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Authors

Ye, Yiwan
Shu, Xiaoling

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Unequal but widespread despairs: Social inequalities and self-rated health trends in the United States in 1972–2018

Yiwan Ye [a,*], Xiaoling Shu [b]

[a] University of Michigan, Dearborn, 19000 Hubbard Dr, Dearborn, MI, 48126, USA
[b] Univerisity of California, Davis, 1283 Social Sciences and Humanities, Davis, CA, 95616, USA

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ABSTRACT

Significance: Past studies show rising mortality and morbidity among middle-aged white Americans since the 21st century. This research analyses trends in declining self-rated health (SRH) across demographic groups, focusing on shifts in SRH inequalities by gender, race, and socioeconomic status (SES). It sheds light on declining health trends in the United States and deepens our understanding of health inequalities and their dynamics in high-income countries.
Method: We analyse 29 waves of cross-sectional data from the General Social Survey (1972–2018, N = 46,133) using Bayesian Hierarchical Age-Period-Cohort Cross-Classified Random Effect models (BHAPC-CCRM) to estimate age, period, and cohort effects, and changes in health gaps over time as interactions between period and race, gender, or SES.
Results: SRH improved until the 21st century but then declined across all gender, race, income, education, and employment groups after controlling for age and cohort effects. The racial health gap has continued since 2000, with a slight erosion of white health privilege. Nonwhite, low-income, non-college-educated, unemployed, and unmarried individuals have seen further declines in SRH. Baby Boomers' health advantage was wiped out after 2000.
Interpretation: In line with the health reversal literature in the U.S. and the U.K., SRH has deteriorated in the 21st century for all racial, gender, and SES groups in the U.S. The diminishing SRH advantage for whites results from a faster decline compared to Blacks and other non-white groups. However, significant racial and SES disparities in SRH persist, with disadvantaged groups experiencing poorer SRH. We discuss the policy implications.

1. Introduction

A landmark study by Case and Deaton (2015) discovered rising mortality and mortality rates among middle-aged non-Hispanic white Americans, a reversed life trend contrary to all the other industrialised countries where these rates have declined continuously. Life expectancy in the US fell as a result of rising mortality among working-age adults aged 25–64, led by an increase in mortality initially among middle-aged whites but became prevalent in all races of this age group (National Academies of Sciences, Engineering, and Medicine, 2021). More alarmingly, this deterioration trend has persisted in the U.S.: The current generation of non-college-educated middle-aged Americans is experiencing a decline in life expectancy, with many now dying at younger ages than their parents (Case and Deaton, 2021). Researchers coined the term "deaths of despair" to describe deaths resulting from drug overdoses, suicide, and alcohol-related causes, such as chronic liver diseases (Case and Deaton, 2015, 2020, 2021; King et al., 2022).

Despite numerous empirical attempts to understand the health reversal in the U.S., a few significant research gaps remain unaddressed: 1) Has self-rated health (SRH hereafter) also experienced a decline since previous research on the death of despair focused primarily on objective health indicators? 2) Is this decline an artefact of the cohort effect as the baby boomers age? Moreover, 3) What are the health trends for the non-white and other marginalised groups?

1.1. Objectives

Our study will examine whether subjective health trends reversed at the turn of the century by analysing self-rated health (SRH) patterns. We will assess changes in period effects, considering age and cohort

* Corresponding author.
E-mail addresses: yiwanye@umich.edu (Y. Ye), xshu@ucdavis.edu (X. Shu).

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influences on SRH. Additionally, we will explore health inequalities across historically marginalised groups. Studies show that the rise in deaths of despair affects various racial, ethnic, socioeconomic, and geographic groups, not limited to non-college-educated, non-Hispanic whites or rural areas (Gaydosh et al., 2019; Snyder, 2016; Wami et al., 2021). Following McCartney et al.'s (2019) definition of health inequalities as "the systematic, avoidable, and unfair differences in health outcomes between populations, between social groups within the same population, or across a gradient ranked by social position," this study examines how negative SRH patterns differ by gender, race, and socioeconomic status (SES) and how these patterns vary over time in the U.S. Additionally, Case and Deaton's research (2015, 2020, 2021) suggests a potential reduction in the racial health gap, warranting investigation into whether this is due to declining health among whites or improvements among non-whites.

This study is among the first to adapt Bayesian logic to the Hierarchical Age-Period-Cohort Classified Random Effect model (BHAPC-CCRM) (Yang, 2006; Fosse and Winship, 2019a, 2019b; Lynch and Bartlett, 2019; Fosse, 2020). The age-period-cohort analysis of general health trends is limited, partly due to the challenges in the age-period-cohort identification problem, specifically the perfect collinearity between age, birth year, and survey year (Luo, 2013; Bell, 2021). Recently, researchers have also used intrinsic estimators, Lexis diagrams, and the Age-Period-Cohort-Interaction models to unpack the age, period, and cohort effects (cohort effects approximated by age-period interactions) on mortality outcome (Minton et al., 2017b; Parkinson et al., 2017; Luo and Hodges, 2020). However, there was a lack of a theory-oriented analytic framework until Fosse (2020) proposed a solution to the identification problem by making theory-guided assumptions about the possible results of age, period, and cohort effects, i.e. informative priors (Su et al., 2022). We adopt this Bayesian approach in our analysis.

2. Background

Many industrialised countries have experienced stagnation or declines in life expectancy and mortality trends in the 21st century, particularly in the United Kingdom and the United States (Hiam et al., 2017; Fenton et al., 2019; McCartney et al., 2022; Case and Deaton, 2015, 2021; Ho and Hendi, 2018). This widespread deterioration in health trajectories among high-income countries has led to a body of literature that aims to understand the sources of health improvement and health inequalities. Some studies suggest that austerity policies adversely affect life expectancy and mental health in high-income countries (Walsh et al., 2020; McCartney et al., 2022; Fahy et al., 2023). Others highlight rising health inequalities linked to changes in socioeconomic conditions, healthcare policies, and the political embrace of neoliberalism and medicalisation in the U.S. (Conrad, 2005, 2007; Schrecker and Bambra, 2015; Knapp et al., 2019) and other high-income countries (Bambra, 2024). Furthermore, researchers highlight socioeconomic inequalities, structural racism, geographical variation, and their interactions within the context of complex sociohistorical dynamics in the United States as fundamental root causes of health inequalities in the U.S. (Williams and Mohammed, 2009; Phelan et al., 2010; Phelan and Link, 2015; Bailey et al., 2017; Wami et al., 2021; Brown and Homan, 2023).

Case and Deaton (2015) found that mortality rates for middle-aged white Americans increased by nearly 8% from 1999 to 2014, while Hispanic Americans experienced a more than 30% reduction during the same period. A similar decline in white Americans' health privilege is evident in self-rated health trends (Cummings, 2023). Studies attribute the higher mortality among non-Hispanic whites to self-destructive health behaviours, such as higher rates of smoking, opioid drug use, sedentary lifestyle, and stigmatisation of mental illness, as well as other underlying social and economic factors in rural communities (Stein et al., 2017; Hedegaard and Warner, 2021).

Despite extensive media coverage, researchers have questioned the methodological validity of Case and Deaton's findings regarding the worsening health outcomes for middle-aged non-Hispanic white Americans (Minton et al., 2017a). First, their findings may be an artefact of shifts in racial composition across age, period, and cohort distributions, such as the earlier mortality of Black Americans, which may result in their underrepresentation in older cohorts (Desai, 2020). Second, the decline in health and life expectancy in the U.S. is not limited to low-educated whites from rural areas (Muennig et al., 2018; Gaydosh et al., 2019).

To illuminate the ongoing debate on the nature and causes of health trends in the US, we examine self-rated health (SRH) in the US population from 1972 to 2018. Studying SRH is important because it indicates overall health and well-being and strongly predicts objective health conditions independent of social status. (Chiavarino et al., 2019; Abdulrahim and El Asmar, 2012). Additionally, SRH can reflect underlying mental and physical health before formal diagnostics or death (Schnittker, 2005; Schnittker and Bacak, 2014).

2.1. Age-cohort-period effects

2.1.1. Period effect on health

Armstrong et al. (1999) and Case and Deaton (2015, 2021) highlight significant temporal trends in mortality and morbidity. The 20th century saw a substantial decline in mortality due to advancements in diagnostic techniques and medical treatments. However, since 2000, there has been an overall increase in mortality and morbidity rates, with a decline in life expectancy observed from 1990 to 2018. The SRH trend increases decreases or becomes inverted U-shaped (Bambra, 2024).

Several potential explanations exist for reversing the positive SRH trend around the 1990s. There has been a significant reduction in spending on social assistance programmes amidst the global restructuring of labour market opportunities and public policies (McCartney et al., 2022). Since 2000, cuts in public expenditure have been linked to slower improvements in life expectancy, as well as heightened risks of mortality and mental illness in the United States and the United Kingdom, particularly among low SES and elderly populations. (Desai et al., 2010; Woolf, 2011; Barr et al., 2015; Harris et al., 2021; Alexiou et al., 2021; Fahy et al., 2023). The reversed mortality trend not only coincided with the rise of neoliberal policies in the U.S. and the U.K. (Mooney, 2012; Schrecker and Bambra, 2015) but also with the fall of Soviet states in Russia (Timonin et al., 2017; King et al., 2022). Studies have found that radical social dislocations in former Soviet states, such as reduced social safety nets, are major drivers of deaths of despair, mirroring the trends seen in Anglo-American countries (Quinn and Cha, 2017). Finally, the disappearance of high-paying manufacturing industries, driven by globalisation, has also contributed to the increase in deaths of despair during this period (King et al., 2022).

Coincident with diminishing economic opportunities and dwindling policy provisions, the rise of the opioid epidemic in the late 1990s has caused deaths of despair to surpass those from lung cancer and diabetes (Bernard et al., 2018; Case and Deaton, 2021). This crisis originated from the overprescribing of opioids and the legalisation of other synthetic pain medications, such as propoxyphene and oxycontin, in the 1980s (Makary et al., 2017; Dasgupta et al., 2018; Simoni et al., 2022), leading to a higher incidence of fatal drug overdoses (Stoicea et al., 2019; Hedegaard and Warner, 2021).

Lastly, the consumption of unhealthy, highly processed food since the 1970s has been linked to higher risks of diabetes, cardiovascular diseases, liver diseases, and other chronic health issues (Nielsen et al., 2002; Rehm et al., 2016; Mozaffarian et al., 2011; Lim et al., 2012; Steele et al., 2016), lowering SRH in the U.S. (Chen et al., 2018).

2.1.2. Age effect on health

It is crucial to control linear and quadratic age effects in epidemiological studies. Previous research shows that self-rated health (SRH) declines with age due to increased risks of mortality from illnesses such as circulatory disease, functional impairments, and frailty, though this association weakens in older age (French et al., 2012; Mitnitski et al., 2002; Parkinson et al., 2020). Thus, the relationship shows a negative but waning trend with age – i.e. an inverted U-shaped curve between SRH and age (Chen et al., 2007). The quadratic age effect can be explained by alterations in the concept of health throughout the life course; as individuals age and observe the decline in their peers' health, they adjust their perceptions of their health accordingly. (Schnittker, 2005).

2.1.3. Cohort effect on health

Research has shown that SRH varies significantly across U.S. and European birth cohorts (Chen et al., 2007; Aguilar-Palacio et al., 2018; Zheng et al., 2021; Zheng and Echave, 2021). Baby boomers report lower self-rated health and higher overdosed deaths compared to pre-boomers of the same age (Chen et al., 2007; Huang et al., 2018). This may be explained by Easterlin's relative cohort size hypothesis, where Baby boomers often face intense competition, higher income inequality, lower happiness, and challenges in the marriage market (Easterlin, 1987, 2010; Macunovich and Easterlin, 2010; Ye and Shu, 2022; Bronson and Mazzocco, 2023).

2.2. Covariates

The study will also account for other salient fundamental social determinants of health and analyse their variations in inequalities (Riley, 2020). For instance, Studies have shown that mortality trends among Black and other racialised groups vary over time across birth cohorts, gender groups, and geographical regions (Zang et al., 2019, 2021; Cummings, 2023). Evidence has also shown that mortality and subjective health are graded by income and education level and change over time (Hill and Jorgenson, 2018; Wachtler et al., 2019; Lamidi, 2022). Traditional institutions that provide social support, such as marriage and church, have eroded in rural communities over time (King et al., 2022; Zhang, 2017). As a result, our analytic models will account for racial minority status, gender, income class, education, employment status, marital status, rural status, and church attendance (Norström et al., 2014; Phelan et al., 2010; Gaydosh et al., 2019; Snyder, 2016). Because the temporal trajectory is the primary focus of our study, we analyse whether this period trend of SRH varies by race, gender, and socioeconomic factors to show the dynamics in the pattern of health inequalities.

