



Cross-sectional Study

COVID-19 fatalities by zip codes and socioeconomic indicators across various U.S. regions

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ABSTRACT

Background: There is a paucity of literature addressing COVID-19 case-fatality ratios (CFR) by zip code (ZC). We aim to analyze trends in COVID-19 CFR, population density, and socioeconomic status (SES) indicators (unemployment, median household income) to identify ZCs heavily burdened by COVID-19.

Methods: Cross-sectional study to investigate the US prevalence of COVID-19 fatalities by ZC and SES. CFRs were calculated from state/county Departments of Health. Inclusion criteria were counties that reported cases/deaths by ZC and a CFR \geq 2%. This study was reported in line with the STROCCS criteria.

Results: 609/1,853 ZCs, spanning 327 counties in 7 states had CFRs \geq 2%. A significant positive correlation was found between the CFR and median household income (Pearson correlation:0.107; 95% CI [289.1,1937.9]; $p < 0.001$). No significant correlations exist between the CFR, and population/mi (Sen-Crowe et al., 2020) [2] or unemployment rate. Significant associations exist between the CFR and young males and elderly females without public insurance. CFR was inversely associated with persons aged <44 and individuals aged ≥ 65 . The percentage of nursing homes (NHs) within cities residing within high CFR ZCs range from 8.7% to 67.6%.

Conclusion: Significant positive association was found between the CFR and median household income. Population/mi (Sen-Crowe et al., 2020) [2] and unemployment rates, did not correlate to CFR. NHs were heavily distributed in high CFR zip codes. We recommend the targeted vaccination of zip codes with a large proportion of long-term care facilities. Finally, we recommend for improved screening and safety guidelines for vulnerable populations (e.g nursing home residents) and established protocols for when there is evidence of substantial infectious spread.

1. Background

The impact of COVID-19 on the United States (US) will likely plague the country longer than we anticipate [1–8]. As of April 2nd, 2021, 554,069 COVID-19-related deaths out of 30,606,648 total confirmed cases, corresponds to a 1.8% case fatality ratio (CFR) [9]. Both acute and chronic health conditions disproportionately affect low socioeconomic status (SES) individuals [3,10,11]. These findings may be related to distributional inhabitation [12–14].

Studies evaluating individual states and local areas have noted significant disparities among individuals who live in socioeconomically disadvantaged areas and have been able to analyze COVID-19 data at the county and zip code (ZC) level. Many studies found correlations between lower SES and higher infection rates and poorer outcomes. ZCs in South Florida, New York City, and Illinois, with particularly low SES and low

mean household income (MHI) saw an increased incidence rate ratio for COVID-19 compared to ZCs with higher SES and increased mean household income [15,16]. This trend of increased incidence rate ratio was also noted in ZCs in New York City and Michigan with an increased population of Black and Hispanic residents [17,18]. Studies have been able to highlight some specific factors that may attribute to the rapid spread of the virus, particularly percent crowding metrics for ZCs with lower SES. Areas with higher population densities saw amongst the highest rates of COVID-19 infection rates, as did areas with the most socioeconomic strain [16].

Furthermore, access to healthcare is a problem seen in low SES regions. Data collected before and during the pandemic revealed that there was a substantial difference between average number of ICU beds per population between predominantly White, higher SES neighborhoods and predominantly Black and Hispanic, lower SES neighborhoods

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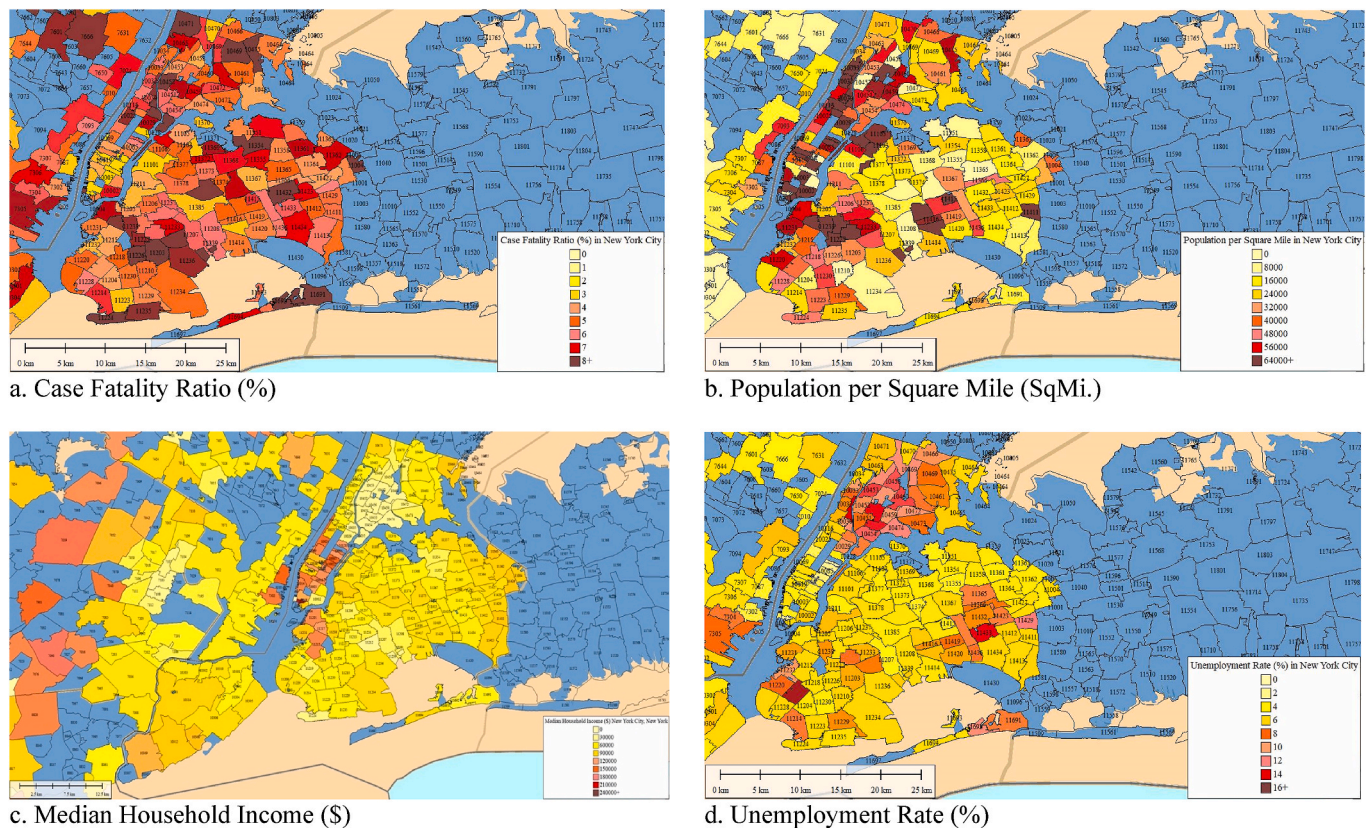


