Lives vs. Livelihoods: The Impact of the Great Recession on Mortality and Welfare

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Abstract

We leverage spatial variation in the severity of the Great Recession across the United States to examine its impact on mortality and explore implications for the welfare consequences of recessions. We estimate that an increase in the unemployment rate of the magnitude of the Great Recession reduces the average, annual age-adjusted mortality rate by 2.3 percent, with effects persisting for at least 10 years. The effects appear across causes of death, but are concentrated in the half of the population with a high school degree or less. We estimate similar percentage reductions in mortality at all ages, with declines in elderly mortality thus responsible for about three-quarters of the total mortality reduction. Recession-induced reductions in air pollution are a quantitatively important mechanism behind the recession-induced mortality decline. Incorporating our estimates into a standard macro framework substantially reduces the welfare costs of recessions, particularly for people with less education, and particularly at older ages where they may even be welfare-improving.

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1 Introduction

Recessions damage the economy, and prompt substantial government intervention. The macroeconomics literature has calibrated their welfare costs, focusing on their impact on the level and volatility of consumption (e.g. Lucas 1987, 2003; Krebs 2007; Krusell et al. 2009). Yet in addition to their economic impacts, recessions may also have important impacts on health. Indeed, an empirical literature in health economics has found that, in the 1970s and 1980s, mortality was pro-cyclical (e.g. Ruhm 2000, 2003, 2005; Stevens et al. 2015), although less so in the subsequent two decades (Ruhm (2015)). Incorporating mortality impacts of recessions could have important implications for their welfare consequences, both overall and across demographic groups.

We consider this possibility in the context of the 2007-2009 Great Recession in the United States. At the time, the Great Recession produced the largest decline in U.S. employment since the Great Depression. Following Yagan (2019), we leverage spatial variation in the economic severity of the Great Recession across the U.S. to provide new empirical evidence on the impact of recessions on mortality and to explore implications for the welfare consequences of recessions.

We find that the Great Recession substantially and persistently reduced mortality. For every one percentage point increase in a Commuting Zone's (CZ) unemployment rate between 2007-2009, we estimate that its age-adjusted mortality rate fell by 0.5 percent. These mortality reductions show up immediately and persist for at least 10 years. Since average unemployment increased by 4.6 percentage points between 2007 and 2009, our estimates imply that the local area unemployment shock from the Great Recession decreased the local area annual mortality rate by 2.3 percent. To put this in perspective, these estimates imply that the Great Recession provided 1 in 20 55-year olds with an extra year of life. Leveraging additional spatial variation in the 2010-2016 persistence of the economic shock across areas that experienced the same initial shock, we find that the mortality reduction associated with the initial shock persists through 2016 even in areas that have completely recovered by then; this suggests the existence of lagged effects of past economic declines on mortality.

Recession-induced mortality declines are entirely concentrated among the half of the population with a high school degree or less, but are otherwise pervasive across groups and causes of death. We find roughly equi-proportional impacts (i.e., similar percentage reductions in mortality rates) across gender, race/Hispanic origin, and age groups. However, because mortality is so much higher among the elderly, about three-quarters of the mortality reduction comes from reduced deaths among those ages 65 and over, roughly the same as their share of pre-recession mortality. The single largest cause of death, cardiovascular mortality, accounted for about one-third of deaths in 2006 and about two-fifths of the estimated mortality declines due to the Great Recession.

Before incorporating these findings into welfare analysis, we consider the evidence for potential mechanisms behind the recession-induced mortality decline. To the extent that they reflect externalities from reduced aggregate economic activity on health, holding constant own employment or consumption, they may mitigate the negative welfare effects of reduced consumption. Consistent with an important role for health externalities, we find a quantitatively important role for recession-induced declines in air pollution—which may explain about 40 percent of the recession-induced mortality declines. However, we do not find evidence of important roles for other mechanisms that have been explored in the literature, including improved health behaviors (as in Ruhm 2000), reduced spread of infectious disease (as in Adda 2016), or improved quality of nursing home care (as in Stevens et al. 2015) as important mechanisms behind the mortality declines.

We conduct two types of exercises to assess the quantitative importance of recession-induced mortality declines for welfare. First, we examine how they alter standard welfare analyses of recessions based solely on their impacts on consumption. To do so, we extend the Krebs (2007) model of the welfare cost of recessions from consumption changes to allow mortality to also vary with recessions and for those mortality changes to affect welfare. Our results suggest that accounting for endogenous mortality substantially reduces the estimated welfare costs of recessions. For example, for a 45-year-old with a coefficient of relative risk aversion of 2 and a value of a statistical life year of $250,000, we estimate that accounting for recession-induced mortality declines (along with consumption declines) reduces their willingness to pay to avoid future recessions by about two-thirds. Accounting for endogenous mortality changes the welfare costs of recessions even more dramatically at older ages. When combined with the more limited impact of recessions on the elderly's consumption, the mortality reductions suggest that recessions may be welfare-enhancing for older individuals.

Second, we directly estimate the consumption declines associated with the Great Recession and use these estimates to assess how accounting for endogenous mortality affects consumption-based welfare analysis of the Great Recession. Once again, accounting for endogenous mortality lowers welfare costs, particularly at older ages. It is also consequential for the distributional impacts of the Great Recession. While a welfare analysis of the Great Recession that focuses solely on economic impacts would suggest that it was worse for the less educated, accounting for the mortality effects of the recession - which are concentrated entirely in the half of the population with a high school degree or less - mitigates, and at some ages reverses, that conclusion.

Our findings contribute to a large literature on the relationship between the economy and health. A considerable body of evidence suggests that improvements in the economy are good for health. There is a well-documented negative relationship between income and mortality within country, across countries, and over time (e.g. Cutler et al. 2006; Costa 2015; Chetty et al. 2016; Cutler et al. 2016).[1] There is also evidence that job loss increases mortality (Sullivan and Von Wachter

[1] The causal evidence of the impact of income on mortality is more limited, and also mixed. Cesarini et al. (2016) find no impact from lottery winnings on adults' mortality up to 10 years later. Dobkin and Puller (2007) and Evans and Moore (2012) find that mortality from substance abuse rises within a month when cash benefits are paid out, suggesting that the impacts of income (or least liquidity) may differ across time horizons and population. Moreover, there are exceptions to the generally negative correlation between income and mortality, such as the so-called 'Antebellum Puzzle' in which, despite rising per-capita income in the 19th century US, average height (a standard measure of health in historical contexts) declined and then stagnated (Floud et al. 2011).

2009), that sustained reductions in economic prospects contribute to "deaths of despair" (Case and Deaton 2021), and that counties exposed to greater job loss from trade liberalization with China experience both increases in fatal drug overdoses among the working-age population (Pierce and Schott 2020) and increased mortality of young men relative to young women (Autor et al. 2019). All of this suggests that the Great Recession would increase mortality.

However, the existing empirical work on the relationship between recessions and mortality raises questions about what to expect for the Great Recession. On the one hand, for the decades before the Great Recession, a series of papers starting with the influential paper of Ruhm (2000) found a negative contemporaneous association between cross-area unemployment rates and mortality.[2] This relationship appears both in the United States (Ruhm 2000; Miller et al. 2009; Stevens et al. 2015), as well as in other countries (e.g. Neumayer (2004) for Germany, Granados (2005) for Spain, Buchmueller et al. (2007) for France, and Ariizumi and Schirle (2012) for Canada).[3] On the other hand, the relationship between local unemployment and mortality in the US appears to have weakened over time and to have disappeared by 2010 (Ruhm 2015).[4] In addition, looking at the relationship between business cycles and mortality across almost three dozen countries and two hundred years, Cutler et al. (2016) conclude that while small recessions are associated with reduced mortality, large recessions are associated with increased mortality. Reinforcing the uncertainty about the impact of the Great Recession on mortality, the existing literature studying its impact on health has produced mixed results.[5]

To document priors for the impact of the Great Recession on the change in the U.S. mortality rate, we conducted a survey of over 300 experts in spring 2023 (see Appendix A.1 for details). We found that 50% of respondents predicted that the Great Recession would increase mortality, and

[2] Even earlier work by Ogburn and Thomas (1922) looking at the time series relationship between business cycles and mortality in the US prior to World War I found that mortality declined during recessions, a finding that they labeled "a surprising result."

[3] In the US, Ruhm (2000) analyzed the time period 1972-1991, while Miller et al. (2009) analyzed 1972 - 2004 and Stevens et al. (2015) analyzed 1978-2006. In other countries, the time period analyzed was 1980-2000 (Germany), 1980-1997 (Spain), 1982-2002 (France), and 1977-2009 (Canada).

[4] In particular, Ruhm (2015) finds that while mortality was strongly pro-cyclical in the US in the 1970s and 1980s—with a one percentage point increase in the state-year unemployment rate associated with a (contemporaneous) 0.5 percent decrease in that state's overall mortality rate—this pro-cyclicality diminished or disappeared over the subsequent two decades; he cannot reject the null hypothesis that increased unemployment during the time period that includes the Great Recession had no impact on overall or age-specific mortality.

[5] For example, Seeman et al. (2018) find that in the time-series, blood pressure and blood glucose levels worsened for adults during the Great Recession, and Lamba and Moffitt (2023) similarly find an increase in pain during the Great Recession. Yet Currie et al. (2015), examining the relationship between mothers' health and changes in the state unemployment rate, find that while the Great Recession worsened physical and mental health of disadvantaged women, it may have improved the health of more advantaged women. In addition, Currie and Tekin (2015) estimate that increased neighborhood foreclosure rates from 2005-2010 are associated with increases in visits to the emergency room or hospital in four states that were among the hardest hit by the foreclosure crisis, while Cutler and Sportiche (2022) find no impact of Great Recession-induced changes in house prices on the average mental health of pre-retirement adults (ages 51-61) in the Health and Retirement Survey. Most closely related to our work, Strumpf et al. (2017) estimate a two-way fixed effects regression relating metropolitan area annual unemployment rates to mortality over the five-year period around the onset of the Great Recession (2005-2010) and find that increases in the unemployment rate are associated with contemporaneous declines in mortality.

only 27% predicted a decrease; 23% predicted no change.[6] Moreover, 98% of respondents provided a predicted impact on mortality larger than our (negative) point estimate, and 86% provided a prediction larger than the upper bound of our 95% confidence interval.

Our empirical approach follows in the spirit of Bartik (1991), Blanchard et al. (1992), and especially Yagan (2019) in exploiting the fact that different areas of the country had very different exposure to this large, aggregate economic shock. This empirical approach complements the existing literature on the mortality impacts of recessions which analyzes the relationship between an area's mortality rate and its contemporaneous unemployment rate, controlling for area and year fixed effects. Relative to this literature, we offer several innovations. First, our use of a single, spatially-differentiated, shock helps us identify the lag structure of the impact of the recession on mortality rather than assuming that any impact of unemployment on mortality is contemporaneous. Our results below are suggestive of a persistent effect of initial economic declines on mortality, as mortality remains suppressed through 2016 even in areas that have completely recovered by then. Second, as emphasized by Arthi et al. (2022), a key limitation to the existing literature on the impact of recessions on mortality is the potential for contamination from migration in response to recessions. For some of our analyses, we are able to leverage individual-level panel data in which we can instrument for current location with pre-recession location and confirm that our results are not spuriously driven by unmeasured changes in the local population. Third, our empirical approach may also help isolate the causal impacts of recessions from potential confounding factors that both increase the local unemployment rate and also directly affect health.[7] We directly examine the pre-trends in our event study to provide support for the plausibility of our identifying assumption of no shocks to mortality that coincide with the timing of the Great Recession and are correlated with the size of its local area employment impact.

Finally, our paper extends the macro-economics literature on the welfare cost of business cycles (e.g. Lucas 1987, 2003; Krebs 2007; Krusell et al. 2009) to incorporate our estimates of endogenous mortality over the business cycle. Our approach is in the spirit of existing work in macro-economics that has incorporated secular improvements in health into welfare comparisons across countries and welfare analyses of economic growth within and across countries (e.g. Nordhaus 2002; Becker et al. 2005; Murphy and Topel 2006; Hall and Jones 2007; Jones and Klenow 2016; Brouillette et al. 2021). There has been relatively less attention, however, to incorporating cyclical fluctuations in

[6]Macro-economists were more likely than health economists to predict that the Great Recession would increase mortality; 61% of macro-economists predicted that it would increase mortality, and only 17% predicted it would decrease mortality; among health economists, 45% predicted an increase and 30% predicted a decrease.

[7]Examples of such potential confounding factors include increased access to disability insurance or increased unemployment insurance generosity, both of which have been shown to increase unemployment as well as to improve health (for disability insurance, see Autor and Duggan (2003); Gelber et al. (2017); for unemployment insurance generosity see Johnston and Mas (2018); Kuka (2020)). Other potential confounders include changes in labor market institutions such as increases in the minimum wage which have been found to increase unemployment and improve health (Flinn 2006; Ruffini 2022), or changes in other labor market institutions which have been shown to affect unemployment (Holmes 1998; Nickell 1998) and might directly affect health as well.

health into welfare analyses of business cycles.[8]

Our analysis comes with important caveats. First, our design will not pick up any impacts of the Great Recession that do not run solely through local labor market impacts. Our estimates thus exclude, for example, any mortality impacts from the nationwide collapse of the stock market, or any nationwide increase in malaise.[9] In this sense, our estimates may be more applicable to the more 'typical' local recessions studied in the literature than to aggregate, national downturns. Second, and relatedly, while the Great Recession is helpful in identifying the impact of local area recessions on mortality, those impacts may not generalize to other, particularly more mild, recessions. Third, our design will not capture impacts of the Great Recession that are spatially differentiated but not perfectly correlated with local labor market declines, such as mortality impacts arising from declines in housing wealth or declines in air pollution that may originate from declines in local labor markets but impact other areas due to wind patterns. Fourth, our analysis focuses primarily on mortality impacts; it is possible that there are important non-mortality health impacts, particularly at younger ages where mortality rates are very low. Finally, although we analyze the 10-year impact of the Great Recession shock, our analysis does not capture impacts at even longer time horizons.[10] These important limitations notwithstanding, our paper sheds new light on the existence, nature, and causes of recession-induced mortality declines, and suggests that recognition of the mortality impact of recessions can have quantitatively important implications for their welfare consequences, both overall and across demographic groups.

The rest of our paper proceeds as follows. Section 2 presents our data and empirical strategy. Section 3 presents our empirical estimates of the impact of the Great Recession on mortality. Section 4 investigates potential mechanisms behind these results. Section 5 explores their implications for the welfare analysis of recessions. There is a brief concluding section.

2 Data and Empirical Strategy

2.1 Data

We restrict our analysis to people in the 50 states and the District of Columbia from 2003 to 2016. Following Yagan (2019), we begin all of our analyses in 2003 to avoid contamination from the 2001/2002 recession.

[8] Two important exceptions are Edwards (2009) who extends Lucas (1987) to allow for cyclical mortality, and Egan et al. (2014) who contrast fluctuations in GDP to fluctuations in mortality-adjusted GDP. They reach different conclusions, with Edwards (2009) finding little effects from incorporating cyclical mortality into the analysis of business cycles, and Egan et al. (2014) finding substantial effects.

[9] For example, exploiting variation in interview dates in the 2008 Health and Retirement Survey, McInerney et al. (2013) find that the October 2008 stock market crash caused immediate declines in subjective measures of mental health, although not in clinically-validated measures.

[10] For example, Schwandt and Von Wachter (2023) find that a temporarily higher state unemployment rate at the age of labor market entry (ages 16-22) is associated with long-run declines in earnings and increased mortality several decades later.

Mortality data. We use two major sources of data to study the mortality impacts of the Great Recession. Appendix A.2 provides more detail on both underlying data sources.

First, following Ruhm (2016), we use death counts from the restricted-use mortality microdata from the Centers for Disease Control and Prevention (CDC), combined with population data—the denominator in constructing mortality rates—from the National Cancer Institutes Surveillance Epidemiology and End Results (SEER) program. The event-level mortality data encompass the universe of mortality events in the United States from 2003 to 2016. For each decedent, we observe county of residence, exact date of death, cause of death,[11] and demographic information including age in years, race, ethnicity, sex, and education. The population data provide annual, county-level population estimates by single year of age, race, ethnicity, and sex.

Our second major source of mortality data comes from a 20% random sample of Medicare enrollees aged 65+ in the United States from 2003 to 2016. The enrollee-level panel data contain information on zip code of residence each year and date of death (if any), along with demographic variables such as date of birth, race, ethnicity, sex, and annual enrollment in Medicaid (a proxy for low income). The death records that we use in the Medicare data come primarily from the Social Security Administration.[12] These data are all available for both Traditional Medicare enrollees and Medicare Advantage enrollees.[13] In addition, for the approximately three-quarters of the elderly who are enrolled in Traditional Medicare for all of 2002, we also observe detailed information about their healthcare use and about their health diagnoses. Specifically, we observe doctor visits, emergency room visits, inpatient hospitalizations, and nursing home stays; we also observe annual indicators capturing the presence of 20 specific chronic conditions that the patient could have been diagnosed for, such as lung cancer, diabetes, or depression.[14] We analyze two primary Medicare samples: a repeated cross section of individuals ages 65-99 each year, and a panel of 2003 Medicare enrollees ages 65-99 in 2003.[15]

The Medicare data offer several advantages over the CDC mortality data, albeit for the 65 and over population only. First, they provide a well-defined population denominator in which mortality can be directly observed. This addresses the well-known challenge with most other US mortality

[11] We use the cause of death recodes from the Department of Vital Statistics' List of 39 Selected Causes of Death for the "underlying cause of death" variable. This gives a single, mutually exclusive cause of death for each decedent; for further information see "Part 9 - Understanding Cause-of-Death Lists for Tabulation Mortality Statistics" from the National Vital Statistics System Instruction Manual (National Center for Health Statistics 2023). We then follow the NCHS-provided hierarchy of classifications and collapse the 39 causes to 23 by combining all malignant neoplasms into a single category and all forms of major cardiovascular disease into a single category.

[12] Unfortunately we do not observe cause of death in the Medicare data.

[13] Medicare Advantage is a program in which private insurers receive capitated payments from the government in return for providing Medicare beneficiaries with health insurance. Insurance claims (and hence health care utilization measures or health measures which are based on diagnoses recorded by physicians) are not available for enrollees in Medicare Advantage.

[14] Chronic conditions are measured for those enrolled in traditional Medicare for one to three prior years (depending on the condition). We focus on the 20 chronic conditions that have a look-back period of one year.

[15] We make a few other minor restrictions as well. See Appendix Tables OA.1 and OA.2 for more details on the sample restrictions and how they affect our sample size in each case.

data in which the numerator (mortality) and the denominator (deaths) come from different datasets, creating concerns about consistency between the two sources, as well as potential mis-estimation of the denominator during intercensal years (Currie and Schwandt 2016). Second, the individual-level panel nature of the Medicare data allow us to define a cohort of individuals based on their initial location and follow them over time; this allows us to address the concern with many existing estimates of pro-cyclical mortality that results may be confounded by endogenous migration in response to economic shocks (Blanchard et al. 1992; Arthi et al. 2022). Third, the panel also allows us to leverage the detailed data on health conditions to analyze heterogeneous impacts on mortality by pre-existing health, in addition to analysis by other demographics available in the CDC data. Finally, we can analyze the impact of the Great Recession on healthcare utilization (a potential channel for health effects).

Economic data. We use publicly available local economic indicators to trace the Great Recession across time and space from 2003-2016. We obtain monthly counts of county-level unemployment, employment, and labor force participants from the Bureau of Labor Statistics' Local Area Unemployment Statistics (LAUS, available at `https://www.bls.gov/lau/`). We obtain annual counts of county-level population (for ages 16+) from the Census.[16,17] We sum these counts across counties within a CZ and average monthly data to the annual level and use these to construct CZ-year estimates of the unemployment rate and the employment-to-population (EPOP) rate. We obtain annual county-year real GDP per capita from the Bureau of Economic Analysis.[18] For a sub-sample of counties for which it is available, we also obtain annual county-year house price data from the Federal Housing Finance Agency's yearly House Price Index (HPI) public release.[19] The HPI is a weighted repeat-sales index of single-family house prices with mortgages purchased or securitized by Fannie Mae or Freddie Mac since 1975 (see Bogin et al. (2019) for details). We average these county-year data to the CZ-year level, weighting the counties with observed HPI by their 2006 population from the SEER data.

We also obtain state-level household total consumption expenditures on (durable and non-durable) goods and services from the Personal Consumption Expenditures (PCE) surveys published by the Bureau of Economic Analysis.[20] We divide these expenditures by the population of each state in each year according to the SEER to obtain a measure of per-capita consumption and use

[16] See `https://www2.census.gov/programs-surveys/popest/datasets/2010-2019/counties/asrh/`

[17] Intercensal estimates are obtained by measuring population change since the previous Census, based on births, deaths, and migration. See `https://www2.census.gov/programs-surveys/popest/technical-documentation/methodology/2010-2020/methods-statement-v2020-final.pdf`

[18] See the CAGDP1 time series at `https://apps.bea.gov/regional/downloadzip.cfm`

[19] This data release is available at `https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx`

[20] Consumption data are provided directly at the state and year level as the sum of all expenditures within a state for different expenditure categories in the PCE. These data are available at `https://apps.bea.gov/regional/downloadzip.cfm`

the Personal Consumption Expenditure Index to adjust all expenditures to 2012 dollars. Finally, we use data from the Current Population Survey to measure the impacts of the Great Recession on earnings both overall and by education and age.

Air pollution data. To examine the potential role of recession-induced pollution declines in contributing to mortality declines, we obtain data on air pollution from the EPA's Air Quality System (AQS) database. This provides annual data at the pollutant-monitor level for pollutants that are regulated by the Clean Air Act. We aggregate these data to the county-year level and analyze them from 2003 through 2016. Specifically, we average pollution monitor readings within a monitoring site to the site-year level, weighting by the number of daily pollution readings for each monitor if there are multiple monitors at the same site. We then average these data to the county-year level, weighting sites by the number of daily pollution readings from the monitors within those sites. As in other papers studying recent air pollution (e.g. Deryugina et al. 2019; Dedoussi et al. 2020; Currie et al. 2023) we focus on fine particulate matter (PM 2.5), which is measured in micrograms per cubic meter (μg/m^3).

Although the EPA monitor data are commonly used to measure air pollution (e.g. Isen et al. 2017; Deryugina et al. 2019; Alexander and Schwandt 2022), a well-known limitation is that the pollution monitoring network is sparse (Fowlie et al. 2019). When we study the impact of the Great Recession on air pollution or the impact of air pollution on mortality, we therefore limit our analysis to the approximately two-thirds (population weighted) of counties for which we have a pollution monitor in any year from 2003-2016, and for which we also have a pollution monitor in 2006 and 2010; Appendix Figure OA.1 shows a map of these counties. Nonetheless, our estimates of the impact of pollution in contributing to recession-induced mortality declines may be biased downward by classical measurement error, since the monitor data produce rather coarse geographic measures of air pollution, whose effects on health may be much more local than the county (Currie et al. 2023). [21]

Data on other outcomes. We draw on several other data sources to probe additional potential mechanisms behind our mortality findings and to explore impacts on non-mortality measures of health.

First, we use data from the Behavioral Risk Factor Surveillance Survey (BRFSS) from 2003-2016 to examine impacts of the Great Recession on self-reported health and on health behaviors. The

[21] To address this, we explored using PM 2.5 estimates for a one kilometer grid for the entire United States from Di et al. (2016); these estimates are based on machine learning models that combine EPA monitor data with information from satellite images, land characteristics and chemical air transport models to form predictions of PM2.5 levels. However, consistent with the analysis in Fowlie et al. (2019), we found substantial within-sample dispersion in the satellite-based estimates around the ground-truth pollution monitors, even when limiting to the same square kilometer at the pollution monitor. We therefore decided to focus our analysis on the more precise if sparse monitor data.

BRFSS is an annual, telephone survey administered to approximately 400,000 individuals across the United States. Over our entire sample period, we observe annual measures of self-reported health behaviors (such as exercise, smoking, and drinking) as well as self-reported health, weight, and diagnoses for diabetes and asthma. The survey also contains information on health insurance coverage. The BRFSS contains information on individuals' state of residence, which allows us to exploit state-level variation in the impact of the Great Recession to estimate its effect on these outcomes. Appendix A.4 provides more detail on the data and the variable definitions.

Second, to measure the impact of the Great Recession on nursing home staffing, we use facility-level administrative data from annual certification inspections of nursing facilities across the United States from 2003-2016.[22] Data are available annually at the facility level, covering a range of nursing home staffing measures as well as other characteristics such as patient volume and composition. We aggregate the data to the CZ-level.

Third, we draw on restricted use data from the Health and Retirement Survey for 2002-2014—a nationally representative, bi-annual survey of older adults—to explore the impact of the Great Recession for individuals 65 and older on self-reported measures of formal and informal care received. In addition, for our welfare analysis below, we use information on earnings for individuals 65 and older to examine the impact of the Great Recession on consumption proxies. The restricted use version allows us access to state identifiers so that we can exploit state-level variation in the impact of the Great Recession. Appendix A.5 provides more detail on the data and the variable definitions.

2.2 Empirical Strategy

Our empirical strategy closely follows Yagan (2019) who exploits spatial variation in the impact of the Great Recession on local labor markets to study its long-term impacts on employment and earnings. Our main estimating equation is:

$$y_{ct} = \beta_t[SHOCK_c * \mathbb{1}(Year_t)] + \alpha_c + \gamma_t + \varepsilon_{ct}, \tag{1}$$

where $SHOCK_c$ is a measure of the impact of the Great Recession on area c, $\mathbb{1}(Year_t)$ is an indicator for calendar year t, α_c and γ_t are location and year fixed effects respectively, and ϵ_{ct} is the error term. The coefficients of interest are the β_ts; they measure impacts on the outcome y_{ct} in year t across areas differentially impacted by the Great Recession. In this equation (and throughout the paper), we omit the interaction with the shock variable in 2006 so that all coefficients are relative to 2006, and we cluster our standard errors at the local area c. Because population varies greatly across different local areas in the US, we follow the prior literature examining effects or recessions

[22] Specifically, we use the Online Survey Certification and Reporting (OSCAR) and Certification and Survey Provided Enhanced Reporting (CASPER) databases. In particular, we use the data compiled by the Shaping Long-Term Care in America Project at Brown University (LTCFocus; detailed information here), which compiles the OSCAR/CASPER data with aggregate facility-level measures from CMS's Minimum Data Set (MDS).

on mortality (e.g. Ruhm 2000, 2015) and weight each area-year by its 2006 population.

We define our main outcome variable y_{ct} to be the log age-adjusted mortality rate in area c and year t.[23] Our analysis of the log mortality rate follows the prior literature on the impacts of recessions on mortality (Ruhm 2000, 2015); in addition, as we will show below, modeling the impact of the Great Recession as a proportional shock to mortality fits the data well. The mortality rate is defined as the share of the population in area c and year t at the beginning of year t who die during year t. In all of our analyses using the death certificate data (except those that disaggregate by age), we examine age-adjusted mortality rates (as is standard in federal mortality statistics (Anderson and Rosenberg 1998)), so that our analysis is not affected by different secular trends in mortality across age groups. Specifically, we calculate the age-adjusted mortality rate in a CZ by averaging over the mortality rate in each of the 19 age bins (roughly equally-sized five-year age bins) within the CZ, weighting each age bin by the national share of the population in that age bin in 2000.[24] This is in the spirit of Ruhm (2000) who controls for the share of the population in various age groups.

We also perform many analyses by sub-group, in which we estimate a fully-saturated model:

$$y_{ctg} = \beta_{tg}[SHOCK_c * \mathbb{1}(Year_t) * \mathbb{1}(Group_g)] + \alpha_{cg} + \gamma_{tg} + \varepsilon_{ctg}, \tag{2}$$

where y_{ctg} is a location-year-group outcome (e.g. the log of a group-specific mortality rate), $\mathbb{1}(Group_g)$ is an indicator for sub-group, α_{cg} is a location-group fixed effect, γ_{tg} is a year-group fixed effect, and ε_{ctg} is the error term.

For all of our analyses of equation (1) and equation (2), the key identifying assumption is that there are no shocks to health that coincide exactly with the timing of the Great Recession and are correlated with the size of the local area employment impact of the Great Recession. We will investigate the plausibility of this assumption by examining the pre-trends in the event study results.

Measuring the Great Recession Shock. Our empirical strategy relies on the large spatial variation in the impact of the Great Recession. This has been previously documented and leveraged to study the impact of the Great Recession on outcomes such as employment (e.g. Yagan (2019); Rinz (2022)), time use (Aguiar et al. 2013), consumption (Mian et al. 2013), and educa-

[23] More specifically we add 1 to the mortality rate to avoid taking logs of zeroes. In practice, for our baseline analysis which uses the 741 Commuting Zones in the United States for the area of analysis c, this is never binding for the aggregated population analysis. Even when we disaggregate by cause of death or various demographics, mortality rates of zero are quite rare. The age group with the largest share of (population weighted) CZs with zero deaths in a CZ-year is ages 5-14 and the share with zero deaths is only 1.6 percent. The cause of death with the largest share of (population-weighted) CZs with zero deaths in a CZ-year is homicides, with a share of zero deaths of 1.5 percent, and by race and ethnicity it is Non-Hispanic Other, with a share of 0.8 percent.

[24] More specifically our age bins are: 0, 1-4, 5-9, and then every five year age bin up through 80-84, with a final bin for 85+.

tional attainment (Charles et al. 2018). Following Yagan (2019), for our baseline specification we parameterize the impact of the Great Recession on area c (i.e. $SHOCK_c$) by the percentage point change in the Commuting Zone's (CZ) unemployment rate between 2007 and 2009.[25] CZs are a standard aggregation of counties that partition the United States into 741 areas that are designed to approximate labor markets. Thus β_t in equation (1) captures the percent change in the mortality rate in CZ c and year t (relative to that CZ's 2006 average mortality rate) associated with a one-percentage-point increase in the unemployment rate from 2007 to 2009 in that CZ.[26]

Figure 1a shows the spatial variation in this baseline measure of $SHOCK_c$ across CZs. The Great Recession was a nationwide shock: virtually every CZ in the country experienced an increase in the unemployment rate between 2007 and 2009. The average (population-weighted) CZ experienced a 4.6 percentage point increase in the unemployment rate. Yet some areas were much harder hit than others; the bottom quartile of CZs experienced an average increase in the unemployment rate of 2.9 percentage points, compared to an increase of 6.7 percentage points in the highest quartile of CZs. Areas that were especially hard hit include the so-called "sand states" of Florida, Arizona, Nevada, and parts of California—where the pre-recession housing and construction booms were concentrated—and the manufacturing states in the Midwest such as Michigan, Indiana, and Ohio. By contrast, most of Texas, Oklahoma, Kansas, Nebraska, and the Dakotas were relatively unscathed.

Our use of the unemployment rate to parameterize the recession follows the existing literature analyzing the relationship between recessions and mortality (e.g. Ruhm 2000, 2003, 2005; Stevens et al. 2015). In practice, of course, all recessions—and the Great Recession was no exception—are multi-faceted economic shocks. Appendix Figure OA.3 shows the national aggregate trends in four economic indicators: the unemployment rate, the EPOP rate, log real output per capita, and log house prices. They all begin to flatten out between 2006 and 2007 and then worsen through 2009; the spatial variation in this worsening is highly, but imperfectly, correlated (see Appendix Figure OA.4).[27] The national aggregate pattern of the recovery, however, looks somewhat different across these indicators, a point we return to in Section 3.

[25] We take this $SHOCK_c$ measure directly from the replication package in Yagan (2019), who calculates annual CZ unemployment rates by summing monthly county-level counts of the unemployed (and also the number of people in the labor force) across counties within the CZ to construct monthly CZ unemployment rates which he then averages across months to obtain annual estimates.

[26] Population varies widely across CZs (Appendix Figure OA.2). As noted, we weight each CZ-year observation by 2006 population. This is consistent with prior analysis in Yagan (2019) analyzing the impact of spatial variation of the Great Recession on labor market outcomes.

[27] The CZ-year EPOP rate is calculated in analogous fashion to the unemployment rate from monthly-county data (see Section 2.1). The CZ-year GDP rate is calculated as the sum of the CZ's county-year GDP measures. The CZ-year house price index (HPI) is computed as the mean of the annual county HPI indices (weighting by 2006 population as in the construction of the unemployment rate and EPOP rate), for the subset of 684 CZs with HPI data for each year in 2003-2016.

Mortality Patterns. Mortality rates vary widely across the United States (e.g. Chetty et al. 2016; Finkelstein et al. 2021). Figure 1b documents the variation in age-adjusted mortality rates across CZs in 2006, immediately prior to the Great Recession. Mortality rates were particularly high in the South-Eastern United States and low in the Western United States.[28] However, there is no correlation between the magnitude of the 2007-2009 Great Recession shock in the CZ and its 2006 (age-adjusted) mortality rate; Figure 1c shows that a 1 percentage point higher Great Recession shock is associated with a statistically insignificant 3.8 per 100,000 (standard error 4.9) higher 2006 mortality rate.

To provide a preliminary look at how changes in mortality correlate with areas more or less hard hit by the Great Recession, Figure 2 plots age-adjusted mortality rates from 1999 through 2016 for the CZs in the lowest quartile of the 2007-2009 unemployment shock (mean unemployment shock of 2.9 percentage points) and the CZs in the highest quartile (mean unemployment shock of 6.7 percentage points). Both exhibit decreasing mortality over this study period. Their mortality rates are indistinguishable in 2003; by 2006, the CZs that will be harder hit by the Great Recession have, if anything, experienced a relative increase in mortality. After 2006, however, there is an immediate and pronounced decline in age-adjusted mortality in the harder-hit CZs relative to the less harder-hit ones, creating a gap in age-adjusted mortality rates that persist through the end of the series in 2016.

3 Mortality Impacts of the Great Recession

3.1 Overall Mortality Estimates

Baseline estimates. Figure 3 shows the results from estimating equation (1) for log age-adjusted mortality, with the coefficient on β_{2006} normalized to zero. For ease of presentation, here (and throughout) we present all estimates of impacts on log-mortality multiplied by 100.

Places that were harder hit by the Great Recession experienced an immediate and pronounced decline in log age-adjusted mortality, which then remained constant—at this lower level—for at least 10 years.[29] The point estimates imply that during the 2007-2009 Great Recession, a one-percentage point greater decline in the local area unemployment rate was associated with a 0.50 percent (standard error = 0.15) decline in the annual age-adjusted mortality rate relative to 2006. Over the next seven years (2010-2016), a one percentage point greater decline in the unemployment rate during the 2007-2009 Great Recession was associated with a 0.58 percent (standard error = 0.34) decline in the annual, age-adjusted mortality rate relative to 2006; this estimate is statistically

[28] For example, while the average annual age-adjusted mortality rates in San Jose, California and Rochester, Minnesota were 613 and 620 per 100,000, respectively, Greenville, Mississippi and Hazard, Kentucky's rates were almost twice as high at 1,210 and 1,275 per 100,000 respectively.

[29] Although the Great Recession officially began in December 2007 (National Bureau of Economic Research 2010), the decline in mortality in 2007 is consistent with the evidence in Appendix Figure OA.5 that in areas that were harder hit by the Great Recession, economic indicators had already begun to deteriorate in 2007.

indistinguishable (p-value = 0.78) from the 0.50 percent estimated mortality decline from 2007-2009.[30]

Given that the Great Recession on average increased unemployment by 4.6 percentage points between 2007 and 2009, these results imply that an increase in the unemployment rate of the magnitude of the Great Recession reduces average mortality by 2.3 percent per year, with effects persisting for at least ten years. One way to gauge the magnitude of these recession-induced mortality declines is to note that for a 55-year old facing the standard population life table, our estimates suggest that 1 in 20 of them gained an extra year of life from the Great Recession.[31] Another benchmark: over the half-century preceding the Great Recession, average annual age-adjusted mortality declined by 1.1 percent per year;[32] the mortality declines from the Great Recession are thus equivalent to those typically achieved over a two-year period. We will assess the magnitude of recession-induced mortality declines more carefully in Section 5 where we consider how they affect estimates of the welfare cost of recessions previously based only on recession-induced consumption declines.

Lag Structure of the Impact of the Economy on Mortality Most of the existing literature on the relationship between recessions and mortality assumes that any such relationship is contemporaneous, and does not allow for possible lagged impacts of economic downturns on subsequent mortality (e.g Ruhm 2000, 2003, 2005; Stevens et al. 2015). Our event-study approach allows us to examine whether such lagged impacts are present by exploiting the spatial variation not only in the initial labor market impact of the Great Recession but also in the labor market recovery, conditional on initial impact. Specifically, we estimate:

$$y_{ct} = \sum_{q \epsilon \{L,H\}} \beta_{qt}[EPOP\_SHOCK_c * \mathbb{1}(Year_t) * \mathbb{1}\left(Recovery_{q(c)}\right)] + \alpha_c + \gamma_t + \epsilon_{ct}, \tag{3}$$

where $\mathbb{1}\left(Recovery_{H(c)}\right)$ is an indicator that CZ c has an above the median 2010-2016 recovery rate among CZs in the same decile of $SHOCK_c$, and $\mathbb{1}\left(Recovery_{L(c)}\right)$ is an indicator that it has a below median recovery.

The standard approach in the literature of using the unemployment rate when measuring the relationship between recessions and mortality becomes problematic when exploring potential lagged effects of a recession. The unemployment rate since the latter is a notoriously challenging measure of recovery; worker exit from the labor force can produce a decline in unemployment without

[30]The slightly positive pre-trend (also visible in Figure 2) indicates that prior to the Great Recession, areas that were subsequently harder hit were experiencing a slight relative increase in mortality; this is consistent with our finding that recessions reduce mortality, since areas that were subsequently harder hit by the Great Recession experienced a relative rise in economic indicators in the preceding years (see Yagan (2019) and Appendix OA.5.)

[31]Specifically, Appendix Table OA.3, Panel (b) shows that our estimates correspond to an increase in life expectancy from the Great Recession of about 18 days for a 55 year old.

[32]Appendix Figure OA.6 shows that age-adjusted mortality declined from about 1,334 per hundred thousand in 1956 to 792 (i.e. 0.79 percent) per 100,000 in 2006, an average annual mortality decline of 1.1 percent. See also Ma et al. (2015).

any corresponding increase in the employment to population ratio. The Great Recession was no exception; Appendix Figure OA.3 shows that in the national time series, the unemployment rate starts to recover after 2009 and by 2016 is essentially back to pre-recession levels, while the three other economic indicators still remain substantially below their 2006 levels (or trend in the case of the national times series for GDP). The same phenomenon appears when comparing more vs. less affected (Appendix Figure (OA.5). We therefore measure the recovery by the change in the area's employment-to-population (EPOP) rate between 2010-2016, rather than the change in the area's unemployment rate. For symmetry, we also measure the initial economic shock ($SHOCK_c$) in equation (3) by the percentage point change in the area's 2007-2009 EPOP; changing the measurement of $SHOCK_c$ in equation (1) from the unemployment rate to the EPOP rate has no noticeable effect on our estimates.[33] Estimation of equation (3) exploits the substantial dispersion across CZs in the rate of the 2010-2016 EPOP recovery *within* each decile of the 2007-2009 EPOP shock (see Appendix Figure OA.7).

Figure 4 show the results. The top two panels show the results of estimating equation (3) when the dependent variable is the EPOP rate. They show that, while in above-median recovery CZs (Panel b) the EPOP has returned to the pre-recession level by the end of the ten years, in the below median recovery CZs (Panel a) it has regained only about half of the estimated decline. The bottom two panels show the impact of the 2007-2009 shock on log mortality, separately for CZs that subsequently experienced below median recovery (Panel c) and above median recovery (Panel d). As expected, the impact of the Great Recession is similar for these two types of CZs in the 2007-2009 period, with a 1 percentage point decline in the EPOP associated with a 0.4 percent decline in mortality.

Strikingly, the 2010-2016 mortality declines are persistent in both the above and below median recovery areas, despite the fact that the above median recovery areas have completely recovered by the end of our study period. Indeed, the point estimates are remarkably similar, with the above median recovery places experiencing a 0.44 percent (standard error = 0.24) average mortality reduction over 2010-2016 relative to 2006, and the below median recovery places experiencing only a slightly large and statistically indistinguishable 0.54 (standard error = 0.33) average mortality reduction These results suggest that there must be some lagged effect of the initial economic downturn, since we continue to see lower mortality in areas even once they have experienced a complete recovery.

3.2 Unpacking the overall mortality decline

Mortality rates vary substantially across demographic groups (Appendix Table OA.4). For example in 2006, the elderly (65 and older) accounted for almost three-quarters of deaths, although they

[33]Specifically, we estimate that a 1 percentage point decline in the area's EPOP is associated with a 0.4 percent decline (standard error = 0.11) in age adjusted mortality from 2007-2009 and a 0.51 percent decline (standard error = 0.27) from 2010-2016 (Appendix Figure OA.8).

were only 12 percent of the population; individuals with a high school degree or less were about half (52 percent) of the population but 70 percent of deaths. Mortality also reflects a number of underlying causes. The two most common causes of (age-adjusted) deaths were cardiovascular disease (34 percent of deaths) and malignant neoplasms—i.e., cancer—(23 percent).

We examine mortality impacts across demographic groups and causes. For ease of presentation, the main text reports figures that present the pooled estimates for the 2007-2009 and 2010-2016 period; the underlying event studies are shown in the Appendix.[34] Because the patterns are largely the same in the 07-09 period and the 10-16 period, we focus our discussion primarily on the 2007-2009 period where we have greater precision.

By cause of death. Figure 5 indicates that mortality declines from the Great Recession appear for essentially all major causes of death, with the important exception of cancer where there is no impact. Panel (a) reports the pooled estimate for each of the top 11 causes of death (arranged in descending order of prevalence) as well as a final residual category for all other columns. No cause of death experiences a statistically significant increase in mortality; most of the point estimates indicate declines, and several are statistically significant. For the 2007-2009 period, we estimate that a 1 percentage point increase in local area unemployment reduces the mortality rate from cardiovascular disease by 0.65% (standard error = 0.21), the mortality rate from motor vehicle accidents by 1.7% (standard error = 0.56), and from liver disease by 1.1% (standard error = 0.43).[35] In addition, several other causes of death—including respiratory disease, influenza/pneumonia, kidney disease, liver disease, and homicides—experience a percentage decline in their mortality rate similar or larger to than that of cardiovascular disease but these declines are not statistically significant. Not surprisingly, we estimate a precise null effect on cancer deaths (0.02 percent, standard error = 0.11), which is the second largest cause of death.

We estimate a decline in suicides that is not statistically significant over the 2007-2009 period, but grows in magnitude in the 2010-2016 period to a statistically significant 1.7 percent (standard error = 0.5) decline in suicide mortality for each percentage point increase in the 2007-2009 unemployment rate. This is striking in light of the secular increases in suicide since 2000 (Marcotte and Hansen 2023) as well as state-year panel estimates that increases in unemployment are associated with contemporaneous increases in suicides (Ruhm 2000; Harper et al. 2015). Not surprisingly in light of the recession-induced declines in both suicides and deaths from liver disease in the 2010-2016 period, we find that the Great Recession also reduced Case and Deaton's measure of "deaths of despair" (Case and Deaton 2015, 2017, 2021)—that is deaths from suicide, liver disease, and drug

[34]See Appendix Figures OA.9, OA.10, OA.11, OA.12, OA.13, OA.14, and Figure OA.15. The point estimates and confidence intervals for all of the 2007-2009 and 2010-2016 estimates, as well as the pooled 2007-2016 estimates, are shown in the bottom left hand corner of these figures.

[35]Interestingly,the event studies in Fig. OA.10 suggest that effects on motor vehicle have entirely dissipated by 2016, while effects on cardiovascular and liver mortality are more persistent.

poisonings (accidental or unknown-intent)—in the 2010-2016 period.[36] Specifically, we find that a one percentage point increase in the 2007-2009 unemployment rate is associated with a statistically significant 1.4 percent (standard error = 0.63) decline in deaths of despair from 2010-2016. This is consistent with Case and Deaton (2017), who also note that there is no evidence of deaths of despair rising during the Great Recession and who interpret deaths of despair arising not from declines in income per se but rather from a more prolonged impact of cumulative disadvantage.

Figure 5 Panel (b) combines the 2007-2009 point estimates on mortality declines for each cause of death with 2006 prevalence rates to report the share of the recession-induced 2007-2009 mortality reduction accounted for by each cause of death. Cardiovascular disease is the largest cause of death (one-third of total mortality in 2006) and accounts for the largest share (48 percent) of the estimated total reduction in deaths. By contrast, motor vehicle accidents and liver disease each account for less than 2% of 2006 mortality, and so their contributions to the total recession-induced mortality decline are only 6.9% and 2.6% respectively.

By age. Figure 6 Panel (a) indicates that the Great Recession is associated with similar percentage reductions in mortality rates across age groups. We estimate reductions in log mortality rates for all age groups, with many statistically significant. The point estimates are also broadly similar; while the decline in log mortality rates appears to be larger for younger population groups, these estimates are quite imprecise. When we aggregate into larger age groups, we are unable to reject the hypothesis that the percentage decline in mortality is the same for ages 25 to 64 and for 65+, although we can reject that percentage decline for 0-24 year olds is the same as either group (not shown). More importantly, even a slightly larger percentage decline for 0-24 year olds has little quantitative significance, given their very low baseline mortality rate. Panel (b) shows this by combining the point estimates with mortality rates by age to show the contribution of different age groups to the estimated recession-induced reduction in total mortality. It shows that the elderly (individuals 65 and older) account for the majority—74.3 percent—of the deaths averted by the Great Recession, which is roughly proportional to their 72.5 percent share of total mortality in 2006. This finding is similar to that of Stevens et al. (2015) who found that in state-year panel data, estimates of reduced deaths associated with contemporary increases in the local unemployment rate were also concentrated in the elderly.

By education, gender and race/ethnicity. Figure 7 summarizes the mortality impacts of the Great Recession separately by mutually exclusive and exhaustive sub-groups by education, sex, and race/ethnicity. We compare the impact of the Great Recession separately for the roughly half of the population age 25 and over those with a high school degree or less and those with more than a high school degree; due to data limitations, this analysis is conducted at the state rather than CZ

[36] Appendix Figure OA.16a shows the event study results for deaths of despair, while Figures OA.10c, OA.10d, and OA.16b show the results for each component.)

level and excludes a few states with missing data;[37] as can be seen this has essentially no impact on our estimates. Strikingly, however, we find that the entire mortality decline is concentrated among those with a high school degree or less.[38] By contrast, there is no evidence of differential mortality impacts by gender, with nearly identical estimates for males and females. While the mortality declines due to the Great Recession appear to be more pronounced for non-white population groups (with particularly large point estimates for Hispanic individuals), we cannot reject equal impacts across population groups.

Health status of marginal lives saved. When examining mortality effects over very short time horizons—such as a day or three days—a natural question is the extent to which mortality reductions are concentrated in relatively frail individuals with high baseline mortality rates. Researchers tend to investigate this so-called "mortality displacement" or "harvesting" possibility by looking at longer time horizons such as a month or a year (see e.g. Chay and Greenstone 2003; Deryugina et al. 2019). Displacement is therefore much less of a concern in our setting where we are looking at effects at the annual level that persist out 10 years. Nonetheless, it is interesting to examine whether the individuals whose deaths are averted due to the Great Recession have higher or lower baseline mortality rates than infra-marginal survivors.

