Covid Mortality and Its Effect on Small-Area Mortality Trends: A Longitudinal Analysis

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Abstract

National excess-mortality estimates suggest that both direct infection and indirect disruptions from the COVID-19 pandemic altered chronic-disease death trends, yet little is known about how these forces interacted with local structural disadvantage. To quantify pandemic-period changes in county-level mortality from heart disease, cancer, and stroke; to test whether those changes differed by (1) cumulative COVID-19 burden and (2) socioeconomic disadvantage. Annual crude death rates (2016–2023) were extracted from CDC WONDER and linked to 2019–2023 American Community Survey indicators. Counties in the top tertile of cumulative COVID-19 mortality (≥198.6/100 000, 2020–2022) were classified as high burden; the middle tertile was excluded to maximize analytic contrast. A difference-in-differences (DiD) model compared 2016–2019 (pre) with 2020–2022 (pandemic) trends, adjusting for county fixed effects and population weights. Period-stratified, population-weighted linear regressions assessed whether standardized poverty, uninsured rate, low education, crowded housing, and median household income predicted mortality differently before and during the pandemic. Nationally, heart-disease mortality rose 5.2 % and stroke 7.3 % during the pandemic, reversing prior declines; cancer remained unchanged (+0.1 %). High-burden counties experienced an additional 11.9 heart-disease deaths/100 000 (95 % CI 6.6–17.1) relative to low-burden counties. Pandemic-period coefficients for low education (+3.45 heart-disease; +4.12 stroke deaths/100 000) and uninsured rate (+7.74 COVID-19 deaths/100 000) more than doubled their pre-pandemic magnitudes. COVID-19 both halted progress against cardiovascular mortality and amplified longstanding socioeconomic gradients. Strengthening chronic-disease care and addressing social determinants are essential components of pandemic preparedness.

Introduction

SARS-CoV-2, the virus responsible for COVID-19, is a positive-sense single-stranded RNA virus of the Coronaviridae family (Centers for Disease Control and Prevention [CDC], 2022; Zhou et al., 2020). The first laboratory-confirmed case in the United States was reported in Washington State on January 20, 2020, and the virus rapidly spread to all 50 states by early March (Holshue et al., 2020). In the early stages of the pandemic, limited testing capacity and widespread asymptomatic transmission meant that surveillance efforts likely captured only 10% to 15% of all infections, with studies estimating that for every documented case, there were 4 to 17 undetected infections (Angulo et al., 2021; Wu et al., 2020). Accurately quantifying COVID-19 mortality has also been challenging due to inconsistent death certification, geographic variation in testing, and difficulties distinguishing deaths directly caused by the virus from those indirectly related to the pandemic (Karlinsky & Kobak, 2021; World Health Organization [WHO], 2022).

While COVID-19 directly accounted for an estimated 1,056,000 deaths in the United States by the end of January 2023 (Johns Hopkins University, 2022), the pandemic also produced substantial secondary effects on health outcomes beyond those attributable to the virus itself. Recent research demonstrates that excess mortality from preventable, non-COVID-19 conditions increased during this period, underscoring the far-reaching indirect consequences of the pandemic (Woolf et al., 2021; Stokes et al., 2021). These indirect effects were especially pronounced in communities already burdened by structural vulnerabilities, such as socioeconomic disadvantage and limited access to healthcare, where disruptions in medical services and avoidance of the healthcare system further exacerbated existing health disparities (Magesh et al., 2021).

Among these secondary effects, preventable chronic diseases such as including heart disease, cancer, and stroke are of particular concern. These conditions are largely avoidable through evidence-based strategies such as effective risk factor management, early diagnosis, and timely access to medical care (American Heart Association [AHA], 2024; Centers for Disease Control and Prevention [CDC], 2024). Prior to the COVID-19 pandemic, mortality rates from heart disease and stroke had been declining, and preventable cancer deaths also showed a downward trend (CDC, 2024). However, during the pandemic, sharp increases in premature deaths from heart disease and stroke were observed, reversing previous progress and likely reflecting both direct effects of COVID-19 infection and indirect effects such as delayed care and healthcare system disruptions (Heart Foundation, 2024; National Institutes of Health, 2024; Stokes et al., 2021).

Despite decades of progress in medical advancements and public health programs, the benefits of these strategies have not been experienced equally across all communities. Variation in healthcare infrastructure, population health indicators, and healthcare availability persists across small geographic areas (University of Wisconsin Population Health Institute, 2024; Vo et al., 2024). Non-clinical factors such as access to health insurance and socioeconomic conditions significantly contribute to these disparities (AHA, 2024). For example, counties with higher proportions of uninsured individuals report elevated rates of uncontrolled hypertension, a major risk factor for cardiovascular disease (AHA, 2024). In rural areas, poorer health outcomes are often linked to limited clinical infrastructure and lower scores on health-related behavior measures (University of Wisconsin Population Health Institute, 2024).

