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Neighborhood Condition Prevalence Rates Correlate With COVID-19 Mortality in Milwaukee County, Wisconsin

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Purpose We sought to determine if census tract-level (ie, neighborhood) COVID-19 death rates in Milwaukee County correlated with the census tract-level condition prevalence rates (CPRs) for individual COVID-19 mortality risk.

Methods This study used Milwaukee County-reported COVID-19 death rates per 100,000 lives for the 296 census tracts within the county to perform a linear regression with individual COVID-19 mortality risk CPR, mean age, racial composition of census tract (by percentage of non-White residents), and poverty (by percentage within census tract), followed by multiple regression with all 7 CPRs as well as the 7 CPRs combined with the additional demographic variables. CPR estimates were accessed from the Centers for Disease Control and Prevention 500 Cities Project. Demographics were accessed from the U.S. Census. The Milwaukee County Medical Examiner's office identified 898 deaths from COVID-19 in Milwaukee County from March 2020 to June 2021.

Results Among the variables included, crude death rate demonstrated a statistically significant association with the 7 COVID-19 mortality risk CPRs (as analyzed collectively), census tract mean age, and several of the CPRs individually. The addition of census tract age, race, and poverty in multiple regression did not improve the association of the 7 CPRs with crude death rate.

Conclusions Results from this population-level study indicated that census tracts with high COVID-19 mortality correlated with high-risk condition prevalence estimates within those census tracts, illustrating how health data collection and analysis at a census tract level could be helpful when planning pandemic-mitigating public health efforts. (*J Patient Cent Res Rev.* 2023;10:38-44.)

Keywords COVID-19; mortality; risk model; public health; neighborhood; prevalence; data science; pandemic

A fatal COVID-19 outcome has been associated with individual preexisting factors. These preexisting factors include age group, race, sex, obesity, hypertension, diabetes mellitus, chronic asthma (CASM), coronary heart disease (CHD), chronic obstructive pulmonary disease (COPD), and chronic renal disease (CRD).[1-7] These demographics and conditions are deemed "risks" for individuals. Populations may not demonstrate similar risks when applying the prevalence rates in forecasting a neighborhood risk of severe COVID-19 outcome, like death rates.[8]

Neighborhoods in Milwaukee County, Wisconsin, contain a wide prevalence range of these individual factors.[9] The variation between neighborhoods offers an opportunity to discover if these individual conditions are also associated in neighborhoods where COVID-19 was most deadly, as represented by a COVID-19 death rate. Disparities in COVID-19 death rates in urban settings, like Milwaukee County, have been reported to be clustered among minorities and in neighborhoods known for having higher preexisting individual risk factor prevalence rates.[10]

The public health response to COVID-19 was mitigation and vaccine promotion. Health interventions such as social distancing, wearing face masks, and good hygiene have been projected to significantly reduce COVID-19 transmission rates.[11] Vaccine awareness and uptake has predicted a decline in COVID-19 cases in the United States.[12] Health promotion interventions to prevent COVID-19 deaths could be better targeted by knowing the location of the highest COVID-19 mortality risk. Critical public health interventions, like health promotion involving the COVID-19 pandemic, are provided in a decentralized fashion at local health departments in the United States. Local data within a health department's responsible area are valuable when creating tailored,

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localized health communication.[13,14] Public health departments must effectively manage available resources to deliver health promotion and vaccine uptake across large populations. The specificity of health data at a U.S. city level (hundreds of thousands of people) or zip code level (tens of thousands of people) can have considerable variation, with wide ranges of disease prevalence, such as was seen in New York City.[16]

Census tracts are smaller geographic regions with information gathered by the U.S. Census every 10 years. A few reports at the census tract level support the consistency of census tract health information.[17,18] Milwaukee County contains 947,735 residents, 30 zip codes (with a mean of 27,232 residents), and 296 census tracts (with a much smaller mean of 3202 residents). For a visual overlay, see https://city.milwaukee.gov/ImageLibrary/Groups/cityDCD/planning/data/pdfs/census_zipcode.pdf. This similarity of census tract data — as opposed to the wider variation of zip code data — and the associated census tract size might allow a better focus on COVID-19 mitigation and vaccination education.

