Geographic mortality and morbidity disparities in the US and Washington State: Migration, rurality, and wildfire smoke

David Coomes

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Reading Committee:

Stephen Mooney, Chair

Anjum Hajat

Ali Rowhani-Rahbar

Program Authorized to Offer Degree:

Department of Epidemiology

University of Washington

Abstract

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David Coomes

Chair of the Supervisory Committee:
Stephen Mooney
Department of Epidemiology

This dissertation examined geographic all-cause and cause-specific mortality disparities in the US and mental health disparities associated with wildfire-specific air pollution exposure in Washington State. Geographic analyses found that migration and rurality were associated with all-cause mortality, and migration, poverty, and rurality were associated with cause-specific mortality patterns in the US from 2000-2019. Higher county-level out migration was associated with higher age-adjusted mortality and with higher chronic mortality. County-level poverty rates were positively associated with mortality from all causes. In Washington, heavy wildfire air pollution led to increased visits to emergency departments with a mental health diagnosis between 2019 and 2023. The observed effects were strongest among men, those aged 26-45, and in urban areas.

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Chapter 1: Introduction

This dissertation focuses on health disparities, with an emphasis on geographic and environmental disparities in morbidity and mortality. To do this, we draw upon a specific conception of the role of place in health that seeks to incorporate a ‘relational’ understanding of place and health.[1] Research on geographic health disparities has often focused on characteristics of the built environment, such as access to healthcare, nutritious food (i.e., food deserts), and transportation,[2] or aggregate individual behavior, such as smoking rates and physical inactivity.[3] While these factors certainly contribute to disparate health outcomes, research on relational understandings of the role of place in health outcomes can contribute to a better understanding of the complex way that populations (composition) and areas (context) mutually reproduce and reinforce each other to create possible health outcomes.[1]

We use a theoretical framework similar to other research on small area health disparities, wherein population-level health outcomes are a function of macro-level social inequalities, meso-level area characteristics, and micro-level individual health.[4, 5] Important in this framework is an understanding of how these drivers of health disparities operate on different scales, but these scales also interact to influence each other. We use this as a framework to better understand how health disparities – as a process – become fixed at specific geographic locations.[6]

We also lean heavily on Fundamental Cause Theory to explain morbidity and mortality disparities.[7] This theory describes how those with more socioeconomic resources – including knowledge, money, power, prestige, and social connections – can use these as “flexible resources” to improve health by avoiding risk or accessing benefits.[8] Fundamental cause theory can be integrated into our contextual understanding of place-based health disparities by highlighting processes through which people or groups can use flexible resources to access place-based benefits, or conversely to avoid places that may confer negative health benefits.

The second chapter of this dissertation focuses on one of these processes by exploring the role of migration in rural-urban mortality disparities. The rural mortality penalty is a phenomenon in which age-adjusted mortality in rural areas of the US are higher compared to urban areas.[9] This disparity first emerged in the 1980s and has grown consistently since then, and it exists within sex, age, racial, and income categories.[10–12] In Chapter 2, we ask whether county-level out-migration is associated with age-adjusted mortality, and whether this association is modified by rurality, geographic location, and age.

This analysis aligns with the relational view of space in thinking about counties as nodes in a (migration) network rather than static geographical boundaries. Categorizing rurality as a geographic characteristic is difficult, not just for the fact that rurality does not fit into distinct categories, but also because material and non-material goods as well as people flow back and forth across the rural-urban interface creating “fuzzy” boundaries.[13] The interrogation of migration and mortality in the rural mortality context can help to consider what upstream drivers impact population composition and therefore area-level mortality measures.

While rurality is a major focus of this dissertation, it is not the only upstream driver of health disparities we are interested in. Chapter 3 further examines geographic and rural disparities in causes of death using a latent class framework. Overall life expectancy in the US has stagnated since 2010 and even declined among working age adults due to increases in suicide, drug poisoning, and alcohol-related mortality along with stalled progress in cardiovascular mortality.[14] For this chapter, we use latent class analysis to construct a typology of counties based on the top 12 causes of death in the US, and measure the association of these classes with rurality, poverty, and migration.

Grouping counties by cause-specific mortality outcomes using our latent class framework allows us to examine potential patterns in spatial mortality inequality without attempting to isolate individual causes or work out how complex patterns of upstream drivers at multiple levels may result in disparate mortality outcomes. Although that work is of course important, a holistic understanding of geographic disparities in cause-specific mortality patterns can support a better understanding of the results of these complex patterns.

Chapter 4 takes a different track than the previous two substantive chapters, examining the impact of wildfire smoke on emergency department (ED) mental health visits in Washington State. We use zip code level data from 2019-2023 to estimate the impact of wildfire-specific fine particulate matter ($PM_{2.5}$) on the number of ED visits with a mental health diagnosis. To examine differences in sociodemographic and geographic characteristics, we also investigate the impact by sex, age, and rurality. While wildfire-specific ambient air pollution may impact populations across the sociodemographic spectrum, including affluent communities, those with more resources are able to mitigate the impact of pollution through better air filtration systems, the ability to work inside or from home, or even to leave the impacted area while pollution levels are high.

We often include areas (like counties or zip codes) or area-level measures in health disparities research without considering the implicit assumptions we make when we include these in our analyses. It is true that these areas may be administrative boundaries (at least in the case of counties), and the administrative processes at that level, along with other levels (i.e., city, state, national), can impact health outcomes within their boundaries. However, because populations and places work to co-constitute each other we should also consider contextual and relational processes that impact population health, and the messy ways in which these processes operate. In other words, we should consider the interaction between populations and places that shape health. This work is important because understanding and quantifying how place impacts health is necessary for creating policy that improves health, particularly among the most disadvantaged groups.

Chapter 2: Migration and the rural mortality penalty: Examining the association of county-level migration and rurality with age-specific mortality

ABSTRACT

The rural mortality penalty describes the phenomenon wherein age-adjusted mortality is higher in rural US counties compared to urban US counties. Previous research has overlooked the role of migration in shaping population health outcomes, including the rural mortality penalty. We use hierarchical regression models with all-cause mortality and yearly migration data by county from 2000-2019 to identify the association between out-migration and mortality and explore whether this association varies by rurality and age-group. We find that each 1% higher out-migration is associated with a 0.82% (95% credible interval: 0.78, 0.86%) higher age-adjusted mortality rate. The association varies by rurality status, with urban counties and rural counties adjacent to urban counties having stronger positive associations compared to rural counties not near urban counties. The association also varies by age, with the youngest and oldest adult (aged 20-30 and 80+) populations having lower mortality in high out-migration counties while middle aged adults (aged 31-79) have higher mortality in such places. Future work should consider the selective role of migration in determining population-level health disparities.

INTRODUCTION

The rural mortality penalty, characterized by higher age-adjusted mortality in rural areas compared to urban areas in the US, has emerged over the last few decades.[9] The gap between rural and urban mortality has continued to widen since it was first noted in 2008, and is driven both by more rapidly declining mortality rates in urban areas as compared to rural areas and increasing mortality rates for some rural populations.[15, 16] Previous research on the underlying causes of the rural mortality penalty has focused on economic characteristics of rural areas, such as lack of access to healthcare,[17, 18] or population level differences in health behaviors such as higher rates of smoking and physical inactivity in rural areas.[3] However, some place-based researchers advocate for focusing on contextul and relational understandings of the association between place and health.[1] Migration is one such process; both urban and rural populations comprise individuals who are mobile over their life course, and urban-rural mortality disparities may be – at least in part – attributed to selective migration patterns.

Rural to urban migration has contributed to consistently declining proportions of Americans living in rural areas.[19] This migration is also selective; historic trends have seen younger (and healthier) individuals moving from rural areas to urban areas.[20] Chronic selective out-migration of young adults, reported in many rural counties, directly drives population loss but also contributes to other demographic processes that indirectly drive population loss, including population aging and lower fertility.[19] This process may be accelerating – despite steadily increasing proportions of people living in urban areas, rural areas in the U.S. saw consistent absolute population growth until 2010, after which the total rural population has declined.[19]

In addition to age-specific patterns, socioeconomic status (SES) also plays a role in migration. Research has shown that poor and non-poor populations have similar migration rates, although they migrate in different patterns. When moving, low-income individuals are more likely to move to higher-poverty counties as compared to individuals with higher-income, resulting in the spatial concentration of poverty.[21, 22] Research examining migration by rurality and poverty found that poverty rates increased over time in both rural and urban high-poverty counties; in rural poor counties it was due to net in-migration of poor individuals and net out-migration of non-poor individuals whereas urban poor counties experienced net out-migration of poor individuals but higher net out-migration of non-poor individuals.[22] Overall, the evidence suggests that migration tends to maintain, or even worsen, spatial patterns of poverty distribution at the county-level for both rural and urban counties, though overall migration patterns may differ by rural/urban status. These age- and SES-specific migration patterns may contribute to increasing rural mortality disparities through the movement of younger and healthier individuals from rural to urban areas, and the concentration of older and poorer [and sicker?] individuals in low-income rural areas.

Poor and non-poor populations have different reasons for migrating.[21] Implicit in our assumptions of health and migration is the idea that people can, and will, migrate for economic opportunity and better health; however, this is not always the case. A lack of affordable housing and appropriate jobs can limit opportunities to move. In fact, affordable housing may be one reason to move to high-poverty rural areas, even if jobs are scarce. The differential opportunities theory describes how labor and housing opportunities for poor individuals differs geographically compared to non-poor individuals, thus shaping migration opportunities and patterns.[21] While non-poor movers may be motivated by pulls towards economic opportunity, relocation for poor movers may often be to high-poverty areas and more affordable housing, motivated by mobility pushes after unexpected economic hardship, such as job loss. In this way, migration may be a mechanism through which people are pushed from economic marginalization to increased healthcare marginalization and other institutional marginalization, particularly if they find affordable housing in rural areas.[23]

In addition to directly changing rural mortality through population composition, the movement or emplacement of poor people in rural areas confers additional disadvantages. The concentration of rural poverty may lead to less institutional support in the form of services – i.e., transportation, adequate schools, medical care, clean drinking water, modern sewage systems – compared to urban poor populations, as many urban centers have large enough populations to better support these systems regardless of population wealth.[24] The out-migration of young, healthy individuals from rural areas may impact the labor market in the area. Out-migration or in-migration of older, wealthier individuals to an area may impact the consumer base that healthcare or food industries rely on. Previous research has shown high rates of rural hospital closures since 2010, driven by market factors and small patient volume, though these closures have not been felt equally across all rural areas.[25]

Fundamental cause theory describes root causes of health inequalities and how access to resources can be used to avoid risks or minimize negative impacts.[26] Selective migration from resource-poor areas to resource-rich areas by individuals who are younger and higher SES fits well within the fundamental cause framework – those with more “flexible resources” are able to use those resources to move to ***areas*** with more resources, and the result is better health through access to built environment factors and labor markets, as well as social influences on individual factors (**Conceptual model, Figure S1**). Another key factor in fundamental cause theory is that individuals in higher SES groups have better individual health practices, not necessarily because they consciously choose those practices but because they are the cultural practices of the group to which they belong. For example, rural areas have higher smoking rates and so those who remain in rural areas may be more likely to smoke because it is more socially acceptable compared to those who migrate to a more urban area. In this way, individual determinants of health are influenced by sociocultural determinants, which are influenced by the ability to migrate.

While previous research on migration using small area measures has shown associations between higher proportions of domestic in-migrants and lower morbidity rates, this research focuses only on migrant receiving areas rather than also considering migrant sending areas.[27] Because migration can be a selective process that influences rural population health, it is important to understand its role in the rural mortality penalty. Doing so may inform policy aimed at reducing rural health disparities; however, little has been described about the impact of migration on the health of rural populations, including health differences between those who migrate and those who remain.

The purpose of this research is to explore whether population-level out-migration is associated with mortality, and whether this association is modified by rurality and age. The use of age-adjusted mortality in measuring the rural mortality penalty may obscure age-specific trends that differ between urban and rural areas. As migration also differs by age it is important to consider these trends when examining the role of migration in rural mortality. To answer this, we use county-level yearly mortality and migration counts in the US from 2000-2019. We ask: 1) Is out-migration associated with age-adjusted mortality at the county level? 2) Does this association differ for urban and rural counties (and by degree of rurality)? 3) Is this association different for age-specific mortality trends? This last question may help to answer which age groups are most affected by migration and rurality contextual factors.

METHODS

We use county-level mortality, migration, and rurality data from 2000-2019 to estimate associations between all-cause mortality and migration, and we examine whether this association is modified by rurality and age-group. Associations are estimated using hierarchical negative binomial models adjusting for age, year, and state-level effects.

Data

To ascertain mortality, we use nationwide deidentified death records available through the National Vital Statistics System (NVSS) from 2000-2019. These data include county of residence and cause of death as well as limited sociodemographic information (race and age) for all recorded deaths in the United States. Outcome is measured as count of all-cause mortality by 5-year age group per county. This analysis will be limited to adults aged 20 and older; age groups include 20-24, 25-29, …, 80-84, 85+. The inclusion of age groups in our models allow us to adjust for differing age structures in rural and urban areas.

County-to-county migration flow data is available from the IRS at yearly increments; we include data from 1990 to 2019. These data capture all persons in the US who file taxes through December of the year following the target year and categorize all filers as migrants or non-migrants. Migrants are defined as those with a filing address in a different county as the previous year, therefore, those who did not file in the year before the data year are not captured as migrants or non-migrants. These data include total number of out-migrants, total number of in-migrants, and non-migrants per county per year. We construct yearly out-migration and in-migration percentages as the number of migrants (out- and in-migrants respectively) divided by the total population (of filers) in each county.

For county rural status we use 2013 Rural-Urban Continuum Codes (RUCC) developed by the US Department of Agriculture's Economic Research Service (**Appendix Figure S1**). RUCC codes include nine categories based on population size for metropolitan counties (RUCC 1-3, population > 250,000) and population size and adjacency to metropolitan counties for non-metropolitan counties. We refer to RUCC 1-3 as metropolitan (metro) or urban counties, and RUCC 4-9 as non-metropolitan or rural counties throughout this paper. RUCC codes are updated approximately every 10 years – we chose the 2013 measurement as it falls roughly in the middle of the mortality data used for this analysis.

Statistical analysis

We create age-adjusted and age-specific mortality rates by year, county, and RUCC to descriptively compare differences in mortality trends between rural and urban counties. Age-adjusted mortality was constructed using the direct method and the 2000 US Census as the reference population.[28] We constructed age-adjusted mortality per county and per RUCC for each year of the study (2000-2019) using this method. We also descriptively examine overall in- and out-migration by RUCC over 20 years.

We estimate the association of migration and mortality, with modification by rurality, using hierarchical Bayesian negative binomial models, adjusting for time-period, age, and state. Deaths are aggregated to 5-year periods (2000-2004, 2005-2009, 2010-2014, 2015-2019) within each county, and migration is calculated as the percent migration (in and out) for the 10 years prior to each 5-year period (i.e., net migration for 2000-2004 deaths is calculated from 1990-1999 migration). Negative binomial models are used to account for the overdispersion in observed count outcomes (deaths) beyond what is included in a Poisson model. Age is modeled in 5-year age-groups starting from age 20-24 with age 85 and over as the highest age group. Age-group and time-period random intercepts are ordered and modeled using a second order random walk prior (RW2). These random walk priors allow for smoothing over the previous two observations rather than towards the overall mean; for example, mortality is highly dependent on age with higher mortality at higher age groups. If we used a normal prior for age, then our random intercept for age group would be pulled towards the overall mean and would not account for this known association between age and mortality. Similarly, a RW2 prior for year allows for smoothing across years while including time trends in mortality.

We included the log of the county population as an offset so that we can interpret the exponentiated coefficients as incidence rate ratios; because our outcome is number of deaths these are specifically mortality rate ratios. We also estimate models with random slopes for out-migration and in-migration to measure the heterogeneous association of out-migration and mortality by rurality, adjusting for state and age-group. These random terms are pulled towards the overall mean while still allowing the group-level effects to vary, with the shrinkage towards the mean mitigating the multiple testing problem of comparing more than one category.[15] In this way, we can compare differences in associations between migration and mortality across all rural categories without defining a specific reference category. We compare differences in the association of migration and mortality across RUCC categories using 1,000 posterior draws from the full distribution. In each draw, we rank RUCC coefficients from lowest to highest and compare the distribution of ranks across RUCC categories. We modeled our intercept and slope terms as independent in both the random intercept and random slope models. Migration estimates are mean-centered such that 0 represents the average percent migration to assist in ease of interpretation of the model estimates.

We also estimate the differential association of migration and mortality by age-group, and by age-group and rurality combined. Models that estimate the association between migration and mortality by age-group are similar to those described in the previous section, except that age-group is also included as a random slope in the model (instead of just a random intercept), which allows us to examine how the association of migration and mortality varies by age-group. Finally, we include a model that measures the association of migration and mortality by age-group and rurality. To do this, we include random intercepts and random slopes of all age-group and rurality combinations.

We use R-INLA to estimate our models. After fitting models, we estimated coefficients by simulating 1,000 draws from the full posterior and calculated median and 95% credible intervals. INLA (integrated nested Laplace approximations) uses Laplace approximations, the benefits of which are much faster computation compared to Markov Chain Monte Carlo (MCMC) methods.[29] As INLA methods approximate full MCMC methods, we checked the approximation by estimating parameters for a subset of the data using an intercept-only negative binomial model and an intercept-only model with an RW2 prior for year, with total mortality counts as the outcome using MCMC and compared these estimates to those using R-INLA (**Figure S2**).

RESULTS

Descriptive results

Age-adjusted mortality was higher among non-metropolitan counties (RUCC 4-9) compared to metropolitan counties (RUCC 1-3) for all years from 2000-2019 (**Figure 1**). Among metro counties, there was an inverse relationship between population size and mortality rates – mortality rates were lowest in counties with the largest populations (RUCC 1). Among non-metro counties, RUCC 6 (population 2,500-19,999, adjacent to metro area) had the highest mortality rate every year during the study period, however, the rankings of the other non-metro counties were not consistent over time.

While age-adjusted mortality decreased in all RUCC categories from 2000-2019, time trends show increasing disparities between metro and non-metro mortality rates over this period. The relative decrease in mortality was higher in metro counties; mortality rates in metro counties decreased by 11-21% from 2000-2019 while they decreased by only 6-8% in non-metro counties (**Supplemental Table S1**). There were also differences in temporal trends by RUCC. Age-adjusted mortality decreased among all RUCC categories from 2000-2010 and then remained relatively flat (+/- 1%) or increased slightly except for the most urban (RUCC 1), where it continued to decline, albeit at a slower rate (4.1%), between 2010 and 2019. RUCC 5 and 6 counties showed the largest increase in mortality rates from 2010-2019 (3.0%, and 2.9% respectively).

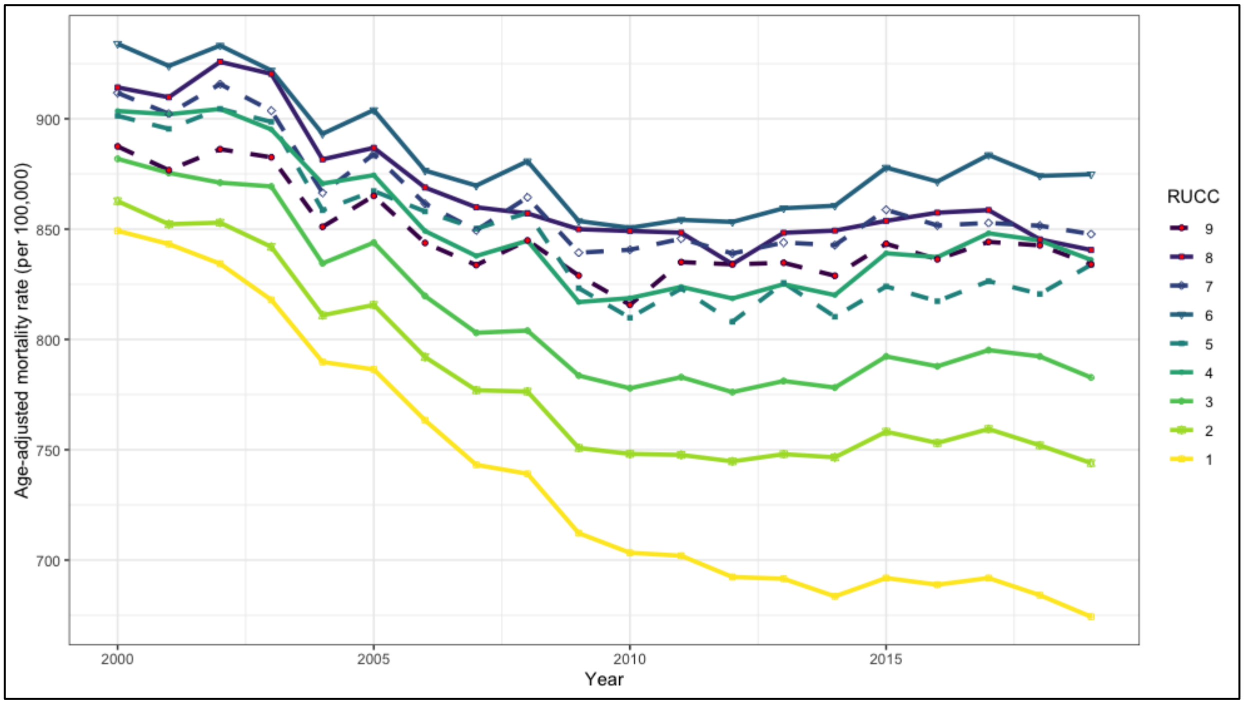

Figure 1. Age-adjusted mortality rate by RUCC and year in the US from 2000-2019. Age adjustment was calculated using the direct method and the 2000 US Census population as reference. Rural counties adjacent to urban areas are indicated by solid lines (RUCC 4, 6, 8). Rural counties not adjacent to urban areas are indicated by dashed lines (RUCC 5, 7, 9). RUCC=Rural-Urban Continuum Codes (1=most urban, 9=most rural).

Changes in mortality differed by age group from 2000-2019. Notably, mortality among those aged 30-44 increased in all RUCC categories from 2010 – 2019 (**Supplement Figure S4**). There were also differential trends in age-specific mortality by rurality. The gap in mortality between metro and non-metro counties widens considerably among those aged 30-79, with large changes among late working age adults (age 40-64), driven by increases in all-cause mortality in non-metropolitan counties from 2010-2019 in these age groups.

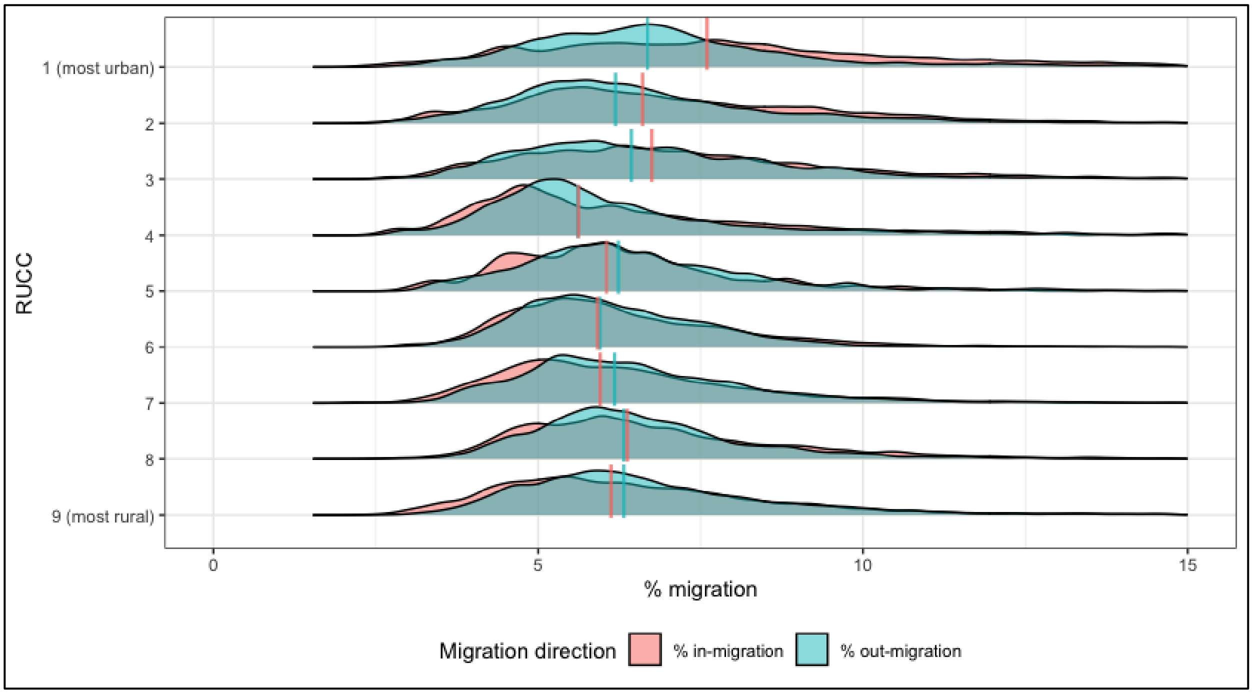

Figure 2. Distribution of county-level % out- and in-migration by rurality status. Migration is measured as number of migrants divided by total population per county. Lines represent median % out- and in-migration per RUCC. RUCC=Rural-Urban Continuum Codes (1=most urban, 9=most rural).

Migration patterns also showed rural-urban trends. Percent in-migration was higher than out-migration rates in all metro categories, with the largest difference in the most urban counties (**Figure 2**). Median percent in- and out-migration was highest in RUCC 1 counties (7.6% and 6.7% respectively), and lowest in RUCC 4 counties (in- and out-migration both 5.6%) (**Supplemental Table S1**). Median out-migration was higher than in-migration in RUCC 5, 7, and 9, which represent non-metro counties not adjacent to metropolitan areas, while in- and out-migration rates were similar in RUCC 4, 6, and 8 (non-metro counties adjacent to metro counties). This indicates that adjacency to metropolitan areas may impact migration trends in non-metropolitan areas. Out-migration and in-migration rates within counties are positively correlated – higher out-migration is associated with higher in-migration (**Supplemental Figure S5**).

Regression results

We found county-level percent out-migration to be associated with higher age-adjusted mortality rates. A 1 percentage point increase in out-migration was associated with a 0.22% (95% CI: 0.11, 0.35) increase in age-adjusted mortality rate (**Figure 3, Table S2**). When examining heterogeneity in this association by rurality, we found it to be positive in urban counties (RUCC 1-3) but there was no association of % out-migration and age-adjusted mortality in rural counties (RUCC 4-9). The strongest effect was in the most urban counties; a 1% increase in out-migration was associated with a 0.88% (95% CI: 0.63, 1.15) increase in age-adjusted mortality rates for RUCC 1 counties. In ranking RUCC random effect coefficients from 1,000 posterior draws in order to compare the size of the association of % out-migration and mortality across RUCC categories, the estimate for RUCC 1 (counties in metro areas > 1 million population) was the highest in 93% of the draws while the association for RUCC 5 (urban populations 2,500-19,999 not adjacent to a metro area) was the lowest in 53% of the draws (**Figure S6**).