Recent data highlight the extent of these disparities, with rural counties experiencing approximately 40% higher rates of preventable death from heart disease and 35% higher rates from stroke compared to urban counties (CDC, 2024). These mortality differences closely correlate with variations in local healthcare infrastructure, socioeconomic conditions, and healthcare accessibility (University of Wisconsin Population Health Institute, 2024). Moreover, counties characterized by higher poverty rates, lack of health insurance, lower educational attainment, lower median household income, and crowded housing have been strongly associated with increased mortality from both COVID-19 and preventable chronic diseases (Magesh et al., 2021; PloS One, 2020). These social determinants of health contribute to unequal exposure, vulnerability, and access to care, thereby amplifying the pandemic's effect in disadvantaged communities. Consequently, many structurally marginalized populations faced a form of ***double jeopardy***, where the risk of direct viral exposure was compounded by diminished access to essential health and social resources during the pandemic (Magesh et al., 2021; Stokes et al., 2021).

Aim & Hypotheses

The aim of this study is to evaluate changes in county-level mortality from heart disease, cancer, and stroke before (2016–2019) versus during (2020–2022) the COVID-19 pandemic, and tests whether those changes vary by (a) local COVID-19 mortality burden and (b) underlying socioeconomic disadvantage. We combine annual crude death rates from CDC WONDER (2016 to 2023) with county characteristics from the 2019–2023 American Community Survey: insurance coverage, educational attainment, median household income, poverty rate, and household crowding.

H_1: Mortality rates from heart disease, cancer, and stroke increased across counties during the pandemic disruption period (2020–2022) compared to the pre-pandemic period (2016–2019).

H_2: Counties with greater socioeconomic disadvantages (e.g., higher poverty rates) will be positively associated with increased mortality from preventable causes during the pandemic disruption period (2020–2022).

Materials and Methods

Mortality Data Source

County-level mortality data were obtained from the Centers for Disease Control and Prevention (CDC) Wide-ranging Online Data for Epidemiologic Research (WONDER) platform (Centers for Disease Control and Prevention [CDC], 2025a). To ensure both completeness and recency, two complementary databases were used: the CDC Multiple Cause of Death, 1999 to 2020 (Final) database for the years 2016 through 2020, and the CDC Multiple Cause of Death, Provisional 2018 to Present database for the years 2021 through 2023. This approach allowed us to leverage finalized data for earlier years while incorporating the most current provisional data available for recent years, in accordance with best practices for mortality surveillance (Ahmad et al., 2023).

Case Identification and Extraction

Mortality data were derived from U.S. death certificates and coded by underlying cause of death according to the International Classification of Diseases, Tenth Revision (ICD-10). For this study, we focused on four major causes of death: heart disease (ICD-10: I00–I02, I05–I09, I11, I13, I20–I25, I26–I28, I30–I51), stroke (ICD-10: I60–I64, I67, I69), cancer (ICD-10: C00–C97), and COVID-19 (ICD-10: U07.1). Mortality queries were conducted separately for each year and stratified by county and cause of death to maximize data granularity and minimize row suppression, as recommended for county-level analyses (Anderson et al., 2001). For each query, we extracted the number of deaths, county population estimates, and crude mortality rates per 100,000 population. Age-adjusted rates were not used due to the instability of county-level estimates in the CDC WONDER system, a limitation noted in prior research (Anderson et al., 2001).

Data Quality and Management

To ensure the validity of our analyses, we restricted data to counties with CDC-designated quality flags marked "OK." Rows with fewer than 10 deaths were automatically suppressed in accordance with CDC privacy protocols and were excluded from rate calculations. To address the platform's 75,000-row limit and minimize data suppression, each cause-year-state combination was queried individually. For most analyses, the geographic scope was restricted to specific U.S. states, such as Texas, to maximize data availability and reliability. All output files were exported in tab-delimited format and processed using R version 4.3.1 (R Core Team, 2023) and Microsoft Excel for data cleaning, aggregation, and visualization. Mortality rates reflect underlying causes of death among all racial and ethnic groups; however, subgroup analyses focused on Latino decedents where possible. COVID-19-related mortality (ICD-10: U07.1) was aggregated for descriptive comparison but was not included in the primary regression analyses of preventable chronic disease mortality.

Methodological Considerations

Provisional death data are subject to reporting lags and should be interpreted with caution, as counts from earlier periods are continually revised as new and updated death certificate data are received from states (Centers for Disease Control and Prevention [CDC], 2025). According to CDC technical guidance, death data are approximately 65% complete within 2 weeks, 85% complete within 4 weeks, and at least 94% complete within 8 weeks of when the death occurred (CDC, 2025). Our analytic approach aligns with CDC recommendations for combining finalized and provisional data in longitudinal mortality research, acknowledging that provisional counts may be underestimated relative to final counts due to the multi-step process involved in death certificate reporting and coding (Ahmad et al., 2024).