To do this, we closely follow the approach of Deryugina et al. (2019). Specifically, we turn to the Medicare data and limit our analysis to the approximately three-quarters of the overall Medicare sample that is on Traditional Medicare in every month of the prior year and for whom, as explained in Section 2, we therefore can observe measures of health. This analysis is thus, by necessity, limited to the elderly population; as we have seen, they account for three-quarters of the estimated mortality decline. We estimate an auxiliary model of mortality as a function of individual demographics and health conditions at the beginning of the year, and use this model to predict counterfactual, remaining life expectancy for each individual in each year. Appendix A.3 provides more details on this approach. As expected, as we add additional covariates to the prediction model, the predicted counterfactual remaining life expectancy among those who die in the following year declines (see Appendix Figure OA.18).

We define life-years-lost for each individual in the data at the beginning of the year to be 0 if they survive, and to be equal to their predicted remaining life expectancy at the beginning of the year if they die that year. We re-estimate equation (1) with the dependent variable now the number of life-years-lost in CZ c and year t per hundred thousand beneficiaries.[39] The key object

[37] As explained in more detail in Appendix A.6, the SEER data do not provide population counts by education, so we construct the population denominator using the American Community Survey, which requires us to conduct the analysis at the state level. We limit our analysis to individuals age 25 and over so that we can observe completed education. We exclude Georgia, New York, Rhode Island and South Dakota because of the large amount of missing data on education in the death records for these states.

[38] Since the education distribution differs by age, Appendix Figure OA.17 confirms that our finding that the impact of the Great Recession is confined to those with high school education or less even when we look within age groups.

[39] Specifically, we define life-years-lost per hundred thousand beneficiaries (LYL_{ct}) as $LYL_{ct} = 100,000 *$

of interest is how our estimate of the impact of the Great Recession on life years lost varies as we use increasingly rich covariates to predict each individual's remaining life expectancy.

Table 1 shows the results; the underlying event studies are all shown in Appendix Figures OA.19. Column (1) indicates that, for a one percentage point increase in the Great Recession shock, we observe a mortality rate reduction of 29 per 100,000 (per percentage point increase in $SHOCK_c$) in the set of beneficiaries covered by Traditional Medicare in the previous year.[40] Columns (2) through (5) then show our estimates of the impact of the Great Recession on life years lost in this population, as we use more and more covariates to predict counterfactual remaining life expectancy for decedents. Assuming that each decedent's counterfactual remaining life expectancy is equal to the predicted mean for this sample (11.00 years), we obtain a decline in life years lost of 320 per 100,000 beneficiaries (that is, 320 life-years gained), which is close to the estimate in column (1). Incorporating age reduces the decline in life years lost substantially, to 206 (column 3) or by about 40 percent. Further incorporating demographic and health covariates reduces the decline in life years lost to 162. These findings suggest that the marginal life saved has about half the remaining life expectancy of a typical Medicare enrollee, which is not surprising as the decedent population in general has a lower remaining life expectancy than the general population. Interestingly, most of the differences are accounted for by age; additional demographics and co-morbidities have relatively little impact. [41]

Morbidity Like most of the literature in health economics, we focus on mortality since it is not only important, but also consistently and comprehensively measured. However it is an imperfect measure of health, particularly at younger ages where mortality is quite low (see Appendix Table OA.4). Indeed, for the non-elderly, we find that a much larger share of the recession-induced mortality declines are accounted for by motor vehicle accidents. For example, while they account for only about 7% of the overall recession-induced mortality decline, they account for almost one-quarter of the decline for 25-64 year olds and roughly half of the decline for those aged 15-44.[42]

$\frac{\sum_{i \epsilon S_{ct}} LYL_{it}}{|S_{ct}|}$, where LYL_{it} is the life-years-lost for individual i in year t and S_{ct} represents the set of beneficiary-years in CZ c in year t.

[40] Figure OA.20 shows the underlying event study for the analysis in column (1) and, for comparison, similar analysis on the entire Medicare sample and on the 65+ sample in the CDC data. It shows that switching from the CDC to the Medicare data and restricting to those that are on Traditional Medicare in the previous year has little impact on our baseline estimates.

[41] A separate question is whether the mortality reductions come from individuals who have shorter counterfactual life expectancies than typical decedents. If, relative to the typical Medicare *decedent* population, the recession saved beneficiaries with lower life expectancy, then the effect of the Great Recession on the percentage of life-years lost will become lower as we incorporate covariates. Appendix Figure OA.21 suggests that is the case. The impact of a one percentage point increase in the unemployment rate on log life years lost declines from -0.61% (standard error = 0.23) when we assume that the marginal individual saved is randomly drawn from the decedent population to -0.53% (standard error = 0.24) when we account for differences in demographics and co-morbidities. Once again, however, most of the decline is accounted for by age.

[42] By contrast, we find no evidence of recession-induced mortality declines due to motor vehicle accidents for the elderly, consistent with recessions not affecting their driving patterns. These coefficients and decomposition estimates

This raises the possibility that we are missing important non-mortality health benefits at younger ages that might only translate into improved mortality with a more-than-ten-year lag.[43]

We therefore briefly explore, where feasible, the impact of the Great Recession on measures of morbidity. Specifically, we analyze the impact of the Great Recession on self-reported measures of health in the BRFSS data.[44] Panel (a) of Figure 8 shows the estimated impacts for 2007-2009 on the log share of respondents with reported health that is less than very good or excellent, any days in the last month with poor mental health, diabetes, asthma, and obesity. We find no statistically or substantively significant effect on any of these measures of health, although the point estimates are all suggestive of improved health.[45] For example, we find that over 2007-2009, a one percentage point increase in the state unemployment rate is associated with a statistically insignificant 1.0 percent (standard error = 0.6) decrease in the share of the population reporting themselves to be in less than very good or excellent health (i.e. fair, poor or good health) and a 1.4 percent (standard error = 1.1) decline in the share who report themselves as having asthma.

3.3 Sensitivity analysis

Population flows. If recessions affect the size or composition of the local population, this could bias the estimated relationship between the recession and mortality. Arthi et al. (2022) suggest that this potential for endogenous, unmeasured changes in the local population in response to economic shocks is a key limitation of the existing literature on the impact of recessions on mortality. Consistent with such concerns, Appendix Figure OA.24 indicates that areas that were harder hit by the recession experienced a relative decline in (measured) population, primarily reflecting an increase in the share of the population that is 65 and over.[46]

The declines in measured population in places more economically impacted by the Great Recession raises concerns that unmeasured population declines might spuriously drive our findings; in other words, what looks like fewer people dying in those places might actually reflect fewer people were living in these places. One finding that mitigates against this driving our findings is that we estimate a precise zero for declines in cancer mortality, the second leading cause of death (see Figure

are presented in Appendix Figure OA.22.

[43]Of course, these longer run impacts need not be beneficial. In particular, for those who are entering the labor market (ages 16-22) during a recession, Schwandt and Von Wachter (2023) find long-run negative mortality impacts.

[44]In the BRFSS we can observe state but not county. We therefore estimate equation (1) at the state level; we show below that our main results are essentially unchanged when switching from the commuting zone to the state level for analysis.

[45]Appendix A.4 provides more details on the variable definitions. Appendix Figure OA.23 reports the underlying event studies and the point estimates for the 2007-2009, 2010-2016, and 2007-2016 periods.

[46]Yagan (2019) similarly documents relative population declines and aging in areas harder hit by the recession; this compositional change primarily reflects a decline in in-migration of prime-age workers to areas particularly affected by the Great Recession, rather than an increase in out-migration (Yagan 2019; Monras 2020; Hershbein and Stuart 2020). Appendix Figure OA.24 also shows that areas that were harder hit by the Great Recession experienced a relative increase in population in the years before it hit, consistent with the Mian and Sufi (2014) finding that the Great Recession hit harder in areas that had experienced local housing booms.

5). If estimated declines in the mortality rate simply reflected unmeasured declines in population, we would expect this to show up as declines in mortality for all major causes of death.[47]

To more directly explore the sensitivity of our findings to unmeasured population changes, we turn to the individual-level panel data for the Medicare population. We define a cohort of Medicare enrollees and their location in 2003, and examine both the impact of the Great Recession for people whose location is defined in 2003 and also how subsequent location changes affect our estimates. To do so, we follow the standard approach in the literature (e.g. Olshansky and Carnes 1997; Chetty et al. 2016; Finkelstein et al. 2021), and adopt a Gompertz specification in which the log of the mortality rate for individual i in year t ($\log(m_{it})$) is linear in age a.

Table 2 summarizes the results; the underlying event studies are shown in Appendix Figure OA.27. In the first row, we estimate a 'reduced form' impact of the Great Recession based on individual's location in 2003:

$$\log(m_{it}(a)) = \rho a + \beta_t[SHOCK_{c(i,2003)} * \mathbf{1}(Year_t)] + \alpha_{c(i,2003)} + \gamma_t + \epsilon_{it} \tag{4}$$

Once again, the coefficients of interest are the β_ts; these capture differential changes in the log mortality rate across areas differentially impacted by the Great Recession. Once again, the γ_t are year fixed effects, and we cluster the standard errors at the Commuting Zone level. However we now measure both the location fixed effects $\alpha_{c(i,2003)}$ and the Great Recession shock $SHOCK_{c(i,2003)}$ based on the enrollees' location in 2003. This alleviates concerns about potential contamination from differential population flows into or out of areas that experience different shocks. The results continue to indicate a statistically significant decline in mortality from an increase in the unemployment rate. Specifically, the 2007-2009 period estimate indicates that a one percentage point increase in the local area unemployment rate reduce the annual mortality rate by 0.35 percent (standard error = 0.16).

This 'reduced form' impact of the Great Recession will be biased downward by any difference between 2003 location and contemporary location. To examine this directly, we estimate the first-stage equation relating the shock a person would have experienced each year based on her current location to the shock that she would have experienced based on her 2003 location:

$$SHOCK_{c(i,t)} * \mathbf{1}(Year_t) = \rho a + \pi_t^{FS}[SHOCK_{c(i,2003)} * \mathbf{1}(Year_t)] + \alpha_{c(i,2003)} + \gamma_t + v_{it} \tag{5}$$

The first stage is quite large, with an average coefficient of 0.95 (standard error = 0.03) in 2007-2009; not surprisingly therefore the reduced form is only slightly smaller than the control function

[47] Of course this logic presumes that migration rates are similar for individuals with different co-morbidities. We confirmed in the Medicare data that people who died of cancer the year before the Great Recession were as likely to have lived in the same CZ in the years leading up to their death as people who died of other causes. For example, the share of patients who moved CZs three years before they died was 5.6 percent for cancer decedents compared to 6.0 percent for those who died of cardiovascular disease.

estimate that we find when we use the the $\hat{v_{it}}$ residuals from equation (5) as a regressor in the following equation:

$$log(m_{it}(a)) = \rho a + \beta_t[SHOCK_{c(i,t)} * \mathbf{1}(Year_t)] + \alpha_{c(i,2003)} + \gamma_t + \phi\hat{v_{it}} + \epsilon_{it} \tag{6}$$

The identifying assumption behind this control function approach is that while a person's 2003 location of residence may have a direct effect on their mortality (reflecting a combination of systematic variation in unobserved health determinants across the elderly in different CZs as well as any direct impact of where you live on your mortality as in Finkelstein et al. (2021)), the Great Recession shock experienced by the place they live in 2003 only affects their mortality through its correlation with the Great Recession shock experienced by the place they live in later years.

To assess how accounting for potential non-random re-sorting of the population across Commuting Zones that is correlated with the Great Recession shock, we estimate a variant of the Gompertz model based on current (yearly) location:

$$log(m_{it}(a)) = \rho a + \beta_t[SHOCK_{c(i,t)} * \mathbf{1}(Year_t)] + \alpha_{c(i,t)} + \gamma_t + \epsilon_{it} \tag{7}$$

The estimated mortality decline of -0.51 (standard error = 0.16) is larger in absolute value—but not statistically distinguishable from—the control function estimate of -0.37 (standard error = 0.17). This difference may reflect the presence of unmeasured population declines in areas harder hit by the Great Recession. Finally, the last row of Table 2 indicates that estimating equation (7) on the sub-sample of 89 percent of beneficiaries that do not move Commuting Zones between 2003 and 2016 increases the magnitude of the point estimate slightly to -0.56 (standard error = 0.18).

Additional sensitivity analysis. We also examined the sensitivity of our estimates to a number of alternative specifications. Table 3 summarizes the findings and Appendix Figures OA.28 and OA.29 present the underlying event studies. The first row of Table 3 replicates our baseline estimates from estimating equation (1), as shown in Figure 3; subsequent rows present one-off deviations from this baseline.

The results are quite stable. The second and third rows show very similar estimates when we re-estimate equation (1) at the state level or county level instead of the CZ level. For example, in 2007-2009 our baseline estimate is that a 1 percentage point increase in the CZ unemployment rate decreases mortality by 0.50 percent (standard error = 0.15). At the state level the estimate increases slightly to 0.62 percent (standard error = 0.25), and at the county level it decreases slightly to 0.49 percent (standard error = 0.09). The fourth row shows that if we replace the dependent variable with the commuting zone age-adjusted mortality rate in levels in year t, we obtain very similar results. For example, in 2007-2009 we estimate that a 1 percentage point increase in the CZ unemployment rate decreases mortality by 3.7 deaths per 100,000 (standard error = 1.0) or about

0.47 percent relative to 2006 mortality of 790 per 100,000. The next row shows that the baseline estimate attenuates slightly to 0.38 percent (standard error = 0.14) if we include fixed effects for each of the nine census divisions by year;[48] Appendix Table OA.5 further shows that the results are robust to dropping any of the nine census divisions.

Our baseline specification assumes that the log mortality rate is linear in the unemployment rate. Appendix Figure OA.30 provides some support for this linear specification in equation (1) by plotting the (population-weighted) average of $SHOCK_c$ in each ventile against the average change in the log mortality rate between 2006 and its average across several post-period years: 2007-2009, 2010-2016, and 2007-2016. The line of best fit computed on the original sample of 741 (population weighted) CZs is displayed in red. The relationship looks roughly linear. To further probe this, in Table 3 we relax the linearity assumption by replacing the $SHOCK_c$ variable in equation (1) with indicators for which quartile of the (population weighted) CZ unemployment rate shock distribution the CZ is in; we omit the first quartile (with a mean shock of 2.89). The results indicate that CZs in the second quartile (mean shock of 4.00) experience a substantially larger mortality decline than those in the first quartile, and CZs in the fourth quartile (mean shock of 6.66) experience an even larger mortality decline than those in the second quartile, but that CZs in the third quartile (mean shock of 5.18) experience roughly similar mortality declines to those in the second quartile. Finally, the last two rows show that the baseline results are essentially unaffected if we drop the top and bottom decile of CZs by the size of the shock, or 10 most populous CZs (as shown in Appendix Figure OA.2 population is very right-skewed).

4 Possible mechanisms

The finding that health is counter-cyclical is, at first glance, puzzling. As discussed in the Introduction, recessions might be expected to reduce health and increase mortality by lowering income and hence overall consumption, and/or by increasing stress, risky alcohol and drug consumption, or suicides. Yet there are a number of potential explanations why recessions might reduce mortality. We find it useful to group them conceptually into internal effects—whereby an individual's reduced employment or consumption reduces her own mortality—and external effects, or externalities from reduced aggregate economic activity on health, holding constant own employment or consumption as these have potentially very different implications for the welfare consequences of our estimates. [49] Positive health externalities from reduced economic activity suggest that recessions may have positive welfare effects that mitigate the negative welfare effects from reduced consumption, while

[48] CZs are assigned to states (and resulting Census Divisions) according to the state with the plurality of the CZ population. Census divisions are the Pacific, Mountain, West North Central, West South Central, East South Central, East North Central, Middle Atlantic, South Atlantic, and New England divisions.

[49] Of course, there are some channels, such as the reduction in motor vehicle fatalities which we find was responsible for about 7 percent of the total recession-induced mortality decline, which may reflect a mix of both internal effects (single car-accidents) and external effects (multi-car accidents).

the welfare implications of mortality reductions that arise from internal effects are less clear cut.[50]

4.1 Internal Effects

There are two main channels for internal effects discussed in the literature. One is that with their increased non-labor time, the newly unemployed may have more time for self-care. This may improve health by reducing stress (Brenner and Mooney 1983; Ruhm 2000) or improving health behaviors (Ruhm 2000). Under this scenario, we might expect to see improved diet, increased exercise, and increased smoking cessation—which was the mechanism behind the pro-cyclical mortality effects emphasized in the original work by Ruhm (2000)—as well as potentially increased use of medical care.[51] A second channel is that recession-induced consumption declines could improve health by decreasing health-harmful consumption such as alcohol and cigarettes (Ruhm 1995; Carpenter and Dobkin 2009; Evans and Moore 2012).

The fact that three-quarters of the mortality reduction comes from a reduction in elderly deaths, a group whom we estimate did not experience any direct income or employment effects from the Great Recession (see Appendix Figure OA.31), mitigates against internal effects as the primary driver of the estimated mortality declines. Nonetheless, we also explored more directly the potential roles for changes in health-harmful consumption and health behaviors.

We do not find any evidence of a quantitatively important role for internal effects in driving recession-induced mortality reductions. The time pattern of the mortality reductions in Figure 3—an immediate decline that does not grow larger over time—is not consistent with an important role for changes in health behaviors; changes in exercise, diet, or smoking would be expected to impact mortality with a lag, and to grow over time as health capital improves.[52] Moreover, we find no statistically significant impact of recessions on improved health behaviors (Figure 8).[53] Specifically, it shows results from re-estimating equation (1) at the state-level with the outcome variables the log share of individuals who report that they currently smoke, that they smoke daily, that they currently drink, that they have consumed more than than 5 drinks in one sitting in the past month, that they have exercised within the past 30 days, or that they got a flu shot in the past year. For example, we estimate that on average over the 2007-2019 period, a 1 percentage point increase in state unemployment from 2007-2009 decreases the share smoking by 1.2 percent (standard error

[50] In a rational agent model in which affected individuals choose to use some of their increased leisure time to produce more health, there may be no welfare consequences of the health effects by the usual envelope theorem argument. Of course, if individuals are engaged in privately sub-optimal health behaviors such as smoking or medication non-adherence (e.g. Gruber and Köszegi 2001), recession-induced changes in behavior could be welfare improving.

[51] Mitigating against any potential increased use in medical care is the loss in health insurance associated with employment losses and reductions in income (Coile et al. (2014)).

[52] For example, studies of the impact of smoking cessation on mortality find that effects grow gradually over a 10- to 15-year period and the effects in the first few years constitute only a small share of the total mortality declines (see e.g. Kawachi et al. 1993; Mons et al. 2015; U.S. Department of Health and Human Services 2020).

[53] Appendix A.4 provides more details on the variable definitions; Appendix Figures OA.23, OA.33, and OA.34 report the underlying event studies.

0.9 percent), increases the share excessively drinking by 0.6 percent (standard error 0.6), and increases the share exercising by 0.2 percent (standard error = 0.2 percent). Interestingly, although statistically insignificant, the point estimates are quite similar in magnitude to those found in Ruhm (2000).[54] In addition, we find no evidence of a substantively or statistically significant impact of the Great Recession on health care use among the elderly, measured in the Medicare data by physician visits, ER visits, or total expenditures (Appendix Figure OA.32).[55] Finally, consistent with a role for declines in health-harmful consumption, we found declines (some statistically significant) in mortality from cirrhosis of the liver, homicide, suicide, and drug poisonings (see Figure 5 and Appendix Figure OA.16b), but combined this account for less than 7 percent of the total reduction in mortality

4.2 Externalities

We explore three main potential sources of positive health externalities from recessions suggested by prior literature: reductions in the spread of infectious disease (Adda 2016), increases in the quality of health care (Stevens et al. 2015), and reductions in pollution (Chay and Greenstone 2003; Heutel and Ruhm 2016). We find little support for a role for the first two externalities, but evidence consistent with a quantitatively important role for recession-induced reductions in air pollution in explaining about 40% of the recession-induced mortality declines.

Reduction in the spread of infectious disease. Influenza and pneumonia accounted for only 2% of deaths in 2006, and experienced statistically insignificant mortality declines from the Great Recession (Figure 5).

Improved quality of nursing home care for the elderly. Tighter labor markets may result in improved quantity and quality of health care workers, particularly for elder care that does not require much formal training and may therefore be relatively elastically supplied. For example, there could be an increase in the relatively low-skilled, direct care workers who provide formal home care and nursing care, sectors where there are widespread concerns about shortages (e.g. Geng et al. 2019; Grabowski et al. 2023).Indeed, Stevens et al. (2015) provides evidence from state-year panel data from 1978-2006 that cyclical fluctuations in the quality of nursing home staff are correlated with reductions in elderly mortality during recessions.[56]

[54] Appendix Table OA.6 shows this more clearly by estimating the specification in levels and reporting the comparable estimates from Ruhm (2000).

[55] The one exception is inpatient visits where there is a statistically significant increase in the share of patient-years with an inpatient admission (0.8 percent) in the 2010-2016 period.

[56] Another potential channel for improved quality of care could be recession-induced decreases in motor vehicle traffic and hence ambulance transport times. There is evidence that increased congestion increases ambulance transport times and increases mortality of individuals admitted to the hospital with acute myocardial infarction or cardiac arrest Jena et al. (2017). However data on ambulance transport times are only available for a few states prior to the Great Recession and annual, state-level information on vehicle miles travel is inconsistently reported and of

We do not find evidence for this channel. When we re-estimate equation (1) in the Medicare data, separately for the 7% of the population was in a nursing home in any given year or the previous year and the 93% that were not, we find that in 2007-2009, the Great Recession reduced mortality rates by the same 0.5% for each group (see Appendix Figure OA.35). Nursing home residents do have much higher mortality—this 7% of the elderly accounts for 30% of their annual deaths—placing an upper bound on the potential role of improved nursing home care in contributing to recession-induced mortality declines of about 30%. Moreover, Appendix Figure OA.36 shows little evidence of an increase in either the number or the skill-mix of nursing staff hours in nursing homes in areas where the Great Recession hit harder.[57] We also find no evidence of an impact of the Great Recession on nursing home occupancy rates or resident characteristics (Appendix Figure OA.37). Finally, we also examined informal care provision, as this might increase with tight labor markets. In the Health and Retirement Survey we are able to separately observe formal home health care from a professional as well as informal care from a spouse, child or other relative. We find no evidence of an impact of the Great Recession on whether individuals report receiving either formal or informal help (Appendix Section A.5 describes the analysis and results).

Reduction in Air Pollution. To examine the impact of the Great Recession on air pollution, we limit our analysis to the approximately two-thirds (population weighted) of counties for which we have a monitor in 2006 and 2010 and re-estimate a variant of equation (1) at the county level with PM2.5 levels as the dependent variable. Specifically we estimate:

$$PM2.5_{ct} = \beta_t[GR\_SHOCK_{cz(c)} * \mathbb{1}(Year_t)] + \alpha_c + \gamma_t + \varepsilon_{ct}, \tag{8}$$

where c now denotes county, cz denotes commuting zone, and GR_SHOCK is our SHOCK measure from equation (1). We estimate the regression at the county level—since we expect any impacts of air pollution to have the biggest impact on people in closer proximity—but continue to measure the Great Recession shock at the commuting zone level since the local labor market is likely the right area for the impact of that shock; we continue to cluster our standard errors at the commuting zone level. The impact of the Great Recession on mortality is very similar when we estimate equation conduct the analysis at the county level in this restricted set of counties (Figure 9 Panel (a)).

Counties that are harder hit economically by the Great Recession experienced greater declines in pollution (Figure 9 Panel (b)). We estimate that a one percentage point increase in the CZ level unemployment rate from 2007-2009 is associated with an average reduction of 0.16 micrograms per

questionable reliability (Federal Highway Administration 2014).

[57]For example, the point estimates suggest that for every one percentage point increase in the local area unemployment during the Great Recession, there is a statistically and substantively insignificant 0.95 percent (standard error = 0.49) increase in direct care hours per resident day during 2007-2009, and 0.54 percent (standard error = 0.28) from 2010 - 2016. By contrast, Stevens et al. (2015) estimate that every 1 percentage point increase in the state-year unemployment rate increases employment in a nursing home by 3 percent.

cubic meter (μg/m^3) (standard error = 0.04) in PM2.5 per county from 2007-2009; this represents a 1.3 percent decline relative to the national average level of PM2.5 in 2006 of about 12 $\mu g/m^3$. This is consistent with existing work showing that recessions decrease air pollution (e.g. Heutel 2012; Feng et al. 2015; Heutel and Ruhm 2016) and likely reflects recession-induced declines in major sources of air pollution such as industrial activity, electricity generation and transportation.

Qualitatively, both the time pattern of the mortality declines from the Great Recession as well as the causes of death affected are consistent with a role for recession-induced declines in PM2.5 contributing to the recession-induced mortality declines. Both PM2.5 and mortality declines show up in 2007, consistent with a large existing literature indicating that changes in air pollution have an immediate impact on mortality (see e.g. Graff Zivin and Neidell (2013) and Currie et al. (2014) for reviews). PM2.5 is understood to affect mortality by reaching deep into the lungs and being absorbed by the blood-stream. This can impair cardiovascular and respiratory function (EPA 2004) and—perhaps more surprisingly—reduce mental health and increase rates of suicide (Jia et al. 2018; Persico and Marcotte 2022). We found statistically significant and substantively large reduction in cardiovascular mortality from the Great Recession, and statistically insignificant but quantitatively similar percentage declines in respiratory mortality (see Figure 5); we also found declines in suicide which became statistically significant after a few years (see Appendix Figure OA.10c.) Prior work also suggests that recession-induced changes in air pollution affect infant mortality (Chay and Greenstone 2003) and total mortality (Heutel and Ruhm 2016).[58]

Assessing the quantitative importance of the recession-induced pollution declines that we estimate in contributing to the recession-induced mortality declines is more challenging. The quasi-experimental literature documenting that air pollution increases mortality has focused primarily on relatively short-run variation in pollution exposure, and studied impacts over relatively short time horizons, typically less than one year, and sometimes over a matter of days (see e.g. EPA (2004), Currie et al. (2014) and Graff Zivin and Neidell (2013) for reviews, or Deryugina et al. (2019) for more recent work).[59] The impact of persistent change in pollution may be proportionally smaller than that of temporary pollution change if harvesting is a primary driver of the short-run impacts; it might be proportionally larger if effects accumulate over time and/or it is harder to avoid exposure for pollution when it persists over a longer period of time; Barreca et al. (2021) find evidence consistent with the latter. The lag structure whereby declines in exposure to pollution today may translate into health improvements in later periods is also not well-understood, although the literature showing impacts of in-utero and early child pollution exposure on later life outcomes (Currie et

[58] Chay and Greenstone (2003) leverage the sharp and differential changes in total suspended particulates (TSP) across counties during the 1981-1982 recession to estimate the impact of air pollution on infant mortality, controlling for other recession consequences that might also affect infant mortality, such as changes in per-capita income. Heutel and Ruhm (2016) augment the standard state-year panel analysis of the relationship between mortality and unemployment to also include air pollution measures and conclude that air pollution may be able to explain about one-third of the decline in mortality from recessions.

[59] Ebenstein et al. (2017) and Anderson (2020) are important exceptions.

al. 2014) is consistent with current exposure having lagged effects. These issues not withstanding, we attempted to use the existing literature on the relationship between one-day changes in pollution exposure and short-run mortality changes to benchmark the potential importance of the Great Recession-induced air decline for mortality. Specifically, we use the estimates from Deryugina et al. (2019) of the impact of PM2.5 on elderly mortality, combined with our estimates of the impact of an increase in the unemployment rate on the levels of PM2.5. Under the (heroic) assumption that one year of increased exposure to PM2.5 has 365 times the impact on mortality as one day of increased exposure, we calculate that the recession-induced pollution declines can explain about about 17 to 35 percent of the 2007-2009 total recession-induced mortality declines.[60]

To try to more directly gauge the potential quantitative importance of the pollution channel, we take advantage of the fact that while the Great Recession shock reduced pollution on average, these impacts were heterogeneous across counties (see Appendix Figure OA.1) and while counties that were harder hit by the Great Recession on average experienced a larger decline in pollution, there is substantial heterogeneity in this relationship (see Figure 9 Panel c). We therefore examine how much the estimated impact of the Great Recession on mortality changes when we control for changes in pollution.[61] Specifically, we estimate:

$$y_{ct} = \beta_t[GR\_SHOCK_{cz(c)} * \mathbb{1}(Year_t)] + \phi_t[PM2.5\_SHOCK_c * \mathbb{1}(Year_t)] + \alpha_c + \gamma_t + \varepsilon_{ct}, \quad (9)$$

where $GR\_SHOCK_{cz(c)}$ is our previous shock measure of the unemployment rate increase and $PM2.5\_SHOCK_c$ measures the decline in PM2.5 in county c between 2006 and 2010 (with positive numbers reflecting a decline).[62] Table 4 shows the results from estimating equation (9); the underlying estimates of β_t are shown in Panel (d) of Figure 9. Column (1) shows the results from

[60] Deryugina et al. (2019) estimate that a 1 microgram per cubic meter increase in PM2.5 exposure for one day causes 0.69 additional deaths per million elderly individuals over a three-day window (see their Table 2 Panel B column 1), and more than double that over a one-month window (see their Figure 6). Assuming these effects are 365 times larger for a one-year increase in PM2.5 exposure, our estimate in Figure 9 (b) that a one-percentage-point increase in the unemployment rate is associated with an average PM2.5 reduction of 0.16 micrograms per cubic meter suggests that the pollution declines associated with a 1 percentage point increase in unemployment would cause a decline in elderly deaths of between 4 and 8 deaths per 100,000. Since we estimated that a one-percentage-point increase in unemployment causes a 0.5 percent decline in the elderly mortality rate, or about 23 deaths per 100,000 given the 2006 elderly mortality rate of about 4,600 per 100,000, this decrease of 4 to 8 deaths per 100,000 represents about 17 to 35 percent of the total estimated recession-induced mortality decline.

[61] Naturally, this analysis is merely suggestive, as counties that experienced greater declines in PM2.5 may have also experienced changes in other factors that directly affect mortality, and declines in PM2.5 may in turn be driven by factors other than the local labor market shock of the Great Recession. The ideal way to gauge the role of pollution in contributing to the Great Recession reduced mortality declines would be to cross-randomize labor market declines and pollution declines across different areas of the United States. Nonetheless, under the admittedly strong assumptions that the Great Recession shock and the PM2.5 shock are independent conditional on covariates, and that the PM2.5 shock is conditionally independent of any other unmeasured mediators of the treatment effect (see e.g. MacKinnon et al. 2002; Fagereng et al. 2021), this mediation analysis allows us to gauge the potential importance of the pollution channel.

[62] We define the pollution shock as 2006-2010 since Figure 9 Panel (b) indicates that the decline in pollution happens immediately in 07, with little further change through 09.

estimating equation (9) with only the Great Recession Shock on the right-hand side, column (2) from re-estimating it with the PM2.5 shock on the right-hand side instead, and column (3) shows the results of the mediation analysis from including both. Comparing columns (1) and (3), we find that controlling for the pollution shock attenuates the estimated impact of the Great Recession on mortality by about 40 percent, from a 1 percentage point increase in unemployment reducing mortality by 0.52 percent to 0.33 percent.[63] Consistent with the back-of-the-envelope calculation based on the Deryugina et al. (2019) estimates above, this suggests a quantitatively important role for pollution reductions in explaining about the recession-induced declines in mortality.

Our findings also suggest that the recession-induced pollution declines have not only an instantaneous but also lagged impact on mortality. Panels (a) and (b) of Figure 9 show that in areas harder hit by the Great Recession, mortality remains at a constant, lower level through 2016, however pollution starts rising in harder hit areas starting in about 2010, and by about 2014 has returned to pre-recession levels; this is consistent with output also returning to pre-recession levels much more quickly than employment as part of the so-called "jobless recovery." Panel (d) of the same figure shows that by 2016, there is no impact of the Great Recession shock on mortality, conditional on the 2006-2010 pollution shock, suggesting that the entire impact of the Great Recession in 2016 is mediated by the (lagged) decline in pollution.

5 Welfare Consequences of Recessions

To gauge the quantitative importance of the recession-induced mortality declines that we have estimated, we consider how incorporating them affects calibrations of the welfare consequences of recessions. We follow the approach of the existing literature that incorporates changes in life expectancy into welfare analyses (e.g. Becker et al. 2005; Jones and Klenow 2016) in assuming that gains in life expectancy represent improvements in well-being. This assumption is consistent with recession-induced mortality improvements arising from positive health externalities—such as the pollution reduction channel explored in the previous section —that are exogenous to the individual's choices.[64]

More specifically, we augment the Krebs (2007) model to allow mortality as well as consumption to vary with the business cycle. We then undertake two main types of exercises. First, we use Krebs (2007)'s calibrations of the income process to consider how the welfare cost of recession risk changes once we account for endogenous mortality. Second, we consider the impact of endogenous mortality

[63]In the Appendix Table OA.7 and Appendix Figure OA.38, we show that the results in Table 4 are robust to measuring the Great Recession shock at the county level rather than the CZ level, and to restricting the analysis to a balanced set of counties for which we can measure pollution in every year from 2003 through 2010.

[64]By contrast, if the recession-induced mortality reductions are the result of optimizing agents choosing to use some of their increased leisure time to produce more health or to reduce their consumption of mortality-increasing goods (such as alcohol or sky-diving), then the consumption impacts of recessions are all that would be relevant for welfare analysis.

on the welfare cost of the Great Recession in particular; here, we use our own estimates of the impact of the Great Recession on consumption to calibrate the model.

5.1 Incorporating Endogenous Mortality into Welfare Analysis of Recessions

5.1.1 Model

Utility. We consider a large N of ex-ante identical agents. The representative agent's expected lifetime utility is given by:

$$U(c(t), m(t)) = \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t S(m(t)) u(c(t)) \right] \tag{10}$$

where $c(t)$ is the agent's consumption in period t, $m(t)$ is the mortality rate (indexed by t because it is allowed to vary by time over the life-cycle), and β is the agent's subjective discount rate. The cumulative survival rate $S(m(t)) = \prod_{\tau=0}^{\tau=t}(1 - m(\tau))$ is calculated using the vector of mortality rates up to time t, and life expectancy T is equal to the sum of the cumulative survival rates (i.e., $T = \sum_{t=0}^{\infty} S(t)$).

The per-period utility function $u(c)$ follows Hall and Jones (2007) and is given by

$$u(c) = b + \frac{c^{1-\gamma}}{1-\gamma}, \tag{11}$$

where b governs the willingness to pay for additional years of life. The value of a statistical life-year (VSLY) is given by:

$$\text{VSLY} = \frac{U(c, m)/u'(c)}{T} = bc^{\gamma} - \frac{c}{\gamma - 1}, \tag{12}$$

which implies that the VSLY is increasing in c if $\gamma > 1$ (Hall and Jones 2007).

The agent receives income $y(t)$ when alive, and, as in Krebs (2007), we assume that consumption always equals income in each period ($c(t) = y(t)$ for all t); i.e., there is no savings, borrowing, or insurance.

Recessions and Income Processes. The aggregate state $S \in \{L, H\}$ affects the agent's stochastic income process. Following Krebs (2007), the aggregate state S is drawn each period, with the probability of a normal state ($S = H$) given by π_H.

Income in period $t = 0$ is normalized to 1, and, up until age 65, evolves according to the following stochastic process which, following Krebs (2007), allows for two types of persistent income shocks:

$$y_{t+1} = (1 + g)(1 + \theta_{t+1})(1 + \eta_{t+1})y_t \tag{13}$$

where g is the exogenous growth rate in income that does not depend on the aggregate state. The first type of income shock θ_{t+1} does not depend on the aggregate state and is an *iid* random variable distributed as $\log(1+\theta) \sim N(-\sigma^2/2, \sigma^2)$. The second type of income shock η_{t+1} represents job displacement; it has a discrete distribution that depends on the aggregate state as follows:

$$\eta_{t+1} = \begin{cases} -d^S & \text{with probability } p^S \\ \frac{p^S d^S}{1-p^S} & \text{with probability } 1-p^S \end{cases} \tag{14}$$

The p^H and p^L values correspond to the approximate job separation rates during normal times and a recession, respectively, and the d^S values likewise correspond to the average earnings loss from job displacement, which is assumed to be greater during recessions, with $p^H > p^L$ and $d^H > d^L$.[65] In other words, both the risk of job loss and the reduction in income conditional on job loss is higher in the bad aggregate state. Since we assume the agent is engaging in hand-to-mouth consumption, any change in income translates one-for-one into a change in consumption.

Unlike in Krebs (2007), we assume that when the representative agent turns 65 they enter retirement and receive a fixed income payment for the remainder of their life when alive; in the spirit of Guvenen and Smith (2014), we assume that fixed income is their income in the last period before retirement. Thus, in our baseline model, we assume that recessions have no effect on consumption for individuals aged 65 and over. While the assumption that recessions have no impact on the consumption of the elderly is unlikely to hold literally, and we relax it in our sensitivity analysis, we suspect it is a reasonable approximation. Most of the 65 and over are retired and living on a fixed income. Time series evidence suggests that the elderly experienced little change in consumption during the Great Recession (see Malmendier and Shen (forthcoming) Figure 1) and our empirical analysis indicates that the Great Recession had no impact on household income for the elderly (see Appendix Figure OA.31).[66]

Welfare Cost of Recessions. Following Krebs (2007), we define the welfare cost of recessions Δ^{dm} as the amount the representative agent would need to be paid, calculated as a percentage of their average annual consumption, to accept the stochastic aggregate state relative to an otherwise similar economy that stays in state $S = H$ for all time periods:[67]

[65] The scaling of $(1 - p^S)$ in the denominator follows Krebs (2007) and ensures that the random variable η is a mean-preserving spread so that income continues to grow at the constant rate g in expectation.

[66] Of course, recessions can also affect both financial and housing assets—the latter was particularly true of the Great Recession—and if we relax the hand-to-mouth assumption in the Krebs (2007) model, this would affect consumption. However, most elderly households have no financial wealth and the available evidence suggests that the consumption response to changes in house prices declines with age (Berger et al. 2018).

[67] We sometimes refer to this as willingness to pay rather than willingness to accept; for small amounts these are equivalent.

$$\underbrace{\mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t S(m^S(t))u((1+\Delta^{dm})y(t))\right]}_{\text{Expected Lifetime Utility with Stochastic Aggregate State}} = \underbrace{\mathbb{E}_0^{S=H}\left[\sum_{t=0}^{\infty}\beta^t S(m^{S=H}(t))u(y(t))\right]}_{\text{Expected Lifetime Utility without Recessions}}, \tag{15}$$

where $m^S(t)$ is age-specific mortality risk in state S (potentially endogenous to the aggregate state). If mortality is exogenous, then $m^{S=H}(t) = m^{S=L}(t) = m(t)$, and the expression above simplifies to the same expression in Krebs (2007) with the only modification being age-specific rather than constant mortality rates. To incorporate endogenous mortality, we assume—consistent with the evidence in Figure 6—that a recession lowers the mortality rate by a constant percentage across all age groups. Thus:

$$m^L(t) = (1 + dm) \cdot m^H(t) \tag{16}$$

for all t, and recall $dm < 0$.

Intuition from a simplified model. To obtain some intuition for how the welfare costs of recessions will be affected by incorporating endogenous mortality we consider a simplified version of the above model in which the aggregate state $S \in \{L, H\}$ is drawn once and for all at $t = 0$ and there is no retirement. We assume that if mortality is exogenous to the aggregate economic state individuals live for T periods. With endogenous mortality, life expectancy is T in the normal state, and $T(1+dT)$ in the recession state. Denoting the welfare cost of a recession with exogenous mortality and endogenous mortality as Δ and Δ^{dT}, respectively, we show in Appendix A.8 that if we set $p^H = 0$ and take a first-order approximation of the formula for Δ^{dT} we obtain:

$$\Delta^{dT} \approx \Delta - dT\frac{\text{VSLY}}{c}. \tag{17}$$

The first-order approximation formula in equation (17) indicates that the welfare cost of a recession with endogenous mortality (Δ^{dT}) is equal to the welfare cost of a recession with exogenous mortality (Δ) minus the welfare benefit from the percentage increase in life expectancy (dT) from the recession.[68] The second term shows that an endogenous increase in life expectancy reduces the willingness to pay to avoid a recession as a percentage of average annual consumption in the normal state by the percentage change in life expectancy dT times the value of this saving ($VSLY$) as a share of annual consumption in the normal state.[69] It also indicates that no matter how costly the

[68]Note that the estimated increase in life expectancy from the recession is *net* of any direct mortality increases from job loss as found by Sullivan and Von Wachter (2009).

[69]Note that if we multiply both sides of this approximation formula by lifetime consumption ($T * c$), we obtain an expression for the total amount an individual is willing to pay to avoid a recession:

$$\Delta^{dT} * (T * c) \approx \Delta * (T * c) - (dT * T) * \text{VSLY}$$

Compared to the total amount an individual is willing to pay to avoid a recession with exogenous mortality ($\Delta*(T*c)$), recession is in terms of labor earnings, there always exists a value of the VSLY (given a change dT) where $\Delta^{dT} < 0$, meaning that the agent would have a positive willingenss to pay for nature to draw the recession state.[70]

The approximation formula in equation (17) also allows us to anticipate that the welfare costs of recessions will fall more with age when we allow for endogenous mortality. To see this, note that equation (17) indicates that the impact of endogenous mortality on the welfare cost of a recession is increasing in the percent change in life expectancy dT caused by the recession and recall that we estimated that the Great Recession caused a constant proportional decline in mortality rates across ages. Appendix Table OA.3 shows, using the 2007 SSA life tables, that a given percentage decline in mortality rates produces larger percentage gains in life expectancy at older ages.[71] For example, at age 35, remaining life expectancy is 44 years, and a 10-year 0.5 percent decline in the mortality rate translates into a 0.04 percent increase in life expectancy, while at age 65, remaining life expectancy is 18 years and a 10-year, 0.5 percent decline in the mortality rate translates into a 0.36 percent increase in life expectancy, which is almost ten times higher.

5.1.2 Calibration and Results

Calibration. Our calibration of the income process follows Krebs (2007) exactly up until retirement at age 65: we set $p^H = 0.03$, $p^L = 0.05$, $d^H = 0.09$, and $d^L = 0.21$, and we set $g = 0.02$, $\sigma = 0.01$, and $\pi_H = 0.5$. We normalize $y(0) = c(0) = 1$, where time 0 corresponds to someone who is age 35. We report results for a range of risk aversion parameters (γ), allowing values of $\gamma = 1.5, 2, 2.5$.

For mortality in "normal" times, we use the 2007 SSA mortality tables to calculate age-specific mortality rates for the $m^H(t)$ vector.[72] We choose a higher discount factor ($\beta = 0.99$) compared to

willingness to pay to avoid a recession with endogenous mortality is increased by the increase in life years ($dT * T$), scaled by the willingness to pay for those life years (VSLY).

[70] Mathematically, this comes from the fact that the value of b is unbounded from above.

[71] For some intuition, assume that the effect of a recession on life expectancy in our basic model comes entirely from an instantaneous change in mortality at $t = 0$, reducing the mortality rate from $m(0)$ to $m(0) * (1 + dm)$ (with $dm < 0$), and after that all of the other mortality rates in future periods revert back to normal (so that $m(t)$ stays the same for all $t > 0$). Using the definitions above, we can calculate dT as follows:

$$\begin{aligned} T(1+dT) &= \frac{1 - m(0) * (1 + dm)}{1 - m(0)} T \\ dT &= \frac{1 - m(0) * (1 + dm)}{1 - m(0)} - 1 \\ dT &= -dm \frac{m(0)}{1 - m(0)} \end{aligned}$$

Thus, for small values of $m(0)$ a given percentage decline in mortality rates produces larger percentage gains in life expectancy at older ages.

[72] The SSA reports separately mortality tables for men and women, available at https://www.ssa.gov/oact/HistEst/PerLifeTables/2022/PerLifeTables2022.html. We calculate the unisex mortality rate as the population-weighted average mortality rate using data from 2007. Specifically, for age a, male mortality rate $m^m(a)$, female mortality rate $m^f(a)$, and a male population share $s^m(a)$ we calculate $m(a) = s^m(a) * m^m(a) + (1 - s^m(a)) * m^f(a)$

$\beta = 0.96$ in Krebs (2007), so that when we use realistic mortality rates we end up with a welfare cost of recessions with exogenous mortality that is fairly similar to Krebs (2007). For the mortality effect of a recession, we set $dm = -0.015$. This is based on our estimates in Section 3 that a 1 percentage point increase in unemployment causes a 0.5 percent decline in the mortality rate, together with our calculation that a typical recession produces a 3.1-percentage-point increase in the unemployment rate.[73]

Given the range of empirical estimates of the VSLY, we report results for a VSLY of \$100k, \$250k, or \$400k.[74] Given an assumption for the VSLY, we compute the implied b in equation (12) for each assumed value of γ and an assumed value of average annual consumption $c = \$50,000$ at age 35. Our assumptions of a VSLY of \$100k, \$250k, or \$400k thus correspond to assuming that the value of a statistical life year is two, five or eight times larger than average annual consumption at age 35 (which is 1 by assumption). Note that because of the assumed 2 percent per year average growth in consumption ($g = 0.02$), the VSLY will also grow with age, flattening out at retirement as consumption also ceases to grow.[75]

To calibrate equation (15), we numerically simulate the economy for a large number of individuals (N) and time periods ($\overline{T}$) to approximate expectations, allowing us to solve for the value of Δ^{dm} that equalizes the following expression:

$$\sum_{i=0}^{N}\left[\sum_{t=0}^{\overline{T}}\beta^t S(m^S(t))u((1+\Delta^{dT})y_i(t))\right] = \sum_{i=0}^{N}\left[\sum_{t=0}^{\overline{T}}\beta^t S(m^{S=H}(t))u(y_i^{S=H}(t))\right] \tag{18}$$

Results. Figure 10 shows our estimates of the welfare cost of recessions by age, with and without accounting for endogenous mortality. The figure shows results for $\gamma = 2$ and the value of b that

[73] Using monthly data from the Federal Reserve (FRED – `https://fred.stlouisfed.org/series/UNRATE`) on the unemployment rate and the NBER's recession dating (`https://fredhelp.stlouisfed.org/fred/data/understanding-the-data/recession-bars/`), we calculate the increase in unemployment in each post World War II recession—excluding the Great Recession and the COVID Recession—as the difference between the minimum and maximum unemployment rate in the period starting 12 months before the official beginning of the recession or the end of the previous recession (whichever is later) and ending 12 months after its official end or when the next recession starts (whichever is sooner).

[74] The high end of the range is based on several different sources described in Kniesner and Viscusi (2019). They report that a \$369,000 VSLY was used by the US Department of Health and Human Services and the Food and Drug Administration in 2016. They also note that much of the literature estimates a value of a statistical life (VSL), and explains that the VSLY can be calculated from an estimate of the VSL using the identity VSLY $= r * \text{VSL}/(1-(1+r)^{-L})$, where L is life expectancy and r is the interest rate. They report that many government agencies use a VSL of about \$10 million; this is also the focal VSL estimate used in Viscusi (2018). Using what they say is the standard assumption in this literature of $r = 0.03$ and assuming that $L = 50$, we recover a VSLY of \$388,000. The low end of the range follows the assumed \$100,000 VSLY made by e.g. Cutler (2005) and Cutler et al. (2022). In a similar vein, Hall and Jones (2007) use as a baseline a VSL estimate of \$3 million, although they note it is at the low end of the range of estimates and they report sensitivity to higher values. Again assuming $r = 0.03$ and $L = 50$, this would imply a VSLY of \$117,000. Finally, we chose a VSLY of \$250,000 as the mid-point of the range of estimates.