Fig. 1. Case-Fatality Ratio, Population/mi², Median Household Income, and Unemployment Rate in New York City, New York. A total of 168 zip codes were included. The average CFR was 5.6% and ranged from 1.5% to 6.2%. The population/mi² ranged from 12,944–128,616, with an average of 43,469. Additionally, the average median household income and unemployment rate was \$73,980 (Range: \$21,447–\$250,000) and 6.2% (Range: 0.4%–15.2%), respectively.

in New York City [19–21]. Additionally, increased primary care physician density per county has been associated with lower COVID-19 death rates [22].

We hypothesized that there would be associations between COVID-19 CFR and population density, SES, other demographic variables and to our knowledge this is the first study to investigate this in a national sampling. This study will further apply these findings to the proportion of nursing homes that reside within zip codes heavily burdened by COVID-19 in order to determine if there are any trends in CFR and indicators of the elderly population.

2. Methods

2.1. Study design

Cross-sectional study utilizing publicly available data to investigate associations between CFR and SES indicators and demographics. We aim to identify ZCs heavily burdened by COVID-19 fatalities with consideration of the proportion of long-term care facilities for allocation of transmission prevention actions. This study was reported in line with the STOCSS criteria [23]. This work was submitted to the Research registry (UIN #: researchregistry6856) which can be found via the following link (<https://www.researchregistry.com/browse-the-registry/#home/registrationdetails/60abe32e274cad001ee00791/>):

2.2. Zip code data collection & selection criteria

COVID-19 cases and fatalities were obtained by ZC via the state/county Department of Health (DOH) and/or state/county public health department as of December 23, 2020. Areas containing ZCs where the total number of COVID-19 cases and/or COVID-19 deaths were not

available were excluded.

ZCs with a case-fatality ratio (CFR), the number of COVID-19 cases divided by the number of COVID-19 deaths, $\geq 2.0\%$ were included in this study, as they represent areas experiencing greater COVID-19 burden compared to the national average of 1.8% at the time this data was collected [9].

2.3. Socioeconomic status (SES) and population data

Unemployment rates and MHI were obtained from the American Community Survey (AmCoS) 5-year data profiles, 2015–2019 [24]. The MHI and unemployment rates of the county the ZC resided within was used to indicate the SES status, according to the classification system set by the US Census Bureau. All SES and demographic attributes were linked to their respective ZC via their associated geographic identification codes (GEOIDs). Finally, population and ZC land area data were obtained from the Census Bureau ZC Tabulation Area (ZCTA) database and used to calculate population density defined as population/square mile (mi [2]) [25].

2.4. Nursing home data

Nursing home (NH) facilities were searched by using the Medicare website by ZC and classification system. These results were compared to compiled NH lists in individual local (state/county/city) DOH resources and simple percentages were calculated for included ZCs in the study [26].