All mortality rates were calculated as population-weighted crude rates per 100,000 population for heart disease, cancer, and stroke to account for varying county population sizes and ensure comparability across geographic areas of different scales. We selected 2020-2022 as the primary pandemic disruption period based on CDC guidance regarding the peak impact of COVID-19 on healthcare systems and mortality reporting, while extending our analysis through 2023 to capture longer-term trends as provisional data became available (Ahmad et al., 2024)

Covariates

To contextualize mortality trends and examine structural determinants of health, we merged the mortality dataset with county-level sociodemographic and structural indicators obtained from the American Community Survey (ACS) 5-Year Estimates (U.S. Census Bureau, 2023). To capture changes in county characteristics over time, we extracted ACS data for both the pre-COVID period (2015–2019) and the post-COVID period (2023). Pre-pandemic values were used as baseline controls, while post-pandemic data allowed us to assess evolving social and economic conditions that may have influenced chronic disease mortality following the onset of the COVID-19 pandemic.

Covariates were selected based on their established relevance to health disparities and social determinants of preventable chronic disease outcomes (Braveman et al., 2010; Krieger et al., 2003). All variables were linked using the county Federal Information Processing Standards (FIPS) code, harmonized across datasets using a standardized five-digit format to ensure consistency. The final merged dataset included the percent of families living below the poverty line (as defined by the U.S. Census Bureau), median household income (adjusted to 2023 inflation dollars), per capita income, percent of the population without health insurance, percent of households classified as crowded (more than one person per room), and percent of adults aged 25 and older with a high school education or less. Each of these variables is recognized as a key social determinant of health and has been shown to influence chronic disease outcomes and access to care (Braveman et al., 2010; Krieger et al., 2003). All continuous covariates were standardized using z-scores prior to inclusion in regression models to facilitate interpretation of regression coefficients and comparability across variables (Gelman & Hill, 2006). Counties with missing covariate data were excluded from the final analytic sample to ensure data completeness and validity.

Additionally, we derived a binary county-level indicator for high versus low COVID-19 burden using the tertile distribution of cumulative crude COVID-19 mortality rates from 2020 through 2022. Counties in the highest tertile were classified as high burden, while those in the lower two tertiles were classified as low burden. This variable enabled stratified and interaction-based analyses to explore the modifying effect of pandemic severity on chronic disease mortality trends. All data merging and processing were conducted in R (R Core Team, 2023), utilizing the *tidycensus* (Walker, 2023) and *dplyr* (Wickham et al., 2023) packages. Both ACS and mortality data were retrieved programmatically via the U.S. Census Bureau and CDC WONDER APIs to ensure reproducibility and consistency.

Analytic Approach

This study examined county-level variation in mortality from heart disease, cancer, and stroke to assess how pandemic burden and structural disadvantage shaped trends in preventable mortality between 2016 and 2023. We used a multi-step analytic strategy to characterize temporal mortality patterns and quantify differences by pandemic burden and structural factors, including poverty, insurance coverage, educational attainment, and housing conditions.

To describe mortality trends, we calculated population-weighted mean crude mortality rates for each cause of death by year, excluding COVID-19 deaths to focus specifically on preventable chronic diseases. These rates were visualized using smoothed line plots generated with ggplot2 in R, with 95% confidence intervals and a shaded region indicating the primary pandemic disruption period (2020–2022).

To evaluate heterogeneity in mortality trends by pandemic impact, counties were classified into high and low COVID-19 burden groups based on their cumulative crude COVID-19 mortality rate during 2020–2022. For each county, the cumulative COVID-19 mortality rate was calculated as the sum of annual COVID-19 deaths per 100,000 population across the three-year period. Counties in the top tertile (≥198.6 deaths per 100,000) were categorized as high burden, while those in the bottom tertile were classified as low burden. Counties in the middle tertile were excluded from regression analyses to enhance contrast between comparison groups and improve statistical power for detecting differences.

We used a difference-in-differences (DiD) approach to estimate the impact of pandemic burden on mortality outcomes. The analytical dataset was filtered to include only heart disease, cancer, and stroke outcomes and merged with COVID-19 burden classifications. Treatment indicators were constructed for the DiD analysis, including a binary variable indicating high-burden counties, a post-pandemic period indicator for observations from 2020–2023, and an interaction term representing the DiD estimator. This modeling strategy allowed us to identify differential changes in preventable mortality attributable to varying levels of pandemic burden while controlling trends and baseline differences between county groups.