Health data using small area estimates are needed but uncommon.[13] The U.S. Centers for Disease Control and Prevention (CDC) 500 Cities Project, supported by the Robert Wood Johnson Foundation, provides a unique estimate of 27 health-related issues at the census tract level.[19] Health outcome measures in 500 Cities Project estimates include cancer, stroke, arthritis, mental health, teeth loss, CASM, CHD, COPD, CRD, diabetes, hypertension, and obesity. These prevalence estimates, based on data from the Behavioral Risk Factor Surveillance Survey, have been validated against samples of national and local prevalence rates.[20,21] These measures have highlighted the significant disparities at the neighborhood level and the need to address disparities at that granular level.[10] 500 Cities Project data have shown associations between health conditions and other external factors, such as green cover, social media posts, and projecting citywide COVID-19 resource needs.[22-24] However, the 500 Cities Project prevalence dataset has not been used as a source to predict novel outcomes like COVID-19 death rates.

This study asked the research question: Does the census tract-level outcome of Milwaukee COVID-19 death rates correlate with the census tract-level condition prevalence rates (CPRs) obtained from the 500 Cities Project dataset? The aim was to confirm whether neighborhoods within Milwaukee County that have higher COVID-19 mortality risk, as per their estimated CPRs, did indeed correlate with the areas that experienced highest COVID-19 death rates.

METHODS

This study protocol was deemed exempt from required oversight by the institutional review boards of both the Imperial College of London (London, United Kingdom) and Ascension (Milwaukee, WI).

Data Sources

Health Prevalence Data. The 500 Cities Project, as described by the CDC, "provided city- and census tract-level small area estimates for chronic condition risk factors, health outcomes, and clinical preventive services use for the largest 500 cities in the United States. These small area estimates allowed cities and local health departments to better understand the burden and geographic distribution of health-related variables in their jurisdictions and assisted them in planning public health interventions."[19]

CPRs are estimates created from data collected in the CDC's Behavioral Risk Factor Surveillance Survey (BRFSS). The BRFSS responses allow mean percentage estimates for survey responses within census tracts. These mean prevalence rate estimates include health outcomes, prevention, and unhealthy behavior prevalence rates for adults (ie, ≥18 years of age). Health outcome prevalence rates include CASM, CHD, COPD, CRD, diabetes, hypertension, and obesity. Prevalence rates were obtained from the CDC website for these health outcomes of interest.[19] The dataset was downloaded containing the relevant census tract-level mean prevalence rates (in percentages) and was reduced to the 7 conditions listed above. The population of each tract, deaths from COVID-19, and these 7 CPRs were arranged into columns in an Excel spreadsheet (Microsoft Corp.) for the 296 census tracts of Milwaukee County. The demographic predictors of mean age, percentage of non-White residents, and percentage of persons in the poverty level were accessed from census.gov for each of the 296 census tracts and arranged in 3 additional columns.

COVID-19 Mortality Data. Deaths occurring in Milwaukee County from COVID-19 were tracked and provided at public request from the Milwaukee County Medical Examiner's Office. This fatality dataset contains the last known address of residents from March 2020 through May 2021. The coroner's office collects these data as part of reporting to the Wisconsin Department of Health for the National Bureau of Vital Statistics.

Data Management

Milwaukee County-specific 500 Cities Project data containing all 27 variables were reduced to a file containing 1) the 296 census tract identifiers, 2) the tract population, 3) the 7 relevant mean prevalence rates (CASM, CHD, COPD, CRD, diabetes, hypertension, obesity), and 4) the mean age, percentage of non-White residents, and percentage in poverty. In May 2021, the Medical Examiner's office provided the residences of persons identified as experiencing COVID-19 death. Census tracts were obtained for these addresses by submitting the file list to census.gov. Unidentified addresses were confirmed to not represent residential addresses in Milwaukee County. Deaths were assessed for residences in Milwaukee County and residences in the census tracts. Autopsies reported outside of Milwaukee County were not classifiable by census tracts in Milwaukee County, and deaths in commercial residences (nursing homes and other extended care facilities) were not included due to those reflecting nonpermanent residents of the recorded census tract.