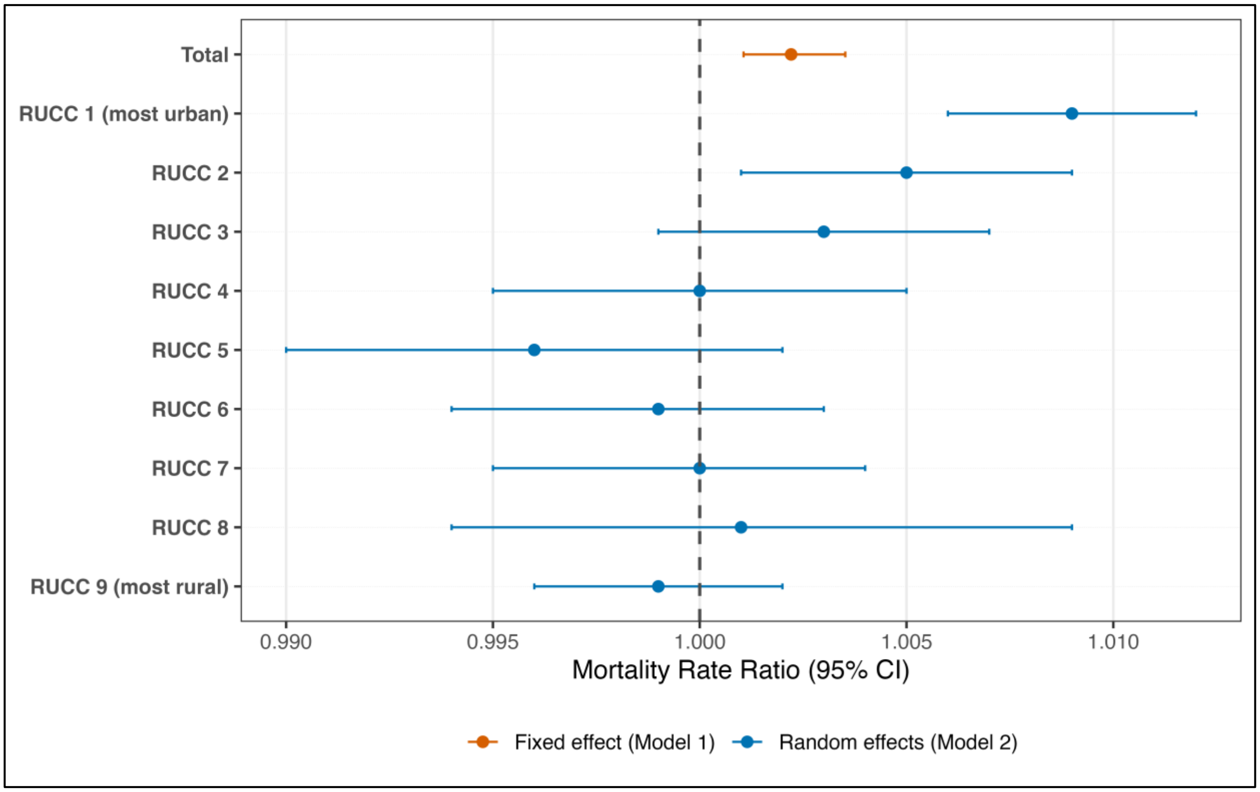

Figure 3. Effect estimates for association of % out-migration and mortality (Total) and % out-migration and mortality by Rural-Urban Continuum code (RUCC). All coefficients are exponentiated and represent mortality rate ratios of age-adjusted mortality associated with a 1% increase in out-migration. Both fixed effect estimate and random effect estimates are from hierarchical negative binomial models that include random effects for time-period and state, and adjust for % in-migration.

There is variation in age-specific mortality associated with county-level % out-migration. Younger age groups (20-24 and 25-29) have mortality rate ratios (MRR) less than 1 as percent out-migration increases, indicating that mortality rates are lower in these age groups as county-level percent out-migration increases (**Figure 4**). Mortality rate ratios are higher than 1 for age groups between 30 and 79, with the highest rates from ages 35-69 (ranging from 1.4% to 2.0% increase in age-adjusted mortality associated with 1% higher percent out-migration), indicating that mortality rates increase in these age groups as percent out migration increases. For age groups over 75 years old the MRR drops below 1 again.

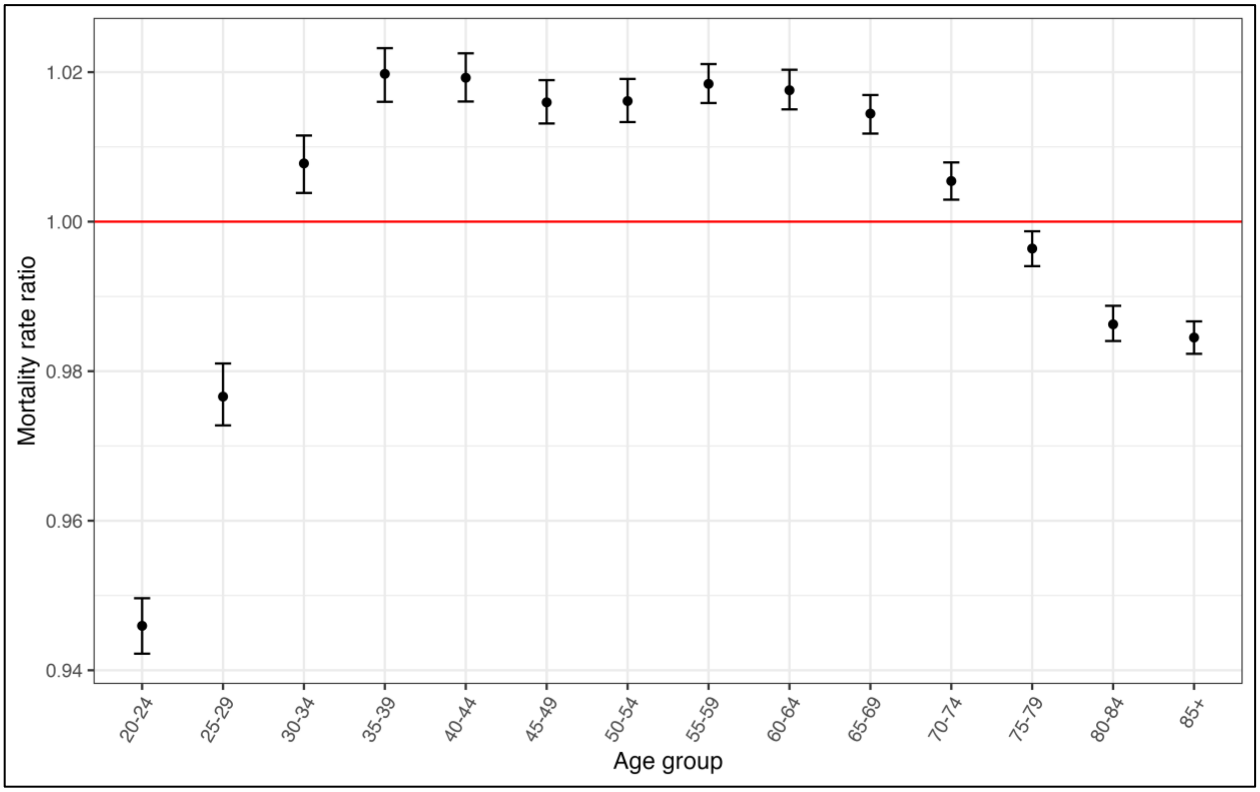

Figure 4. Age-group-specific adult mortality rate ratio association with % out-migration. Estimates indicate the age-group-specific association of county-level % out-migration and age-specific mortality.

These age-specific patterns differed across RUCC categories (**Figure 5**). The most urban counties showed the strongest associations of out-migration and mortality, which occurred among young working age adults (aged 35-49). A 1% increase in percent out-migrants was associated with a 5.8% (5.2, 6.4) increase in age-specific mortality for those aged 40-44 in RUCC 1 counties. For smaller metro counties (RUCC 2 & 3) the positive associations were not as strong and shifted notably towards older adults. Most rural categories included negative associations (MRR < 1) between out-migration and mortality for young adults (<30) but no strong associations for adults older than 30. The exception to this was in the most rural counties (RUCC 9) where we found a positive association between out-migration and mortality among adults younger than 30. A 1%

increase in out-migration was associated with a 2.7% (1.2, 4.3) increase in age-specific mortality among those aged 20-24 in the most rural counties.

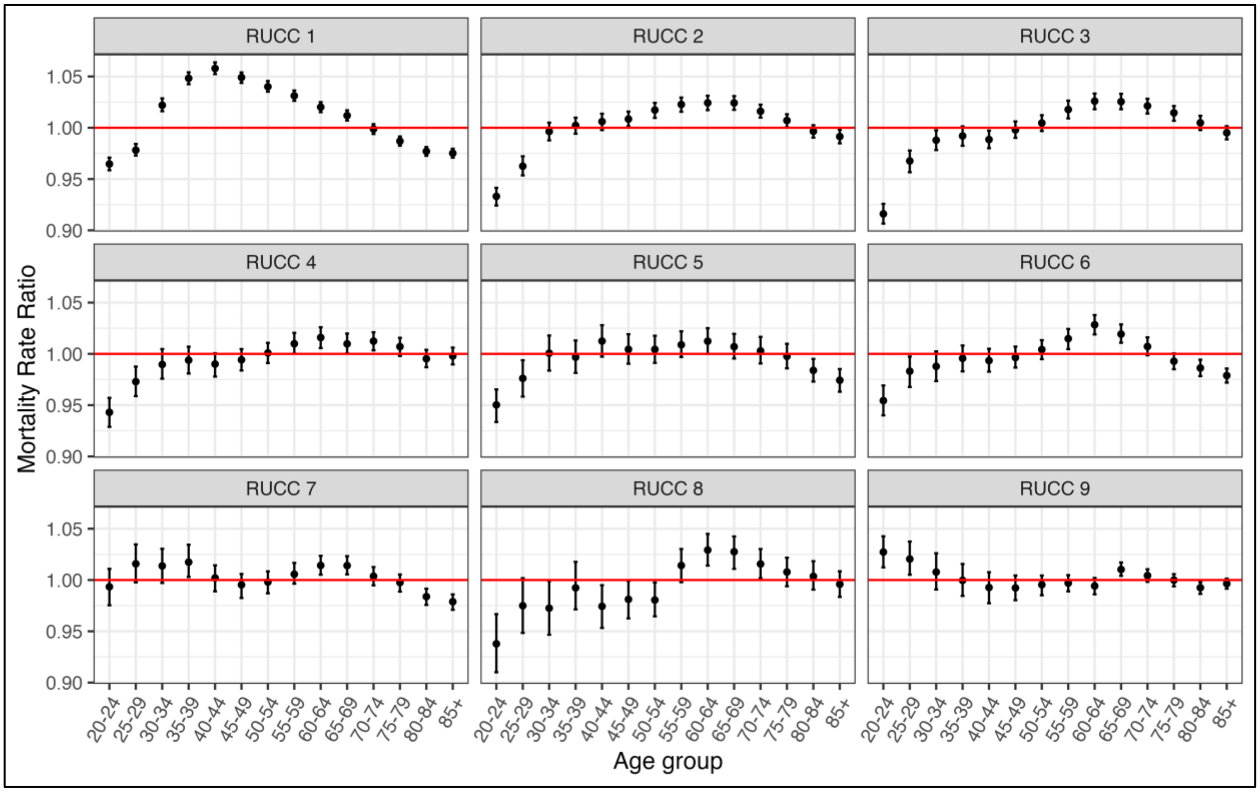

Figure 5. Age-group-specific adult mortality rate ratio association with % out-migration by Rural-Urban Continuum Code (RUCC). Estimates indicate the age-group-specific association of county-level % out-migration and age-specific mortality.

Rural counties adjacent to urban counties showed patterns that were more similar to urban counties compared to rural counties not adjacent to urban counties. Rural counties adjacent to urban counties (RUCC 6 & 8) had positive associations for older adults and negative associations for younger adults (<30), similar to urban areas. Among rural counties not adjacent to urban areas (RUCC 7 & 9), the MRR was generally equal to or greater than 1 for younger adults (<30).

DISCUSSION

We found that the proportion of the population migrating away from a county is associated with age-adjusted mortality rates – a one percentage point increase in the proportion of a population moving away from a county was associated with a 0.22% increase in age-adjusted mortality. This association varied by rurality status, with the strongest association in the most urban counties and no association in rural counties. We also found that out-migration was associated with age-specific mortality – the strongest association between out-migration and higher mortality was found among middle aged adults – and these age-specific patterns differed by rurality. Multiple other studies have examined the role of migration on individual health (i.e., health differences between those who migrate and those who do not), but there is limited previous evidence on the association between county-level out migration and mortality. While individual-level analyses show the impact of migrating or not-migrating on individual health outcomes, our ecological analysis, while limited, can show area-level effects of population migration patterns on population health outcomes, potentially highlighting migration as a process that changes population composition and aggregate health measures (e.g., mortality rates) or area-level effects (i.e., concentrations of poverty can compound individual lack of access to resources).

Our findings align with previous work in England and Wales that identified increasing inequalities in health outcomes between more and less deprived areas, driven largely by selective migration of healthier individuals – particularly among young adults – from more deprived areas to less deprived areas.[30] Other previous work has measured associations between population size changes and mortality, largely in Northern Europe, finding that population reductions were correlated with higher mortality,[31] suggesting that this association was the result of selective migration processes wherein those with better health left socially deprived areas, leaving behind a population with worse health. Our data did not allow us to examine mortality outcomes of migrants vs non-migrants; however, selective migration is one possible explanation for our population-level findings of the association between out-migration and mortality.

Our finding that out-migration is associated with higher age-adjusted mortality in urban counties but not rural counties is new. This was counter to our hypothesis that out-migration would increase age-adjusted mortality in rural counties the most. However, this finding does not take into account differences in migration patterns among rural and urban counties, particularly differences in income or wealth of migrants. ~~Limited previous research has focused mainly on individual health outcomes associated with rural to urban migration, finding higher mortality among those who migrated from rural to urban areas compared to those who stayed in rural areas.[32]~~ County-level research on poverty and migration has found that poor urban areas tend to have high out-migration of both poor and non-poor individuals, while poor rural areas tend to have in-migration of poor individuals and out migration of non-poor individuals.[22] In the context of a higher association of migration and mortality in urban areas, the in-migration of poor (and less healthy) individuals seeking a lower cost of living in rural areas may be driving this difference. Future work should consider selective processes, such as differential income or wealth of migrants moving to urban and rural areas, in examining associations between migration and mortality.

Our findings that the association of migration and mortality varies by age-group aligns with previous studies examining age-specific migration and health outcomes. While there is limited work on the variation in health outcomes associated with domestic migration, the large body of literature examining the "healthy migrant effect" among international migrants supports the idea that migrants tend to have better health than non-migrants, particularly during middle age.[35] At a population level, this would imply that net migration receiving areas would have lower age-specific mortality compared to net migration sending areas, as is seen in our analysis. An interesting finding in our study is that there is an inverse relationship between migration and mortality in younger age groups (20-29) – county level out-migration is associated with lower mortality among these ages, with particularly strong effects among those 20-24. One reason for this could be that this age group is relatively mobile compared to older age groups. There are potentially selective processes in which younger adults who stay behind in high-outmigration counties do so because there are benefits (economic, social), while those who are not able to realize those benefits move elsewhere.

The similar association in migration and age-specific mortality seen in rural areas adjacent to urban areas – different from that of rural areas not adjacent to urban areas – highlights differences between those rural areas that are more connected to urban areas compared to those that are not. One challenge to understanding rural mortality disparities is the fact that the boundary between rural and urban spaces is not easily defined. Most definitions are based on population size, however, capital, labor, people, information, and goods move between rural and urban areas, sometimes blurring the distinctions between categories.[13] Despite there being no clear boundary between rural and urban areas in the US, the creation of these categories implies a social hierarchy that can both reveal spatial disparities as well as obfuscate them.[13] In this context, some research has argued for a more nuanced understanding of rurality, distinguishing between “dim” rural areas - those that are on the periphery and well-integrated with urban areas - and “bright” rural areas - sites of economic disadvantage, such as Appalachia or Southern Black rural communities.[13] This is an argument for thinking about heterogeneity within the rural mortality penalty and the processes that shape this, such as migration.

There are important limitations to consider in interpreting this study. First, we examine total migration as a predictor of mortality but there may be age-specific migration patterns that are important in this relationship – future work should consider these. Additionally, the use of IRS data to determine mortality rates is likely selective as older and lower income individuals are less likely to file taxes, potentially biasing our estimates. Second, rurality can be measured in many ways but previous work on the rural mortality penalty has shown that it is consistent across multiple different definitions of rurality.[36] Additionally, we use a static definition of rurality which ignores the process of urbanization that may be occurring in some areas. Previous work has shown that the rural mortality penalty is influenced by reclassification, however, this was outside the scope of the current analysis.[37] Third, our study uses an ecologic design that does not allow us to extrapolate our findings to individual-level effects. Our finding of an association between out-migration and population-level mortality does not imply that those who migrate have shorter or longer life expectancy compared to those that do not migrate. Nevertheless, migration as a contextual process can still highlight population-level mortality disparities. Fourth, the use of random effects to estimate heterogeneity in the association between migration and mortality in this study relies on assumptions that may not hold true in our data, specifically the independence of our random effects with covariates and potential misspecification of our random effect distributions.[38] Finally, our analysis was exploratory in nature, and therefore our results should be interpreted accordingly.

CONCLUSION

This study found county-level out-migration to be associated with higher age-adjusted adult mortality in the US, driven by positive associations in metropolitan counties. While we did not find this association to hold in rural counties, we note that out-migration is associated with higher age-specific mortality among middle aged adults, and this association differs by rurality status. In particular, higher age-specific mortality among young adults (<30) is associated with out-migration in the most rural counties. Future research should consider the role of migration in population level composition, and how this may lead to health disparities. Policymakers may also consider the role of migration in concentrating upstream drivers of morbidity and mortality disparities, such as poverty, and how local and national policies impact migration and health outcomes in this context.

CHAPTER 2: SUPPLEMENTAL FIGURES AND TABLES

2013 Rural-Urban Continuum Codes

Code	Description
Metro counties:	
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
Nonmetro counties:	
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 2,500 to 19,999, adjacent to a metro area
7	Urban population of 2,500 to 19,999, not adjacent to a metro area
8	Completely rural or less than 2,500 urban population, adjacent to a metro area
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area

Figure S1. Rural Urban Continuum Codes (RUCC). Accessed from documentation on RUCC from the US Department of Agriculture Economic Research Service.[39]

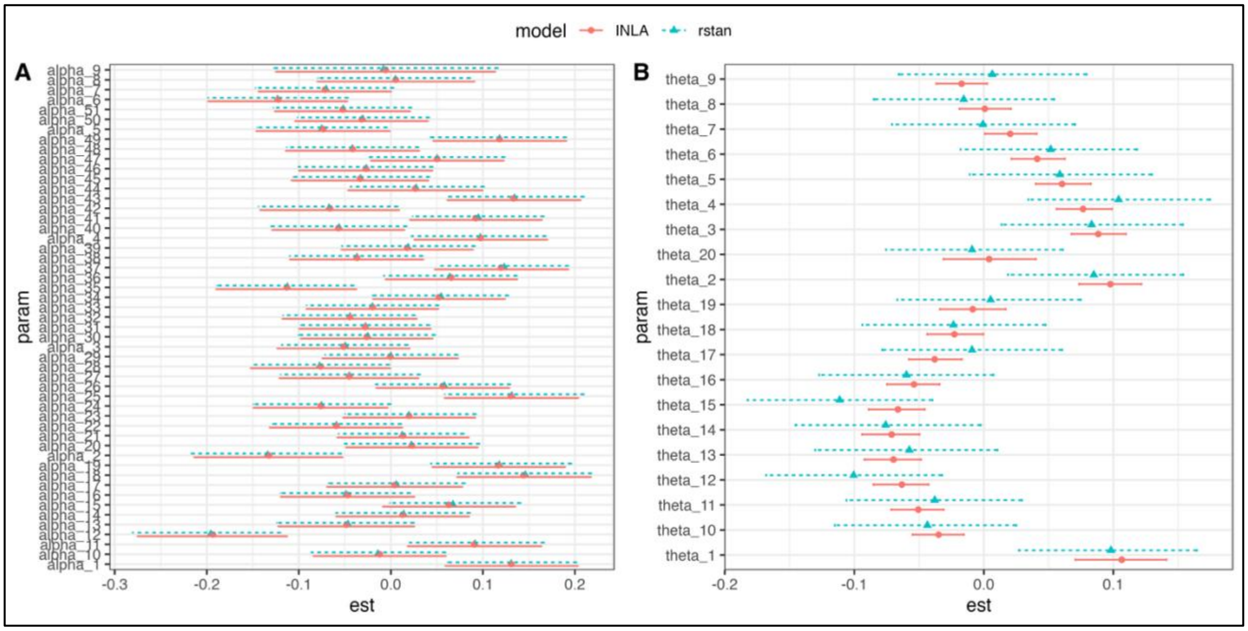

Figure S2. Model parameter estimation comparing R-INLA and rstan intercept-only negative binomial models. Model included number of deaths per county as outcome, state-level random effects, and year random effects. Prior for state random effects was normal and for time random effects a random walk 2. (A) shows the state random intercepts for INLA and rstan (MCMC) models and (B) shows the year random intercepts for INLA and rstan (MCMC) models.

Table S1. Age-adjusted mortality rates and percent change in age-adjusted mortality rates by RUCC from 2000, 2010, and 2019. RUCC = Rural-Urban Continuum Codes (1=most urban, 9=most rural).

RUCC	Mortality rate 2000	Mortality rate 2010	Mortality rate 2019	% change mortality 2000-2010	% change mortality 2010-2019	% change mortality 2000-2019
1 (most urban)	849	703	674	-17.2	-4.1	-20.6
2	863	748	744	-13.3	-0.6	-13.8
3	882	778	783	-11.8	0.6	-11.2
4	904	819	836	-9.4	2.1	-7.5
5	901	810	834	-10.2	3.0	-7.5
6	934	851	875	-8.9	2.9	-6.3
7	912	841	848	-7.8	0.8	-7.0
8	914	849	841	-7.1	-1.0	-8.1
9 (most rural)	887	816	834	-8.1	2.2	-6.0

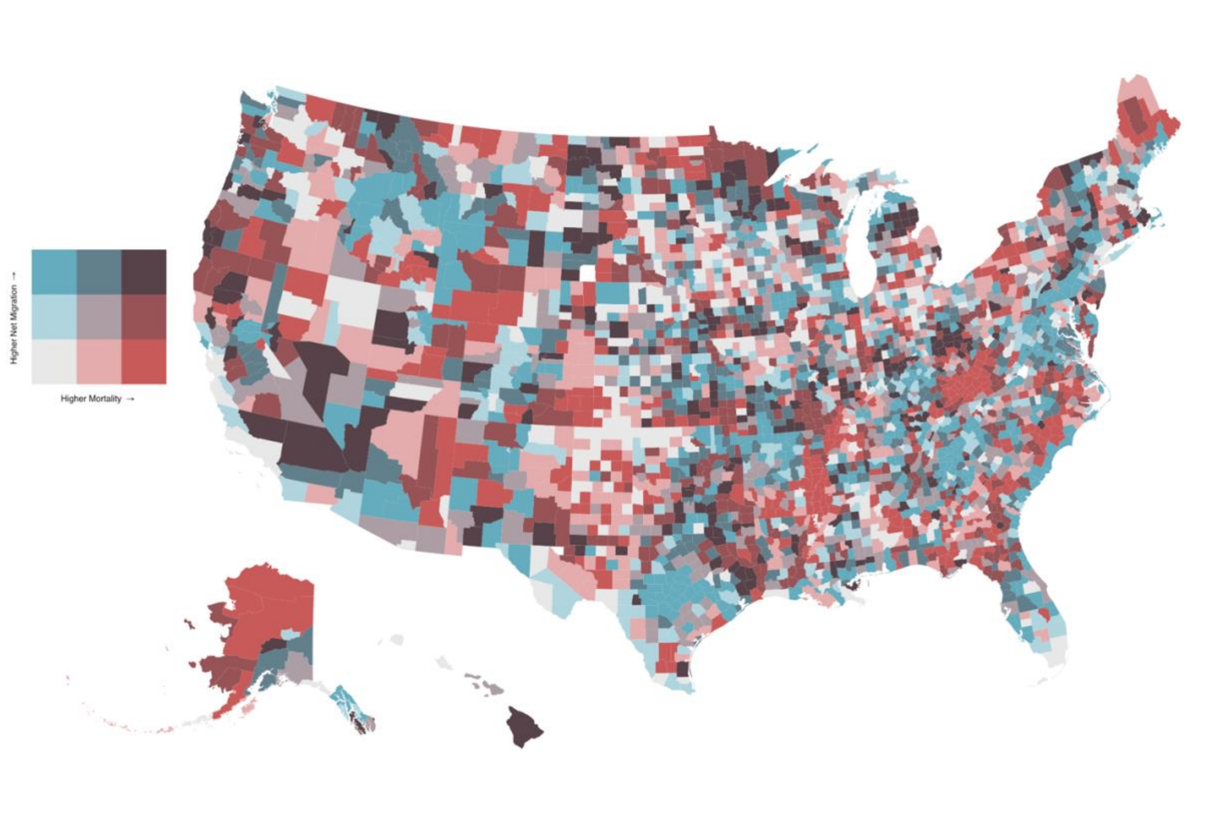

Figure S3. Bivariate chloropleth map of age-adjusted mortality (by state-specific tertile) and average yearly net migration (as % of population) from 2000-2019. Legend indicates higher mortality towards the right and higher migration towards the top. Top right color indicates high mortality and high migration while bottom right color indicates high mortality and low migration.

Table S1. Median (IQR) percent out-migration and % in-migration by RUCC. RUCC=Rural-Urban Continuum Codes (1=most urban, 9=most rural).

RUCC category	Median % out-migration (IQR)	Median % in-migration (IQR)
1 (most urban)	6.68 (5.45, 7.92)	7.60 (5.64, 9.56)
2	6.19 (5.01, 7.37)	6.60 (4.97, 8.24)
3	6.43 (5.06, 7.81)	6.75 (5.19, 8.31)
4	5.61 (4.58, 6.64)	5.62 (4.23, 7.01)
5	6.23 (5.12, 7.35)	6.05 (4.95, 7.15)
6	5.95 (4.98, 6.92)	5.91 (4.82, 7.00)
7	6.18 (5.09, 7.26)	5.95 (4.78, 7.12)
8	6.32 (5.37, 7.26)	6.37 (5.11, 7.63)
9 (most rural)	6.32 (5.14, 7.49)	6.12 (4.78, 7.47)

Figure S4. Annual age-specific mortality by RUCC in the US from 2000-2019. Mortality rates were calculated by dividing the total number of deaths in each age group by the total population for each age group in each RUCC. RUCC=Rural-Urban Continuum Code (1=most urban, 9=most rural). Note the different y-axes scales for each age group.

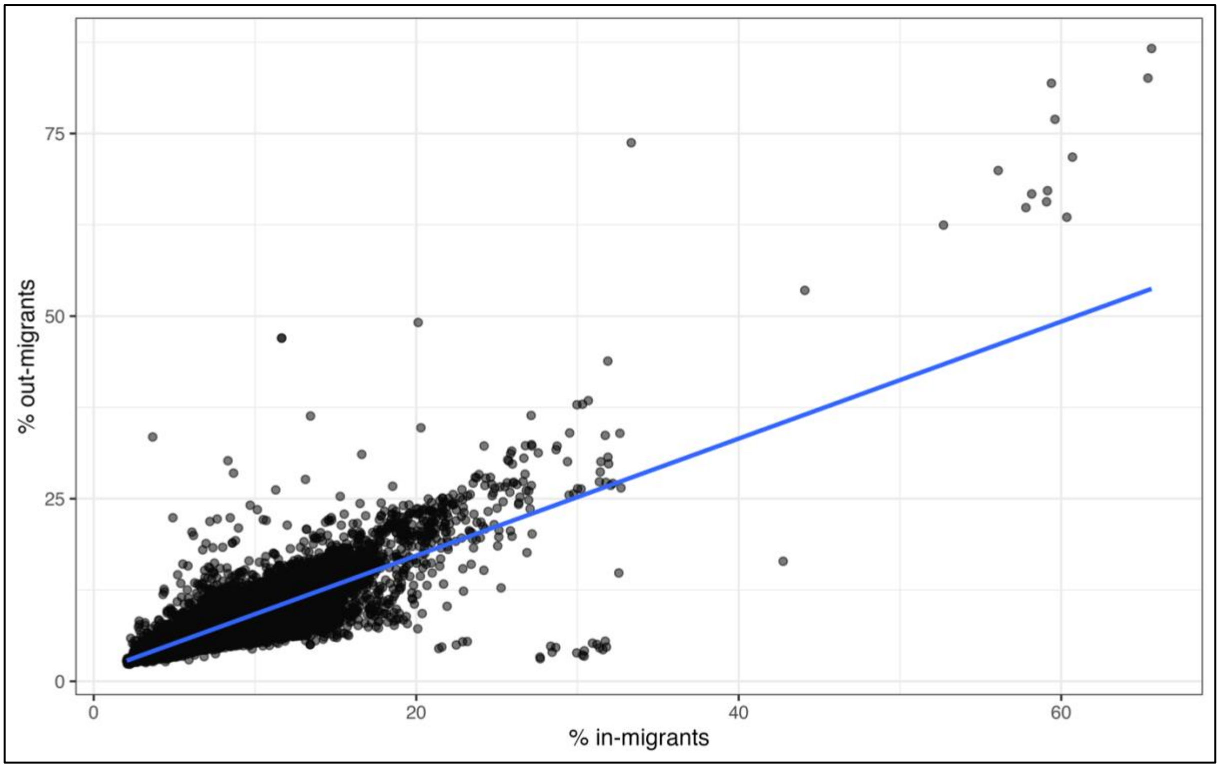

Figure S5. County-level association of % in-migration and % out-migration from 2000-2019. % migration was calculated as the total number of migrants (in or out) divided by the total population.