To assess the role of structural determinants, we conducted a z-score shift analysis by standardizing five American Community Survey (ACS) indicators (poverty rate, uninsured rate, proportion with high school education or less, crowded housing rate, and inflation-adjusted median household income) across all counties and years. Mean z-scores for each indicator were compared between the pre-pandemic (2016–2019) and pandemic (2020–2022) periods using independent-samples *t*-tests with unequal variances, stratified by disease. This analysis quantified how structural disadvantages shifted in counties experiencing high preventable mortality.

We then estimated period-stratified, population-weighted linear regression models to examine whether these standardized predictors were differentially associated with crude mortality rates before and during the pandemic. For each disease, separate models were estimated for the pre-pandemic and pandemic periods, with the outcome variable defined as the county-year crude mortality rate per 100,000 population and predictors including the z-scored ACS variables. This approach enabled a direct comparison of the magnitude and direction of associations between structural determinants and mortality across periods.

All regression models were implemented in R using the lm() function, with robust standard errors computed using the HC1 sandwich variance estimator via the sandwich package (Zeileis, 2004, 2006). County-year observations were weighted by population to stabilize the variance in mortality rates. Model outputs, including coefficients, robust standard errors, 95% confidence intervals, and p-values, were extracted using the broom package and compiled into summary tables grouped by disease and time period. Statistical significance was assessed at the $\alpha = .05$ level using two-tailed tests.

AI-Assisted Coding

We used ChatGPT (OpenAI, 2024) as a coding assistant to troubleshoot R syntax errors, refine `dplyr` pipelines, optimize `ggplot2` visualizations, and streamline routines such as `group_split()`, `broom::tidy()`, and `gt()`. All AI-generated suggestions were inspected and validated by the authors before implementation.

Results

Hypothesis 1:

Figure 1 illustrates smoothed annual trends in population-weighted crude mortality rates for heart disease, cancer, and stroke from 2016 to 2023, with the shaded region indicating the pandemic disruption period (2020–2022).