3. Data and measures

3.1. Data

The data for this study were derived from the General Social Survey (GSS), a nationally representative repeated cross-sectional survey in the USA. GSS collects data on contemporary American society to study social structures and trends in opinion, behaviours, and indicators across various population subgroups. GSS uses a multistage stratified probability sampling strategy to choose non-institutionalized English-speaking adults aged 18 or older, which yields a.

The sample of 64,133 unique respondents in the 29 surveys conducted between 1972 and 2018.[1] GSS contains the self-rated health, demographic variables, and other social indicators necessary for this study. Among the missing samples, 95.7% were lost due to self-rated health (mostly inapplicable cases), and 4.3% were lost to the combination of covariates - cohort groups, church attendance, education attainment, and marital status.[2] We used listwise deletion to adjust for item non-responses and excluded the oversampled cases. Since these cases were not missing at random and may be correlated with the period effect, complete case analysis or imputation methods were not appropriate. Therefore, we used the Missing Indicator method to reduce nonresponse bias by creating binary variables to represent missing cases as separate categories. (Lavrakas, 2008; Groenwold et al., 2012). We included missing indicators for missing family income (23%) and employment status (47.4%). The final analytic sample contains 46,133 cases.

3.2. Measures

3.2.1. Outcome variable

Self-rated Health (SRH) indicates if respondents report good or excellent health. It comes from a single-item questionnaire that asks respondents to rate their overall health. Prior studies show these measures are valid and reliable predictors of objective health outcomes like morbidity and mortality (Schnittker and Bacak, 2014; Wu et al., 2013). We dichotomise SRH at the midpoint of a four-point scale, classifying responses as either "good and excellent health" or "poor and fair health." This approach considers several factors: the distribution of SRH is skewed, with over 72% reporting "good and excellent health" and only 4.22% reporting "poor health." Treating SRH as an ordinal variable would misrepresent this imbalance. We aim to differentiate age-period-cohort effects on these health categories rather than maximise SRH. Additionally, we truncated the scale at the midpoint to align with the conceptual boundary between "healthy" and "unhealthy" (Ragland, 1992; MacCallum et al., 2002). This common practice enhances clinical relevance in health research (Feenstra et al., 2020; Yang, 2008a, 2008b; Schwei et al., 2017).

3.2.2. Independent variables

The variables of interest were age, period, and cohort groups approximated by respondents' age, survey waves, and respondents' birth year. In this context, age refers to individual differences in health across the life course. At the same time, period effects reflect the impact of historical events and social changes on health outcomes at a given time. Cohort effects are differences between people born and raised in similar social, economic, and environmental conditions. To estimate each temporal component independently, we aggregated the values among age, period, and cohort variables into meaningful analytic groups:

Age is set up as an individual-level control variable in the multilevel models. We categorised the interval age variable into 5-year intervals, then centred the age group at 41–45 years old. We also included a quadratic age term (i.e., age squared) to estimate the well-documented U-shaped relationship between age and subjective health (Schnittker, 2005; French et al., 2012).

We constructed 10-period groups based on the 29 surveys from 1972 to 2018. These waves were grouped into five-year intervals, each containing roughly 2 to 4 survey years. For example, the 'early 70s′ period includes four survey years: 1972, 1973, 1974, and 1975, while the 'early 2000s′ group consists of only two survey years: 2002 and 2004.

We constructed 16 birth cohort groups using respondents' birth years, which range from 1883 to 2000. First, we categorised birth years into six generations - the Greatest Generation (1900–1927), the Silent Generation (1928–1945), Baby Boomers (1946–1964), Generation X (1965–1980), Millennials (1981–1996), and early Generation Z (1997–2000). Then, we divided each culturally meaningful generation

[1] The 2020 and 2022 datasets were excluded due to delays and different sampling weights from changes during the COVID-19 pandemic. The GSS advises against comparing results from 2018 and earlier with those from 2021 onwards analysis. See https://gssdataexplorer.norc.org/gssweighting.

[2] To avoid distortion in estimates of racial inequality in SRH, we omitted 691 oversampled Black respondents from the 1982 and 1987 surveys, reducing the analytic sample by 1.5%.

into three equal-sized cohorts, allowing us to estimate early, mid, and late cohort effects for each generation (Shu and Meagher, 2018; Ye and Shu, 2022; Zhu and Ye, 2020). Therefore, 46,824 samples are cross-classified into 10-period groups by 16 cohort groups at the 2nd level, resulting in 160 period-by-cohort clusters or categories.

3.2.3. Covariates

We include individual covariates that either improve or weaken SRH and correlate with changes in SRH over time. These include gender, race, income, education, and employment status.

We coded "female" as 1 and "male" as 0 for the gender variable. We constructed a binary variable for racialised identities where "white" was coded as "0", "nonwhite" or "black", and "other race" as "1". Early waves of the GSS only had three categories of racial identities: white, black, and other.[3] Unfortunately, the GSS only added more detailed categories for non-white and non-Black racial groups (e.g., Hispanics, Asians, and Native Americans) in more recent waves after 2000. This limitation makes it impossible to examine detailed racial and ethnic disparities for other groups in earlier periods.

The income variable measures respondents' family income in constant, inflation-adjusted dollars. We created a four-category income class variable from the "coninc" variable by dividing income into quartiles and rounding to the nearest \$1,000. The first quartile is labelled "low-income class" (below \$18,000), the second "lower-middle income class" (\$18,000–\$36,000), the third "middle-income class" (\$36,000–\$60,000), and the fourth "upper-income class" (above \$60,000). An "income missing" category was created for about 9.5% of the sample with missing income data.

The education variable measures the "highest year of school completed," which ranges from 0 to 20 years. We centred the education variable at 12 years, i.e., completed high school. We coded the employment status variable - "if respondent ever unemployed in the last ten years", with 0 as employed, 1 as unemployed, and 2 for missing employment status (e.g. not in the labour force).

We use this covariate not only to analyse their main effects but, more importantly, to highlight their interactions with the period effect to reveal the variations in temporal change by race, gender and SES to discover the historical dynamics in inequalities in SRH over the four and half decades in 1972–2018 under study.

3.2.4. Controls

We also include additional control variables: rural-urban status, church attendance, and marital status. Rurality or rural status measured whether respondents lived in a rural area (rural as 1, non-rural as 0). Non-rural areas were chosen as the reference group because most of the U.S. population resides in urban areas (Center for Sustainable Systems, 2023). The church attendance variable measures "how often a respondent attends religious services." We created a variable indicating whether respondents have never attended a religious service (1) or have attended at least once (0). Marital status is measured as a series of dummy variables – married, single or never married, divorced, separated, and widowed.

3.3. Method

Age Period Cohort analysis is plagued with the collinearity issue, where it is impossible to simultaneously estimate age, period, and cohort effects in the same model (Bell, 2021). To overcome this issue, our study employed a Bayesian hierarchical age-period-cohort model with cross-classified random effects (BHAPC-CCRM) (Fosse, 2020; Gelman et al., 2014; Yang, 2006; Yang and Land, 2013; Su et al., 2022). The BHAPC model can theoretically resolve the collinearity problem of APC using weakly informative priors and explicit assumptions and generate more computationally stable results (Gelman and Pardoe, 2006; Bell and Jones, 2015; Su et al., 2022). We followed Lee et al.'s (2023) suggestion for the Bayesian-specific workflow cycle for choosing priors – search for background knowledge, prior elicitation, formalising prior distribution, and prior predictive check. We also included a sensitivity analysis using the frequentist version of the HAPC-CCRM model.

The hierarchical age-period-cohort cross-classified random effect model categorises individuals into 116 cohort-by-period groups. For the base model, we included an age linear effect, an age quadratic effect, a linear period effect, and a period quadratic effect at the individual level, as well as cohort and period random effects at the group level, to account for the variation across interview years and birth cohorts.

$$\phi_{ijk} \in \{0,1\}$$

$$Y_{ijk}\Big|\phi_{ijk} \overset{ind}{\sim} Bern\ (\phi_{ijk});\ Y_{ijk} = ln\ \frac{\phi_{ijk}}{1-\phi_{ijk}} \qquad [1]$$

$$Y_{ijk} = \mu_{0jk} + \alpha_{ijk}{*}Age + \pi_{ijk}{*}Age^2 + \beta_{ijk}{*}Period + \varphi_{ijk}{*}Period^2 + \sum_{i=5}^{8}\gamma_{ijk}{*}Covariates\ \varepsilon_{ijk} \qquad [2]$$

$$\mu_{0jk} = \theta_0 + p_{0j} + c_{0k} \qquad [3]$$

$$Y_{ijk}\ \Big|\ \theta_0,\ \beta_{ijk}, \gamma_{ijk}\ \sim\ N(0,10) \qquad [4]$$

$$\alpha_{ijk}\ \sim\ N(-0.2, 0.1) \qquad [5]$$

$$Y_{ijk}\ \Big|\ \pi_{ijk,}\ \varphi_{ijk} \sim\ Laplace(0, 0.01) \qquad [6]$$

$$p_{0j}\ \sim\ N\left(0, \sigma^2_{p_j}\right)$$

$$c_{0k}\ \sim\ N\left(0, \sigma^2_{c_k}\right) \qquad [7]$$

$$\sigma^2_p\ \sim\ igamma(0.1, 0.1) \qquad [8]$$

$$\sigma^2_c\ \sim\ igamma(0.1, 0.1)$$

Since the SRH can only take on the values of 0 and 1, we considered the Bayesian Bernoulli regression model. Equation (1) represents the logit link function predicting the log odds of reporting good or excellent health for individual 'i' in survey year 'j' and birth cohort 'k'. Equation (2) denotes the full individual-level model. It includes the intercept μ_{0jk}, main age effect α_{ijk}, quadratic age effect π_{ijk}, main period effect β_{ijk}, quadratic period effect φ_{ijk}, covariates γ_{ijk}, and the individual-level error term ε_{ijk}. Equation (3) denotes the overall mean independent of random effects θ_0. b_{0k} and c_{0k} are period and cohort random effects embedded in the group level.

Equations (4) (5) (6) (7)((8) outline the prior distributions for the model parameters. Equation (4) assigns "very weak" informative priors with normal distributions to the intercept, main period term, and other covariates, assuming a mean of 0 and standard error of 10. In Equation (5), we constrained the main age effect to follow a normal distribution with a mean of −0.2 and a variance of 1 based on evidence that health declines with age (Yashin et al., 2007; Belsky et al., 2015). To estimate period and cohort effects, a highly informative prior age is required (Bell and Jones, 2015; Fosse and Winship, 2019b). We performed a sensitivity analysis, starting with weak assumptions on the age effect and narrowing the bounds to improve the model fit (Fosse and Winship, 2019a). No cohort-fixed effect was included to avoid collinearity. In Equation (6), quadratic age and period effects are modelled using a Laplace distribution centred at zero with a scale parameter of 0.01, which is suitable for polynomial effects (Fosse, 2020). Period and cohort effects are

[3] GSS has a Hispanic identity variable, but this variable wasn't available prior to 2000.