[75] Recall from equation (17) that the impact of endogenous mortality on the welfare cost of recessions is proportional to the ratio of the $VSLY$ to average annual consumption in the normal state c.

corresponds to a VSLY of $250k$, and for people starting at different ages between 35 and 75.[76] With exogenous mortality, we find that a 35 year old would be willing to pay 2.09 percent of average annual consumption for the rest of their lives to avoid the risk of all future recessions.[77] This willingness to pay declines monotonically with age since older people have fewer working years remaining and hence fewer periods in which they risk recession-induced consumption declines before retirement. The welfare cost of recessions with exogenous mortality is by construction zero starting at age 65 because we assume that at that age individuals retire with a stable income stream.

Accounting for endogenous mortality lowers the welfare cost of recession at all ages, and this effect grows more pronounced with age. For example, for a 35 year old, accounting for endogenous mortality lowers the welfare cost of recessions from 2.09 percent of average annual consumption to 1.4 percent, a decline of 0.69 percentage points of average annual consumption (or about one third), while for a 45 year old, endogenous mortality lowers the welfare cost of recessions from 1.56 percent of average annual consumption to 0.54 percent; thus accounting for endogenous mortality lowers the welfare cost of recessions for a 45 year old by about two-thirds. The intuition for the larger effects of endogenous mortality at older ages was previewed above: the percentage increase in life expectancy from recessions rises with age at onset (see Appendix Table OA.3 Panel (a)). By age 55, accounting for endogenous mortality makes recessions welfare improving, with a welfare gain of about 0.5 percent of average annual consumption.

Although these qualitative patterns are fairly robust, the specific numbers are naturally sensitive to our assumptions. Intuitively, welfare costs of recessions are increasing in the assumed level of risk aversion (γ), and the impact of endogenous mortality in lowering the welfare cost of recessions is increasing with the assumed value of a statistical life year. Appendix Table OA.8 shows the welfare cost of recessions at various ages for different values of γ and of the VSLY. For example, under exogenous mortality, the welfare cost of recessions for a 35 year old ranges from 1.52 percent of average annual consumption for risk aversion of 1.5 to 2.74 percent with risk aversion of 2.5. And the reduction in the welfare cost of a recession for a 35 year old with $\gamma = 2$ when endogeneous mortality is accounted for increases from 0.28 percentage points for a VSLY of $100k$ to 1.14 percentage points for a VSLY of $400k$.

Appendix Table OA.9 shows the intuitive result that the impact of replacing the (extreme) assumption that consumption declines from recessions are mechanically zero for individuals 65 and over with the (extreme) assumption that consumption declines from recessions are the same for all ages. The welfare cost of recessions still declines with age, since people have fewer years left in

[76]As mentioned, Schwandt and Von Wachter (2023) finds that workers who are entering the labor market (i.e. ages 16-22) during a recession have higher mortality several decades later relative to cohorts that enter the labor market before or after the recession. Since our welfare analysis begins at age 35, it does not account for such potential earlier-life impacts of recessions.

[77]This is somewhat lower than Krebs (2007)'s estimate of a welfare cost of recessions of 2.4 percent of average annual consumption for $\gamma = 2$. Our baseline model differs from his because it accounts for (exogenous) mortality rather than assuming infinitely lived agents with a (different than what we assume) discount factor, and because we assume that individuals retire at age 65. Without these differences we replicate his estimates.

which they face the stochastic risk of the recession state, but the decline is now less steep. Even still, for an assumed VSLY of $250k$, we still find that with endogenous mortality, recessions are welfare increasing for 65 year olds.

5.2 Welfare Analysis of the Great Recession

Thus far we have considered how accounting for endogenous mortality affects prior consumption-based analyses of the welfare consequences of eliminating the risk of all future recessions. We now consider how endogenous mortality affects welfare analysis of eliminating a particular recession, namely the Great Recession. For this analysis, we estimate the impact of the Great Recession on consumption directly, rather than use the assumed income process in Krebs (2007). Importantly, our estimates of both economic and mortality impacts reflect the differential impact of the Great Recession across local labor markets, and do not capture any national, general equilibrium effects of this recession. This contrasts with a series of papers which have calibrated the welfare losses from the Great Recession using life cycle consumption models and the time series declines in asset prices, income and/or earnings (see e.g. Hur 2018; Peterman and Sommer 2019; Glover et al. 2020; Menno and Oliviero 2020).

5.2.1 Economic impacts of the Great Recession

We re-estimate equation (1) with state-level log consumption per capita as the dependent variable. Figure 11 shows the results. It indicates that, on average over the 2007-2016 period, a 1 percentage point increase in the state unemployment rate from 2007-2009 is associated with 1.2 percent decline in personal consumption expenditures per capita (standard error 0.40). Given the 4.6 percentage point national average increase in the unemployment rate from 2007-2009, these estimates imply that on average over the 2007-2016 period, consumption was about 5.5 percent lower. This analysis complements existing descriptions of the decline in consumption during the Great Recession, overall and across demographic groups (e.g. De Nardi et al. 2011; Petev et al. 2011); to our knowledge we are the first to exploit the geographic variation in the economic impact of the Great Recession to estimate its impact on consumption.[78]

To consider how economic impacts vary for those with more or less education, we use the Current Population Survey to estimate state-level earnings effects of the Great Recession for those 25 and over, overall and separately for the half of the population with a high school degree or less and the half of the population with more than a high school degree. Appendix A.7 presents our analysis and results. On average over the 2007-2016 period, we find that a 1 percentage point increase in the unemployment rate from 2007-2009 is associated with a 1.7 percent (standard error = 0.62)

[78] In a closely related exercise, Mian et al. (2013) and Kaplan et al. (2020) have previously exploited geographic variation in the Great Recession-induced changes in net housing worth to estimate a marginal propensity to consume out of housing net worth.

decline in earnings. This suggests that the Great-Recession induced declines in consumption that we estimated in Figure 11 are about 70 percent of the Great-Recession reduced earnings declines; this is is consistent with estimates suggesting substantial—albeit incomplete—insurance against income shocks Blundell et al. (2008), and different from our assumption in the previous sub-section which followed Krebs (2007) model in assuming that consumption equals income in each period.

Consistent with other studies of the distributional nature of the economic impact of recessions (e.g. Guvenen et al. 2014; Mian and Sufi 2016), we find that the economic impacts of the Great Recession are larger for those with a high school education or less. Specifically, we estimate that a 1 percentage point increase in the unemployment rate reduced average annual earnings by 2.7 percent for those with a high school degree or less, compared to a 1.0 percent decline in average annual earnings for those with more than a high school degree.

5.2.2 Calibration and Results

Calibration. We replace the assumed income process in the Krebs (2007) model with our empirical estimates of the impact of Great Recession on consumption. Thus the consumption path in equation 13 becomes instead:

$$c_{i,t} = 1 + \lambda_{i,t} \tag{19}$$

where λ_t is based on our estimate of the impact of the Great Recession on consumption. For $t > 9$ and for any agent 65 years or over, we assume $\lambda_{i,t} = 0$. In other words, we assume that the Great Recession had no impact on consumption after 10 years - which is as long as we follow it in the data - and, to be parallel with our welfare analysis of recessions in general, that it had no impact on consumption of the elderly.[79]

We translate our estimates of the Great Recession-induced earnings declines by education into estimates of consumption declines by education by assuming that the relationship between overall earnings declines and overall consumption declines that we estimated above applies to both education groups. In other words, we assume that for both groups, consumption declines are 70 percent of the estimated average income declines. [80]

To incorporate endogenous mortality into our welfare analyses, we assume $dm = -0.023$ for each of the ten years of the Great Recession. This comes from our empirical estimates that a 1 percentage point increase in unemployment causes a 0.5 percent decline in the mortality rate together with the average increase in unemployment during the Great Recession of 4.6 percentage points.[81] For our analyses by education, we assume $dm = -0.037$ for those with a high school

[79]Because of this retirement assumption, we scale up our estimate of $\lambda_{i,t}$ for ages under 65 (and $t <= 9$) from 5.5 percent to 6.3 percent to reflect the fact that we are assuming the impact on consumption is 0 for the 12.6 percent of the population that (according to the SEER data from 2007) was 65 and older).

[80]To the extent that the consumption response to income shocks is larger for those who have less education (Blundell et al. 2008), we may under-estimate differences in economic damages by education.

[81]Accounting for health differences (beyond age differences) reduces dm by a (statistically insignificant) 5%, as

education or less and $dm = 0.0006$ for those with more than high school (whch we get from our estimates in figure OA.15, multiplied by 4.6 percentage points). We adjust our baseline age-specific mortality rates down for those with high school education or less and up by the same percentage for those with more than high school education to capture Meara et al. (2008)'s estimate that those with more than a high school education have 14% higher remaining life expectancy at 25 than those with a high school education or less.[82]

Results. Figure 12 shows the welfare costs by age, under the baseline assumptions of $\gamma = 2$ and VSLY of $250k$.[83] With exogenous mortality, we find that the Great Recession imposed a welfare cost of about 1.86 percent of average annual consumption for a 35 year old. This welfare cost rises with age; since older individuals have fewer years remaining, the (constant) willingness to pay in terms of consumption translates into a higher share of remaining lifetime consumption. Accounting for endogenous mortality only slightly decreases the welfare cost of the Great Recession for prime-age individuals, but for older individuals the decline in welfare costs becomes more pronounced. For example, accounting for endogenous mortality reduces the welfare cost of the Great Recession at age 35 by around 5 percent (from 1.86 percent of average annual consumption to 1.72 percent). However, for a 55-year-old, endogenous mortality reduces the welfare cost of the Great Recession by about 20 percent (from 2.76 percent of average annual consumption to 2.16 percent.) The intuition for the larger effects of endogenous mortality at older ages was previewed above in the context of the simplified model: the percentage increase in life expectancy from the Great Recession rises with age at onset (see Appendix Table OA.3 Panel (b)).[84]

Figure 13 shows how the welfare costs of the Great Recession vary by education, under the baseline assumptions of $\gamma = 2$ and VSLY of $250k$.[85] We show welfare estimates by age separately for those with a high school degree or less and those with more than a high school degree, both with exogenous mortality and with endogenous mortality; these are effectively the same for those with more than a high school degree since we estimate no mortality impacts of the Great Recession for this group. Without accounting for endogenous mortality, the welfare costs of the Great Recession are higher for the less educated, since their estimated earnings declines are larger. However the regressive nature of the Great Recession is mitigated once we account for the fact that its mortality benefits are concentrated solely in the less educated. Indeed, by about age 60 accounting for endogenous mortality reverses the education gradient, with the Great Recession now inflicting the

per the difference between columns 5 and 7 of Appendix Table OA.10.

[82]Specifically, we adjust the age-specific mortality rates in our baseline SSA life table down by 31 percent for those with high school education or less and up by 31 percent for those with more education.

[83]Appendix Table OA.12 shows results for other assumptions about γ and the VSLY.

[84]Analogous to Appendix Table OA.9, Appendix Table OA.13 shows how our welfare analysis is affected if we assume that the consumption declines from the Great Recession are the same for all ages. In this case, naturally, we do not scale up the consumption estimates based on the population share 65 and over. Intuitively, in this approach the welfare costs of the Great Recession with exogenous mortality do not decrease for starting ages of 55 or more, given that the consumption impacts correspond to a bigger share of their lifetime consumption. However, endogenous mortality continues to have a larger effect on the welfare costs of recession at older ages.

[85]Appendix Table 13 shows results for other assumptions about γ and the VSLY

same - or less - harm on the less educated relative to the more educated.

6 Conclusions

We examined the the impact of the Great Recession on mortality and explored its implications for the welfare consequences of recessions. We find that mortality is pro-cyclical, driven in large part from the externalities from recession-induced pollution declines. Accounting for pro-cyclical mortality substantially reduces estimates of the welfare costs of recessions, with effects more pronounced for those with less education and for those at older ages. Indeed, for some reasonable parameter values, we find that recessions in general—and the Great Recession in particular—may be welfare-improving for older people. These results suggest important trade-offs between economic activity and mortality, at least given current public policy toward pollution-generating economic activity.

An important caveat to our analysis is that it may not reflect the total health impacts of the Great Recession. It does not capture any national impacts of recessions on health that may operate through changes in stock markets or interest rates. We may also miss important non-mortality health impacts, particularly at younger ages where mortality may be a worse proxy for overall health. Nonetheless, our findings highlight the importance of considering the link between changes in economic activity and in mortality in considering the welfare consequences of recessions and of potential public policies designed to blunt their impacts.

References

Adda, Jérôme, "Economic Activity and the Spread of Viral Diseases: Evidence from High Frequency Data," *The Quarterly Journal of Economics*, 2016, *131* (2), 891–941.

Aguiar, Mark, Erik Hurst, and Loukas Karabarbounis, "Time Use During the Great Recession," *American Economic Review*, 2013, *103* (5), 1664–96.

Alexander, Diane and Hannes Schwandt, "The Impact of Car Pollution on Infant and Child Health: Evidence from Emissions Cheating," *The Review of Economic Studies*, 2022, *89* (6), 2872–2910.

Anderson, Michael L, "As the Wind Blows: The Effects of Long-Term Exposure to Air Pollution on Mortality," *Journal of the European Economic Association*, 2020, *18* (4), 1886–1927.

Anderson, Robert N and Harry M Rosenberg, "Age Standardization of Death Rates; Implementation of the Year 2000 Standard," *National Vital Statistics Reports*, 1998, *47* (3).

Ariizumi, Hideki and Tammy Schirle, "Are Recessions Really Good For Your Health? Evidence From Canada," *Social Science & Medicine*, 2012, *74* (8), 1224–1231.

Arthi, Vellore, Brian Beach, and W Walker Hanlon, "Recessions, Mortality, and Migration Bias: Evidence from the Lancashire Cotton Famine," *American Economic Journal: Applied Economics*, 2022, *14* (2), 228–55.

Autor, David, David Dorn, and Gordon Hanson, "When Work Disappears: Manufacturing Decline and the Falling Marriage Market Value of Young Men," *American Economic Review: Insights*, 2019, *1* (2), 161–178.

Autor, David H and Mark G Duggan, "The Rise in the Disability Rolls and the Decline in Unemployment," *The Quarterly Journal of Economics*, 2003, *118* (1), 157–206.

Barreca, Alan I, Matthew Neidell, and Nicholas J Sanders, "Long-run Pollution Exposure and Mortality: Evidence from the Acid Rain Program," *Journal of Public Economics*, 2021, *200*, 104440.

Bartik, Timothy J, *Who Benefits from State and Local Economic Development Policies?*, Kalamazoo, Michigan: W.E. Upjohn Institute for Employment Research, 1991.

Becker, Gary S, Tomas J Philipson, and Rodrigo R Soares, "The Quantity and Quality of Life and the Evolution of World Inequality," *American Economic Review*, 2005, *95* (1), 277–291.

Berger, David, Veronica Guerrieri, Guido Lorenzoni, and Joseph Vavra, "House Prices and Consumer Spending," *The Review of Economic Studies*, 2018, *85* (3), 1502–1542.

Blanchard, Olivier Jean, Lawrence F Katz et al., "Regional Evolutions," *Brookings Papers on Economic Activity*, 1992, *23* (1), 1–76.

Blundell, Richard, Luigi Pistaferri, and Ian Preston, "Consumption Inequality and Partial Insurance," *American Economic Review*, 2008, *98* (5), 1887–1921.

Bogin, Alexander, William Doerner, and William Larson, "Local House Price Dynamics: New Indices and Stylized Facts," *Real Estate Economics*, 2019, *47* (2), 365–398.

Brenner, M Harvey and Anne Mooney, "Unemployment and Health in the Context of Economic Change," *Social Science & Medicine*, 1983, *17* (16), 1125–1138.

Brouillette, Jean-Felix, Charles I Jones, and Peter J Klenow, "Race and Economic Well-Being in the United States," *National Bureau of Economic Research Working Paper No:29539*, 2021.

Buchmueller, Thomas C, Florence Jusot, Michel Grignon et al., "Unemployment and Mortality in France, 1982-2002," *Centre for Health Economics and Policy Analysis Working Paper Series, McMaster University*, 2007.

Bugliari, Delia, Joanna Carroll, Orla Hayden, Jessica Hayes, Michael D Hurd, Adam Karabatakis, Regan Main, Colleen M McCullough, Erik Meijer, Michael B Moldoff et al., *RAND HRS Longitudinal File 2018 (V2) Documentation: Includes 1992-2018 (Final Release)*, RAND, 2022.

Carey, Colleen, Nolan H Miller, and David Molitor, "Why Does Disability Increase During Recessions? Evidence from Medicare," *National Bureau of Economic Research Working Paper No:29988*, 2022.

Carpenter, Christopher and Carlos Dobkin, "The Effect of Alcohol Consumption on Mortality: Regression Discontinuity Evidence from the Minimum Drinking Age," *American Economic Journal: Applied Economics*, 2009, *1* (1), 164–182.

Case, Anne and Angus Deaton, "Rising Morbidity and Mortality in Midlife Among White Non-Hispanic Americans in the 21st Century," *Proceedings of the National Academy of Sciences*, 2015, *112* (49), 15078–15083.

_ **and** _ , "Mortality and Morbidity in the 21st Century," *Brookings Papers on Economic Activity*, 2017, *2017*, 397.

_ **and** _ , *Deaths of Despair and the Future of Capitalism*, Princeton University Press, 2021.

Cesarini, David, Erik Lindqvist, Robert Östling, and Björn Wallace, "Wealth, Health, and Child Development: Evidence from Administrative Data on Swedish Lottery Players," *The Quarterly Journal of Economics*, 2016, *131* (2), 687–738.

Charles, Kerwin Kofi, Erik Hurst, and Matthew J Notowidigdo, "Housing Booms and Busts, Labor Market Opportunities, and College Attendance," *American Economic Review*, October 2018, *108* (10), 2947–94.

Chay, Kenneth Y and Michael Greenstone, "The Impact of Air Pollution on Infant Mortality: Evidence from Geographic Variation in Pollution Shocks Induced by a Recession," *The Quarterly Journal of Economics*, 2003, *118* (3), 1121–1167.

Chen, Jiafeng and Jonathan Roth, "Log-like? Identified ATEs defined with zero-valued outcomes are (arbitrarily) scale-dependent," *Working Paper*, 2023.

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler, "The Association Between Income and Life Expectancy in the United States, 2001-2014," *Journal of the American Medical Association*, 2016, *315* (16), 1750–1766.

Coile, Courtney C, Phillip B Levine, and Robin McKnight, "Recessions, Older Workers, and Longevity: How Long Are Recessions Good for Your Health?," *American Economic Journal: Economic Policy*, 2014, *6* (3), 92–119.

Costa, Dora L, "Health and the Economy in the United States from 1750 to the Present," *Journal of Economic Literature*, 2015, *53* (3), 503–570.

Currie, Janet and Erdal Tekin, "Is There a Link Between Foreclosure and Health?," *American Economic Journal: Economic Policy*, 2015, *7* (1), 63–94.

_ **and Hannes Schwandt**, "Mortality Inequality: The Good News from a County-Level Approach," *Journal of Economic Perspectives*, 2016, *30* (2), 29–52.

_ **, John Voorheis, and Reed Walker**, "What Caused Racial Disparities in Particulate Exposure to Fall? New Evidence from the Clean Air Act and Satellite-Based Measures of Air Quality," *American Economic Review*, 2023, *113* (1), 71–97.

_ **, Joshua Graff Zivin, Jamie Mullins, and Matthew Neidell**, "What Do We Know About Short-and Long-Term Effects of Early-Life Exposure to Pollution?," *Annual Review of Resource Economics*, 2014, *6* (1), 217–247.

_ **, Valentina Duque, and Irwin Garfinkel**, "The Great Recession and Mothers' Health," *The Economic Journal*, 2015, *125* (588), F311–F346.

Cutler, David, Angus Deaton, and Adriana Lleras-Muney, "The Determinants of Mortality," *Journal of Economic Perspectives*, 2006, *20* (3), 97–120.

Cutler, David M, *Your Money or Your Life: Strong Medicine for America's Health Care System*, Oxford University Press, 2005.

_ **and Noémie Sportiche**, "Economic Crises and Mental Health: Effects of the Great Recession on Older Americans," *National Bureau of Economic Research Working Paper No:29817*, 2022.

_ **, Kaushik Ghosh, Kassandra L Messer, Trivellore Raghunathan, Allison B Rosen, and Susan T Stewart**, "A Satellite Account for Health in the United States," *American Economic Review*, 2022, *112* (2), 494–533.

_ **, Wei Huang, and Adriana Lleras-Muney**, "Economic Conditions and Mortality: Evidence from 200 Years of Data," *National Bureau of Economic Research Working Paper No:22690*, 2016.

Dedoussi, Irene C, Sebastian D Eastham, Erwan Monier, and Steven RH Barrett, "Premature Mortality Related to United States Cross-state Air Pollution," *Nature*, 2020, *578* (7794), 261–265.

Deryugina, Tatyana, Garth Heutel, Nolan H Miller, David Molitor, and Julian Reif, "The Mortality and Medical Costs of Air Pollution: Evidence from Changes in Wind Direction," *American Economic Review*, 2019, *109* (12), 4178–4219.

Di, Qian, Itai Kloog, Petros Koutrakis, Alexei Lyapustin, Yujie Wang, and Joel Schwartz, "Assessing PM2. 5 Exposures with High Spatiotemporal Resolution Across the Continental United States," *Environmental Science & Technology*, 2016, *50* (9), 4712–4721.

Dobkin, Carlos and Steven L Puller, "The Effects of Government Transfers on Monthly Cycles in Drug Abuse, Hospitalization and Mortality," *Journal of Public Economics*, 2007, *91* (11-12), 2137–2157.

Ebenstein, Avraham, Maoyong Fan, Michael Greenstone, Guojun He, and Maigeng Zhou, "New Evidence on the Impact of Sustained Exposure to Air Pollution on Life Expectancy from China's Huai River Policy," *Proceedings of the National Academy of Sciences*, 2017, *114* (39), 10384–10389.

Edwards, Ryan D, "The Cost of Cyclical Mortality," *The BE Journal of Macroeconomics*, 2009, *9* (1).

Egan, Mark, Casey Mulligan, and Tomas J Philipson, "Adjusting National Accounting for Health," *National Bureau of Economic Research Working Paper No:19058*, 2014.

EPA, US, "Air Quality Criteria for Particulate Matter," *US Environmental Protection Agency, Research Triangle Park*, 2004.

Evans, William N and Timothy J Moore, "Liquidity, Economic Activity, and Mortality," *Review of Economics and Statistics*, 2012, *94* (2), 400–418.

Fagereng, Andreas, Magne Mogstad, and Marte Rønning, "Why Do Wealthy Parents Have Wealthy Children?," *Journal of Political Economy*, 2021, *129* (3), 703–756.

Federal Highway Administration, "Highway Performance Monitoring System (HPMS): State Practices Used to Report Local Area Travel," November 2014. https://www.fhwa.dot.gov/policyinformation/hpms/statepractices.cfm.

Feng, Kuishuang, Steven J Davis, Laixiang Sun, and Klaus Hubacek, "Drivers of the US CO2 emissions 1997–2013," *Nature Communications*, 2015, *6* (1), 1–8.

Finkelstein, Amy, Matthew Gentzkow, and Heidi Williams, "Place-Based Drivers of Mortality: Evidence from Migration," *American Economic Review*, 2021, *111* (8), 2697–2735.

Flinn, Christopher J, "Minimum Wage Effects on Labor Market Outcomes under Search, Matching, and Endogenous Contact Rates," *Econometrica*, 2006, *74* (4), 1013–1062.

Floud, Roderick, Robert W Fogel, Bernard Harris, and Sok Chul Hong, *The Changing Body: Health, Nutrition, and Human Development in the Western World Since 1700*, Cambridge University Press, 2011.

Fowlie, Meredith, Edward Rubin, and Reed Walker, "Bringing Satellite-Based Air Quality Estimates Down to Earth," in "AEA Papers and Proceedings," Vol. 109 2019, pp. 283–88.

Gelber, Alexander, Timothy J Moore, and Alexander Strand, "The Effect of Disability Insurance Payments on Beneficiaries' Earnings," *American Economic Journal: Economic Policy*, 2017, *9* (3), 229–61.

Geng, Fangli, David G Stevenson, and David C Grabowski, "Daily Nursing Home Staffing Levels Highly Variable, Often Below CMS Expectations," *Health Affairs*, 2019, *38* (7), 1095–1100.

Glover, Andrew, Jonathan Heathcote, Dirk Krueger, and José-Víctor Ríos-Rull, "Intergenerational Redistribution in the Great Recession," *Journal of Political Economy*, 2020, *128* (10), 3730–3778.

Grabowski, David C, Jonathan Gruber, and Brian McGarry, "Immigration, The Long-Term Care Workforce, and Elder Outcomes in the US," *National Bureau of Economic Research Working Paper No:30960*, 2023.

Graff Zivin, Joshua and Matthew Neidell, "Environment, Health, and Human Capital," *Journal of Economic Literature*, 2013, *51* (3), 689–730.

Granados, José A Tapia, "Recessions and Mortality in Spain, 1980–1997," *European Journal of Population*, 2005, *21* (4), 393–422.

Gruber, Jonathan and Botond Köszegi, "Is Addiction "Rational"? Theory and Evidence," *The Quarterly Journal of Economics*, 2001, *116* (4), 1261–1303.

Guvenen, Fatih and Anthony A Smith, "Inferring Labor Income Risk and Partial Insurance from Economic Choices," *Econometrica*, 2014, *82* (6), 2085–2129.

_ , Serdar Ozkan, and Jae Song, "The nature of countercyclical income risk," *Journal of Political Economy*, 2014, *122* (3), 621–660.

Hall, Robert E and Charles I Jones, "The Value of Life and the Rise in Health Spending," *The Quarterly Journal of Economics*, 2007, *122* (1), 39–72.

Harper, Sam, Thomas J Charters, Erin C Strumpf, Sandro Galea, and Arijit Nandi, "Economic Downturns and Suicide Mortality in the USA, 1980–2010: Observational Study," *International Journal of Epidemiology*, 2015, *44* (3), 956–966.

Hershbein, Brad and Bryan A Stuart, "Recessions and Local Labor Market Hysteresis," *Upjohn Institute Working Paper 20-325*, 2020.

Heutel, Garth, "How Should Environmental Policy Respond to Business Cycles? Optimal Policy Under Persistent Productivity Shocks," *Review of Economic Dynamics*, 2012, *15* (2), 244–264.

_ and Christopher J Ruhm, "Air Pollution and Procyclical Mortality," *Journal of the Association of Environmental and Resource Economists*, 2016, *3* (3), 667–706.

Holmes, Thomas J, "The Effect of State Policies on the Location of Manufacturing: Evidence from State Borders," *Journal of Political Economy*, 1998, *106* (4), 667–705.

HRS Staff, "Sample Sizes and Response Rates," Technical Report, Survey Research Center, Institute for Social Research, University of Michigan 2011.

Hur, Sewon, "The Lost Generation of the Great Recession," *Review of Economic Dynamics*, 2018, *30*, 179–202.

Isen, Adam, Maya Rossin-Slater, and W Reed Walker, "Every Breath You Take—Every Dollar You'll Make: The Long-Term Consequences of the Clean Air Act of 1970," *Journal of Political Economy*, 2017, *125* (3), 848–902.

Jarosek, Stephanie, "ResDAC: Death Information in the Research Identifiable Medicare Data," https://resdac.org/articles/death-information-research-identifiable-medicare-data 2022.

Jena, Anupam B, N Clay Mann, Leia N Wedlund, and Andrew Olenski, "Delays in Emergency Care and Mortality during Major US Marathons," *New England Journal of Medicine*, 2017, *376* (15), 1441–1450.

Jia, Zhen, Yongjie Wei, Xiaoqian Li, Lixin Yang, Huijie Liu, Chen Guo, Lulu Zhang, Nannan Li, Shaojuan Guo, Yan Qian et al., "Exposure to Ambient Air Particles Increases the Risk of Mental Disorder: Findings From a Natural Experiment in Beijing," *International Journal of Environmental Research and Public Health*, 2018, *15* (1), 160.

Johnston, Andrew C and Alexandre Mas, "Potential Unemployment Insurance Duration and Labor Supply: The Individual and Market-Level Response to a Benefit Cut," *Journal of Political Economy*, 2018, *126* (6), 2480–2522.

Jones, Charles I and Peter J Klenow, "Beyond GDP? Welfare across Countries and Time," *American Economic Review*, 2016, *106* (9), 2426–57.

Kaplan, Greg, Kurt Mitman, and Giovanni L Violante, "Non-durable Consumption and Housing Net Worth in the Great Recession: Evidence from Easily Accessible Data," *Journal of Public Economics*, 2020, *189*, 104176.

Kawachi, Ichiro, Graham A. Colditz, Meir J. Stampfer, Walter C. Willett, JoAnn E. Manson, Bernard Rosner, David J. Hunter, Charles H. Hennekens, and Frank E. Speizer, "Smoking Cessation in Relation to Total Mortality Rates in Women: A Prospective Cohort Study," *Annals of Internal Medicine*, 1993, *119* (10), 992–1000.

Kniesner, Thomas J and W Kip Viscusi, "The Value of a Statistical Life," *Vanderbilt Law Research Paper*, 2019, (19-15).

Krebs, Tom, "Job Displacement Risk and the Cost of Business Cycles," *American Economic Review*, 2007, *97* (3), 664–686.

Krusell, Per, Toshihiko Mukoyama, Ayşegül Şahin, and Anthony A Smith Jr, "Revisiting the welfare effects of eliminating business cycles," *Review of Economic Dynamics*, 2009, *12* (3), 393–404.

Kuka, Elira, "Quantifying the Benefits of Social Insurance: Unemployment Insurance and Health," *Review of Economics and Statistics*, 2020, *102* (3), 490–505.

Lamba, Sneha and Robert A. Moffitt, "The Rise in American Pain: The Importance of the Great Recession," *National Bureau of Economic Research Working Paper No:31455*, 2023.

Lee, S., R. Nishimura, P. Burton, and R. McCammon, "HRS 2016 Sampling Weights," Technical Report, Survey Research Center, Institute for Social Research, University of Michigan 2021.

Lucas, Robert E, *Models of Business Cycles*, Vol. 26, Basil Blackwell Oxford, 1987.

_ , "Macroeconomic Priorities," *American Economic Review*, 2003, *93* (1), 1–14.

Ma, Jiemin, Elizabeth M Ward, Rebecca L Siegel, and Ahmedin Jemal, "Temporal Trends in Mortality in the United States, 1969-2013," *Journal of the American Medical Association*, 2015, *314* (16), 1731–1739.

MacKinnon, David P, Chondra M Lockwood, Jeanne M Hoffman, Stephen G West, and Virgil Sheets, "A Comparison of Methods to Test Mediation and Other Intervening Variable Effects," *Psychological Methods*, 2002, *7* (1), 83.

Malmendier, Ulrike and Leslie Sheng Shen, "Scarred Consumption," *American Economic Journal: Macroeconomics*, forthcoming.

Marcotte, Dave E and Benjamin Hansen, "The Re-Emerging Suicide Crisis in the US: Patterns, Causes and Solutions," *National Bureau of Economic Research Working Paper No:31242*, 2023.

McInerney, Melissa, Jennifer M Mellor, and Lauren Hersch Nicholas, "Recession Depression: Mental Health Effects of the 2008 Stock Market Crash," *Journal of Health Economics*, 2013, *32* (6), 1090–1104.

Meara, Ellen R, Seth Richards, and David M Cutler, "The gap gets bigger: changes in mortality and life expectancy, by education, 1981–2000," *Health affairs*, 2008, *27* (2), 350–360.

Menno, Dominik and Tommaso Oliviero, "Financial Intermediation, House Prices, and the welfare Effects of the US Great Recession," *European Economic Review*, 2020, *129*, 103568.

Mian, Atif and Amir Sufi, "What Explains the 2007–2009 Drop in Employment?," *Econometrica*, 2014, *82* (6), 2197–2223.

_ **and** _ , "Who bears the cost of recessions? The role of house prices and household debt," *Handbook of Macroeconomics*, 2016, *2*, 255–296.

_ **, Kamalesh Rao, and Amir Sufi**, "Household Balance Sheets, Consumption, and the Economic Slump," *The Quarterly Journal of Economics*, 2013, *128* (4), 1687–1726.

Miller, Douglas L, Marianne E Page, Ann Huff Stevens, and Mateusz Filipski, "Why Are Recessions Good for Your Health?," *American Economic Review*, 2009, *99* (2), 122–27.

Monras, Joan, "Economic Shocks and Internal Migration," 2020. Working Paper, https://joanmonras.weebly.com/uploads/7/6/7/9/76790475/spatial˙mobility˙joan˙monras˙v19.pdf.

Mons, Ute, Aysel Müezzinler, Carolin Gellert, Ben Schöttker, Christian C. Abnet, Martin Bobak, Lisette de Groot, Neal D. Freedman, Eugène Jansen, Frank Kee et al., "Impact of Smoking and Smoking Cessation on Cardiovascular Events and Mortality

Among Older Adults: Meta-analysis of Individual Participant Data from Prospective Cohort Studies of the CHANCES Consortium," *BMJ*, 2015, *350*, h1551.

Murphy, Kevin M and Robert H Topel, "The Value of Health and Longevity," *Journal of Political Economy*, 2006, *114* (5), 871–904.

Nardi, Mariacristina De, Eric French, and David Benson, "Consumption and the Great Recession," *National Bureau of Economic Research Working Paper No:17688*, 2011.

National Bureau of Economic Research, "Business Cycle Dating Committee Announcement - September 20, 2010," 2010. https://www.nber.org/news/business-cycle-dating-committee-announcement-september-20-2010.

National Center for Health Statistics, "NVSS - Instructional Manuals," https://www.cdc.gov/nchs/nvss/instruction-manuals.htm April 2023.

Neumayer, Eric, "Recessions Lower (Some) Mortality Rates: Evidence From Germany," *Social Science & Medicine*, 2004, *58* (6), 1037–1047.

Nickell, Stephen, "Unemployment: Questions and Some Answers," *The Economic Journal*, 1998, *108* (448), 802–816.

Nordhaus, William D, "The Health of Nations: The Contribution of Improved Health to Living Standards," *National Bureau of Economic Research Working Paper No:8818*, 2002.

Office of Disease Prevention and Health Promotion, "National Vital Statistics System - Mortality (NVSS-M)." https://health.gov/healthypeople/objectives-and-data/data-sources-and-methods/data-sources/national-vital-statistics-system-mortality-nvss-m.

Ogburn, William F and Dorothy S Thomas, "The Influence of the Business Cycle on Certain Social Conditions," *Journal of the American Statistical Association*, 1922, *18* (139), 324–340.

Olshansky, S Jay and Bruce A Carnes, "Ever Since Gompertz," *Demography*, 1997, *34* (1), 1–15.

Persico, Claudia and Dave E Marcotte, "Air Quality and Suicide," *National Bureau of Economic Research Working Paper No:30626*, 2022.

Peterman, William B and Kamila Sommer, "How Well Did Social Security Mitigate the Effects of the Great Recession?," *International Economic Review*, 2019, *60* (3), 1433–1466.

Petev, Ivaylo, Luigi Pistaferri, and Itay Saporta Eksten, "Consumption and the Great Recession: An Analysis of Trends, Perceptions, and Distributional Effects," in "Analyses of the Great Recession," Russell Sage Foundation, 2011.

Pierce, Justin R and Peter K Schott, "Trade Liberalization and Mortality: Evidence from US Counties," *American Economic Review: Insights*, 2020, *2* (1), 47–64.

Rinz, Kevin, "Did Timing Matter? Life Cycle Differences in Effects of Exposure to the Great Recession," *Journal of Labor Economics*, 2022, *40* (3), 703–735.

Ruffini, Krista, "Worker Earnings, Service Quality, and Firm Profitability: Evidence from Nursing Homes and Minimum Wage Reforms," *The Review of Economics and Statistics*, 2022.

Ruhm, Christopher J, "Economic Conditions and Alcohol Problems," *Journal of Health Economics*, 1995, *14* (5), 583–603.

_ , "Are Recessions Good for Your Health?," *The Quarterly Journal of Economics*, 2000, *115* (2), 617–650.

_ , "Good Times Make You Sick," *Journal of Health Economics*, 2003, *22* (4), 637–658.

_ , "Healthy Living in Hard Times," *Journal of Health Economics*, 2005, *24* (2), 341–363.

_ , "Recessions, Healthy No More?," *Journal of Health Economics*, 2015, *42*, 17–28.

_ , "Health Effects of Economic Crises," *Health Economics*, 2016, *25*, 6–24.

Schwandt, Hannes and Till Von Wachter, "Socio-Economic Decline and Death: The Life-Cycle Impacts of Recessions for Labor Market Entrants," *National Bureu of Economic Research Working Paper No:26638*, 2023.

Seeman, Teresa, Duncan Thomas, Sharon Stein Merkin, Kari Moore, Karol Watson, and Arun Karlamangla, "The Great Recession Worsened Blood Pressure and Blood Glucose Levels in American Adults," *Proceedings of the National Academy of Sciences*, 2018, *115* (13), 3296–3301.

Social Security Administration, "Requesting SSA's Death Information," https://www.ssa.gov/dataexchange/request_dmf.html 2023.

Song, Yunjie, Jonathan Skinner, Julie Bynum, Jason Sutherland, John E Wennberg, and Elliott S Fisher, "Regional Variations in Diagnostic Practices," *New England Journal of Medicine*, 2010, *363* (1), 45–53.

Stevens, Ann H, Douglas L Miller, Marianne E Page, and Mateusz Filipski, "The Best of Times, the Worst of Times: Understanding Pro-cyclical Mortality," *American Economic Journal: Economic Policy*, 2015, *7* (4), 279–311.

Strumpf, Erin C, Thomas J Charters, Sam Harper, and Arijit Nandi, "Did the Great Recession Affect Mortality Rates in the Metropolitan United States? Effects on Mortality by Age, Gender and Cause of Death," *Social Science & Medicine*, 2017, *189*, 11–16.

Sullivan, Daniel and Till Von Wachter, "Job Displacement and Mortality: An Analysis Using Administrative Data," *The Quarterly Journal of Economics*, 2009, *124* (3), 1265–1306.

U.S. Department of Health and Human Services, *Smoking Cessation. A Report of the Surgeon General.*, Atlanta: Office of the Surgeon General, 2020.

Viscusi, W Kip, *Pricing Lives: Guideposts for a Safer Society*, Princeton University Press, 2018.

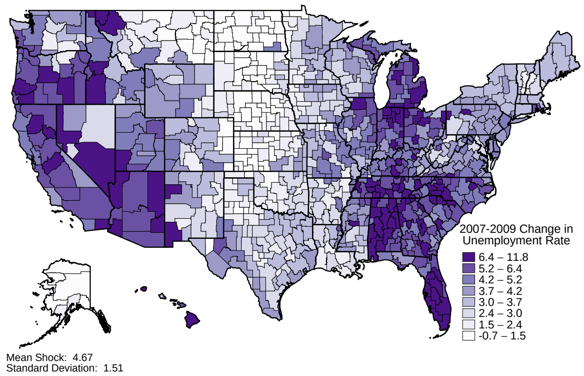
Welch, H Gilbert, Sandra M Sharp, Dan J Gottlieb, Jonathan S Skinner, and John E Wennberg, "Geographic Variation in Diagnosis Frequency and Risk of Death Among Medicare Beneficiaries," *Journal of the American Medical Association*, 2011, *305* (11), 1113–1118.

Yagan, Danny, "Employment Hysteresis from the Great Recession," *Journal of Political Economy*, 2019, *127* (5), 2505–2558.

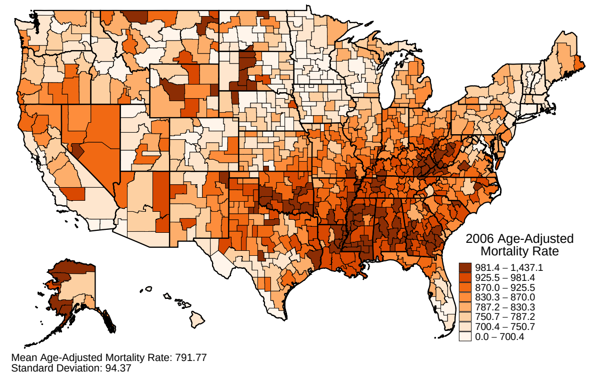
Figures

Figure 1: Geographic Patterns and Correlation of Unemployment and Mortality

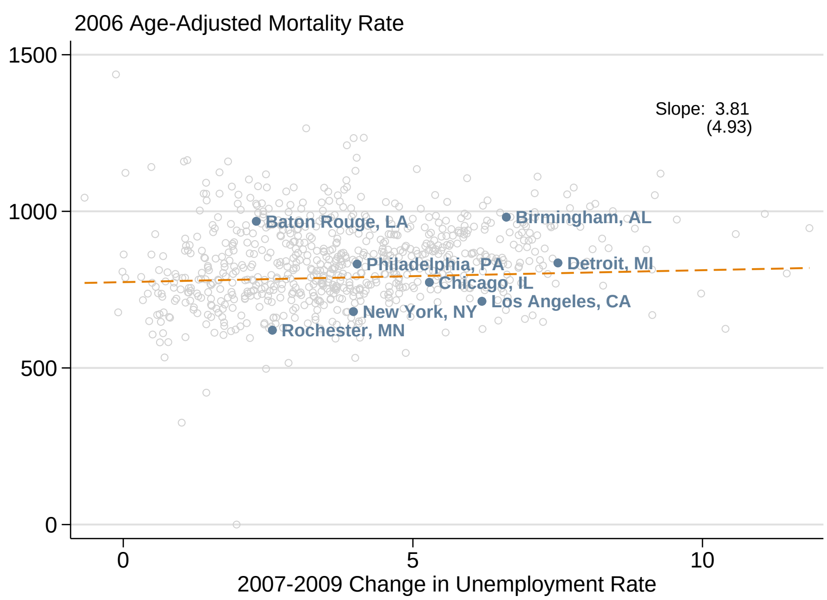
(a) 2007-2009 Change in Unemployment Rate



(b) 2006 Age-Adjusted Mortality Rate

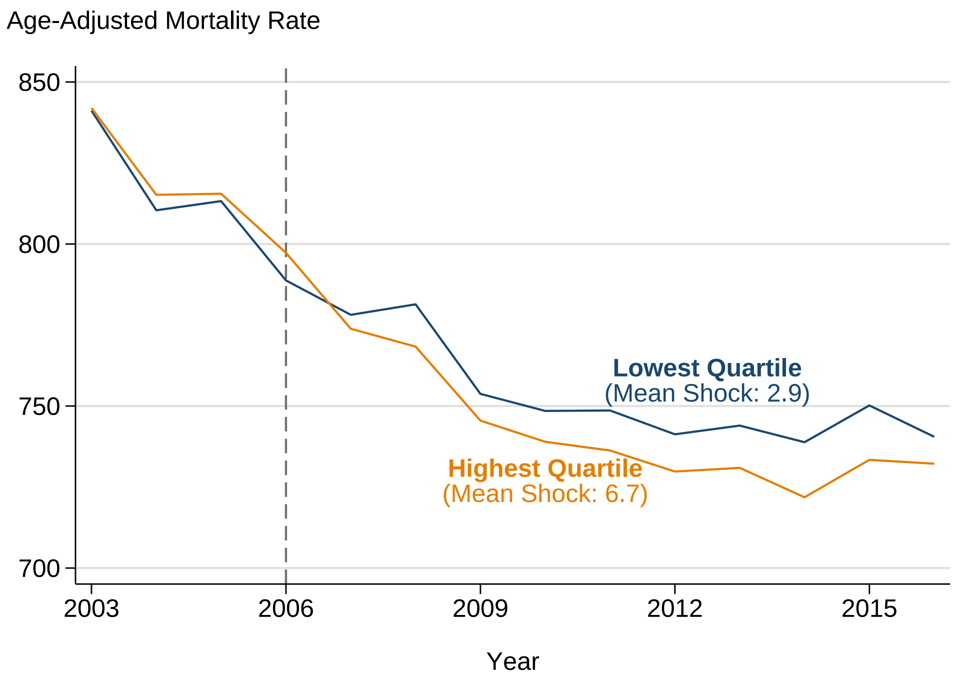


(c) Correlation of Pre-Recession Mortality Rates and Unemployment Shock



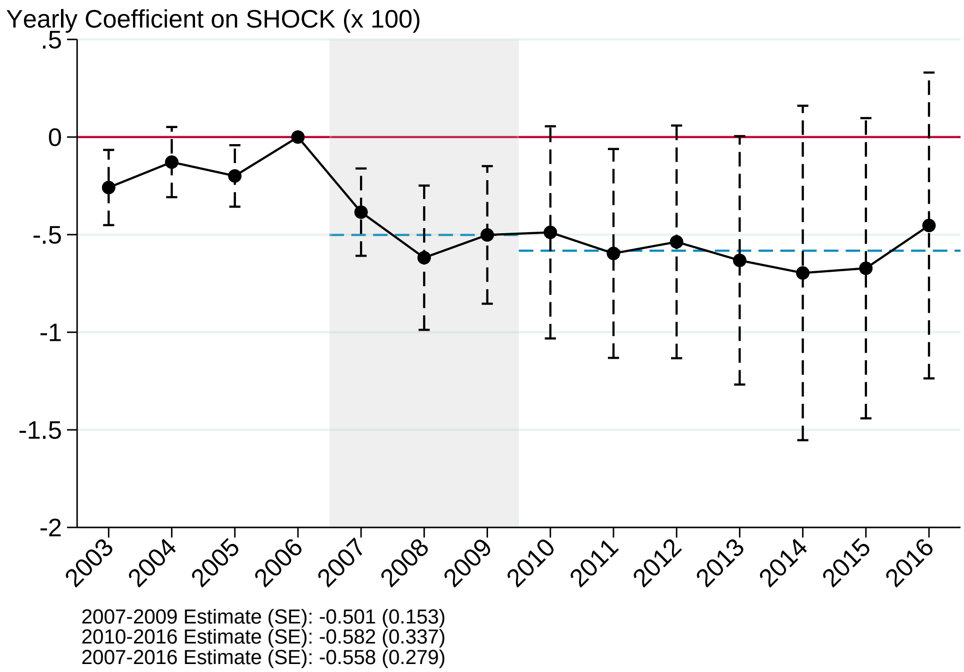
Notes: Figure 1a displays a heat map of the change in Commuting Zone unemployment rates from 2007-2009, drawn from Yagan (2019) and binned into octiles. Figure 1b displays a heatmap of 2006 Commuting Zone age-adjusted mortality rates per 100,000. Colors are assigned according to octiles, with darker orange indicating higher mortality rates. The 2006 CZ population-weighted mean and standard deviation of the unemployment shock and mortality rates are reported in the lower left-hand corner of each figure. N=741 CZs in each heatmap. Figure 1c displays a scatterplot of the 2006 CZ age-adjusted mortality rate against the 2007-2009 change in CZ unemployment rates. Each circle represents one of the 741 CZs. The linear fit between the 2006 mortality rate and the (2006 population weighted) 2007-2009 change in unemployment rate is plotted as a dashed orange line, with the slope and heteroskedasticity robust standard error reported in the top right hand corner of the figure.

Figure 2: Age-Adjusted Mortality Rate by Severity of Unemployment Shock



Notes: Figure displays trends in the (population-weighted) mean age-adjusted CZ mortality rate (per 100,000) over our study period, from 2003-2016. Mean mortality among CZs in the highest population-weighted quartile (N = 125 CZs) of the Great Recession unemployment shock is displayed in orange; the mean among the lowest population-weighted quartile (N=348 CZs) of CZs is displayed in blue. Weights throughout are the 2006 CZ population as estimated in the SEER. The (weighted) mean change in unemployment experienced by the highest quartile of CZs is 6.66 percentage points, and the change experienced by the lowest is 2.89 percentage points.