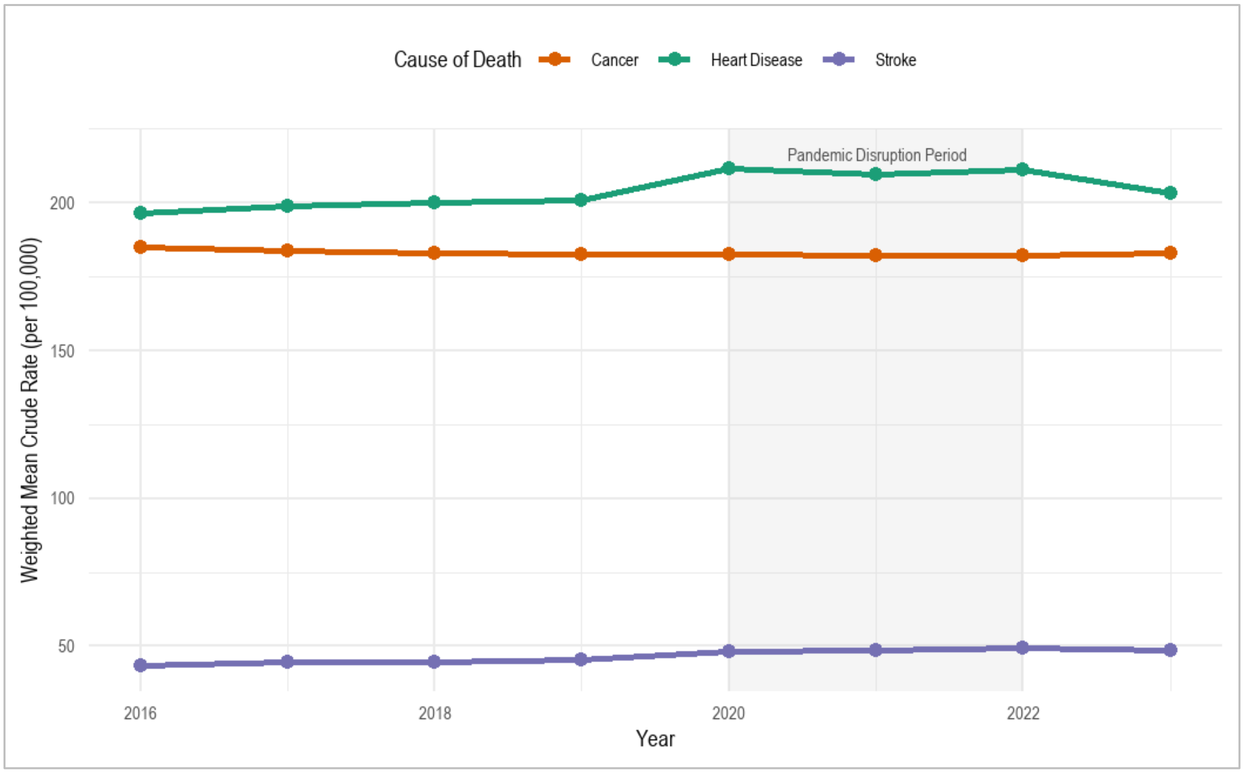

***Figure 1**. Weighted Mean Crude Mortality Rates for Heart Disease, Cancer, and Stroke (2016–2023)*

The population-weighted crude mortality rate for heart disease increased from 201.2 (*SE* = 1.6) deaths per 100,000 population in the pre-pandemic period (2016–2019) to 211.6 (*SE* = 1.5) during the pandemic period (2020–2022), representing a 5.2% increase. For stroke, mortality rose from 45.2 (*SE* = 0.4) to 48.5 (*SE* = 0.5) deaths per 100,000 population, reflecting a 7.3% increase between the same time periods. In contrast, cancer mortality remained stable, changing only slightly from 181.9 (*SE* = 0.5) pre-pandemic to 182.1 (*SE* = 0.4) post-pandemic: an increase of just 0.1%. Heart disease exhibited the most pronounced increase at the onset of the pandemic, followed by stroke, while cancer mortality remained remarkably stable. Rates declined slightly in 2023 but remained above pre-pandemic levels for both heart disease and stroke.

Figure 2 illustrates differential changes in preventable mortality between high and low COVID-19 burden counties. High-burden counties experienced significant absolute increases in heart disease mortality (311.4 to 325.6/100,000; +4.6%) and stroke mortality (71.6 to 76.4/100,000; +6.6%) during the pandemic period, while cancer mortality remained stable. Although low-burden counties showed greater relative increases in stroke mortality (45.8 to 51.2/100,000;

+11.8%), high-burden counties demonstrated consistently larger absolute mortality increases for heart disease and stroke during the pandemic period.