2.5. Geospatial informational system (GIS) mapping

Blue Marble Geographics Global Mapper v20.0 was used for GIS

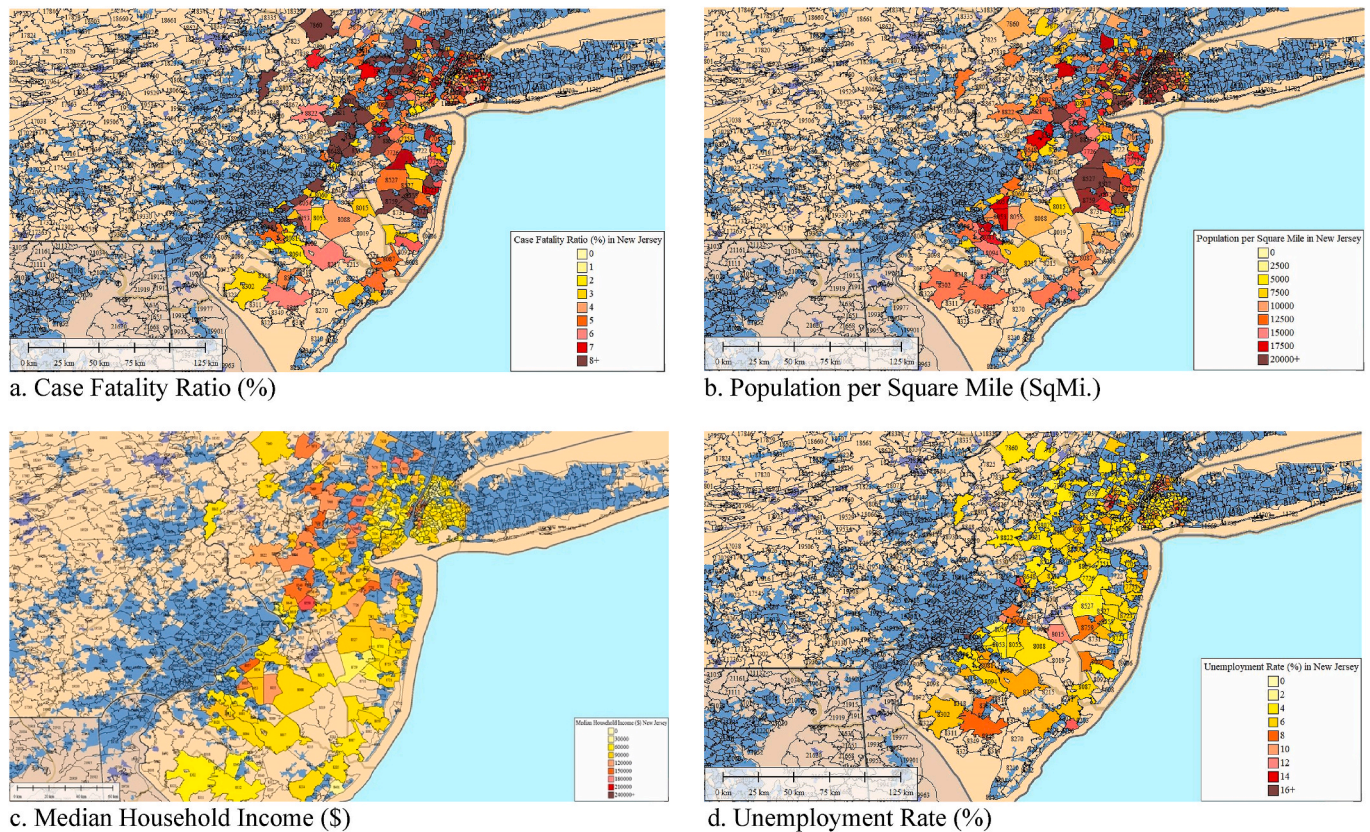


Fig. 2. Case-Fatality Ratio, Population/mi², Median Household Income, and Unemployment Rate in New Jersey. A total of 160 zip codes were included. The average CFR was 6.1% and ranged from 2.0% to 17.8%. The population/mi² ranged from 173 to 53,316, with an average of 6,909. Additionally, the average median household income and unemployment rate was \$80,763 (Range: \$29,232–\$154,688) and 5.8% (Range: 2.7%–17.4%), respectively.

mapping. We defined heavily COVID-19 burdened ZCs as those experiencing a CFR greater than the national average. ZC locations were plotted according to the ZCTAs. ZCTAs are generalized representations of ZCs that have been assigned to census blocks and representative of the geographic locations of populated areas [25]. ZCTA boundaries were constructed utilizing shapefiles (.shp) and geodatabases (.gdb) from TIGER/Line Shapefiles [25,27]. In addition, the TIGER/Line Database was utilized to stratify county areas including/surrounding the ZCs as the following: urban cluster areas (2,500–<50,000 population), urbanized areas (50,000–99,999 population), and metropolitan areas ($\geq 100,000$ population). Demographic, population, and SES (e.g. unemployment rate, MHI, etc.) attributes obtained from the AmCoS were linked to the ZCTAs via their associated GEOIDs. Attributes (e.g. CFR, population, urbanized areas, ZCTA boundaries, etc.) were superimposed in layers in order to generate a geospatial representation of ZCs heavily burdened with COVID-19. Finally, ZC locations were further classified by US region (Northeast, Midwest, South, West) as defined by the US Census Bureau.

2.6. Statistical analysis

IBM SPSS Statistics v26.0 (Armonk, NY) was used for statistical analysis. Analysis of variance (ANOVA) was used to evaluate differences in CFR, MHI, Unemployment Rate, and Population/mi [2], and corresponding US Census Bureau data. In addition, linear regression analysis was used in order to determine any significant correlations between the four analyzed variables. Significance was defined as $p < 0.05$. This study was conducted in compliance with ethical standards and deemed exempt by our Institutional Review Board.

3. Results

Fourteen states offered data by ZC of which only three states (North Carolina, Oklahoma, and New Jersey) reported both total cases and total deaths by ZC for the entire state. Apart from those, four states (California, Illinois, Washington, and New York) reported total cases and total deaths by ZC for ≥ 1 county, which were also included in this study.

In total, we included 327 counties that spanned the above seven states. 609/1,853 (32.9%) total ZCs had CFRs $\geq 2\%$ and were included in subsequent analyses.

3.1. Northeast region

A total of 328 ZCs in New York City, NY (168) and New Jersey (160) represented the Northeast region. All ZCs were contained within metropolitan divisions (Figs. 1 and 2). The average CFR and population/mi [2] were 5.9% and 25,635, respectively. (Fig. 1ab,2 ab) In addition, the average MHI was \$78,925, and the unemployment rate was 6.0%. (Fig. 1cd,2cd).

3.2. West region

A total of 51 ZCs in King County, Washington (26) and Orange County, California (25) represented the West region. All analyzed ZCs were contained within a metropolitan division (Figs. 3 and 4). The average CFR and population/mi [2] was 5.2% and 6,134, respectively. (Fig. 3ab,4 ab) In addition, the average MHI was \$103,132 and the unemployment rate was 4.0%. (Fig. 3cd,4cd).

