 | 3 | 2377 | 0.0000 |
| Medium Metro | 1,116 | 1228.05 | 598.7799 | 12 | 2358 | 0.0000 |
| Small Metro | 1,901 | 1388.38 | 609.5129 | 2 | 2384 | 0.0000 |
| Micropolitan (Nonmetro) | 3,916 | 1106.96 | 640.8605 | 1 | 2373 | 0.0000 |
| Noncore (Nonmetro) | 1,072 | 979.130 | 715.0424 | 1 | 2384 | N/A |
| | | 6 | | | | |

Despite what most people would think the most urban areas on average do not necessarily have the greatest number of deaths. In fact, the area with the highest average mean of deaths is small metro. T-test of the average number of deaths for the other five categories compared to the Noncore (Nonmetro) Metro category each individually produced statistically different values with p-values all being 0.

METHOD

In this study I estimated a linear multivariate model. Given the random assignment because the data spans over 3000 counties in the United States with varying numbers of physicians per capita the econometric model is straightforward. The base model for regressions performed is the following:

$$\text{Model (1) } \textit{mortalitiespercapita}_{it} = \beta_0 + \beta_1 \textit{doctorspercapita}_{it} + \beta'(Year) + \beta'(County) + u$$

Where, $\textit{mortalitiespercapita}_{it}$ is the number of mortalities per the capita of each county i in a given year t . β_1 is the parameter of medical providers per capita in a given year and county. This will act as a proxy variable in place of access to healthcare as there is no standard of measurement for access to healthcare. The $\beta'Year$ term represents the year fixed effects, as different years will have varying numbers of deaths. This is especially important in the case of the year 2020 when the COVID-19 pandemic occurred. The $\beta'County$ term represents county fixed effects as different counties may have a higher or lower number of deaths on a regular basis.

To be able to compare between different level of urbanicities and the effects that doctors have on the mortalities per capita we will be testing for heterogenous effects. I will run Model (1), above, for the counties in each of the 6 urbanization classifications mentioned previously. This will allow for the analysis and comparison between the classifications.

This model allows me to identify if access to healthcare plays a significant role in mortality rates within the United States. All variables in the model are linear in parameters. Given the sample covers 3,000 counties spanning the United States there is a random sample. Given the level of measure is at the county and each county having varying numbers of deaths in each county there is variation between the variables.

RESULTS

Table 3 presents the main results. Column (1) shows the most basic model being simply the effect of doctors per capita on mortalities per capita. This shows that for every increase in doctors per capita the number of mortalities per capita will decrease by 17.64. When adding year fixed effects to the model as shown in Column (2) the effect is not changed. However, in Column (3) when county fixed effects for the whole nation are controlled for, every increase in doctors there is an increase of 23.62 deaths. All three of these findings are statistically significant at the 99% level. The results from column (3) suggests that doctors are increasing the mortalities per capita. There is potential bias in this model as physicians are employed where there is a need. If there is a location in which the rate of deaths is increasing at an increasing rate this could show a positive bias in that an increase in doctors could result in an increase in the number of deaths.

Table 4 presents the results when testing for heterogenous effects. These were a series of six regressions, in which each represents one of the six urbanization classes. Column 1 represents the Large Central Metro category in which an increase in mortalities per capita is expected to have an increase of 1.259 for every increase in doctors per capita at the 95% level. Column 2 represents the Large Fringe Metro category in which an increase in mortalities per capita is expected to have a decrease of 0.938 for every increase in doctors per capita not being statistically significant. Column 3 represents the Medium Metro category in which an increase in mortalities per capita is expected to have a decrease of 4.997 for every increase in doctors per capita not being statistically significant. Column 4 represents the Small Metro category in which an increase in mortalities per capita is expected to have a decrease of 4.499 for every increase in doctors per capita not being statistically significant. Column 5 represents the Micropolitan (Nonmetro) category in which an increase in mortalities per capita is expected to have an

increase of 31.54 for every increase in doctors per capita being statistically significant at the 99% level. Column 6 represents the Non-Core (Nonmetro) category in which an increase in mortalities per capita is expected to have an increase of 48.16 for every increase in doctors per capita being statistically significant at the 99% level. As mentioned earlier there is a potential bias in that an area with an increasing mortality rate would result in a positive bias in the number of mortalities in a certain area.

The limitation of my model include we are not accounting for natural disasters in which areas would have many mortalities would result in areas that would generally not have that high of a mortality rate. There is also a limitation in that the resources, technology, and medicine available to the doctors cannot be accounted for. Even if there is a physician present there are times when they do not have the resources to save a life, though the knowledge and ability of the doctor is present. The data does not exist for every piece of technology that every doctor has to perform a life saving operation.

CONCLUSION

It can be argued that it is not necessarily doctors alone that prevent deaths, which can be true. However, it is generally necessary for a physician to call the time of death as well as make medical decision. The results and models provided do not paint a clear trend in whether an increase in doctors will result in a decrease in mortalities per capita when comparing urbanization classifications. In fact, according to the half of the models an increase in doctors per capita results in an increase mortalities per capita. However, I do not believe that doctors are killing people more often than they are helping people. In the other half of cases, it is shown that doctors are decreasing mortalities per capita however, these results are not statistically significant. There are a few theories that could explain the results found in research.