Table 1
Cross-classified data by cohorts and survey periods (general social survey, N = 46,133).[a]

	1971–75	1976–80	1981–85	1986–90	1991–95	1996–2000	2001–05	2006–10	2011–15	2016–20	Total
Greatest I: Pre-1910	998	536	325	182	70	37	0	0	0	0	2,148
Greatest II: 1910–18	778	563	438	380	243	251	56	34	0	0	2,743
Greatest III: 1919–27	937	619	569	489	367	507	156	226	59	13	3,942
Silent I: 1928–33	561	377	324	280	227	399	166	252	72	93	2,751
Silent II: 1934–39	661	417	356	325	285	446	188	325	141	122	3,266
Silent III: 1940–45	719	524	426	414	369	587	242	449	198	189	4,117
Boomers I: 1946–52	1,034	753	703	663	578	953	385	748	329	360	6,506
Boomers II: 1953–58	314	536	670	621	580	1,032	367	701	316	342	5,479
Boomers III: 1959–64	0	89	552	552	567	1,054	372	751	354	377	4,668
Gen X I: 1965–70	0	0	70	394	477	972	426	729	290	341	3,699
Gen X II: 1971–75	0	0	0	19	197	668	299	563	288	262	2,296
Gen X III: 1976–80	0	0	0	0	5	394	333	551	261	297	1,841
Millennials I: 1981–86	0	0	0	0	0	42	181	570	333	393	1,519
Millennials II: 1987–90	0	0	0	0	0	0	0	182	237	318	737
Millennials III: 1992–96	0	0	0	0	0	0	0	2	107	230	339
Gen Z: 1997–2003	0	0	0	0	0	0	0	0	0	82	82
Total	6,002	4,414	4,433	4,319	3,965	7,342	3,171	6,083	2,985	3,419	46,133

[a] Analytic sample is pooled from 29 waves of the General Social Survey and adjusted for oversampling of Blacks in 1982 and 1987.

treated as random intercepts with default normal priors (0, 10). Lastly, according to Equations (7) & (8), the prior distributions for period σ_p^2 cohort σ_c^2 random effects are modelled using an inverse gamma distribution with 0.1 and 0.1 (Polson and Scott, 2012; Brehm et al., 2021).[4]

4. Results

4.1. Descriptive analysis

Table 2 shows the distribution of the mean values for the analytic variables over ten-year survey periods (see Table 1). The weighted descriptive results reveal variations in the proportion of respondents reporting excellent or good health before and after the 1990s. Fig. 1 illustrates this trend across five-year periods by generational cohort. The Greatest Generation experienced a stable self-reported health trend, except for a dip in the early 2010s due to limited data. The Silent Generation witnessed a steady decline in health, while Baby Boomers peaked in the late 1980s before undergoing a steep decline. Generation X's health peaked in the late 1990s and has since declined, reflecting the overall trend of the sample. Generations Y and Z have experienced a gradual decline in self-reported health since the late 1990s, with notably lower health than Generation X between 1995 and 2005 and no improvement since reaching adulthood.

4.2. Bayesian models

Table 3 shows the posterior average odd ratios of reporting good or excellent health (i.e. positive self-rated health) using Bayesian hierarchical age-period-cohort cross-classified random effect models (BHAPC-CCRM). We included additional models (I to L) that test the interactions of the period effect and other variables.

Model A is the baseline model that estimates the null BHAPC-CCRM models with only age effects. For every five-year increase in age, the likelihood of reporting positive SRH decreases by about three percentage points (O.R. = 0.873). Still, this decline slows slightly over time, increasing by 0.15 percentage points per year squared (O.R. = 1.006). Results also show that the random period and cohort group-level variance does not contain zero within the 95% credible interval, indicating significant differences in SRH among some birth cohorts and survey years.

Model B shows a gradual decline in SRH since 1972, accounting for

Table 2
Descriptive statistics of variables in the analytic sample across 10-year periods (general social survey, N = 46,133).[a]

	1970s	1980s	1990s	2000s	2010s	% of Total Sample
Subjective Rate of Health						
% Fair or poor health	27	23.6	21.7	24.9	28	24.8
% Excellent or good	73	76.4	78.3	75.1	72	75.2
Age (average)	44.7	45.3	45.4	47	48.9	46
Gender						
% Male	46	43	44	44.9	44.5	44.4
% Female	54	57	56	55.1	55.5	55.6
Race						
% Non-Hispanic whites	88	85.4	80.9	76.5	73.6	81.5
% Blacks	11.4	11.2	13.6	14	16.1	13.1
% Other non-whites	0.6	3.4	5.5	9.5	10.3	5.5
Community						
% Non-rural	80.5	83.2	89.8	87.6	91.2	86.2
% Rural area	19.5	16.8	10.2	12.4	8.8	13.8
Religiosity						
% Attend religious service	87.4	86.1	82.6	79.3	73.3	82.3
% Never attend	12.6	13.9	17.4	20.7	26.7	17.7
Household Income class						
% Low-income class	21.2	24	20.9	20.2	24	21.7
% Lower-middle income	26.1	24.8	23.5	20.4	21	23.4
% Middle-income class	26.2	21.6	22.4	22.6	20.9	23.0
% Upper-income class	19.2	21.3	22.3	24.6	25.3	22.4
% Missing	7.2	8.3	10.8	12.2	8.8	9.5
Education (in years)	11.7	12.4	13.2	13.4	13.7	–
Employment Status						
% Employed	61.3	21.6	39.6	23	32.1	36.9
% Unemployed	23.3	10	18	11.3	18.7	16.5
% Missing	15.4	68.4	42.4	65.7	49.2	46.6
Marital Status						
% Married	67.9	54.9	48.5	48	44.6	53.6
% Single	13.6	18.9	22.9	25	27	21.0
% Divorce	5.8	11.4	15.3	15.7	16.4	12.6
% Separated	3.2	3.7	3.6	3.3	3.5	3.4
% Widowed	9.5	11.2	9.8	8.1	8.4	9.4

[a] Analytic sample is pooled from 29 waves of the General Social Survey (1972–2018) and adjusted for oversampling of Blacks in 1982 and 1987.

[4] Detailed Bayesian model specifications and STATA codes are available upon request.

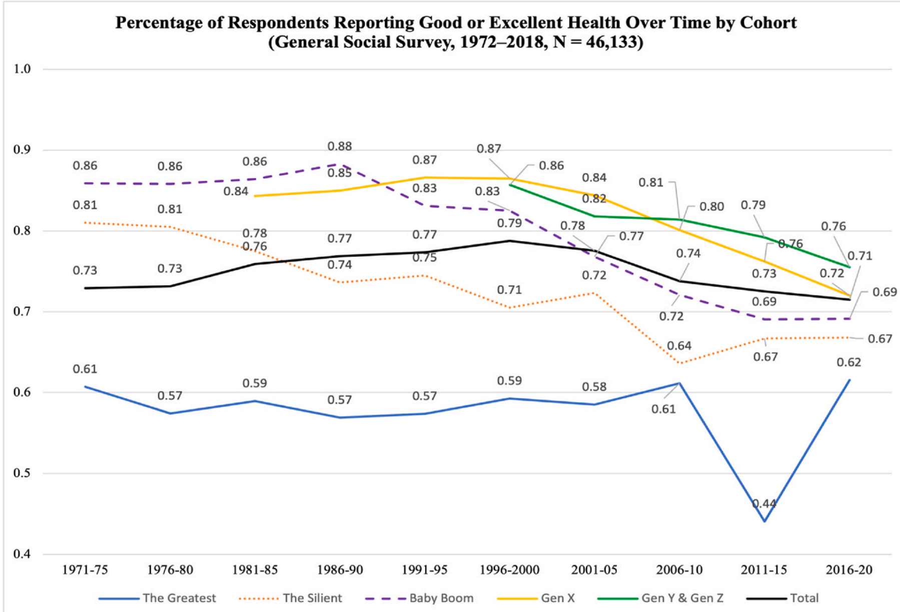

Fig. 1.

age, random cohort, and random period effects on negative SRH trends. Model C added a quadratic period effect (a squared of the period variable) to Model B. Model C shows a positive period effect on SRH and a negative quadratic period effect on SRH at a 90% credible interval, indicating a waning improvement of SRH over time.

Model D controls for essential demographic variables: gender, racialised groups, rural status, and church attendance. The main period effect suggests that for every five-year increase in the survey period, the probability of reporting positive health increases by approximately 4.6% (average odds ratio = 1.046 at a 90% credible interval). However, the quadratic period effect is not significant.

Holding age and period effects constant, female respondents are, on average, 2.7% less likely than male respondents to report positive health (O.R. = 0.882). Black respondents are, on average, 15.6% less likely than white respondents to report positive self-rated health (O.R. = 0.546). In contrast, respondents of other races are, on average, approximately 13.1% less likely to report positive SRH than white respondents (O.R. = 0.584). Rural respondents are, on average, 5.8% less likely to do so than their non-rural counterparts (O.R. = 0.772). Additionally, individuals who have never attended religious services in their lifetime are typically about 8.8% less likely to report positive SRH than those who have attended at least once, holding all else constant (O.R. = 0.687).

From Model E to Model H, both the main period effects and quadratic period effects remain significant at a 95% credible interval. For instance, in Model E, a one-unit increase in the period effect increases the odds of reporting good SRH by approximately 13.1% on average. However, the quadratic effect (O.R. = 0.986) slightly reduces this linear growth.

Model E adds family income to Model D. Individuals from the lower-income class and lower-middle-income class are, on average, 27.3% (O. R. = 0.337) and 9.3% (O.R. = 0.652) less likely to report positive SRH compared to the middle-income class, holding all else constant. Upper-income class members are, on average, 7.9% more likely to report positive health than middle-income class members (O.R. = 1.631). Furthermore, the Bayesian model indicates that respondents who did not disclose their family income are, on average, 11.5% less likely to have positive SRH than those in the middle-income class, holding all else constant (O.R. = 0.603). The gender effect on SRH is no longer significant within the 95% credible interval.

Model F accounts for education and finds that, on average, an extra year of schooling increases the likelihood of reporting positive SRH by two percentage points (O.R. = 1.14). Model G includes employment status. The results show that, on average, unemployed individuals are 3.6% less likely to report good or excellent health than their employed counterparts, holding all else constant (O.R. = 0.807).

Model H includes marital status variables. The results indicate that, on average, single, divorced, and separated individuals are 1.3%, 1%, and 4% less likely to report positive health outcomes than married individuals (O.R. = 0.918, 0.937, and 0.78, respectively), holding all else constant. There is no significant difference between widowed and married individuals. Like Model E, the main period and quadratic effects are significant, with a 95% credible interval. The average odds ratio for the primary period effect is 1.081, while that for the quadratic period effect is 0.986.

Fig. 2 presents Model H's average predicted probability of positive SRH from 1972 to 2018, accounting for age, cohort effects, and covariates. The model shows that the predicted probability of positive SRH started at 70.5% (1972–1975), peaked at 75.4% (1986–1995), and declined to 67.9% (2016–2018), exhibiting an inverted U-shaped trend.

Models I through L build on Model H and incorporate various interaction effects. Models I through L build on Model H and incorporate various groups of interaction effects. Model I examines the interaction between period effects and gender and racialised identities separately. The model reveals significantly diminishing racial inequalities over time for both genders (Blacks O.R. = 1.02; Other Races O.R. = 1.019). Figs. 3 and 4 illustrate the racial gaps in the average predicted probability of SRH over time for males and females, respectively. Fig. 3 shows diminishing SRH gaps between whites and Blacks and between whites and other races for males, while Fig. 4 shows similar trends for females. Both figures reveal an inverted U-shaped trend for all racialised groups and demonstrate that the SRH advantage of whites over nonwhites has persisted across decades for both genders. Additionally, the figures highlight that the gender effect reversed around the turn of the century (2001–2005), with females' average predicted SRH surpassing that of males.