Table S2. Coefficients of interest from out-migration fixed effect (Model 1), out-migration random slope by RUCC (Model 2), and out-migration random slope by age-group (Model 3). All models are negative binomial models with count of deaths by age-group as outcome, including state-level and year random effects. All coefficients were exponentiated and represent the mortality rate ratio associated with a 1% increase in % out-migration.

Coefficient	**Effect estimate (95% CI)**
Model 1	
Intercept	0.00749 (0.00714, 0.00782)
% out-migration	**1.00221 (1.00106, 1.00352)**
% in-migration	1.00016 (0.99866, 1.00146
Model 2	
Intercept	0.00750 (0.00719, 0.00780)
% out-migration by RUCC (random slope estimates)	
RUCC 1	**1.0088 (1.0063, 1.0115)**
RUCC 2	**1.0050 (1.0014, 1.0087)**
RUCC 3	1.0028 (0.9987, 1.0069)
RUCC 4	0.9996 (0.9947, 1.0048)
RUCC 5	0.9963 (0.9904, 1.0018)
RUCC 6	0.9987 (0.9937, 1.0033)
RUCC 7	1.0000 (0.9953, 1.0043)
RUCC 8	1.0010 (0.9935, 1.0087)
RUCC 9	0.9993 (0.9965, 1.0023)
Model 3	
Intercept	0.00750 (0.00714, 0.00786)
% out-migration by age-group (random slope estimates)	
age 20-24	**0.946 (0.942, 0.950)**
age 25-29	**0.977 (0.973, 0.981)**
age 30-34	**1.008 (1.004, 1.012)**
age 35-39	**1.020 (1.016, 1.023)**
age 40-44	**1.019 (1.016, 1.023)**
age 45-49	**1.016 (1.013, 1.019)**
age 50-54	**1.016 (1.013, 1.019)**
age 55-59	**1.018 (1.016, 1.021)**
age 60-64	**1.018 (1.015, 1.020)**
age 65-69	**1.014 (1.012, 1.017)**
age 70-74	**1.005 (1.003, 1.008)**
age 75-79	**0.996 (0.994, 0.999)**
age 80-84	**0.986 (0.984, 0.989)**
age 85+	**0.985 (0.982, 0.987)**

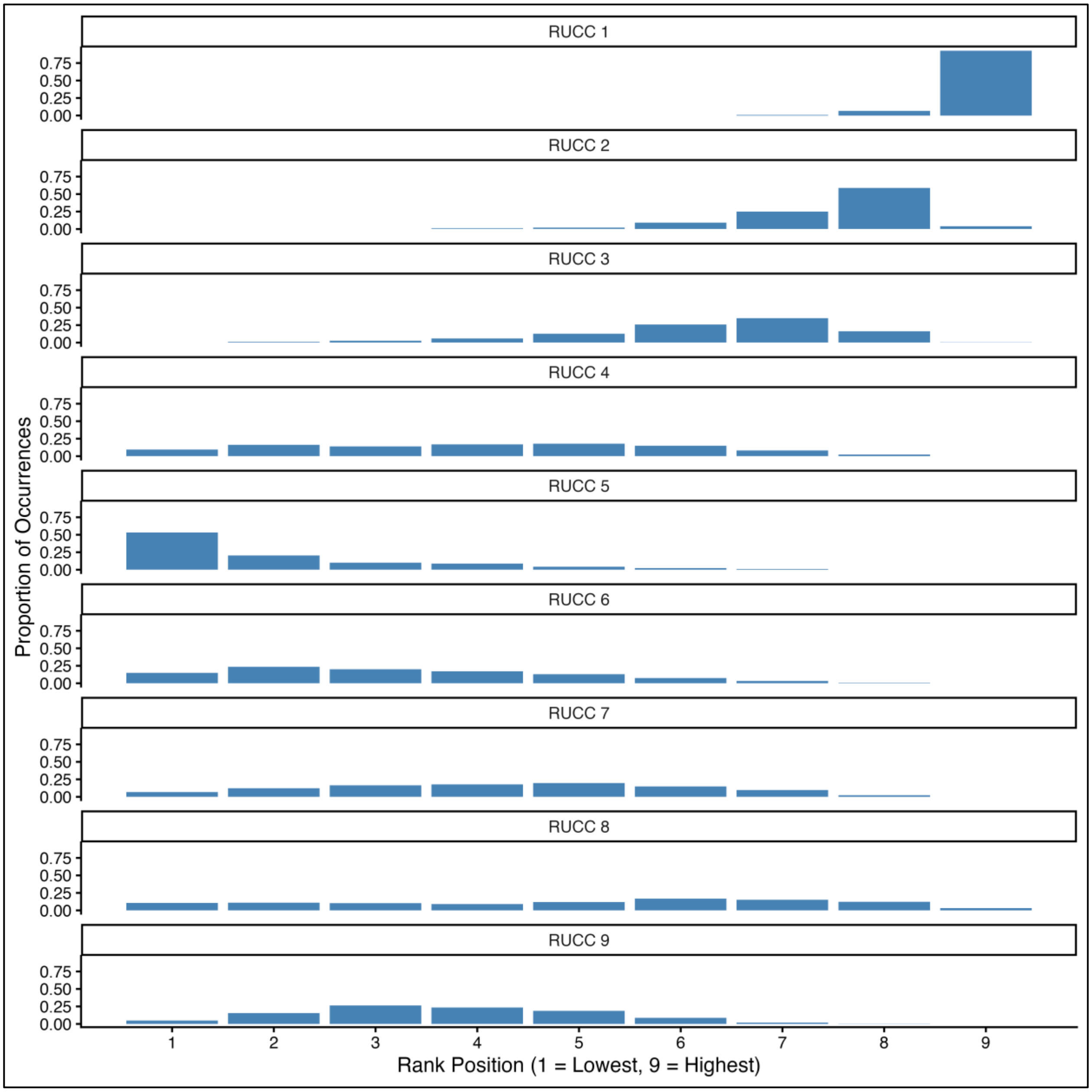

Figure S6. Ranking of random slope coefficients for the association of out-migration and mortality by RUCC. Random slope coefficients for the variation of the association of out-migration and mortality were ranked in order from 1 (lowest) to 9 (highest) for each of 1,000 posterior draws. Bars indicate the proportion of each rank from the draws. RUCC=Rural-Urban Continuum Codes (1=most urban, 9=most rural).

Table S3. Random effect estimates for the association of % out-migration and age-specific mortality by Rural-Urban Continuum Code (RUCC). Effect estimates were modeled using negative binomial models with count of deaths by age-group as outcome, including random intercepts and slopes for age-group and RUCC, and state-level and year random effects. All coefficients were exponentiated and represent the mortality rate ratio associated with a 1% increase in % out-migration within each age-group-RUCC combination.

Age group	RUCC Category								
	1	2	3	4	5	6	7	8	9
20-24	0.965 (0.959, 0.971)	0.933 (0.924, 0.941)	0.916 (0.907, 0.926)	0.943 (0.929, 0.957)	0.950 (0.934, 0.965)	0.954 (0.940, 0.969)	0.993 (0.975, 1.011)	0.938 (0.910, 0.967)	1.027 (1.012, 1.043)
25-29	0.978 (0.973, 0.984)	0.963 (0.954, 0.972)	0.968 (0.957, 0.978)	0.973 (0.959, 0.988)	0.976 (0.958, 0.994)	0.983 (0.968, 0.997)	1.016 (0.998, 1.035)	0.975 (0.948, 1.002)	1.020 (1.005, 1.037)
30-34	1.022 (1.016, 1.029)	0.996 (0.988, 1.005)	0.988 (0.978, 0.997)	0.990 (0.976, 1.005)	1.001 (0.984, 1.018)	0.988 (0.973, 1.002)	1.014 (0.997, 1.030)	0.973 (0.947, 0.999)	1.008 (0.991, 1.026)
35-39	1.048 (1.042, 1.054)	1.002 (0.994, 1.010)	0.992 (0.982, 1.001)	0.994 (0.981, 1.007)	0.997 (0.981, 1.013)	0.996 (0.983, 1.008)	1.017 (1.003, 1.034)	0.992 (0.971, 1.018)	1.000 (0.985, 1.016)
40-44	1.058 (1.052, 1.064)	1.006 (0.998, 1.014)	0.989 (0.980, 0.997)	0.990 (0.978, 1.001)	1.012 (0.997, 1.028)	0.993 (0.983, 1.005)	1.002 (0.989, 1.014)	0.974 (0.953, 0.995)	0.993 (0.977, 1.008)
45-49	1.049 (1.044, 1.054)	1.008 (1.001, 1.016)	0.998 (0.990, 1.006)	0.994 (0.984, 1.005)	1.004 (0.990, 1.019)	0.996 (0.987, 1.007)	0.995 (0.983, 1.006)	0.981 (0.963, 0.999)	0.992 (0.980, 1.004)
50-54	1.040 (1.035, 1.046)	1.017 (1.010, 1.024)	1.005 (0.997, 1.012)	1.001 (0.991, 1.011)	1.004 (0.991, 1.018)	1.004 (0.995, 1.013)	0.998 (0.987, 1.008)	0.980 (0.965, 0.998)	0.995 (0.985, 1.004)
55-59	1.031 (1.026, 1.036)	1.023 (1.016, 1.029)	1.018 (1.009, 1.026)	1.010 (1.000, 1.020)	1.009 (0.997, 1.022)	1.015 (1.005, 1.024)	1.006 (0.996, 1.017)	1.014 (0.998, 1.030)	0.997 (0.989, 1.005)
60-64	1.020 (1.015, 1.025)	1.024 (1.017, 1.031)	1.026 (1.018, 1.033)	1.016 (1.006, 1.026)	1.012 (1.000, 1.025)	1.028 (1.019, 1.038)	1.014 (1.005, 1.024)	1.029 (1.014, 1.045)	0.994 (0.986, 1.002)
65-69	1.012 (1.007, 1.017)	1.024 (1.017, 1.031)	1.025 (1.018, 1.033)	1.010 (1.000, 1.020)	1.007 (0.995, 1.020)	1.019 (1.011, 1.029)	1.014 (1.006, 1.023)	1.028 (1.011, 1.042)	1.010 (1.004, 1.017)
70-74	0.999 (0.994, 1.004)	1.016 (1.010, 1.023)	1.021 (1.014, 1.028)	1.012 (1.003, 1.021)	1.003 (0.991, 1.017)	1.007 (0.999, 1.016)	1.004 (0.995, 1.013)	1.016 (1.002, 1.030)	1.004 (0.998, 1.010)
75-79	0.987 (0.982, 0.991)	1.007 (1.001, 1.013)	1.015 (1.007, 1.021)	1.007 (0.998, 1.016)	0.998 (0.986, 1.010)	0.993 (0.985, 1.000)	0.998 (0.989, 1.005)	1.008 (0.994, 1.022)	1.000 (0.994, 1.006)
80-84	0.977 (0.973, 0.981)	0.997 (0.990, 1.003)	1.005 (0.998, 1.012)	0.995 (0.987, 1.004)	0.984 (0.973, 0.995)	0.986 (0.978, 0.994)	0.984 (0.976, 0.992)	1.004 (0.991, 1.018)	0.993 (0.986, 0.998)
85+	0.975 (0.971, 0.980)	0.991 (0.985, 0.998)	0.995 (0.989, 1.002)	0.998 (0.990, 1.006)	0.974 (0.963, 0.985)	0.979 (0.972, 0.986)	0.979 (0.971, 0.986)	0.996 (0.984, 1.009)	0.996 (0.992, 1.001)

Chapter 3: Geographic and rural disparities in causes of death: Latent class analysis of cause-specific county-level mortality

ABSTRACT

Life expectancy in the US has stagnated since 2010 and has even declined for some specific sub-populations, leading to increasing mortality disparities by geography, age, and socioeconomic conditions. Particularly troubling are the so called “Deaths of Despair” – deaths from suicide, drug poisoning, and alcohol-related mortality – that have been increasing among working age adults. To investigate the geographic and contextual patterns of these and other leading causes of death, we examined county-level patterns of cause-specific mortality in the US from 2000-2019. We used latent class analysis to construct a typology of counties based on age-adjusted cause-specific mortality rates from 2000-2019 for the top 12 causes of death in the US, and we measured the association of poverty, migration, and rurality with our classes. We found a model that separated counties into five classes: 1) low mortality, 2) moderate mortality, 3) high suicide, accident and chronic liver disease (CLD) mortality, 4) high chronic disease mortality, and 5) high mortality. The percent of the population below the poverty line was associated class membership, with higher odds of being in any class compared to the low mortality class associated with increasing poverty. This association was strongest among high mortality counties; these counties had 2.00 (95% CI: 1.89-2.11) times higher odds of being in the high mortality latent class compared to the low mortality latent class per one percentage point increase in the population under the poverty line. Net migration was negatively associated with high chronic mortality counties. Rurality was highly associated with the high suicide, accident, and CLD mortality counties. Our classes also showed strong geographic clustering.

INTRODUCTION

Overall life expectancy in the US has stagnated since 2010 after a long period of growth, while other high-income countries have continued to see improved longevity, increasing the gap between the US and peer countries.[40] Considerable research has been conducted on the reasons why – and which particular groups, based on sex, age, race, geographic location, and socioeconomic indicators – are driving this trend. An emerging consensus is that working age adults, particularly those without a college degree, have contributed the most to stagnating or declining life-expectancy in the US, driven in large part by early deaths due to drug poisoning, alcohol-related deaths, suicide, and cardiovascular diseases.[14, 15, 41]

Among sociodemographic characteristics predicting early mortality, education and income have been extensively studied. A prominent example is the influential "Deaths of Despair" work showing increases in mortality rates among working age adults in the US without a college education.[42, 43] Work on life expectancy and income show a positive and increasing association; the gap in life expectancy between the richest and poorest 1% is 14.6 and 10.1 years for men and women respectively. This gap has increased since 2001.[44] Education and income likely do not impact mortality separately; subsequent work on educational mortality disparities has argued that the association between education and mortality is driven primarily by economic factors.[45]

Along with sociodemographic characteristics, a large body of literature has focused on place-based differences in mortality, including geographic patterns and rural-urban differences. These studies have pointed to lower life expectancy in the Southern US and Appalachian regions and higher life expectancy in coastal cities.[46] Another body of work has focused on rural mortality penalties across the US showing that mortality rates are higher in rural compared to urban areas for all-causes and cause-specific deaths, including heart disease, stroke, cancer, unintentional injury, and chronic lower respiratory disease.[9, 47] Additional research has combined geographic and rural mortality disparities showing that rural counties in the South have higher mortality rates than Southern urban counties as well as non-Southern rural counties.[48] This previous work on geographic and rural mortality disparities has generally focused on all-cause mortality or assessed each cause of death individually,[12, 46, 49] without examining how diseases may group together geographically or across the rural-urban divide. Additionally, while research on place-based and sociodemographic characteristics as drivers of mortality disparities are often presented separately, these factors are likely interrelated in complex ways that impact health outcomes.

Fundamental cause theory posits that health inequalities derive from the application of flexible resources to improve health, resulting in health disparities across multiple outcomes between groups that differ by socioeconomic status (SES).[26] Disparities in specific health outcomes can also shift over time as a result of differential employment of these flexible resources, as mechanisms of disease change over time.[26] This works on both an individual level wherein those with more resources can access or afford more health-protective practices, as well as at the community level wherein cumulative area (neighborhood or county) resources may impact everyone's ability to access health-protective behaviors. One example of an area-level impact is rurality – rural populations have less access to healthcare and public health compared to urban populations.[23]

An often-overlooked factor in mortality disparities research is the impact of migration on individual and population level health. Migration is one way in which individuals might shift their exposure to area-level resource availability, although there is limited work on domestic migration and the results are mixed. Earlier work indicated that domestic migrants from rural to urban areas in the US had worse health than those who did not move,[32] however, more recent work has argued that those who move from poorer to better resourced areas live longer and that outmigration can provide a path to upward mobility for those growing up in low-income areas.[50, 51] In the end, who can move – and where they can move to – is a selective process that often concentrates poverty.[21] Some research has argued that socioeconomic variables explain rural health disparities,[52] but this work ignores selective migration as well as the complex interaction between place and individual characteristics. While rurality and income are area-level attributes that may interact to impact health outcomes, migration is a process which impacts area-level population composition. All three of these factors can contribute to population-level mortality disparities.

While income (or poverty), rurality, and migration have all been considered in mortality disparities research, their effects on mortality are often examined independently. Recently, there have been calls to consider complex systems and the impact of broader social and structural contexts on mortality disparities rather than each individual factor.[53] Latent modeling is one way to examine patterns of area-level characteristics, such as mortality, although it has rarely been used in this line of inquiry. We aim to contribute to the body of research on place-based mortality disparities by analyzing cause-of-death data for counties from 2000-2019 using a latent class analysis to construct a typology of counties based on cause-specific mortality rates. We also aim to examine associations of this typology with area-level predictors including rurality, poverty, and migration. We hypothesize that cause-specific mortality rates will group within counties, and that rurality, poverty, and migration will predict grouping because they are upstream drivers of mortality disparities.

METHODS

To better understand potential underlying processes that shape rural mortality, we conducted a latent class analysis (LCA) to construct a typology of counties using a cross-sectional measure of age-adjusted cause-specific mortality by county in the US from 2000-2019. We used the top 12 causes of death in the US as indicators to inform our LCA in order to include several causes of death that have been increasing among rural populations (10 – suicide, 12 – chronic liver disease, CLD) and to aid in interpretability of the latent classes. Cause-specific mortality was defined using ICD-10 codes and grouped based on the National Center for Health Statistics rankable 113 selected causes of death.[54] They include (in order of descending age-adjusted mortality rate) cardiovascular disease (I00-I09, I11, I13, I20-I51), cancers (C00-C97), stroke (I60-I69), chronic lower respiratory diseases (J40-J47), accidents (V01-X59, Y85-Y86), Alzheimer disease (G30), diabetes (E10-E14), influenza and pneumonia (J09-J18), nephritis (N00-N07, N17-N19, N25-N27), suicide (U03, X60-X84, Y87.0), septicemia (A40-A41), and chronic liver disease (K70, K73-K74). Mortality data was measured using the All Counties – Detailed Multiple Cause of Death Files restricted use data from the National Center for Health Statistics. These data contain cause of death, county of residence, and limited demographic information for all recorded deaths in the US. Cause-specific mortality rates for each county were aggregated across all years of the study (2000 – 2019) and counties were categorized in tertiles (low, medium, high) for each age-adjusted cause-specific mortality rate. Age adjustment was calculated using the direct method and the 2000 US population as reference.[28]

Covariates for this analysis included rurality, poverty, and migration. We included these as we consider them to be the main upstream drivers of geographic mortality disparities. Mediators that result from these drivers and may impact mortality, including healthcare access and health behaviors, are not included in the present analysis. Rurality was measured using 2013 Rural Urban Continuum Codes (RUCC) which classifies counties based on population size (for metropolitan counties), and population size and adjacency to metro counties for non-metro counties. RUCC includes nine categories with 1 being the most urban (counties in metro areas of 1 million population or more) and 9 being the most rural (counties with population less than 2,500, not adjacent to a metro area) (**Supplement Figure S1**). Poverty was measured as the percent of the county population below the federal poverty line using the 2008-2012 five-year American Community Survey (ACS) data. Migration was measured by net percent migration using the Net

Migration Patterns for US Counties data from the University of Wisconsin Applied Population Laboratory.[55] These data calculate the number of net migrants (in migrants minus out migrants) and the total population by age for each county in the US using decennial census counts along with birth and death records.[56] We calculate net percent migration over the period from 2000-2019 by combining the number of net migrants and the total population from the 2000-2009 data and the 2010-2019 data and dividing the total net migrants by the total population. Negative percent net migration indicates more out-migrants than in-migrants.

We first fit latent class models to county-level cause-of-death data aggregated over the 20-year study period without including covariates. We fit models from 1-10 latent classes using the top 12 age-adjusted cause-specific mortality rate tertiles (high, medium, low) as items; the final latent class model was chosen based on fit and interpretability. We evaluated model fit using Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) and evaluated interpretability using a qualitative interpretation of the classes.[57] We next fit a latent class model using the same number of classes and include covariates (rurality, % poverty, % net migration) using a single-step approach in order to measure predictors of latent classes. In the single-step approach covariates are included in the latent class model, and class prevalences are estimated as a function of the regression coefficients.[58] This allows us to assess characteristics that predict latent class membership; the exponentiated coefficients can be interpreted as the odds of membership in each latent class in relation to the reference class associated with a unit change in the covariate. Because one drawback of the single-step approach is that the inclusion of covariates may influence the latent class construction,[59] we descriptively compare our latent class model without covariates to our model including covariates to determine consistency. Poverty and migration estimates were mean centered for ease of interpretation. Because we want our latent class model without covariates to include the same data as the model with covariates, we limit both models to observations that include all covariates.

To examine longitudinal changes over the study period[30] we fit latent class models to the first 10-year period (2000-2009) and second period (2010-2019) separately, including all covariates (rurality, poverty, migration) and the same number of latent classes identified in the initial model. We use the same poverty measure as above (ACS 2008-2012) that is centered between these two periods, and 2013 RUCC codes, which are the closest RUCC update to the center of the study period (RUCC are updated every 10 years). We compared these class outcomes descriptively to assess consistency across waves. We then calculated transition probabilities from the first period to the second period using logistic regression models for each class level.[60]

We used R (version 4.4.1) for data cleaning and analysis, and R package 'poLCA' (version 1.6.0.1) to fit the LCA models. All LCA models (univariate and multivariable) were fit using 20 random starting values.

RESULTS

Cardiovascular disease (CVD) and cancer were the leading causes of age-adjusted mortality in the US from 2000-2019 (191.0 and 171.1 deaths per 100,000 person-years respectively), accounting for 60.4% of total age-adjusted mortality from the top 12 causes of death (**Supplemental Figure S2**). Most causes in the top 12 are chronic diseases or acute outcomes that are disproportionately fatal among older and frailer adults,[61, 62] with the exception of accidents (#5, 41 per 100,000) and suicide (#10, 12.2 per 100,000).

Age-adjusted mortality for all top 12 causes of death was higher in rural counties compared to urban counties from 2000-2019 (**Figure 1**). The top three causes of death – CVD, cancer, and stroke – declined in all RUCC categories over this time period, although absolute declines were larger for CVD and cancer in the most urban counties (RUCC 1) compared to all others (**Supplemental Table S1**). Accidental death (#5), Alzheimer disease (#6), suicide (#10), and chronic liver disease (#12) mortality increased in all RUCC during the study period. Chronic lower respiratory disease (#4) and diabetes (#7) both decreased in metro counties (RUCC 1-3) while increasing in non-metro counties.

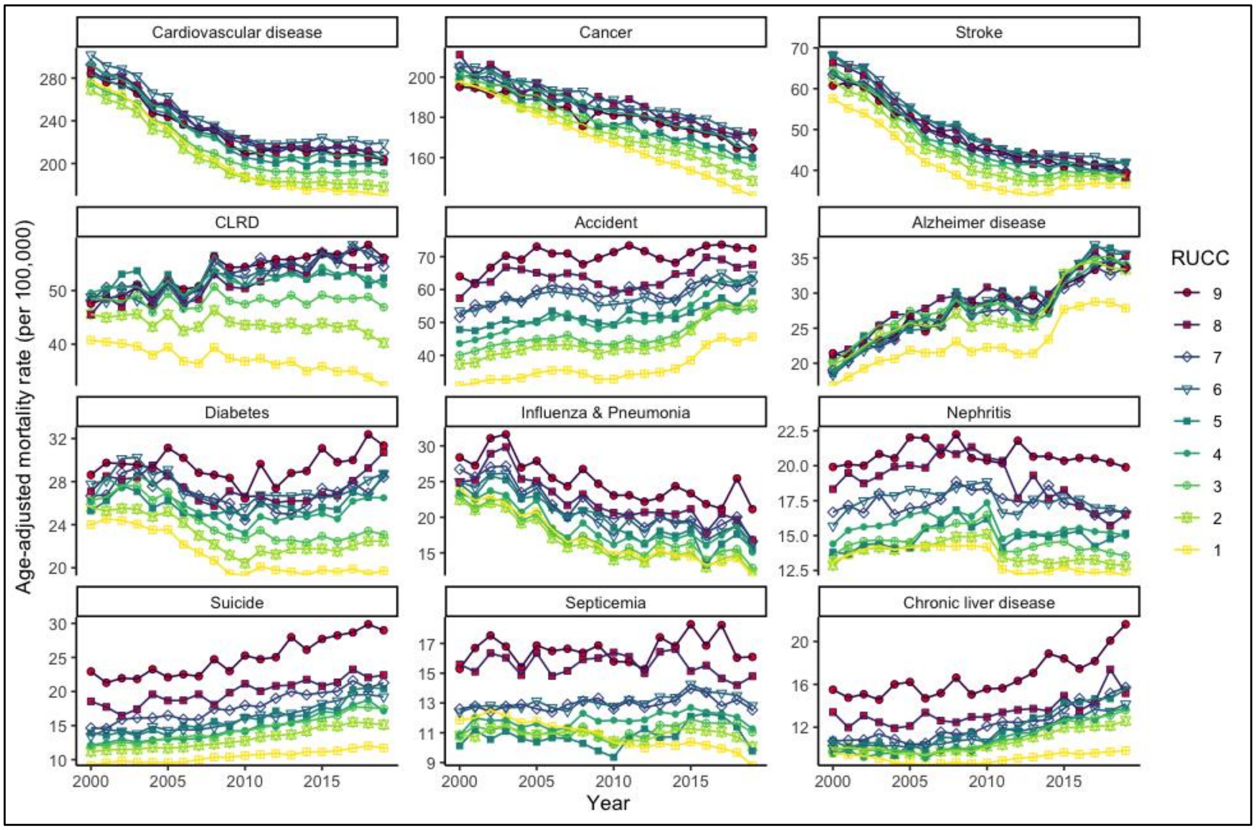

Figure 1. Age-adjusted cause-specific mortality by year and Rural-Urban Continuum Code (RUCC). The top 12 causes of death in the US from 2000-2019 are listed. RUCC codes depend on population size for metropolitan counties (RUCC 1-3, population > 250,000) and population size and adjacency to metropolitan counties for non-metropolitan counties (RUCC 4-9). RUCC are ordinal and go from 1 (most urban) to 9 (most rural)**.** CLRD=chronic lower respiratory disease. Note the different y-axis scales.