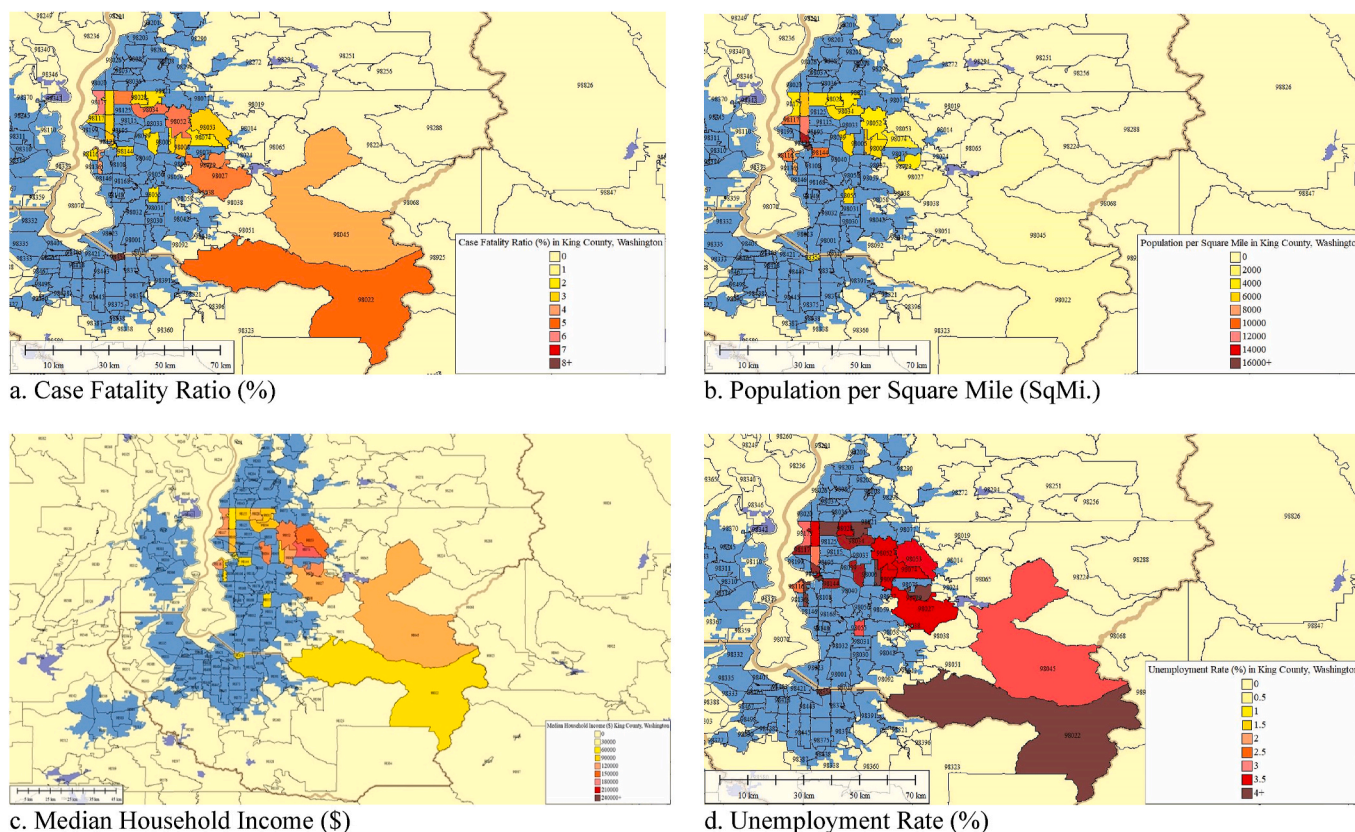


Fig. 3. Case-Fatality Ratio, Population/mi2, Median Household Income, and Unemployment Rate in King County, Washington. A total of 26 zip codes were included. The average CFR was 3.6% and ranged from 2.0% to 9.1%. The population/mi2 ranged from 45.5 to 26,984, with an average of 6,568 population/mi2. Additionally, the average median household income and unemployment rate was \$105,633 (Range: \$68,994–\$188,900) and 3.7% (Range: 2.7%–4.6%), respectively.

3.3. Midwest region

A total of 26 ZCs within Chicago, Illinois, represented the Midwest region. All ZCs were contained within a metropolitan division (Fig. 5). The average CFR and population/mi [2] was 3.22% and 14,823, respectively. (Fig. 5ab) In addition, the average MHI was \$53,259 and the unemployment rate was 11.0%. (Fig. 5cd).

3.4. South region

A total of 204 ZCs in Oklahoma (43) and North Carolina (161) represented the South region. 97 ZCs are contained within urbanized areas and 22 ZCs contained in an urbanized cluster. The remaining 85 ZCs were not contained within an urban cluster, urbanized area, or metropolitan division. Oklahoma did not contain any ZCs within metropolitan divisions or urbanized areas (Figs. 6 and 7). The average CFR and population/mi [2] was 3.19% and 19,506, respectively. (Fig. 6ab,7 ab) In addition, the average MHI was \$46,432 and the unemployment rate was 6.7%. (Fig. 6cd,7cd).

3.5. Nursing homes

The percentage of NHs within a city that reside within the ZCs included in this study range from 8.7% to 67.6%. In New York City, 169/250 (67.6%) NHs resided within heavily burdened ZCs. 234/366 (63.9%) of NHs in New Jersey resided within heavily burdened ZCs, followed by Chicago (64/129 = 49.6%), King County, Washington (25/52 = 48.0%), Orange County, California (32/75 = 42.7%), North Carolina (147/423 = 34.8%), and Oklahoma (25/288 = 8.7%).

Multiple significant differences in regional CFR ($f(3,95.4) = 82.8$; $p < 0.001$), population/mi [2] ($f(3,128.3) = 47.1$; $p < 0.001$), MHI ($f(3,$

$83.8) = 117.4$; $p < 0.001$), and Unemployment Rate ($f(3,97.0) = 38.8$; $p < 0.001$) exist.

3.6. Case fatality rate

The overall mean CFR across all regions was 4.7%. The Northeast region ($\mu = 5.9\%$) exhibited a significantly higher mean CFR than the South ($\mu = 3.2\%$) and Midwest regions ($\mu = 3.2\%$) (Table 1). Significant inverse correlations were found between CFRs and the proportion of persons aged <44 years old (Pearson Correlation = -0.049 ; 95% CI $[-0.193,-0.025]$; $p = 0.011$) and the proportion of elderly individuals aged ≥ 65 (Pearson Correlation = -0.033 ; 95% CI $[-0.222,-0.046]$; $p = 0.011$). These results are consistent with the regional CFRs, as the Midwest region exhibited significantly larger proportions of persons aged <44 than all other regions and would be expected to demonstrate an inverse correlation. Similarly, the South region exhibited significantly larger proportions of elderly individuals than the Midwest and Northeast regions, but not the West region.

A significant inverse correlation was found between CFR and males aged <44 without public health insurance (Pearson Correlation = -0.134 ; 95% CI $[0.014,0.351]$; $p = 0.034$). The Northeast displayed significantly smaller proportions of young males aged <44 without health insurance than all other regions and is consistent with the regional CFR and inverse association. In contrast, the West displayed significantly larger proportions of persons aged ≥ 65 than all other regions.

However, a significant direct correlation was found between CFR and females over the age of 65 who did not have public health insurance (Pearson Correlation = 0.142 ; 95% CI $[0.262,2.792]$; $p = 0.018$). Consistent with these results, the Northeast region displayed significantly larger proportions of elderly females without public health