Figure 3: Impact of Great Recession Unemployment Shock on Log Age-Adjusted Mortality Rate



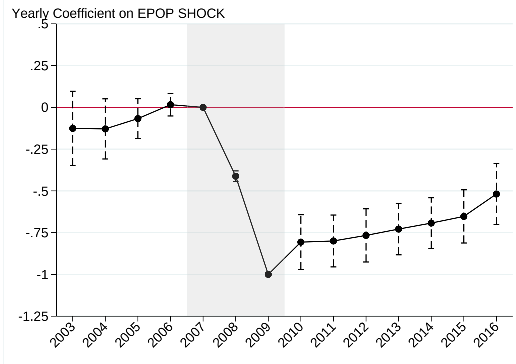
Notes: Figure displays the yearly coefficients β_t (multiplied by 100) from equation (1). The outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000 population. Regression observations are weighted by CZ population in 2006. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the average annual point estimate for the periods 2007-2009 and 2010-2016. These estimates (and corresponding standard errors) are reported in the lower left hand corner along with the corresponding estimate for the entire 2007-2016 period. Standard errors are clustered at the CZ level (N=741 CZs).

Figure 4: Impact on Recession on Mortality, by Rates of Subsequent Recovery (Conditional on Size of Great Recession Shock)

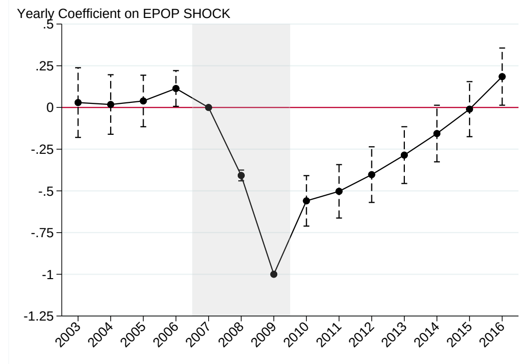
Below Median Recovery | **Above Median Recovery**

EPOP

(a)

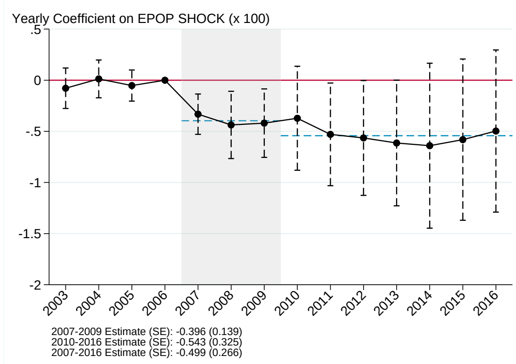


(b)

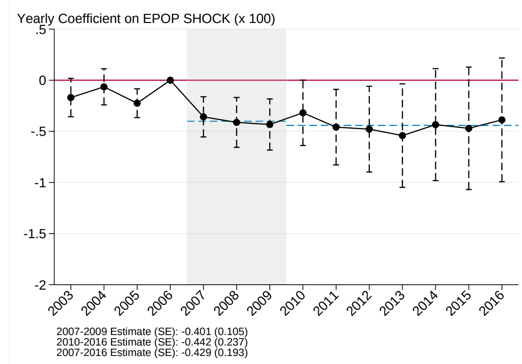


Log Mortality Rate

(c)



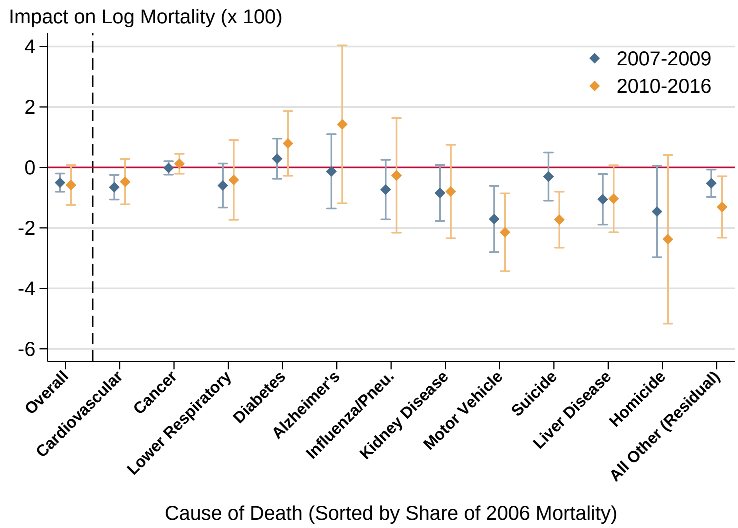
(d)



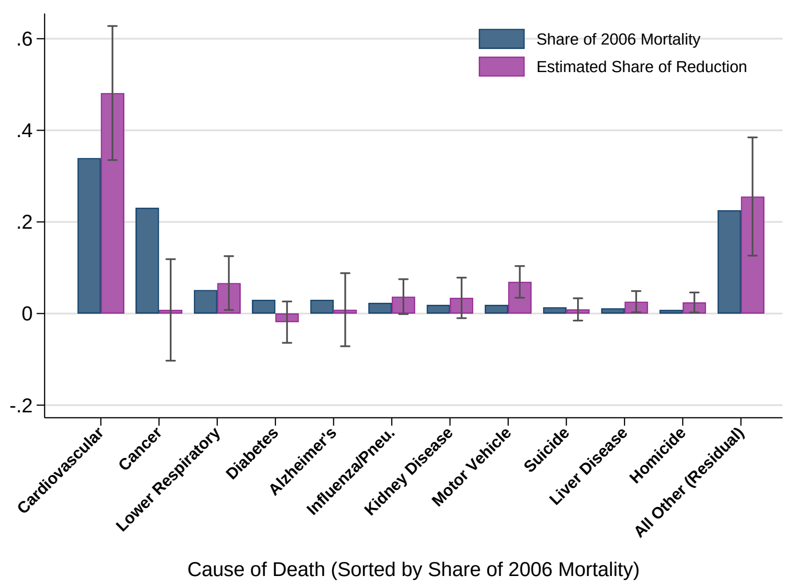
Notes: Figure displays annual coefficients β_{qt} from equation (3) where $\mathbb{1}\left(Recovery_{H(c)}\right)$ is an indicator that CZ c has an above the median 2010-2016 recovery rate among CZs in the same decile of $SHOCK_c$, and $\mathbb{1}\left(Recovery_{L(c)}\right)$ is an indicator that it has a below median recovery. Figures 4a and 4c display estimates for below-median recovery CZs, where the dependent variables y_{ct} are the CZ EPOP and log mortality rate, respectively; Figures 4b and 4d report the same for above-median recovery CZs (again, with the dependent variables as the CZ EPOP and log mortality rate). Coefficients in models of log mortality rates (Fig. 4c and 4d) are multiplied by 100 for ease of interpretation. Estimates of coefficients β_{qt} are weighted by 2006 CZ population. Employment-to-population rate coefficients are normalized to zero in 2007 instead of 2006 to ensure that the 2009 estimate is mechanically negative one. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs in total; 460 are below-median recovery, and 281 are above-median recovery.

Figure 5: Impact of Unemployment Shock on Log Mortality, by Cause of Death

(a) Pooled Estimates



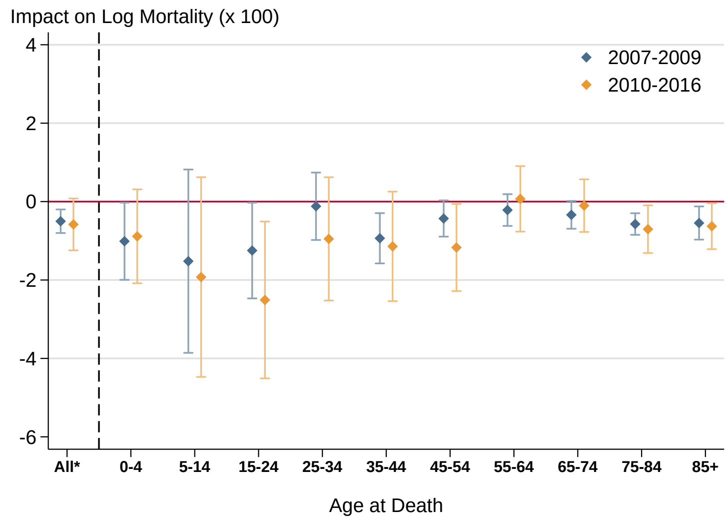
(b) 2007-2009 Decomposition



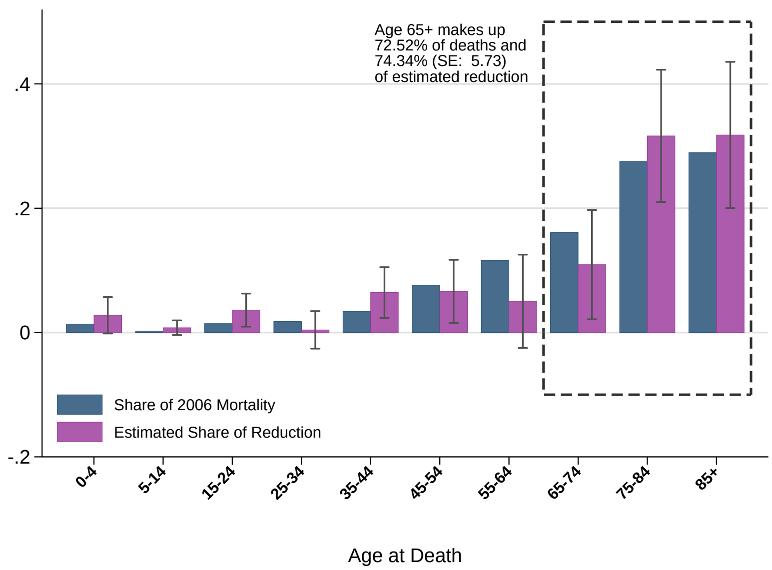
Notes: Figure 5a displays the group-specific 2007-2009 and 2010-2016 averages of coefficients β_{tg} from equation (2), where groups g are defined as the 11 most common causes of death in the ICD10 39-group classification (presented in order of decreasing prevalence), and the final category is a residual category which captures all other mortality. Displayed coefficients are multiplied by 100 for ease of interpretation. All estimates are of the log age-adjusted mortality rate, and weighted by 2006 CZ population from the SEER. Point estimates are displayed as diamonds; vertical bars indicate 95% confidence intervals, clustered at the CZ level. Figure 5b decomposes the contribution of each of these 12 mutually-exclusive and exhaustive cause of death categories to the overall estimated 2007-2009 pooled reduction in mortality (i.e. estimate from Figure 5a). The blue bars indicate each cause of death's share of 2006 mortality. The purple bars present the implied share of the mortality decline accounted for by a given cause of death. To construct these, we multiply each estimated cause-of-death reduction in 2007-2009 by the number of deaths from that cause in 2006, and divide by the sum of all such reduction-death products. Note that the implied "overall" reduction from this exercise is -0.46%, very close to our estimate from Figure 3 of -0.5%. 95% confidence intervals for these estimates, clustered by CZ, are shown as vertical lines. N=741 CZs.

Figure 6: Impact of Unemployment Shock on Log Mortality, by Age

(a) Pooled Estimates



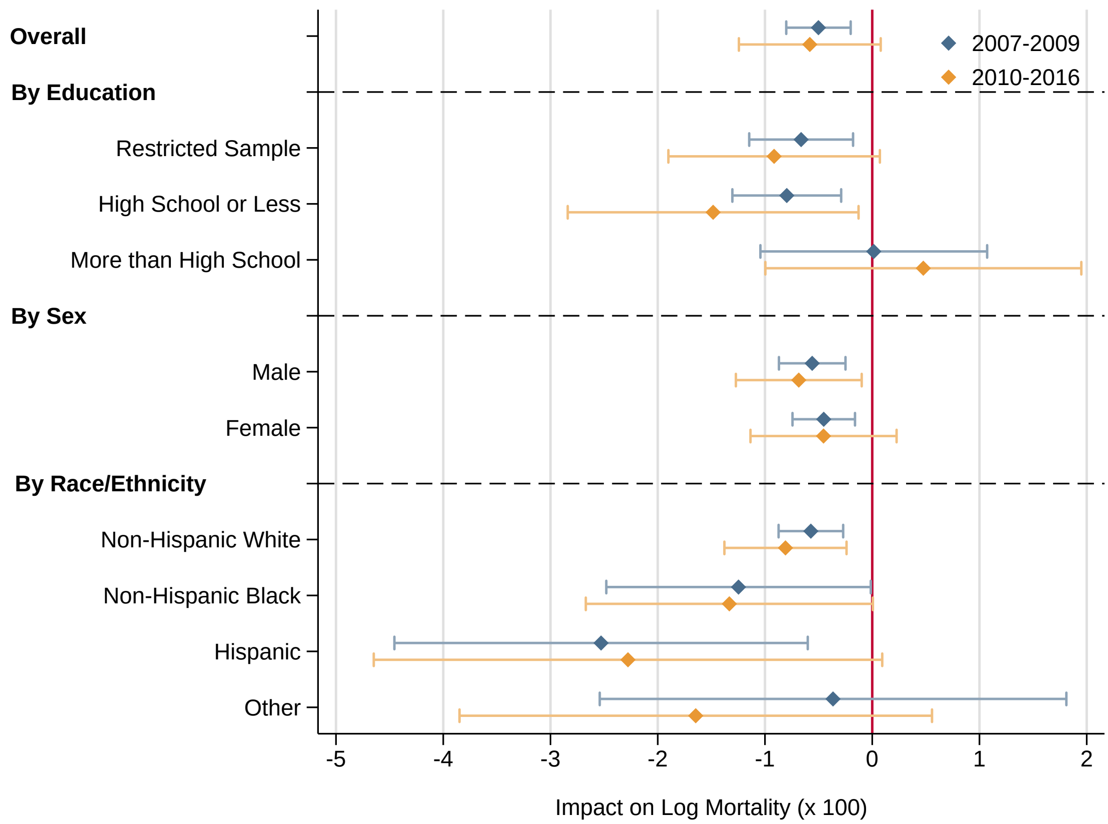
(b) 2007-2009 Decomposition



*"All" Age Group estimate is of log age-adjusted mortality

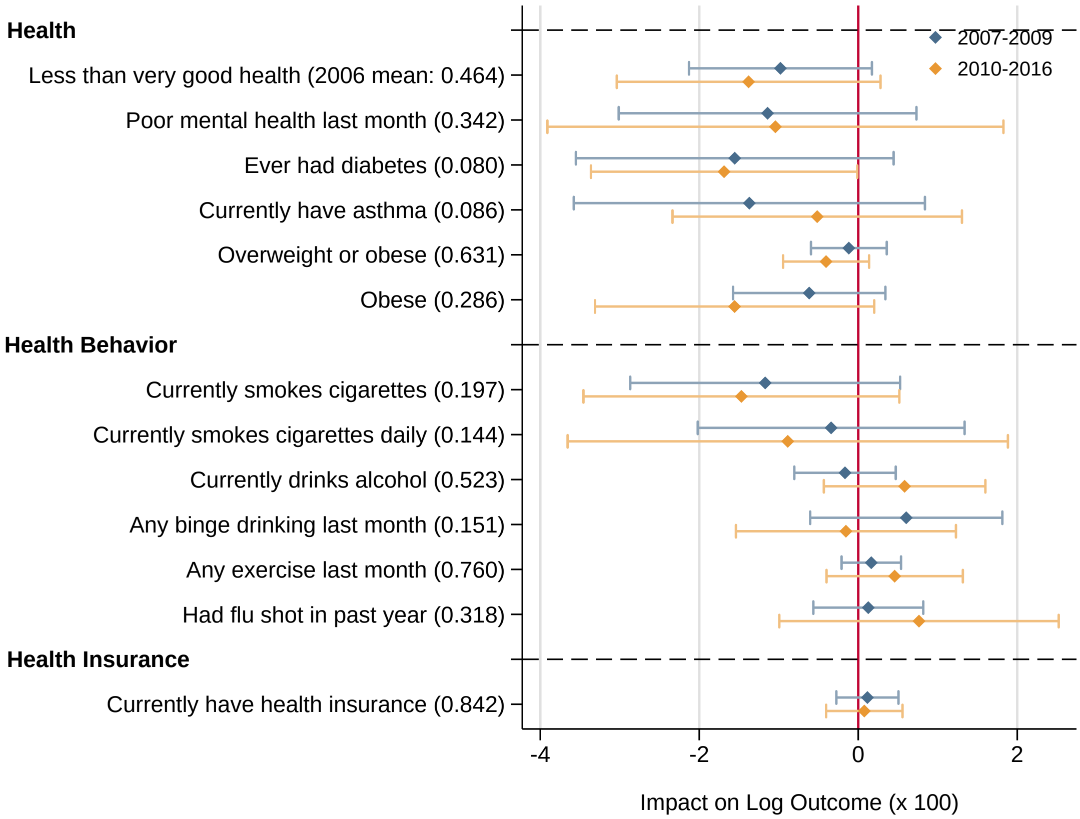
Notes: Figure 6a displays the group-specific 2007-2009 and 2010-2016 average of coefficients β_{tg} from equation (2), where groups g are defined by 10 age groups; the dependent variable is the log mortality rate for a given age group, without any age adjustment. Displayed coefficients are multiplied by 100 for ease of interpretation. All estimates are weighted by 2006 CZ population from the SEER. Period estimates are displayed as diamonds; vertical bars indicate 95% confidence intervals, clustered at the CZ level. Figure 6b decomposes the contribution of each of these 10 age groups to the overall estimated 2007-2009 pooled reduction in mortality (i.e. estimate from Figure 6a). The blue bars indicate each cause of death's share of 2006 mortality. The purple bars present the share of the mortality reduction explained by each age group. We estimate these shares algebraically: For groups i with base period mortality rate r_i, population share w_i, and percent mortality reduction δ_i, the share of the overall mortality reduction contributed by group i is $\frac{r_i w_i \delta_i}{\sum_i r_i w_i \delta_i}$. Age group mortality reductions δ_i are estimated as the period average of the β_{tg} from equation (2), where $Group_g$is one of ten age bins. 95% confidence intervals for these estimates, clustered by CZ, are shown as vertical lines. N=741 CZs.

Figure 7: Impact of Unemployment Shock on Log Mortality, by Education, Sex and Race



Notes: Figure 7 displays the group-specific 2007-2009 and 2010-2016 average of coefficients β_{tg} from equation (2), where the outcome is log age-adjusted mortality and groups g are defined by education, sex, and race categories. Coefficients are multiplied by 100 for ease of interpretation. The top row replicates the baseline estimates for the full sample, weighting by the 2006 CZ population. Impacts by education are estimated on a restricted sample and at the state level, weighting by 2006 state population Impacts by sex and race are estimated at the CZ level, weighting by 2006 CZ population. Horizontal bars indicate 95% confidence intervals, clustered at the CZ level. N=47 states for estimates by education, N=740 CZs for estimates by sex, and N=735 for estimates by race.

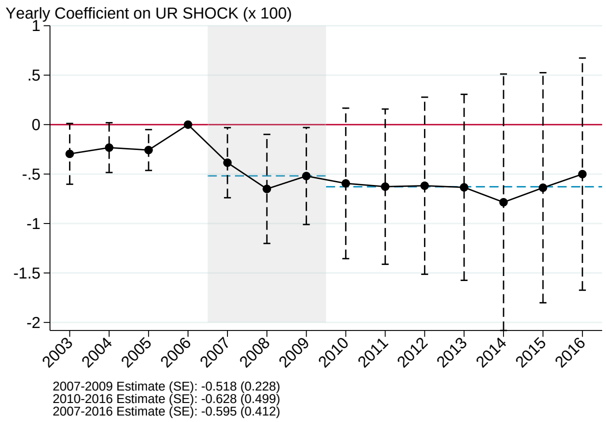
Figure 8: Impact of Unemployment Shock on Self-Reported Health and Health Behaviors



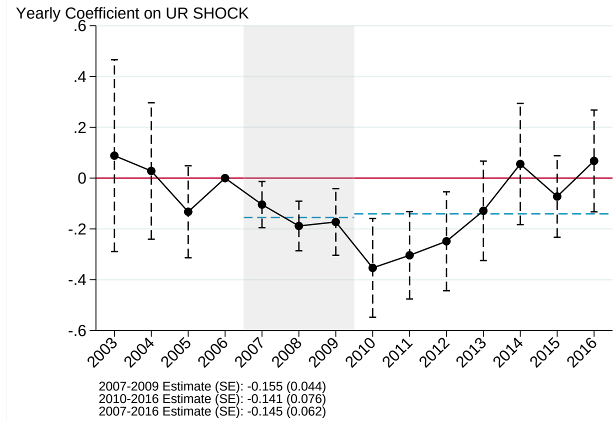
Notes: Figure plots estimates of the impact of the Great Recession unemployment shock on health and health behavior from the 2003-2016 BRFSS. Blue diamond markers indicate 2007-2009 averages of coefficients β_t from equation (1), where the outcome y_{st} is the log share of respondents in each state to whom each row's characteristic applies. Coefficients are multiplied by 100 for ease of interpretation. Orange diamond markers indicate the 2010-2016 averages of β_t from the same regressions. 95% confidence intervals for these period estimates are plotted as horizontal capped bars. State averages are generated as the mean value of individual reports in a given state, weighted by BRFSS survey weights. Estimates are weighted by state 2006 population, and standard errors are clustered at the state level. N=51. The population average of each characteristic in 2006 is noted in parentheses next to each variable label (i.e. 2006 population weighted means of each state estimate). The underlying event studies are shown in Appendix Figures OA.23, OA.33, and OA.34

Figure 9: Impact of Unemployment Shock on Mortality Rate and Pollution

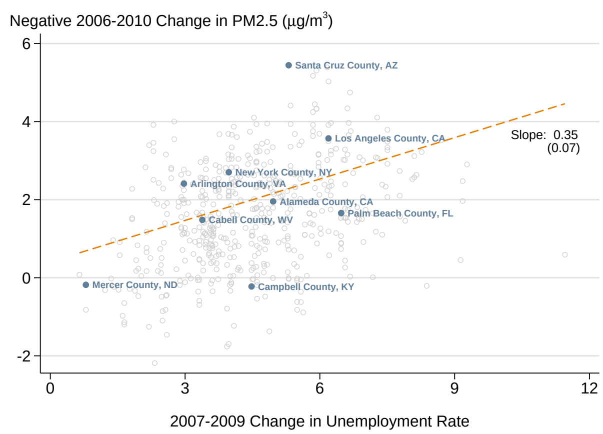
(a) Log Age-Adjusted Mortality Rate



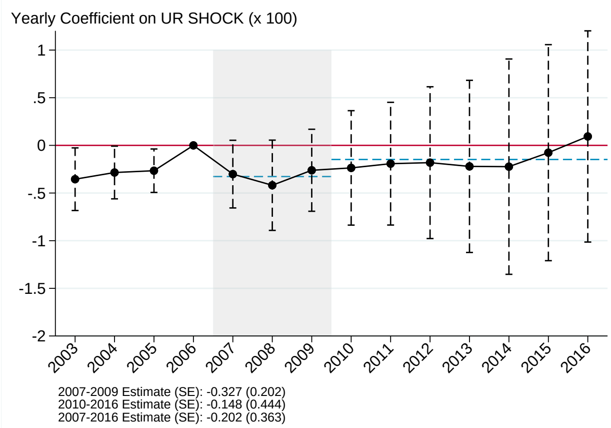
(b) PM2.5 Levels ($\mu g/m^3$)



(c) Correlation of Unemployment and PM2.5 Shock

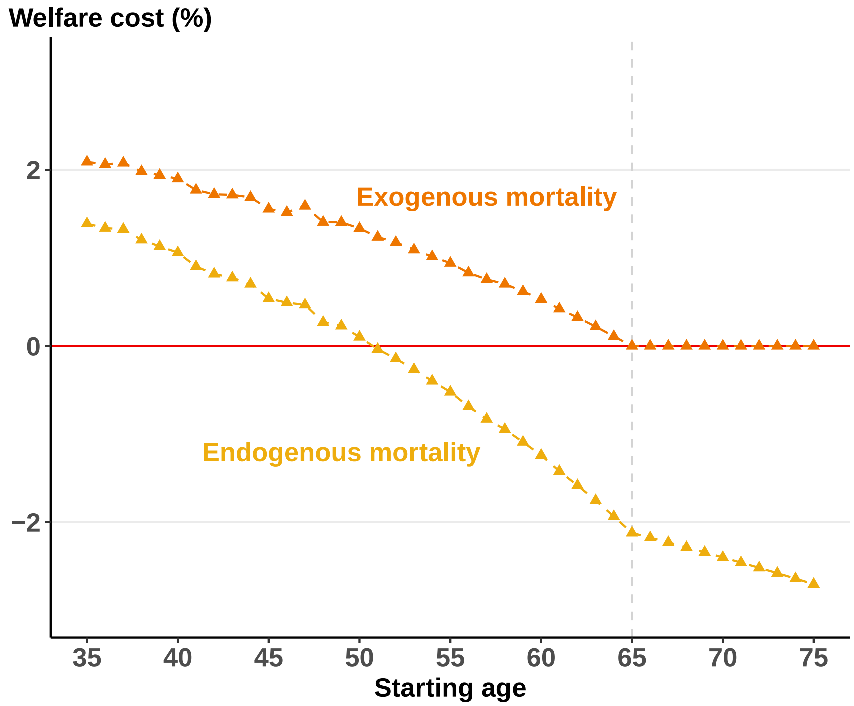


(d) Log Mortality, Controlling for PM2.5 Shock



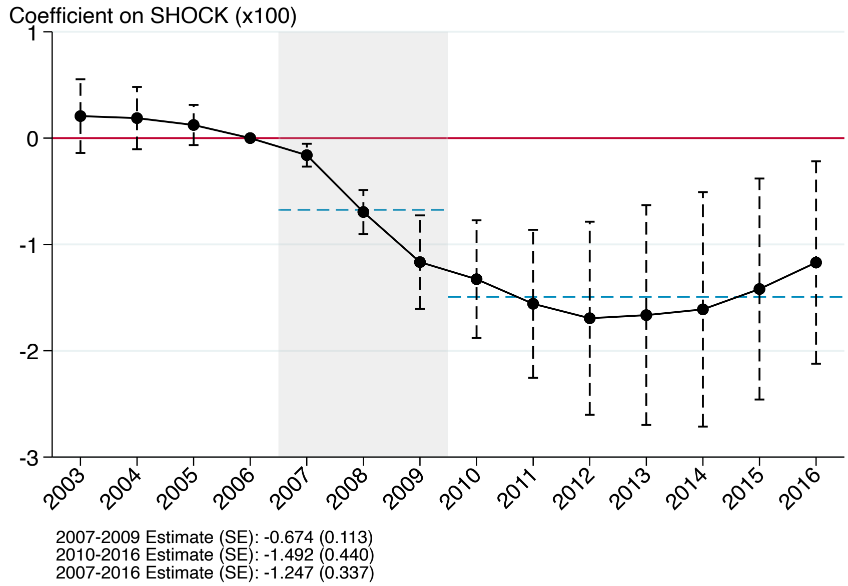
Notes: Panels 9a and 9b display coefficients β_t from equation (8), where the outcome y_{ct} is the log age-adjusted county mortality rate per 100,000 population (Panel 9a) or the annual county PM2.5 level (Panel 9b). Panel 9c scatters the the negative 2006-2010 change in the county PM2.5 level against the 2007-2009 change in CZ unemployment rate for the 542 counties (representing 64.4% of the US population) for which we observe PM2.5 in both 2006 and 2010. The dashed line plots a linear fit, weighted by 2006 county population, with the corresponding slope and standard error to the right side of the figure. Panel 9d plots coefficients β_t and ϕ_t, respectively, from equation (9), where the outcome y_{ct} is the log age-adjusted county mortality rate per 100,000 population. β_t is the coefficient on the 2007-2009 change in the CZ unemployment rate interacted with calendar year, and ϕ_t is the coefficient on the negative 2006-2010 change in PM2.5 interacted with calendar year. Analysis is restricted only to the 542 counties for which we observe a PM2.5 monitor in 2006 and 2010 (i.e. an unbalanced panel). In event study figures across all panels, observations are weighted by county population in 2006. Dashed vertical lines indicate 95% confidence intervals on each coefficient, and horizontal blue dashed lines indicate the average annual point estimate for the periods 2007-2009 and 2010-2016. These estimates (and corresponding standard errors) are reported in the lower left hand corner. Standard errors are clustered at the CZ level. Coefficients on log mortality and their corresponding standard errors are multiplied by 100 throughout for ease of interpretation.

Figure 10: Welfare Costs of Recessions by Age



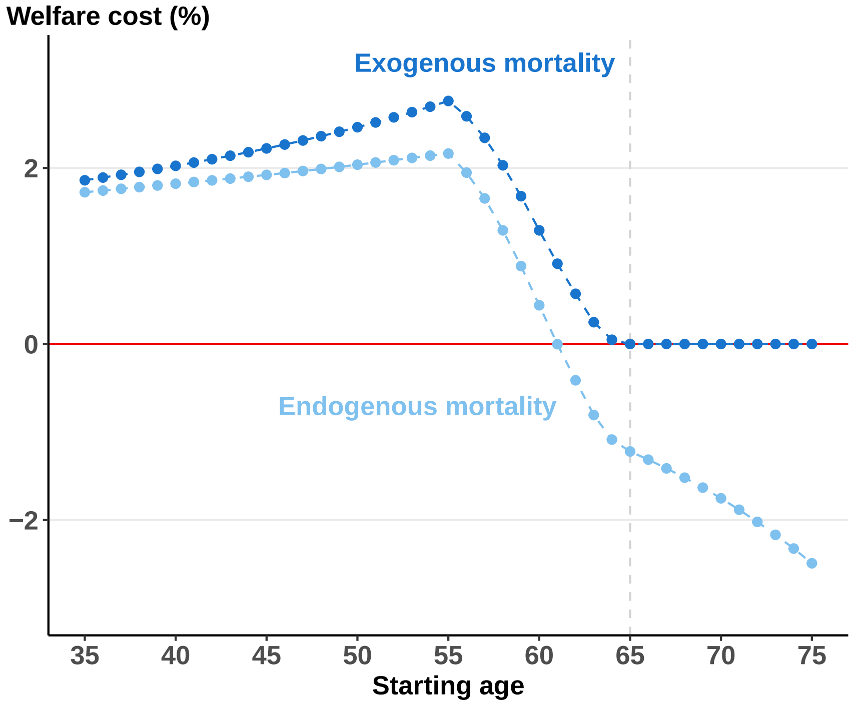
Notes: Figure displays welfare cost of recessions at various ages under exogenous and endogenous mortality. The welfare cost is measured as a percentage of average annual consumption. These estimates assume $\gamma = 2$, and b corresponding to a $VSLY$ of \$250k.

Figure 11: Impact of Unemployment Shock on Log Personal Consumption Expenditure Per Capita



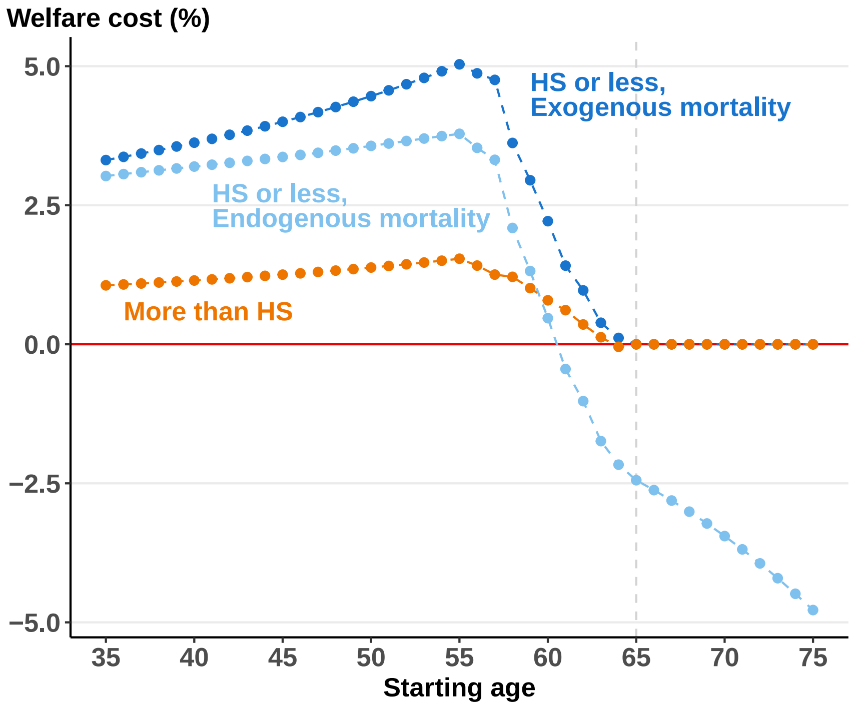
Notes: Figure 11 plots coefficients β_t from estimating equation (1) at the state level, where the right hand independent variable is the 2007-2009 change in the state unemployment rate and the outcome y_{ct} is the log state personal consumption expenditure per capita, inflation-adjusted to 2012 dollars. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the average annual point estimate for the periods 2007-2009 and 2010-2016. These estimates (and corresponding standard errors) are reported in the lower left hand corner along with the corresponding estimate for the entire 2007-2016 period. Standard errors are clustered at the state level. N=51 states.

Figure 12: Welfare Costs of the Great Recession by Age



Notes: Figure displays welfare cost of the Great Recession at various ages under exogenous and endogenous mortality. The welfare cost is measured as a percentage of average annual consumption. These estimates assume $\gamma = 2$, and b corresponding to a $VSLY$ of \$250k.

Figure 13: Welfare Costs of the Great Recession by Age and Education



* For "more than HS" , the estimates with exogenous and endogenous mortality are visually indistinguishable.

Notes: Figure displays welfare cost of the Great Recession at various ages under exogenous and endogenous mortality regimes for different education groups: those with a High School (HS) diploma or less, and those with more than HS diploma. The welfare cost is measured as a percentage of average annual consumption. These estimates use group-specific consumption and mortality effects of the Great Recession, as well as group-specific mortality rates, and assume $\gamma = 2$, and b corresponding to a $VSLY$ of \$250k.

Tables

Table 1: Impact of Unemployment Shock on Mortality and Life-Years Lost (2007-2009 Period Estimates)

		Life-Years Lost Regressions			
	Medicare Repeated Cross Section (TM in $t-1$)	No Covariates (TM in $t-1$)	Age (TM in $t-1$)	Age + Demographic (TM in $t-1$)	Age + Demographic + Chronic Conditions (TM in $t-1$)
	(1)	(2)	(3)	(4)	(5)
Great Recession Shock	-29.1	-320.5	-205.6	-201.4	-162.4
	(12.4)	(131.4)	(97.1)	(96.8)	(79.7)
Mean Mortality Rate (per 100,000)	5332.6	NA	NA	NA	NA
Mean LYL per Decedent	NA	11.00	7.87	7.74	6.45
Observations	738	738	738	738	738

Notes: This table displays the point estimate for the linear combination of yearly coefficients from 2007-2009; estimates are based on coefficients β_t from equation (1). In column (1), the dependent variable is the (not age-adjusted) mortality rate per 100,000 among the 65+ population, using Medicare data. In the life-years lost regressions in columns (2)-(5), the dependent variable is CZ-year level life-years lost LYL_{ct}. Life years lost is defined as $LYL_{ct} = 100,000 * \frac{\sum_{i \epsilon S_{ct}} LYL_{it}}{|S_{ct}|}$, in which S_{ct} denotes the set of individuals in CZ c and year t. Great Recession shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. CZ observations are weighted based on 2006 SEER data. Regressions are calculated with standard errors clustered by CZ; standard errors are reported in parentheses below each period estimate. Medicare beneficiaries are subject to the restrictions in Table OA.2. Life-years lost regressions are based on the Repeated Cross Section (TM in $t-1$) sample, which further restricts patient-years in 2003-2016 to those that were enrolled in Traditional Medicare (TM) in the previous year. CZs are restricted to those with at least one beneficiary in every year in the 2003-2016 period, which restricts to 738 CZs.

Table 2: Sensitivity to Current vs. 2003 Location

Regression Specification	2007-2009 Period Estimate	2010-2016 Period Estimate	2007-2016 Period Estimate
2003 Residence (Reduced Form) (π_t^{RF}, eq. 4)	-0.347	-0.268	-0.292
	(0.157)	(0.234)	(0.203)
First Stage (π_t^{FS}, eq. 5)	0.945	0.916	0.925
	(0.003)	(0.005)	(0.004)
Control Function (β_t, eq. 6)	-0.369	-0.325	-0.338
	(0.165)	(0.251)	(0.223)
Yearly Residence (β_t, eq. 7)	-0.511	-0.531	-0.525
	(0.162)	(0.242)	(0.211)
Yearly Residence (Non-Movers) (β_t, eq. 7)	-0.558	-0.664	-0.632
	(0.179)	(0.245)	(0.218)

Notes: This table displays the point estimate and standard errors (in parentheses) for the linear combination of yearly coefficients from 2007-2009, 2010-2016, and 2007-2016; estimates are based on coefficients β_t from equation (4) (for the reduced form specification), coefficients β_t from equation (6) (for the control function specification), and coefficients β_t from equation (7) (for yearly residence specifications), with outcome $log(m_{it}(a))$ defined as the log of the individual-level hazard rate at age a. Estimates are also based on coefficients π_t^{FS} from equation (5) (for the first stage regression), with outcome defined as the sum of the interactions of GR shock based on yearly CZ of residence and yearly dummies. Shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. Standard errors are clustered at the CZ level, except for Control Function standard errors which are calculated by performing a Bayesian bootstrap of the two-stage procedure with 500 repetitions so that first-stage residuals are redrawn for every re-weighted sample. The sample is all 2003 Medicare beneficiaries, subject to the restrictions in Table OA.1. N = 6,638,488. N(non-movers) = 5,841,523.

Table 3: Sensitivity Analysis

	(1) 2007-2009 Period Estimate	(2) 2010-2016 Period Estimate	(3) 2007-2016 Period Estimate
Baseline	-0.501	-0.582	-0.558
	(0.153)	(0.337)	(0.279)
Panel A: Geography			
State	-0.619	-0.839	-0.773
	(0.245)	(0.500)	(0.418)
County	-0.489	-0.590	-0.560
	(0.095)	(0.211)	(0.172)
Panel B: Functional Form			
Mortality Rate in Levels	-3.721	-3.940	-3.874
	(1.022)	(2.045)	(1.706)
Add Census-Division-by-Year Effects	-0.384	-0.339	-0.353
	(0.135)	(0.277)	(0.229)
Shock in Quartiles			
Second Quartile Indicator (Mean Shock: 4.00)	-1.063	-2.008	-1.725
	(0.435)	(1.250)	(0.986)
Third Quartile Indicator (Mean Shock: 5.18)	-1.255	-1.898	-1.705
	(0.464)	(1.108)	(0.887)
Fourth Quartile Indicator (Mean Shock: 6.66)	-2.309	-3.149	-2.897
	(0.662)	(1.598)	(1.301)
Panel C: Sample			
Drop the Top/Bottom Decile of Shocked CZs	-0.785	-1.037	-0.961
	(0.264)	(0.676)	(0.546)
Drop the 10 Most Populous CZs	-0.516	-0.624	-0.592
	(0.103)	(0.195)	(0.163)

Notes: Table displays estimates of one-off deviations from equation (1). Columns (1), (2), and (3) display averages of coefficients β_t across 2007-2009, 2010-2016, and 2007-2016, respectively. Standard errors for the period are displayed below each period estimate in parentheses. The first row displays our main baseline estimate, from Figure 3. In Panel A when we estimate equation (1) at the state and county level, the Great Recession shock also defined as the 2007-2009 change in the state or county unemployment rate. When we replace the linear $ShOCK_c$ variable with indicator for the quartile of the shock, we estimate the equation $y_{ct} = \sum_{j=2}^{4} \beta_t^{(j)} \left[SHOCKQ_c^{(j)} * \mathbb{1}(Year_t)\right] + \alpha_c + \gamma_t$, where e.g. $SHOCKQ_c^{(k)}$ is an indicator for the kth quatile of the 2006 CZ population-weighted CZ unemployment rate shock; we omit the 1st quartile (with a mean shock of 2.89) and report estimates of $\beta_t^{(2)}$, $\beta_t^{(3)}$, and $\beta_t^{(4)}$. All estimates except those in Panel A are weighted by 2006 CZ population as estimated from the SEER, with standard errors clustered at the CZ level; Panel A estimates are weighted by state and county populations, with standard errors clustered at the same level. N=741 for CZ estimates; N=51 for state analysis; N=3,101 for county analysis.

Table 4: Impact of Great Recession Unemployment and Pollution Shocks on Log Mortality

	(1) 2007-2009 Period Estimate	(2) 2007-2009 Period Estimate	(3) 2007-2009 Period Estimate
Unemployment Shock	-0.518		-0.327
	(0.228)		(0.202)
PM2.5 Shock		-0.665	-0.541
		(0.195)	(0.170)

Notes: Table displays the average annual impact of the Great Recession unemployment and/or PM2.5 pollution shock on log age-adjusted mortality over 2007-2009. The unemployment shock is the 2007-2009 change in the CZ unemployment rate, and the PM2.5 shock is defined as the negative of the county-level change in PM2.5 level between 2006 and 2010. Columns (1) and (2) report the 2007-2009 average of the β_t's from equation (8), where $SHOCK_c$ is defined as either the CZ unemployment or county pollution shock. Column (3) reports the 2007-2009 average of β_ts and ϕ_ts from equation (9). Standard errors, clustered at the CZ level, are reported in parentheses below each period estimate. Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation. Analysis is restricted to the 524 counties for which we observe a PM2.5 monitor in both 2006 and 2010.

A Appendix

A.1 Expert Survey

We designed and implemented a survey of experts to assess their priors on the direction and magnitude of change in the average annual U.S. mortality rate due to the Great Recession. The survey was hosted on Qualtrics and publicized via three channels: (i) a personalized email from co-author Matthew Notowidigdo, (ii) Twitter posts, and (iii) the Social Science Prediction Platform. Notowidigdo sent a personalized email to each of the NBER affiliates in the Health Care, Health Economics, Economic Fluctuations and Growth, and Labor Studies programs (737 total). Notowidigdo also advertised the survey on Twitter, particularly targeting users identifying as experts in healthcare, labor markets, macroeconomics, public health, epidemiology, or medicine.

Anonymous survey responses were collected with IRB approval (MIT COUHES protocol E-4838) between March 29 and April 11, 2023. In total, we received 249 responses from the NBER group, 126 responses from Twitter, and 5 responses from the Social Science Prediction Platform.

Survey Design. The survey first asked for educational background and field of research or specialization. After providing information of the magnitude of the change in the aggregate U.S. unemployment rate during the Great Regression (i.e., "The aggregate U.S. unemployment rate increased by 4.6 percentage points from 2007-2009."), we elicited a multiple-choice prediction of whether the Great Recession increased, decreased, or did not impact the average annual mortality rate in the United States from 2007–2009. We then asked respondents for their predicted magnitude of the percent change in the annual mortality rate from 2007 to 2009 caused by the Great Recession. Finally, we elicited a multiple-choice prediction of whether the Great Recession increased, decreased, or did not impact the average annual mortality rate in the United States from 2007–2009 separately for three age bins: individuals aged 0–24, 25–64, and 65 and above. After this, we posed several free-response questions. First, we asked (in a free response box) what factors had influenced the respondent's predictions. We also asked respondents to indicate whether they had heard or seen any results from our study before the time of response, so we could exclude responses of participants with prior knowledge of our paper from our analysis. Respondents were finally invited to note any outstanding questions, comments, or suggestions.

Analysis Sample. We discarded 17 responses with no prediction for the direction of change in mortality, as well as 9 responses from participants who indicated that they were aware of early-stage results from our paper. The remaining analysis sample consisted 354 responses: 237 NBER responses, 112 Twitter responses, and 5 Social Science Prediction Platform responses. Of these respondents, 56% self-identified as health economists, 20% as macro-economists, and 25% as other economists or researchers. Approximately 84% of respondents identified as faculty or post-doctoral researchers.

Of the 354 responses, 317 responses provided a guess for the magnitude of change. For the quantitative results pertaining to the magnitude and direction of change, we trimmed this sample of 317 respondents by dropping the responses with a prediction in the top 5% or bottom 5%, for a sample of 287.

Results. Figure OA.39 shows the distribution of the direction of change in mortality rates predicted by respondents in the analysis sample. Panel OA.39a indicates that nearly half of all respondents predicted an increase in mortality, while Panel OA.39c shows differences in the predicted direction of change by age group. Panel OA.39d shows heterogeneity in predictions by respondent subfield: macroeconomists are more likely to predict an increase than health economists.

Figure OA.39b describes the distribution of the predicted direction and magnitude of change in the cumulative distribution function. We find that 98% of respondents provided a predicted impact on mortality larger than our (negative) point estimate, and 86% provided a prediction above our confidence interval.

A.2 Mortality Data

CDC Data. The CDC mortality data are derived from state death certificates which in turn are completed by physicians, coroners, medical examiners, and funeral directors (Office of Disease Prevention and Health Promotion n.d.). Information on how to apply for the CDC restricted-use microdata is available at `https://www.cdc.gov/nchs/nvss/nvss-restricted-data.html`.

These microdata offer several key advantages over the publicly-available CDC mortality data, which can be found at `https://wonder.cdc.gov/wonder/help/ucd.html`. In particular, the public data report only coarse age bins, do not allow an analysis of mortality for combinations of sub-groups (e.g. certain causes of death within a certain age group), omit certain demographics such as education, and suppress mortality information for cells with less than 10 deaths; this threshold can prevent the publication of county data for groups with low mortality rates (e.g. younger individuals), or small population shares (e.g. less common causes of death or demographic groups). We confirmed that we can replicate our aggregate findings in the public-use data.

To turn the death counts in the CDC microdata into mortality rates, we use population data from the National Cancer Institutes Surveillance Epidemiology and End Results (SEER) program. More information about these data can be found here: `https://seer.cancer.gov/popdata/`. The SEER population estimates are a modification of the US Census Bureau's intercensal population estimates. As noted by e.g., Ruhm (2015), they are designed to provide more accurate population estimates for intercensal years. In practice, we have verified that our results are not sensitive to our choice of the SEER or Census population measure.

Medicare data. We use the Medicare data to analyze mortality for the near-universe of Americans 65 and over. Although the data also contain information on under 65 Medicare enrollees, in particular recipients of Social Security Disability Income (SSDI), we exclude these individuals from our analysis since both the number and composition of SSDI recipients change during recessions (Carey et al. 2022).

The death records that we use in the Medicare data come primarily from the Social Security administration. Specifically, we use the mortality information in the Master Beneficiary Summary File. More information on the source of the mortality data on this file can be found in Jarosek (2022). The Social Security Administration in turn receives death reports directly from most sources, "including family members, funeral homes, financial institutional, postal authorities, States and other Federal agencies" (Social Security Administration 2023).