LCA model fitting

For the LCA, model fit statistics indicated a four or five class model (**Supplemental Figure S4**). Based on class interpretation we chose a five-class model. Visual inspection of latent classes with and without covariates showed similar distributions, supporting the use of a single-step method. **Supplemental Table S2** and **Figure S3** show the proportion of counties with each tertile of cause-specific mortality conditional on class. The first class (22.9% of counties) is characterized by moderate mortality – the largest proportion of counties fall within the middle tertile of age-adjusted mortality for most causes of death, except for accidental deaths in which more than half of counties in this category are in the lowest tertile. We classify the second class as high chronic mortality (10.5% of counties), which is the smallest class. In this class, most counties fall within the highest mortality tertile for all causes except for chronic lower respiratory disease, accident, suicide, and chronic liver disease. The third, and largest, category represents high mortality (25.6% of counties). In this class, more counties fall in the highest tertile of mortality for every cause of death, and only Alzheimer disease mortality has less than 50% of counties falling into the highest tertile. The fourth class is high accident, suicide, and chronic liver disease (22.1% of counties). In this class relatively higher proportions fall within the highest tertile for accident (48.1%), suicide (70.2%), and chronic liver disease (45.7%). Counties in this class have high probability of falling within the lowest tertile for cause-specific mortality for many chronic diseases, including cardiovascular disease, cancer, and stroke. Finally, the fifth class is considered low mortality (18.9% of counties). This class has the highest proportion of counties in the lowest tertile of mortality for all causes of death, and only for Alzheimer disease does the proportion in the lowest tertile fall below 50%.

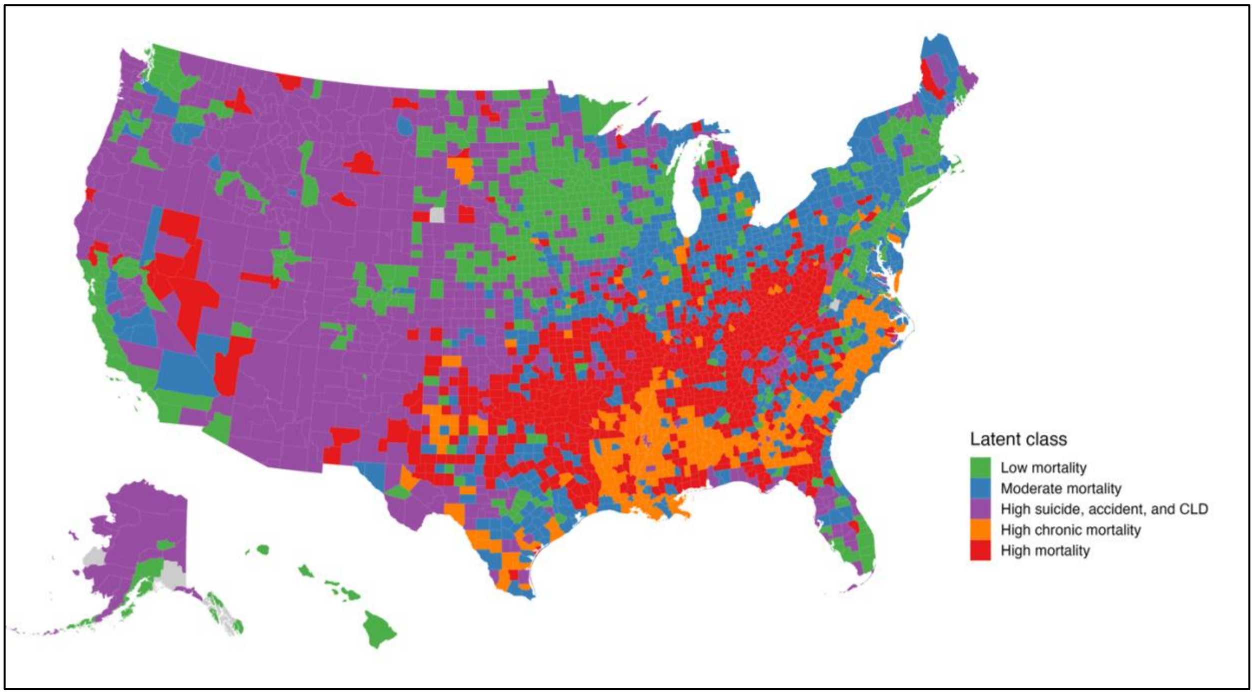

Figure 2. Spatial distribution of latent classes. Map of 5 class latent model with covariates (% poverty, % migration, rurality). LCA model was fit using cause-specific age-adjusted mortality rates per county for the top 12 causes of death from 2000-2019.

Our latent classes show geographic clustering (**Figure 2**). Low mortality counties cluster in the Northeastern US and western Midwest with smaller pockets in the Mountain West and West Coast. High chronic mortality and high mortality are concentrated in the Southern and Southeastern US. High suicide, accident, and chronic liver disease are common in the Western US while moderate mortality is distributed throughout the Midwest and Northeast.

LCA covariates

Low mortality counties have the lowest proportion of the population under the federal poverty line (6.1%), while high mortality counties have the highest (13.2%) (**Table S4**). Low mortality counties also had the highest percent net-migration (3.8%), indicating higher in-migration, while high chronic mortality was the only category with negative net percent migration (-6.0%). Within each latent class, poverty rates were lowest and net migration rates highest (indicating net in-migration) in the most urban counties (RUCC 1). The highest percent net migration rate was found in the most urban (RUCC 1) counties in the high suicide, accident, and CLD class (net % migration = 17.0%).

Figure 3 presents odds ratios for the five-class model with covariates. The odds ratios can be interpreted as the change in odds of membership in the latent class in relation to the reference latent class (ref=low mortality) associated with a one-unit increase in covariate. Poverty was negatively associated with the low mortality class; compared to the low mortality class, counties had higher odds of being in all other classes as the percent of population under the federal poverty line increased. This association was strongest for high mortality counties – counties had 2.00 (95% CI: 1.89-2.11) times higher odds of being in the high mortality latent class per 1 percentage point increase in poverty. Counties with higher percent net migration (indicating in-migration) were more likely to be in the high accident, suicide, and CLD category, and less likely to be in the high chronic mortality category compared to the low mortality class. Counties had 0.77 (95% CI: 0.75, 0.80) lower odds of being in the high chronic mortality class compared to the low mortality class per 1 percentage point increase in net migration.

The association of rurality and latent class was strongest for high suicide, accident, and CLD classes. The odds of being in the high suicide, accident, and CLD latent class compared to the low mortality class was higher for all RUCC categories compared to the most urban counties (RUCC 1), with the highest odds being in the most rural areas (RUCC 8 & 9). For the most rural (RUCC 9) relative to the most urban (RUCC 1), the odds of being in the high suicide, accident, and CLD class is 35.0 (95% CI: 14.8, 82.9) times higher than the odds of being in the low mortality class, adjusting for migration and poverty. RUCC 9 counties, compared to RUCC 1 counties, are less likely to be in the moderate mortality, high chronic mortality, and high mortality class compared to the low mortality class.

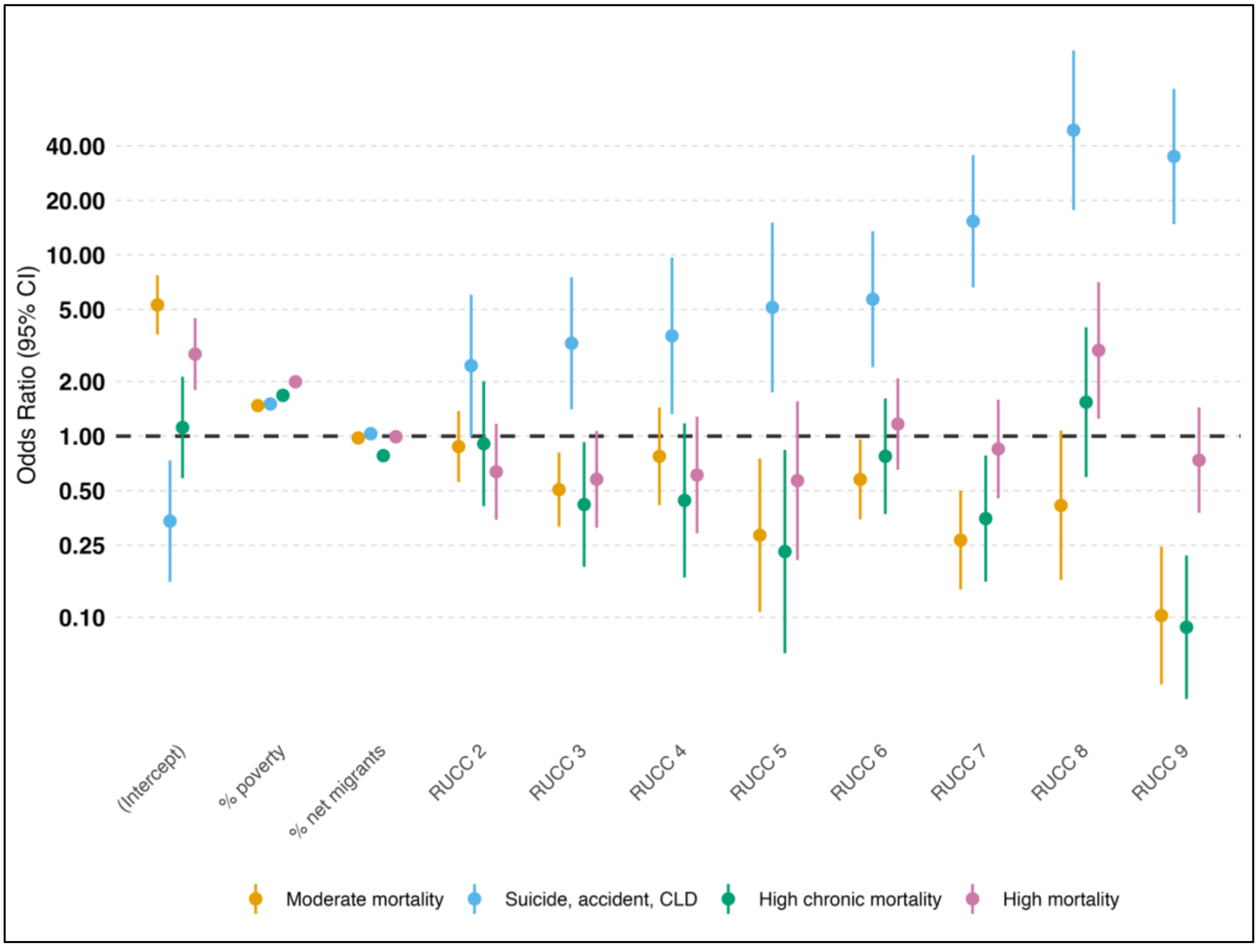

Figure 3. Odds ratios (OR) for predictors of latent class. Reference category is low mortality counties. Rural-Urban Continuum Codes (RUCC) indicate rurality (1=most urban, 9=most rural). OR for the intercept can be interpreted as the odds of membership in each latent class in relation to the reference latent class at RUCC=1 and mean % migration and % poverty. OR for covariates can be interpreted as the change in odds of membership in the latent class in relation to the reference latent class (low mortality) associated with a one-unit increase in covariate. Reference class for rurality is the most urban counties (RUCC 1). CLD=chronic liver disease.

There are differences in the association of rurality and class depending on adjacency to metropolitan areas. RUCC 8 counties (the smallest population counties *adjacent* to metropolitan areas), have similar odds to RUCC 1 counties of being in the moderate mortality or high chronic morality classes, while RUCC 9 (the smallest population counties *not adjacent* to metropolitan areas) are less likely to fall in these classes compared to RUCC 1 counties. This pattern is similar in RUCC 6 and RUCC 7 counties (same population size but RUCC 6 is adjacent to metropolitan areas), although the association is not as strong. The odds of being in the moderate mortality, high chronic mortality, and high mortality latent classes compared to the low mortality latent class was lower for all RUCC categories compared to the most urban counties, with the strongest association being in RUCC 9, although this association was not always significant. The exception is RUCC 8, where the odds of being in the high mortality latent class is higher (2.97; 95% CI: 1.25, 7.09) compared to RUCC 1 counties.

Longitudinal changes

Models fit separately for 2000-2009 and 2010-2019 showed good consistency in latent class construction across waves (**Figure S5**), and consistency in geographic patterns (**Figure S6**). Between the waves, 920 counties (29.4%) transitioned from one class to a different class. The low mortality class was the most consistent between waves, with 85% of low mortality counties from the first wave remaining in this class in the second wave (**Table 1**). The biggest shift in class from wave 1 to wave 2 was among high chronic mortality counties moving to high mortality counties (21%), followed by moderate mortality to low mortality (16%). There were also relatively large transitions from low mortality to high suicide, accident, and CLD mortality and vice versa (8% and 13% respectively). There were low transition rates from low mortality to high chronic or high mortality as well as vice versa, as well as from high suicide, accident, and CLD counties to high chronic mortality counties.

Table 1. Transition probabilities and number of counties moving between classes from first period (2000-2009) to second period (2010-2019). Each cell represents the proportion of counties that moved from the initial class to the final class (number in parentheses). The diagonal shaded classes represent those that did not transition.

Initial class (2000-2009)	Final class (2010-2019)				
	Low mortality	Moderate mortality	Suicide, accident, and CLD	High chronic mortality	High mortality
Low mortality	85.1% (388)	6.4% (29)	8.1% (37)	0.2% (1)	0.2% (1)
Moderate mortality	15.6% (110)	64.3% (452)	5.0% (35)	5.4% (38)	9.7% (68)

Suicide, accident, and CLD	13.4% (111)	11.0% (91)	67.7% (560)	1.7% (14)	6.2% (51)
High chronic mortality	0.3% (1)	9.8% (32)	3.1% (10)	65.5% (213)	21.2% (69)
High mortality	0.0% (0)	12.4% (102)	7.8% (64)	6.8% (56)	73.0% (600)

Movement between latent classes showed some geographic trends (**Figure S7**). Counties that moved from high chronic mortality to high mortality were located primarily in the Southern US while counties that moved from high suicide, accident, and CLD to low mortality were primarily located in the Midwest and Western US. Those that moved from moderate mortality to low mortality were spread throughout several regions although a substantial cluster was located on the Northeast coast.

Age adjusted mortality rate over time showed differing trends by latent class (**Figure S8**). All latent classes had declining mortality rates from 2000-2010, although the rate of decline was slowest for high mortality counties. After 2010, low mortality counties continued to decline, albeit at a slower pace, while all other classes flattened off or slightly increased. Also notable from these trends is that high suicide, accident, and CLD counties had lower age-adjusted mortality rates compared to moderate mortality counties over the entire time period (2000-2019), likely due to the fact that chronic mortality was much lower in high suicide, accident, and CLD counties.

DISCUSSION

We found a five-class latent model that explains cause-specific mortality variation patterns in the US that is consistent over time from 2000-2019. The mortality disparities that we found in this study are supported by numerous other studies indicating an increasing gap in mortality in the US among different populations.[12, 33, 44, 45, 63] The spatial pattern of our classes is consistent with results from other studies of geographic mortality patterns in the US. [46, 64] We add to this literature by differentiating between high overall mortality and high chronic mortality.

We also identified areas of high suicide, accident, and CLD, but low chronic mortality in the West. This is consistent with previous research on high suicide rates in the Intermountain West,[65] although our findings of co-located low chronic mortality in this region adds to this. We found that county-level poverty rates are a strong predictor of our latent classes, particularly for high mortality counties, adding to the abundant literature on the link between area-level poverty and mortality.[66, 67] We also find that net migration is associated with high chronic mortality counties; counties with higher net in migration as a proportion of the population are less likely to be classified as high chronic mortality counties in our model. Finally, we found that rurality is a strong predictor of high suicide, accident, and CLD counties, with increasing rurality associated with this class.

Our finding of poverty associated with mortality at the county level supports Fundamental Cause Theory, although we are unable to disentangle the effects of individual poverty and area-level poverty on mortality in the current study. Interestingly, while much of the literature on "Deaths of Despair" has focused on economic drivers – and subsequent feelings of hopelessness – of higher mortality,[43] we find a stronger association for poverty with high chronic mortality counties compared to high suicide, accident, and CLD counties. This finding should not detract from the impact of growing inequality on increasing suicide, accident, and alcohol-related deaths in the US,[68] but we should also consider the ways that persistent poverty impacts mortality over long time periods. The highest effect estimate for poverty in our study was in high mortality counties – those with elevated rates of both chronic mortality as well as suicide, accident, and CLD. Economic drivers of mortality may work on multiple time scales, including acute economic shocks that drives acute mortality (suicide and drug overdose), as well as long-term economic marginalization which may drive increased chronic disease mortality through differential access to healthy food and recreational activities.

Our finding of the association of net migration with high chronic mortality counties is novel within the geographic morality disparities literature. We found that net in-migration was negatively associated with high chronic mortality counties after adjusting for poverty and rurality. This could be the result of selective migration of younger and healthier individuals out of high chronic mortality counties and/or the in-migration of older and less healthy individuals into these counties. The small, but significant, association of in-migration with high suicide, accident, and CLD counties is an interesting finding as the theoretical driving force behind the increase in these causes is economic. Domestic migration can happen for multiple reasons, and previous research has shown that high-income and low-income people tend to move at similar rates, although the reasons for moving and locations that people are able to move to are influenced by income.[69] Higher in-migration to high suicide, accident, and CLD counties compared to low mortality counties may be due, at least in part, to economically distressed individuals looking for cheap housing or new jobs. More research is needed on the link between domestic migration and mortality outcomes, particularly on the role of SES in driving migration choices and possibilities.

Our finding that rurality is a strong predictor of high suicide, accident, and CLD counties aligns with previous research on the rural mortality penalty.[15, 70] In our latent classification, we also found that more rural counties were less likely to be moderate mortality compared to low mortality. The findings were mixed for high chronic mortality and high mortality counties. This may point to the problematic conception of rurality as a monolithic category. While upstream drivers of mortality – labor, climate, nutrition, built environment – often have large rural/urban divides, there are also large flows of material and non-material (i.e., information, capital) goods between rural and urban places in the US.[71] Previous work on “Bright” vs “Dim” rural areas argues that we should differentiate between those that are well-integrated with urban centers compared to those that are economically disadvantaged.[71]

Our analysis of latent class transitions between 2000-2009 and 2010-2019 found that low mortality counties were the most stable class, but that these counties were more likely to transition to high suicide, accident, and CLD counties compared to any other class. First, the stability of this class indicates that place-based geographic inequalities tend to change slowly over time, particularly for areas with more resources. Second, this finding makes sense if we believe that chronic mortality is the result of long-term processes that include persistent economic depression while suicide, accident, and CLD are the result of relatively short-term decreases in economic outcomes. The large transition from high chronic mortality to high mortality is a troubling trend that may indicate an increasing geographic concentration of early mortality.

An interesting finding was that Alzheimer's disease (AD) was not a strong predictor of class in our model – none of our classes included more than 50% of counties with Alzheimer's deaths in the top tertile. Although age-adjusted AD mortality increased substantially from 2000-2019 (see Figure 1), the increase seemingly did not impact our latent class formation. This is consistent with recent research on AD trends increasing across race, sex, geography, and age group although this same research points to more recent increases in AD deaths during the COVID pandemic.[72] AD mortality may have been more influential in class formation if our analysis had included deaths from 2020 and later.

Another interesting finding was that – for rural counties – adjacency to metropolitan areas was associated with class membership. Particularly for our high mortality class, rural areas adjacent to metropolitan areas (RUCC 8) were more likely to be in the high mortality class than the low mortality compared to RUCC 1 counties. This association was flipped for rural areas not adjacent to metropolitan areas (RUCC 9), although the odds ratios were not significant. Rural counties not adjacent to metropolitan areas (RUCC 7 & 9) were also less likely to be moderate mortality or high chronic mortality than the low mortality class compared to the most urban counties, while the findings among rural counties adjacent to metropolitan areas (RUCC 6 & 8) were mixed. These findings may indicate that rural counties close to metropolitan areas have health profiles similar to metropolitan areas, potentially because of better integration into urban labor markets or access to urban amenities such as healthcare.

Our study had several limitations. First, this study is ecological in nature, and we cannot ascribe any associations we find to occur on the individual level. Second, we do not separate accidental poisoning from other accidents. The majority of accidental poisoning deaths are due to drug overdose which increased substantially over our study period. There may be important geographic distinctions between drug overdose and other accidental deaths that we missed in our analysis. Third, the causes of death that we use are broad categories that fail to differentiate between underlying drivers of interest. For example, cancer mortality includes many types of cancers which can be influenced by health behaviors such as smoking or diet, genetic factors, or access to preventative care. However, recent work has shown that medical access is not strongly correlated with spatial mortality inequality and screenable cancers have relatively low geographic inequality compared to other causes of death.[33] Fourth, our decision to use tertiles of mortality as indicators for the latent class analysis is an arbitrary cut-off, however, we feel that it strikes a good balance between separability and interpretability of classes. Fifth, our covariate measures of rurality and net migration are also somewhat arbitrary, although previous work on the rural mortality penalty has shown good consistency across different measures of rurality.[73] Sixth, our model uses aggregated mortality across 10-20 years, which does not consider any trends in these associations. Future research may use longitudinal clustering methods to measure these changes over time. Finally, net migration used in this analysis does not consider age-specific migration patterns that may be important in mortality disparities.

CONCLUSION

Cause-specific mortality for the top 12 causes of death in the US cluster at the county level to define five distinct classes. These classes show geographic clustering and are associated with poverty, migration, and rurality. Policy makers at local, state, and national levels interested in improving health should look beyond the proximate causes of death and consider upstream factors that may impact population health.

CHAPTER 3: SUPPLEMENTAL FIGURES AND TABLES

2013 Rural-Urban Continuum Codes

Code	Description
Metro counties:	
1	Counties in metro areas of 1 million population or more
2	Counties in metro areas of 250,000 to 1 million population
3	Counties in metro areas of fewer than 250,000 population
Nonmetro counties:	
4	Urban population of 20,000 or more, adjacent to a metro area
5	Urban population of 20,000 or more, not adjacent to a metro area
6	Urban population of 2,500 to 19,999, adjacent to a metro area
7	Urban population of 2,500 to 19,999, not adjacent to a metro area
8	Completely rural or less than 2,500 urban population, adjacent to a metro area
9	Completely rural or less than 2,500 urban population, not adjacent to a metro area

Figure S1. Rural-Urban Continuum Codes.[39]

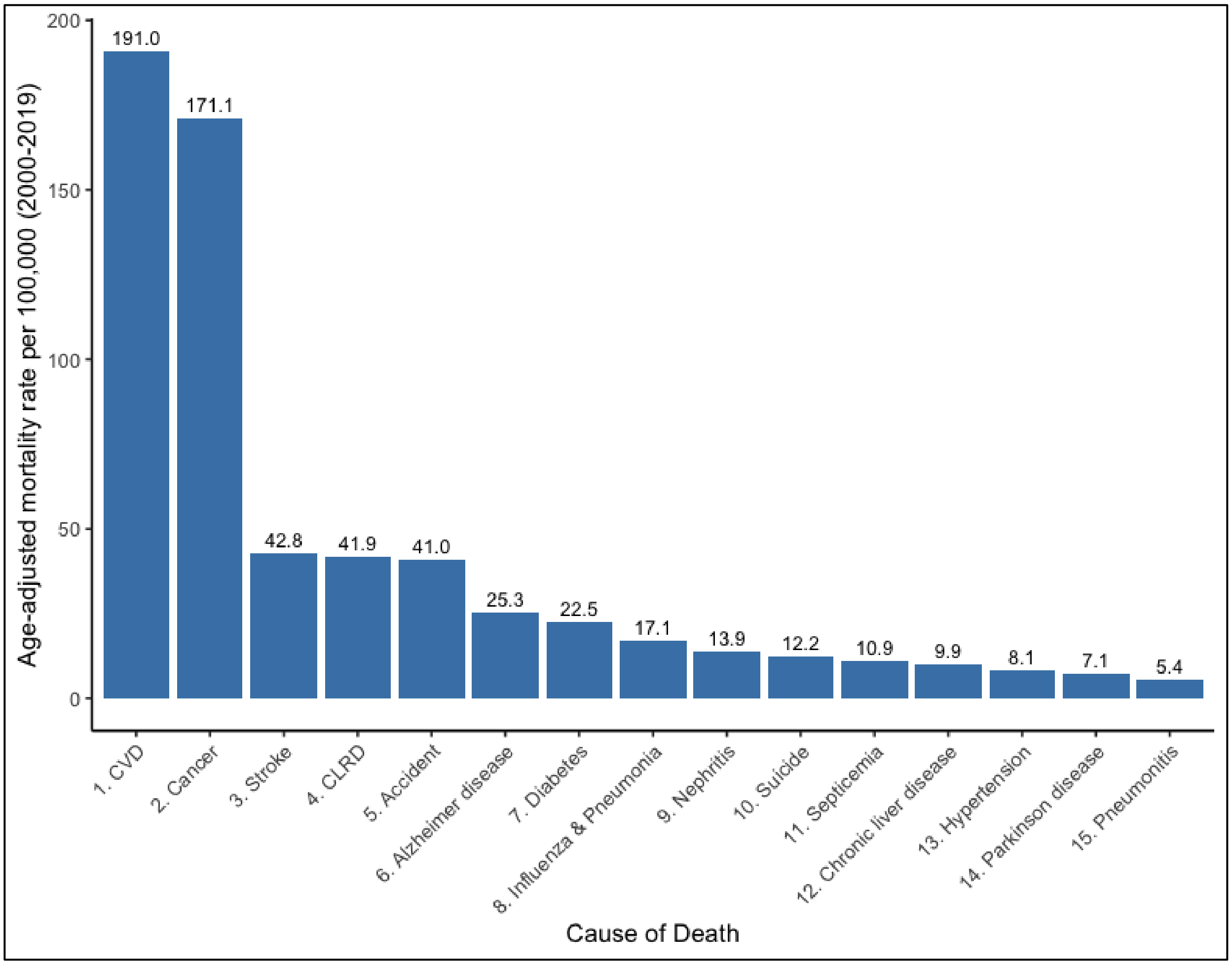

Figure S2. Age-adjusted cause-specific mortality rates (per 100,000) in the US for the top 15 causes of death from 2000-2019. Age adjustment is carried out using the direct method and the 2000 US Census population. CVD=cardiovascular disease, CLRD=chronic lower respiratory disease. Hypertension includes essential hypertension and hypertensive renal disease.

Table S1. Change in age-adjusted cause-specific mortality rate by Rural Urban Continuum Codes (RUCC) from 2000-2019. Green shading indicates a reduction in mortality from 2000-2019 while red shading indicates an increase in mortality.