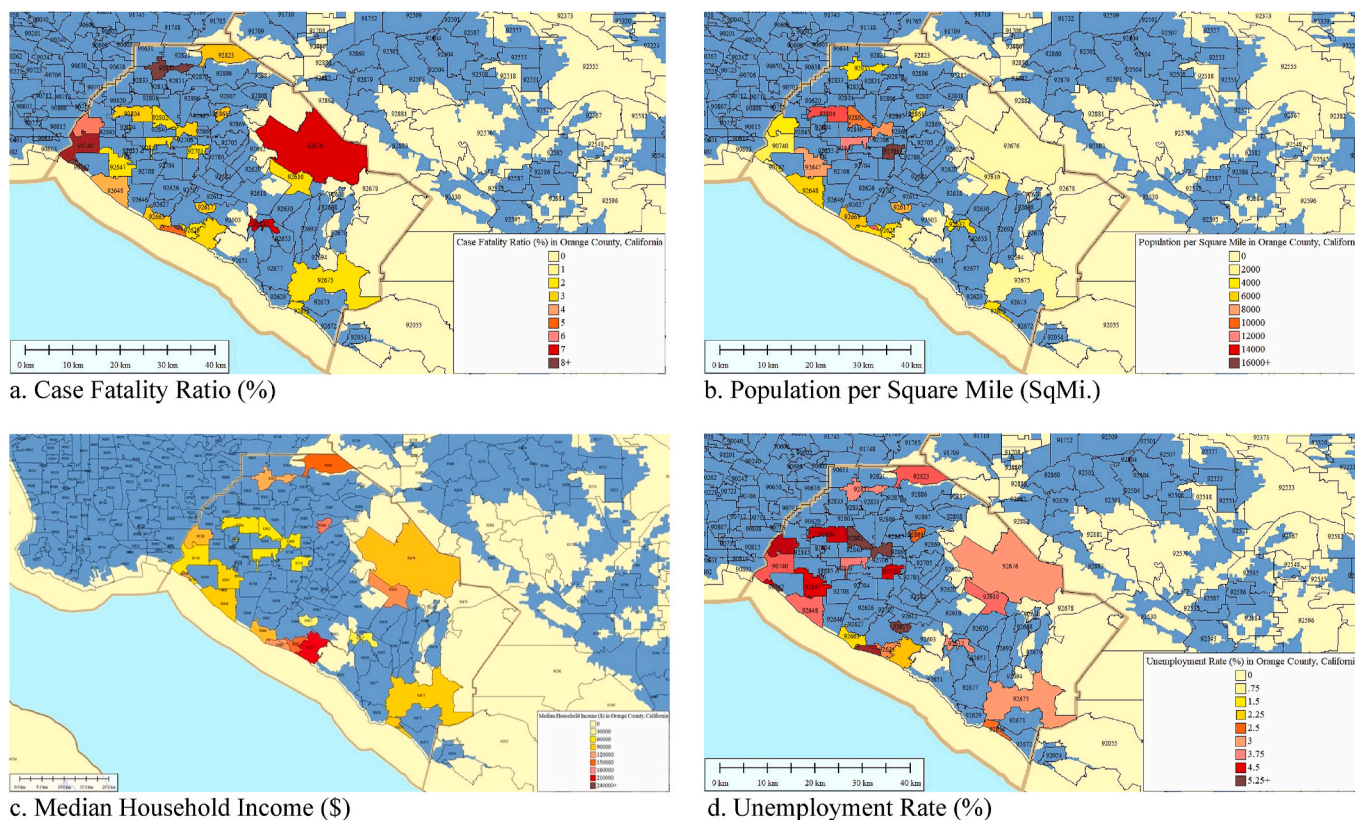


Fig. 4. Case-Fatality Ratio, Population/mi², Median Household Income, and Unemployment Rate in Orange County, California. A total of 25 zip codes were included. The average CFR was 6.9% and ranged from 2.2% to 57.1%. The population/mi² ranged from 31.2 to 16,684, with an average of 2,682 population/mi². Additionally, the average median household income and unemployment rate was \$100,531 (Range: \$36,824-\$204,291) and 4.3% (Range: 1.9%–8.9%), respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

insurance than all other regions. No significant correlations were found between CFRs and race.

3.7. Population/square mile

The nationwide mean was 21,537 population/mi [2]. The Northeast region ($\mu = 25,634.8$ population/mi [2]) exhibited a significantly larger population/mi [2] than the Midwest region ($\mu = 14,823.1$ population/mi [2]). In addition, the Northeast, South ($\mu = 19,506.3$ population/mi [2]) and Midwest regions displayed a significantly larger population/mi [2] than the West region ($\mu = 6,133.8$ population/mi [2]). (Table 2)

3.8. Median household income

The overall MHI across all ZCs was \$69,030. The West region ($\mu = \$103,132$) displayed a significantly higher MHI than the Northeast ($\mu = \$78,925$), South ($\mu = \$46,432$), and Midwest regions ($\mu = \$53,259$). In addition, the Northeast region exhibited a significantly higher average MHI than the Midwest and South regions (Table 3). No significant associations exist between the Midwest and South regions.

3.9. Unemployment rate

The average unemployment rate was 6.3%. The Midwest region ($\mu = 11.0\%$) exhibited a significantly larger average unemployment rate than the South ($\mu = 6.7\%$), West ($\mu = 4.0\%$), and Northeast regions ($\mu = 6.0\%$). In addition, the Northeast region displayed a significantly higher average unemployment rate than the West region. No significant difference existed between the Northeast and South region (Table 4).