The COVID-19 crude death rate (CDR) was expressed as assessable deaths per 100,000 for each of the 296 census tracts.

Analysis

500 Cities Project data and COVID-19 mortality data were combined into a single Excel (.csv) file and imported for analysis into the open-source statistical package R (R Foundation for Statistical Computing). The R code was: ModelCDRandCM<-lm(CDR~CASM+CHD+COPD+CRD+diabetes+hypertension+obesity) — with CDR defined as assessable deaths per 100,000 lives in each of the 296 census tracts and the 7 CPRs (CASM, CHD, COPD, CRD, diabetes, hypertension, and obesity) indicating the mean prevalence rates in percentages for each illness. The mean prevalence rate values and their first and third quartiles were calculated to verify a normal distribution for applying a linear regression analysis. The assumptions of linearity, variance, independence, and normality were established by reviewing the data prior to its inclusion in the analysis. Data were reviewed in a scatter plot, with residuals reviewed for variance and distribution. The alpha value was set at 0.05.

All analysis was conducted in R version 3.6.3, with base R statistical packages. The R^2 statistic, as a measure of how well the parameters predicted the outcome, and the F-statistic, as a measure of the variance from the model, were included in analysis.

RESULTS

Table 1 shows the mean and interquartile range for the 7 CPRs and 3 demographics across the 296 Milwaukee County census tracts. A normal distribution of values was demonstrated for the 296 census tracts in the analysis.

The Milwaukee County Medical Examiner, which also provides autopsies for surrounding counties as an accredited office, reported 1129 deaths from COVID-19 from March 2020 to June 2021. Deaths were provided by the last known residence. Some addresses were in surrounding counties, and some were in nonresidences (nursing homes, rehabilitation units, other extended care facilities). The COVID-19 related deaths included in the final assessment was 898. Deaths excluded from the analysis included a) those not part of Milwaukee

Table 1. Mean and Quartile Values for Condition Prevalence Rates and Demographics for all 296 Census Tracts in Milwaukee County (pop. 947,735)

Census tract variable	Mean	First quartile	Third quartile
Health conditions			
Chronic asthma	11.1%	9.4%	12.7%
Cardiac heart disease	6.1%	5.1%	6.9%
COPD	5.3%	6.7%	7.8%
Hypertension	31.0%	26.0%	36.0%
Diabetes	8.1%	11.1%	13.9%
Chronic renal disease	3.2%	2.6%	3.7%
Obesity	37.2%	30.9%	44.1%
Demographics			
Mean age (in years)	34.9	30.1	39.5
Race (as % of non-White residents)	52.5%	22.0%	87.0%
Income (as % of those in poverty)	21.8%	9.0%	33.0%

Mean prevalence rate values and their first and third quartiles were calculated to verify a normal distribution for applying a linear regression analysis.

COPD, chronic obstructive pulmonary disease.

County census tracts (n=132), and b) those recorded as nonresidents of the tract (n=174). Some exclusions belonged to both groups (n=75).

The mean CDR for census tracts was 94 deaths/100,000 (range: 0–443/100,000; first quartile: 33/100,000; third quartile: 134/100,000).

Table 2 includes linear regression analysis results for mean age, percentage of non-White residents, and percentage in poverty from the 2010 U.S. Census. Several conditions were correlated with the CDR at statistically significant levels, including CHD, hypertension, CRD, COPD, and diabetes (Table 2). The R^2 and F-statistic provide measures of how much that statistical relationship denotes about the relationship between the independent factors, the CPRs, and the outcome, ie, CDR. Table 2 shows mean age, a known individual contributor to COVID-19 mortality, was statistically significant, whereas non-White race and poverty rates were not individually significant. The interaction between the three demographics was more statistically significant (ie, had a higher R^2). The analysis that included all the previously known risk conditions provided the greatest level of statistical significance, the best R^2, and satisfactory F-statistic. The highest R^2 assessed resulted when all the condition prevalences were combined.