A.3 Predicting Remaining Life Expectancy

The rich, detailed information on individual demographics and health conditions in the Medicare data allow us to estimate a mortality model and use it to generate predicted counterfactual remaining life expectancy for each decedent in our data. Specifically, in addition to age, race and sex, the Medicare data contain measures of individual health conditions derived from health diagnoses recorded in claims data.[86]

To estimate remaining life expectancy, we follow the standard approach in the literature (e.g. Olshansky and Carnes 1997; Chetty et al. 2016; Finkelstein et al. 2021), and adopt a Gompertz specification in which the log of the mortality hazard rate for individual i in year t ($\log(m_{it})$) is linear in age a:

$$log(m_{it}(a)) = \rho a + \beta X_{i(t-1)} + \epsilon_{it} \tag{20}$$

We estimate this prediction model on the mortality experience of 2002 Medicare enrollees who were also enrolled in Traditional Medicare (Part B) in 2001. We do so for three different definitions of $X_{i(t-1)}$: (i) no covariates (i.e. only age), (ii) demographic covariates (race, sex), and (iii) demographic covariates plus chronic condition indicators, where we restrict our attention to the 20 chronic conditions that have a look-back period of one year. We also specify a prediction model with constant remaining life expectancy, which we set to the average of 2002 enrollees' predicted remaining life expectancies in the specification with no covariates (only age).

We then use the estimates from equation (20) to predict remaining life expectancy for each patient-year in the sample from 2003-2016 where, recall, the sample is limited to individuals who are alive at the beginning of the year and were on Traditional Medicare for all months of the previous year. Specifically, given the Gompertz assumption, we can estimate remaining life expectancy conditional on being alive at age $a = A_o$ as:

$$LE_{it} = \int_{A_o}^{\infty} exp[\frac{e^{\beta X_{i(t-1)}}}{\rho} * (e^{\rho a} - e^{\rho A_0})]da \tag{21}$$

A.4 BRFSS Data Description

The Behavioral Risk Factor Surveillance Survey is an annual telephone survey administered to approximately 400,000 individuals age 18 or older across the United States. The survey modules elicit demographic information and responses to a series of questions covering self-reported health, health behavior, and health care access. These data are collected by state departments of health in coordination with the CDC. Survey questions are divided between core modules (which are in principle always asked) and optional modules (which may or may not be asked, according to state discretion). The BRFSS is designed to produce representative estimates of these responses at the state level. Initial sampling is conducted via random digit dialing and each data release includes post-stratification weights.

We analyze the BRFSS sample from 2003-2016. For each variable of interest, we generate the state-year mean according to the BRFSS final respondent weights. Our analysis then proceeds at the state-year level, weighting estimates by the 2006 SEER state population. (Note that the core questionnaire was not asked in Hawaii in 2004; otherwise, our BRFSS sample includes all 50 states and the District of Columbia.)

[86] As documented by Song et al. (2010) and Welch et al. (2011), these claims-based measures of health reflect both the enrollee's underlying health as well as a large measurement error component that varies systematically by place, as places that tend to treat patients more aggressively are also more likely to diagnose and record underlying conditions. However, since our analysis looks at within-area differences in the impact of the Great Recession by measured health, such place-specific measurement error is unlikely to bias our analyses.

The BRFSS methodology was refined in 2011 to incorporate reports from cell phone users and to improve survey weighting. While this change increased the reach and representation of the survey, it also generates a potential confound when comparing raw survey tabulations from before and after the 2011 adjustment. For several variables (share who smoke or drink; share with very good or excellent health; share obese) we observe these changes reflected as sharp, though generally small, changes in the aggregate time series from 2010-2011. However, our empirical approach includes year fixed effects which should take a first step towards mitigating these effects, and we are comforted by the observation that our event study results do *not* include similar discrete jumps at 2011.

A.4.1 BRFSS Variable Definitions

Our analyses examine several BRFSS measures of self-reported health, health behavior, and health care. We describe each self-report and (if necessary) our modifications in detail below:

- **Poor subjective health:** We construct an indicator for whether the respondent describes their current state of health less than "Very Good" or "Excellent" (i.e. "Good", "Fair", or "Poor").

- **Mental health:** We construct an indicator for whether the respondent reports any days out of the past 30 in which their "mental health, which includes stress, depression, and problems with emotions," was not good

- **Ever had diabetes:** Respondents report whether a doctor has ever told them that they have diabetes.

- **Currently have asthma:** Respondents report whether a doctor has ever told them that they have asthma. If they respond affirmatively, they are subsequently asked if they still have asthma. We define "currently having asthma" as an affirmative response to both questions (i.e. we define this variable as zero for both individuals who have never had asthma and those who were previously diagnosed but do not currently have asthma).

- **Weight:** From respondent self-reported height and weight, the BRFSS constructs BMI (as weight in kilograms divided by the square of height in meters). Following BRFSS documentation, we define individuals as overweight or obese if they have a BMI greater than or equal to 25, and as obese if they have a BMI greater than or equal to 30.

- **Currently smoke/smoke daily:** Respondents are asked if they have smoked at least 100 cigarettes before in their life. If they respond affirmatively, they are asked if they currently smoke every day, some days, or never at all. From these two questions, the BRFSS defines an indicator for whether the respondent currently smokes cigarettes (i.e. every day or some days, vs. not smoking). From the same set of questions, we define "smokes daily" as an indicator for whether the respondent smokes every day (unconditionally—i.e. smoking daily instead of some days or never).

- **Currently drink/binge drinking:** We report an indicator for whether individuals currently drink (alcohol), which corresponds to a question in the BRFSS asking whether respondents have had any alcoholic beverage in the past 30 days. Respondents are subsequently asked how many times in the past 30 days they have consumed at least five drinks (for men) or four drinks (for women). The BRFSS then constructs an indicator for binge drinking in the past month, defined as one for a positive response to having 4/5 or more drinks at a time in the past month and as zero for individuals who have not (whether they report any alcohol consumption or not).

- **Exercise:** We lift directly from the BRFSS a question asking whether respondents "participate[d] in any physical activities or exercises such as running, calisthenics, golf, gardening, or walking for exercise" during the past month.

- **Flu shot:** Similarly, respondents report whether they had a flu shot in the past 12 months, and we lift this variable directly.

- **Health insurance:** We define currently having health insurance as an affirmative response to "Do you have any kind of health care coverage, including health insurance, prepaid plans such as HMOs, or government plans such as Medicare?" This question is asked of all respondents.

A.5 Analysis of Health and Retirement Study Data

A.5.1 Data and Sample

The Health and Retirement Study (HRS) of the University of Michigan is an ongoing longitudinal study of individuals in the United States born between 1924 and 1965. The HRS is sponsored by the National Institute on Aging (grant number NIA U01AG009740) and is conducted by the University of Michigan. Survey respondents are divided into cohorts based on the year in which they were first interviewed; the HRS began interviewing cohorts in 1992 and has added additional cohorts four times since, in 1998, 2004, 2010, and 2016. Households are sampled according to a multi-stage area-probability sampling procedure which first draws Primary Sampling Units (metropolitan areas, counties, or groups of counties), census divisions within these units, and then households from within those divisions (Lee et al. 2021). Over the survey's history, eligibility has been determined by screeners of housing units, the Medicare enrollment files, or some combination of the two (HRS Staff 2011). The HRS over-samples Hispanic and Black individuals as well as residents of Florida.

The HRS interviews these sampled respondents and their spouses/partners (if applicable), regardless of whether spouses are themselves age-eligible. Each interview covers demographic, financial, health, cognitive, housing, employment, and insurance data for respondents, their households, and their spouses. Our data comes from the RAND HRS Longitudinal File, a dataset based on the HRS core data. This file was developed at RAND with funding from the National Institute on Aging and the Social Security Administration.

We obtained access to a restricted-use version of the HRS that allows us to observe state of residence for interviews conducted bi-annually between 2002 and 2014. Our analyses therefore focuses on a bi-annual, repeated cross-section of HRS respondents from 2002-2014. We restrict each year's sample to respondents from households where both the respondent and their spouse (if present) are at least 65 years old in that year. Note that this permits individuals to "age in" to the sample, even if they were previously interviewed for the HRS and would have been excluded based on this age criteria. We do not consider households interviewed outside of the 50 US states and the District of Columbia.

A.5.2 HRS Variable Definitions

We analyze four measures of home care in the HRS: (1) the number of individuals from whom respondents report receiving help with their activities of daily living (ADLs), instrumental activities of daily living (IADLs), or managing their finances; and indicators for whether respondents report any such helpers, whether (2) paid, (3) unpaid, or (4) either.

Respondents in the HRS are first asked whether they have ever received help with ADLs, IADLs, or finances during any period and, if affirmative, they are asked who helped them. In a separate section of the survey, respondents are then asked for details about each of these helpers, including the frequency of help in the past month and whether each helper was paid in the past month, except those who are employees of institutions. RAND then takes this "helper list" and computes the number of helpers as the number of individuals on the helper list who helped in the past month and are not employees of institutions (because the "number of employees of an institution cannot be accurately counted due to the nature of institutional care" (Bugliari et al. 2022)).

The RAND HRS Longitudinal File reports directly the number of helpers each respondent reports in the past month (including zero) and the number of helpers who were paid (again including zero). From these reports, we additionally define *any helpers* as an indicator for whether the number of helpers is non-zero or zero; *any paid helpers* as an indicator for whether the number of *paid* helpers is non-zero or zero; and *any unpaid helpers* as an indicator for whether the number of helpers is (strictly) greater than the number of paid helpers.

Note that the mean number of helpers in the past month across respondents in 2006 is 0.29. 17% of the sample reports any help in the past month, 16% of the sample reports any unpaid helpers, and 4% of the sample reports any paid helpers.

A.5.3 Estimation and Results

We estimate a variant of our baseline estimating equation (1), where the unit of observation is now the individual, the Great Recession Shock is measured at the state level, and the data include even years only between 2002-2014 (as we are only able to match respondents to their state, not CZ, and the HRS is only administered every two years). Specifically, we estimate (for continuous outcomes):

$$y_{it} = \beta_t[SHOCK_{s(i,t)} * \mathbb{1}(Year_t)] + \alpha_{s(i,t)} + \gamma_t + \epsilon_{it} \tag{22}$$

where $s(i,t)$ indexes the state of respondent i in year t, observed from 2002-2014, and y_{it} is respondent i's report of e.g. the number of individuals who helped them last month. $SHOCK_{s(i,t)}$ denotes the 2007-2009 change in the state unemployment rate in state $s(i,t)$.

When we then turn to binary outcomes (e.g. any helpers in the past month), we instead estimate a logistic regression model of the form:

$$ln\left(\frac{P(y_{it}=1)}{1-P(y_{it}=1)}\right) = \beta_t[SHOCK_{s(i,t)} * \mathbb{1}(Year_t)] + \alpha_{s(i,t)} + \gamma_t + \epsilon_{it} \tag{23}$$

As before, we report β_t in our coefficient plots (not the odds ratios e^{β_t}).

We estimate the analysis at the individual level since the means of many of these variables at the state-year level would be zero, complicating a log specification. We weight each estimate by the HRS respondent weights,[87] and cluster standard errors at the state level.

[87] These person-level weights are designed to align the HRS waves with population estimates from the American

Appendix Figure OA.40 displays the results. It shows no evidence of an impact of the Great Recession on any of these care measures.

A.6 Mortality Impacts by Education

The NCHS mortality data contain information on education which we can use to obtain the number of deaths in each education-age-location-year bin. However, the SEER population data do not contain population counts by education. To construct the population denominator for mortality impacts by education, we therefore turn to the American Community Survey (ACS). The ACS is sent by the U.S. Census Bureau to approximately 3.5 million U.S. households each year, and it collects information including participants' age, years of education, and location. Since we use the publicly available ACS data, the only non-suppressed location variable is each individual's state of residence; as a result, we conduct the analysis by education at the state level, using ACS data from 2003-2016.

Specifically, we compute the number of surveyed individuals who fall into categories defined by five-year age bins (with the first bin ages 25-29, and the last bin 85+), education bins (high school or less or more than high school), and state of residence. Since the ACS only surveys a subset of Americans, we then compute the share of individuals in each category (adjusting for survey weights) and multiply by the total population in each year according to the SEER data to obtain an estimate of the number of individuals falling in each age/education/state/year bin.

Combining these data with the NCHS data allow us to produce a state-year panel of age-adjusted mortality rates for both education bins, which we use to conduct our analysis.

Note, however, that the education level is missing for a small share (4.5%) of deaths in the NCHS data. Furthermore, these deaths are concentrated in specific state-years. We therefore drop any state for which at least one state-year is missing education information for over 45% of its deaths. In practice, this means that we exclude Georgia, New York, Rhode Island, and South Dakota from the sample; together, these four states account for 52.6% of the deaths with missing education information. The state-year with the next largest share of deaths with missing education information after excluding these four states is Maine in 2011, and this share is just 10.6%. We do not expect this alternative sample definition to have a major impact on our results; as seen in Figure OA.41, the 2007-2009 period estimate is -0.66 (standard error = 0.25), which is very similar to the corresponding estimate of -0.62 (standard error = 0.25) using all 50 states in Table 3.

A.7 Analysis of Impacts on Earnings in the Current Population Survey Data

A.7.1 Data and Sample

We use data from the Current Population Survey (CPS), administered jointly by the U.S. Census Bureau and the Bureau of Labor Statistics to study the impact of the Great Recession on earnings, overall and by education group. . The CPS is a monthly survey administered to a nationally representative sample of individuals aged 15 years or older and not in the Armed Forces. The survey excludes institutionalized people, such as those in prisons, long-term care hospitals, and nursing homes. Since we are interested in heterogeneity by education, we further restrict the sample to be those aged 25 or older only; this gives respondents enough time to have completed

Community Survey 1-year Public Use Micro Samples (Lee et al. 2021). Of note, respondents who are institutionalized (i.e. in live in a nursing home), live outside the United States, or are out of the HRS age range have weights of zero.

their education. To match the yearly structure of our data, we use the CPS survey results from March of each year.

A.7.2 Estimation and Results

Using survey weights provided in the data, we find state-year averages of earnings for (1) the entire sample, (2) those with a high school diploma or less, and (3) those with more than a high school diploma. As with the HRS, we use the logarithm of these averages as the outcomes in estimating the state-level equivalent of equation (1) (i.e. equation 23). Estimates of β_t in this specification are displayed in Appendix Figure OA.25.

Note that for this linear specification, the dependent variable (a logarithm) is well-defined since these state-year average earnings are never non-zero; however, the underlying individual-level regression with log earnings as the outcome would be problematic because there are many individuals with zero earnings. Chen and Roth (2023) show that in such cases, transformations (such as adding one and then taking the logarithm, or using arcsines) may lead to coefficients that do not truly identify treatment effects in percentage terms. One solution they offer is to run a Poisson regression instead; specifically, estimating the equation

$$y_{it} = \exp\left(\beta_t \left[\text{SHOCK}_{s(i,t)} \times \mathbb{1}(Year_t)\right] + \alpha_{s(i,t)} + \gamma_t\right) \tag{24}$$

where y_{it} denotes earnings for individual i in year t in levels rather than logs; the right-hand side variables are identical to those in the state-year equivalent of equation (1). Estimates of β_t in equation (24) are plotted in Figure OA.26; these are both qualitatively and quantitatively similar to the estimates in Appendix Figure OA.25, which is reassuring that the linear equation is not mis-specified.

A.8 Simplified Welfare Model

We consider a simplified version of the model in Section 5 in which the aggregate state $S \in \{L, H\}$ is drawn once and for all at $t = 0$, and there is no retirement. We consider two scenarios. In the first, mortality is exogenous to the aggregate economic state and individuals live for T periods. Under these assumptions, the agent's lifetime utility in the two states of the world is given by:

- *Normal state.* Expected lifetime utility if nature draws the normal state:

$$\mathbb{E}[U(c,m)]^{\text{normal}} = p^H * T * u((1-d^H)c) + (1-p^H) * T * u(c) \tag{25}$$

- *Recession.* Expected lifetime utility if nature draws the recession state:

$$\mathbb{E}[U(c,m)]^{\text{recession}} = p^L * T * u((1-d^L)c) + (1-p^L) * T * u(c) \tag{26}$$

We define the welfare consequence of a recession with exogenous mortality as Δ and it is thus given by:

$$\mathbb{E}[U((1+\Delta)c,m)]^{recession} = \mathbb{E}[U(c,m)]^{normal} \tag{27}$$

Given the constant elasticity of marginal utility with respect to consumption in the per-period utility function, we can solve for the following closed-form expression for Δ:

$$\Delta = \left(\frac{p^H(1-d^H)^{(1-\gamma)} + (1-p^H)}{p^L(1-d^L)^{(1-\gamma)} + (1-p^L)} \right)^{1/(1-\gamma)} - 1 \tag{28}$$

This expression is increasing in p^L (the probability of job displacement in a recession) and d^L (the reduction in consumption in a recession), as expected. The welfare cost of the recession is independent of b, the parameter which governs the VSLY, or life expectancy T. Since life expectancy is assumed to be independent of the aggregate state, neither it nor the VSLY affects the agent's willingness to pay to avoid the recession state.[88]

In the second scenario, we allow for mortality to be endogenous to the aggregate state. In the normal state, life expectancy is T, while in the recession state, life expectancy is $T(1+dT)$. Now we obtain the following expressions for expected lifetime utility in the two states:

$$\mathbb{E}[U]^{\text{normal}} = p^H * T * u((1-d^H)c) + (1-p^H) * T * u(c) \tag{29}$$

$$\begin{aligned} \mathbb{E}[U]^{\text{recession}} = {} & p^L * T(1+dT) * u((1-d^L)c) \\ & +(1-p^L) * T(1+dT)u(c) \end{aligned} \tag{30}$$

Using the above expressions, we can solve for the welfare cost of a recession in the case with

[88] We can also simplify the basic model even further by assuming $p^H = 0$ and $d^H = 0$. In this case, we have $\Delta = (p^L * (1-d^L)^{(1-\gamma)} + 1 - p^L)^{(1/(\gamma-1))} - 1$. From this expression, we see that for $0 < p^L < 1$ and $\gamma > 1$, we have that as d^L goes towards 1 we have Δ going to ∞, implying that the agent is willing to pay an arbitrary high percentage of consumption to avoid the recession state as the earnings consequences of job displacement grow large, exactly as in Krebs (2007).

endogenous mortality (Δ^{dT}):

$$\Delta^{dT} = \left(\frac{-dT * b/\tilde{u}(c) + p^H (1-d^H)^{(1-\gamma)} + (1-p^H)}{(1+dT)(p^L(1-d^L)^{(1-\gamma)} + (1-p^L))} \right)^{1/(1-\gamma)} - 1 \tag{31}$$

where $\tilde{u}(c) = u(c) - b = \frac{c^{1-\gamma}}{1-\gamma}$, which transforms the per-period utility function into a standard CRRA utility function. Note that the expression for Δ^{dT} in equation (31) is valid for any value of dT and it simplifies to the expression for Δ in equation (28) if $dT = 0$.[89]

We can build further intuition by setting $p^H = 0$ and then taking a first-order approximation around the left-hand side of equation (31), which leads to the following expression:

$$1 + (1-\gamma) * \Delta^{dT} \approx \frac{-dT * b + \tilde{u}(c)}{(1+dT) * (p^L * (1-d^L)^{(1-\gamma)} \tilde{u}(c) + (1-p^L)\tilde{u}(c))} \tag{32}$$

$$\Delta^{dT} \approx \Delta - dT \frac{\text{VSLY}}{c} \tag{33}$$

where Δ is the welfare cost of a recession with exogenous mortality, and the second term is the adjustment for the percent change in life expectancy dT.

[89]To see this, note that the $-dT * b$ term in the numerator and the $(1 + dT)$ term in the denominator in the expression for Δ^{dT} are the only differences with the expression for Δ. This also means that if $dT > 0$, then $\Delta^{dT} < \Delta$, meaning that a recession that is "good for your health" is less costly to the agent than an otherwise similar recession that has no impact on mortality risk ($dT = 0$). While the agent continues to dislike possible reductions in consumption during a recession, the agent values the increase in life expectancy associated with a recession, thus depressing their willingness to pay to avoid recessions.

A.9 Figures

Figure OA.1: Heatmap of PM2.5 Shock

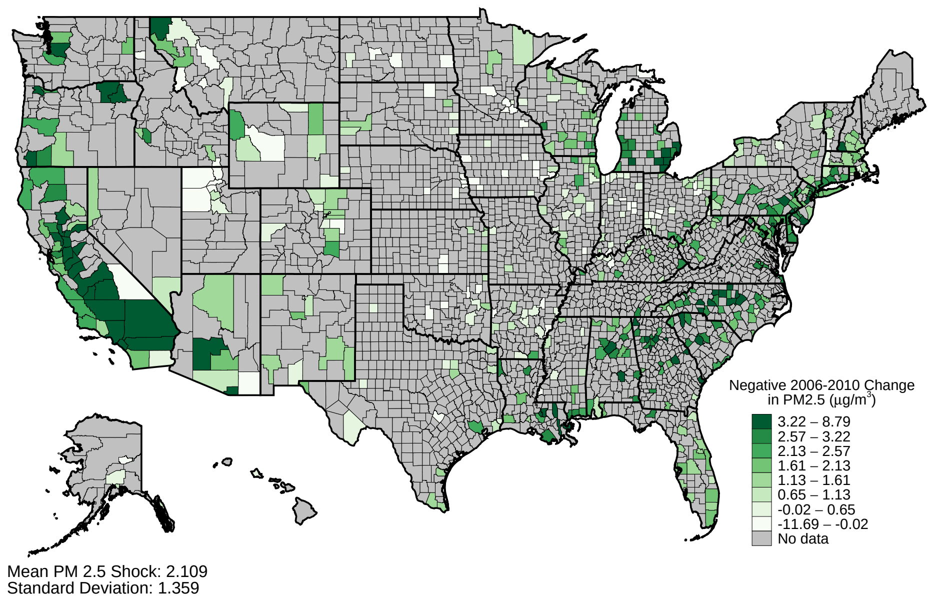
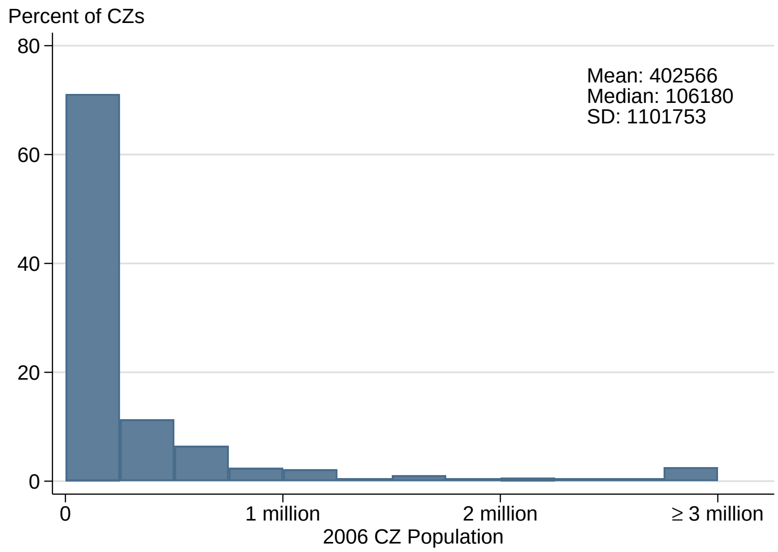


Figure displays heatmap of the negative 2006-2010 change in PM2.5 for all counties with observed PM2.5 levels in those two years (N=524). County colors are assigned according to population-weighted octiles, with cutpoints noted in the figure legend. Population-weighted mean and standard deviation are noted in the bottom left corner.

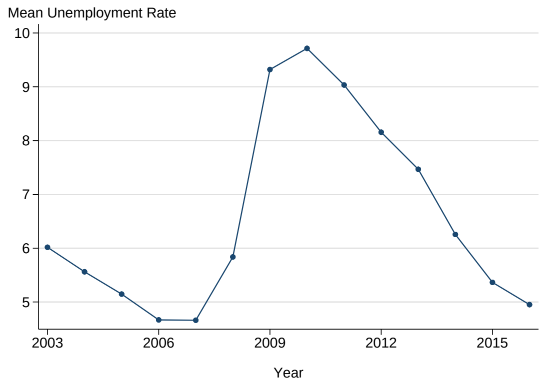
Figure OA.2: 2006 Commuting Zone Population



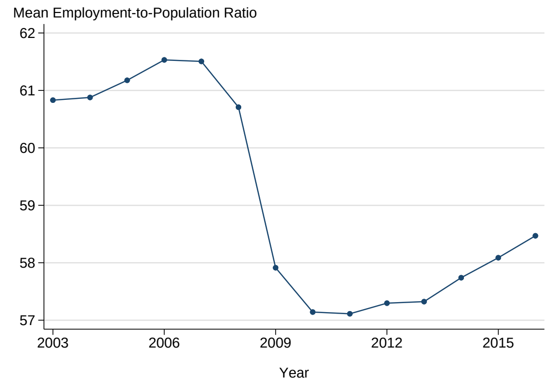
Notes: Figure displays a histogram of 2006 Commuting Zone populations as reported in the SEER, in bins of 250,000. For visualization purposes, Commuting Zones with populations larger than three million are binned to three million. Descriptive statistics in the upper right hand corner are reported for the full distribution. N=741 CZs.

Figure OA.3: Time Series of the Great Recession

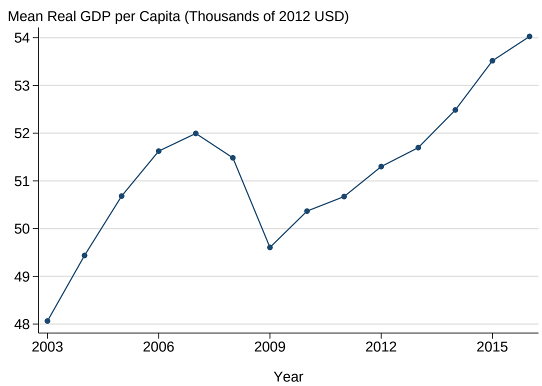
(a) Unemployment Rate



(b) Employment-to-Population Rate

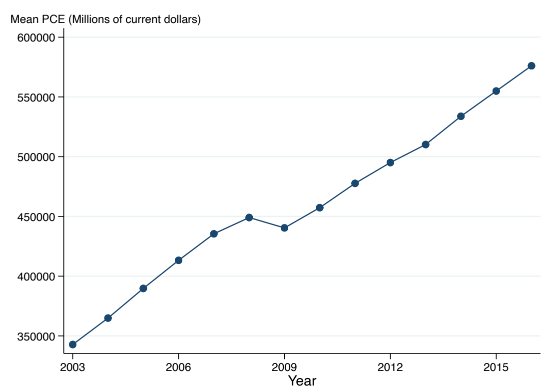


(c) Real GDP per Capita



(d) House Price Index

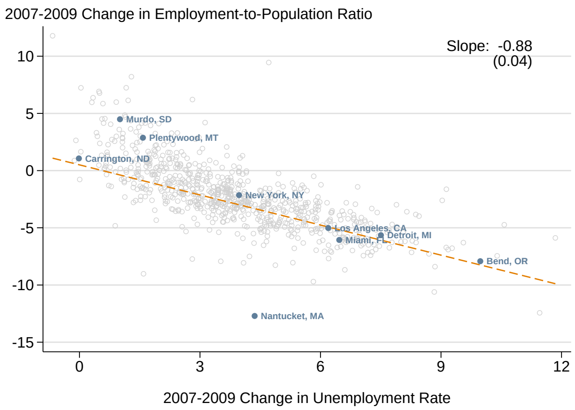
(e) Personal Consumption Expenditure



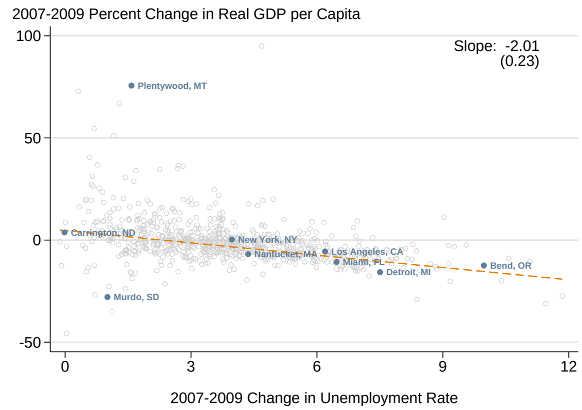
Notes: Figure displays annual time series of the 2006-CZ-population-weighted mean of measures of the Great Recession. Panel OA.3a plots the unemployment rate; Panel OA.3b plots the the employment-to-population rate; Panel OA.3c plots real GDP per capita in thousands of 2012 chained USD; and Panel OA.3d plots the annual house price index. Note that in Panels OA.3a and OA.3b the sample is all 741 CZs; in Panels OA.3c and OA.3d the sample is the 740 and 684 CZs (respectively) for which we have complete data from 2003-2016. Panel OA.3e plots the mean state total personal consumption expenditure over the same time horizon, weighted by 2006 state population. N=51 (including DC).

Figure OA.4: Correlation of Alternative Shocks

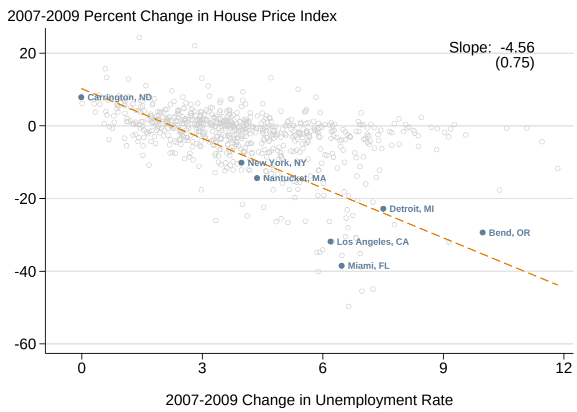
(a) 2007-09 Employment-to-Population Change



(b) 2007-09 Real GDP per Capita Percent Change



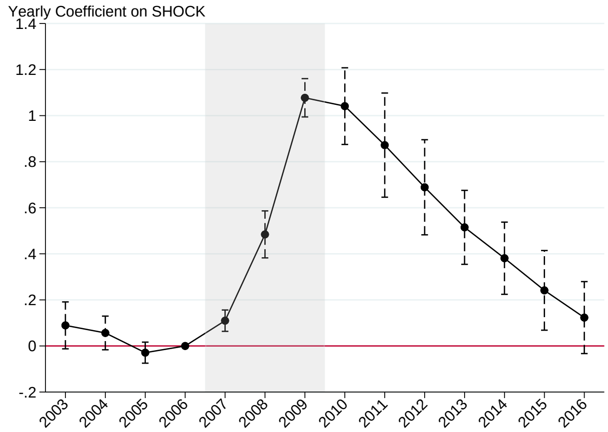
(c) 2007-09 House Price Index Percent Change



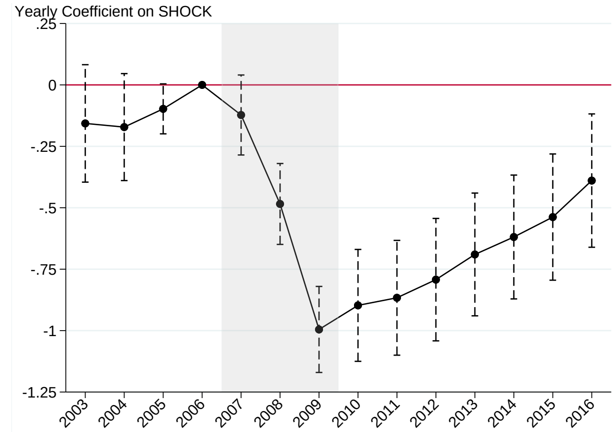
Notes: Figure displays scatterplots of measures of the Great Recession shock. Panel OA.4a plots the 2007-2009 change in the employment-to-population rate against the 2007-2009 change in the unemployment rate. Panel OA.4b plots the change in real GDP per capita (in thousands of 2012 chained USD) against the same unemployment rate shock, and Panel OA.4c plots the 2007-2009 change in the annual house price index against the unemployment rate shock. Note that in Panel OA.4a the sample is all 741 CZs; in Panels OA.4b and OA.4c the sample is the 740 and 684 CZs (respectively) for which we have complete data from 2003-2016.

Figure OA.5: Impact of Unemployment Shock on Measures of the Great Recession

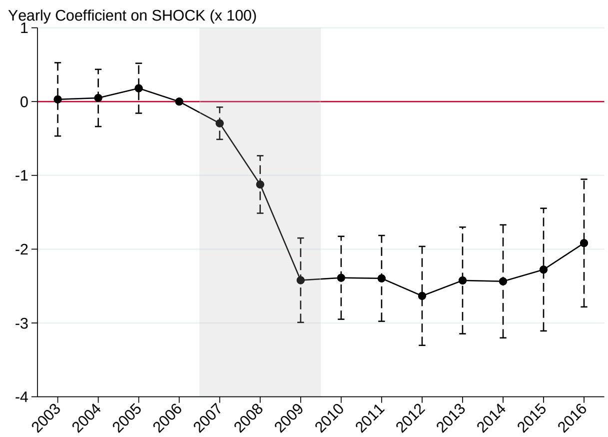
(a) Unemployment Rate



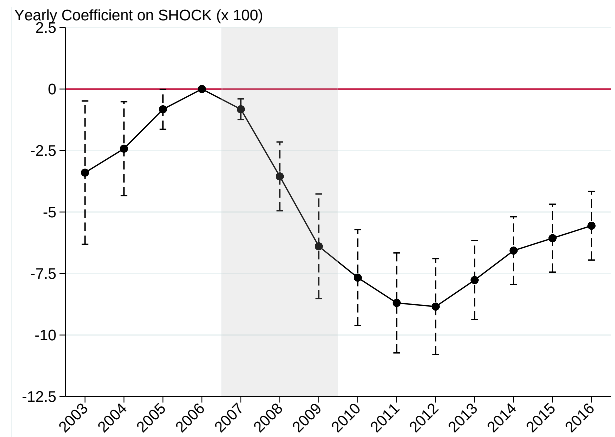
(b) Employment-to-Population Rate



(c) Log Real GDP per Capita

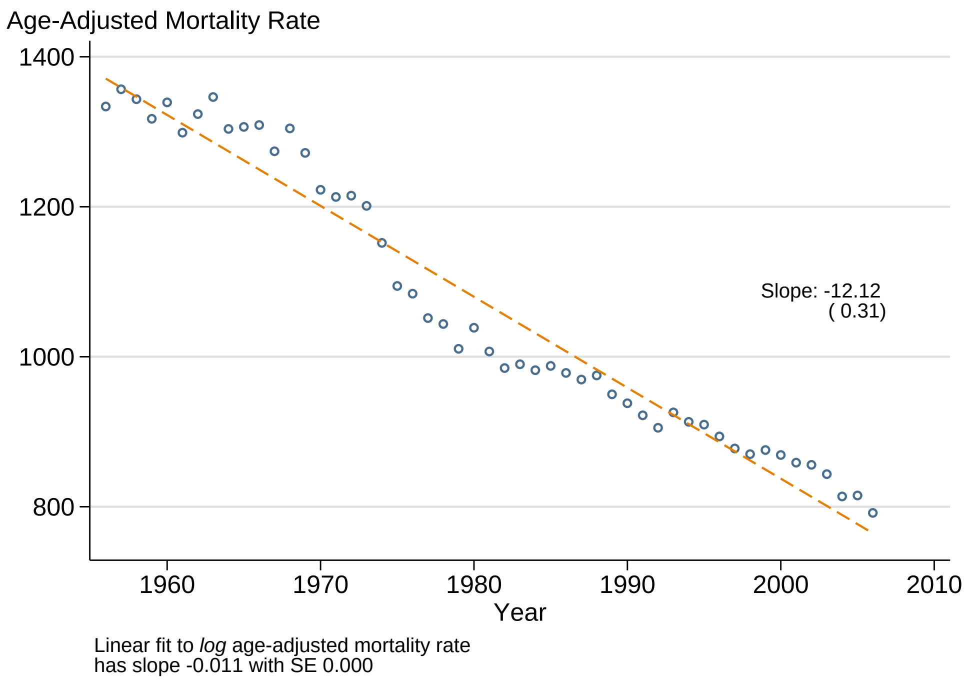


(d) Log House Price Index



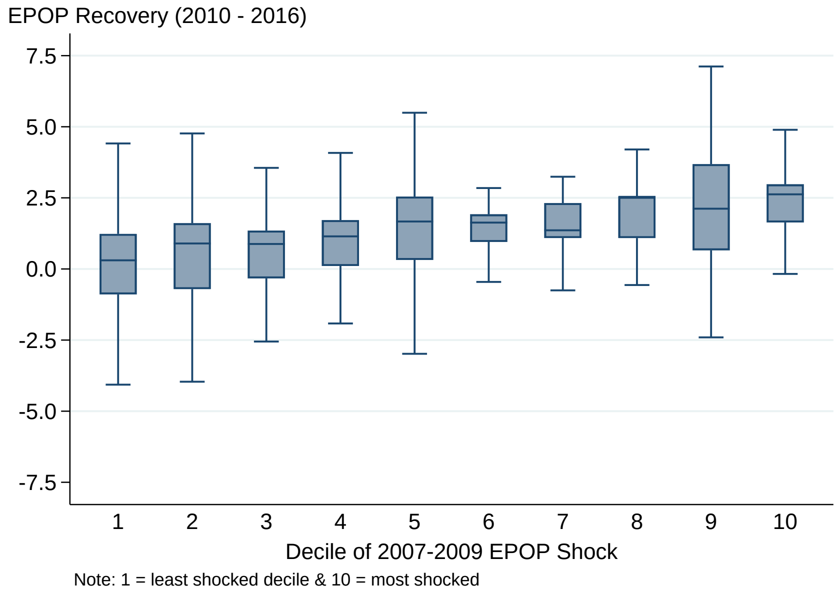
Notes: Figure plots yearly coefficients β_t estimated from equation (1), where the right hand independent variable is the 2007-2009 change in the CZ unemployment rate and the outcome y_{ct} is either the CZ unemployment rate (Fig. OA.5a), Employment-to-Population Rate (Fig. OA.5b), log real GDP per capita (Fig. OA.5c), or the log House Price Index (Fig. OA.5d). Note that in Panels OA.5a and OA.5b the sample is all 741 CZs; in Panels OA.5c and OA.5d the sample is the 740 and 684 CZs (respectively) for which we have complete data from 2003-2016. Coefficients and corresponding standard errors in Figures OA.5c and OA.5d are multiplied by 100 for ease of interpretation. Observations are weighted by CZ population in 2006. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Standard errors are clustered at the CZ level.

Figure OA.6: Age-Adjusted Mortality Rates in the United States, 1956-2006



Notes: Figure reports trends in age-adjusted mortality rates per 100,000 in the United States from 1956-2006. Data are drawn from the National Center for Health Statistics, "Mortality Trends in the United States, 1900-2018." The dashed line represents a linear fit of the age-adjusted mortality rate to a linear time trend. The slope and robust standard error of this fit are reported to the right of the dashed line. The slope reported in the note below the figure is from a regression of the *log* age-adjusted mortality rate to the same time trend, similarly with robust standard errors. N=51 years.

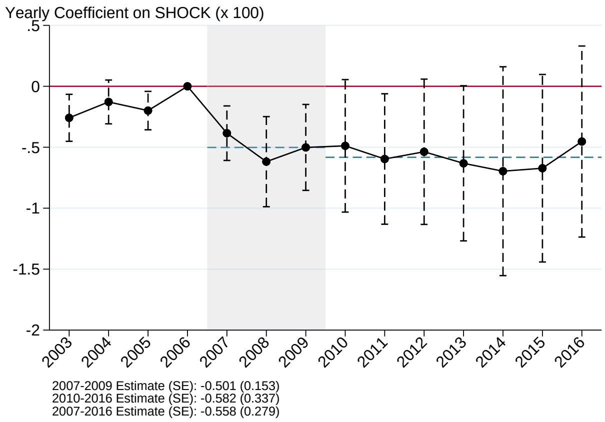
Figure OA.7: Distribution of Employment-to-Population Recovery, by EPOP Shock Decile



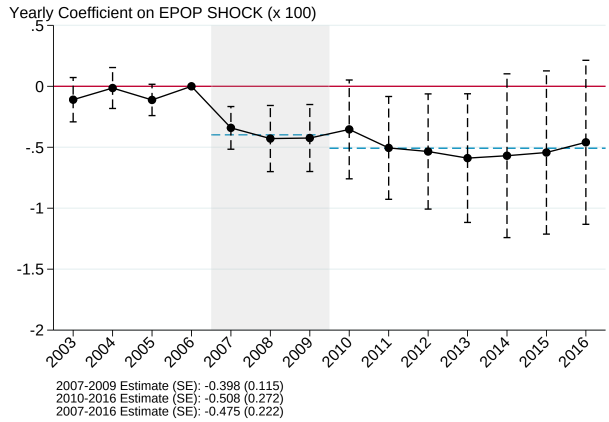
Notes: Figure displays the distribution across CZs of the "EPOP Recovery" (2016 EPOP minus 2010 EPOP) by decile of 2007-2009 EPOP shock. EPOP shock is defined as the negative of the 2007-2009 change in the employment to population rate. CZs are weighted by 2007 16+ population, with population data drawn from the Census. Monthly EPOP is defined as monthly 16+ employment (as per the Local Area Unemployment Statistics) divided by yearly 16+ population (as per the Census). Shocks deciles are population weighted, so that the collection of CZs in each decile represent a similar share of the total population. N=741 CZs.

Figure OA.8: Impact of Unemployment vs. Employment-to-Population Shocks on Log Age-Adjusted Mortality Rate

(a) Unemployment Shock (Baseline)



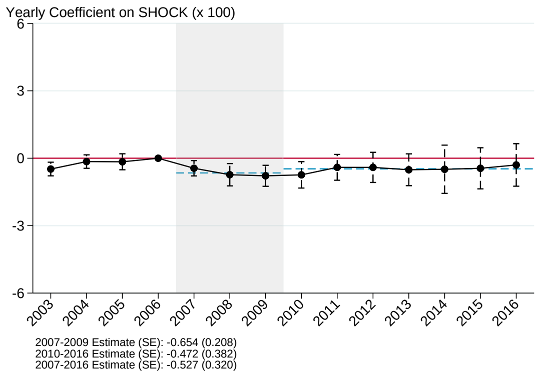
(b) EPOP Shock



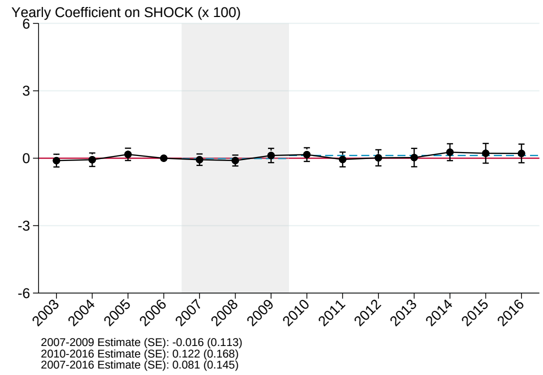
Notes: Figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000 population and the Great Recession shock is defined as the 2007-2009 change in the unemployment rate (Fig. OA.8a) or the negative 2007-2009 change in the employment-to-population (EPOP) rate (Fig. OA.8b). Coefficients and corresponding standard errors are multiplied by 100 for ease of interpretation. Observations are weighted by CZ population in 2006. Data on EPOP rate are drawn from the Local Area Unemployment Statistics Data. Annual mortality is constructed according to the county of residence observed in the NCHS detailed mortality microdata, and population estimates are drawn from the SEER. The age-adjustment procedure weights age-bin specific mortality rates according to their population share in the US 2000 Standard Population. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the average annual point estimate for the periods 2007-2009 and 2010-2016. These estimates (and corresponding standard errors) are reported in the lower left hand corner along with the corresponding estimate for the entire 2007-2016 period. Standard errors are clustered at the CZ level (N=741 CZs).

Figure OA.9: Impact of Unemployment Shock on Log Mortality Rate, by Cause of Death I

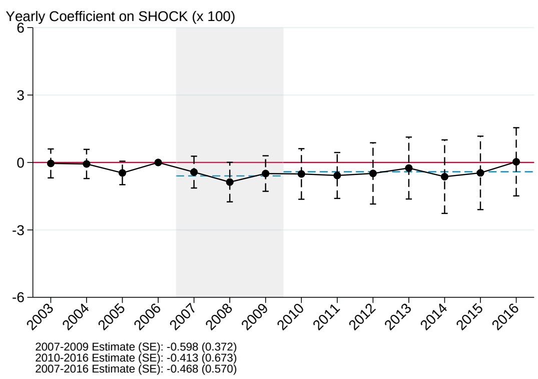
(a) Cardiovascular Disease



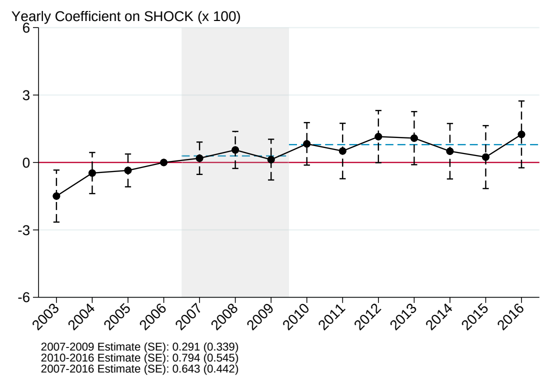
(b) Malignant Neoplasms



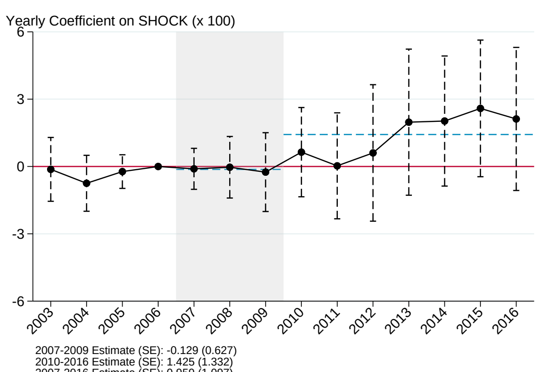
(c) Chronic Lower Respiratory Disease



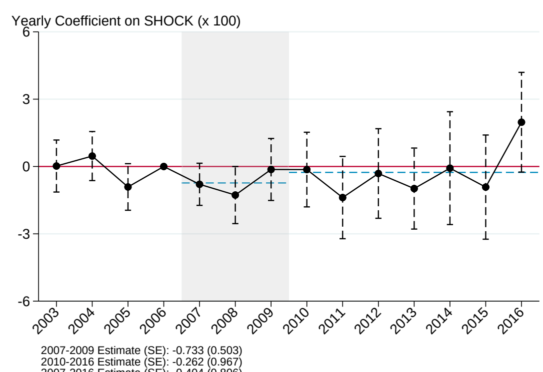
(d) Diabetes



(e) Alzheimer's Disease



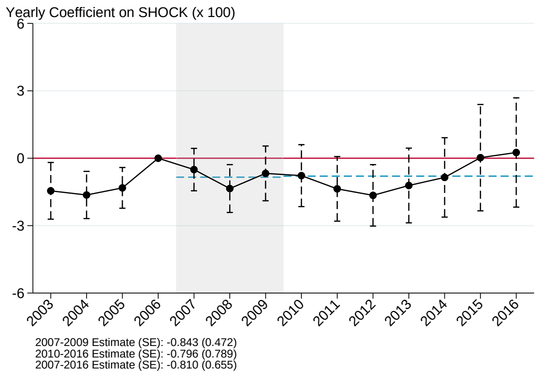
(f) Influenza/Pneumonia



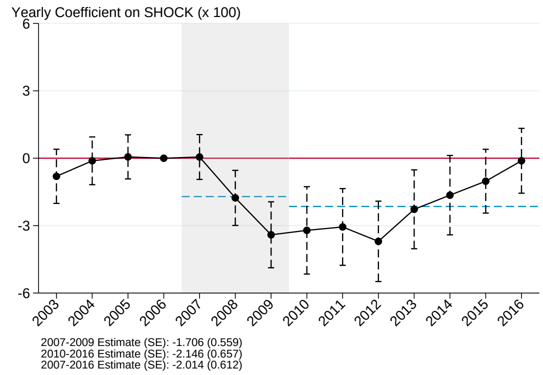
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log CZ mortality rate from one of six causes of death. Panel OA.9a displays event studies of the log mortality rate from cardiovascular disease; Panel OA.9b from cancer; Panel OA.9c from chronic lower respiratory disease; Panel OA.9d from diabetes; Panel OA.9e from Alzheimer's disease; and Panel OA.9f from influenza or pneumonia. Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation. Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at the CZ level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel. N=741 CZs.