The first mentioned earlier, being that there could be an omitted variable in which we are not controlling for the resources available to the physicians that would provide the ability to save people's lives. Though the doctor has the know-how and ability, there is no practical way in which the doctor can perform the procedure, administer the medicine, etc. This would explain as to why the three statistically significant results do have a trend. In a large central metro area, there would be more resources available in comparison to a Micropolitan (Nonmetro) or Non-Core (Nonmetro) area. If we analyze those three areas, then we see an increase in the number of mortalities per capita as we move more rural. Though the mortalities are increase, they increase more as we move more rural.

Another thing of note is that doctors do not necessarily stop death, they simply push it off. We have yet to discover a way to escape death altogether. Regardless of who someone is they will eventually pass away. Doctors serve to avoid it a little while longer. The next step of

research would be to regress life expectancies on the number of doctors per capita. This would be providing the answer to see if doctors are in fact helping people.

This work has aimed to answer the question of whether the number of doctors per capita influences mortalities per capita. This was analyzed at the county level. The results though not completely understood demonstrate that for half the cases an increase in the number of doctors per capita will result in an increase in the number of mortalities per capita. The mechanism for this finding is not understood.

Table 1: Summary Statistics of Data

| Urbanization Class | Observations | Mean | Std. Dev | Min | Max | p-value |
|-------------------------|--------------|----------|----------|-----|------|---------|
| Large Central Metro | 204 | 1308.97 | 756.7874 | 5 | 2382 | 0.0000 |
| Large Fringe Metro | 1,104 | 1196.53 | 661.7934 | 3 | 2377 | 0.0000 |
| Medium Metro | 1,116 | 1228.05 | 598.7799 | 12 | 2358 | 0.0000 |
| Small Metro | 1,901 | 1388.38 | 609.5129 | 2 | 2384 | 0.0000 |
| Micropolitan (Nonmetro) | 3,916 | 1106.96 | 640.8605 | 1 | 2373 | 0.0000 |
| Noncore (Nonmetro) | 1,072 | 979.1306 | 715.0424 | 1 | 2384 | N/A |

Table 2: Distribution of Data

| Urbanization Class | Frequency | Percent |
|-------------------------|-----------|---------|
| Large Central Metro | 204 | 2.19% |
| Large Fringe Metro | 1,104 | 11.85% |
| Medium Metro | 1,116 | 11.98% |
| Small Metro | 1,901 | 20.41% |
| Micropolitan (Nonmetro) | 3,916 | 42.05% |
| Noncore (Nonmetro) | 1,072 | 11.51% |
| Total | 9,313 | 100% |

| | (1) Mortalities per Capita | (2) Mortalities per Capita | (3) Mortalities per Capita |
|----------------------|----------------------------------|----------------------------------|----------------------------------|
| Doctors per Capita | -17.64*** [0.827] | -17.64*** [0.827] | 23.62*** [6.875] |
| Constant | 0.111*** [0.00179] | 0.110*** [0.00272] | 0.0590*** [0.00862] |
| Year Fixed Effects | No | Yes | Yes |
| County Fixed Effects | No | No | Yes |
| Observations | 9,312 | 9,312 | 9,312 |
| R-squared | 0.047 | 0.047 | 0.937 |

| | Large Central Metro | Large Fringe Metro | Medium Metro | Small Metro | Micropolitan (Nonmetro) | Non-Core (Nonmetro) |
|----------------------|------------------------|------------------------|------------------------|------------------------|-------------------------|------------------------|
| | Mortalities per Capita | Mortalities per Capita | Mortalities per Capita | Mortalities per Capita | Mortalities per Capita | Mortalities per Capita |
| Doctors per Capita | 1.259** [0.632] | -0.938 [14.59] | -4.997 [7.878] | -4.499 [9.057] | 31.54*** [8.864] | 48.16*** [14.93] |
| Constant | -0.00406 [0.00295] | 0.0256 [0.0239] | 0.0395*** [0.0148] | 0.0493*** [0.0176] | 0.014 [0.0108] | 0.129*** [0.00932] |
| Year Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| County Fixed Effects | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 204 | 1,104 | 1,116 | 1,072 | 1,901 | 3,915 |
| R-squared | 0.904 | 0.808 | 0.967 | 0.924 | 0.944 | 0.922 |

REFERENCES

Center for Medicare & Medicaid Services (CMS). National health expenditure data. Accessed at <https://www.cms.gov/data-research/statistics-trends-and-reports/national-health-expenditure-data/nhe-fact-sheet> on 29 October 2023.

Public Health Infrastructure Center. (2023, May 09). *About Rural Health*. Center for Disease Control and Prevention. <https://www.cdc.gov/ruralhealth/about.html>

Health Resources and Services Administration. (2023, October 01). *Designated Health Professional Shortage Area Statistics Fourth Quarter of Fiscal Year 2023*. Bureau of Health Workforce Health Resources and Services Administration (HRSA) U.S. Department of Health & Human Services. <https://data.hrsa.gov/default/generatehpsaquarterlyreport>

Cosby, A. G., McDoom-Echebiri, M. M., James, W., Khandekar, H., Brown, W., & Hanna, H. L. (2019). Growth and persistence of place-based mortality in the United States: the rural mortality penalty. *American journal of public health*, 109(1), 155-162.

Brems, C., Johnson, M. E., Warner, T. D., & Roberts, L. W. (2006). Barriers to healthcare as reported by rural and urban interprofessional providers. *Journal of interprofessional care*, 20(2), 105-118.

American Medical Association & American Medical Association. (2023, July 3). *AMA Physician Professional Data™*. American Medical Association. <https://www.ama-assn.org/about/physician-professional-data/ama-physician-professional-data>