Table 3 shows results from multiple regression analyses for the 7 CPRs, the 3 demographic parameters, and the combination of both prevalence rates and demographics. All three analyses were statistically significant. The inclusion of the demographics with the CPRs did not improve the probability, R^2, or F-statistic over those of the CPRs alone.

Table 2. Two Linear Regression Results for Crude Death Rate and Factors

Conditions/demographics	R^2	F-stat	*P*
Chronic asthma	0.004	1.05	0.321
Coronary heart disease	0.11	37.60	<0.001
COPD	0.05	15.37	<0.001
Hypertension	0.06	20.40	<0.001
Diabetes	0.04	11.40	<0.001
Chronic renal disease	0.07	22.07	<0.001
Obesity	0.01	1.90	0.186
Mean age	0.03	10.70	0.004
Percentage non-White	0.004	1.10	0.366
Percentage poverty	0.0006	0.17	0.712

COPD, chronic obstructive pulmonary disease.

Table 3. Multiple Regression Results

Variables	R^2	F-stat	*P*
All health outcomes	0.18	8.80	<0.001
All demographics	0.06	6.64	<0.001
All health outcomes and demographics	0.18	6.50	<0.001

DISCUSSION

This study showed that mean prevalence rates for several conditions (CHD, CRD, COPD, CASM, diabetes, hypertension, and obesity) within a census tract are positively associated with the worst COVID-19 death rates in census tracts. Some of the CPRs were associated with COVID-19 death rates in linear regressions. Higher CHD, hypertension, CRD, COPD, and diabetes prevalence rates were all associated with higher death rates in a census tract but with little individual contribution to the explanation of the CDR. CASM and obesity, associated with greater COVID-19 mortality in individual patients, were not associated with higher COVID-19 CDR. CASM and obesity did increase the predictive value of the analysis with the other mean condition rates. Mean age was a significant factor associated with higher CDR from COVID-19. Census tract percentage of non-White residents was not associated with higher CDR from COVID-19, nor was percentage in poverty. The 7 CPRs, when analyzed collectively, had the greatest association without addition of the demographics.

These results do highlight the complexities of population and individual risk factors. Age has been reported to have a strong association for poor COVID-19 outcomes in individuals,[1-7] as was seen in this population study. Many of the individual COVID-19 mortality risk conditions do increase with age. Therefore, the mean age of a neighborhood would be expected to be associated with higher CPRs for CHD, diabetes, and hypertension. This association of age and COVID-19 risk factors may explain why the mean age does not identify additional risk in a neighborhood. Our study suggests that CPRs are more specific drivers of COVID-19 CDR at a population level.

Poverty is complicated by other factors. Students living around the several college campuses had neighborhoods with higher poverty rates but at a younger mean age. Younger age people in poverty make the risk from poverty less for COVID-19 mortality due to their age and may explain the lack of a poverty association. COVID-19 risk health condition rates may have greater associations with communities at risk at the population level due to these complexities.

This study indicates that small population sizes may have advantages in detecting at-risk groups. Focusing on mitigation measures and vaccine education for a smaller target population is theoretically more managable.[25] Few population-level studies exist to verify that smaller populations have less variation than larger population. Kong and Zhang have documented the greater homogeneity in smaller area analysis; and their documentation showed zip codes as having more heterogeneity than neighborhood-level health data.[13] The mean Milwaukee County zip code contains 27,232 people while the mean Milwaukee County tract contain 3202 people. A few census tracts identified as having greater risk within a zip code could provide a more manageable target population for public health interventions.