Figure OA.10: Impact of Unemployment Shock on Log Mortality Rate, by Cause of Death II

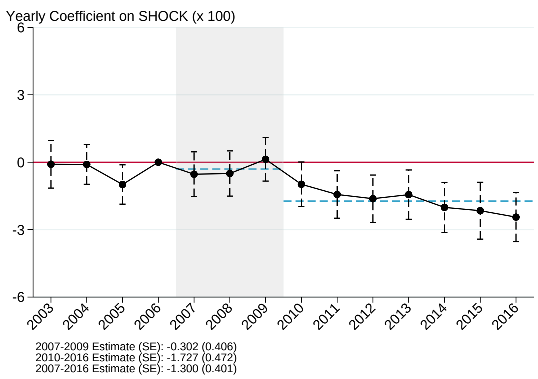
(a) Kidney Disease



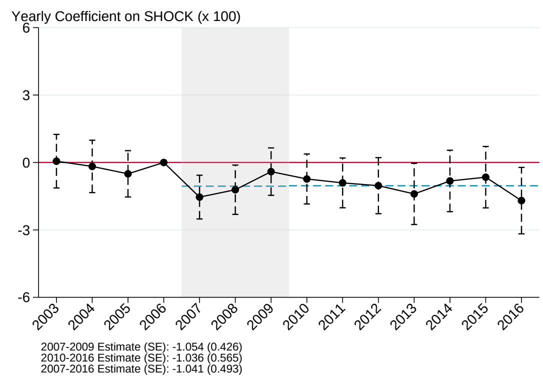
(b) Motor Vehicle Accidents



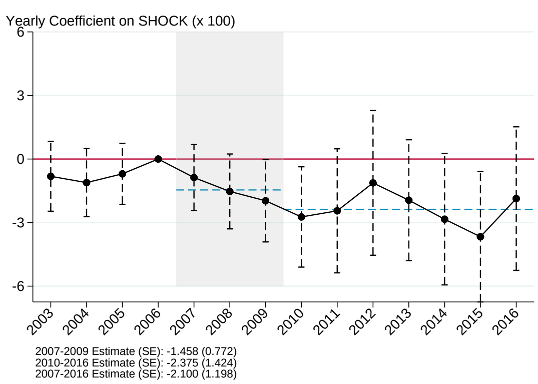
(c) Suicide



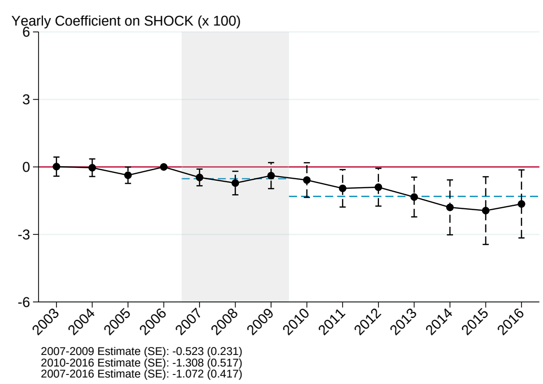
(d) Liver Disease/Cirrhosis



(e) Homicide



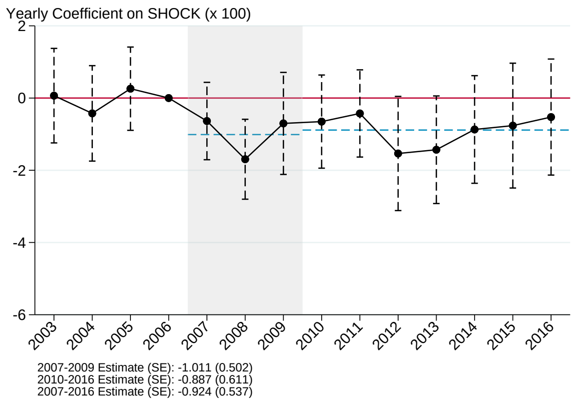
(f) All Other Causes (Residual)



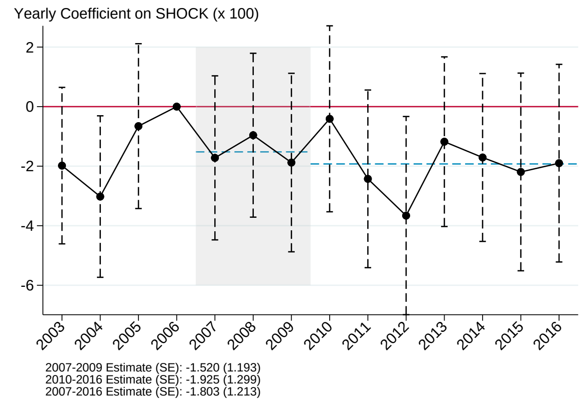
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log CZ mortality rate from one of six causes of death. Panel OA.10a displays event studies of the log mortality rate from kidney disease; Panel OA.10b from motor vehicle accidents; Panel OA.10c from suicide; Panel OA.10d from liver disease; Panel OA.10e from homicide; and Panel OA.10f from all other causes of death not described in Figure OA.9 or OA.10. Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation. Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at the CZ level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel. N=741 CZs.

Figure OA.11: Impact of Unemployment Shock on Log Mortality Rate, by Age Group: Age 0-54

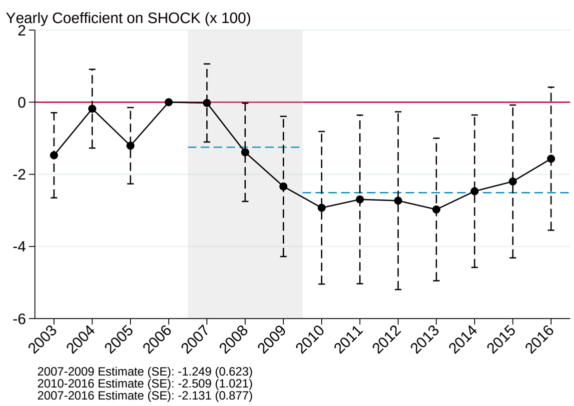
(a) Age 0-4



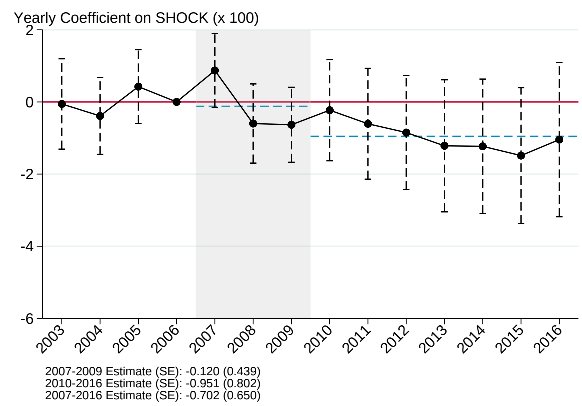
(b) Age 5-14



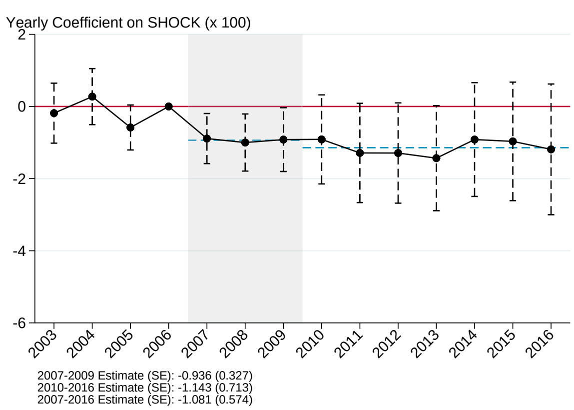
(c) Age 15-24



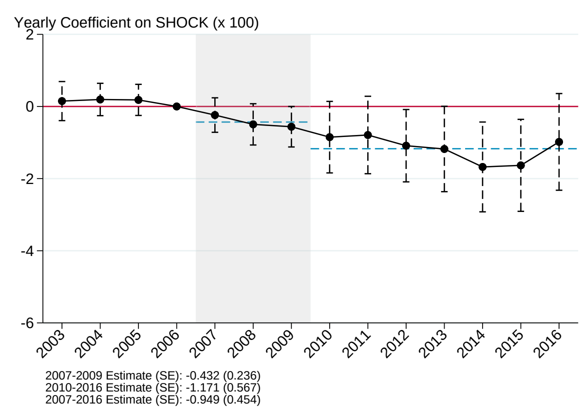
(d) Age 25-34



(e) Age 35-44



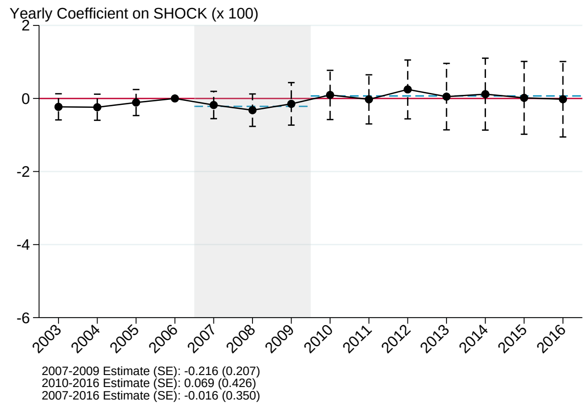
(f) Age 45-54



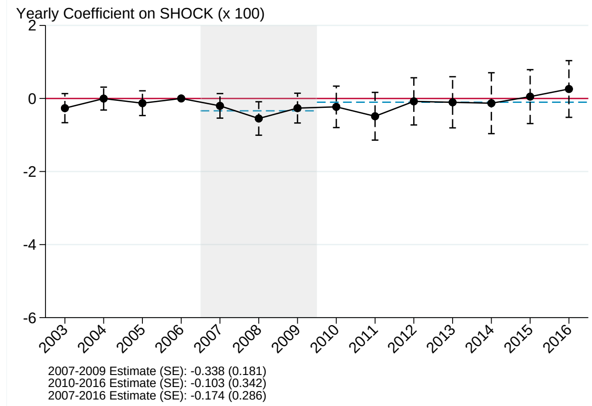
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ct} is the log mortality rate of the CZ population in one of six age bins (all estimated from the SEER). Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at the CZ level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel. N=741 CZs.

Figure OA.12: Impact of Unemployment Shock on Log Mortality Rate, by Age Group: Age 55+

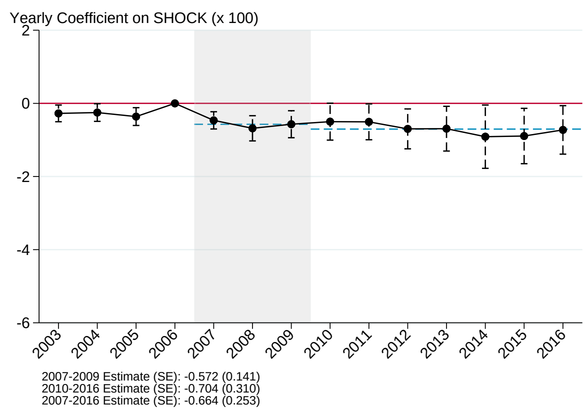
(a) Age 55-64



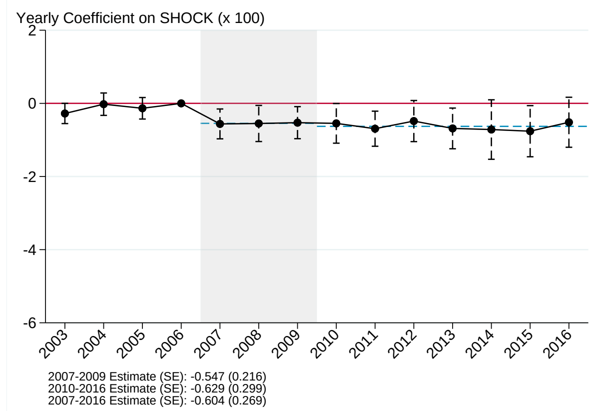
(b) Age 65-74



(c) Age 75-84



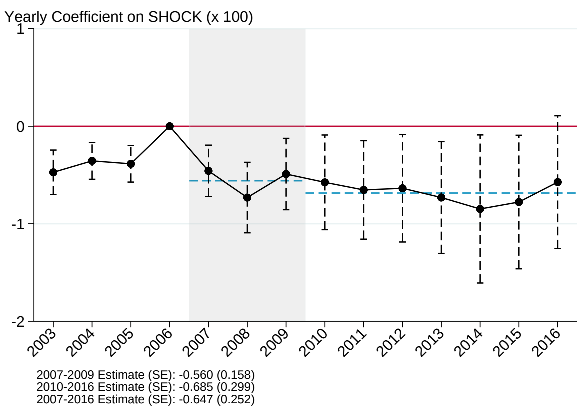
(d) Age 85+



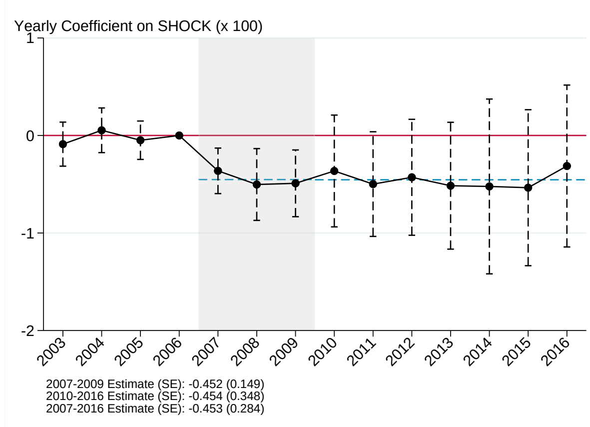
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ct} is the log mortality rate of the CZ population in one of four age bins (all estimated from the SEER). Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation. Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at the CZ level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel. N=741 CZs.

Figure OA.13: Impact of Unemployment Shock on Log Mortality Rate, by Sex

(a) Male

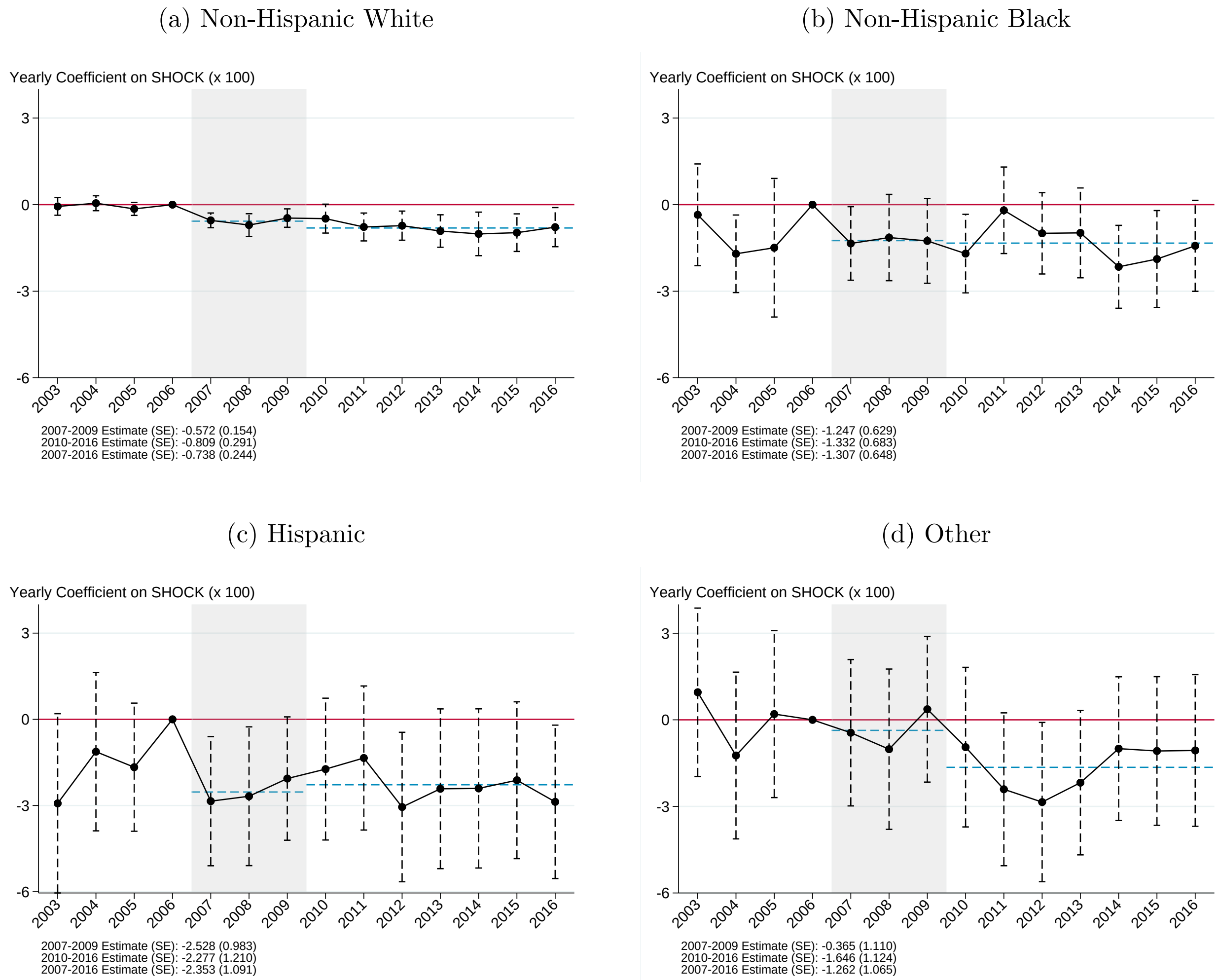


(b) Female



Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log CZ mortality rate among either males (Panel OA.13a) or females (Panel OA.13b). Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation. Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at the CZ level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel. N=740 CZs with observed male and female mortality in all years.

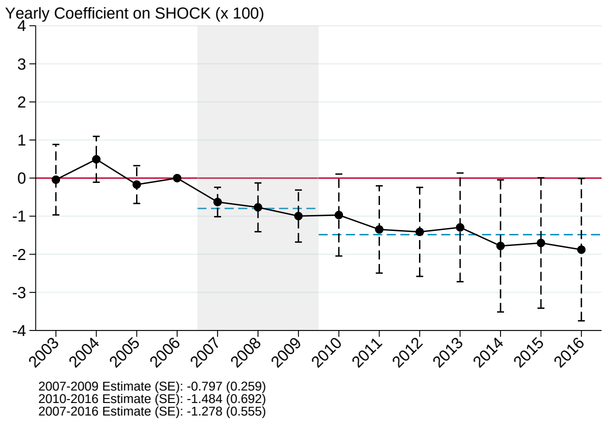
Figure OA.14: Impact of Unemployment Shock on Log Mortality Rate, by Race/Hispanic Origin



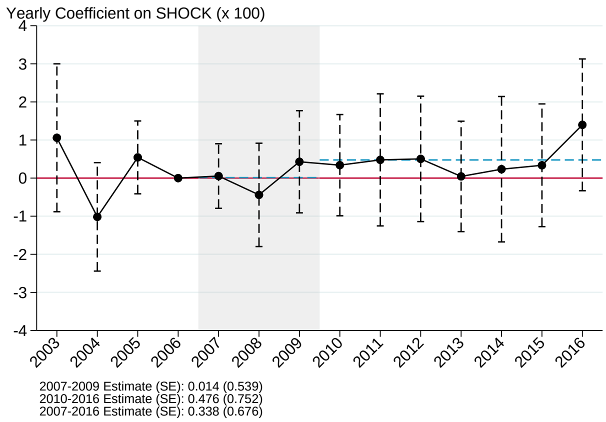
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log mortality rate among the CZ population that is Non-Hispanic White (Panel OA.14a), Non-Hispanic Black (Panel OA.14b), Hispanic (Panel OA.14c) or Other (Panel OA.14d). Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation. Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at the CZ level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel. N=735 CZs with observed mortality in each race/Hispanic origin category in all years.

Figure OA.15: Impact of Unemployment Shock on Log Mortality Rate, by Education

(a) HS or Less



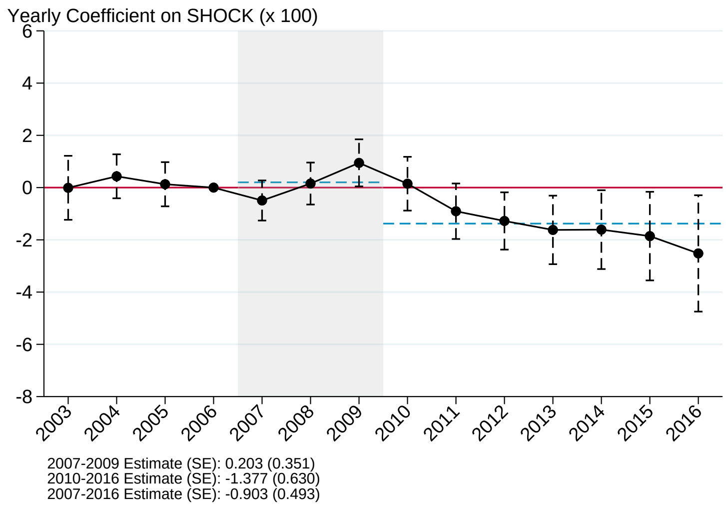
(b) More Than HS



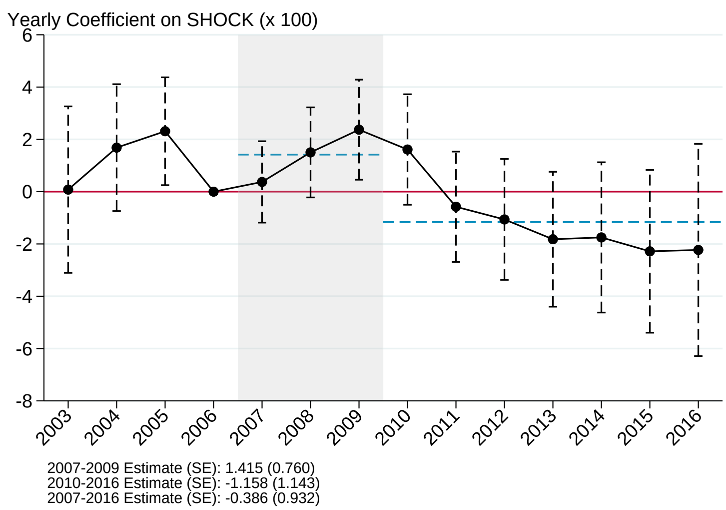
Notes: Figure plots yearly coefficients β_t estimated from equation 1, where the outcome y_{ct} is the log state age-adjusted mortality rate for 25+ year-olds with a high school diploma or less (Panel (a)) or more than a HS diploma (Panel (b)). Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation. Event study estimates are weighted by 2006 state population as measured in the SEER. Standard errors are clustered at the state level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel. Georgia, New York, Rhode Island, and South Dakota are excluded from the sample due to missing data issues (see Appendix A.6 for details).

Figure OA.16: Impact of Unemployment Shock on Log Mortality Rate From “Deaths of Despair”

(a) Suicides, Liver Disease, and Drug Poisonings



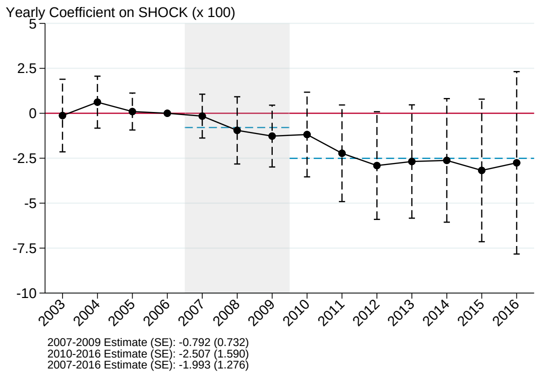
(b) Drug Poisonings Only



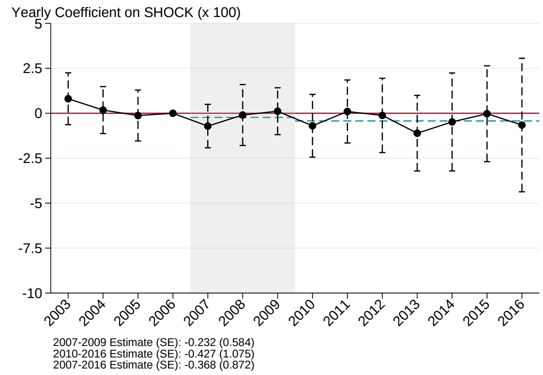
Notes: Figure plots yearly coefficients β_t estimated from equation (1), where the outcome y_{ct} is the log CZ mortality rate from suicides, liver disease, and drug poisonings (Sub-Figure OA.16a) or accidental and unknown-intent drug poisonings only (Sub-Figure OA.16b). Coefficients and corresponding standard errors are multiplied by 100 for ease of interpretation. Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at the CZ level. Period estimates for 2007-2009, 2010-2016, and 2007-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel. N=741 CZs.

Figure OA.17: Impact of Unemployment Shock on Log Mortality Rate, by Education and Age

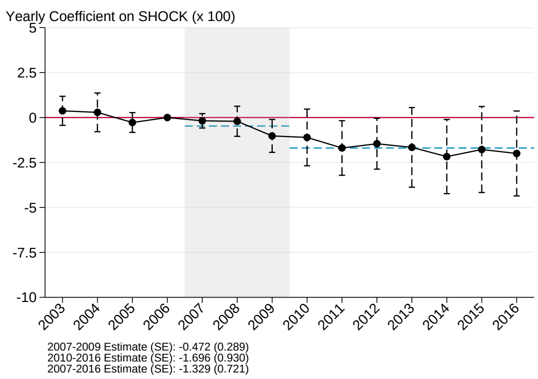
(a) HS or Less, 25-44 Year-Olds



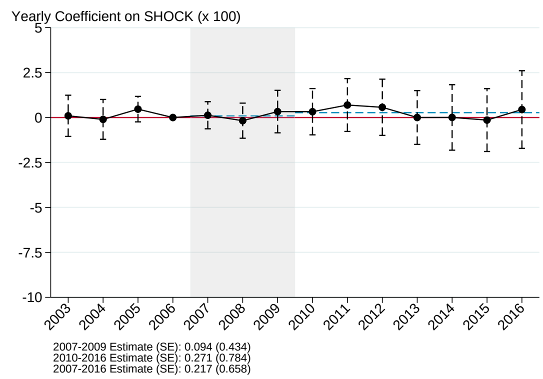
(b) More Than HS, 25-44 Year-Olds



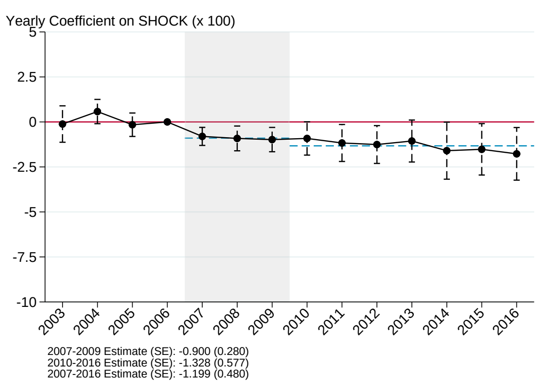
(c) HS or Less, 45-64 Year-Olds



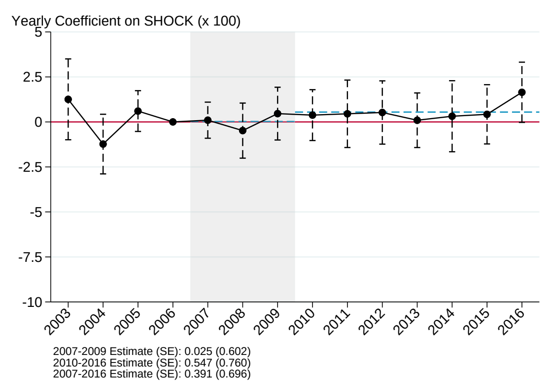
(d) More Than HS, 45-64 Year-Olds



(e) HS or Less, 65+ Year Olds

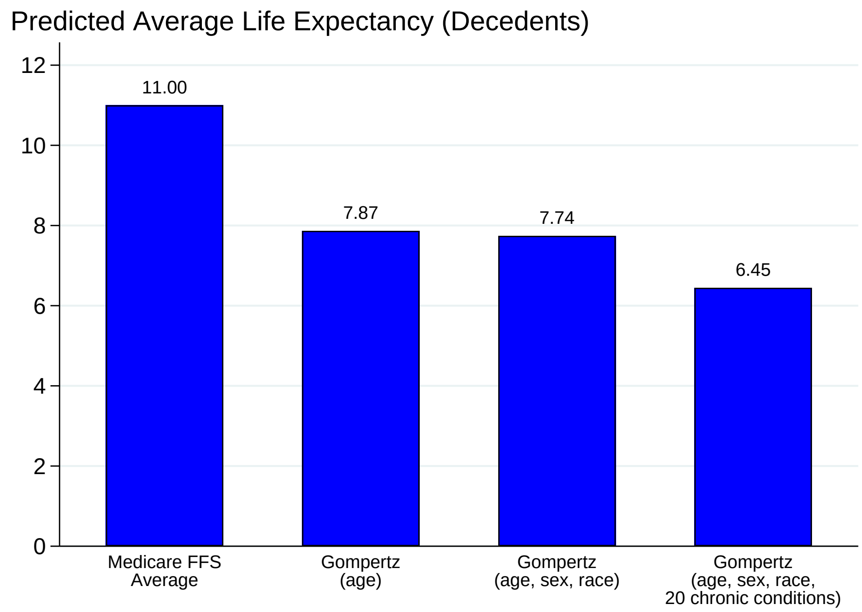


(f) More Than HS, 65+ Year Olds



Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log state age-adjusted mortality rate for individuals of each education/age bin combination. Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation. Event study estimates are weighted by 2006 state population as measured in the SEER. Standard errors are clustered at the state level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel. Georgia, New York, Rhode Island, and South Dakota are excluded from the sample due to missing data issues (see Appendix A.6 for details). N=47 states.

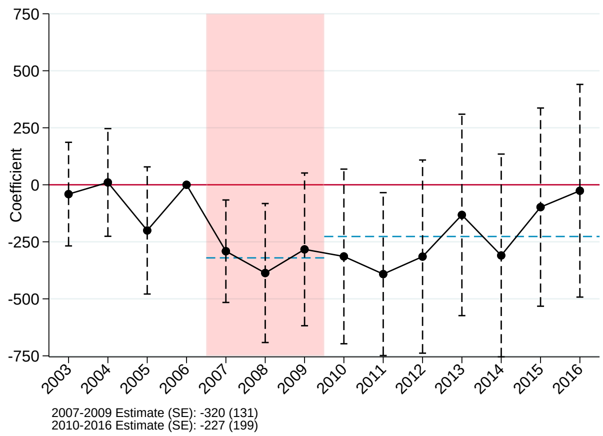
Figure OA.18: Average, Counterfactual Predicted Remaining Life Expectancy of Decedents



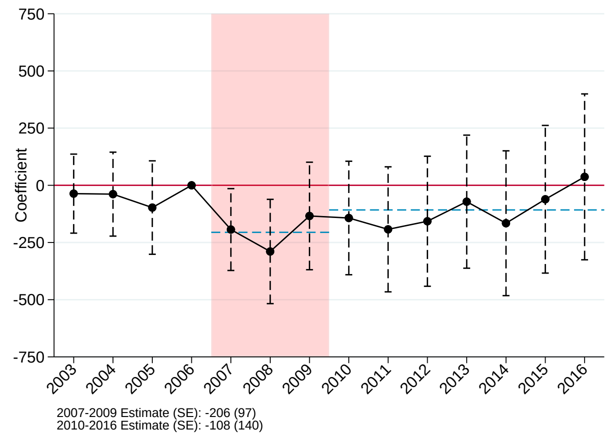
Notes: This figure displays the average predicted counterfactual remaining life expectancy at the start of the year for Medicare beneficiaries who subsequently die within the year. Remaining life expectancy is determined as of January 1st of a given year and is estimated as per equation (20), using a Gompertz model with an increasingly rich set of covariates. The sample utilized is patient-years associated with a mortality event, within the Repeated Cross Section (FFS in $t-1$) sample. This sample restricts patient-years as per Table OA.2, further restricting beneficiaries to those enrolled in Medicare FFS in the previous year. N = 3,684,457 patient-years.

Figure OA.19: Effect of Great Recession Shock on Life Years Lost (per 100,000 Beneficiaries)

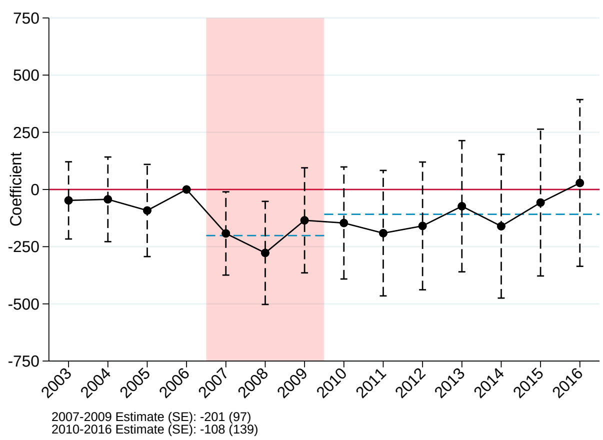
(a) No Covariates (Average Life Expectancy)



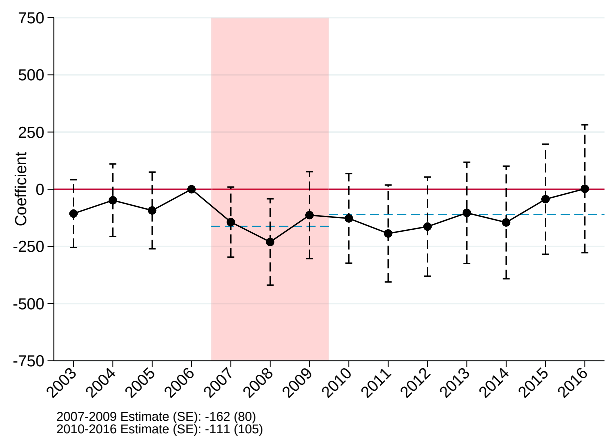
(b) Age



(c) Age + Demographic Covariates



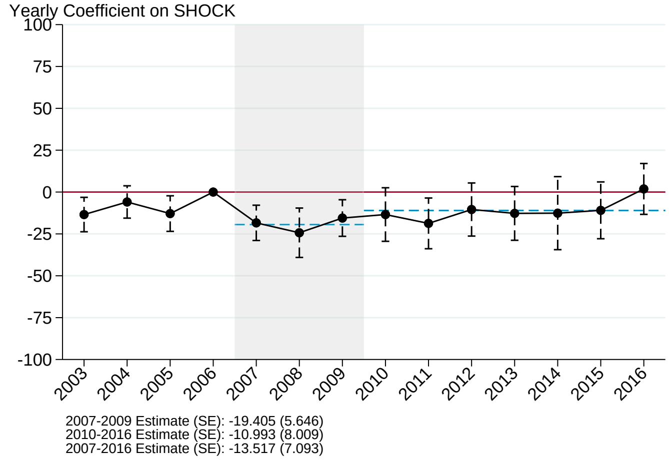
(d) Age + Demographic + Chronic Condition Covariates



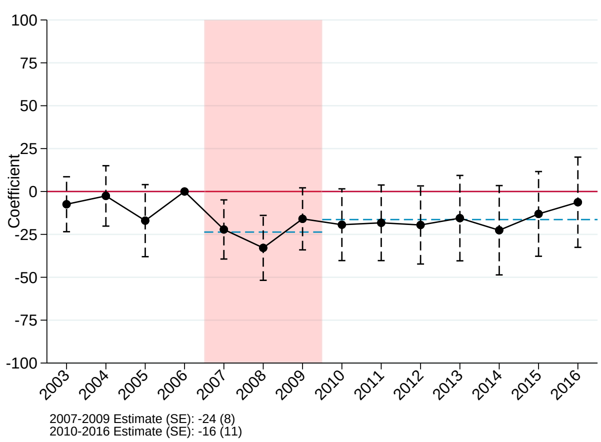
Notes: This figure displays coefficients β_t from equation (1), with outcome LYL_{ct} defined as the number of life-years lost per 100,000 beneficiaries in CZ c and year t. Each individual is assigned their yearly CZ of residence, and shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the point estimate for the linear combination of coefficients from 2007-2009 and 2010-2016. CZ observations are weighted based on 2006 SEER population data. Standard errors are clustered by CZ. We utilize the Repeated Cross Section (FFS in $t-1$) sample, which restricts patient-years in 2003-2016 to those that were enrolled in Medicare FFS in the previous year. Beneficiaries are also subject to the restrictions in Table OA.2. N = 739 CZs.

Figure OA.20: Effect of Unemployment Shock on Mortality Rate in Medicare Cross Section

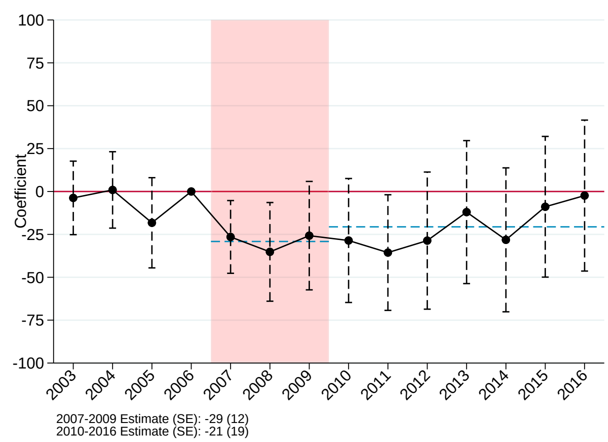
(a) Impact on 65+ Mortality Rate in the CDC Data



(b) Medicare Repeated Cross Section



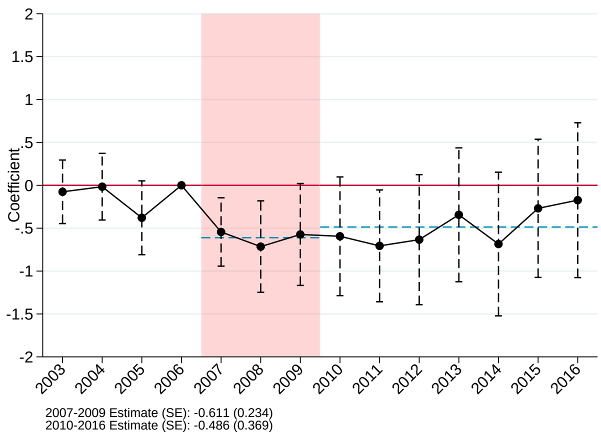
(c) Medicare Repeated Cross Section (TM in $t-1$)



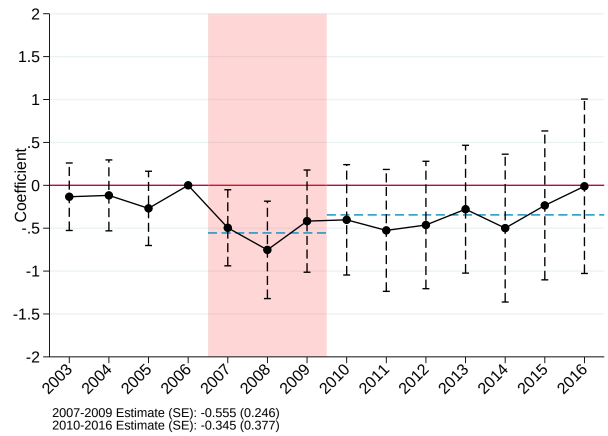
Notes: This figure displays coefficients β_t from equation (1), with outcome Y_{ct} defined as the (non age-adjusted) mortality rate in CZ c and year t. Each individual is assigned their yearly CZ of residence, and shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the point estimate for the linear combination of coefficients from 2007-2009 and 2010-2016. CZ observations are weighted based on 2006 SEER population data. Standard errors are clustered by CZ. We utilize the Repeated Cross Section sample, which restricts to beneficiaries based on Table OA.2. Repeated Cross Section (TM in $t-1$) further restricts beneficiaries to those enrolled in Traditional Medicare (TM) in the previous year. In the first three columns, the outcome variable is the mortality rate on CZ c and year t. Panel (a) shows results of estimating equation (1) with the outcome as the non-adjusted 65+ mortality rate using the CDC data. Panel (b) shows results as described above using the Medicare data; they are virtually identical. Panel (c) restricts attention to the set of Medicare enrollees who were covered by Traditional Medicare in every month of the previous year. Appendix Table OA.11 shows that relative to the overall Medicare sample, this sample is slightly older (average patient-year age of 76.0 compared to 74.8) and slightly more likely to be enrolled in Medicaid in 2003 (14 percent compared to 13 percent). N = 741 CZs in the CDC data; N = 738 CZs in the Medicare data.

Figure OA.21: Effect of Unemployment Shock on Log Life Years Lost (per 100,000 Beneficiaries)

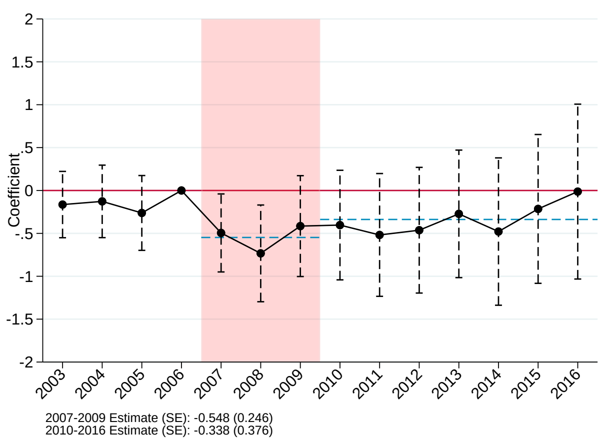
(a) No Covariates (Average Life Expectancy)



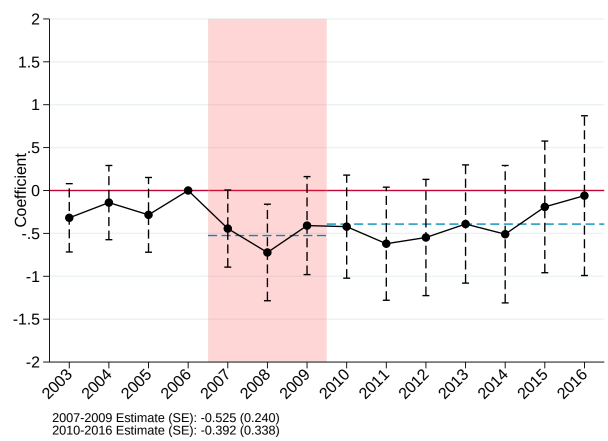
(b) Age



(c) Age + Demographic Covariates



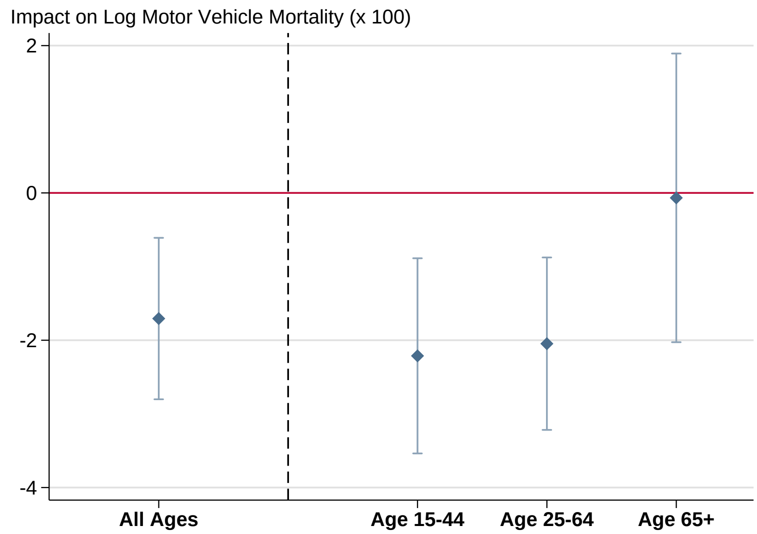
(d) Age + Demographic + Chronic Condition Covariates



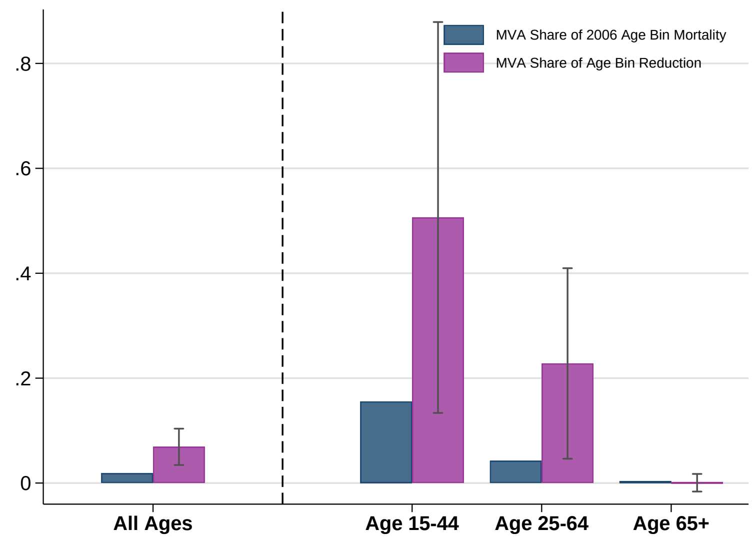
Notes: This figure displays coefficients β_t from equation (1), with outcome $log(LYL_{ct}+1)$ defined as the log of number of life-years lost per 100,000 beneficiaries in CZ c and year t. Life years lost is defined as $LYL_{ct} = 100,000 * \frac{\sum_{i \epsilon S_{ct}} LYL_{it}}{|S_{ct}|}$, in which S_{ct} denotes the set of individuals in CZ c and year t. Each individual is assigned their yearly CZ of residence, and shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the point estimate for the linear combination of coefficients from 2007-2009 and 2010-2016. CZ observations are weighted based on 2006 SEER population data. Standard errors are clustered by CZ. We utilize the Repeated Cross Section (FFS in $t-1$) sample, which restricts patient-years in 2003-2016 to those enrolled in Medicare FFS in the previous year. Beneficiaries are also subject to the restrictions in Table OA.2. N = 739 CZs.