Cause-specific mortality	RUCC code (1=most urban, 9=most rural)								
	1	2	3	4	5	6	7	8	9
1. Cardiovascular disease	-107.5	-90.50	-84.64	-87.01	-82.20	-82.51	-82.41	-85.30	-80.49
2. Cancer	-57.07	-48.60	-45.74	-39.39	-40.15	-34.12	-40.70	-38.69	-30.40
3. Stroke	-20.86	-23.31	-26.19	-25.13	-26.38	-26.26	-23.85	-28.10	-21.35
4. Chronic lower respiratory disease	-8.50	-5.37	-1.53	1.52	4.04	6.97	6.33	10.19	8.59
5. Accident	14.93	18.11	14.11	19.79	11.65	11.06	10.99	10.15	8.48
6. Alzheimer disease	11.02	13.55	13.88	15.17	17.07	17.22	14.57	14.10	12.18
7. Diabetes	-4.29	-3.10	-3.16	0.38	3.45	0.97	1.74	3.63	2.72
8. Influenza & Pneumonia	-12.08	-10.26	-10.10	-8.35	-9.15	-8.78	-10.07	-8.12	-7.26
9. Nephritis	-1.04	-0.01	-0.01	0.60	1.35	0.87	-0.01	-1.82	-0.02
10. Suicide	2.56	3.98	5.47	4.99	6.47	5.78	6.64	3.86	6.05
11. Septicemia	-3.04	-0.75	0.25	0.43	-0.35	0.43	-0.06	-0.80	0.80
12. Chronic liver disease	0.26	2.60	3.80	4.25	4.78	4.11	5.00	1.76	6.10

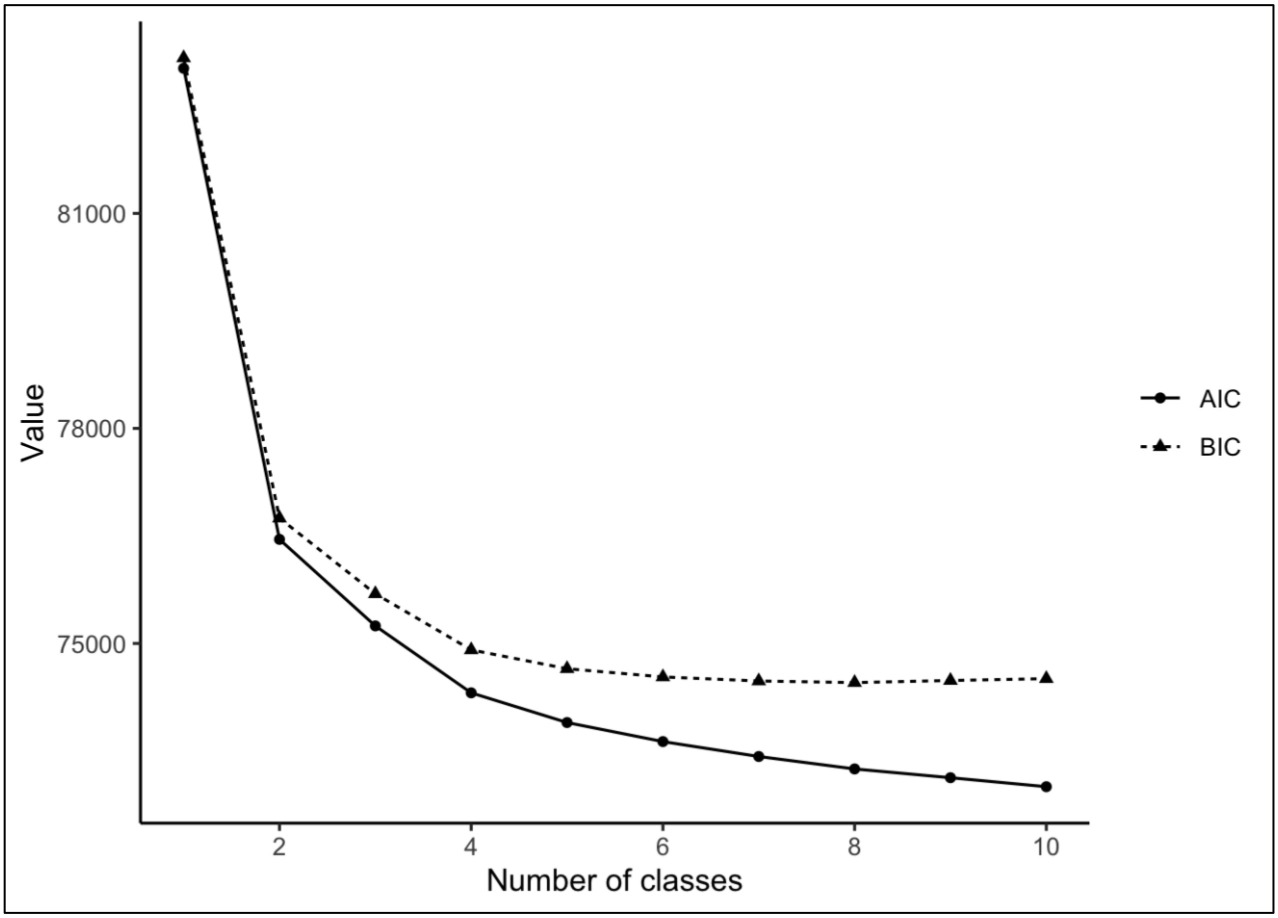

Figure S3. Fit statistics for models with 1-10 classes. Models were fit using age-adjusted cause-specific mortality for top 12 leading causes of death as items.

Table S2. Class probabilities for five class model with covariates (% poverty, % migration, rurality). Classes were fit using cause-specific age-adjusted mortality per county from 2000-2019. Values above 0.5 are bolded.

Item	**Tertile**	**Moderate mortality**	**High chronic mortality**	**High mortality**	**High suicide, accident, CLD**	**Low mortality**
Class proportion	NA	22.9%	10.5%	25.6%	22.1%	18.9%
Cardiovascular disease	Lowest	0.154	0.011	0.005	**0.577**	**0.875**
	Middle	**0.675**	0.197	0.238	0.347	0.116
	Highest	0.171	**0.792**	**0.757**	0.076	0.009
Cancer	Lowest	0.128	0.077	0.018	**0.587**	**0.844**
	Middle	**0.691**	0.211	0.211	0.319	0.156
	Highest	0.181	**0.711**	**0.771**	0.094	0.000
Stroke	Lowest	0.246	0.058	0.084	**0.546**	**0.672**
	Middle	0.488	0.201	0.311	0.313	0.279
	Highest	0.266	**0.741**	**0.605**	0.141	0.049
CLRD	Lowest	0.277	0.351	0.008	0.334	**0.821**
	Middle	**0.530**	0.461	0.158	0.416	0.173
	Highest	0.193	0.188	**0.834**	0.250	0.006
Accident	Lowest	**0.553**	0.157	0.032	0.104	**0.834**
	Middle	0.383	0.436	0.316	0.415	0.147
	Highest	0.064	0.407	**0.652**	0.481	0.020
Alzheimer disease	Lowest	0.280	0.282	0.202	0.495	0.402
	Middle	0.394	0.337	0.309	0.288	0.350
	Highest	0.327	0.381	0.489	0.217	0.248
Diabetes	Lowest	0.308	0.125	0.126	0.375	**0.699**
	Middle	0.440	0.186	0.360	0.327	0.264
	Highest	0.252	**0.689**	**0.514**	0.298	0.037
Influenza & Pneumonia	Lowest	0.316	0.137	0.094	0.417	**0.677**
	Middle	**0.508**	0.320	0.267	0.312	0.251
	Highest	0.175	**0.543**	**0.638**	0.272	0.072
Nephritis	Lowest	0.160	0.000	0.084	**0.601**	**0.744**
	Middle	**0.560**	0.061	0.339	0.301	0.242
	Highest	0.280	**0.939**	**0.577**	0.097	0.014
Suicide	Lowest	0.437	**0.707**	0.063	0.125	**0.602**
	Middle	0.477	0.260	0.405	0.172	0.297
	Highest	0.086	0.033	**0.533**	**0.702**	0.100
Septicemia	Lowest	0.160	0.007	0.049	**0.652**	**0.729**

	Middle	**0.508**	0.041	0.430	0.295	0.200
	Highest	0.332	**0.952**	**0.521**	0.053	0.071
Chronic liver disease	Lowest	0.344	0.229	0.124	0.302	**0.691**
	Middle	0.470	0.449	0.307	0.242	0.249
	Highest	0.186	0.322	**0.569**	0.457	0.059

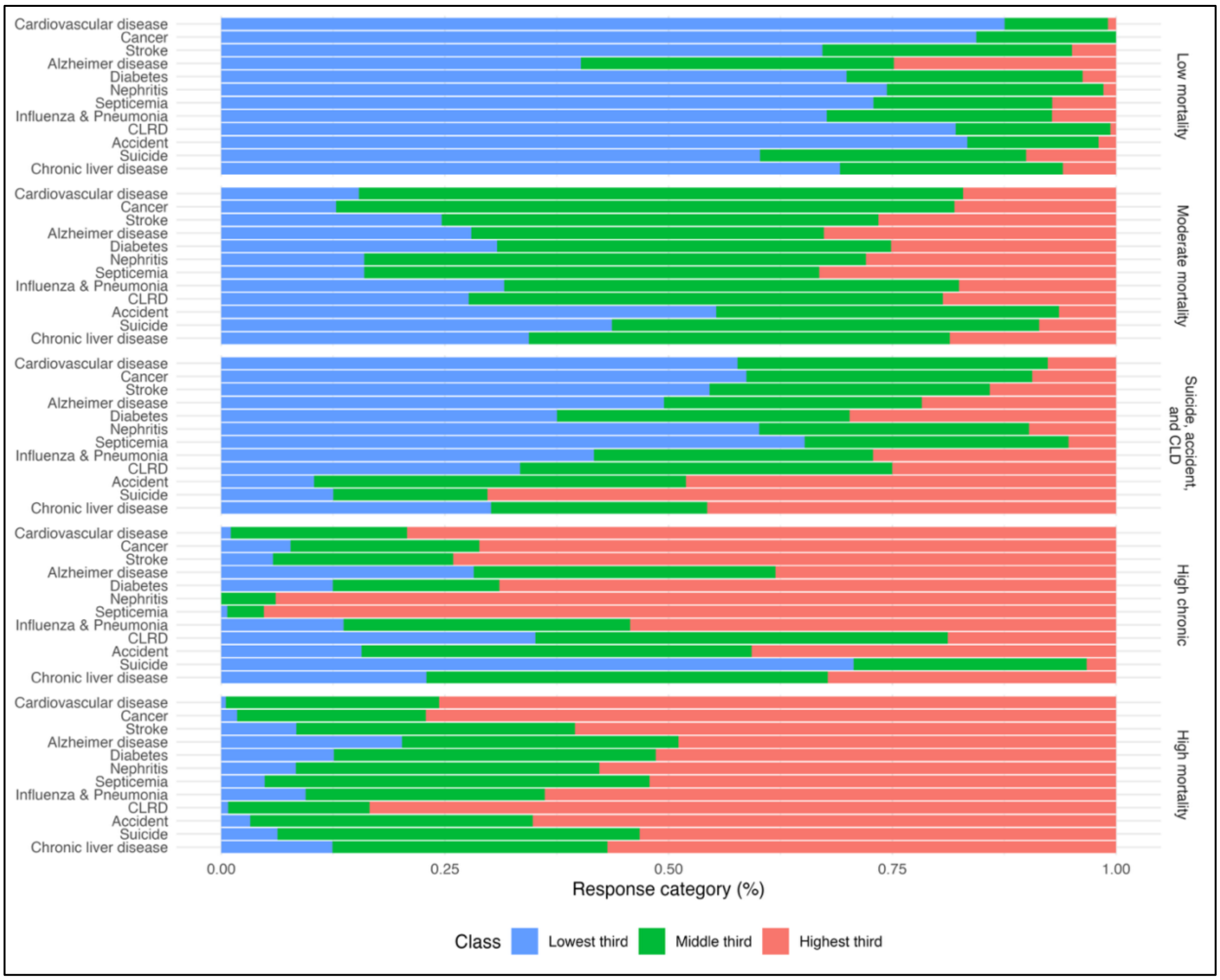

Figure S4. Latent class fit for 5-class model with covariates. Bars indicate which proportion of counties in each class. 1=moderate mortality, 2=high chronic mortality, 3=high mortality, 4=high suicide, accident, chronic liver disease, low chronic disease, 5=low mortality. Covariates included in model were % poverty, % net migration, and rurality (RUCC).

Table S4. Latent class category descriptive statistics for rurality, migration, and poverty. Estimates are mean (standard deviation). Net % migration is number of in-migrants minus number of out-migrants divided by the total population over the time period (2000-2019). Positive net % migration indicates there were more in-migrants than out migrants. % poverty is the percent of the population below the federal poverty line in the 2008-2012 ACS.

Measure	Class				
	Low mortality (n=592)	Moderate mortality (n=722)	High suicide, accident, and CLD (n=679)	High chronic mortality (n=320)	High mortality (n=820)
% poverty	6.1 (2.4)	8.8 (3.2)	9.3 (3.9)	10.4 (4.5)	13.2 (4.2)
% net migration	3.8 (9.4)	3.1 (7.8)	1.4 (9.5)	-6.0 (6.3)	1.0 (6.4)
% Poverty by rurality					
RUCC 1	5.0 (2.5)	7.1 (2.4)	8.4 (1.8)	7.5 (3.0)	10.7 (3.0)
RUCC 2	6.1 (1.7)	9.1 (4.5)	10.8 (4.1)	9.5 (3.2)	12.3 (3.5)
RUCC 3	6.4 (2.2)	9.1 (2.4)	9.4 (3.2)	9.5 (3.2)	12.0 (2.9)
RUCC 4	7.1 (2.0)	9.7 (2.4)	11.7 (2.8)	13.2 (7.2)	12.5 (2.4)
RUCC 5	6.5 (1.6)	10.3 (1.9)	9.2 (2.4)	12.5 (6.5)	12.4 (2.3)
RUCC 6	7.2 (1.8)	9.7 (2.9)	10.7 (4.1)	11.3 (4.2)	13.1 (3.4)
RUCC 7	6.1 (2.1)	9.4 (2.3)	9.1 (3.7)	11.5 (4.9)	14.4 (5.2)
RUCC 8	5.6 (2.6)	6.4 (2.6)	8.7 (3.6)	8.4 (3.6)	13.9 (4.2)
RUCC 9	6.5 (3.1)	9.6 (4.0)	8.9 (4.2)	10.0 (3.8)	16.1 (5.8)
% net migration by rurality					
RUCC 1	8.3 (10.7)	8.2 (9.3)	17.0 (12.6)	-6.3 (5.9)	6.1 (7.5)
RUCC 2	7.9 (10.0)	4.7 (7.7)	8.1 (9.2)	-3.7 (7.2)	3.4 (6.3)
RUCC 3	5.1 (8.5)	1.7 (6.4)	8.3 (13.5)	-4.0 (6.6)	1.3 (5.8)
RUCC 4	3.3 (5.0)	0.5 (5.3)	6.1 (6.8)	-5.3 (4.4)	3.8 (7.7)
RUCC 5	3.5 (6.9)	-2.5 (4.7)	3.2 (7.6)	-8.8 (6.9)	-0.0 (3.7)
RUCC 6	0.0 (4.2)	-0.1 (4.4)	3.0 (8.3)	-5.7 (5.6)	0.7 (5.2)
RUCC 7	-0.8 (5.9)	-2.3 (4.0)	0.2 (6.9)	-7.6 (6.3)	-1.2 (5.4)
RUCC 8	-4.3 (4.4)	3.9 (6.8)	1.2 (8.2)	-6.8 (7.0)	0.4 (6.0)
RUCC 9	-3.8 (5.9)	0.5 (6.5)	-2.0 (8.6)	-9.3 (4.9)	-2.0 (7.0)

Table S5. Odds ratios (OR) for single-step latent class model. Reference category is low mortality counties. Rural-Urban Continuum Codes (RUCC) indicate rurality (1=most urban, 9=most rural). OR for the intercept can be interpreted as the odds of membership in each latent class in relation to the reference latent class at RUCC=1 and mean % migration and mean % poverty. OR for covariates can be interpreted as the change in odds of membership in the latent class in relation to the reference latent class associated with a one-unit increase in covariate.

Ref = low mortality	**Moderate mortality**	**High suicide, accident, and CLD**	**High chronic mortality**	**High mortality**
(Intercept)	5.3 (3.64, 7.73)	0.34 (0.16, 0.73)	1.12 (0.59, 2.13)	2.84 (1.8, 4.48)
% poverty	**1.47 (1.39, 1.56)**	**1.50 (1.43, 1.59)**	**1.68 (1.58, 1.79)**	**2.00 (1.89, 2.11)**
% net migrants	0.98 (0.96, 1.00)	**1.03 (1.01, 1.05)**	**0.78 (0.75, 0.81)**	0.99 (0.97, 1.01)
Rurality (ref = RUCC 1)				
RUCC 2	0.88 (0.56, 1.37)	**2.45 (1.00, 6.04)**	0.91 (0.41, 2.01)	0.64 (0.35, 1.17)
RUCC 3	**0.51 (0.32, 0.81)**	**3.25 (1.41, 7.54)**	**0.42 (0.19, 0.93)**	0.58 (0.31, 1.07)
RUCC 4	0.77 (0.42, 1.44)	**3.58 (1.32, 9.67)**	0.44 (0.17, 1.18)	0.61 (0.29, 1.28)
RUCC 5	**0.28 (0.11, 0.75)**	**5.13 (1.74, 15.11)**	**0.23 (0.06, 0.84)**	0.57 (0.21, 1.56)
RUCC 6	**0.58 (0.35, 0.96)**	**5.70 (2.40, 13.53)**	0.77 (0.37, 1.61)	1.17 (0.65, 2.09)
RUCC 7	**0.27 (0.14, 0.50)**	**15.34 (6.62, 35.57)**	**0.35 (0.16, 0.78)**	0.85 (0.45, 1.59)
RUCC 8	0.41 (0.16, 1.07)	**48.81 (17.71, 134.49)**	1.54 (0.59, 3.99)	**2.97 (1.25, 7.09)**
RUCC 9	**0.10 (0.04, 0.25)**	**34.96 (14.80, 82.58)**	**0.09 (0.04, 0.22)**	0.74 (0.38, 1.44)

Table S6. Latent class membership by RUCC. Latent class membership is fit using model with covariates. Percentages are row-wise (each row sums to 100%).

RUCC	Low mortality	Moderate mortality	High suicide, accident, and CLD	High chronic mortality	High mortality
1	138 (34%)	164 (41%)	15 (4%)	18 (4%)	69 (17%)
2	88 (24%)	147 (40%)	27 (7%)	39 (11%)	69 (19%)
3	84 (24%)	101 (29%)	48 (14%)	32 (9%)	79 (23%)
4	30 (14%)	82 (39%)	25 (12%)	19 (9%)	54 (26%)
5	18 (20%)	16 (17%)	20 (22%)	10 (11%)	28 (30%)
6	67 (12%)	123 (21%)	70 (12%)	92 (16%)	230 (40%)
7	68 (16%)	41 (10%)	147 (34%)	50 (12%)	122 (29%)
8	17 (8%)	9 (4%)	90 (41%)	35 (16%)	68 (31%)
9	72 (18%)	12 (3%)	221 (54%)	20 (5%)	86 (21%)
Total	582 (19%)	695 (23%)	663 (22%)	315 (10%)	805 (26%)

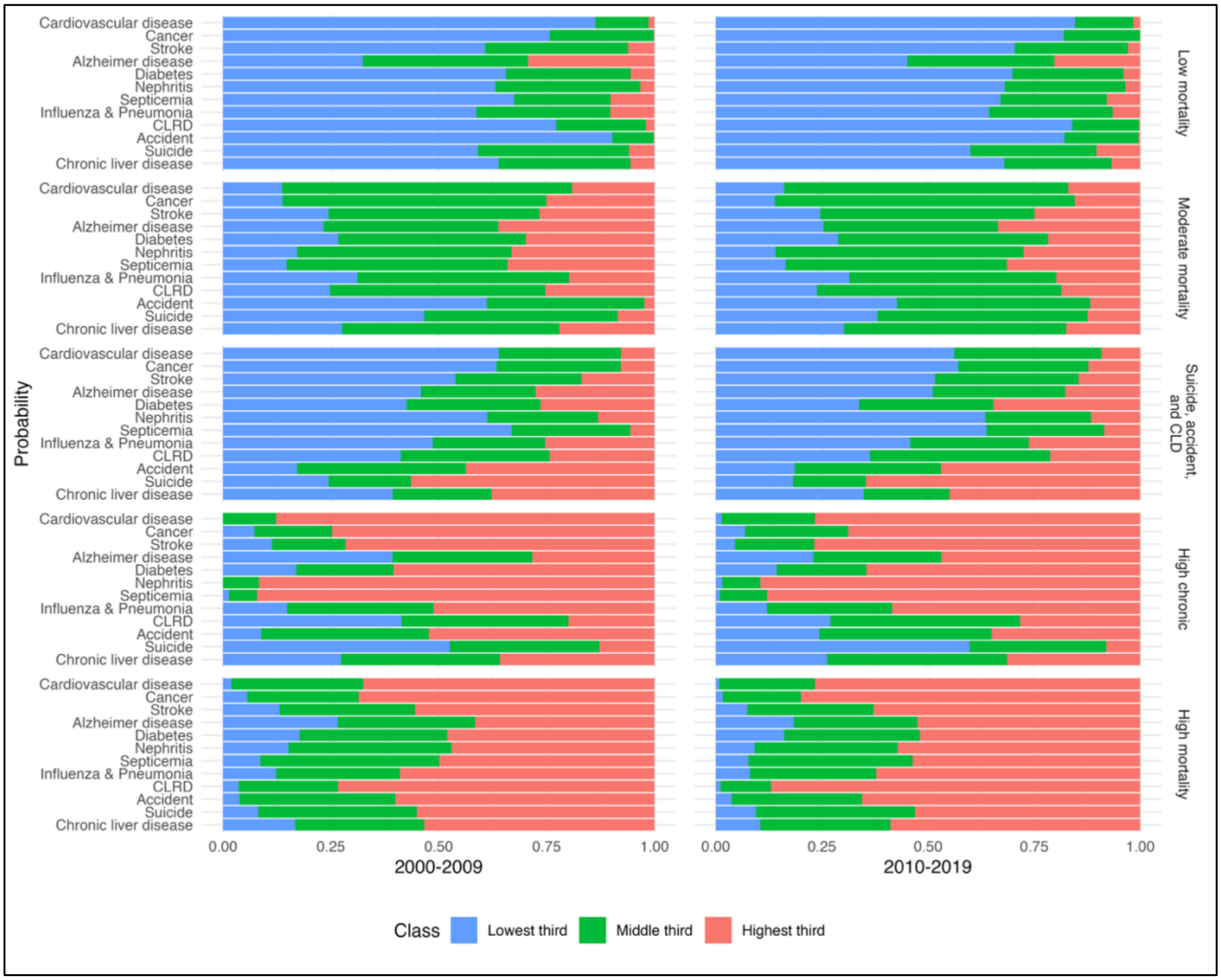

Figure S5. Latent class fit for 5-class model with covariates for two time periods (2000-2009, 2010-2019). Bars indicate which proportion of counties in each class. Covariates included in model were % poverty, % net migration, and rurality (RUCC).

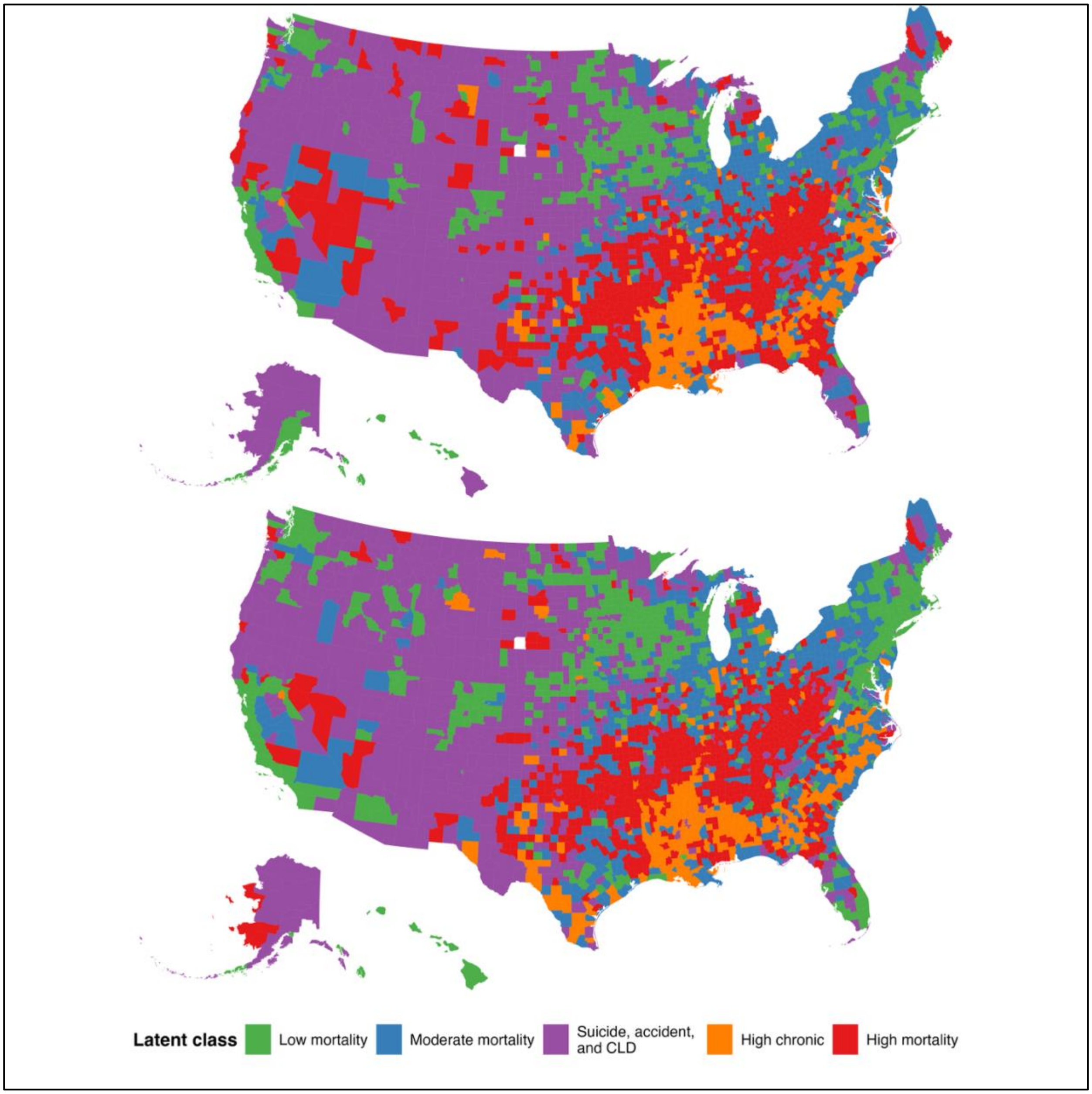

Figure S6. Map of latent classes by time period. Top=2000-2009, bottom=2010-2019. Latent class models were fit separately for the time periods 2000-2009 and 2010-2019.

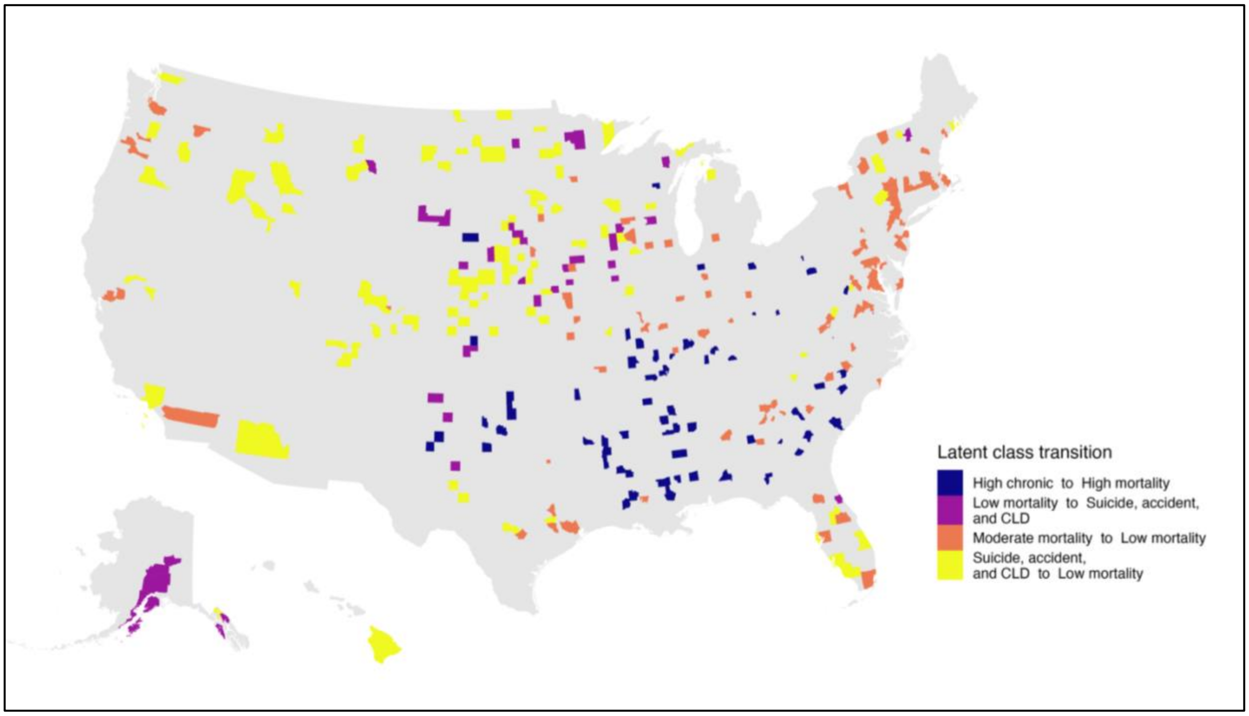

Figure S7. Select transitions in LCA classes from Wave 1 (2000-2009) to Wave 2 (2010-2019). Included are the top 4 transition categories.