This geographic analysis remains a work in progress. The statistics suggest that a relationship exists, but the strength of that relationship, as judged by R^2 values, could be better. The best R^2 would only predict 18% of the factors leading to COVID-19 mortality in a census tract. Part of the study's weakness may be that the census tracts have smaller populations. Small places enhance the population similarity and may improve sensitivity. Small numbers also may have very local factors, such as the loss of a local clinic, contributing to lower R^2 values, which may not avail themselves to this type of approach.

This study illustrates that gathering health data helps in monitoring the conditions reported and can also help in unexpected fashions, such as risk assessment for infectious disease.[26] Bu et al described how these data are used to direct public health services in the management of hypertension, diabetes, and medicine adherence. The data gathered by the BRFSS allowed the creation of prevalence rate estimates in the 500 Cities Project for public health practitioners to target health promotion. The COVID-19 pandemic identified one unexpected value of health information in a community. This study suggests the CPRs that were estimated from local data collection might have value in directing local public health interventions.

Limitations

Limitations of this study are several. First, the sample is only valid in Milwaukee County. The 500 Cities Project reaches many cities where additional validation could be confirmed. Milwaukee County's significant health disparities provided an opportunity for study to demonstrate the value of the CPR data.[9] Milwaukee County does have common issues with other metropolitan cities, but wider confirmation will be needed. Second, the 500 Cities Project data are estimates of condition prevalence based on the surveys done; the validity of the projections has been confirmed in 2 studies,[20,21] although one report warned against using these data for projections.[27] This report's conclusion was that the estimates are best used when two separate data sources are employed; in our case, we used both 500 Cities Project data and Milwaukee County Medical Examiner reports. Additionally, the data were available for this urban area, however, COVID-19 also spread rapidly in rural areas. Better systems for providing condition rates for census tract-level rural communities would be useful in the future.

The choice of conditions that influence COVID-19 mortality has undergone further evaluations. For example, since this project began, Wang et al conducted a meta-analysis for chronic asthma.[28] They identified 4 studies with sufficient information on asthma and COVID-19 mortality. They concluded that their initial review did not support asthma but that it was based on a small number of studies. Therefore, the conditions included may change but the analysis continues to include those factors identified in the earliest reports.

Finally, the death rates from COVID-19 have been challenged as underestimates.[29] The incorrect cause of death entry in many locations has suggested these reports are potentially inaccurate. Milwaukee County has a full-time medical examiner and an accredited office, reducing that concern.

Public Health Implications

The COVID-19 pandemic illustrates that health data collection may have many unexpected health promotion-planning benefits. Condition prevalence estimates from the 500 Cities Project correlate with death outcomes and can help local health departments direct health promotion resources. Funding for health data survey expansion could improve public health resource use and health promotion effectiveness in a broader fashion. The 500 Cities Project dataset may demonstrate where resources can be used, not just in this health emergency context but for noncommunicable condition projections and management.[30] More frequent and wider collections of health data should be a national priority to 1) plan health promotion, and b) assess the success of promotion-related interventions.

CONCLUSIONS

Health data found in the 500 Cities Project may identify at-risk communities for specific COVID-19 health promotion. The universal approach of promoting mitigation early in the pandemic may have avoided some deaths. A more targeted mitigation effect on these higher-risk census tracts may have reduced even more deaths.[31] The COVID-19 pandemic is not over, and knowing where mitigation and vaccinations will prevent the most deaths is potentially valuable.

Patient-Friendly Recap

- Public health efforts to prevent deaths from COVID-19 use local prevalence of known risk factors, such as older age or diabetes, to assess risk level for a given geographic area.
- For Milwaukee County, authors compared neighborhood-specific data from the CDC's 500 Cities Project to the COVID-19 death rates reported for those neighborhoods to confirm whether presence of risk factors in a small area actually aligned with higher mortality.
- They found that use of 500 Cities Project data was able to identify at-risk communities and could be valuable when pursuing targeted pandemic mitigation or health promotion, including vaccines.

Author Contributions

Study design: Morris. Data acquisition or analysis: Morris. Manuscript drafting: Morris. Critical revision: Morris.

Conflicts of Interest

None.

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