Figure OA.22: Impact of Unemployment Shock on Log Motor Vehicle Mortality by Age Group

(a) 2007-2009 Impact of Unemployment Shock on Log Motor Vehicle Mortality



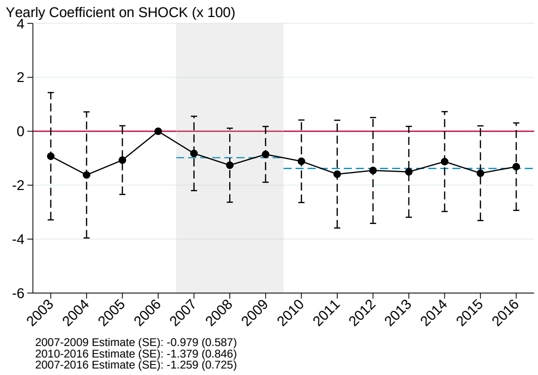
(b) Share of Age Group Mortality Reductions Attributable to Reductions in Motor Vehicle Deaths



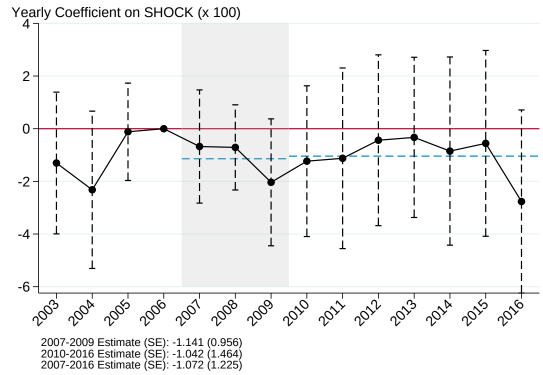
Notes: Figure OA.22a displays the impact of the unemployment shock on log age-group mortality rates from motor vehicle accidents. Estimates are group-specific 2007-2009 averages of coefficients β_{tg} from equation (2), where groups g are the 11 most common causes of death in the ICD10 39-group classification and a residual category; only coefficients for log motor vehicle accidents are shown. Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation. All estimates are of the log age-adjusted mortality rate, and are weighted by 2006 CZ population from the SEER. Mortality rates are age-adjusted within each age group, benchmarked to the US 2000 Standard Population. Point estimates are displayed as diamonds; vertical bars indicate 95% confidence intervals, clustered at the CZ level. Figure OA.22b presents the share of reductions in overall mortality attributable to motor vehicle accidents by age group. The blue bars indicate each cause of death's share of 2006 mortality. The purple bars present the implied share of the mortality decline accounted for by a given cause of death. To construct these, we multiply each estimated cause-of-death reduction in 2007-2009 by the number of deaths from that cause in 2006, and divide by the sum of all such reduction-death products. These reductions are computed within age groups. 95% confidence intervals for these estimates, clustered by CZ, are shown as vertical capped lines. N=741 CZs.

Figure OA.23: Impact of Unemployment Shock on Self-Reported Health in the BRFSS

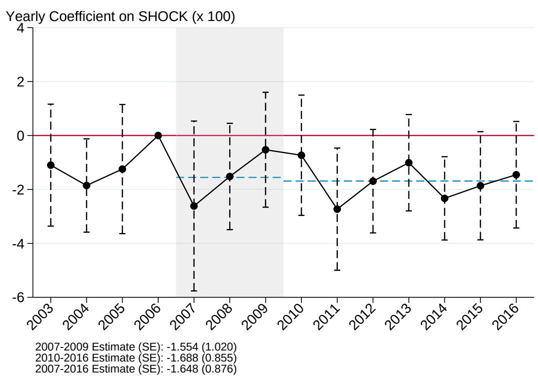
(a) Log share less than very good health



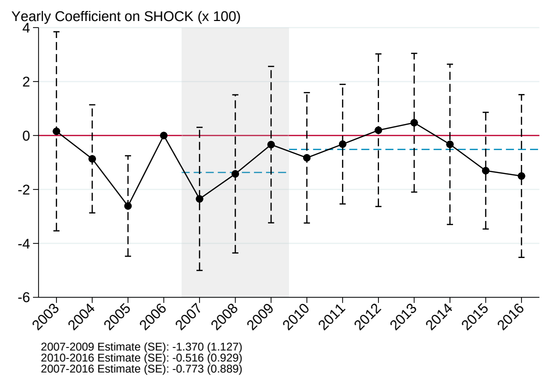
(b) Log share poor mental health last month



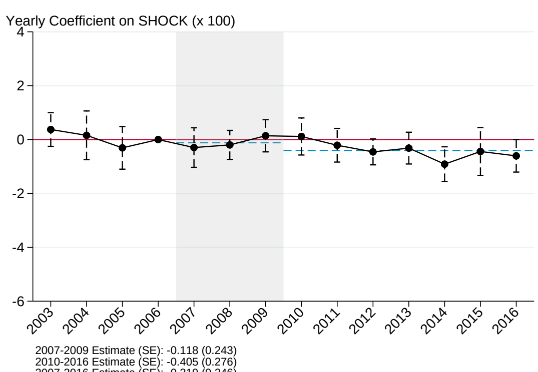
(c) Log share ever had diabetes



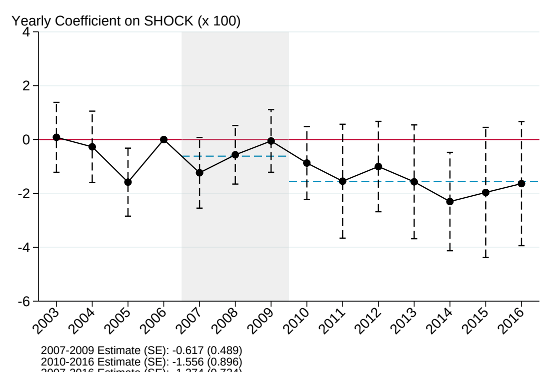
(d) Log share with asthma



(e) Log share overweight or obese



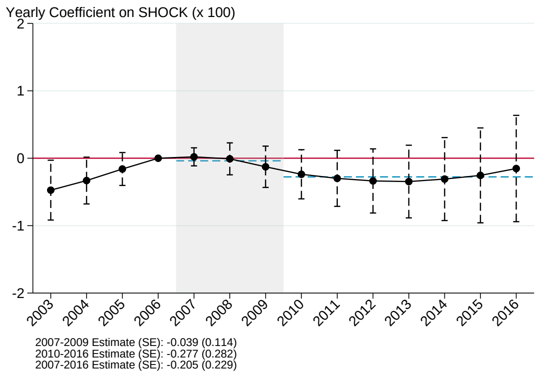
(f) Log share obese



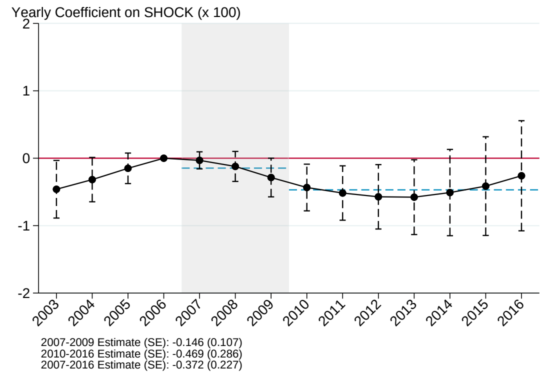
Notes: Figure displays coefficients β_t from equation $y_{st} = \beta_t[SHOCK_s * \mathbb{1}(Year_t)] + \alpha_s + \gamma_t + \varepsilon_{st}$ from 2003-2016, where s indexes states. The outcome y_{st} is the share of the state population with each characteristic. These shares are calculated as the mean of respondent-level BRFSS variables (weighted according to BRFSS survey weights). Variable construction is described in further detail in Appendix Section A.4. Coefficients and corresponding standard errors are multiplied by 100 for ease of interpretation. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the mean estimates β_t over the 2007-2009 and 2010-2016 periods (presented with standard errors in the lower left hand corner). State observations are weighted by 2006 state population from the SEER, and standard errors are clustered at the state level. N=51 states.

Figure OA.24: Population Impact of the Great Recession

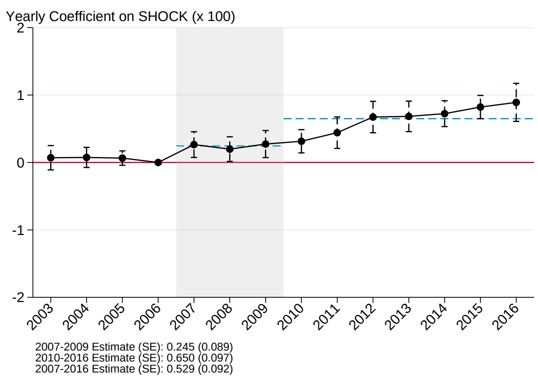
(a) Log Total Population



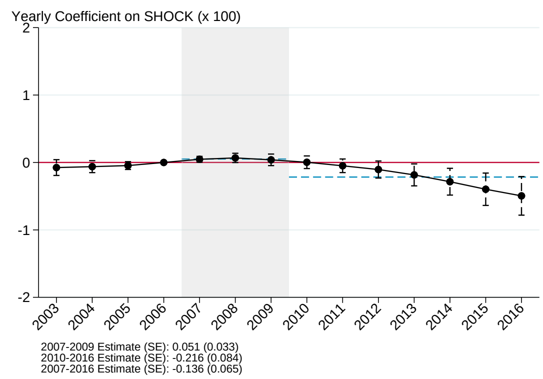
(b) Log Population Age 25-64



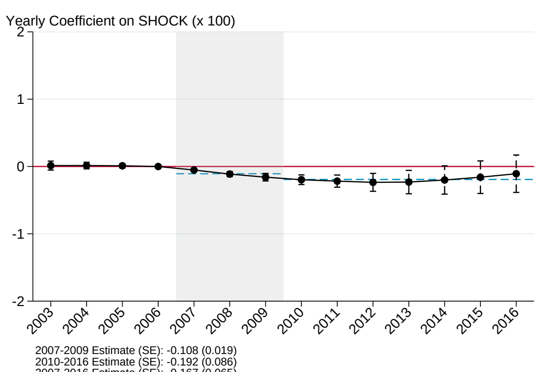
(c) Log Median Age



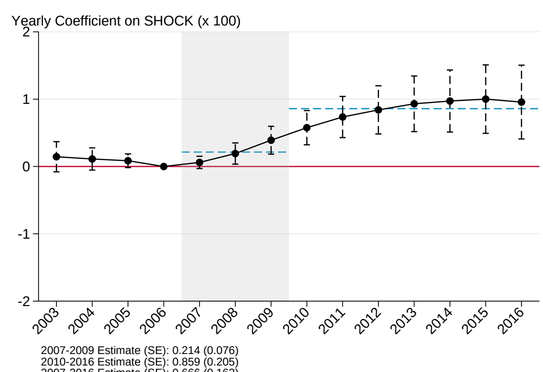
(d) Log Share $<$ 25 Years Old



(e) Log Share 25-64 Years Old



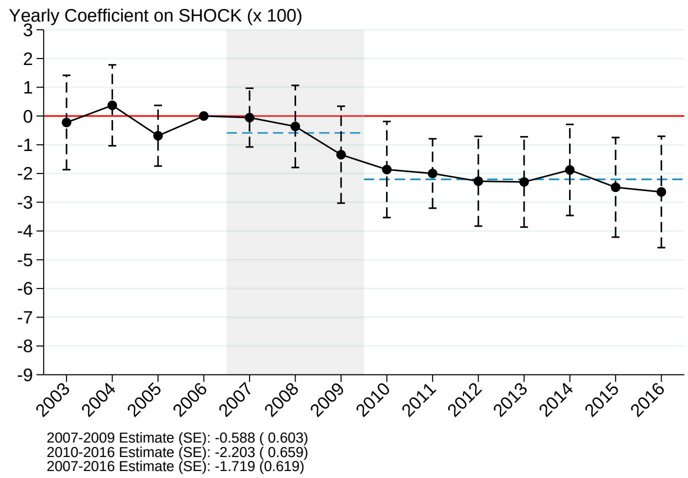
(f) Log Share $\geq$ 65 Years Old



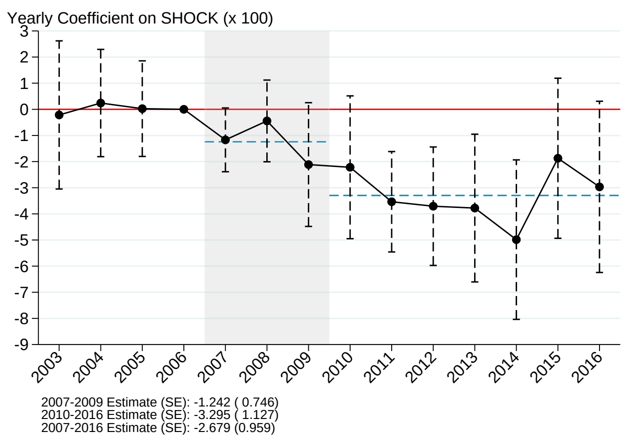
Notes: Figures plot yearly coefficients β_t estimated from equation (1), where the outcome y_{ct} is the log annual total CZ population from the SEER (Panels OA.24a); the age 25-64 CZ population (OA.24b); the log median age in the CZ (Panel OA.24c); the log share of the population under age 25 (Panel OA.24d); the log share age 25-64 (Panel OA.24e); and the log share 65+ years old (Panel OA.24f). Coefficients and corresponding standard errors are multiplied by 100 for ease of interpretation. Event study estimates are weighted by 2006 CZ population. Standard errors are clustered at the CZ level. Period estimates for 2007-2009, 2010-2016, and 2007-2016 are presented with the corresponding standard errors in the lower left hand corner. N=741 CZs.

Figure OA.25: Effect of Unemployment Shock on Earnings

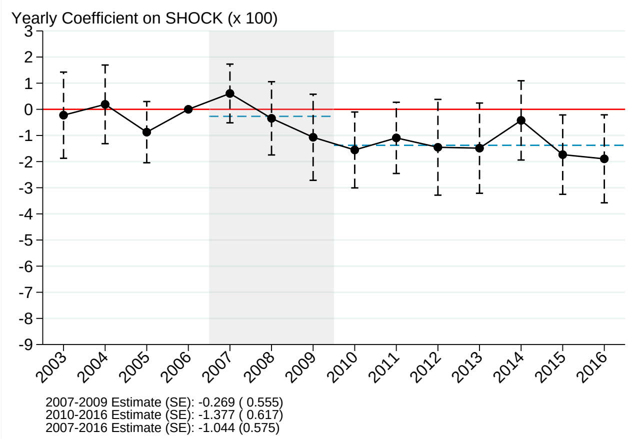
(a) Overall Impact, 25+ Year-Olds



(b) High School or Less



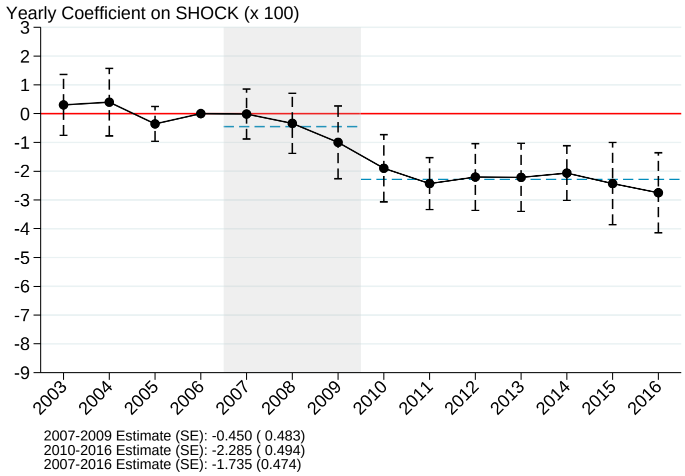
(c) More Than High School



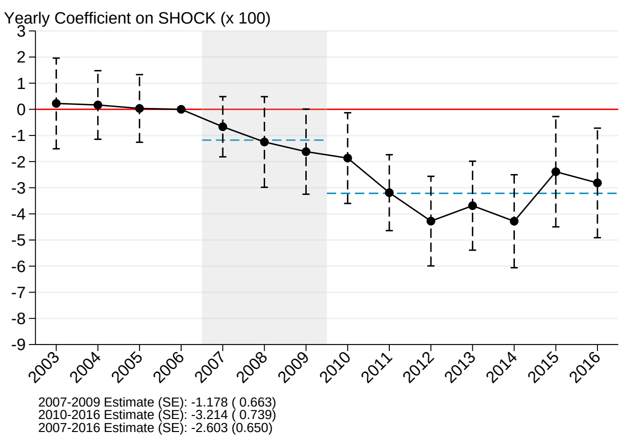
Notes: This figure displays coefficients β_t from equation (1) estimated at the state level, with the outcome defined as the log average earnings for individuals belonging to several demographic groups in each state-year according to the Current Population Survey (CPS). Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the point estimate for the linear combination of coefficients from 2007-2009 and 2010-2016. Observations are weighted based on 2006 SEER population data. Standard errors are clustered by state. Panel (a) shows results of estimating equation (1) with the outcome as the log average earnings across all individuals aged 25+ in each state-year. Panel (b) shows results with the outcome as the log average earnings across all individuals aged 25+ with a high school diploma or less in each state-year. Panel (c) shows results with the outcome as the log average earnings across all individuals aged 25+ with more than a high school diploma in each state-year.

Figure OA.26: Effect of Unemployment Shock on Earnings: Poisson Specification

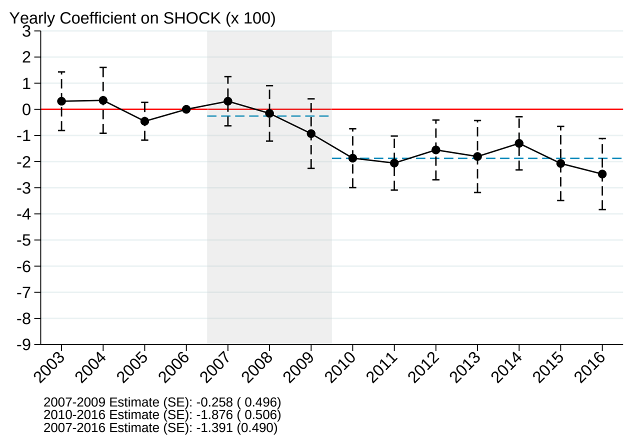
(a) Overall Impact, 25+ Year-Olds



(b) High School or Less



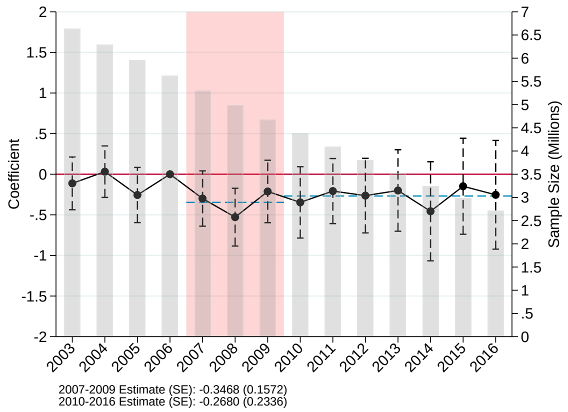
(c) More Than High School



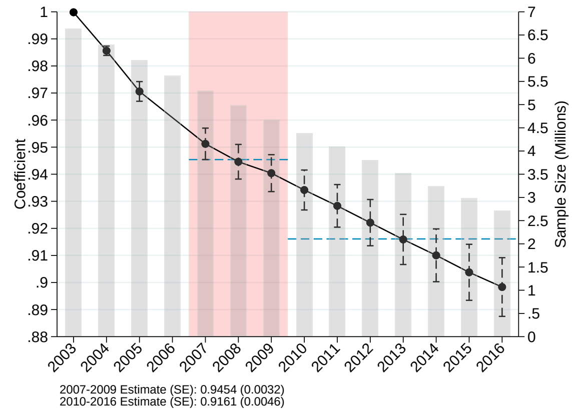
Notes: This figure displays coefficients β_t from equation (24), with the outcome defined as earnings for individuals i in each year t according to the Current Population Survey (CPS). Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the point estimate for the linear combination of coefficients from 2007-2009 and 2010-2016. Panel (a) shows results of estimating equation (24) using the sample of all respondents aged 25 or older (N = 1,788,643 person-years). Panel (b) restricts the sample to contain individuals aged 25 or older with a high school diploma or less (N = 781,637 person-years). Panel (c) restricts the sample to contain individuals aged 25 or older with more than a high school diploma (N = 1,007,006 person-years).

Figure OA.27: Sensitivity to Yearly vs. Baseline Residence

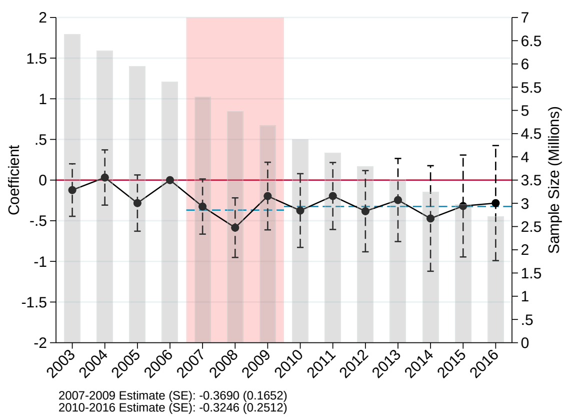
(a) 2003 Residence (Reduced Form) (β_t, equation (4))



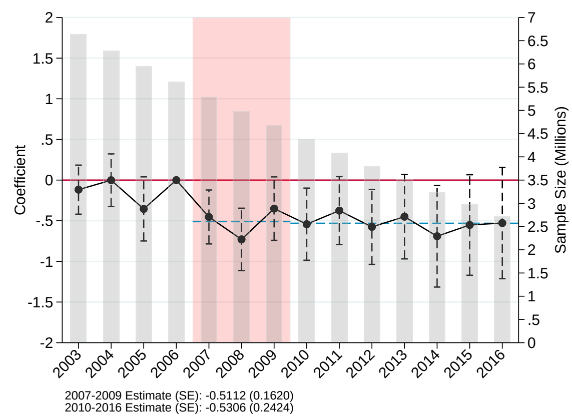
(b) First Stage (π_t^{FS}, equation (5))



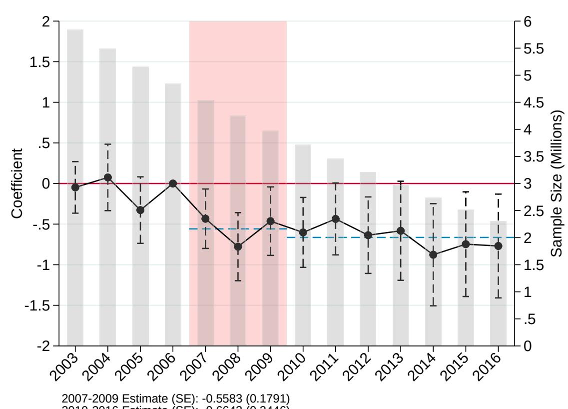
(c) Control Function (β_t, equation (6))



(d) Yearly Residence (β_t, equation (7))



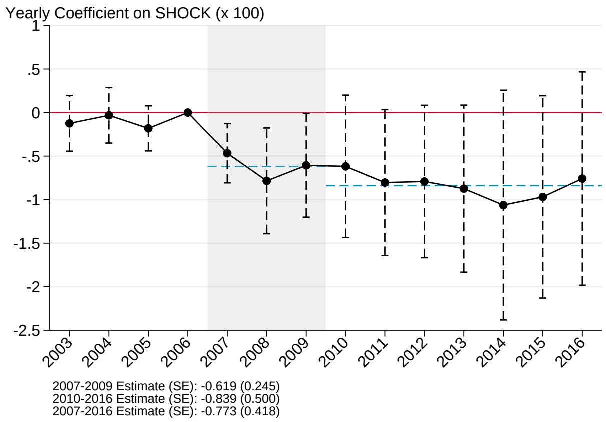
(e) Yearly Residence (Non-Movers) (β_t, equation (7))



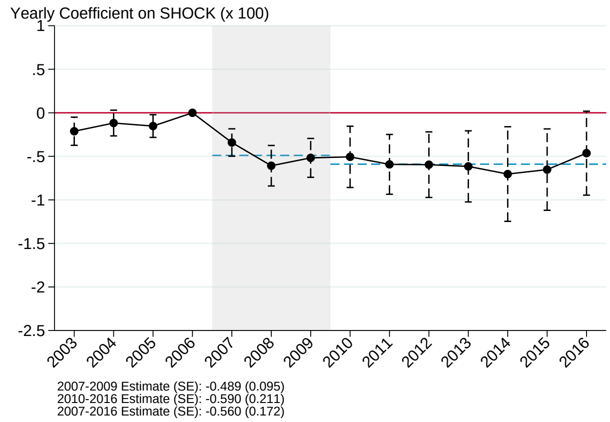
Notes: This figure displays coefficients β_t from equation (4) (Panel (a); coefficients multiplied by 100), equation (6) (Panel (c)), and equation (7) (Panels (d) & (e)), with outcome $log(m_{it}(a))$ defined as the log of the individual-level mortality hazard rate at age a. The figure also displays coefficients π_t^{FS} from equation (5) (Panel (b)), with outcome defined as the sum of the interactions of GR shock based on yearly CZ of residence and yearly dummies. In Panels (b)/(c)/(d)/(e), individuals are assigned their yearly CZ of residence, while in Panel (a) individuals are assigned their 2003 CZ of residence. Shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the point estimate for the linear combination of coefficients from 2007-2009 and 2010-2016. Standard errors are clustered by CZ. Control function standard errors are calculated via a Bayesian bootstrap procedure with 500 repetitions. The sample reflects a panel of 2003 Medicare beneficiaries, subject to the restrictions in Table OA.1. Gray bars indicate the sample size by year (which is reduced each year due to mortality); scale is determined by the secondary y-axis. N(2003) = 6,638,488.

Figure OA.28: Sensitivity to Geography and Sample

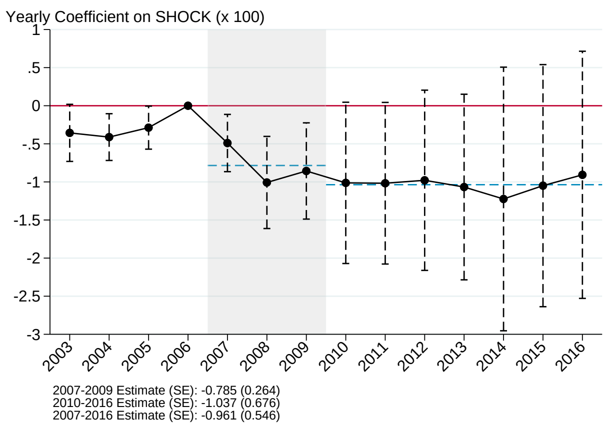
(a) State Level Analysis



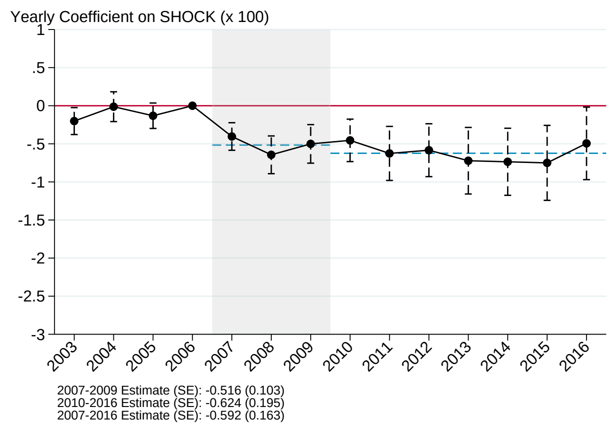
(b) County Level Analysis



(c) Drop Top/Bottom Decile of Shocked CZs



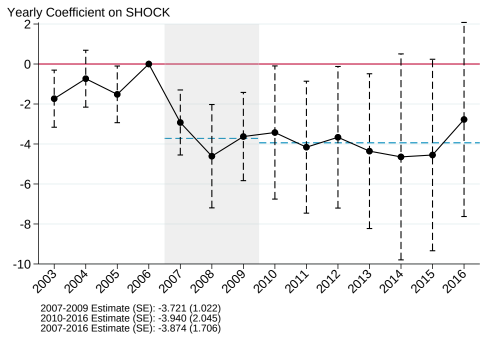
(d) Drop 10 Most Populous CZs



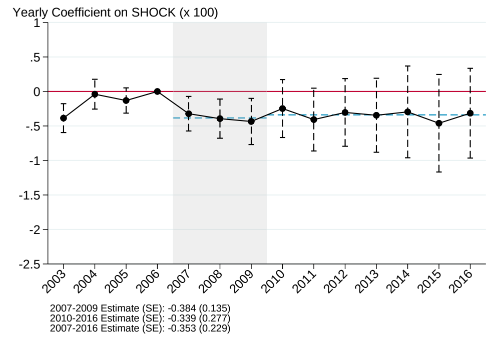
Notes: Figure displays the yearly coefficients β_t (multiplied by 100) from equation (1), varying the geographic level of the regression and the sample. The outcome y_{ct} is the log age-adjusted mortality rate per 100,000 population. Panel OA.28a estimates equation (1) at the state level, defining the shock as the 2007-2009 change in the state unemployment rate and the outcome as the state log age-adjusted mortality rate; Panel OA.28b makes the same adjustments, save at the county level. Panel OA.28c drops the top and bottom 2006 population-weighted deciles of shocked CZs and estimates equation (1) at the CZ level. Panel OA.28d drops the 10 most populous CZs (Los Angeles, CA; New York, NY; Chicago, IL; Newark, NJ; Philadelphia, PA; Detroit, MI; Houston, TX; Washington, DC; Boston, MA; and San Fransisco, CA) and then estimates (1) at the CZ level. Regression observations are weighted by state, county, or CZ population in 2006 according to the levels described. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the average annual point estimate for the periods 2007-2009 and 2010-2016. These estimates (and corresponding standard errors) are reported in the lower left hand corner along with the corresponding estimate for the entire 2007-2016 period. Standard errors are clustered at the state level in Fig. OA.28a, county level in OA.28b, and CZ level in OA.28c and OA.28d. N=51 states in Panel OA.28a; N=3,131 counties in Panel OA.28b; N=393 CZs in Panel OA.28c; and N=731 CZs in Panel OA.28d.

Figure OA.29: Sensitivity to Functional Form

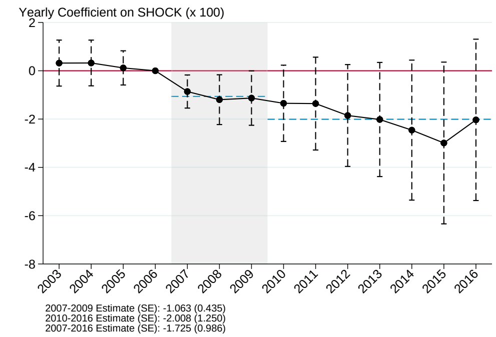
(a) Mortality Rate in Levels



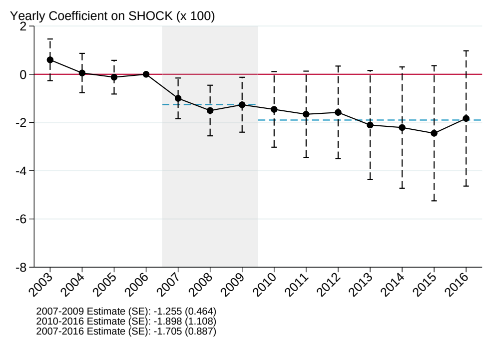
(b) Add Census-Division-by-Year Fixed Effects



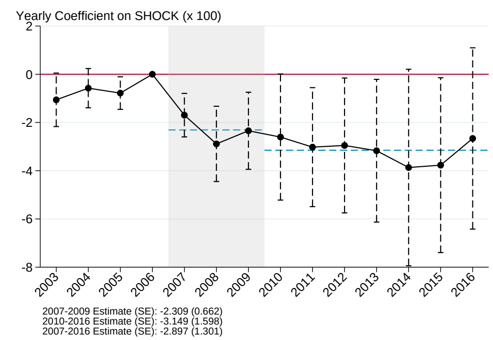
(c) SHOCK Quartiles: Second Quartile



(d) SHOCK Quartiles: Third Quartile



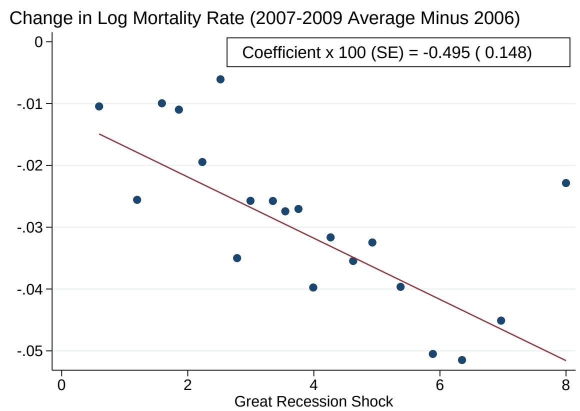
(e) SHOCK Quartiles: Fourth Quartile



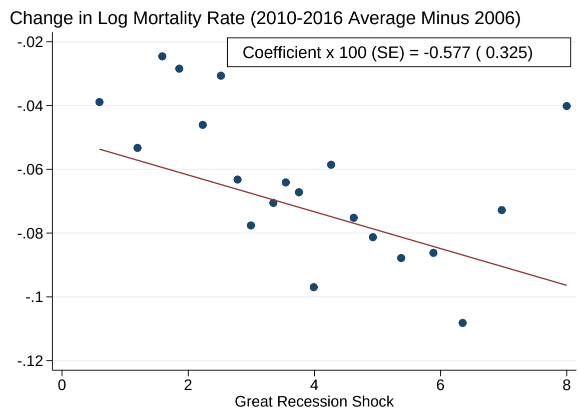
Notes: Figure displays the yearly coefficients β_t (multiplied by 100) from equation (1). The outcome in Panel OA.29a is the age-adjusted CZ mortality rate per 100,000 population; in all other figures, it is the log age-adjusted CZ mortality rate per 100,000 population. In Panel OA.29b, we add census-division by year fixed effects for the 9 census divisions and 14 years of the sample. In Panels, OA.29c, OA.29d, and OA.29e, we replace the linear $SHOCK_c$ variable with indicator for the quartile of the shock, and we estimate the equation $y_{ct} = \sum_{j=2}^{4} \beta_t^{(j)} \left[SHOCKQ_c^{(j)} * \mathbb{1}(Year_t)\right] + \alpha_c + \gamma_t$, where e.g. $SHOCKQ_c^{(k)}$ is an indicator for the kth quartile of the 2006 CZ population-weighted CZ unemployment rate shock; we omit the 1st quartile and report estimates of $\beta_t^{(2)}$, $\beta_t^{(3)}$, and $\beta_t^{(4)}$. The first through fourth shock quartiles have means 2.89, 4.00, 5.18, and 6.66, respectively. All regression estimates are weighted by CZ population in 2006. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the average annual point estimate for the periods 2007-2009 and 2010-2016. These estimates (and corresponding standard errors) are reported in the lower left hand corner along with the corresponding estimate for the entire 2007-2016 period. Standard errors are clustered at the CZ level. N=741 CZs.

Figure OA.30: Non-Parametric Check of Linearity Assumption

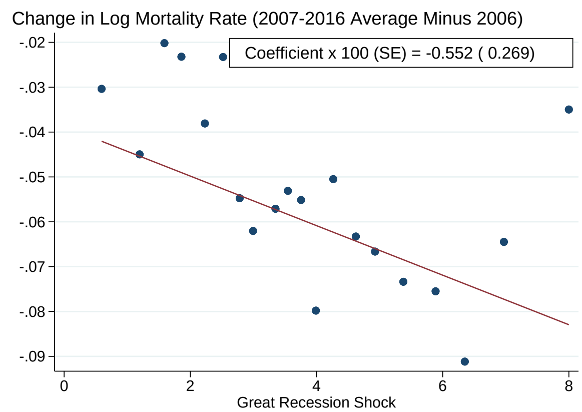
(a) Change in Log Mortality, 2006 vs 2007-09 Average, by GR Shock



(b) Change in Log Mortality, 2006 vs 2010-16 Average, by GR Shock



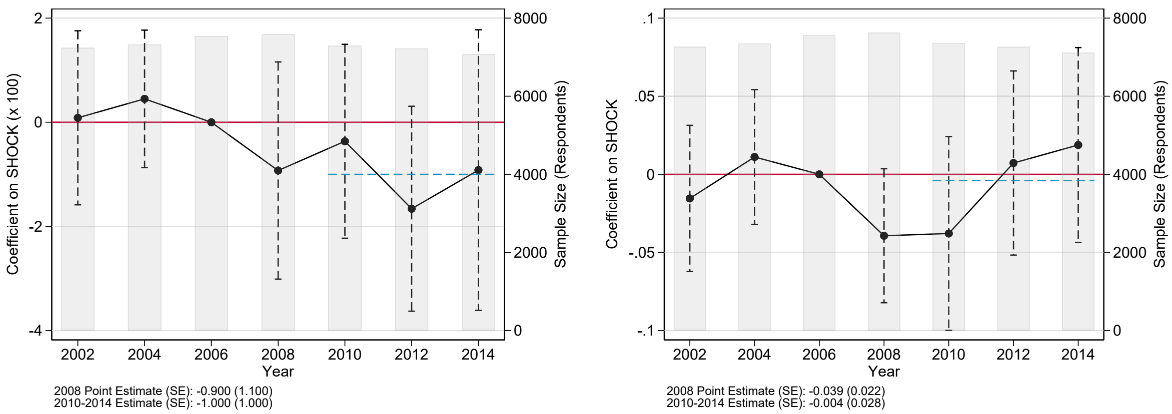
(c) Change in Log Mortality, 2006 vs 2007-16 Average, by GR Shock



Notes: Figure plots the 2006 population-weighted average difference in the log age-adjusted mortality rate between various post periods and a fixed 2006 pre-period against the 2006 population-weighted average Great Recession shock across CZs in each ventile of the Great Recession shock distribution. The line of best fit is plotted in red, and it is computed on the underlying sample of 741 CZs (weighting each CZ's 2006 population). The coefficient and heteroskedasticity-robust standard error are displayed in the top right corner of each panel.

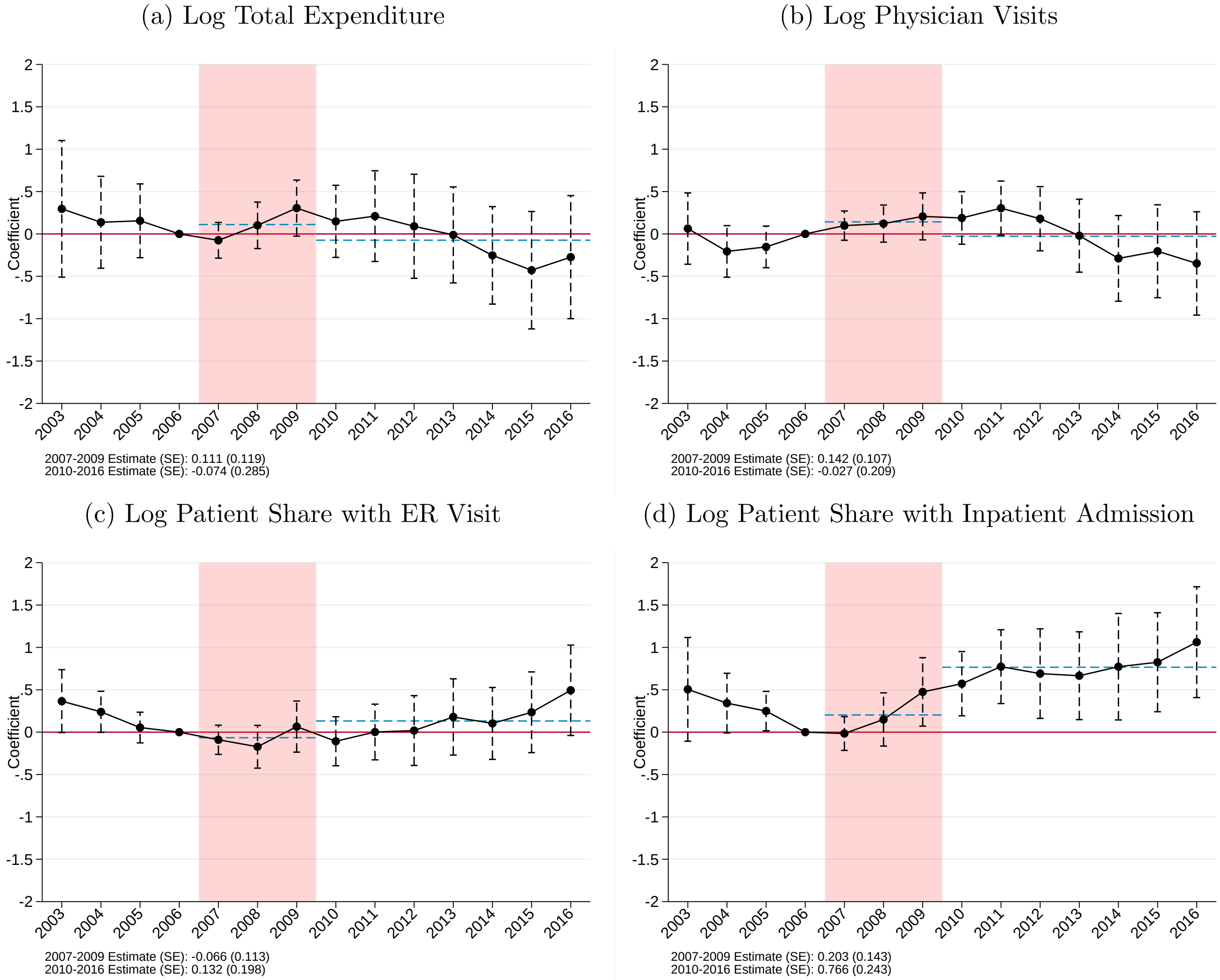
Figure OA.31: Impact of Unemployment Shock on Income and Earnings in the HRS

(a) Log Total Household Income (b) Any Earned Household Income



Notes: Figure displays the yearly coefficients β_t from equations (22) and (23), where the outcome y_{it} is either the log total household income reported by the respondent and possibly their spouse (Sub-Figure OA.31a, using equation (22)) or a binary indicator for any reported earned household income (Sub-Figure OA.31b, run as logistic regression with equation (23)). In each plot, the left vertical axis reports values for each coefficient β_t and its corresponding standard error (i.e. marginal effects for logistic regression, not odds ratios). The right vertical axis reports the number of respondents observed in each year, marked as light grey bars behind each coefficient. Dashed vertical lines indicate 95% confidence intervals on each coefficient, clustered at the state level. Horizontal blue dashed lines indicate the average annual point estimate for 2010-2014. These estimates (and corresponding standard errors) are reported in the lower left hand corner along with the point estimate for 2008. Estimates are weighted by the HRS respondent weights. N=7,189 respondent households.

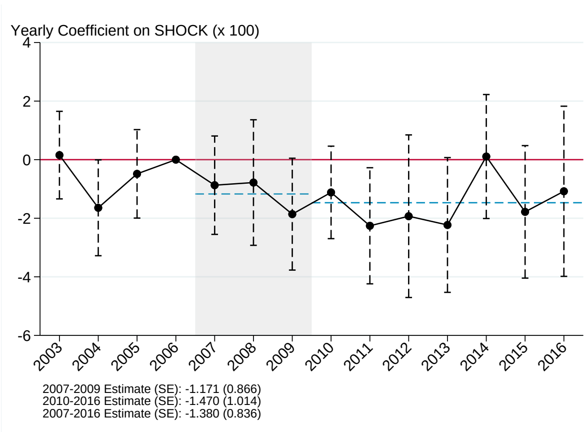
Figure OA.32: Impact of Unemployment Shock on Medicare Healthcare Utilization Measures



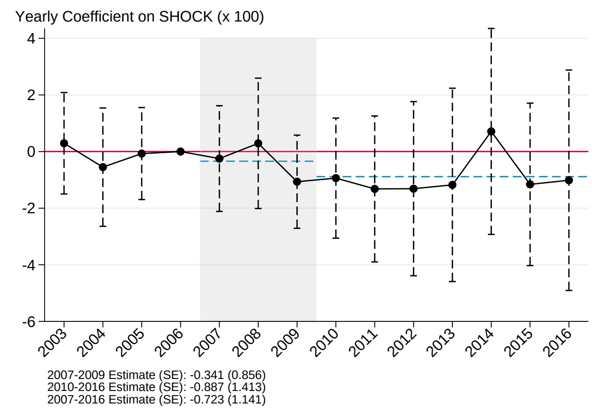
Notes: This figure displays coefficients β_t from equation (1), multiplied by 100, with outcome $log(Y_{ct})$ defined as the log of various healthcare utilization measures in CZ c and year t. Each individual is assigned their yearly CZ of residence, and CZ-year utilization measures are constructed as the average of its patient-year measures. Shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the point estimate for the linear combination of coefficients from 2007-2009 and 2010-2016. CZ observations are weighted based on 2006 SEER population data. Standard errors are clustered by CZ. We utilize the Repeated Cross Section sample, which restricts Medicare beneficiaries as per Table OA.2. Patient-years are further restricted to those that were enrolled in Medicare FFS in the current year (FFS in year t) and did not die during the year. N = 738.

Figure OA.33: Impact of Unemployment Shock on Health Behavior in the BRFSS

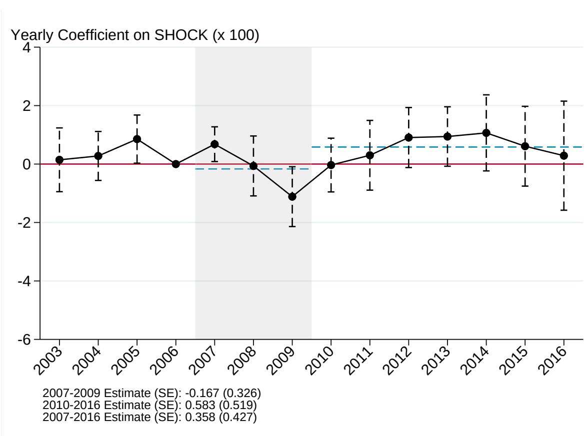
(a) Log share who currently smoke



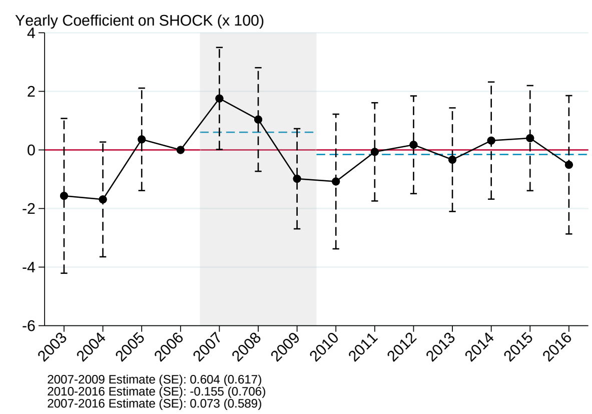
(b) Log share who smoke daily



(c) Log share who currently drink alcohol



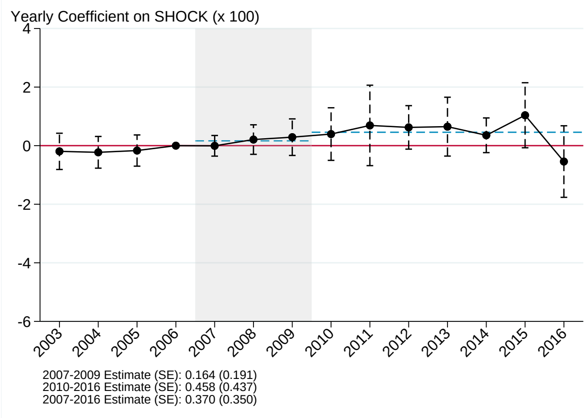
(d) Log share binge drinking last month



Notes: Figure displays coefficients β_t from equation $y_{st} = \beta_t[SHOCK_s * \mathbb{1}(Year_t)] + \alpha_s + \gamma_t + \varepsilon_{st}$ from 2003-2016, where s indexes states. The outcome y_{it} is the share of the state population with each characteristic. These shares are calculated as the mean of respondent-level BRFSS variables (weighted according to BRFSS survey weights). Variable construction is described in further detail in Appendix Section A.4. Coefficients and corresponding standard errors are multiplied by 100 for ease of interpretation. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the mean estimates β_t over the 2007-2009 and 2010-2016 periods (presented with standard errors in the lower left hand corner). State observations are weighted by 2006 state population from the SEER, and standard errors are clustered at the state level. N=51 states.