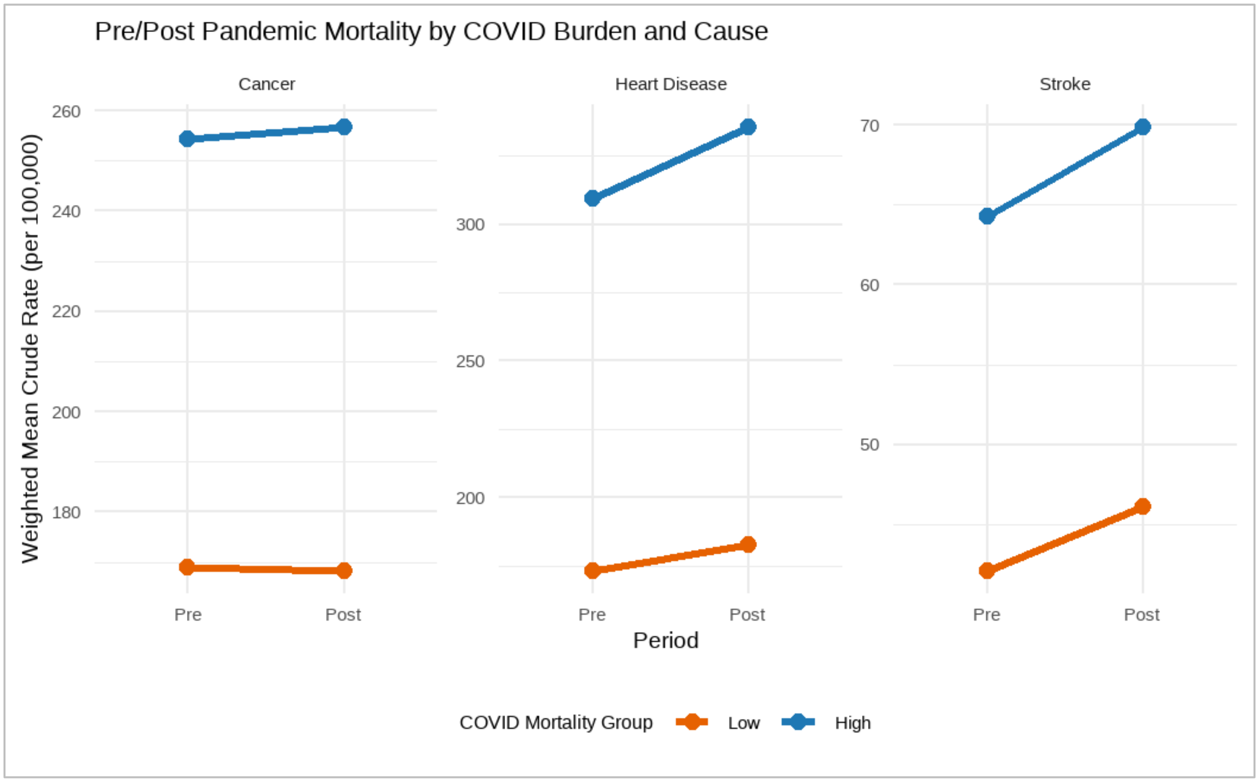

***Figure 2**. Rates for Heart Disease, Cancer, and Stroke (2016–2023)*

Difference-in-differences regression models were used to estimate the association between pandemic period, county COVID-19 burden, and mortality rates for heart disease, cancer, and stroke. For heart disease, the interaction between high COVID-19 burden and the pandemic period was statistically significant ($\beta = 11.88$, 95% CI [6.62, 17.14], $p < .001$), indicating that counties with higher COVID-19 mortality experienced a greater increase in heart disease mortality during the pandemic than counties with lower COVID-19 burden. For cancer, the interaction term was not statistically significant ($\beta = 1.15$, 95% CI [−3.01, 5.30], $p = .59$), suggesting no differential change in cancer mortality by COVID-19 burden. For stroke, the interaction term approached but did not reach statistical significance ($\beta = 2.07$, 95% CI [−0.43, 4.57], $p = .10$). Across all models, high COVID-19 burden counties had significantly higher baseline mortality rates for heart disease ($\beta = 125.84$, $p < .001$), cancer ($\beta = 78.44$, $p < .001$), and stroke ($\beta = 24.97$, $p < .001$) compared to low-burden counties. The pandemic period was associated with an overall increase in mortality for heart disease ($\beta = 11.41$, 95% CI [8.66, 14.16], $p < .001$), cancer ($\beta = 2.30$, 95% CI [−0.03, 4.63], $p = .053$), and stroke ($\beta = 3.97$, 95% CI [3.12, 4.83], $p < .001$).

Hypothesis 2:

Figure 3 illustrates both the direction (risk vs. protective), the magnitude, and the comparative importance of socioeconomic predictors on county mortality, side-by-side for four major causes of death in the post–COVID era. Multivariable models revealed that for Cancer, higher educational disadvantage ($\beta = 3.45$, $SE = 0.92$, 95% CI [1.67, 5.24], $p < .001$) and lower median income ($\beta = -4.21$, SE = 0.79, 95% CI [−5.73, −2.70], $p < .001$) were the strongest predictors of increased crude mortality; uninsured rate also contributed ($\beta = 1.87$, $SE = 0.81$, 95% CI [0.27, 3.47], $p = .022$). For Heart Disease, similar associations emerged (HS-or-Less: $\beta = 4.12$, $SE = 0.95$, 95% CI [2.26, 6.00], $p < .001$; median income: $\beta = -5.03$, $SE = 0.85$, 95% CI [−6.68, −3.38], $p < .001$). Stroke mortality showed smaller but significant links with poverty ($\beta = 1.98$, $SE = 0.87$, 95% CI [0.27, 3.69], $p = .023$), low education ($\beta = 2.08$, $SE = 0.78$, 95% CI [0.56, 3.60], p = .008), and income ($\beta = -3.17$, SE = 0.68, 95% CI [−4.51, −1.83], $p < .001$).