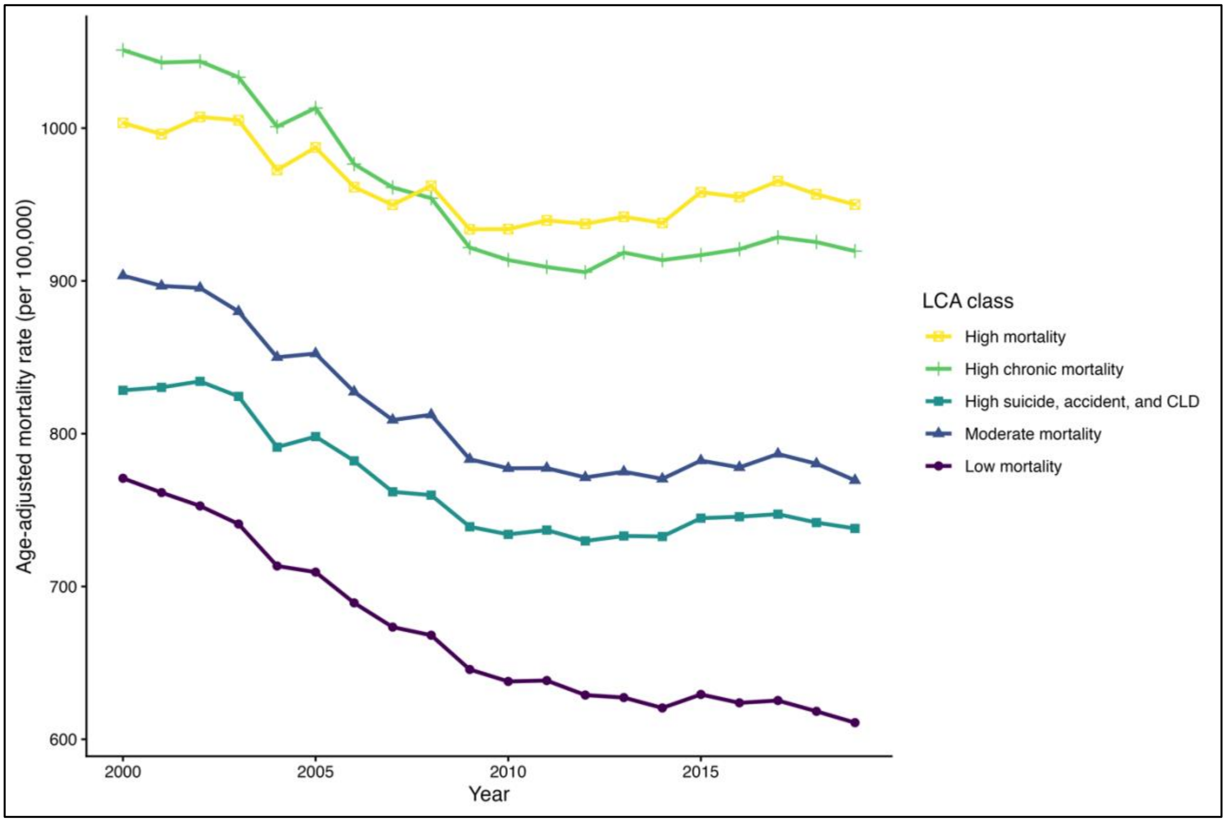

Figure S8. Yearly age-adjusted mortality rate by latent class from 2000-2019.

Chapter 4: Emergency department mental health visits associated with wildfire smoke exposure in Washington State from 2019-2023

ABSTRACT

Wildfire smoke particulate matter ($PM_{2.5}$) has been associated with adverse cardiorespiratory outcomes, but the mental health impacts of wildfire air pollution have not been extensively studied. Non-wildfire $PM_{2.5}$ has been associated with depression and anxiety, however, there are key differences in composition as well as in patterns of exposure strength and length of exposure between non-wildfire and wildfire-specific air pollution. We assessed the impact of wildfire-specific $PM_{2.5}$ on the number of mental health emergency department (ED) visits per zip code in Washington State from 2019-2023 using a case time series study design. We found a 4.6% (0.9%, 8.5%) increase in emergency department visits with a mental health condition associated with heavy wildfire-specific smoke days (> 35 $\mu g/m^3$). These effects were stronger for men, those in middle age groups (26-45), and in urban areas. Given increasing wildfire air pollution output over the last decade and predicted increases, particularly in the US Northwest, these findings should help direct public health communications during anticipated wildfire smoke events.

INTRODUCTION

Wildfire smoke exposure has been linked to multiple poor health outcomes, including respiratory hospitalizations and emergency department (ED) visits, cardiovascular disease hospitalizations, and all-cause mortality.[74, 75] Wildfires produce numerous toxins, including particulate matter, carbon monoxide, nitrous oxide, methane, volatile organic compounds, and secondary ozone formation, although most health research uses measurements of fine particulate matter ($PM_{2.5}$ – particles < 2.5 $\mu g/m^3$) as $PM_{2.5}$ is a good proxy for wildfire smoke, is widely monitored, and these particles can penetrate deep into the lungs and enter the bloodstream.[76] While $PM_{2.5}$ levels are decreasing across much of the U.S., the highest daily $PM_{2.5}$ levels (during wildfire days) and total yearly carbon output are increasing in the US Northwest due to increased wildfire activity.[87] Recent work in Washington has reported negative physical health impacts including increased cardiovascular and respiratory disease hospital visits and mortality associated with wildfire activity.[88, 89] Qualitative research in Washington has also highlighted the lengthened wildfire smoke season due to both local fires and drift smoke from large fires further away, as well as the potential mental health impacts of this.[81] While there is abundant evidence showing the negative impact of wildfire smoke $PM_{2.5}$ on physical health outcomes, there is limited empirical evidence of the effect of wildfire smoke $PM_{2.5}$ on mental health.

Despite the lack of research examining wildfire smoke $PM_{2.5}$ and mental health outcomes, a number of studies have provided limited evidence of an association between general (non-wildfire specific) particulate matter and mental health outcomes. Long-term $PM_{2.5}$ was found to be associated with increased risk of depression, with as much as a 50% increase in depressive symptoms among the 75th percentile of exposure compared to the 25th percentile.[105–107] A meta-analysis of air pollution and depression found a smaller positive association between long-term $PM_{2.5}$ and depression, but they note high heterogeneity in findings between studies and publication bias that limits conclusions on this association. Another systematic review and meta-analysis of air pollution and mental health found that long-term all-source $PM_{2.5}$ exposure was positively associated with depression and anxiety, and short-term $PM_{2.5}$ exposure associated with depression-related ED visits, although this study noted methodological and other challenges that limit causal claims.[77] Overall, the evidence of long-term impacts of $PM_{2.5}$ on mental health outcomes is limited by potential unadjusted confounders, and there is limited evidence of the impact of short-term $PM_{2.5}$ on mental health outcomes.

Although there are numerous studies examining general $PM_{2.5}$ and mental health outcomes, wildfire smoke $PM_{2.5}$ has several key differences compared to $PM_{2.5}$ from other sources, necessitating studies that examine wildfire-specific smoke exposures. First, wildfire smoke $PM_{2.5}$ may have important spatial and temporal distribution differences compared to non-wildfire $PM_{2.5}$; previous research has suggested that poor mental health may be due to consistent long-term exposure to $PM_{2.5}$ while wildfires are often short-term events, albeit with the potential for extremely high $PM_{2.5}$ concentrations. Second, wildfire smoke $PM_{2.5}$ may have a stronger dose-conditional effect on health outcomes compared to non-wildfire $PM_{2.5}$. Wildfire $PM_{2.5}$ has been associated with larger increases in pediatric and adult respiratory hospital visits as compared to similar exposures to non-wildfire $PM_{2.5}$, however, this work is currently limited to respiratory outcomes and requires additional research to determine mechanisms.[78, 79, 108]

There is limited research on wildfire-specific $PM_{2.5}$ exposure associations with mental health outcomes. A study examining all ED visits in California from July-December 2020 found increased visits for all-cause mental health conditions, particularly among women, but this association was found to be significant only for low-income individuals (Medicaid recipients) upon stratification.[84] Other research, conducted in the Western US from 2007-2018, found an increase in ED visits for anxiety following wildfire smoke events, particularly for older age groups and women, and among men for major smoke events.[85] Another study found mixed results for the association of mental health ED visits and wildfire smoke, finding positive associations with schizophrenia but negative associations for substance use disorders and suicide.[75] Overall, prior research shows potential increases in mental health ED visits related to short-term wildfire smoke exposure, however, the lack of a standard definition for smoke exposure across studies makes comparison difficult and limited temporal, geographic, or outcome definitions restrict generalizability.

Wildfire smoke $PM_{2.5}$ may impact mental health through physical, social, and economic pathways. Research on $PM_{2.5}$ in general indicates that elevated levels may induce inflammation of the central nervous system and lead to impaired cognitive function.[77, 80] Wildfire-specific smoke has been reported to impact mental health through social isolation as people avoid leaving their house during heavy smoke events, and can increase anxiety due to perceived or actual risk of asthma or other respiratory illnesses.[81, 82] Additional pathways include sleep disturbance, reduced physical activity, family stress or violence, and reduced access to livelihoods or nature.[83] These impacts may be moderated by behaviors and socioeconomic conditions that constrain behavior, such as the ability to access information about exposure risk or differential ability to take protective action.[82]

Wildfire smoke $PM_{2.5}$ likely does not affect all populations equally. Rural and low-income populations may be at higher risk of poor health outcomes due to wildfire smoke because of closer proximity to wildfires, reduced access to healthcare, and higher levels of comorbidities such as cardiovascular disease, asthma, and chronic obstructive pulmonary disorder (COPD). Socioeconomic status (SES) may also modify exposure to air pollution in other ways; research has shown that wildfires increase indoor air pollution in low-income homes by a factor of four, and this may be even greater for low-income homes without air filtration systems.[86] Other research has shown that while homes in high- and low-income areas have similar ambient $PM_{2.5}$ levels during wildfire events, indoor $PM_{2.5}$ levels are lower in high-income areas and newer buildings and those with air conditioning also have lower $PM_{2.5}$ levels.[109, 110] Additionally, wildfire smoke

$PM_{2.5}$ has been shown to impact health outcomes differentially across age and sex groups, with mixed results for respiratory and mental health outcomes.[78, 85, 91]

For this analysis, we use cause-specific surveillance data on emergency department (ED) visits in Washington State from 2019 – 2023 to estimate the association of short-term wildfire fine particulate matter ($PM_{2.5}$) exposure and mental health-related ED clinic visits. Additionally, we examine potential effect modification by age, sex, rurality, and SES to assess potential differential effects of wildfire smoke pollution across the population.

METHODS

Study overview

We used a case time series study design to estimate the impact of wildfire-specific $PM_{2.5}$ on the number of mental health-related emergency department visits in Washington State zip codes from 2019-2023.

Data

Our exposure was publicly available daily average wildfire-specific $PM_{2.5}$ estimates from a previously developed model.[90] This model generated estimates of wildfire smoke $PM_{2.5}$ for a 10-km^2 grid over the contiguous US using smoke plume classification, ground-based air-pollution monitoring stations, and meteorological and land-use covariates in a gradient boosted tree machine learning model. The model performs well across the range of observed $PM_{2.5}$ estimates in the current study and 94% of out-of-sample predictions were within 5 $\mu g/m^3$ of observed measurements.[90] The daily 10-km^2 estimates of wildfire-specific $PM_{2.5}$ were aggregated to zip code tabulation area (ZCTA) using population-weighted means to estimate daily population-weighted ZCTA wildfire-specific $PM_{2.5}$.

Our outcome were daily counts of mental health ED visits from the Washington State Department of Health Rapid Health Information Network (RHINO) program. RHINO is a syndromic surveillance system that includes all ED visits from non-federal EDs in Washington State. We leveraged a Centers for Disease Control and Prevention (CDC) search query designed to capture all visits with a mental health-related diagnosis code or text entry (Supplemental material - CDC Mental Health v1). This query includes not only visits where the primary reason is related to mental health but also visits where mental health conditions are included in the discharge diagnosis or chief complaint text. Because of this, our counts include visits where the *primary* reason for the ED visit is not a mental health concern. ED visit counts are aggregated to the ZCTA-day level based on the patient's residential address. Because facilities were onboarding into RHINO prior to June 2019, we limit our primary analysis to data from facilities that had started reporting by June 1, 2019 and continued reporting through October 31, 2023 (**Figure S1**). We included only visits from June 1 – October 31 for each year of the study to capture the primary wildfire season in Washington State.

We include daily humidex, a measure of temperature and humidity, as an adjustment variable in our models. Humidex is often included as a confounder in studies on the impact of wildfire smoke on physical health outcomes because heat and humidity are associated with both increased cardiorespiratory outcomes and risk of wildfire,[91, 111, 112] and is appropriate here because heat and humidity also increase adverse mental health outcomes.[113] We calculate humidex using daily maximum temperature and minimum relative humidity per ZCTA.[93]

We also stratify our analyses by several factors, including age, sex, rural/urban, and social deprivation index (SDI). Age and sex of patients are included in the RHINO visit data. Rurality was defined using 2020 Rural-Urban Commuting Area Codes (RUCA) from the US Department of Agriculture Economic Research Service. RUCA codes are created using census tracts and indicate urban/rural using a combination of population density, size, and built environment criteria.[94] We include four categories: Metropolitan (within urban area > 50,000 people), Micropolitan (within urban area 10,000 – 49,999 people), Small town (urban area < 10,000 people), and Rural not in urban area).[114] The tracts are then aggregated to ZCTA using the RUCA code with the largest population within each ZCTA (**Figure S2**).

Social Deprivation Index (SDI) is an area-level composite index created using the America Community Survey (ACS) comprised of percent living in poverty, percent with <12 years of education, percent single-parent households, precent living in rental housing, percent living in overcrowded housing, percent of households without a car, and percent non-employed adults under 65 (**Figure S3**).[95] SDI used here was constructed using ZCTA-level estimates from the ACS. We also present age-adjusted mental health visits by ZCTA. Population counts by age for age adjustment are from the 2020 US Census count and age-adjustment was calculated using the direct method.[28] For all analyses, we exclude ZCTAs that have 0 population from the 2020 US census count. This study was determined human subjects exempt by the Washington State Institutional Review Board.

Analysis

We used a case time series study design that compared ED visit counts for each ZCTA on days on the same weekday in the same month and year within the same ZCTA.[96] This within-case design uses a stratified quasi-Poisson model, with strata defined by the weekday, month, year, and ZCTA; for example, all Mondays in July of 2019 are included in one stratum. This study design automatically adjusts for time-invariant confounding, seasonality, and slowly changing trends. To estimate the impact of wildfire smoke on ED visits we used a conditional quasi-Poisson model, which conditions on the total mental health ED visit count within each stratum, to model the number of mental health-related ED visits per ZCTA as our outcome.[97] We also adjusted for humidex, modeled as a natural cubic spline with three degrees of freedom similar to previous studies,[88, 91] as well as federal holidays, including official holidays and observed holidays (i.e., if July 4th falls on a Saturday we included both July 3rd and July 4th as holidays in our model).

Our primary analysis categorized daily average wildfire smoke $PM_{2.5}$ exposures to allow for non-linearity because the association of wildfire smoke $PM_{2.5}$ and *all-cause* ED visits has been characterized by increased visits at low levels of smoke (compared to no smoke) and reduced visits at higher concentrations.[74] We expect a potential non-linear association between wildfire $PM_{2.5}$ and mental health ED visits as well, and so we model our exposure categorically with four levels. The reference level includes $PM_{2.5}$ < 9 $\mu g/m^3$: we compare this to >9–20.4 $\mu g/m^3$ (light smoke), >20.4–35 $\mu g/m^3$ (moderate smoke), and >35 $\mu g/m^3$ (heavy smoke). The lower cut-offs (9 and 20.4 $\mu g/m^3$) correspond to previous research on wildfires in Washington examining total $PM_{2.5}$,[88, 91] and the highest level corresponds to air quality index cut-offs used for public health messaging and Environmental Protection Agency (EPA) 24-hour standards.[92] The use of categorical measures here, as opposed to other non-linear modeling techniques such as splines, simplifies the interpretation of our association.

We included a distributed lag term for time, modeled as a natural cubic spline with three degrees of freedom over 7 days (day of visit plus 6 days prior) as used in previous studies,[88, 91] to capture potential lag effects of wildfire smoke on ED visits.[98] To accomplish this, we fitted crossbasis functions for each categorical exposure level (except the reference category) and the lag period, and then combined the crossbasis functions together into a single model.

Specifically, we model the number of ED visits (Y) on day t for ZCTA i using:

$$Y_{i,t} = \alpha_{i(k)} + f(x_{1,i,t}, l) + f(x_{2,i,t}, l) + f(x_{3,i,t}, l) + \beta_1 x_{holiday} + s(x_{humidex})$$

Where $\alpha_{i(k)}$ is the stratum-specific intercept (defined as ZCTA, day of week, month, and year), the f functions are the crossbasis functions that incorporate the lag term (l) and the exposures (x).

$x_{1,i,t}$ is a binary indicator for light smoke exposure (>9–20.4 $\mu g/m^3$), $x_{2,i,t}$ a binary indicator for moderate smoke exposure (>20.4–35 $\mu g/m^3$), and $x_{3,i,t}$ a binary indicator for heavy smoke exposure (>35 $\mu g/m^3$). These crossbasis terms are modeled as natural cubic splines with 3 degrees of freedom over 7 days (day of ED visit plus 6 prior days), requiring the model to estimate three parameters to describe each exposure level over time. We also include an indicator for holiday and humidex (modeled as a natural cubic spline with 3 degrees of freedom). By combining all crossbasis functions, we can adjust for lagged effects of each exposure level on our outcome (i.e., adjusting for lagged effects of light smoke exposure on heavy smoke exposure). We report cumulative effects which are the combined effects across all lag days. Finally, the conditional Poisson model does not estimate the stratum-specific indicators ($\alpha_{i(k)}$), but instead conditions on the sum of events within the stratum for computational efficiency.

We stratified our analyses by age-group, sex, RUCA categories, and social deprivation index (SDI) quartile to examine heterogeneity in the association of mental health outcomes and wildfire-specific $PM_{2.5}$. Age-group and sex were available at the ED visit level; therefore, those analyses were conducted on each sub-group separately (i.e., we examined the association of wildfire $PM_{2.5}$ limited to those male and female in separate models). Included age groups were 12-17, 18-25, 26-35, 36-45, 56-65, and over 65. Age groups under 5 and 5-11 were not included in age-group specific analyses due to the small number of mental health visits for these two groups, but they were included in the total effect estimate. Analyses for sex included male and female as those were the only categories available in the data. Rural/urban and SDI are area-level attributes; therefore, we conducted those analyses limited to geographic areas within each group (i.e., all Metropolitan ZCTAs and all Rural ZCTAs are each included in separate models).

We were also interested in the effects of cumulative days of smoke exposure on mental health outcomes because we hypothesize that more consecutive days of smoke exposure may have a stronger effect on mental health through potential biological and/or social mechanisms. To understand this, we modeled the number of ED visits as our outcome, and the number of consecutive days at or above each smoke level prior to the outcome (including the day of visit) as our exposure. Each smoke exposure level (>9 μg/m^3, >20.4 μg/m^3, >35 μg/m^3) was included in a separate model.

In sensitivity analyses, we included data from 2018 (during RHINO facility onboarding). For this, we included data from all facilities during 2018-2023 for all months in which they reported for the entire month. For example, if a facility started reporting in July of 2018, then we include data from that facility for August 2018 onward. Additional sensitivity analyses include removing data from June of each year as wildfire-specific $PM_{2.5}$ are relatively low for that month in Washington State as well as examining effects for each year separately in order to examine potential differences in health seeking behavior during COVID. Finally, we estimated the effect of wildfire smoke $PM_{2.5}$ on mental health outcomes using a model that assumed a linear relationship between smoke exposure and outcomes. This model included wildfire smoke exposure as a linear predictor and a 7-day lag effect. All analyses were conducted using R statistical software (version 4.5.0), the `dlnm` package to fit crossbasis functions, and the ‘gnm’ package to fit our stratified conditional Poisson models.

RESULTS

Descriptive Results

In this case-crossover study in Washington State from 2019-2023, there were 438,345 ZCTA-days included in the study, 166,792 (38.1%) of which had any modeled wildfire-specific smoke present. Mean wildfire smoke per ZCTA-day over the study period was 3.76 μg/m^3 (SD=1.36) on all days, and 9.89 μg/m^3 (SD=5.83) on days in which wildfire-specific smoke was present (defined as > 0 μg/m^3 of modeled wildfire smoke). This varied substantially by year: 2020 had the highest mean wildfire smoke (8.02 μg/m^3 and 28.9 μg/m^3 for all days and wildfire-smoke days respectively) while 2019 had the lowest (0.44 $\mu g/m^3$ and 2.18 $\mu g/m^3$ respectively) (**Figure S4**). Mean wildfire-specific $PM_{2.5}$ was concentrated geographically and temporally in Washington from 2019-2023 (**Figure 1, Figure S5, Figure S6**). North Central Washington had the highest mean $PM_{2.5}$ while levels in the Western part of the state were relatively low. September was the smokiest month over the study period, with a mean of 10.0 $\mu g/m^3$ (SD=33.9) for all days while June had the lowest wildfire smoke concentration (mean=0.28, SD=1.23). Every ZCTA in Washington State had at least 6 days over the study period (2019-2023) with heavy wildfire-specific smoke (>35 $\mu g/m^3$), and the most impacted ZCTA (located in Okanogan County) had 57 days over this threshold.

Most ZCTA-days included in the study had zero or low levels of wildfire-specific $PM_{2.5}$ (92.5%), while 9,472 ZCTA-days (2.2%) had heavy (> 35 $\mu g/m^3$) smoke concentrations (**Table 1**). Small town and rural ZCTAs had slightly higher levels of heavier smoke exposure categories (>9 $\mu g/m^3$) compared to metropolitan and micropolitan ZCTAs, as did more advantaged ZCTAs measured by SDI (3rd and 4th quartiles compared to 1st and 2nd quartiles).

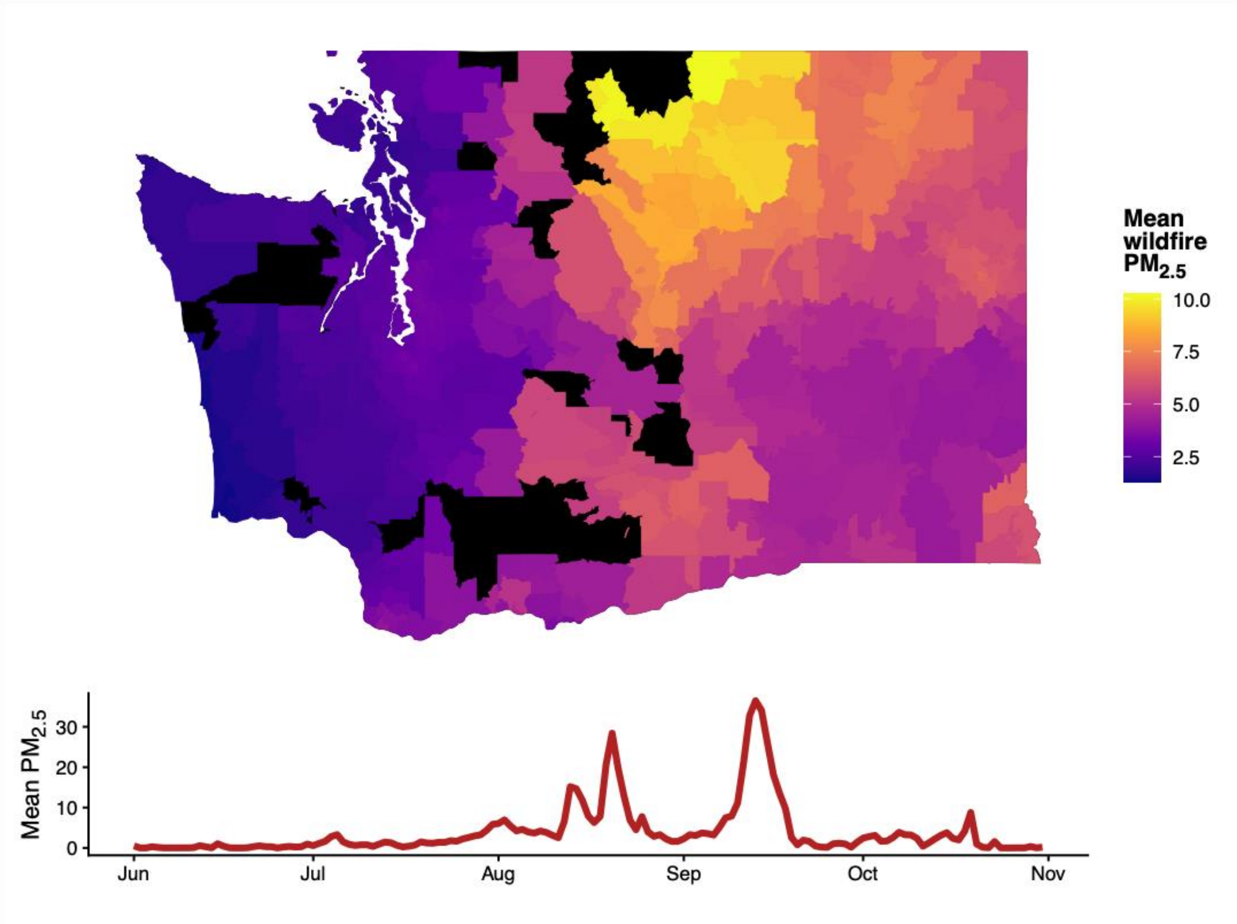

Figure 1. Mean wildfire-specific $PM_{2.5}$ by zip code tabulation area (ZCTA) in Washington State (top) from 2019-2023 and mean wildfire-specific $PM_{2.5}$ by day of year (bottom). Wildfire $PM_{2.5}$ is measured in $\mu g/m^3$. Data are limited to June 1-October 31 for each year. Black areas in the map are those with zero population.

From 2019-2023 there were 438,977 ED visits with a mental health related diagnosis code or text entry in Washington (9.6% of all visits) (**Table 1**). Mental health ED visits as a proportion of overall visits varied substantially by age, with those aged under 5 and 5-11 having much lower proportions of mental health ED visits (0.1% and 1.8% respectively). Mental health visit proportions were similar across adolescent (12-17) and adult age groups (9.5% - 11.3%). Women had slightly higher proportions of mental health visits compared to men (10.3% compared to 8.9%). Age-adjusted mental health visit rates by ZCTA showed geographic clustering; they were higher in Northeastern, Southcentral, and Western Washington (on the Olympic Peninsula)

(**Figure S7**). There were also temporal trends in mental health related ED visits; visits slightly increased during the year in 2019 and 2020 but decreased during 2022 (**Figure S8**). The highest number of consecutive days of light smoke or worse (> 9 μg/m3) per ZCTA was 43, moderate smoke (> 20.4 μg/m3) was 26, and heavy smoke (> 35 μg/m3) was 25 days. There were 39 ZCTAs that had more than 10 consecutive days of heavy smoke, 32 in 2020 and 9 in 2021 (2 of these ZCTAs had more than 10 consecutive days of heavy smoke in both years).

Table 1. Study characteristics by wildfire-specific $PM_{2.5}$ thresholds. Percentages for wildfire smoke characteristics (top section) in each smoke exposure category column represent the proportion of days in each category (row-wise).