Model J estimates the interaction effects between the survey period and communal demographic factors, such as rural status and church attendance. The results show no interaction effects between the period and church attendance but predict a positive interaction effect between the period and rural status. Fig. 5 illustrates that urban and suburban

Table 3
Average odd ratios for good or excellent health using Bayesian hierarchical age-period-cohort cross-classified random effect models in general social survey (N = 46,133).[a]

	Model A	Model B	Model C	Model D	Model E	Model F	Model G	Model H
Fixed Effects[b]								
Constant (odds)[c]	2.79*	3.311*	2.91*	3.711*	4.276*	4.141*	4.200*	4.511*
Age (5 year)	0.873*	0.877*	0.88*	0.861*	0.853*	0.872*	0.869*	0.867*
Age Squared	1.006*	1.005*	1.005*	1.005*	1.013*	1.012*	1.012*	1.012*
Period (5 years)		0.989	1.131+	1.046+	1.131*	1.062*	1.068*	1.081*
Period Squared			0.985+	0.996	0.986*	0.990*	0.988*	0.986*
Demographics								
Female				0.882*	0.999	0.976	0.965*	0.955*
Black				0.532*	0.686*	0.750*	0.742*	0.754*
Other Non-whites				0.584*	0.707*	0.781*	0.788*	0.798*
Rural				0.772*	0.875*	0.972	0.968*	0.966*
Never Attend Church				0.687*	0.773*	0.772*	0.776*	0.78*
Income Class (vs. Middle income class)								
Lower					0.337*	0.425*	0.437*	0.447*
Lower Middle					0.652*	0.74*	0.738*	0.749*
Upper					1.631*	1.40*	1.363*	1.374*
Income N/A					0.593*	0.683*	0.697*	0.693*
Education Years (vs. H.S.)						1.140*	1.142*	1.139*
Employment Status (vs. Employed)								
Unemployed							0.807*	0.799*
Employment N/A							1.034	1.009*
Marital Status (vs. Married)								
Single								0.918*
Divorced								0.937*
Separated								0.78*
Widowed								1.007
Random Components (Variance)								
Period Effect	0.042*	0.04*	0.039*	0.036*	0.035*	0.03*	0.031*	0.032*
Cohort Effect	0.102*	0.103*	0.100*	0.087*	0.053*	0.036*	0.039*	0.04*
Total Variance[d]	49183.4	49194	49198.2	48652.7	46807.8	45827.5	45769.7	45831.4

Cont. odd ratios for good or excellent health using Bayesian hierarchical age-period-cohort cross-classified models with metropolis-hastings sampling in general social survey (N = 46,133)[a]

	Model I	Model J	Model K	Model L
Fixed Effects[b]				
Constant (odds)[c]	4.559*	4.339*	4.633*	4.474*
Age (5 years)	0.862*	0.865*	0.870*	0.867*
Age Squared	1.012*	1.012*	1.012*	1.011*
Period (5 years)	1.043*	1.032*	1.054*	1.045*
Period Squared	0.986*	0.99*	0.976*	0.983*
Demographics				
Female	0.86*	0.963*	0.958*	0.958*
Black	0.706*	0.788*	0.810*	0.757*
Other Races	0.728*	0.819*	0.794*	0.802*
Rural	0.967*	0.935*	0.990	0.958*
Not Religious	0.785*	0.818*	0.772*	0.811*
Period ×Female	1.031*			
Period × Black	1.020*			
Period × Other Non-whites	1.019*			
Period × Rural		1.017*		
Period × Not Religious		0.994		
Income Class (Reference = lower income class)				
Lower	0.459*	0.458*	0.428*	0.435*
Lower Middle	0.735*	0.761*	0.717*	0.739*
Upper	1.363*	1.32*	1.289*	1.384*
Income N/A	0.675*	0.693*	0.58*	0.716*
Period × Lower			1.017*	
Period × Lower Middle			1.012*	
Period × Upper			1.017*	
Period × Income N/A			1.042*	
Education (years)				
Education	1.137*	1.143*	1.133*	1.138*
Period × Education			1.002*	
Employment Status				
Unemployed	0.827*	0.805*	0.913*	0.802*
Employment N/A	1.018*	1.027*	1.144*	1.019*
Period × Unemployed			0.978*	
Period × Employment N/A			0.981*	
Marital Status (Reference – Married)				
Single	0.861*	0.893*	0.857*	1.031*
Divorced	0.894*	0.912*	0.921*	0.819*
Separated	0.727*	0.757*	0.778*	0.774*

(*continued on next page*)

Table 3 (*continued*)

Cont. odd ratios for good or excellent health using Bayesian hierarchical age-period-cohort cross-classified models with metropolis-hastings sampling in general social survey (N = 46,133)[a]

	Model I	Model J	Model K	Model L
Widowed	0.979	0.958*	0.976	0.891*
Period × Single				0.972*
Period × Divorced				1.024*
Period × Separated				1.012
Period × Widowed				1.032*
Random Components (Variance)				
Period Effects	0.036*	0.032*	0.296*	0.217*
Cohort Effects	0.036*	0.035*	0.042*	0.035*
Total Variance	45929.3	45927.2	45890.6	45900.1

* indicates significance at a 95% credible interval. + indicates significance at a 90% credible interval.

[a] All models are adjusted for the oversampling of blacks in 1982 and 1987. The second level has ten-period groups and 16 cohort groups. Each model ran 7,000 iterations of Metropolis-Hastings sampling simulations.

[b] Priors for the fixed effects: age ~ specified normal distribution (−0.2, 1), quadratic age and period effects ~ *Laplace* (0, 0.01), constant term and other covariates ~ normal distribution (0, 10). Priors for random effects: cohort and period variance components ~ *inverse gamma* (0.1, 0.1).

[c] The referenced individual is a married, church-attending, non-rural white male in his early 40s. He graduated from a middle-income household with a high school education and was surveyed from 1996 to 2000. The constant term estimates the baseline odds, conditioned on zero random effects.

[d] Total variance is based on −2 log marginal likelihood.

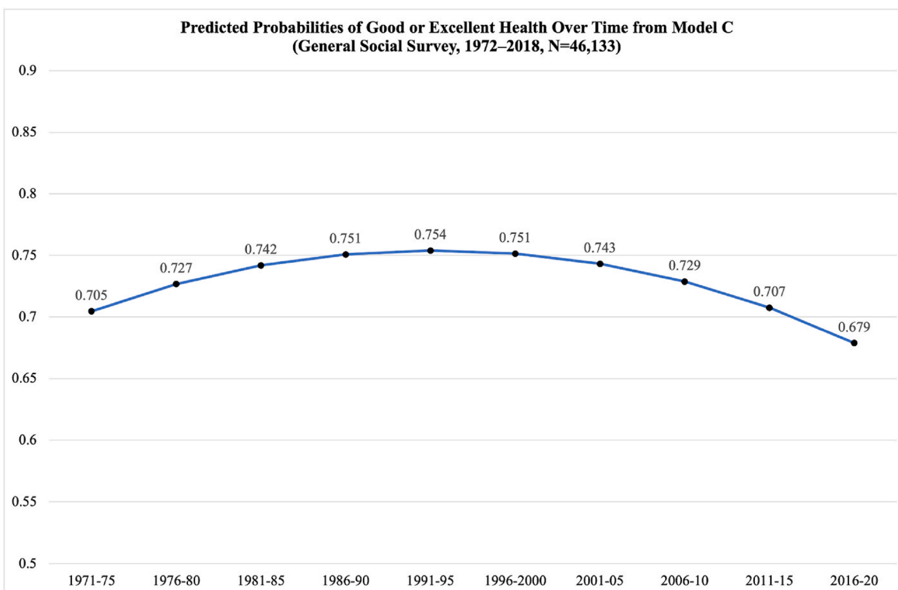

Fig. 2.

residents experienced a relative decline compared to rural dwellers over time.

Model K includes interactions between period trends and SES factors—income class, education, and employment status. The model shows significant interaction effects across all socioeconomic categories. Fig. 6 reveals a narrowing SRH gap between the middle and lower-middle-income classes and a widening gap between the upper-income and other income classes over five decades. Overall, SRH has declined considerably across all income classes, including the wealthiest group, whose SRH dropped from 86% in the early 1970s to 60% in the late 2010s. During the same period, the predicted SRH for the lowest-income group fell from 66.5% to 33.1%.

Model K indicates a widening education gradient in SRH, with a positive interaction between education and period trends. Fig. 7 demonstrates a decline in predicted SRH across education levels, with the most significant drop among those with less than a high school education, falling from 73.8% in the early 1970s to 35.6% by the late 2010s. High school graduates experienced a decline from 82.2% to around 50%, while SRH remained stable for individuals with college degrees or higher. Lastly, Model K shows a significant interaction effect between period trends and employment status. Fig. 8 suggests that the SRH gap between the employed and unemployed has widened over the five decades, highlighting an increased health risk associated with unemployment (see Fig. 9).

Finally, Model L estimates the interaction effects between period trends and marital status, revealing varying SRH patterns across marital status subgroups. Fig. 9 shows that the predicted SRH of singles has been declining faster than all other marital status groups over time. Notably, the model predicts that by the early 2010s, the SRH of singles fell below that of separated individuals, making singles the least healthy marital status group. Additionally, the SRH advantage of married individuals over divorced and widowed individuals diminished over the decades.

Fig. 10A to D illustrate the posterior distributions of period or cohort random effects for reporting "having good or excellent health" across ten periods and sixteen cohorts (Marchenko, 2022). The X-axis represents the scaled random effects. A random intercept has a positive effect if 95% of its distribution curve is above zero and vice versa.

Fig. 10A and B shows the posterior distributions of predicted period

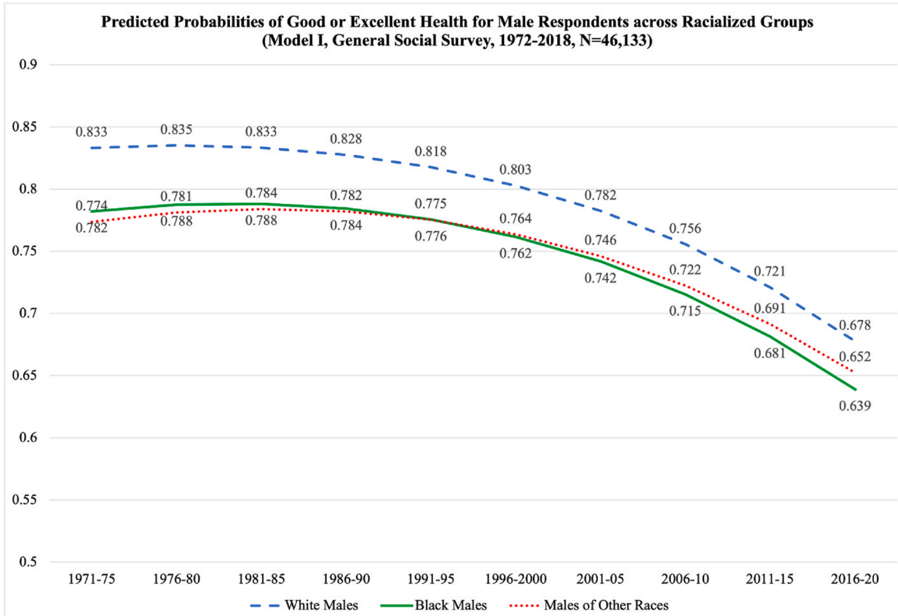

Fig. 3.

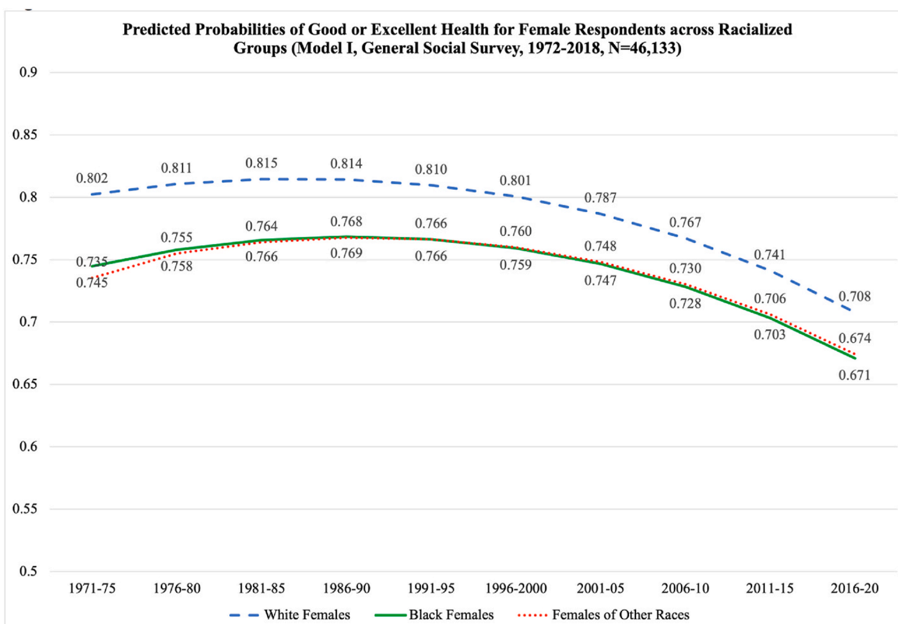

Fig. 4.

random effects from the null model (A) and the full model (B). Fig. 10A indicates that the period intercept distributions do not significantly deviate from zero during the 1970s to early 1990s. The late 1990s period appears to have higher-than-average SRH. In the early 2000s, random period effects on positive SRH gradually shift toward negative values. For example, the periods "2006–2010," "2011–2015," and "2016–2018" seem to have lower-than-average SRH. However, in Fig. 10B, after accounting for all covariates, the period random effects are no longer significantly different from the overall average SRH (as the posterior distributions overlap zero).

Fig. 10C and D presents the posterior distributions of predicted cohort random effects from the null model (C) and the full model (D). Fig. 10C shows that several cohorts have intercepts significantly different from zero. Early and mid-Greatest Generation I cohorts (pre-1910 and 1910–1918) and late Millennials (1992–1996) report poorer health than the population average, while the mid and late Silent Generation (1934–1945), Baby Boomers (1946–1964), and early Gen X (1965–1970) report better health.