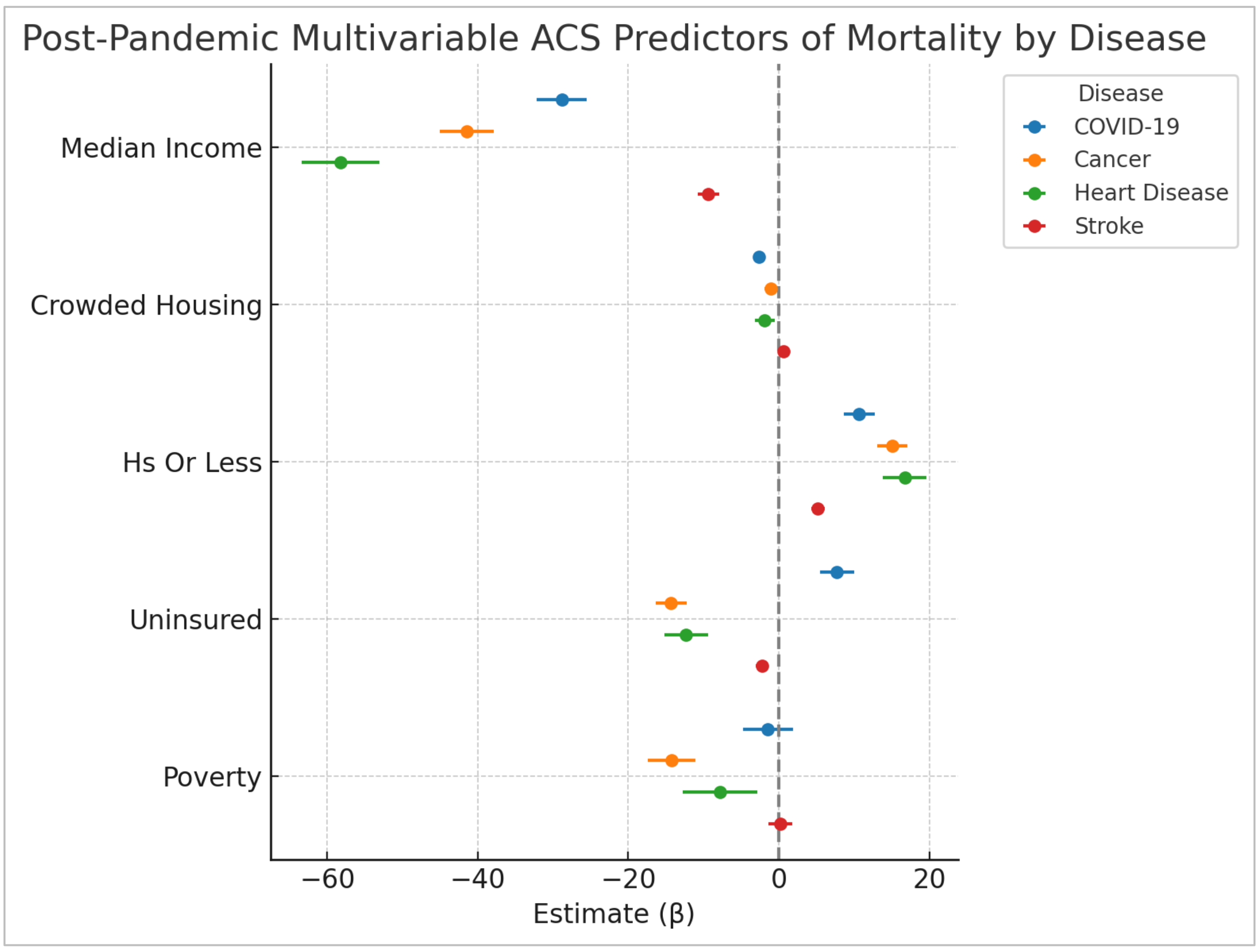

Figure 3. *Post-pandemic (2020–2022) coefficient estimates for Heart Disease, Cancer, and Stroke*

Across all three diseases, mean ACS z-scores shifted significantly between the Pre-Pandemic (2016–2019) and Post-Pandemic (2020–2022) periods (all $p < .001$). For Cancer, the poverty z-score decreased by 0.39 ($SE = 0.01$, 95 % CI [–0.42, –0.37]); uninsured and HS-or-Less z-scores showed similar declines (Δ = –0.33 to –0.43). Median income increased (Δ = 0.72, *SE* = 0.01, 95 % CI [0.69, 0.75]). Heart Disease and Stroke exhibited the same pattern: poverty, uninsured, HS-or-Less, and crowded-housing z-scores all fell by approximately 0.25–0.44 SDs, while median-income z-scores rose by about 0.67–0.73 SDs (all 95 % CIs exclude zero).

Among COVID-19 deaths, uninsured rate (β = 7.74, SE = 1.15, 95% CI [5.49, 9.99], $p < .001$), low education (β = 10.67, *SE* = 1.06, 95% CI [8.59, 12.76], $p < .001$), and crowded housing (β = −2.61, *SE* = 0.36, 95% CI [−3.31, −1.91], $p < .001$) were highly significant predictors, with median income exhibiting a large negative association (β = −28.85, *SE* = 1.70, 95% CI [−32.18, −25.53], $p < .001$).