Characteristic	**Daily wildfire $PM_{2.5}$ exposure category**				
	Low (0-9 μg/m3)	**Light (>9-20.4 μg/m3)**	**Medium (>20.4-35 μg/m3)**	**Heavy (>35 μg/m3)**	**Total***
Wildfire smoke characteristics					
Total ZCTA days (#)	405,528 (92.5%)	17,055 (3.9%)	6,290 (1.4%)	9,472 (2.2%)	438,345
Year					
2019	86,946 (99.2%)	579 (0.7%)	132 (0.2%)	12 (0.0%)	87,669 (20%)
2020	79,846 (91.1%)	2,185 (2.5%)	1,032 (1.2%)	4,606 (5.3%)	87,669 (20%)
2021	79,280 (90.4%)	4,283 (4.9%)	1,921 (2.2%)	2,185 (2.5%)	87,669 (20%)
2022	76,942 (87.8%)	6,674 (7.6%)	2,430 (2.8%)	1,623 (1.9%)	87,669 (20%)
2023	82,514 (94.1%)	3,334 (3.8%)	775 (0.9%)	1,046 (1.2%)	87,669 (20%)
Humidex (mean, sd)	32.9 (13.3)	42.4 (11.9)	43.1 (11.8)	38.5 (12.3)	33.5 (13.4)
Rural/urban (#)					
Metropolitan	236,818 (93.0%)	9,224 (3.6%)	3,688 (1.4%)	5,015 (2.0%)	254,745 (58.1%)
Micropolitan	32,971 (93.7%)	1,225 (3.5%)	377 (1.1%)	617 (1.8%)	35,190 (8.0%)
Small town	22,883 (90.6%)	1,211 (4.8%)	421 (1.7%)	730 (2.9%)	25,245 (5.8%)
Rural	112,856 (91.6%)	5,395 (4.4%)	1,804 (1.5%)	3,110 (2.5%)	123,165 (28.1%)
SDI					
1st quartile	97,710 (93.2%)	3,738 (3.6%)	1,386 (1.3%)	1,971 (1.9%)	104,805 (23.9%)
2nd quartile	101,492 (93.4%)	3,779 (3.5%)	1,350 (1.2%)	2,009 (1.8%)	108,630 (24.8%)
3rd quartile	97,109 (92.0%)	4,378 (4.1%)	1,580 (1.5%)	2,503 (2.4%)	105,570 (24.1%)
4th quartile (most disadvantaged)	106,406 (91.5%)	5,032 (4.3%)	1,930 (1.7%)	2,912 (2.5%)	116,280 (26.5%)
Mental health characteristics**					

Total mental health ED visits (% of overall visits)	410,198 (9.6%)	14,884 (9.1%)	5,778 (9%)	8,117 (10.2%)	438,977 (9.6%)
Age group					
Under 5‡	213 (0.1%)	4 (0%)	6 (0.2%)	4 (0.1%)	227 (0.1%)
5-11‡	2,746 (1.8%)	108 (1.6%)	46 (1.8%)	51 (1.8%)	2,951 (1.8%)
12-17	16,780 (9.8%)	657 (9.1%)	265 (9.7%)	341 (11%)	46,592 (9.7%)
18-25	43,395 (9.7%)	1,608 (9.4%)	672 (10.1%)	917 (10.6%)	75,973 (10.7%)
26-35	71,030 (10.7%)	2,512 (10.1%)	995 (10.2%)	1,436 (11.5%)	68,529 (11.2%)
36-45	63,881 (11.2%)	2,400 (10.9%)	939 (10.7%)	1,309 (12.2%)	59,852 (11.3%)
46-55	56,122 (11.3%)	1,905 (10.2%)	792 (10.5%)	1,033 (10.9%)	46,592 (9.7%)
56-65	59,916 (11.3%)	2,108 (10.6%)	824 (10.6%)	1,199 (11.9%)	64,047 (11.3%)
>65	95,578 (9.6%)	3,576 (9.3%)	1,238 (8.6%)	1,821 (10%)	102,213 (9.5%)
Sex					
Female	234,546 (10.3%)	8,371 (9.6%)	3,222 (9.5%)	4,658 (10.9%)	250,797 (10.3%)
Male	175,421 (8.9%)	6,506 (8.5%)	2,553 (8.6%)	3,452 (9.4%)	187,932 (8.9%)

*Percentages in the "Total" column represent proportions in each characteristic category (column-wise per characteristic).
**Percentages for mental health characteristics represent proportion of ED visits that included a mental health diagnosis (out of all ED visits).
‡Excluded from age-group specific analysis

Regression Results

We found that mental health ED visits increased by 4.6% (95% CI: 0.9%, 8.5%) on days with heavy smoke (> 35 $\mu g/m^3$) compared to reference days (0-9 $\mu g/m^3$) (**Figure 2, Table S2**). Visits decreased by 6.8% (95% CI: 5.7%, 10.0%) on days with light smoke (>9-20.4 $\mu g/m^3$) and there was no change in ED visits on days with moderate smoke (>20.4-35 $\mu g/m^3$) compared to the reference.

There were significant differences in the effect of wildfire smoke PM2.5 on mental health ED visits by age group, sex, rurality, and SDI. ED visit counts were elevated for most age groups on heavy smoke days, but highest for those aged 26-35 (9.9%; 95% CI: 3.2%, 16.9%) and 36-45 (13.7%; 6.6%, 21.3%). Heavy smoke was associated with higher mental health ED visits for both men (6.5%; 1.4%, 11.8%) and women (3.1%; -1.4, 7.8%). Among rural-urban status areas, the most urban ZCTAs (metropolitan and micropolitan) had higher ED visit counts on heavy smoke days (5.4%; 0.8%, 10.2% and 5.7%; -8.4, 21.9% higher visits respectively) while rural ZCTAs had 6.3% (-3.9, 15.4%) fewer visits. Less deprived areas (higher SDI quartile) had elevated mental health ED visit counts on heavy smoke days, with the strongest effect found for ZCTAs in the 3rd quartile (10.1%; 95% CI: 2.4%, 18.3%). There was no evidence to support an effect of heavy smoke on the most deprived ZCTAs.

Moderate smoke (>20.4-35 μg/m^3) was generally not associated with mental health ED visits within strata except for rurality. Rural counties showed an 18.9% (95% CI: 3.4%, 31.9%) reduction in visits while micropolitan counties had an increase in visits by 50.5% (95% CI: 15.7%, 95.5%) when comparing moderate smoke to low smoke (< 9 μg/m^3). Light smoke (> 9-20.4 μg/m^3) generally had fewer mental health ED visits compared to the reference or no effect across strata.

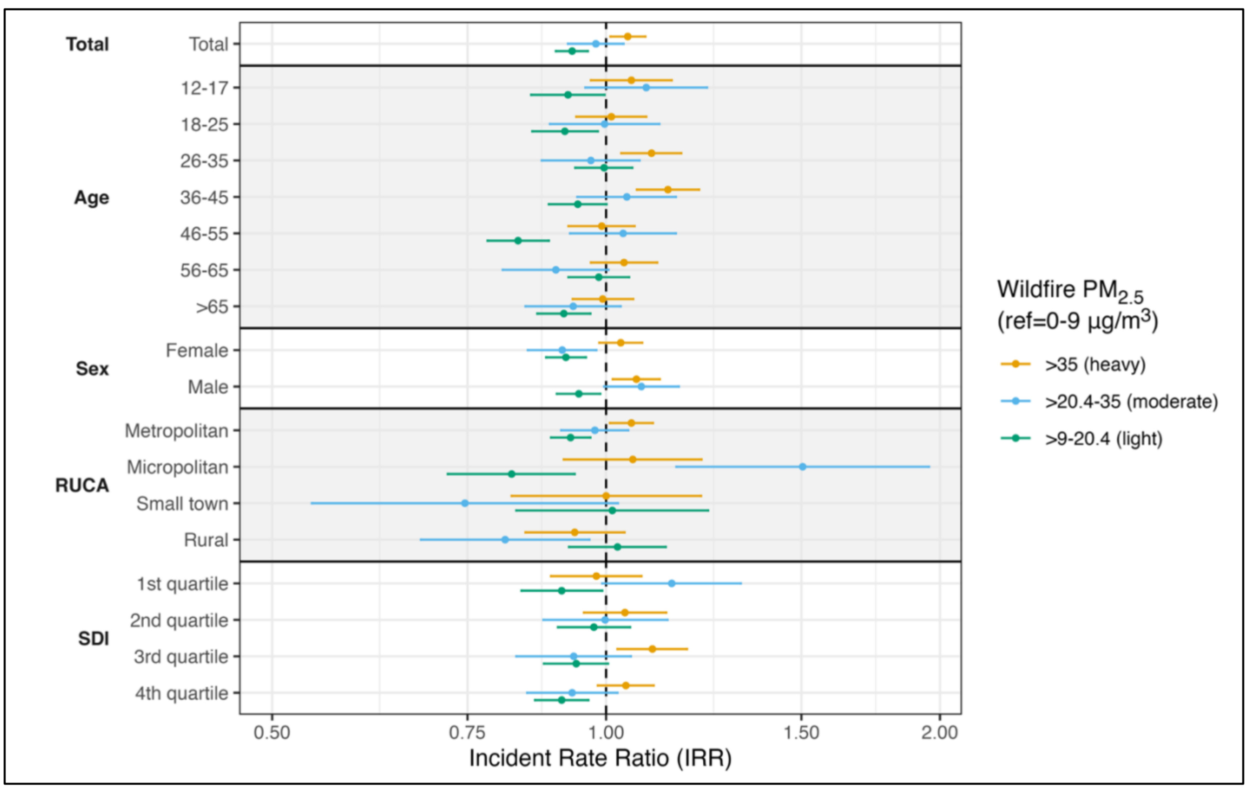

Figure 2. Incident Rate Ratio of wildfire smoke exposure on the number of mental health emergency visit (ED) visits per zip code tabulation area (ZCTA) in Washington State from 2019-2023. Estimates were calculated using a stratified quasi-Poisson model adjusting for humidex, and they can be interpreted as the percent change in the number of ED visits in each smoke exposure category compared to the reference category. “Total” category includes all ED visits

during the time frame. Stratified results are limited to each sub-group (e.g., results for those aged 12-17 include only counts of ED visits for that age group). SDI 4th quartile is most disadvantaged. RUCA=Rural-Urban Commuting Area; SDI=Social Deprivation Index.

Results were similar when examining the effect of consecutive days of smoke exposure on mental health ED visits. We found that for each consecutive day of heavy smoke the number of mental health ED visits increased by 0.8% (0.0, 1.7%) compared to low smoke (0-9μg/m^3) (**Table S3**). There were 2.5% (1.2, 3.9%) fewer mental health ED visits for each consecutive day of light smoke compared to the reference, and no strong evidence of a change in ED visits for moderate smoke.

In sensitivity analyses, we found similar effect estimates when we removed June from the analysis, and when we used all years of data (including 2018) (**Table S3**). Year-specific effects were generally consistent with overall effects. The exception was 2021 in which heavy smoke exposure was associated with 16.5% (5.7%, 26.1%) fewer mental health ED visits compared to the reference. In the model assuming a linear association between continuous wildfire smoke $PM_{2.5}$ we found a positive effect of wildfire smoke on mental health outcomes; mental health ED visits increased by 0.29% (95% CI: 0.02%, 0.56%) per 10 μg/m^3 increase in wildfire-specific $PM_{2.5}$.

DISCUSSION

In Washington State from 2019-2023, we found heavy wildfire smoke days were associated with an almost 5% increase in emergency department visits with a mental health condition. Conversely, light wildfire smoke days were associated with an approximately 7% decrease in ED visits. The increase in visits on heavy smoke days was highest for those aged 26-45 and for males, and effects were stronger in more urban and in less socially deprived ZCTAs. Interestingly, the reduction of ED visits during light wildfire smoke days were found in some of the same groups, in particular among more urban and less socially deprived ZCTAs.

The findings of increased ED visits for mental health conditions associated with heavy wildfire smoke aligns with previous work on ED-specific mental health outcomes. A study conducted in California in 2020 found an 8% higher cumulative relative risk (RR) per 10 $\mu g/m^3$ increase in wildfire-specific $PM_{2.5}$ for all-cause mental conditions using only the primary ED diagnosis code.[84] These findings were strongest among women and those on Medicaid. Another study conducted across multiple Western states from 2007-2018 found a 0.6% increase in odds of an ED visit for anxiety associated with a 10 $\mu g/m^3$ increase in 48-hour wildfire smoke $PM_{2.5}$, with findings pronounced among older people and adult women.[85] Our findings differed in that we found a stronger association among men compared to women; however, these studies differed from ours in exposure measurement (continuous vs categorical) and outcome (primary ED visit reason vs any mental health indication). Because of the difference in outcome measurement, our study may be more likely to capture sub-clinical mental health outcomes.

Group-level differences in the effect of wildfire smoke exposure on mental health visits are also a novel finding in the current study, particularly by rurality and SDI. Previous qualitative research in rural communities in Washington has indicated that reduced time spent outdoors, either for recreation or work, may be a factor in poor mental health outcomes.[81] In contrast, we find the strongest effect for heavy smoke among more urban ZCTAs. One reason for this could be differential care seeking behaviors in rural vs urban areas. Rural areas in Washington State are more accustomed to wildfire smoke air pollution, and, while it may impact overall mental health (particularly sub-clinical mental health outcomes), wildfire pollution may not cause an increase in care seeking behavior for mental health outcomes. Additionally, the null impact of heavy wildfire smoke but increased visits due to moderate smoke on those in the most socially deprived quartile (SDI quartile 1) is an interesting finding. Previous research has found that online searches for wildfire smoke information is similar across poorer and wealthier counties, however, populations in wealthier counties are more likely to search for air filters and to stay home during acute wildfire smoke events, potentially limiting personal exposure.[82] Because health impacts from wildfire smoke depend not just on ambient air pollution levels, but on individual factors that may mitigate exposure or adaptation, more research is needed on differential exposures and impacts of wildfire smoke $PM_{2.5}$ by SES.

The decrease in ED visits associated with light wildfire smoke pollution (< 9-20.4 $\mu g/m^3$) is an interesting finding that has not been shown before. One reason for this could be unmeasured time-varying confounding in our study. Wildfire smoke may be more present on days in which weather is more appealing and conducive to spending time outdoors (e.g., warmer temperature, less rain). Light, temperature, cloud cover, and precipitation have all been found to impact mood or well-being.[103] Numerous studies have also documented the mental health benefits of spending time outdoors and in nature.[104] Light wildfire smoke days may be more likely to fall on relatively nice weather days, where people spend more time outdoors but the pollution levels are not high enough to impact mental health, although controlling for humidex in our model should have, at least partially, accounted for this.

The yearly differences we found in the association of heavy wildfire smoke and mental health ED visits, particularly the reduction in visits associated with heavy wildfire smoke in 2021, may indicate potential time-varying confounding in this relationship. The heaviest smoke that year came in late August and early September, while there was a spike in mental health ED visits at the end of September.[99] This increase in mental health ED visits corresponded to an increase in COVID-19 diagnoses. Little work has been conducted on co-occurring disasters that include wildfire exposure, however, one study among adolescents in California found no association between wildfire exposure and mental health crisis texts during COVID.[100] Another study found that mental health and all-cause ED visits decreased during the first year of the COVID-19 pandemic while the proportion of ED visits related to mental health increased, potentially indicating that people with mental health related conditions may have less flexibility in emergency care seeking during public health emergencies.[101] Additional research is needed on mental health impacts of wildfire smoke along with co-occurring public health emergencies.

A major difference in the current study compared to previous research on the effect of wildfire smoke $PM_{2.5}$ on mental health ED visits is that we include visits where the mental health diagnosis is not listed as the primary reason for the visit. A strength of this approach is that we capture mental health outcomes that may be mediated through adverse physical health outcomes due to wildfire smoke exposure. Qualitative research among care providers in Washington reported that some patients may primarily report physical symptoms, even if there are none, due to anxiety or other mental health concerns from wildfire smoke.[81] The limitation in our outcome definition is that we may incorrectly attribute some mental health ED visits to wildfire smoke; there are likely patients experiencing mental health outcomes independently of wildfire smoke exposure, but who visit an ED for exposure reasons. However, previous research has shown that all-cause ED visits are reduced at moderate and high levels of wildfire smoke ($> 20\ \mu g/m^3$) due to reductions in injuries and other non-respiratory symptoms,[102] meaning we could potentially underestimate the effect of wildfire smoke as patients experiencing mental health outcomes may be less likely to visit the ED during wildfire smoke events. The impact of our outcome definition to accurately capture mental health ED visits related to wildfire smoke depends on the association between mental health diagnoses and other ED visit reasons. Regardless, this definition limits the comparison of the current study with previous research on this topic.

Our study has several strengths. The case time series study design automatically adjusts for non-time varying confounding, providing stronger evidence of the effect of wildfire-specific smoke on mental health ED visits compared to non-self-matched study designs. Additionally, the inclusion of a comprehensive surveillance system with multiple years of data ensure that we are able to capture most ED visits with a mental health diagnosis in Washington State over the study period. Finally, the inclusion of multiple categorical exposure categories allowed us to examine potential non-linear impacts of wildfire smoke on mental health ED visits.

Our study also has several limitations. First, we only capture mental health diagnoses related to ED visits, potentially limiting our analyses to the most severe cases – future studies should consider incorporating primary and urgent care visits. Second, we only examine wildfire $PM_{2.5}$ concentrations as our wildfire smoke exposure. There could be additional pollutants in wildfire smoke that impact mental health, although particulate matter is thought to be the main contributor of adverse health effects from wildfire air pollution.[77] Third, we base our exposure on a modeled estimate of ambient $PM_{2.5}$ at the patient's home zip code. This is not necessarily a measure of individual exposure as there are many mitigating factors – individual exposure depends on how long a person spends at their home as well as what protective measures they take. These modeled estimates are also based on instruments that include some inherent measurement error (classical error),[115] and include a single estimate for an area (Berkson error).[116] Both of these measurement errors likely attenuate our effect estimate. Additionally, zip codes can be quite large (especially in rural areas) – we try to mitigate this as best we can by using a population-weighted measure of exposure. We also do not adjust for non-wildfire $PM_{2.5}$ in our analysis, which makes comparison with other studies difficult. Particularly in urban areas, non-wildfire $PM_{2.5}$ may present non-trivial exposures that impact mental health outcomes. Fourth the modeled wildfire-specific smoke relies on ground-based Environmental Protection Agency (EPA) pollution monitors which are not distributed evenly in space (they tend to be concentrated in more populous areas). The $PM_{2.5}$ estimates in rural areas may have more uncertainty associated with them, although this was not taken into account. Finally, we do not capture all ED visits in our data – visits to federal EDs (e.g., VA hospitals) are not included in Washington State surveillance – limiting the generalizability of our findings.

CONCLUSION

We find that heavy wildfire smoke exposure is associated with increased ED visits with a mental health diagnosis in Washington State. Public health practitioners and clinical providers should consider these findings in the context of expected increases in wildfire-specific air pollution in future years.

CHAPTER 4: SUPPLEMENTAL FIGURES AND TABLES

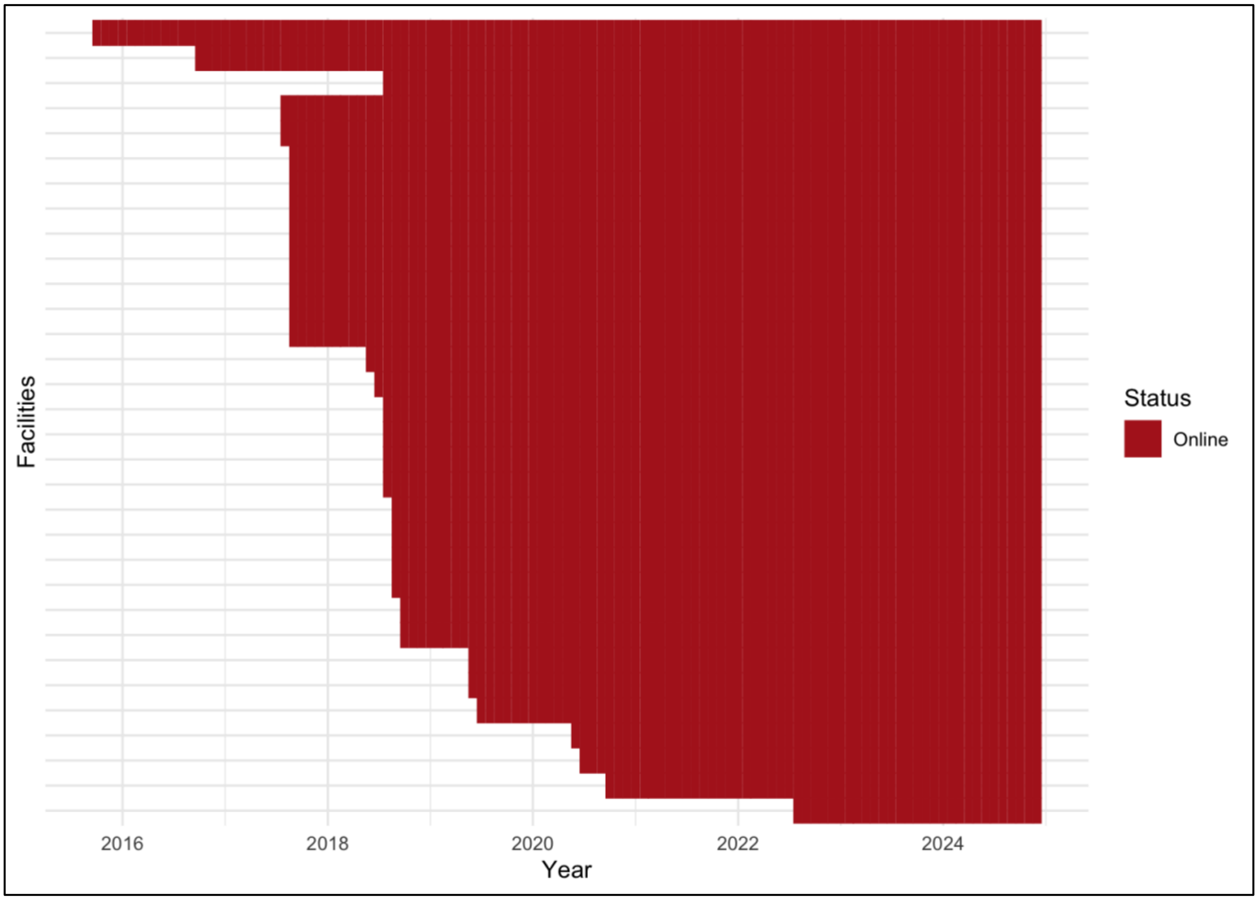

Figure S1. Facility onboarding over time. Rows represent unique facilities and red indicates when each started reporting to the Washington Department of Health (DOH). For the main analysis we include all facilities that started reporting before June 1, 2019, and continued reporting without interruption until October 31, 2023. Sensitivity analysis included all facilities for each month that they reported for the entire month from June 1, 2018 – October 31, 2023.

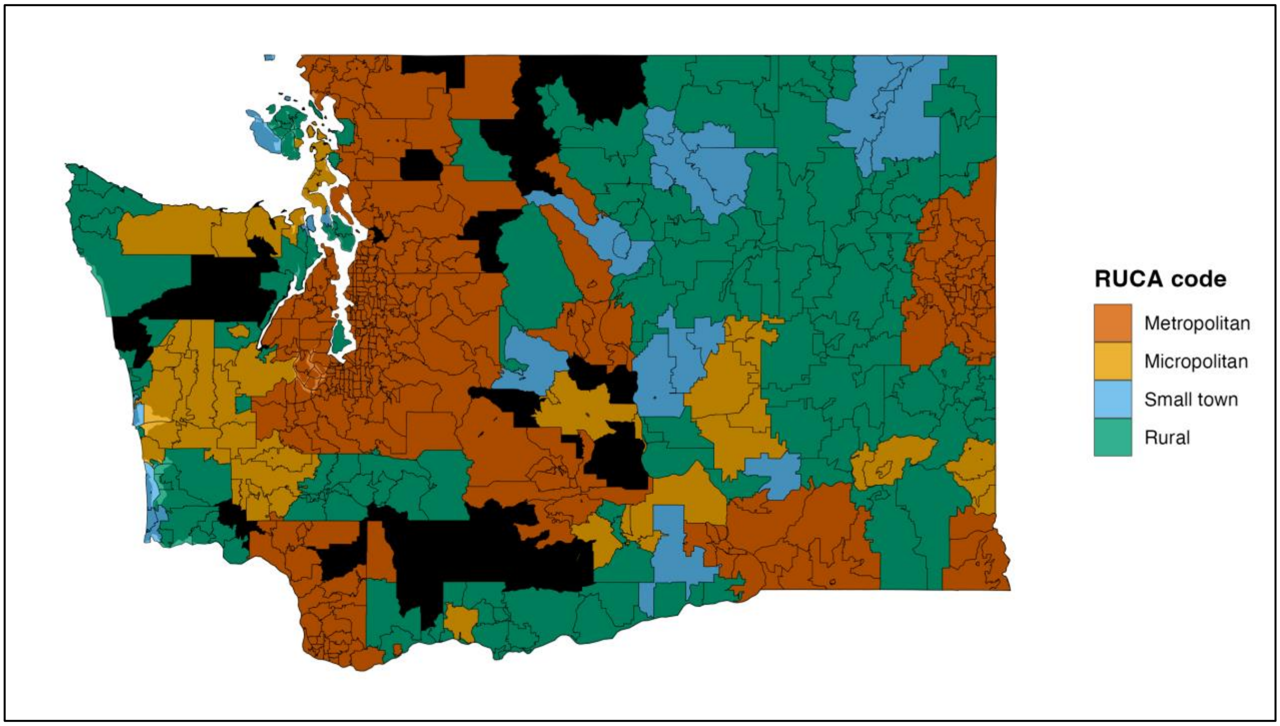

Figure S2. Map of 2020 Rural-Urban Commuting Area Codes (RUCA) by zip code tabulation area (ZCTA) in Washington State. Metropolitan=within urban area > 50,000 people; Micropolitan=within urban area 10,000-49,999 people; Small town=within urban area < 10,000 people; Rural=not in urban area. Black indicates areas with 0 population.

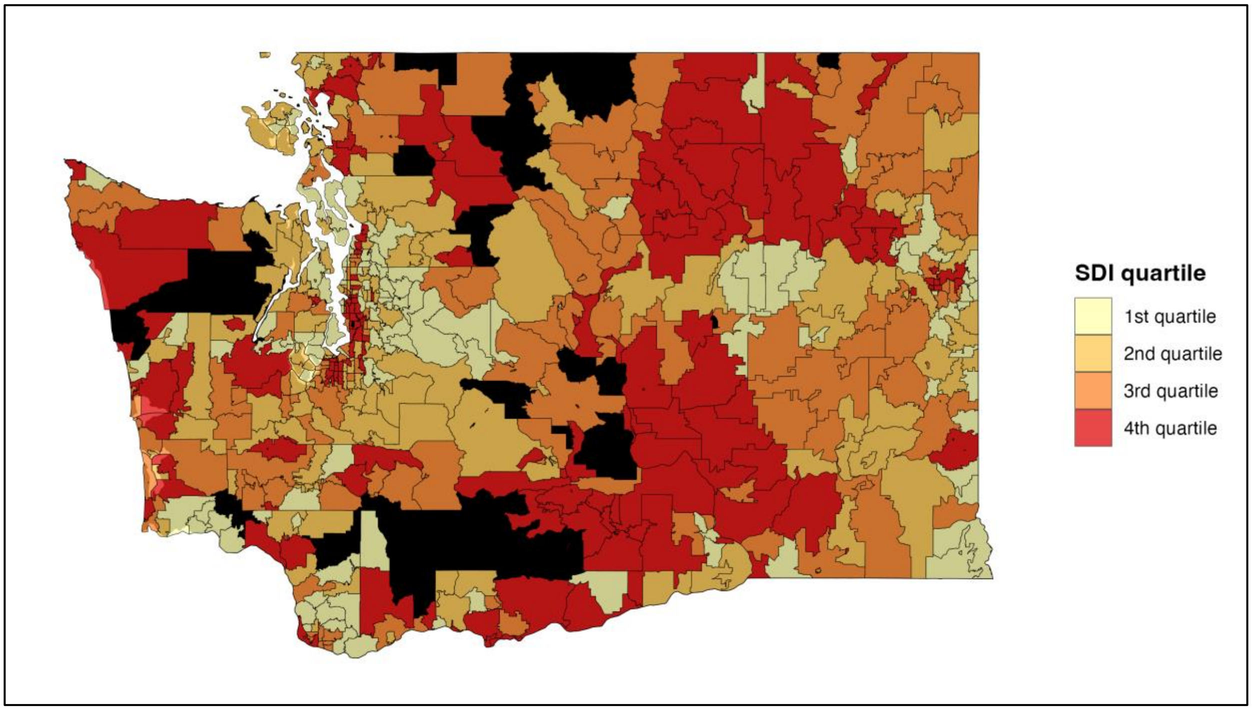

Figure S3. Map of 2019 Social Deprivation Index (SDI) by zip code tabulation area (ZCTA) in Washington State. 4th quartile indicates most disadvantaged. Black indicates areas with 0 population or missing SDI values.