Some cohort random effects disappear after controlling for covariates (Fig. 10D). The SRH of the Greatest Generation (pre-1910 to 1927) remains below the population average, but early and mid-Boomer cohorts (1946–1958) no longer show above-average SRH within the 95% credible intervals. These results suggest that covariates, such as race, gender, and SES, only partially explain cohort variations in SRH.

5. Discussion

Our study has three findings: 1) At the turn of the 21st century,

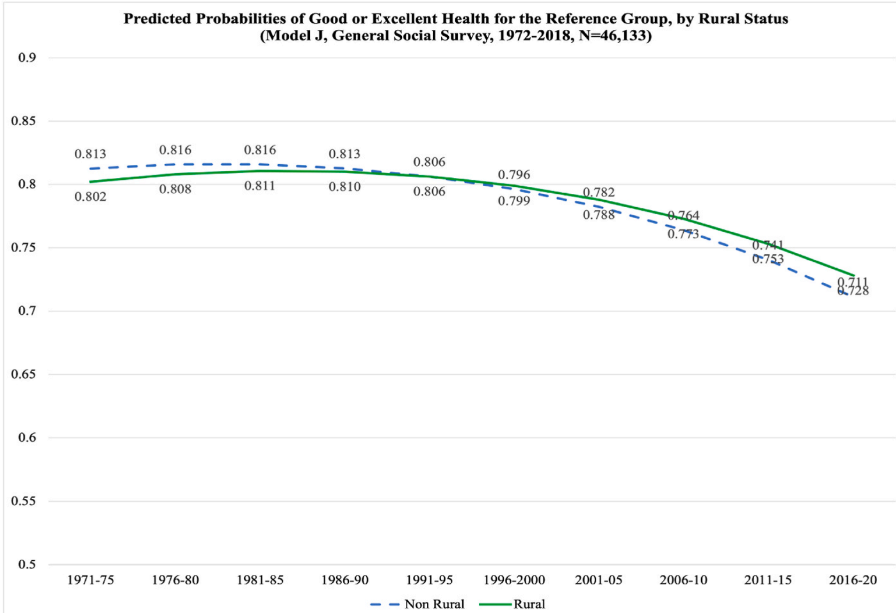

Fig. 5.

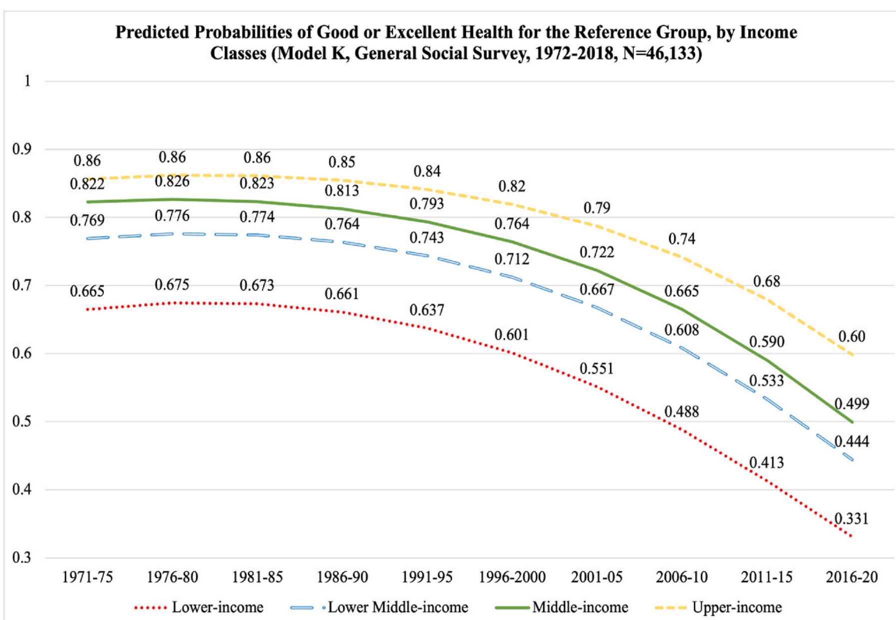

Fig. 6.

Americans' subjective health evaluation reversed from positive to negative change. 2) SRH worsens for everyone in the study, both males and females, white, Black, and other non-white Americans, regardless of family income and education levels. The racial gap in health has persisted since 2000, although some of the white privilege in health has eroded somewhat. Despite this, the subjective health of lower socioeconomic status (SES) groups (nonwhite, low-income, non-college-educated, unemployed, and non-married) suffer more than their counterparts during this health reversal. 3) Although Baby Boomers report some of the highest levels of SRH compared to other groups, their advantage appears to be offset by the health reversal.

5.1. Reversed health trend

Our study unveils the significant decline in self-rated health (SRH) among Americans at the turn of the 21st century, indicated by a significant positive period main effect and a negative quadratic period effect across all models. Specifically, our models identify a plateau in self-rated health (SRH) during the 1990s, followed by a decline since the onset of the 21st century, reflecting a time-variant inverted U-shaped trend from 1970 to 2018 net of cohort and age effects. By 2016–2018, the predicted probability of positive SRH (67.9%) had fallen below the levels predicted in 1972–1975 (70.5%). Our study corroborates the inverted U-shaped objective health trend identified in previous literature (Case and Deaton, 2015, 2021; Bambra, 2024).

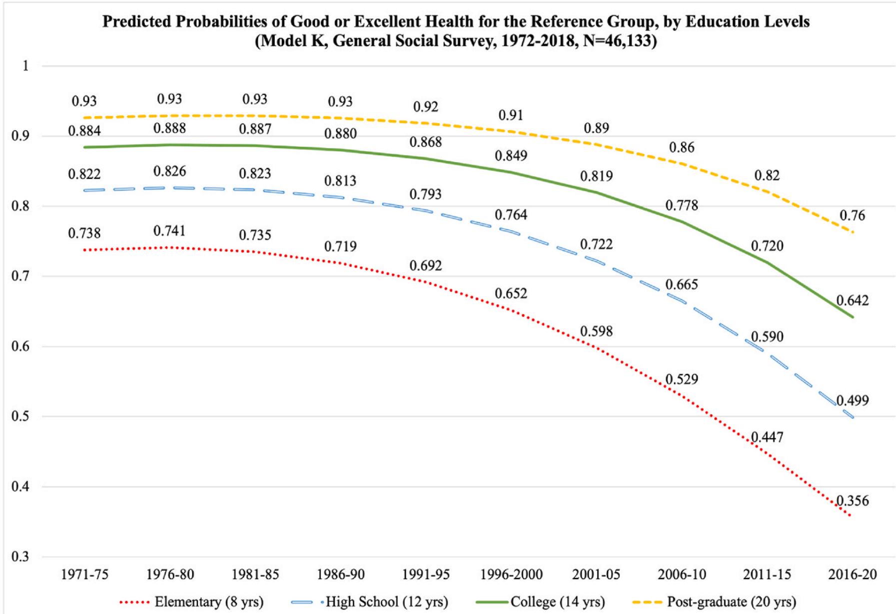

Fig. 7.

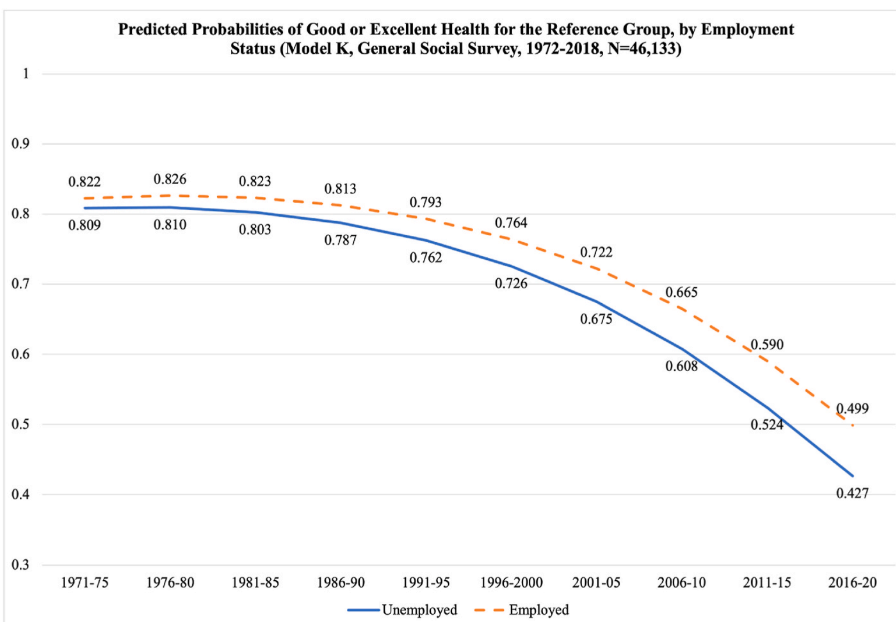

Fig. 8.

5.2. *Eroded racial privilege and persistent racial gap in self-rated health*

The second significant finding is the narrowing health gap between whites and non-whites, driven by a sharper health decline among whites rather than improved SRH among non-whites. This shift in racial health inequalities may be due to deindustrialisation's impact on predominantly white, rural, working-class communities. Researchers suggest that health decline and 'deaths of despair' in non-Hispanic white communities might stem from a perceived challenge to their privilege (King et al., 2022; Metzl, 2019). Studies posited that populism and anti-progressive policies were reactions to the perceived erosion of white privilege and political disenfranchisement, and they were seeking to reinstate white privilege and a conservative social order (Blacksher and Valles, 2021; Williams, 2017).

Case and Deaton (2021) may unintentionally overemphasise the decline in the health advantage among non-Hispanic whites while downplaying the significant health challenges faced by people of colour. Our study reveals that non-white populations consistently experience poorer health than the white population over time, and the net SRH of Black and other non-white groups has also drastically declined from their previously substantially lower SRH levels. This finding is consistent with prior health disparities research, which demonstrates that the racial health gap can largely be attributed to systemic racism (Williams and Mohammed, 2009, 2013) and other forms of discrimination, including hate crimes (Department of Justice, 2023) and a policing system that disproportionately affects racial and ethnic minorities (Lee et al., 2023).

The results further indicate an overall health decline and shifting

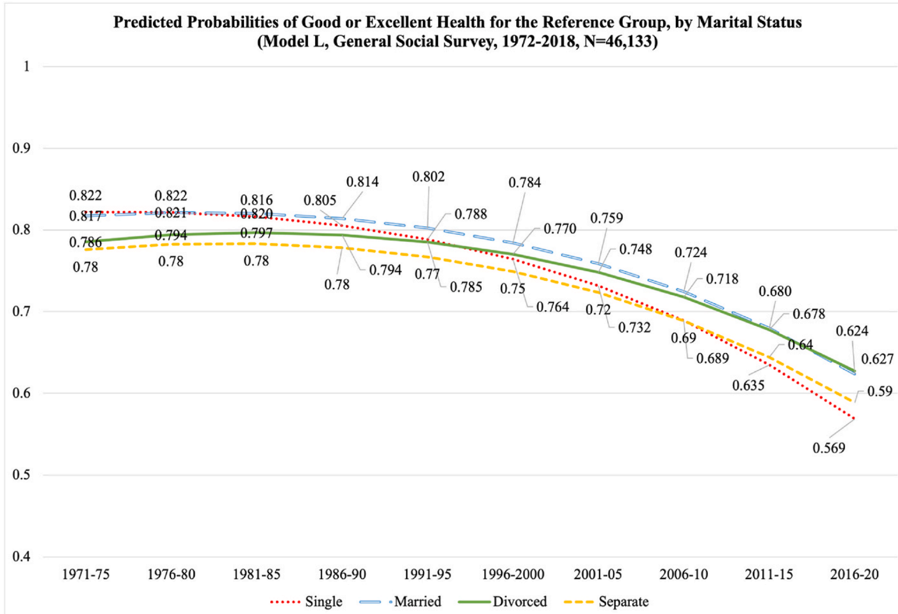

Fig. 9.