A weak but significant positive correlation was found between CFRs

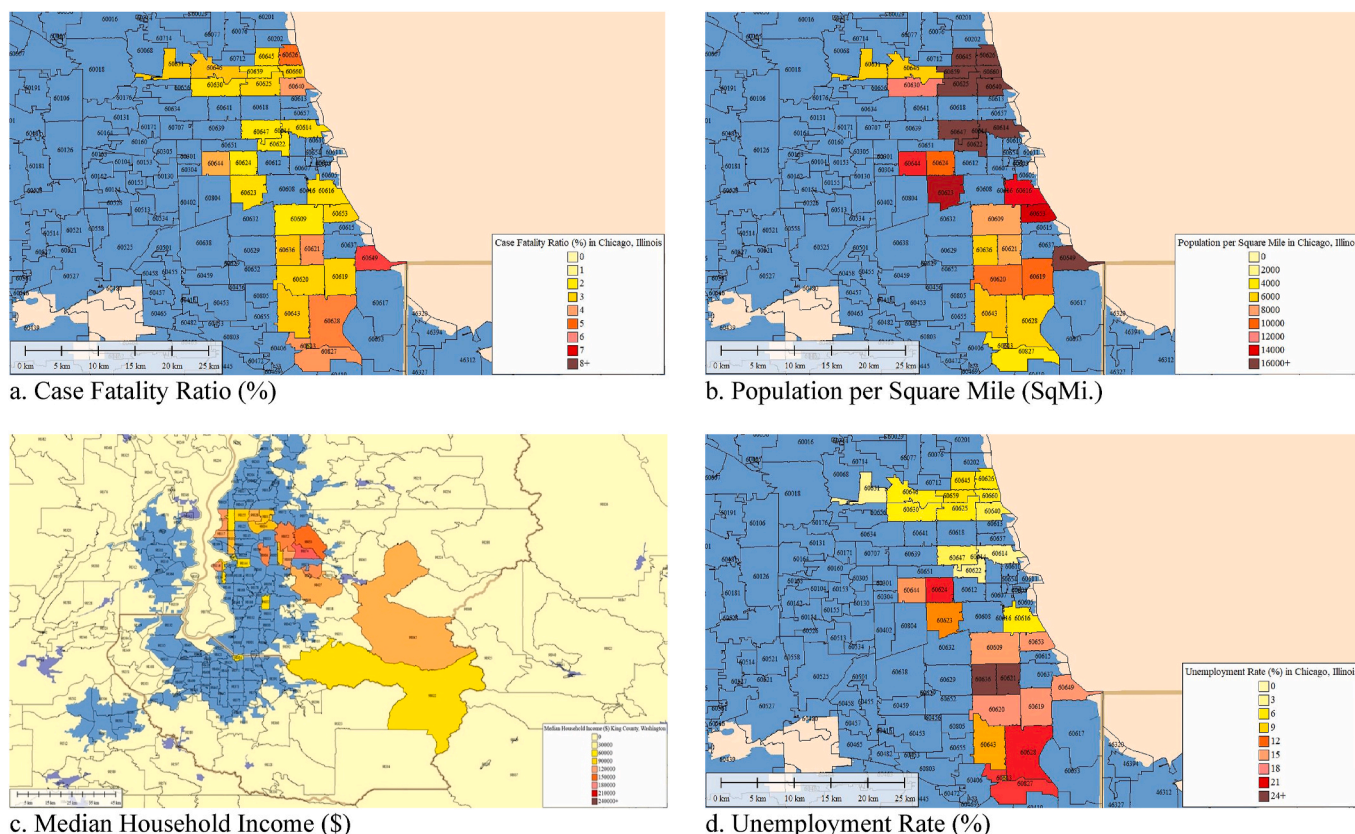
and MHI (Pearson correlation:0.107; 95% CI [289.1,1937.9]; $p < 0.001$). In addition, there was a moderate negative and significant correlation between the unemployment rate and MHI (Pearson correlation: -0.336 ; 95% CI [-3492.3,-2214.4]; $p < 0.001$). No significant correlations exist between CFRs, and population/mi [2] or unemployment rate.

4. Discussion

The Northeast region exhibited the largest CFR (5.9%), then the West (5.2%), Midwest (3.22%), and South (3.19%) region. The Northeast mean CFR was significantly larger than the Midwest and South regions. The Northeast exhibited the largest population/mi [2] (25,635), followed by the South (19,506), Midwest (14,823), and West (6,134) region. Our results varied slightly from other studies. Another study found the Northeast exhibited the largest CFR (5.9%), then the Midwest (5.6%), West (5.1%) and South (5.05%) [28]. One possible explanation of this inconsistency is the ZCs representing the West region reside within metropolitan areas, where larger population densities can facilitate increased spread and elevated CFRs. On the other hand, our data may suggest that some COVID-19 data interpretations at the county level may mask harder hit communities and trends in local infection rates and mortality.

In contrast to other studies, we did not find significant associations between CFR and race [29]. Our study was limited by the small sample size and narrow area designations (metropolitan vs. urban vs. rural). We recommend states make CFR reporting consistent at ZC levels for more granular analysis.

Our study found a significant inverse correlation between CFR and individuals aged <44 as well as CFR and individuals aged ≥ 65 . When controlled by gender, there was a significant direct correlation between CFR and females with no public insurance aged ≥ 65 . The association