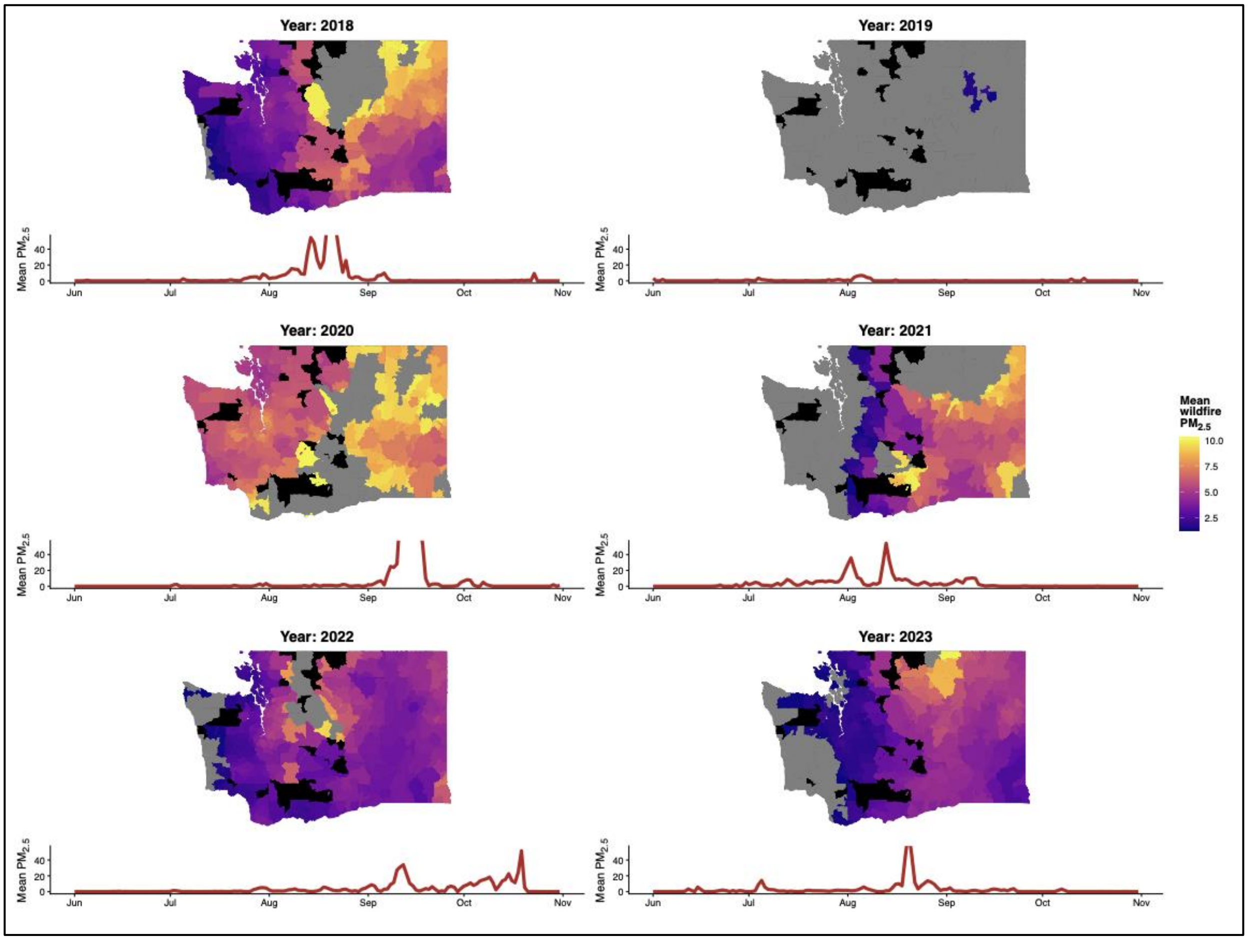

Figure S4. Map of mean wildfire-specific $PM_{2.5}$ by zip code tabulation area (ZCTA) (top) and year and mean wildfire-specific $PM_{2.5}$ by day (bottom) in Washington from 2018-2023. Wildfire $PM_{2.5}$ is measured in $\mu g/m^3$. Line plots top out at 55 $\mu g/m^3$ to aid in comparison and support readability – missing gaps in lines indicate mean wildfire-specific $PM_{2.5}$ higher than 55 $\mu g/m^3$. Grey indicates no modeled wildfire-specific $PM_{2.5}$ for that ZCTA. Black areas are those with zero population (national parks and forests).

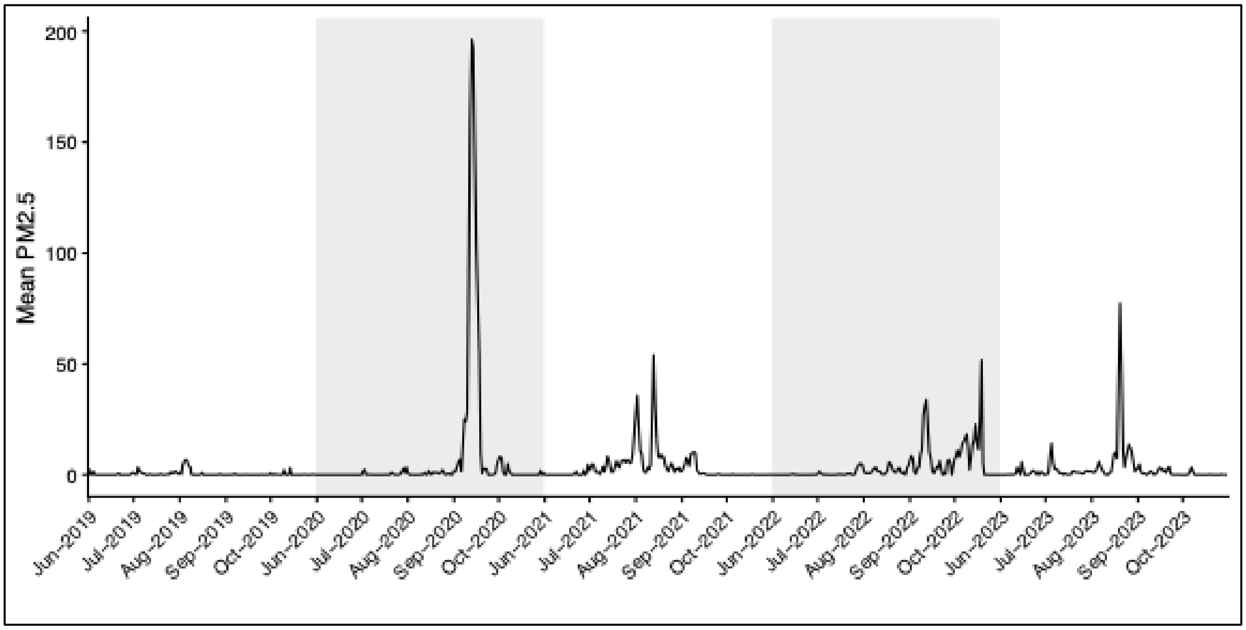

Figure S5. Mean smoke by zip code tabulation area (ZCTA) day from June-October 2019-2023 in Washington State.

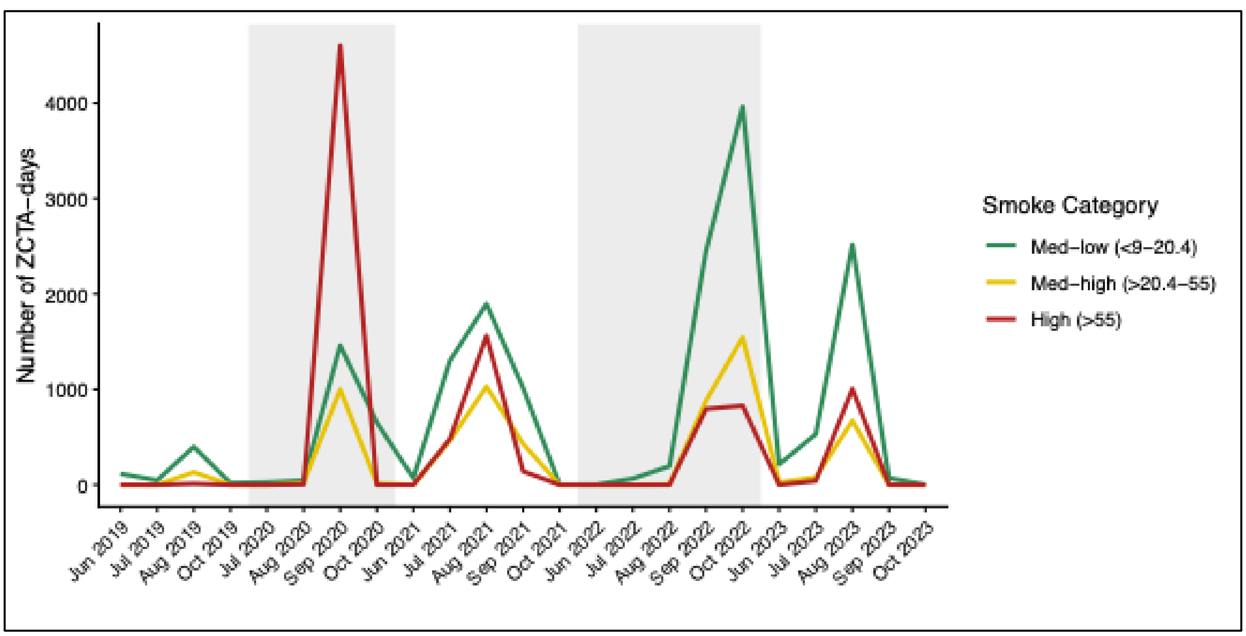

Figure S6. Number of zip code tabulation area (ZCTA) days at each smoke category per month from June-October 2019-2023 in Washington State.

Table S1. Study characteristics by wildfire-specific $PM_{2.5}$ thresholds limited to days when there was > 0 $\mu g/m^3$ of modeled wildfire-specific smoke. Percentages for wildfire smoke characteristics (top) in each smoke exposure category column represent the proportion of days in each category (row-wise). Percentages in the “Total” column represent proportions in each characteristic category (column-wise per characteristic). Percentages in for mental health characteristics represent proportion of ED visits that included a mental health diagnosis (out of all ED visits).

Characteristic	Smoke exposure				
	0-9 μg/m3	>9-20.4 μg/m3	>20.4-35 μg/m3	>35 μg/m3	Total
Wildfire smoke characteristics					
ZCTA days (#)	133,975 (80.3%)	17,055 (10.2%)	6,290 (3.8%)	9,472 (5.7%)	166,792
Year					
2019	16,878 (95.9%)	579 (3.3%)	132 (0.7%)	12 (0.1%)	17,601 (11%)
2020	16,553 (67.9%)	2,185 (9.0%)	1,032 (4.2%)	4,606 (18.9%)	24,376 (14%)
2021	23,325 (73.5%)	4,283 (13.5%)	1,921 (6.1%)	2,185 (6.9%)	31,714 (15%)
2022	35,940 (77.0%)	6,674 (14.3%)	2,430 (5.2%)	1,623 (3.5%)	46,667 (28%)
2023	41,279 (88.9%)	3,334 (7.2%)	775 (1.7%)	1,046 (2.3%)	46,434 (28%)
Humidex (mean, sd)					
Rural/urban (#)					
Metropolitan	75,461 (80.8%)	9,224 (9.9%)	3,688 (3.9%)	5,015 (5.4%)	93,388 (56%)
Micropolitan	11,045 (83.3%)	1,225 (9.2%)	377 (2.8%)	617 (4.7%)	13,264 (8%)
Small town	7,777 (76.7%)	1,211 (11.9%)	421 (4.2%)	730 (7.2%)	10,139 (6%)
Rural	39,692 (79.4%)	5,395 (10.8%)	1,804 (3.6%)	3,110 (6.2%)	50,001 (30%)
SDI					
1st quartile (most disadvantaged)	31,723 (81.7%)	3,738 (9.6%)	1,386 (3.6%)	1,971 (5.1%)	38,818 (23%)
2nd quartile	33,000 (82.2%)	3,779 (9.4%)	1,350 (3.4%)	2,009 (5.0%)	40,138 (24%)
3rd quartile	32,987 (79.6%)	4,378 (10.6%)	1,580 (3.8%)	2,503 (6.0%)	41,448 (25%)
4th quartile	35,368 (78.2%)	5,032 (11.1%)	1,930 (4.3%)	2,912 (6.4%)	45,242 (27%)
Mental health characteristics					
Total mental health ED visits (% of overall visits)	127,418 (9.2%)	14,884 (9.1%)	5,778 (9%)	8,117 (10.2%)	156,197 (50.8%)
Age group					
Under 5	76 (0.1%)	4 (0%)	6 (0.2%)	4 (0.1%)	90 (0.1%)

5-11	882 (1.7%)	108 (1.6%)	46 (1.8%)	51 (1.8%)	1,087 (1.7%)
12-17	5,057 (9.1%)	657 (9.1%)	265 (9.7%)	341 (11%)	6,320 (9.2%)
18-25	13,088 (9.1%)	1,608 (9.4%)	672 (10.1%)	917 (10.6%)	16,285 (9.2%)
26-35	21,617 (10.1%)	2,512 (10.1%)	995 (10.2%)	1,436 (11.5%)	26,560 (10.2%)
36-45	19,682 (10.6%)	2,400 (10.9%)	939 (10.7%)	1,309 (12.2%)	24,330 (10.7%)
46-55	17,057 (10.7%)	1,905 (10.2%)	792 (10.5%)	1,033 (10.9%)	20,787 (10.6%)
56-65	18,588 (10.7%)	2,108 (10.6%)	824 (10.6%)	1,199 (11.9%)	22,719 (10.8%)
>65	31,250 (9.3%)	3,576 (9.3%)	1,238 (8.6%)	1,821 (10%)	37,885 (9.3%)
Sex					
Female	72,959 (9.8%)	8,371 (9.6%)	3,222 (9.5%)	4,658 (10.9%)	89,210 (9.8%)
Male	54,379 (8.4%)	6,506 (8.5%)	2,553 (8.6%)	3,452 (9.4%)	66,890 (8.5%)

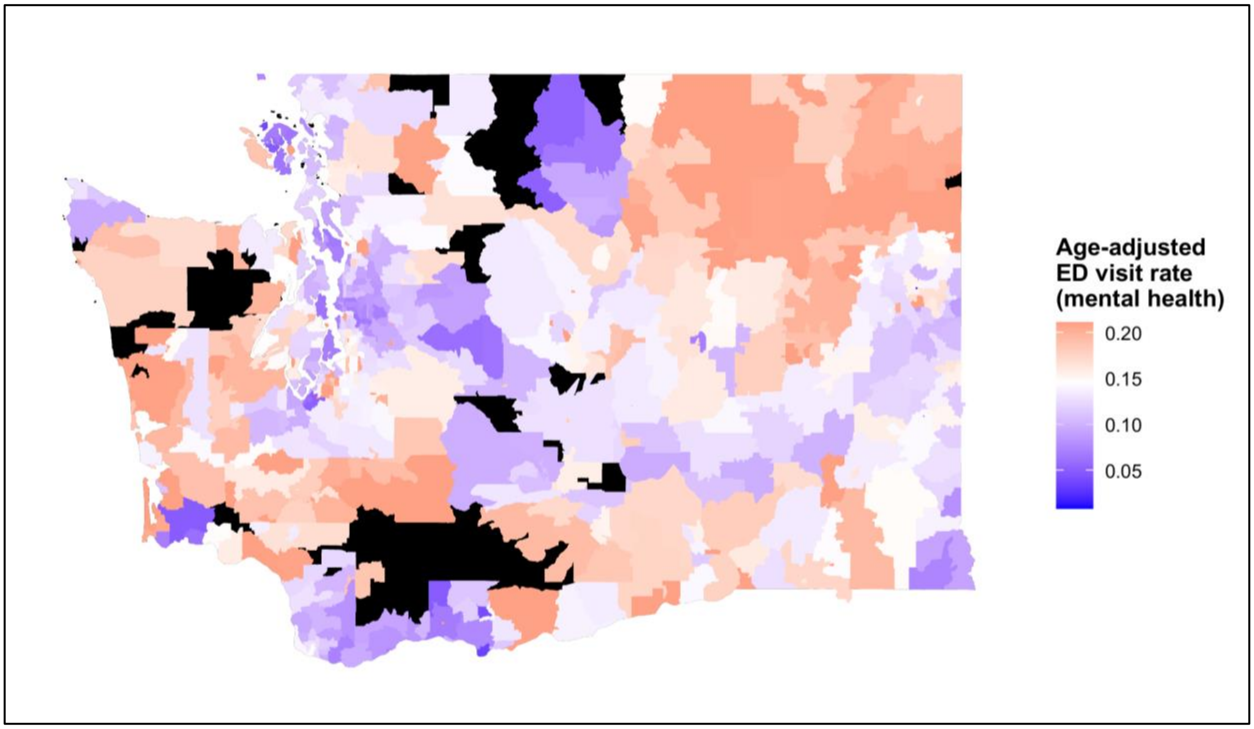

Figure S7. Age-adjusted emergency department visit rate by zip code tabulation area (ZCTA) in Washington from 2019-2023.

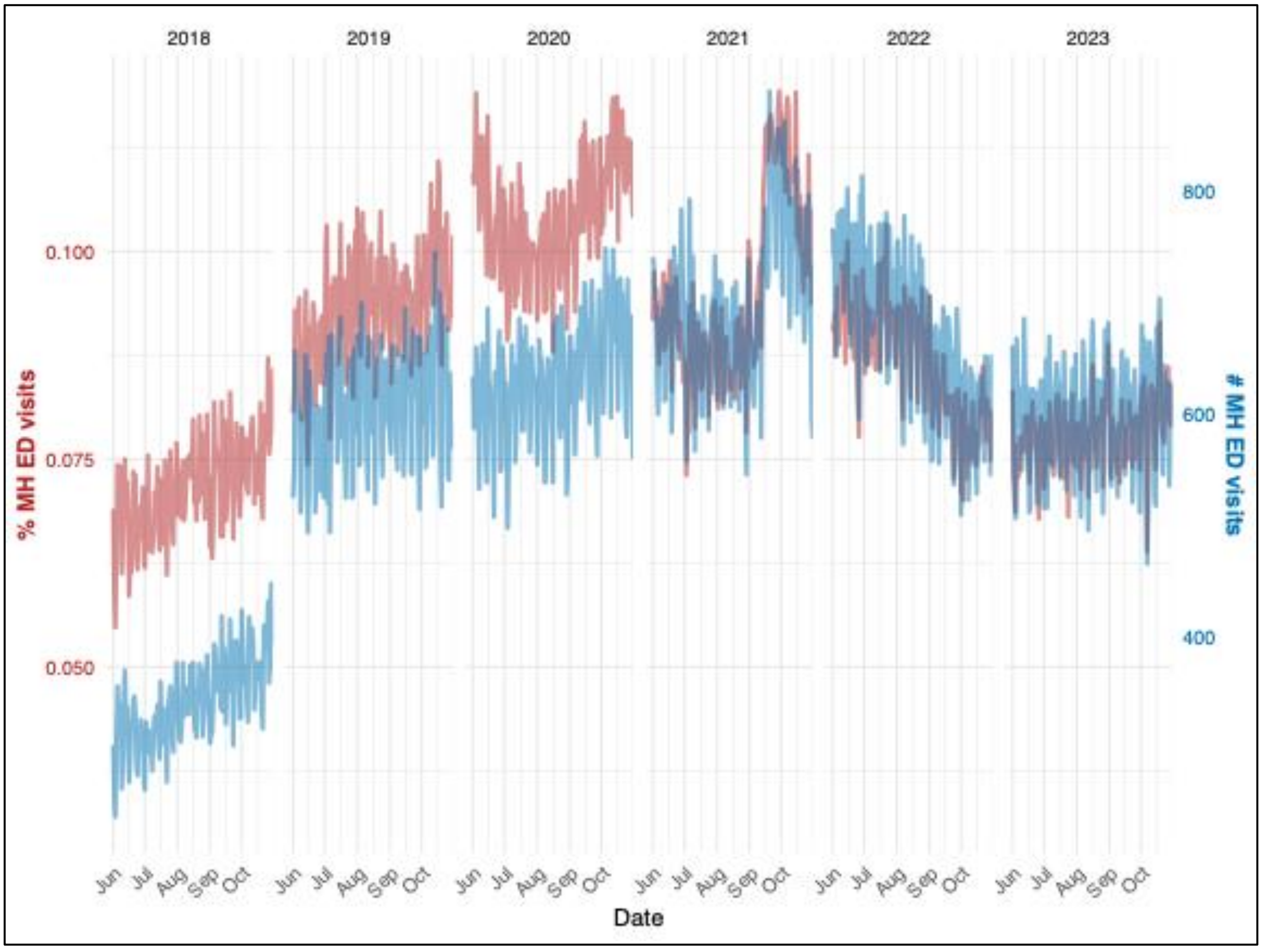

Figure S8. Number (blue - left y axis) and percent of overall ED visits (red - right y axis) of ED visits with a mental health diagnosis over time.

Table S2. Estimated effect of wildfire smoke exposure on the number of mental health emergency department visits per zip code tabulation area (ZCTA). Results are from stratified Poisson model for counts by ZCTA. Stratified models are limited to each sub-group.

Stratification	Sub-group	Wildfire smoke exposure (reference = 0-9 μg/m^3)		
		>9-20.4	>20.4-35	>35
Total	Total	0.932 (0.901, 0.963)	0.979 (0.924, 1.037)	1.046 (1.009, 1.085)
Age	12-17	0.924 (0.856, 0.997)	1.087 (0.958, 1.233)	1.054 (0.969, 1.146)
	18-25	0.918 (0.858, 0.983)	0.997 (0.890, 1.117)	1.011 (0.940, 1.087)
	26-35	0.996 (0.938, 1.056)	0.969 (0.875, 1.072)	1.099 (1.032, 1.169)
	36-45	0.943 (0.888, 1.001)	1.044 (0.942, 1.156)	1.137 (1.066, 1.213)
	46-55	0.833 (0.782, 0.888)	1.036 (0.928, 1.156)	0.991 (0.925, 1.061)
	56-65	0.985 (0.925, 1.049)	0.901 (0.807, 1.005)	1.038 (0.969, 1.112)
	>65	0.916 (0.867, 0.968)	0.934 (0.846, 1.031)	0.993 (0.933, 1.058)
Sex	Female	0.920 (0.883, 0.959)	0.913 (0.850, 0.980)	1.031 (0.986, 1.078)
	Male	0.945 (0.903, 0.988)	1.076 (0.996, 1.163)	1.065 (1.014, 1.118)
RUCA	Metropolitan	0.929 (0.892, 0.968)	0.977 (0.911, 1.047)	1.054 (1.008, 1.102)
	Micropolitan	0.822 (0.720, 0.937)	1.504 (1.157, 1.955)	1.057 (0.916, 1.219)
	Small town	1.013 (0.830, 1.236)	0.746 (0.543, 1.025)	1.000 (0.822, 1.218)
	Rural	1.024 (0.926, 1.132)	0.811 (0.681, 0.966)	0.937 (0.846, 1.039)
SDI	1st quartile (most disadvantaged)	0.912 (0.839, 0.992)	1.146 (0.992, 1.323)	0.980 (0.892, 1.076)
	2nd quartile	0.975 (0.905, 1.051)	0.998 (0.878, 1.136)	1.040 (0.955, 1.133)
	3rd quartile	0.940 (0.879, 1.004)	0.935 (0.830, 1.053)	1.101 (1.024, 1.183)
	4th quartile	0.912 (0.863, 0.964)	0.932 (0.849, 1.024)	1.042 (0.983, 1.104)

Table S3. Additional models and sensitivity analyses. Consecutive days models the number of consecutive days at each exposure level as the main exposure variable (each exposure level is a separate model). No June excludes all observations from the month of June. Year results model each year separately. 2019 was excluded from year results as there were only 12 ZCTA days with heavy smoke.

Model	**Sub-group**	**Wildfire smoke exposure (reference = 0-9 μg/m³)**		
		>9-20.4	>20.4-35	>35
Consecutive days	NA	0.975 (0.961, 0.988)	0.971 (0.939, 1.003)	**1.008 (1.000, 1.017)**
No June	NA	0.934 (0.905, 0.963)	1.002 (0.951, 1.056)	**1.041 (1.008, 1.076)**
Year results	2018	0.937 (0.861, 1.020)	1.049 (0.905, 1.216)	1.084 (0.998, 1.176)
	2020	0.957 (0.866, 1.057)	0.946 (0.811, 1.103)	**1.061 (1.007, 1.118)**
	2021	**0.886 (0.817, 0.961)**	0.968 (0.848, 1.104)	**0.835 (0.739, 0.943)**
	2022	**0.918 (0.870, 0.970)**	0.992 (0.911, 1.080)	**1.136 (1.019, 1.266)**
	2023	0.961 (0.892, 1.036)	**1.414 (1.156, 1.728)**	1.006 (0.855, 1.185)

Chapter 5: Conclusion

This dissertation examined geographic all-cause and cause-specific mortality patterns and found that migration was associated with all-cause mortality and specifically with chronic mortality. Counties with higher out-migration rates had higher all-cause age-adjusted mortality rates after adjusting for in-migration. Our latent class analysis also found that out-migration was associated with high chronic mortality counties after adjusting for poverty and rurality. Additionally, out-migration was negatively associated with high suicide, accident, and chronic liver disease counties, although this association was much weaker compared to the positive associations with all-cause and chronic mortality. Taken together, these findings suggest that selective migration may play a role in mortality outcomes, particularly chronic mortality outcomes, through changing population composition. More research is needed to better understand the specific mechanisms this may be working through. This dissertation was limited by ecologic study designs that did not allow us to measure the impact of migration on those who move and those who stayed; future work should focus on following individual migration across geographic areas in order to better understand the role migration plays in population level mortality outcomes.

Our analysis of wildfire smoke exposure and mental health outcomes found that heavy wildfire-specific air pollution led to increased emergency department visits with a diagnosed mental health condition. These results were strongest for men, those aged 26-45, and in urban areas. This work was different from previous work on the mental health impacts associated with wildfire smoke in several important ways. First, we included all visits that had a mental health diagnosis rather than just those in which the primary visit reason was for mental health. This is both a strength and a weakness of our study. Including all visits with a mental health diagnosis captures those in which the wildfire smoke-mental health relationship includes other health outcomes as a mediator. For example, those who suffer from asthma may be more likely to develop anxiety or depression from health complications or isolation. But it does not allow us to measure the direct effect of wildfire smoke on mental health, outside of these potential mediators. The total effect is important to understand but ultimately makes our findings difficult to compare with previous work.

Another challenge with this study was that we were unable to disaggregate by specific mental health outcomes. There may be important differences between wildfire smoke's impact on anxiety, depression, and other mental health outcomes. Finally, we only included emergency department visits, representing the most severe immediate health outcomes. Many people may use primary or urgent care to access immediate mental health care services during wildfire smoke events.

Despite these limitations, this study contributes to a better understanding of the impact of wildfire smoke on mental health outcomes. Interesting findings include the stronger effect on men compared to women, which runs counter to previous research. Another interesting finding was the positive association of heavy wildfire smoke on mental health outcomes in more urban areas, but no effect in more rural areas. More work is needed to better understand how wildfire smoke impacts different groups based on sex, age, SES, and geography.

In conclusion, this dissertation contributes to research on place-based morbidity and mortality through highlighting geographic and social health disparities in all-cause and cause-specific mortality as well as mental health emergency department visits. While individual-level determinants of health are, of course, essential in understanding health disparities, we should not overlook the importance of place in creating health possibilities.

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