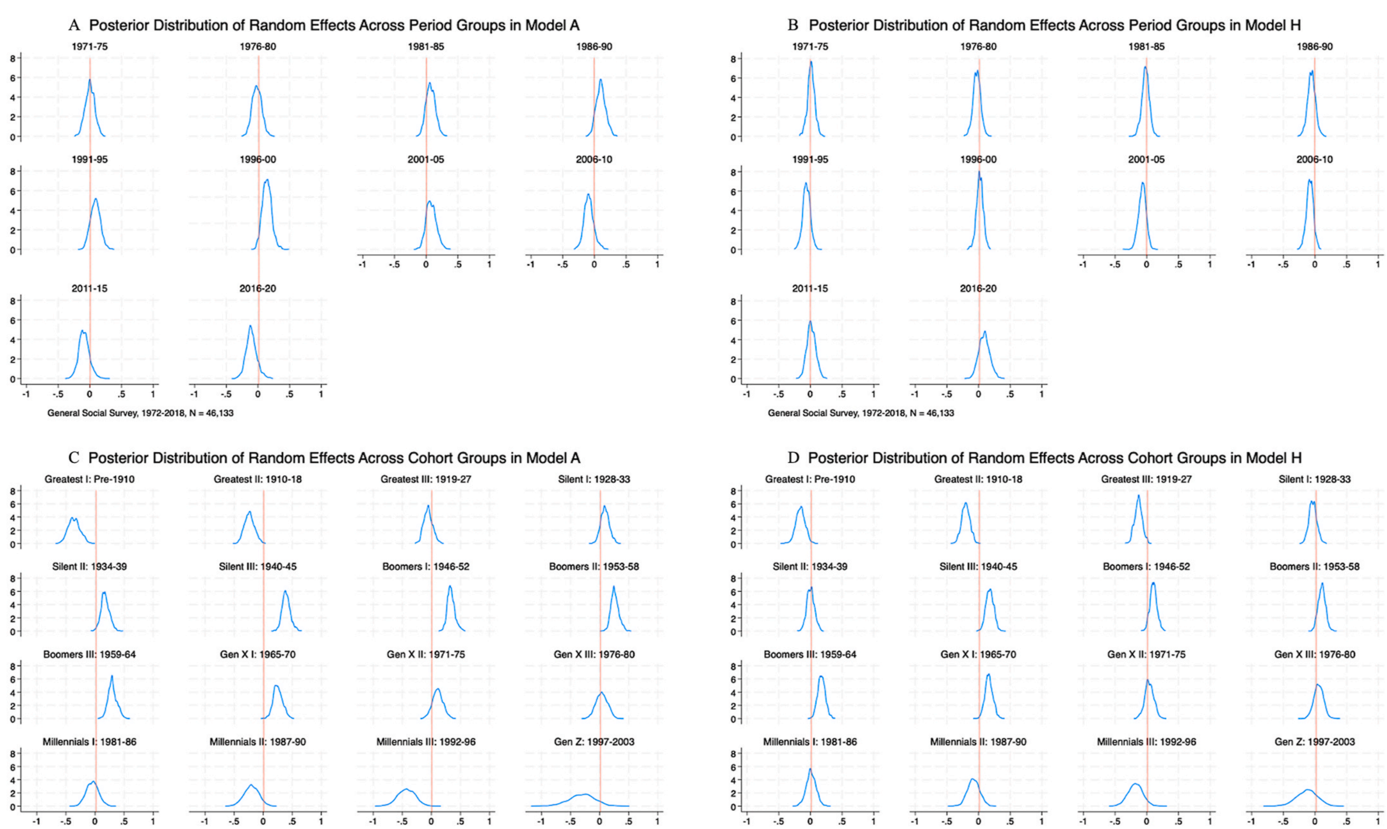

Fig. 10.

health disparities across disadvantaged income, education, employment, and marital status groups. This health decline is prevalent among all racial/ethnic groups and nearly ubiquitous among disadvantaged SES groups. Our study uncovers systematic health disadvantages among people of colour and other underprivileged populations, stressing the need for an intersectional analysis of this health reversal (Brown et al., 2016).

5.3. A Baby Boomer paradox

A health paradox emerges - Baby Boomers are the least healthy middle-aged adults at the start of the 21st century, despite being the healthiest generation when accounting for age and period effects. This suggests that negative period effects diminish the protective health factors of Baby Boomers, contrary to Easterlin's literature predicting worse outcomes for them (Macunovich and Easterlin, 2010). One explanation could be that economic booms and busts affect birth cohorts' access to better nutrition, education, and healthcare (Barbi and Vaupel, 2005). Future studies should investigate why Baby Boomers report better health than other cohorts, as more evidence will emerge when younger generations reach middle age.

5.4. Limitation

The usefulness of Bayesian estimations depends on the specification of informative priors, as there is no standardised approach for handling the uncertainty inherent in background knowledge (Wang, 2004). Fortunately, abundant research suggests using highly informative priors on one of the age-period-cohort components (Bell and Jones, 2015; Fosse, 2020; Lynch and Bartlett, 2019), and our sensitivity analysis using a frequentist approach yields similar results. More discussion of Bayesian applications in social science is needed to guide researchers in connecting and translating theories into the choice and specification of priors.

Additionally, this study lacks a nuanced analysis of other nonwhite groups, such as Hispanics, Asians, and Native Americans, due to data limitations. Such a study required a different dataset. Secondly, although the patterns of income and employment disparities in health do not contradict any prior studies, readers need to consider the missing categories when interpreting these two variables. Lastly, since the primary aim of this study is to illustrate temporal patterns in SRH and changes in racial, gender, and SES inequalities, our study is, therefore, exploratory in nature, and we refrain from making causal claims due to the apparent limitation of using cross-sectional data.

5.5. Policy implications

Our study reveals a persistent racial and ethnic health gap, with whites consistently reporting better health than nonwhites since the survey began. While SRH is lower among non-college-educated whites, it has worsened across all racial-ethnic and socioeconomic groups. Focusing solely on the narrowing white advantage can be misleading because, despite this narrowing health gap, the health status of people of colour remains worse and may continue to deteriorate. Policy decisions based only on changes in the health gap could be misleading, as this represents just one aspect of inequality. For example, policymakers may mistakenly interpret the shrinking white-nonwhite health gap as a public health victory when all social groups are worsening while systemic health inequalities persist. To gain a holistic understanding of social inequalities in health, it is crucial to consider the relative position and size of the health gap, its persistence over time, and the direction of health trends in both advantaged and disadvantaged social groups.

Lastly, middle-aged Baby Boomers surveyed in the 21st century received the blunt end of the reversal health effect. However, Baby Boomers surveyed before the 21st century had the highest subjective health compared to other birth cohorts. This finding is alarming because our models imply that younger generations, such as Gen X, Millennials, and Gen Z, might experience a more significant hit in SRH when they reach their mid-life nadirs if the SRH trend continues.

5.6. Conclusion

Using Bayesian models, we identify a universal decline in SRH across gender, race, income, education, and employment status, independent of age and cohort effects. Despite narrowing advantages in SRH among white Americans, significant racial disparities persist. We also observed a substantial time-dependent decline in SRH for socio-economically disadvantaged groups. Lastly, although Baby Boomers reported the highest subjective health overall compared to other birth cohorts, the epidemiological reversal has wiped out their SRH advantage as they reached middle age.

The SRH trends we discovered align with findings on objective health measures (Ho and Hendi, 2018; Hill and Jorgenson, 2018; Muennig et al., 2018; Harris et al., 2021). The widespread decline in SRH, coupled with persistent and unjustifiable inequalities in health related to race, gender, and SES in the US, signifies stalled progress towards improvements in health and quality of life. This also underscores long-term deep structural problems plaguing the entire US population. The white population still occupies the most advantageous position in the racialised health hierarchy despite a decline in SRH. Blacks, other non-whites, females, individuals with lower education levels, and those with lower incomes have disproportionately suffered from societal issues such as inadequate social welfare, economic restructuring, income inequality, rising healthcare costs, stress, depression, and substance misuse. Indeed, despair is widespread but remains unequal.

CRediT authorship contribution statement

Yiwan Ye: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Xiaoling Shu:** Writing – review & editing, Supervision, Investigation, Conceptualization.

Ethics approval

Ethics approval/Statement EA not required.

Declaration of generative AI in scientific writing

During the preparation of this work, the first author used generative AIs (ChatGPT and Grammarly) during the writing process to enhance the manuscript's readability and language. After using this service, the authors reviewed and edited the content as needed and take(s) full responsibility for the publication's content.

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Declaration of competing interest

To the best of our knowledge, the two authors have no conflict of interest, financial or otherwise.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.socscimed.2025.117732.

Data availability

Data will be made available on request.

References

Abdulrahim, S., El Asmar, K., 2012. Is self-rated health a valid measure to use in social inequities and health research? Evidence from the PAPFAM women's data in six Arab countries. Int. J. Equity Health 11 (1), 53. https://doi.org/10.1186/1475-9276-11-53.

Aguilar-Palacio, I., Gil-Lacruz, A.I., Sánchez-Recio, R., Rabanaque, M.J., 2018. Self-rated health in Europe and its determinants: does generation matter? Int. J. Publ. Health 63 (2), 223–232. https://doi.org/10.1007/s00038-018-1079-5.

Alexiou, A., Fahy, K., Mason, K., Bennett, D., Brown, H., Bambra, C., Taylor-Robinson, D., Barr, B., 2021. Local government funding and life expectancy in England: a longitudinal ecological study. Lancet Public Health 6 (9), e641–e647. https://doi.org/10.1016/S2468-2667(21)00110-9.

Armstrong, G.L., Conn, L.A., Pinner, R.W., 1999. Trends in infectious disease mortality in the United States during the 20th century. JAMA 281 (1), 61–66. https://doi.org/10.1001/jama.281.1.61.

Bailey, Z.D., Krieger, N., Agénor, M., Graves, J., Linos, N., Bassett, M.T., 2017. Structural racism and health inequities in the USA: evidence and interventions. Lancet 389 (10077), 1453–1463. https://doi.org/10.1016/S0140-6736(17)30569-X.

Bambra, C., 2024. The U-shaped curve of health inequalities over the 20th and 21st centuries. Int. J. Soc. Determ. Health Health Serv. 54 (3), 199–205. https://doi.org/10.1177/27551938241244695.

Barbi, E., Vaupel, J.W., 2005. Comment on "Inflammatory exposure and historical changes in human life-spans.". Science 308 (5729), 1743. https://doi.org/10.1126/science.1108707, 1743.

Barr, B., Kinderman, P., Whitehead, M., 2015. Trends in mental health inequalities in England during a period of recession, austerity and welfare reform 2004 to 2013. Soc. Sci. Med. 147, 324–331. https://doi.org/10.1016/j.socscimed.2015.11.009.

Bell, A., 2021. Age, Period and Cohort Effects: Statistical Analysis and the Identification Problem. Routledge & CRC Press. https://www.routledge.com/Age-Period-and-Cohort-Effects-Statistical-Analysis-and-the-Identification/Bell/p/book/9780367174439.

Bell, A., Jones, K., 2015. Bayesian informative priors with Yang and Land's hierarchical age–period–cohort model. Qual. Quantity 49 (1), 255–266. https://doi.org/10.1007/s11135-013-9985-3.

Belsky, D.W., Caspi, A., Houts, R., Cohen, H.J., Corcoran, D.L., Danese, A., Harrington, H., Israel, S., Levine, M.E., Schaefer, J.D., Sugden, K., Williams, B., Yashin, A.I., Poulton, R., Moffitt, T.E., 2015. Quantification of biological aging in young adults. Proc. Natl. Acad. Sci. USA 112 (30), E4104–E4110. https://doi.org/10.1073/pnas.1506264112.

Bernard, S.A., Chelminski, P.R., Ives, T.J., Ranapurwala, S.I., 2018. Management of pain in the United States-a brief history and implications for the opioid epidemic. Health Serv. Insights 11, 1178632918819440. https://doi.org/10.1177/1178632918819440.

Blacksher, E., Valles, S.A., 2021. White privilege, white poverty: reckoning with class and race in America. Hastings Cent. Rep. 51 (S1), S51–S57. https://doi.org/10.1002/hast.1230.

Brehm, Z., Wagner, A., VonKaenel, E., Burton, D., Weisenthal, S.J., Cole, M., Pang, Y., Thurston, S.W., 2021. Selection of inverse gamma and half-t priors for hierarchical models: sensitivity and recommendations. arXiv:2108.12045). https://doi.org/10.48550/arXiv.2108.12045 arXiv.

Bronson, M.A., Mazzocco, M., 2023. Cohort size and the marriage market: explaining nearly a century of changes in U.S. Marriage Rates. J. Labor Econ. https://doi.org/10.1086/724047.