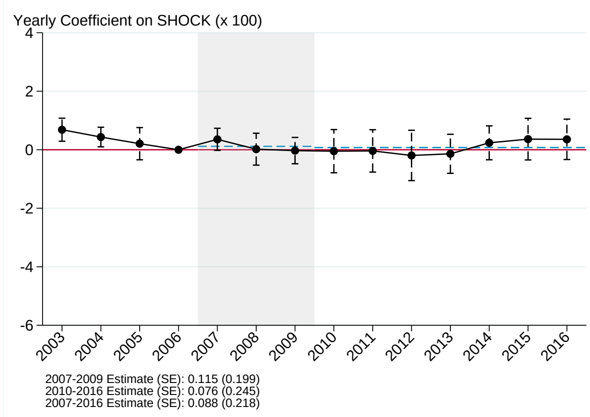
Figure OA.34: Impact of Unemployment Shock on Health Behavior and Health Care in the BRFSS

(a) Log share who exercised last month



(b) Log share who had a flu shot last year

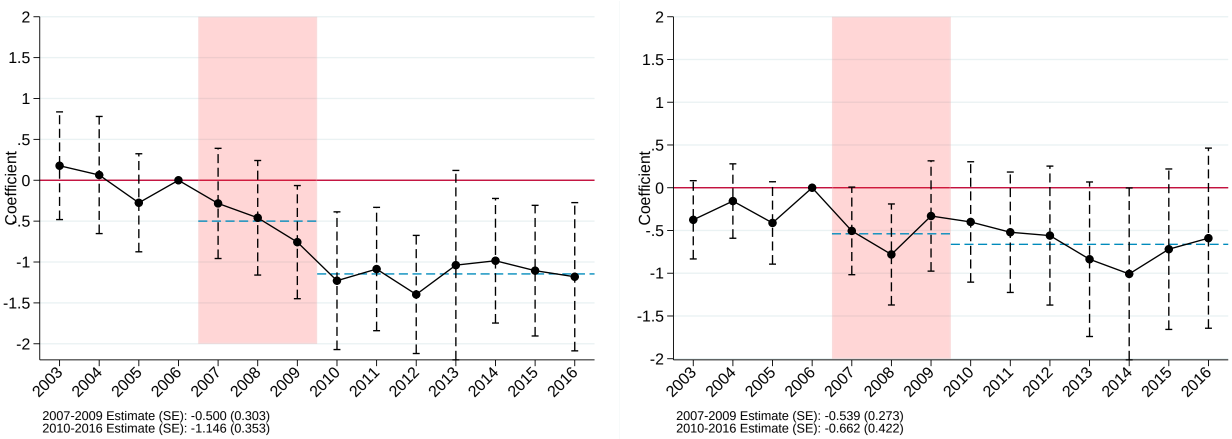
(c) Log share who currently have health insurance



Notes: Figure displays coefficients β_t from equation $y_{st} = \beta_t[SHOCK_s * \mathbb{1}(Year_t)] + \alpha_s + \gamma_t + \varepsilon_{st}$ from 2003-2016, where s indexes states. The outcome y_{it} is the share of the state population with each characteristic. These shares are calculated as the mean of respondent-level BRFSS variables (weighted according to BRFSS survey weights). Variable construction is described in further detail in Appendix Section A.4. Coefficients and corresponding standard errors are multiplied by 100 for ease of interpretation. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the mean estimates β_t over the 2007-2009 and 2010-2016 periods (presented with standard errors in the lower left hand corner). State observations are weighted by 2006 state population from the SEER, and standard errors are clustered at the state level. N=51 states.

Figure OA.35: Impact of the Unemployment Shock on Log Mortality Rate by SNF Use

(a) SNF use in t or $t-1$ | (b) No SNF use in t or $t-1$

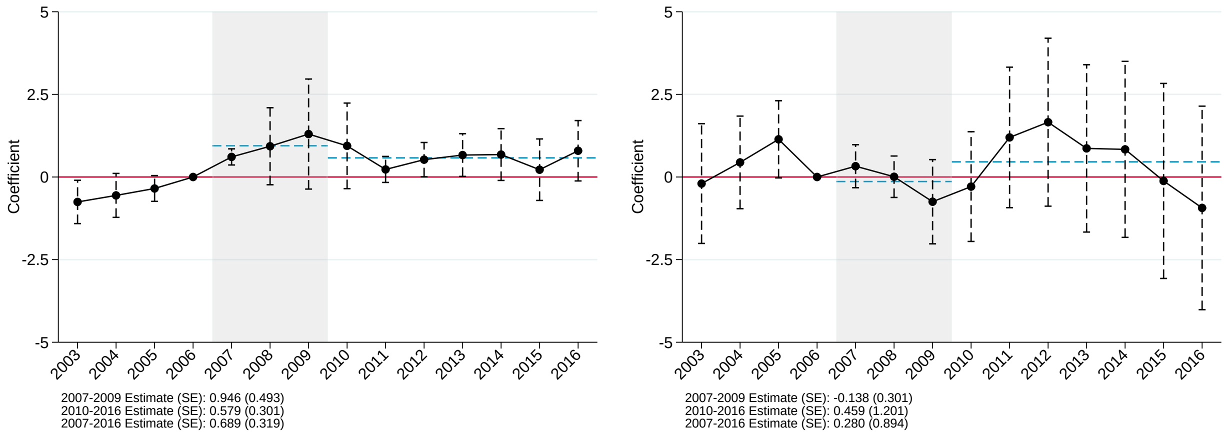


Notes: This figure displays coefficients β_t from equation (1), multiplied by 100, with outcome $log(Y_{ct}+1)$ defined as the log of the CZ-level mortality rate. Panel (a) is based on the mortality rate of individuals involved with SNF utilization in a given year or the year prior, as per MedPAR data. Panel (b) is based on the mortality of those not associated with recent SNF utilization. Each individual is assigned their yearly CZ of residence, and shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the point estimate for the linear combination of coefficients from 2007-2009 and 2010-2016. Standard errors are clustered by CZ. The sample of CZs is limited to those with at least one beneficiary associated with SNF utilization and one not associated with SNFs in every year. We utilize the Repeated Cross Section sample, which restricts patient-years in 2003-2016 to those between 65 and 99. Beneficiaries are also subject to the restrictions in Table OA.2. N = 733 CZs.

Figure OA.36: Impact of Unemployment Shock on Nursing Home Staffing

(a) Log Direct-Care Staff Hours

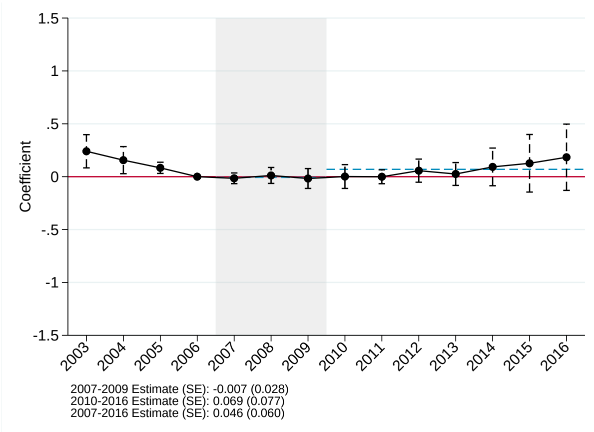
(b) Log Highly Skilled Nurses Ratio



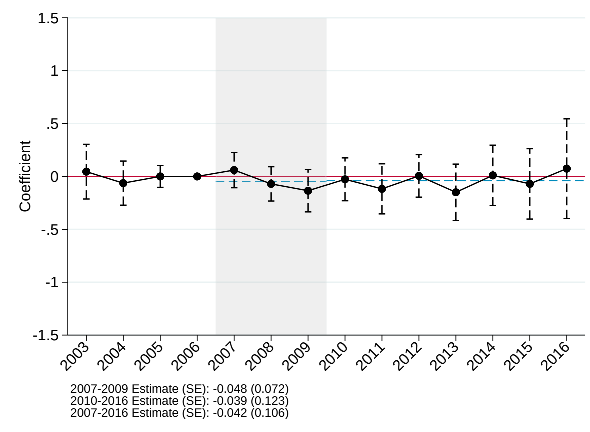
Notes: Figure displays coefficients β_t from equation 1 from 2003-2016 (in Panel (a)) and 2003-2015 (in Panel (b)), where i indexes skilled nursing facilities and $c(i)$ the Commuting Zone of facility i. Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation. In Panel (a), the outcome y_{it} is the log of the sum of the hours worked by registered nurse, licensed practical nurse, and certified nursing assistant staff per resident day at facility i during the two weeks prior to the annual OSCAR survey. In Panel (b), the outcome y_{it} is the log of the ratio of registered nurse full-time equivalents divided by the number of registered nurse + licensed practical nurse full-time equivalents in nursing homes. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the mean estimates β_t over the 2007-2009 and 2010-2016 periods (presented with standard errors in the lower left hand corner). Facility observations are weighted by 2006 CZ population from the SEER, and standard errors are clustered at the CZ level. N=17,582 facilities

Figure OA.37: Impact of Unemployment Shock on Nursing Home Volume and Resident Characteristics

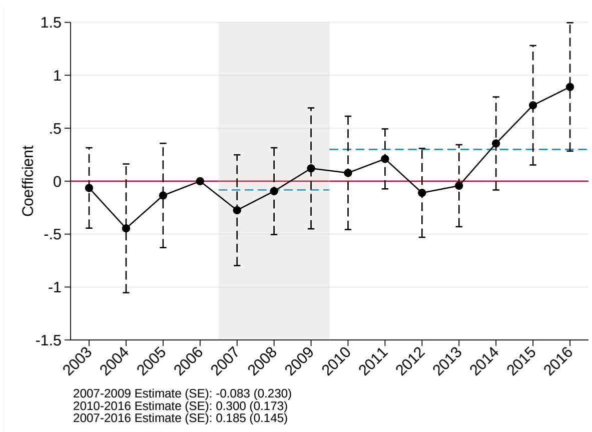
(a) Log Average Age



(b) Log Female Resident Share



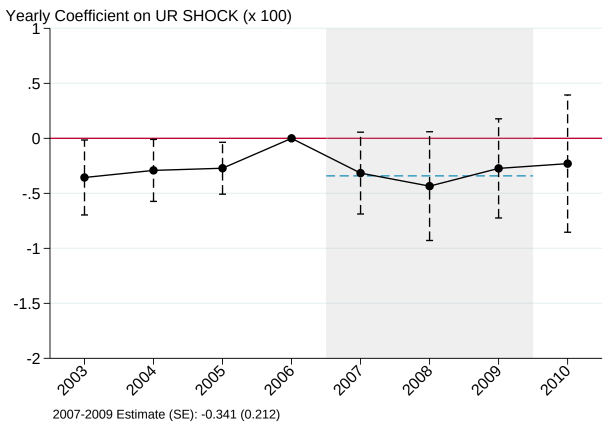
(c) Log Occupants per Bed



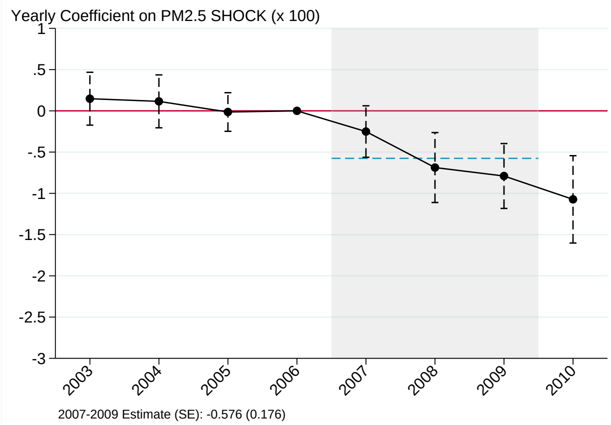
Notes: Figure displays coefficients β_t from equation $y_{it} = \beta_t[SHOCK_{c(i)} * \mathbb{1}(Year_t)] + \alpha_{c(i)} + \gamma_t + \varepsilon_{it}$ from 2003-2016, where i indexes skilled nursing facilities and $c(i)$ the Commuting Zone of facility i. Coefficients and corresponding standard errors are multiplied by 100 for ease of interpretation. The outcome y_{it} in Panel OA.37a is the log average age of residents in facility i as of the first Thursday in April of the survey year (from the MDS); in Panel OA.37b, the log share of facility residents who are female on the same day (from the MDS); and in Panel OA.37c, the log number of occupants per facility bed (the numerator calculated directly from the OSCAR, and the denominator from LTCFocus). Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the mean estimates β_t over the 2007-2009 and 2010-2016 periods (presented with standard errors in the lower left hand corner). Facility observations are weighted by 2006 CZ population from the SEER, and standard errors are clustered at the CZ level. N=17,582 facilities.

Figure OA.38: Impact of Unemployment and PM2.5 Shocks on Log Mortality Rate: Balanced Panel

(a) Coefficient on UR Shock (β_t)



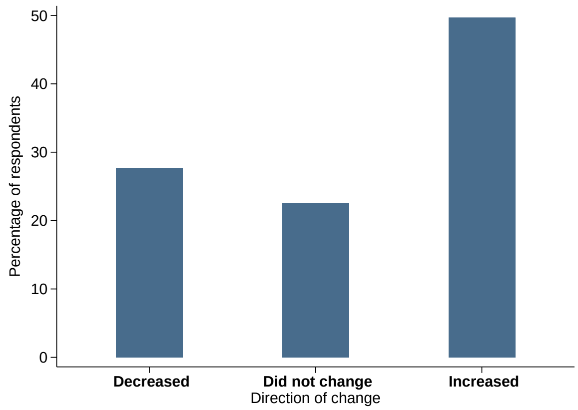
(b) Coefficient on PM 2.5 Shock (ϕ_t)



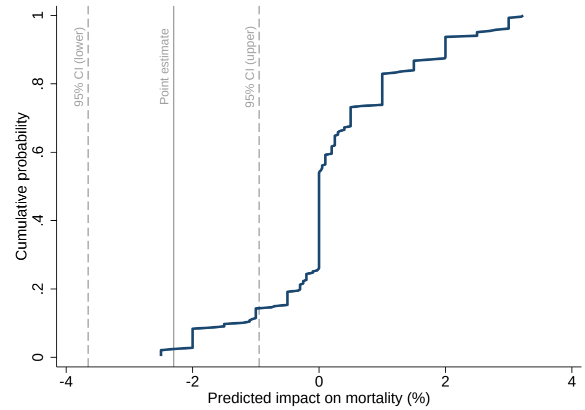
Panels OA.38a and OA.38b display coefficients β_t and ϕ_t, respectively, from equation (9), where the outcome y_{ct} is the log age-adjusted county mortality rate per 100,000 population. Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation. Analysis is restricted to the 497 counties for which we observe a PM2.5 monitor in every year between 2003 and 2010. β_t is the coefficient on the 2007-2009 change in the CZ unemployment rate interacted with calendar year, and ϕ_t is the coefficient on the negative 2006-2010 change in PM2.5 interacted with calendar year. Observations are weighted by county population in 2006. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the average annual point estimate for the periods 2007-2009. These estimates (and corresponding standard errors) are reported in the lower left hand corner. Standard errors are clustered at the CZ level.

Figure OA.39: Expert Survey Predicted Direction of Change in Mortality

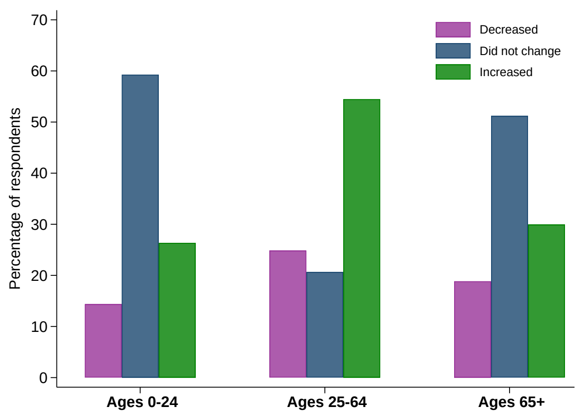
(a) Overall Prediction



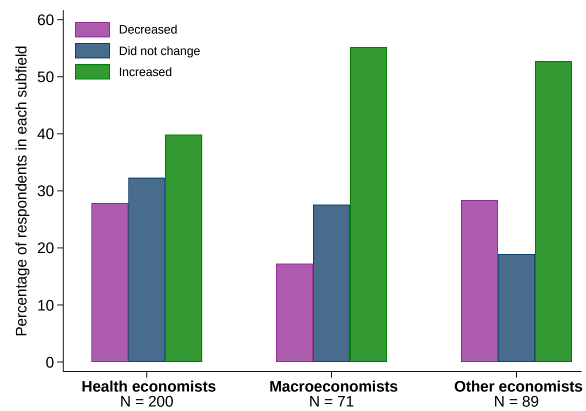
(b) Predicted Change in Mortality, Empirical CDF



(c) Prediction by Age Bin



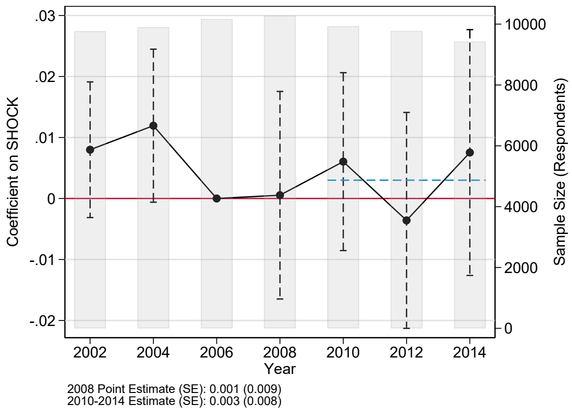
(d) Prediction by Respondent Subfield



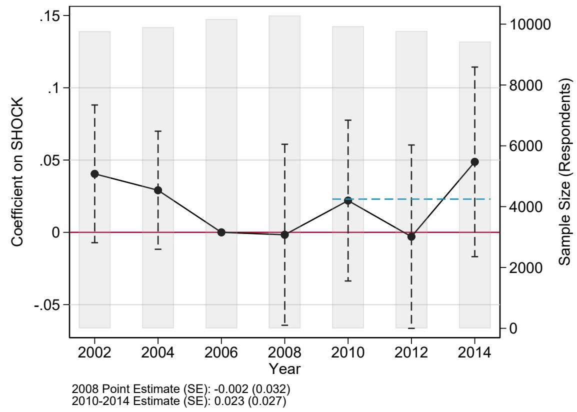
Notes: Figure shows results of an expert survey eliciting predictions about the impact of the Great Recession on mortality. Panels show the predicted direction of change in the U.S. mortality rate (OA.39a) overall, (OA.39c) for each of the three age bins appearing in the survey, and (OA.39d) by respondent subfield. The sample consists of 354 respondents. Figure OA.39b shows the distribution of the predicted direction and magnitude of change in the overall U.S. mortality rate from the expert survey as an empirical CDF. For visual clarity, responses are reported for the 287 respondents who predicted a change between the 5th (−2.5%) and 95th percentiles (3.23%) of the 317 respondents providing guesses for both the direction and magnitude of the change. The solid vertical line represents our point estimate (−2.3%), which is the 2nd percentile of the trimmed sample. The dashed vertical lines indicate the bounds for the confidence interval; the upper bound (−0.95%) of our confidence interval is the 14th percentile of the trimmed responses.

Figure OA.40: Impact of Unemployment Shock on Measures of Care in the HRS

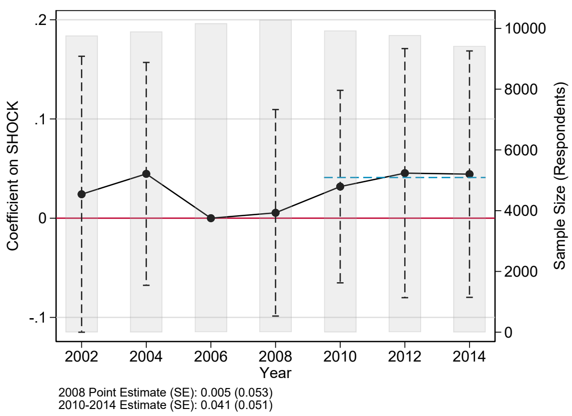
(a) Number of Helpers in the Past Month



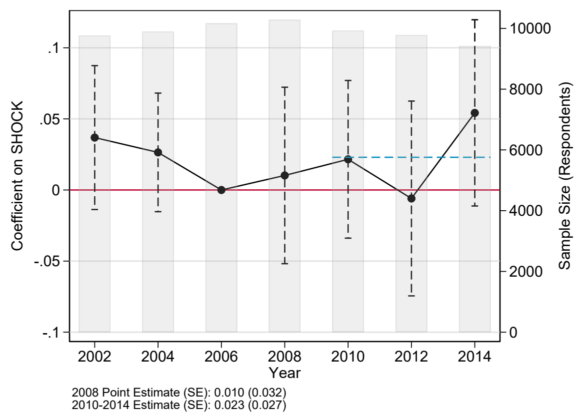
(b) Any Helpers in the Past Month



(c) Any Paid Helpers in the Past Month

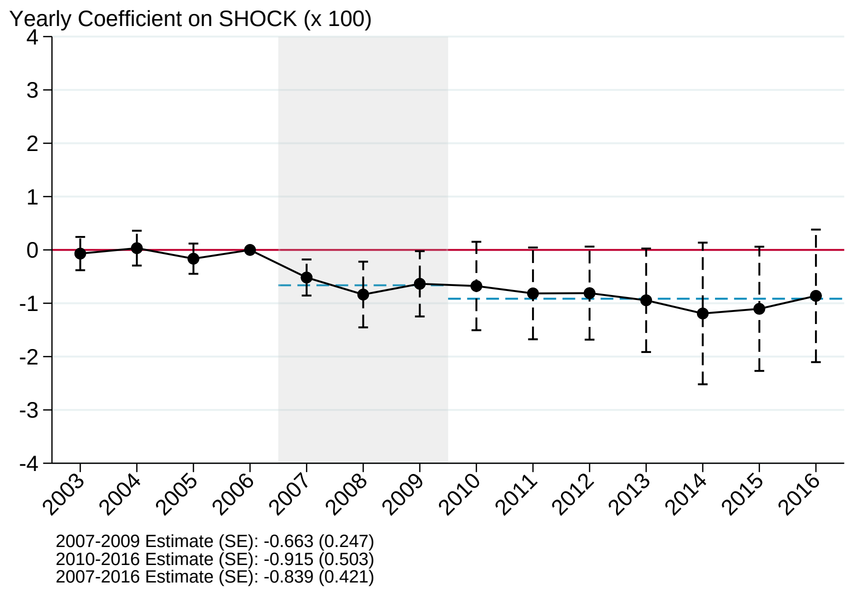


(d) Any Unpaid Helpers in the Past Month



Notes: Figure displays the yearly coefficients β_t from equations (22) and (23), where the outcome y_{it} is either the number of helpers reported by the respondent (Sub-Figure OA.40a, using equation (22)) or a binary indicator for any reported helpers, any reported paid helpers, and any reported unpaid helpers (Sub-Figures OA.40b, OA.40c, and OA.40d, all run as logistic regression with equation (23)). In each plot, the left vertical axis reports values for each coefficient β_t and its corresponding standard error (i.e. marginal effects for logistic regression, not odds ratios). The right vertical axis reports the number of respondents observed in each year, marked as light grey bars behind each coefficient. Dashed vertical lines indicate 95% confidence intervals on each coefficient, clustered at the state level. Horizontal blue dashed lines indicate the average annual point estimate for 2010-2014. These estimates (and corresponding standard errors) are reported in the lower left hand corner along with the point estimate for 2008. Estimates are weighted by the HRS respondent weights. N=9,750 respondents.

Figure OA.41: Impact on Log Mortality Rate, All Levels of Education



Notes: Figure plots yearly coefficients β_t estimated from equation (1), where the outcome y_{ct} is the log state age-adjusted mortality rate for 25+ year-olds. Event study estimates are weighted by 2006 state population as measured in the SEER. Standard errors are clustered at the state level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel. Georgia, New York, Rhode Island, and South Dakota are excluded from the sample due to missing data issues (see Appendix A.6 for details).

A.10 Tables

Table OA.1: Medicare Beneficiary Sample Restrictions (All 2003 Medicare Beneficiaries)

	Number of Beneficiaries (2003)
Unique beneficiaries in the 2003 Medicare beneficiary 20% sample	8,624,883
Exclude beneficiaries that are:	
Younger than 65 or older than 99 in 2003	6,856,815
Living overseas or in US territories in at least one year	6,702,425
Observed with incomplete data (gaps, inconsistent age data, etc.)	6,641,219
Not matched with a commuting zone in at least one year	6,638,488
Number of beneficiaries	**6,638,488**

Notes: The table shows the impact of each of our restrictions on the 2003 Medicare sample size in terms of beneficiaries. We begin with a 20 percent sample of all 2003 Medicare beneficiaries, based on the Medicare Master Beneficiary Summary File (MBSF). The count includes beneficiaries enrolled in Medicare Parts C & D, as well as those who were not enrolled in Parts A & B for all months in 2003 (such as beneficiaries entering Medicare in 2003).

Table OA.2: Medicare Beneficiary Sample Restrictions (2003-2016 Repeated Cross Section)

	Number of Beneficiaries
Unique 2001-2016 beneficiaries in the 20% Denominator data sample	18,400,912
Exclude beneficiaries that are:	
Younger than 65 in a given year or older than 99 in first year	15,027,505
Living overseas or in US territories in at least one year	14,647,175
Observed with incomplete data (gaps, inconsistent age data, etc.)	14,412,901
Not matched with a commuting zone in at least one year	14,406,107
Not observed from 2003 onwards	13,705,472
Number of beneficiaries	**13,705,472**

Notes: The table shows the impact of each of our restrictions on the number of Medicare beneficiaries, for the 2003-2016 Repeated Cross Section sample. We begin with a 20 percent sample of all 2001-2016 Medicare patient-years, based on the Medicare Master Beneficiary Summary File (MBSF). The count includes beneficiaries enrolled in Medicare Parts C & D, as well as those who were not enrolled in Parts A & B for all months in 2003 (such as beneficiaries entering Medicare in 2003).

Table OA.3: Recession Effect on Remaining Life Expectancy by Age and Recession Type

A. Regular Recession (2-year duration, 3 percentage point increase in unemployment)

Age	Mortality Rate (per 100,000)	Life Expectancy (without recession)	Life Expectancy (with recession)	Percent Difference	Increase in Life Expectancy
35	128	44.071	44.073	0.004%	0.002
45	286	34.788	34.791	0.009%	0.003
55	623	26.061	26.066	0.019%	0.005
65	1385	18.004	18.012	0.042%	0.008
75	3388	11.068	11.080	0.104%	0.012

B. Great Recession (10-year duration, 4.6 percentage point increase in unemployment)

Age	Mortality Rate (per 100,000)	Life Expectancy (without recession)	Life Expectancy (with recession)	Percent Difference	Increase in Life Expectancy
35	128	44.071	44.088	0.037%	0.016
45	286	34.788	34.817	0.083%	0.029
55	623	26.061	26.104	0.165%	0.043
65	1385	18.004	18.069	0.359%	0.065
75	3388	11.068	11.154	0.778%	0.086

Notes: Table displays unisex mortality rates and remaining life expectancy given a regular recession (Panel (a)) and the Great Recession (Panel (b)), in comparison to a no-recession scenario. Remaining life expectancy is calculated given age-specific mortality rates for males and females, which are based on Social Security Administration 2007 male and female life tables, available at https://www.ssa.gov/oact/HistEst/PerLifeTables/2022/PerLifeTables2022.html. Remaining life expectancy at age A (L_A) is defined as the average number of years lived past age A, assuming an equivalent number of males and females starting at this age. Thus, $L_A = \frac{1}{2}L_{A,F} + \frac{1}{2}L_{A,M}$, where $L_{A,F}$ and $L_{A,M}$ represent female and male remaining life expectancy, respectively. $L_{A,F}$ is then defined as $L_{A,F} = \sum_{x=A+1}^{120}[(x-A) * m_{SSA,F}(x) * \prod_{z=A}^{x-1}(1 - m_{SSA,F}(z))]$, where $m_{SSA,F}(x)$ represents SSA female life table death probability at age x, and similarly for males. That is, female life expectancy is obtained as the sum over each age x of the share of females that die at age x ($m_{SSA,F}(x) * \prod_{z=A}^{x-1}(1 - m_{SSA,F}(z))$, or death probability multiplied by the share of females alive by age x) multiplied by the number of years lived $(x - A)$. To calculate mortality rates with recessions, we assume that a one percentage point increase in unemployment generates a 0.5% decrease in mortality rates for the duration of the recession, as per the empirical sections of this paper.

Table OA.4: Descriptive Statistics – 2006 Mortality

Group	Share of Population	Number of Deaths	Mortality Rate per 100,000	Share of Deaths
Full Population*	1.00	2426023	790.28	1.00
Age Bins				
0-4 years	0.07	33157	166.33	0.01
5-14 years	0.14	6149	15.16	0.00
15-24 years	0.14	34886	81.44	0.01
25-34 years	0.13	42950	109.04	0.02
35-44 years	0.14	83042	192.08	0.03
45-54 years	0.15	185029	427.59	0.08
55-64 years	0.11	281397	881.59	0.12
65-74 years	0.06	390089	2032.10	0.16
74-84 years	0.04	667335	5097.46	0.28
85+ years	0.02	701989	14430.00	0.29
Gender*				
Male	0.49	1201760	945.62	0.50
Female	0.51	1224263	668.58	0.50
Race*				
Non-Hispanic White	0.67	1947877	787.63	0.80
Non-Hispanic Black	0.13	287796	1027.73	0.12
Hispanic	0.15	132968	608.72	0.05
Non-Hispanic Other	0.06	57382	503.88	0.02
Education*†				
HS or Less	0.52	1536814	1243.46	0.70
More than HS	0.48	611009	982.18	0.28
Cause of Death*				
Cardiovascular Disease	.	823701	267.39	0.34
Malignant Neoplasms	.	559875	182.08	0.23
Chronic Lower Respiratory Disease	.	124578	41.04	0.05
Diabetes	.	72448	23.57	0.03
Alzheimer's Disease	.	72432	23.49	0.03
Influenza/Pneumonia	.	56323	18.32	0.02
Kidney Disease	.	45343	14.79	0.02
Motor Vehicle Accidents	.	45301	15.00	0.02
Suicide	.	33292	10.98	0.01
Liver Disease	.	27550	8.76	0.01
Homicide	.	18553	6.20	0.01
All Other Causes (Residual)	.	546627	178.67	0.23

* Age-adjusted mortality rates reported for these categories. † These statistics exclude the states of Georgia, New York, Rhode Island, and South Dakota due to missing data on education. They also report age-adjusted mortality per 100,000 25+ year olds instead of the entire population.
Notes: This table presents descriptive statistics of mortality events in the United States in 2006 in the National Center for Health Statistics microdata. The sample is all mortality events among the resident US population with observed age at death (99.99% of resident mortality events). Population estimates are drawn from the annual SEER data.

Table OA.5: Sensitivity to Dropping Census Divisions

	(1) 2007-2009 Period Estimate	(2) 2010-2016 Period Estimate	(3) 2007-2016 Period Estimate
Baseline (all CZs)	-0.501	-0.582	-0.558
	(0.153)	(0.337)	(0.279)
Drop Census Divisions			
Drop New England Division	-0.400	-0.351	-0.365
	(0.137)	(0.282)	(0.233)
Drop Middle Atlantic Division	-0.356	-0.264	-0.292
	(0.136)	(0.276)	(0.227)
Drop East North Central Division	-0.542	-0.541	-0.542
	(0.156)	(0.361)	(0.294)
Drop West North Central Division	-0.366	-0.291	-0.313
	(0.141)	(0.289)	(0.239)
Drop South Atlantic Division	-0.471	-0.651	-0.597
	(0.161)	(0.238)	(0.209)
Drop East South Central Division	-0.459	-0.408	-0.423
	(0.151)	(0.311)	(0.257)
Drop West South Central Division	-0.412	-0.307	-0.339
	(0.141)	(0.284)	(0.234)
Drop Mountain Division	-0.251	-0.175	-0.198
	(0.134)	(0.289)	(0.236)
Drop Pacific Division	-0.229	-0.160	-0.181
	(0.131)	(0.286)	(0.233)

Notes: Table displays period estimates of one-off deviations from equation (1). Columns (1), (2), and (3) display averages of coefficients β_t across 2007-2009, 2010-2016, and 2007-2016, respectively. Standard errors for the period are displayed below each period estimate in parentheses. The first row displays our main baseline estimate, from Figure 3. The subsequent rows estimate the same model, dropping CZ observations from each noted census division. CZs are assigned to states (and resulting Census Divisions) according to the state with the plurality of the CZ population. Census divisions are the Pacific, Mountain, West North Central, West South Central, East South Central, East North Central, Middle Atlantic, South Atlantic, and New England divisions. All estimates are weighted by 2006 CZ population as estimated from the SEER, with standard errors clustered at the CZ level.

Table OA.6: Period Estimates of Health Behaviors and Weight in Levels

	(1) 2006 Mean	(2) 2007-2009 Period Estimate	(3) 2010-2016 Period Estimate	(4) 2007-2016 Period Estimate	(5) Ruhm Estimate (1987-1995)
Health Behaviors					
Currently smoke cigarettes	0.1967	-0.0020	-0.0024	-0.0023	–0.0031
		(0.0017)	(0.0016)	(0.0014)	(0.0007)
Currently drink alcohol	0.5233	-0.0012	0.0021	0.0011	0.0039
		(0.0017)	(0.0021)	(0.0018)	(0.0024)
Any physical activity last month	0.7604	0.0014	0.0036	0.0030	0.0064
		(0.0014)	(0.0034)	(0.0027)	(0.0021)
Weight					
Overweight or obese (BMI $\geq$ 25)	0.6311	-0.0008	-0.0027	-0.0021	–0.0017
		(0.0016)	(0.0018)	(0.0016)	(0.0006)
Obese (BMI $\geq$ 30)	0.2864	-0.0019	-0.0045	-0.0037	–0.0021
		(0.0014)	(0.0024)	(0.0020)	(0.0005)

Notes: Table displays estimates of health behavior and health from the 2003-2016 BRFSS, and the corresponding estimates for the same categories from Ruhm (2000). Column (1) displays the 2006 share of the national population with each characteristic (i.e. the population-weighted mean of state estimates), while columns (2)-(4) display the 2007-2009, 2010-2016, and 2007-2016 averages of coefficients β_t from equation $y_{st} = \beta_t[SHOCK_s * \mathbb{1}(Year_t)] + \alpha_s + \gamma_t + \varepsilon_{st}$, where the outcome y_{st} is the share of state s's population with each characteristic in year t. Note that individuals are defined as overweight for a BMI greater than or equal to 25, and obese for a BMI greater than or equal to 30. State averages are generated as the mean value of individual reports in a given state, weighted by BRFSS survey weights. Estimates are weighted by state 2006 population, and standard errors are clustered at the state level. Column (5) displays the corresponding estimates (the coefficient on the unemployment rate) for an individual level regression of the BRFSS on 1987-1995 state unemployment rates in Tables VI and VII of Ruhm (2000). Ruhm (2000) notes: "All specifications include vectors of year and state dummy variables and control for education..., age..., race..., ethnicity..., marital status, and sex. Robust standard errors, estimated assuming observations are independent across years and states but not within states in a given year, are displayed in parentheses. Individuals are defined to be underweight if BMI is less than 19, overweight if BMI exceeds 27.3 for females or 27.8 for males, and obese if BMI is over 30. Linear probability models are estimated when the dependent variable is dichotomous....Data are from the BRFSS for the years 1987–1995."

Table OA.7: Mortality Impact of County Unemployment and Pollution Shocks

	(1) 2007-2009 Period Estimate	(2) 2007-2009 Period Estimate	(3) 2007-2009 Period Estimate
Unemployment Shock	-0.618		-0.461
	(0.178)		(0.150)
PM2.5 Shock		-0.665	-0.469
		(0.195)	(0.150)

Notes: Table displays the average annual impact of the Great Recession and/or PM2.5 pollution shock on log age-adjusted mortality over 2007-2009. Coefficients and their corresponding standard errors are multiplied by 100 for ease of interpretation. The unemployment shock is defined as the county-level change in the unemployment rate from 2007-2009, and the PM2.5 shock is defined as the negative of the county-level change in PM2.5 level between 2006 and 2010. Columns (1) and (2) report the 2007-2009 average of β_t from equation (8), varying the $SHOCK$ measure, and column (3) reports the 2007-2009 average of β_t and ϕ_t from equation (9). Standard errors, clustered at the CZ level, are reported in parentheses below each period estimate. Analysis is restricted to the 524 counties for which we observe a PM2.5 monitor in both 2006 and 2010.

Table OA.8: Welfare Costs of Recessions by Age

	Mortality			
	Exogenous	Endogenous		
	(1)	(2)	(3)	(4)
Panel A. Starting age 35				
$\gamma = 1.5$	1.52	1.21	0.77	0.33
$\gamma = 2$	2.09	1.81	1.39	0.97
$\gamma = 2.5$	2.74	2.49	2.11	1.74
Panel B. Starting age 45				
$\gamma = 1.5$	1.11	0.69	0.12	-0.45
$\gamma = 2$	1.56	1.13	0.54	-0.05
$\gamma = 2.5$	2.05	1.64	1.05	0.47
Panel C. Starting age 55				
$\gamma = 1.5$	0.68	0.11	-0.65	-1.40
$\gamma = 2$	0.94	0.31	-0.52	-1.34
$\gamma = 2.5$	1.23	0.55	-0.35	-1.24
Panel D. Starting age 65				
$\gamma = 1.5$	0.00	-0.79	-1.80	-2.80
$\gamma = 2$	0.00	-0.93	-2.12	-3.28
$\gamma = 2.5$	0.00	-1.10	-2.49	-3.84
VSLY	-	\$100k	\$250k	\$400k

Notes: The welfare cost is measured as a percentage of average annual consumption. In all specifications: agents die when they are 100 years old, the model includes retirement, and mortality rates are realistic (age-specific).

Table OA.9: Welfare Costs of Recessions by Age: Without Retirement

	Mortality			
	Exogenous	Endogenous		
	(1)	(2)	(3)	(4)
Panel A. Starting age 35				
$\gamma = 1.5$	1.74	1.40	0.96	0.51
$\gamma = 2$	2.36	2.06	1.63	1.20
$\gamma = 2.5$	3.09	2.83	2.44	2.05
Panel B. Starting age 45				
$\gamma = 1.5$	1.46	0.99	0.40	-0.18
$\gamma = 2$	2.00	1.53	0.91	0.30
$\gamma = 2.5$	2.62	2.17	1.56	0.95
Panel C. Starting age 55				
$\gamma = 1.5$	1.20	0.56	-0.23	-1.01
$\gamma = 2$	1.63	0.93	0.04	-0.83
$\gamma = 2.5$	2.12	1.38	0.41	-0.54
Panel D. Starting age 65				
$\gamma = 1.5$	0.92	0.00	-1.08	-2.14
$\gamma = 2$	1.26	0.17	-1.15	-2.44
$\gamma = 2.5$	1.64	0.37	-1.20	-2.70
VSLY	-	$100k	$250k	$400k

Notes: The welfare cost is measured as a percentage of average annual consumption. In all specifications: agents die when they are 100 years old, the model does not include retirement, and mortality rates are realistic (age-specific).

Table OA.10: Impact of Unemployment Shock on Log Mortality and Log Life Years Lost (2007-2009 Period Estimates)

		Log Life-Years Lost Regressions			
	Medicare Repeated Cross Section (TM in $t-1$)	No Covariates (TM in $t-1$)	Age (TM in $t-1$)	Age + Demographic (TM in $t-1$)	Age + Demographic + Chronic Conditions (TM in $t-1$)
	(1)	(2)	(3)	(4)	(5)
Great Recession Shock	-0.598	-0.611	-0.555	-0.548	-0.525
	(0.241)	(0.234)	(0.246)	(0.246)	(0.240)
Mean Mortality Rate (per 100,000)	5332.6	NA	NA	NA	NA
Mean LYL per Decedent	NA	11.00	7.87	7.74	6.45
Observations	738	738	738	738	738

Notes: This table displays the point estimate for the linear combination of yearly coefficients from 2007-2009, multiplied by 100 for ease of interpretation; estimates are based on coefficients β_t from equation (1). In columns (1), the dependent variable is the log of the (non age-adjusted) mortality rate per 100,000 among the 65+ population, using CDC and Medicare data. In the log life-years lost regressions in columns (2)-(5), the dependent variable is the log of the CZ-year level life-years lost LYL_{ct} Life years lost is defined as $LYL_{ct} = 100,000 * \frac{\sum_{i \epsilon S_{ct}} LYL_{it}}{|S_{ct}|}$, in which S_{ct} denotes the set of individuals in CZ c and year t. In the Medicare data, each individual is assigned their yearly CZ of residence. Great Recession shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. CZ observations are weighted based on 2006 population SEER data. Regressions are calculated with standard errors clustered by CZ; standard errors are reported in parentheses below each period estimate. In the Repeated Cross Section sample, Medicare beneficiaries are subject to the restrictions in Table OA.2. The Repeated Cross Section (FFS in $t-1$) sample further restricts patient-years in 2003-2016 to those enrolled in Medicare FFS in the previous year. CZs are restricted to those with at least one beneficiary in every year in the 2003-2016 period, which restricts to 738 CZs.

Table OA.11: Medicare Patient-Year Sample Demographic Summary Statistics

	All 2003 Beneficiaries (1)	Repeated Cross Section (2)	Repeated Cross Section (FFS in $t-1$) (3)
Share female	0.59	0.56	0.58
Share white	0.87	0.85	0.87
Mean age	78.81	74.84	76.02
Share in age group			
65-74	0.28	0.54	0.48
75-84	0.51	0.33	0.37
85+	0.21	0.13	0.15
Share movers	0.14	0.12	0.12
Share enrolled in Medicaid	0.13	0.13	0.14
Share enrolled in Medicare Advantage	0.24	0.26	0.03
Mortality rate (per 100,000)	6,482	4,692	5,348
Number of patients	6,638,488	13,705,472	10,036,555
Number of patient-years	64,215,757	106,076,423	68,891,400

Notes: The table displays summary statistics on three Medicare patient-year samples: All 2003 Beneficiaries, Repeated Cross Section, and Repeated Cross Section (FFS in t-1). The All 2003 Beneficiaries sample represents a panel of 2003 Medicare beneficiaries, subject to the restrictions in Table OA.1. The Repeated Cross Section sample draws beneficiaries in every year during the 2003-2016 period, subject to the restrictions in Table OA.2. Repeated Cross Section (FFS in t-1) further restricts patient-years to those enrolled in Medicare Part B and not enrolled in Medicare Advantage in every month of the previous year.

Table OA.12: Welfare Costs of the Great Recession by Age

	Mortality			
	Exogenous	Endogenous		
	(1)	(2)	(3)	(4)
Panel A. Starting age 35				
$\gamma = 1.5$	1.83	1.77	1.68	1.58
$\gamma = 2$	1.86	1.81	1.72	1.64
$\gamma = 2.5$	1.89	1.84	1.77	1.69
Panel B. Starting age 45				
$\gamma = 1.5$	2.19	2.06	1.85	1.64
$\gamma = 2$	2.22	2.11	1.92	1.73
$\gamma = 2.5$	2.25	2.15	1.99	1.82
Panel C. Starting age 55				
$\gamma = 1.5$	2.73	2.48	2.05	1.63
$\gamma = 2$	2.76	2.54	2.16	1.79
$\gamma = 2.5$	2.80	2.60	2.27	1.94
Panel D. Starting age 65				
$\gamma = 1.5$	0.00	-0.51	-1.38	-2.23
$\gamma = 2$	0.00	-0.45	-1.22	-1.98
$\gamma = 2.5$	0.00	-0.40	-1.08	-1.75
VSLY	-	\$100k	\$250k	\$400k

Notes: The welfare cost is measured as a percentage of average annual consumption. In all specifications: agents die when they are 100 years old, the model includes retirement, and mortality rates are realistic (age-specific). A 10-year duration of the Great Recession is considered, followed by a period without recessions until the end of life.

Table OA.13: Welfare Costs of the Great Recession by Age: Without Retirement

	Mortality			
	Exogenous	Endogenous		
	(1)	(2)	(3)	(4)
Panel A. Starting age 35				
$\gamma = 1.5$	1.59	1.53	1.44	1.34
$\gamma = 2$	1.61	1.56	1.47	1.39
$\gamma = 2.5$	1.63	1.59	1.51	1.44
Panel B. Starting age 45				
$\gamma = 1.5$	1.90	1.77	1.56	1.35
$\gamma = 2$	1.92	1.81	1.62	1.43
$\gamma = 2.5$	1.95	1.85	1.68	1.51
Panel C. Starting age 55				
$\gamma = 1.5$	2.36	2.12	1.69	1.28
$\gamma = 2$	2.39	2.17	1.80	1.42
$\gamma = 2.5$	2.42	2.22	1.89	1.56
Panel D. Starting age 65				
$\gamma = 1.5$	3.07	2.54	1.65	0.77
$\gamma = 2$	3.10	2.63	1.84	1.06
$\gamma = 2.5$	3.13	2.72	2.01	1.32
VSLY	-	\$100k	\$250k	\$400k

Notes: The welfare cost is measured as a percentage of average annual consumption. In all specifications: agents die when they are 100 years old, the model does not include retirement, and mortality rates are realistic (age-specific). A 10-year duration of the Great Recession is considered, followed by a period without recessions until the end of life.

Table OA.14: Welfare Costs of the Great Recession by Age and Education

Mortality	Exogenous		Endogenous					
Education	$\leq$ HS	$>$ HS	$\leq$ HS	$>$ HS	$\leq$ HS	$>$ HS	$\leq$ HS	$>$ HS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A. Starting age 35								
$\gamma = 1.5$	3.21	1.05	3.09	1.05	2.89	1.05	2.69	1.05
$\gamma = 2$	3.31	1.06	3.21	1.06	3.02	1.06	2.85	1.06
$\gamma = 2.5$	3.42	1.07	3.32	1.07	3.16	1.07	3.00	1.07
Panel B. Starting age 45								
$\gamma = 1.5$	3.89	1.24	3.62	1.24	3.17	1.25	2.73	1.25
$\gamma = 2$	4.00	1.25	3.77	1.25	3.37	1.26	2.97	1.26
$\gamma = 2.5$	4.12	1.26	3.91	1.27	3.56	1.27	3.21	1.27
Panel C. Starting age 55								
$\gamma = 1.5$	4.90	1.52	4.37	1.53	3.49	1.54	2.62	1.54
$\gamma = 2$	5.03	1.54	4.57	1.54	3.78	1.55	3.01	1.56
$\gamma = 2.5$	5.17	1.55	4.76	1.56	4.06	1.56	3.37	1.57
Panel D. Starting age 65								
$\gamma = 1.5$	0.00	0.00	-1.03	0.01	-2.76	0.03	-4.45	0.05
$\gamma = 2$	0.00	0.00	-0.91	0.01	-2.44	0.02	-3.93	0.04
$\gamma = 2.5$	0.00	0.00	-0.80	0.01	-2.16	0.02	-3.48	0.04
VSLY	-		\$100k		\$250k		\$400k	

Notes: The welfare cost is measured as a percentage of average annual consumption. We measure the costs for different education groups. The two groups are individuals with High School (HS) diploma or less, and individuals with more than HS diploma. The estimates use group-specific consumption and mortality effects of the Great Recession, as well as group-specific mortality rates. In all specifications: agents die when they are 100 years old, the model does not include retirement, and mortality rates are realistic (age-specific). A 10-year duration of the Great Recession is considered, followed by a period without recessions until the end of life.