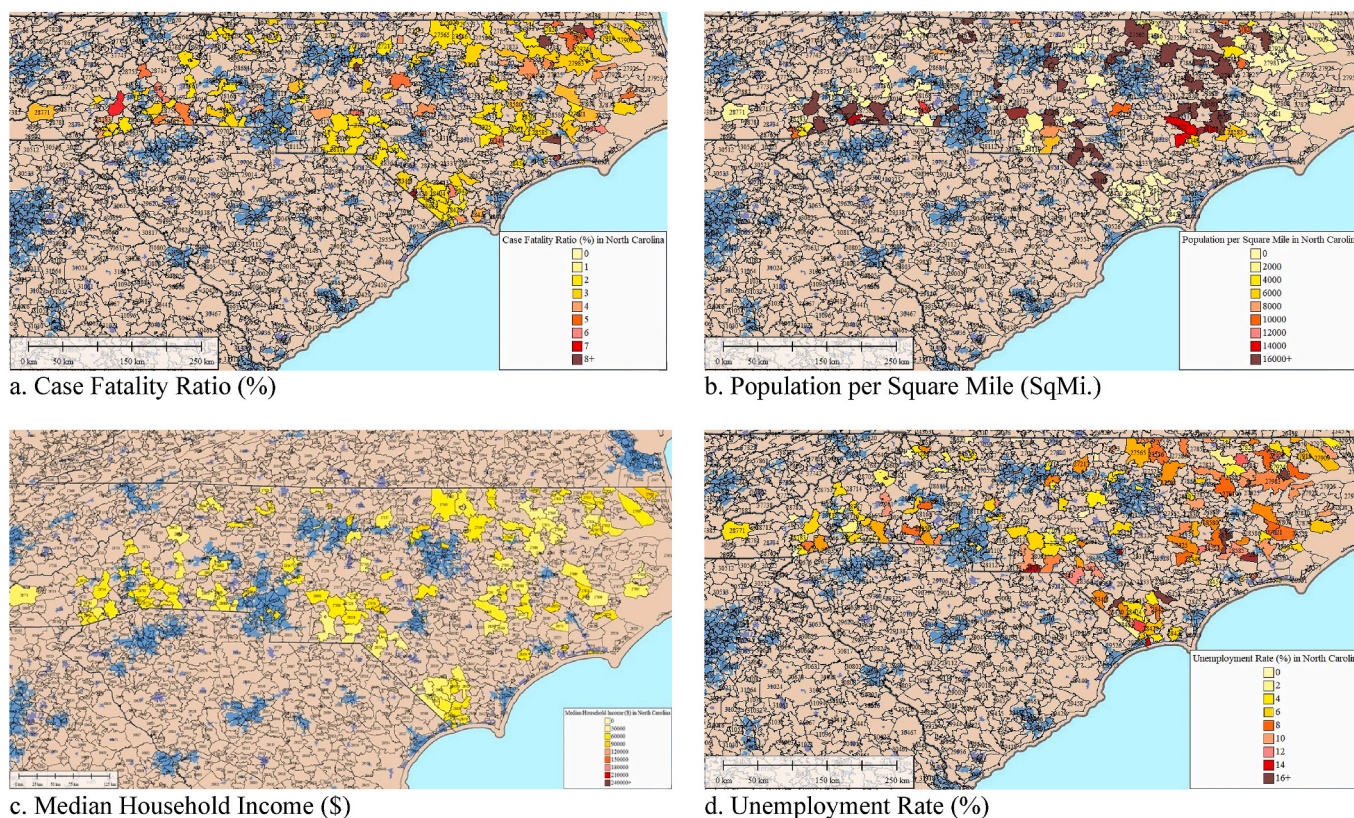


Fig. 6. Case-Fatality Ratio, Population/mi², Median Household Income, and Unemployment Rate in North Carolina. A total of 161 zip codes were included. The average CFR was 3.3% and ranged from 2.0% to 9.8%. The average population/mi² was 25,239. Additionally, the average median household income and unemployment rate was \$46,316 (Range: \$19,954-\$86,250) and 7.1% (Range: 0.0%–36.0%), respectively.

continued routine testing, COVID-19 status, and temperature screening. We recommend for improved education of staff members working in nursing homes regarding the risks of community exposures and the importance of adhering to safety and social distancing guidelines, in accordance with the recommendations of the CDC [45].

Our study has limitations. First, 36/50 (72%) states do not offer comprehensive COVID-19 data at ZC levels. The majority of ZCs analyzed resided within metropolitan divisions and are not representative of entire regions. Moreover, when considering the available data regarding the number of NHs in each state, our search relied on [Medicare.gov](https://www.medicare.gov) and local DOH resources, where inconsistencies in how they define NHs or reported NHs deaths may exist. Furthermore, our relatively small sample size limits our ability to generalize trends across the US. Additionally, it is important to contemplate that patients may seek care outside of their residential areas, affecting ZC data.

We have several recommendations. First, we recommend for states to make data publicly available at ZC levels. Second, future investigations should include demographic characteristics by ZC, which could provide for a more specific targeted strategy. Third, states are encouraged to provide information NHs within their state. In the event of another public health emergency, we recommend for nationwide prioritization of the vaccination of high-risk populations, particularly those residing in long-term care facilities and for all SES members [12,31,32,46,47]. Finally, we recommend for improved, consistent health screening and safety protocols for vulnerable populations, such as NH residents in future emergency situations. In addition, safety protocols may include specific guidelines for those working in nursing homes who may place the residents at risk of infection. Our study demonstrates correlations between CFR with those aged 65 and older and revealed high proportions of nursing homes within these zip codes. These results provide evidence for the substantial risk placed on these populations and call for improved safety protocols to match the elevated risk. By learning from

the past year and a half and implementing aggressive preventative guidelines, we can minimize the number of preventable deaths early on in the event of another tremendous surge in COVID-19 cases.

5. Conclusion

CFRs ranged from 3.1% in the West region to 5.9% in the Northeast region. The West region displayed a significantly larger median household income than other regions and the lowest population density, whereas the Northeast exhibited the highest population density. A significant weak positive correlation was found between CFRs and median household income and no correlation was found between population density and unemployment status. These novel findings may be due to a lack of available COVID-19 data at the zip code level nationwide, which is required to make generalizable claims about regions as a whole. This study emphasizes the need for states to make COVID-19 data available at the zip code level. In addition, the percentage of a state's nursing homes residing within zip codes heavily burdened by COVID-19 ranged from 8.7%, up to 67.6% in New York City. Zip code analysis can help with identifying COVID-19 risk groups and locations, including long-term care facilities towards targeted vaccine distribution. Most importantly, we recommend for improved and more stringent screening and safety practices, such as distancing protocols and sanitation guidelines for those living and working in nursing homes when there is evidence of infectious spread.

Provenance and peer review

Not commissioned, externally peer-reviewed.