Brown, T.H., Homan, P., 2023. The future of social determinants of health: looking upstream to structural drivers. Milbank Q. 101 (S1), 36–60. https://doi.org/10.1111/1468-0009.12641.

Brown, T.H., Richardson, L.J., Hargrove, T.W., Thomas, C.S., 2016. Using multiple-hierarchy stratification and life course approaches to understand health inequalities: the intersecting consequences of race, sex, SES, and age. J. Health Soc. Behav. 57 (2), 200–222. https://doi.org/10.1177/0022146516645165.

Case, A., Deaton, A., 2015. Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century. Proc. Natl. Acad. Sci. USA 112 (49), 15078–15083. https://doi.org/10.1073/pnas.1518393112.

Case, A., Deaton, A., 2020. Deaths of Despair and the Future of Capitalism. Princeton. https://doi.org/10.2307/j.ctvpr7rb2.

Case, A., Deaton, A., 2021. Life expectancy in adulthood is falling for those without a BA degree, but as educational gaps have widened, racial gaps have narrowed. Proc. Natl. Acad. Sci. USA 118 (11), e2024777118. https://doi.org/10.1073/pnas.2024777118.

Center for Sustainable Systems, University of Michigan, 2023. "U.S. Cities Factsheet." Pub. No. CSS09-06.

Chen, H., Cohen, P., Kasen, S., 2007. Cohort differences in self-rated health: evidence from a three-decade, community-based, longitudinal study of women. Am. J. Epidemiol. 166 (4), 439–446. https://doi.org/10.1093/aje/kwm100.

Chen, Y., Holahan, C., Li, X., 2018. Loneliness, physical activity, and self-rated health in middle-aged and older adults. Innov. Aging 2 (Suppl. _1), 967. https://doi.org/10.1093/geroni/igy031.3582.

Chiavarino, C., Poggio, C., Rusconi, F., Beretta, A.A.R., Aglieri, S., 2019. Psychological factors and self-rated health: an observative study on cardiological patients. J. Health Psychol. 24 (14), 1993–2002. https://doi.org/10.1177/1359105317712591.

Conrad, P., 2005. The shifting engines of medicalization. J. Health Soc. Behav. 46 (1), 3–14. https://doi.org/10.1177/002214650504600102.

Conrad, P., 2007. The Medicalization of Society: on the Transformation of Human Conditions into Treatable Disorders. Johns Hopkins University Press.

Cummings, J.L., 2023. Entangled inequalities: U.S. Trends in self-rated health at the intersection of gender and race, 1972–2018. Soc. Indicat. Res. 169 (3), 759–774. https://doi.org/10.1007/s11205-023-03180-z.

Dasgupta, N., Beletsky, L., Ciccarone, D., 2018. Opioid crisis: No easy fix to its social and economic determinants. Am. J. Publ. Health 108 (2), 182–186. https://doi.org/10.2105/AJPH.2017.304187.

Desai, M., Rachet, B., Coleman, M.P., McKee, M., 2010. Two countries divided by a common language: health systems in the UK and USA. J. R. Soc. Med. 103 (7), 283–287. https://doi.org/10.1258/jrsm.2010.100126.

Desai, S., 2020. Anne Case and Angus Deaton, Deaths of Despair and the Future of Capitalism. Princeton University Press, Princeton, NJ, pp. 387–390. https://doi.org/10.1111/padr.12345, 2020. 312 p. $27.95. Population and Development Review, 46 (2).

Department of Justice, 2023. 2020 hate crime statistics. https://www.justice.gov/hatecrimes/2020-hate-crime-statistics.

Easterlin, R.A., 1987. Birth and Fortune: the Impact of Numbers on Personal Welfare. University of Chicago Press.

Easterlin, R.A., 2010. In: Hinte, Holger, Zimmermann, Klaus F. (Eds.), Happiness Growth, and the Life Cycle. Oxford University Press. Oxford, United Kingdom.

Fahy, K., Alexiou, A., Daras, K., Mason, K., Bennett, D., Taylor-Robinson, D., Barr, B., 2023. Mental health impact of cuts to local government spending on cultural, environmental and planning services in England: a longitudinal ecological study. BMC Publ. Health 23 (1), 1441. https://doi.org/10.1186/s12889-023-16340-0.

Feenstra, M., van Munster, B.C., Vroomen, J.L.M., de Rooij, S.E., Smidt, N., 2020. Trajectories of self-rated health in an older general population and their determinants: the lifelines cohort study. BMJ Open 10 (2), e035012. https://doi.org/10.1136/bmjopen-2019-035012.

Fenton, L., Wyper, G.M., McCartney, G., Minton, J., 2019. Socioeconomic inequality in recent adverse all-cause mortality trends in Scotland. J. Epidemiol. Community Health 73 (10), 971–974. https://doi.org/10.1136/jech-2019-212300.

Fosse, E., 2020. Bayesian age-period-cohort models. In: Bell, A. (Ed.), Age, Period and Cohort Effects: Statistical Analysis and the Identification Problem. Routledge. https://doi.org/10.4324/9780429056819-8.

Fosse, E., Winship, C., 2019a. Analyzing age-period-cohort data: a review and critique. Annu. Rev. Sociol. 45 (1), 467–492. https://doi.org/10.1146/annurev-soc-073018-022616.

Fosse, E., Winship, C., 2019b. Bounding analyses of Age-Period-Cohort effects. Demography 56 (5), 1975–2004. https://doi.org/10.1007/s13524-019-00801-6.

French, D.J., Sargent-Cox, K., Luszcz, M.A., 2012. Correlates of subjective health across the aging lifespan: understanding self-rated health in the oldest old. J. Aging Health 24 (8), 1449–1469. https://doi.org/10.1177/0898264312461151.

Gaydosh, L., Hummer, R.A., Hargrove, T.W., Halpern, C.T., Hussey, J.M., Whitsel, E.A., Dole, N., Harris, K.M., 2019. The depths of despair among US adults entering midlife. Am. J. Publ. Health 109 (5), 774–780. https://doi.org/10.2105/AJPH.2019.305002.

Gelman, A., Pardoe, I., 2006. Bayesian measures of explained variance and pooling in multilevel (hierarchical) models. Technometrics 48 (2), 241–251. https://doi.org/10.1198/004017005000000517.

Gelman, A., Carlin, J., Stern, H., Dunson, D., Vehtari, A., Rubin, D., 2014. Bayesian Data Analysis, third ed. CRC Press. https://doi.org/10.1201/b16018.

Groenwold, R.H.H., White, I.R., Donders, A.R.T., Carpenter, J.R., Altman, D.G., Moons, K.G.M., 2012. Missing covariate data in clinical research: when and when not to use the missing-indicator method for analysis. CMAJ (Can. Med. Assoc. J.) 184 (11), 1265–1269. https://doi.org/10.1503/cmaj.110977.

Harris, K.M., Woolf, S.H., Gaskin, D.J., 2021. High and rising working-age mortality in the US: a report from the National Academies of Sciences, Engineering, and Medicine. JAMA 325 (20), 2045–2046. https://doi.org/10.1001/jama.2021.4073.

Hedegaard, H., Warner, M., 2021. *Drug Overdose Deaths in the United States, 1999-2020* (Data Brief No. 428). National Center for Health Statistics. https://doi.org/10.15620/cdc:112340.

Hiam, L., Dorling, D., Harrison, D., McKee, M., 2017. Why has mortality in England and Wales been increasing? An iterative demographic analysis. J. R. Soc. Med. 110 (4), 153–162. https://doi.org/10.1177/0141076817693599.

Hill, T.D., Jorgenson, A., 2018. Bring out your dead!: a study of income inequality and life expectancy in the United States, 2000–2010. Health Place 49, 1–6. https://doi.org/10.1016/j.healthplace.2017.11.001.

Ho, J.Y., Hendi, A.S., 2018. Recent trends in life expectancy across high income countries: retrospective observational study. BMJ 362, k2562. https://doi.org/10.1136/bmj.k2562.

Huang, X., Keyes, K.M., Li, G., 2018. Increasing prescription opioid and heroin overdose mortality in the United States, 1999–2014: an age–period–cohort analysis. Am. J. Public Health 108 (1), 131–136. https://doi.org/10.2105/AJPH.2017.304142.

King, L., Scheiring, G., Nosrati, E., 2022. Deaths of despair in comparative perspective. Annu. Rev. Sociol. 48 (1), 299–317. https://doi.org/10.1146/annurev-soc-030320-031757.

Knapp, E.A., Bilal, U., Dean, L.T., Lazo, M., Celentano, D.D., 2019. Economic insecurity and deaths of despair in US counties. Am. J. Epidemiol. 188 (12), 2131–2139. https://doi.org/10.1093/aje/kwz103.

Lavrakas, P., 2008. Encyclopedia of Survey Research Methods. Sage Publications, Inc. https://doi.org/10.4135/9781412963947.

Lamidi, E.O., 2022. Educational differences in self-rated health trends among middle-aged and older adults living alone, 1972–2018. J. Aging Health 34 (4–5), 626–639. https://doi.org/10.1177/08982643211052718.

Lee, H., Larimore, S., Esposito, M., 2023. Policing and population health: Past, present, and future. Milbank Q. 101 (S1), 444–459. https://doi.org/10.1111/1468-0009.12628.

Lim, S.S., Vos, T., Flaxman, A.D., Danaei, G., Shibuya, K., Adair-Rohani, H., AlMazroa, M. A., Amann, M., Anderson, H.R., Andrews, K.G., Aryee, M., Atkinson, C., Bacchus, L. J., Bahalim, A.N., Balakrishnan, K., Balmes, J., Barker-Collo, S., Baxter, A., Bell, M. L., Ezzati, M., 2012. A comparative risk assessment of burden of disease and injury attributable to 67 risk factors and risk factor clusters in 21 regions, 1990-2010: a systematic analysis for the Global burden of disease study 2010. Lancet 380 (9859), 2224–2260. https://doi.org/10.1016/S0140-6736(12)61766-8.

Luo, L., 2013. Paradigm shift in Age-Period-Cohort analysis: a response to Yang and Land, O'Brien, Held and Riebler, and Fienberg. Demography 50 (6), 1985–1988. https://doi.org/10.1007/s13524-013-0263-8.

Luo, L., Hodges, J.S., 2020. The Age-Period-Cohort-Interaction model for describing and investigating inter-cohort deviations and intra-cohort life-course dynamics. Socio. Methods Res., 0049124119882451 https://doi.org/10.1177/0049124119882451.

Lynch, S.M., Bartlett, B., 2019. Bayesian statistics in sociology: Past, present, and future. Annu. Rev. Sociol. 45 (1), 47–68. https://doi.org/10.1146/annurev-soc-073018-022457.

MacCallum, R.C., Zhang, S., Preacher, K.J., Rucker, D.D., 2002. On the practice of dichotomisation of quantitative variables. Psychol. Methods 7 (1), 19–40. https://doi.org/10.1037/1082-989X.7.1.19.

Macunovich, D.J., Easterlin, R.A., 2010. Easterlin hypothesis. In: Durlauf, S.N., Blume, L. E. (Eds.), Economic Growth. Palgrave Macmillan UK, pp. 30–37. https://doi.org/10.1057/9780230280823_6.

Makary, M.A., Overton, H.N., Wang, P., 2017. Overprescribing is major contributor to opioid crisis. BMJ 359, j4792. https://doi.org/10.1136/bmj.j4792.

Marchenko, Y., 2022. Bayesian Multilevel Modeling Using Stata. UK Stata Conference.

McCartney, G., Popham, F., McMaster, R., Cumbers, A., 2019. Defining health and health inequalities. Publ. Health 172, 22–30 pmc.ncbi.nlm.nih.gov/articles/PMC6558275/.

McCartney, G., McMaster, R., Popham, F., Dundas, R., Walsh, D., 2022. Is austerity a cause of slower improvements in mortality in high-income countries? A panel analysis. Soc. Sci. Med. 313, 115397. https://doi.org/10.1016/j.socscimed.2022.115397.

Metzl, J., 2019. Dying of Whiteness: How the Politics of Racial Resentment Is Killing America's Heartland. Basic Books. https://www.amazon.com/Dying-Whiteness-Politics-Resentment-Heartland/dp/1541644980.

Minton, J., Green, M., McCartney, G., Shaw, R., Vanderbloemen, L., Pickett, K., 2017a. Two cheers for a small giant? Why we need better ways of seeing data: a commentary on: 'Rising morbidity and mortality in midlife among White non-Hispanic Americans in the 21st century.'. Int. J. Epidemiol. 46 (1), 356–361. https://doi.org/10.1093/ije/dyw095.