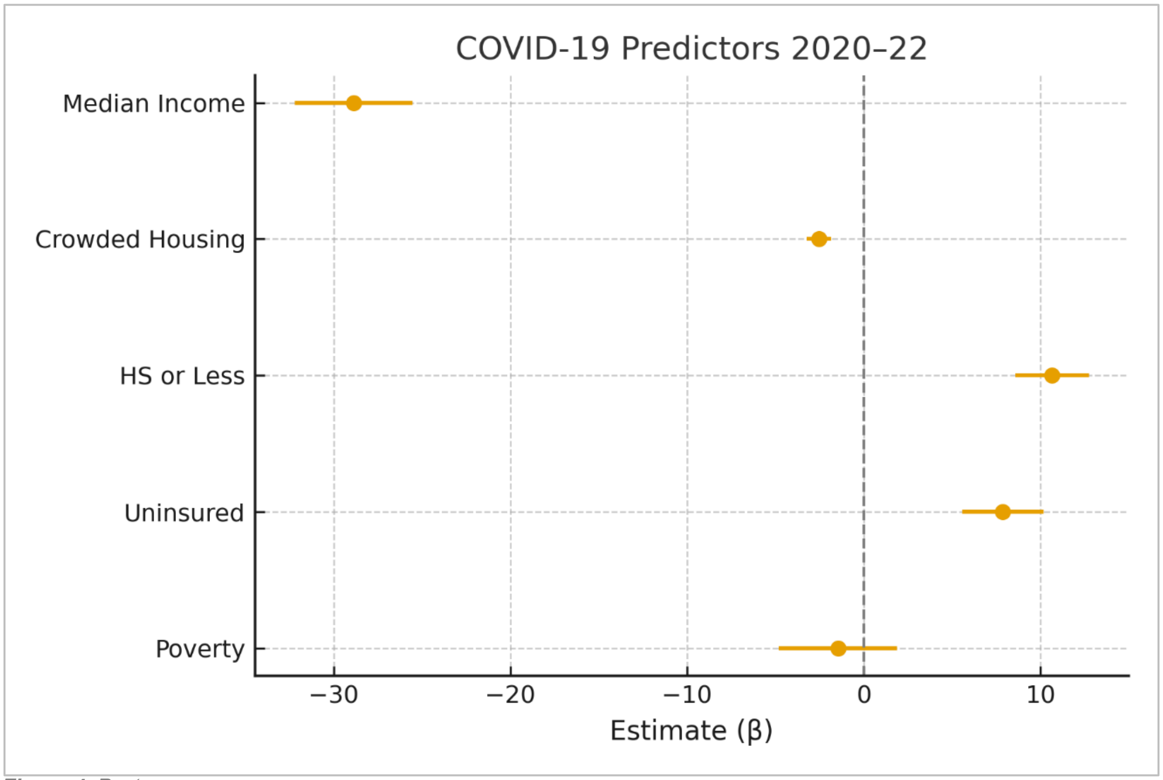

Figure 4. *Post-pa*

Discussion

This county-level study evaluated changes in preventable mortality from heart disease, cancer, and stroke in the United States before and after the onset of the COVID-19 pandemic, with a focus on the effects of COVID-19 burden and structural socioeconomic disadvantage. Our findings demonstrate that the pandemic period (2020–2022) was associated with a marked reversal of prior declines in heart disease and stroke mortality, while cancer mortality remained largely unchanged. Specifically, heart disease mortality increased by 5.2% and stroke mortality by 7.3% during the pandemic, whereas cancer mortality showed only a negligible change. These results are consistent with recent national reports documenting excess mortality from cardiovascular causes during the pandemic (Woolf et al., 2021; Stokes et al., 2021). Counties with higher COVID-19 mortality burden experienced significantly greater increases in heart disease mortality compared to counties with lower burden, as evidenced by a significant difference-in-differences interaction. In contrast, changes in cancer and stroke mortality did not differ significantly by COVID-19 burden. This pattern suggests that direct effects of SARS-CoV-2 infection, as well as indirect effects such as health system strain and deferred care, disproportionately impacted cardiovascular outcomes. A key finding of this study is the amplification of socioeconomic gradients in preventable mortality during the pandemic. Structural disadvantage, as measured by poverty, lower educational attainment, lack of insurance, and crowded housing, became much stronger predictors of mortality for heart disease and stroke after 2020. For example, a one-standard-deviation increase in low educational attainment was associated with 3 to 4 additional deaths per 100,000 for heart disease and cancer, and nearly 11 additional deaths per 100,000 for COVID-19 itself. These results highlight how the pandemic exacerbated preexisting health disparities, particularly in communities already facing socioeconomic vulnerabilities (Magesh et al., 2021; Braveman et al., 2010). The stability of cancer mortality, despite widespread disruptions to screening and preventive care, may reflect the longer latency and progression of oncologic outcomes compared to cardiovascular events (Fedewa et al., 2023). It is possible that the full impact of pandemic-related delays in cancer care will become apparent in subsequent years. Our findings are consistent with international analyses showing that excess mortality during the pandemic was not solely attributable to direct viral effects, but also to indirect consequences such as health care disruptions and socioeconomic stressors (Karlinsky & Kobak, 2021).

Limitations

This study has several limitations. First, the ecological design, which relies on county-level aggregated data, precludes causal inference at the individual level and may be subject to residual confounding from unmeasured factors such as local healthcare capacity, behavioral risk factors, or policy differences. Second, the use of provisional mortality data for recent years introduces the potential for reporting lags and underestimation of mortality rates, particularly for causes of death that require more complex adjudication. Third, to maximize the contrast between groups, counties in the middle tertile of COVID-19 mortality burden were excluded from certain analyses, which may limit the generalizability of findings to counties with moderate pandemic impact.

Conclusion

In summary, the COVID-19 pandemic reversed longstanding declines in preventable mortality from heart disease and stroke in the United States, with the greatest increases observed in counties with high COVID-19 burden and greater socioeconomic disadvantage. These findings underscore the critical role of structural determinants in shaping health outcomes during public health crises. Targeted interventions to strengthen healthcare infrastructure, address social determinants of health, and ensure equitable access to care are essential to mitigate the impact of future pandemics and reduce persistent disparities in preventable mortality.

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