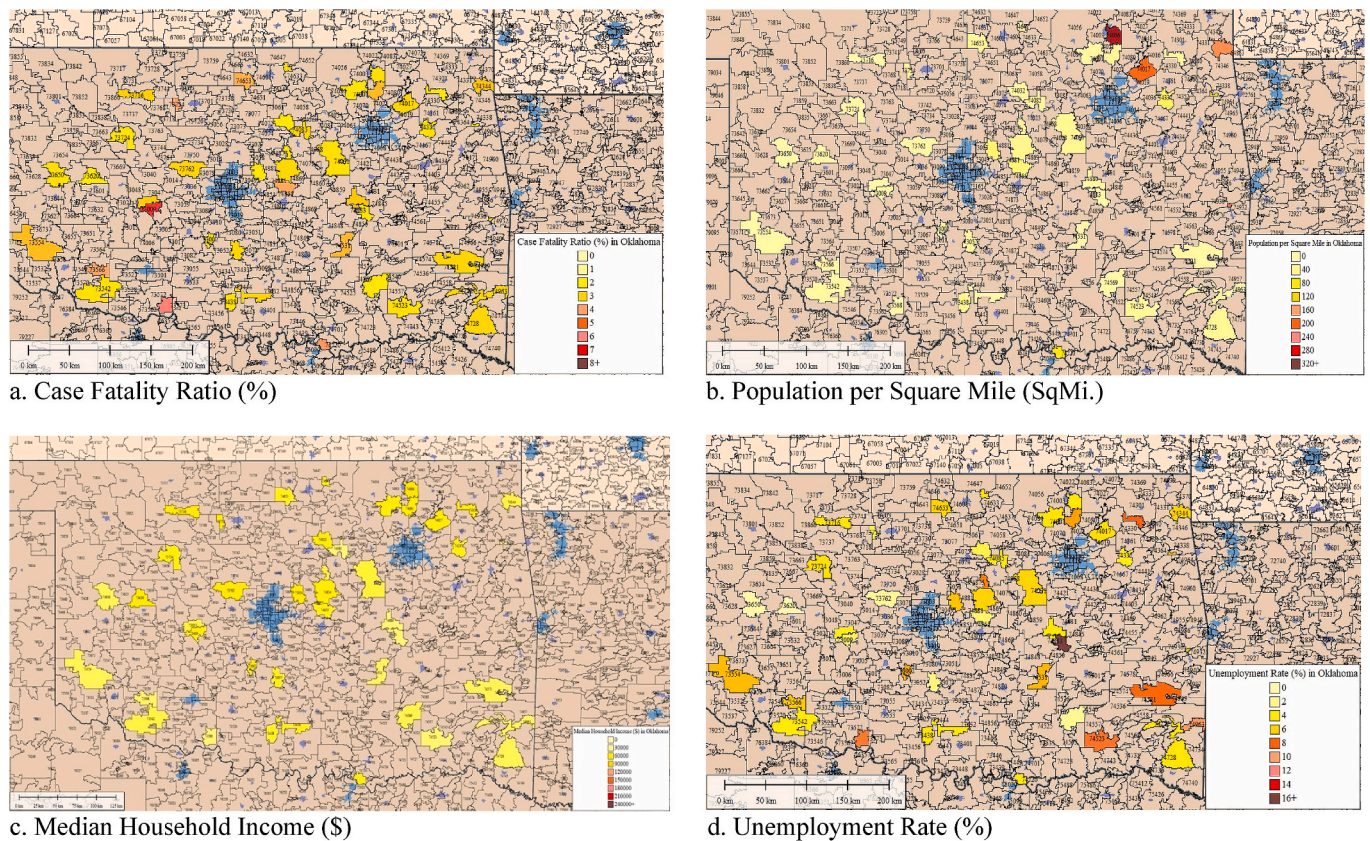


Fig. 7. Case-Fatality Ratio, Population/mi2, Median Household Income, and Unemployment Rate in Oklahoma. A total of 43 zip codes were included. The average CFR was 3.0% and ranged from 2.0% to 6.6%. The average population/mi2 was 42.4 and ranged from 5.0 to 302.9. Additionally, the average median household income and unemployment rate was \$46,863 (Range: \$31,923-\$66,323) and 5.4% (Range: 0.0%–29.5%), respectively.

Table 1
Comparison of the case fatality ratio (%) by U.S. Region.

Census Region		Mean Difference	95% Confidence Interval of Mean		Significance
			Lower Bound	Upper Bound	
South Region	Midwest Region	0.022	-0.58	0.63	1.000
	West Region	-2.01	-4.98	0.96	0.286
	Northeast Region	-2.65	-3.09	-2.20	0.0001
Midwest Region	South Region	-0.022	-0.63	0.58	1.000
	West Region	-2.03	-5.03	0.97	0.287
	Northeast Region	-2.67	-3.33	-2.01	0.0001
West Region	South Region	2.01	-0.96	4.98	0.286
	Midwest Region	2.03	-0.97	5.03	0.287
	Northeast Region	-0.64	-3.62	2.34	0.941
Northeast Region	South Region	2.65	2.20	3.09	0.0001
	Midwest Region	2.67	2.01	3.33	0.0001
	West Region	0.64	-2.34	3.62	0.941

Ethical approval

This study was conducted in compliance with ethical standards, reviewed by our institutional review board and deemed exempt.

Source of funding

None.

Author contribution

Study design and conception: AE. Data collection, interpretation and analysis: BS, IL, RA, MM, AE. Manuscript preparation: BS, IL, RA, MM, AE. Critical revision of manuscript: BS, IL, RA, MM, AE. All authors read and approved the final manuscript.

Trial registry number

Not applicable.

Guarantor

Mark McKenney.
Adel Elkbuli.

Declaration of competing interest

Authors declare no competing interests.

Table 2
Comparison of the population per square mile by U.S. Region.

Census Region		Mean Difference	95% Confidence Interval of Mean		Significance
			Lower Bound	Upper Bound	
South Region	Midwest Region	4683.24	-5303.37	14669.84	0.618
	West Region	13372.46	4125.14	22619.78	0.001
	Northeast Region	-6128.50	-16024.57	3767.58	0.380
Midwest Region	South Region	-4683.24	-14669.84	5303.37	0.618
	West Region	8689.22	3870.02	13508.42	0.0001
	Northeast Region	-10811.74	-16729.97	-4893.50	0.0001
West Region	South Region	-13372.46	-22619.78	-4125.14	0.001
	Midwest Region	-8689.22	-13508.42	-3870.02	0.0001
	Northeast Region	-19500.96	-23957.66	-15044.25	0.0001
Northeast Region	South Region	6128.50	-3767.58	16024.57	0.380
	Midwest Region	10811.74	4893.4993	16729.97	0.0001
	West Region	19500.96	15044.25	23957.66	0.0001

Table 3
Comparison of the median household income (\$) by U.S. Region.

Census Region		Mean Difference	95% Confidence Interval of Mean		Significance
			Lower Bound	Upper Bound	
South Region	Midwest Region	-6,827.13	-21,226.88	7,572.62	0.571
	West Region	-56,699.88	-69,837.68	-43,562.09	0.0001
	Northeast Region	-32,492.43	-37,774.93	-27,209.93	0.0001
Midwest Region	South Region	6,827.13	-7,572.62	21,226.88	0.571
	West Region	-49,872.75	-68,646.47	-31,099.04	0.0001
	Northeast Region	-25,665.30	-40,585.62	-10,744.99	0.0001
West Region	South Region	56,699.88	43,562.09	69,837.68	0.0001
	Midwest Region	49,872.75	31,099.04	68,646.47	0.0001
	Northeast Region	24,207.45	10,449.21	37,965.69	0.0001
Northeast Region	South Region	32,492.43	27,209.93	37,774.93	0.0001
	Midwest Region	25,665.30	10,744.99	40,585.62	0.0001
	West Region	-24,207.45	-37,965.69	-10,449.21	0.0001

Table 4
Comparison of the unemployment rate (%) by U.S. Region.

Census Region		Mean Difference	95% Confidence Interval of Mean		Significance
			Lower Bound	Upper Bound	
South Region	Midwest Region	-4.32	-8.39	-0.26	0.034
	West Region	2.72	1.75	3.68	0.0001
	Northeast Region	0.66	-0.28	1.61	0.269
Midwest Region	South Region	4.32	0.26	8.39	0.034
	West Region	7.04	3.03	11.05	0.0001
	Northeast Region	4.99	0.98	8.99	0.011
West Region	South Region	-2.72	-3.68	-1.75	0.0001
	Midwest Region	-7.04	-11.05	-3.03	0.0001
	Northeast Region	-2.05	-2.64	-1.46	0.0001
Northeast Region	South Region	-0.66	-1.61	0.28	0.269
	Midwest Region	-4.99	-8.99	-0.98	0.011
	West Region	2.05	1.46	2.64	0.0001

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