Minton, J., Shaw, R., Green, M.A., Vanderbloemen, L., Popham, F., McCartney, G., 2017b. Visualising and quantifying 'excess deaths' in Scotland compared with the rest of the UK and the rest of Western Europe. J. Epidemiol. Community Health 71 (5), 461–467. https://doi.org/10.1136/jech-2016-207379.

Mitnitski, A.B., Graham, J.E., Mogilner, A.J., Rockwood, K., 2002. Frailty, fitness and late-life mortality in relation to chronological and biological age. BMC Geriatr. 2 (1), 1. https://doi.org/10.1186/1471-2318-2-1.

Mooney, G., 2012. Neoliberalism is bad for our health. Int. J. Health Serv. 42 (3), 383–401. https://doi.org/10.2190/HS.42.3.b.

Mozaffarian, D., Hao, T., Rimm, E.B., Willett, W.C., Hu, F.B., 2011. Changes in diet and lifestyle and long-term weight gain in women and men. N. Engl. J. Med. 364 (25), 2392–2404. https://doi.org/10.1056/NEJMoa1014296.

Muennig, P.A., Reynolds, M., Fink, D.S., Zafari, Z., Geronimus, A.T., 2018. America's declining well-being, health, and life expectancy: not just a White problem. Am. J. Publ. Health 108 (12), 1626–1631. https://doi.org/10.2105/AJPH.2018.304585.

National Academies of Sciences, Engineering, and Medicine, 2021. High and Rising Mortality Rates Among Working-Age Adults. The National Academies Press, Washington, DC. https://doi.org/10.17226/25976.

Nielsen, S.J., Siega-Riz, A.M., Popkin, B.M., 2002. Trends in energy intake in U.S. Between 1977 and 1996: similar shifts seen across age groups. Obes. Res. 10 (5), 370–378. https://doi.org/10.1038/oby.2002.51.

Norström, F., Virtanen, P., Hammarström, A., Gustafsson, P.E., Janlert, U., 2014. How does unemployment affect self-assessed health? A systematic review focusing on subgroup effects. BMC Publ. Health 14 (1), 1310. https://doi.org/10.1186/1471-2458-14-1310.

Parkinson, J., Minton, J., Bouttell, J., Lewsey, J., Shah, A., McCartney, G., 2020. Do age, period or cohort effects explain circulatory disease mortality trends, Scotland 1974–2015? Heart 106 (8), 584–589. https://doi.org/10.1136/heartjnl-2019-315029.

Parkinson, J., Minton, J., Lewsey, J., Bouttell, J., McCartney, G., 2017. Investigation of age, period, and cohort effects to understand Scotland's excess mortality: use of Lexis diagrams and intrinsic estimator regression modelling. Lancet 390, S67. https://doi.org/10.1016/S0140-6736(17)33002-7.

Phelan, J.C., Link, B.G., 2015. Is racism a fundamental cause of inequalities in health? Annu. Rev. Sociol. 41 (1), 311–330. https://doi.org/10.1146/annurev-soc-073014-112305.

Phelan, J.C., Link, B.G., Tehranifar, P., 2010. Social conditions as fundamental causes of health inequalities: theory, evidence, and policy implications. J. Health Soc. Behav. 51 (1_Suppl.), S28–S40. https://doi.org/10.1177/0022146510383498.

Polson, N.G., Scott, J.G., 2012. On the half-cauchy prior for a global scale parameter. Bayesian Anal. 7 (4), 887–902. https://doi.org/10.1214/12-BA730.

Quinn, C.W., Cha, Y., 2017. Did declining unionization contribute to the US middle-class squeeze? Evidence from the early 2000s. Soc. Sci. Med. 187, 209–218. https://doi.org/10.1016/j.socscimed.2017.06.042.

Ragland, D.R., 1992. Dichotomizing continuous outcome variables: dependence of the magnitude of association and statistical power on the cutpoint. Epidemiology 3 (5), 434–440.

Rehm, C.D., Peñalvo, J.L., Afshin, A., Mozaffarian, D., 2016. Dietary intake among US adults, 1999-2012. J. Am. Med. Assoc. 315 (23), 2542–2553. https://doi.org/10.1001/jama.2016.7491.

Riley, A.R., 2020. Advancing the study of health inequality: fundamental causes as systems of exposure. SSM - Popul. Health 10, 100555. https://doi.org/10.1016/j.ssmph.2020.100555.

Schnittker, J., 2005. When mental health becomes health: age and the shifting meaning of self-evaluations of general health. Milbank Q. 83 (3), 397–423. https://doi.org/10.1111/j.1468-0009.2005.00407.x.

Schnittker, J., Bacak, V., 2014. The increasing predictive validity of self-rated health. PLoS One 9 (1), e84933. https://doi.org/10.1371/journal.pone.0084933.

Schrecker, T., Bambra, C., 2015. How Politics Makes Us Sick. Palgrave Macmillan UK. https://doi.org/10.1057/9781137463074.

Schwei, R.J., Johnson, T.P., Matthews, A.K., Jacobs, E.A., 2017. Perceptions of negative health-care experiences and self-reported health behavior change in three racial and ethnic groups. Ethn. Health 22 (2), 156–168. https://doi.org/10.1080/13557858.2016.1244621.

Shu, X., Meagher, K.D., 2018. Beyond the stalled gender revolution: historical and cohort dynamics in gender attitudes from 1977-2016. Soc. Forces 96 (3), 1243–1274. https://doi.org/10.1093/sf/sox090.

Simoni, Z., Day, P., Schneider, D., Strenth, C., Kale, N., 2022. Pharmaceuticalization to opioid pharmacovigilance: a qualitative investigation of the impact of opioid-related policy changes and the perspectives of residents and chronic non-cancer pain patients. Socio. Perspect. 65 (6), 1099–1116. https://doi.org/10.1177/07311214221097086.

Snyder, S.E., 2016. Urban and rural divergence in mortality trends: a comment on case and deaton. Proc. Natl. Acad. Sci. USA 113 (7), E815. https://doi.org/10.1073/pnas.1523659113. E815.

Steele, E.M., Baraldi, L.G., Louzada, M.L. da C., Moubarac, J.-C., Mozaffarian, D., Monteiro, C.A., 2016. Ultra-processed foods and added sugars in the US diet: evidence from a nationally representative cross-sectional study. BMJ Open 6 (3), e009892. https://doi.org/10.1136/bmjopen-2015-009892.

Stein, E.M., Gennuso, K.P., Ugboaja, D.C., Remington, P.L., 2017. The epidemic of despair among White Americans: trends in the leading causes of premature death, 1999–2015. Am. J. Publ. Health 107 (10), 1541–1547. https://doi.org/10.2105/AJPH.2017.303941.

Stoicea, N., Costa, A., Periel, L., Uribe, A., Weaver, T., Bergese, S.D., 2019. Current perspectives on the opioid crisis in the US healthcare system. Medicine 98 (20), e15425. https://doi.org/10.1097/MD.0000000000015425.

Su, Y.-S., Lien, D., Yao, Y., 2022. Economic growth and happiness in China: a Bayesian multilevel age-period-cohort analysis based on the CGSS data 2005-2015. Int. Rev. Econ. Finance 77, 191–205. https://doi.org/10.1016/j.iref.2021.09.018.

Timonin, S., Danilova, I., Andreev, E., Shkolnikov, V.M., 2017. Recent mortality trend reversal in Russia: are regions following the same tempo? Eur. J. Popul. 33 (5), 733–763. https://doi.org/10.1007/s10680-017-9451-3.

Wachtler, B., Hoebel, J., Lampert, T., 2019. Trends in socioeconomic inequalities in self-rated health in Germany: a time-trend analysis of repeated cross-sectional health surveys between 2003 and 2012. BMJ Open 9 (9), e030216. https://doi.org/10.1136/bmjopen-2019-030216.

Walsh, D., McCartney, G., Minton, J., Parkinson, J., Shipton, D., Whyte, B., 2020. Changing mortality trends in countries and cities of the UK: a population-based trend analysis. BMJ Open 10 (11), e038135. https://doi.org/10.1136/bmjopen-2020-038135.

Wami, W., Walsh, D., Hennig, B.D., McCartney, G., Dorling, D., Galea, S., Sampson, L., Dundas, R., 2021. Spatial and temporal inequalities in mortality in the USA, 1968–2016. Health Place 70, 102586. https://doi.org/10.1016/j.healthplace.2021.102586.

Wang, P., 2004. The limitation of Bayesianism. Artif. Intell. 158 (1), 97–106. https://doi.org/10.1016/j.artint.2003.09.003.

Williams, D.R., Mohammed, S.A., 2013. Racism and health I: pathways and scientific evidence. Am. Behav. Sci. 57 (8), 1152–1173. https://doi.org/10.1177/0002764213487340.

Williams, D.R., Mohammed, S.A., 2009. Discrimination and racial disparities in health: evidence and needed research. J. Behav. Med. 32 (1), 20–47. https://doi.org/10.1007/s10865-008-9185-0.

Williams, J.C., 2017. White Working Class: Overcoming Class Cluelessness in America. Harvard Business Review Press.

Woolf, S.H., 2011. Public health implications of government spending reductions. JAMA 305 (18), 1902–1903. https://doi.org/10.1001/jama.2011.617.

Wu, S., Wang, R., Zhao, Y., Ma, X., Wu, M., Yan, X., He, J., 2013. The relationship between self-rated health and objective health status: a population-based study. BMC Publ. Health 13 (1), 320. https://doi.org/10.1186/1471-2458-13-320.

Yang, Y., 2006. Bayesian inference for hierarchical age-period-cohort models of repeated cross-section survey data. Socio. Methodol. 36 (1), 39–74. https://doi.org/10.1111/j.1467-9531.2006.00174.x.

Yang, Y., 2008a. Social inequalities in happiness in the United States, 1972 to 2004: an age-period-cohort analysis. Am. Socio. Rev. 73 (2), 204–226. https://doi.org/10.1177/000312240807300202.

Yang, Y., 2008b. Trends in U.S. Adult chronic disease mortality, 1960-1999: age, period, and cohort variations. Demography 45 (2), 387–416. https://doi.org/10.1353/dem.0.0000.

Yang, Y., Land, K.C., 2013. Age-period-cohort Analysis: New Models, Methods, and Empirical Applications. CRC Press. https://doi.org/10.1201/CHINTSTASER.

Yashin, A.I., Arbeev, K.G., Kulminski, A., Akushevich, I., Akushevich, L., Ukraintseva, S. V., 2007. Health decline, aging and mortality: how are they related? Biogerontology 8 (3), 291–302. https://doi.org/10.1007/s10522-006-9073-3.

Ye, Y., Shu, X., 2022. Lonely in a crowd: cohort size and happiness in the United Kingdom. J. Happiness Stud. 23, 2235–2257. https://doi.org/10.1007/s10902-021-00495-x.

Zang, E., West, J., Kim, N., Pao, C., 2021. U.S. regional differences in physical distancing: evaluating racial and socioeconomic divides during the COVID-19 pandemic. PLoS One 16 (11), e0259665. https://doi.org/10.1371/journal.pone.0259665.

Zang, E., Zheng, H., Yang, Y.C., Land, K.C., 2019. Recent trends in US mortality in early and middle adulthood: racial/ethnic disparities in inter-cohort patterns. Int. J. Epidemiol. 48 (3), 934–944. https://doi.org/10.1093/ije/dyy255.

Zhang, L., 2017. An age-period-cohort analysis of religious involvement and adult self-rated health: results from the USA, 1972-2008. J. Relig. Health 56 (3), 916–945. https://doi.org/10.1007/s10943-016-0292-x.

Zheng, H., Echave, P., 2021. Are recent cohorts getting worse? Trends in US adult physiological status, mental health, and health behaviors across a century of birth cohorts. Am. J. Epidemiol. 190 (11), 2242–2255. https://doi.org/10.1093/aje/kwab076.

Zheng, H., Dirlam, J., Echave, P., 2021. Divergent trends in the effects of early life factors on adult health. Popul. Res. Pol. Rev. 40 (5), 1119–1148. https://doi.org/10.1007/s11113-020-09602-x.

Zhu, B., Ye, Y., 2020. Sex disparities in the education gradient in self-reported health across birth cohorts in China. BMC Publ. Health 20, 375. https://doi.org/10.1186/s12889-020-08520-z.