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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 to 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. Mortality reductions appear across causes of death and 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 mortality declines are driven primarily by external effects of reduced aggregate economic activity on mortality, and recession-induced reductions in air pollution appear to be a quantitatively important mechanism. Incorporating our estimates of pro-cyclical mortality into a standard macroeconomics framework substantially reduces the welfare costs of recessions, particularly for people with less education, and 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 impacts on the level and volatility of consumption (e.g., Lucas 1987, 2003; Krebs 2007; Krusell et al. 2009). Yet recessions may also have important impacts on health. Indeed, an empirical literature in health economics has found mortality to be pro-cyclical in the 1970s and 1980s (e.g., Ruhm 2000; Stevens et al. 2015), although perhaps less so in the subsequent two decades (Ruhm 2015). Incorporating the 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.

The Great Recession substantially reduced mortality. We estimate that for every one-percentage-point increase in a Commuting Zone's (CZ) unemployment rate between 2007-2009, its age-adjusted mortality rate fell by 0.5 percent. These mortality reductions appear immediately, and they persist for at least 10 years. Since the average national unemployment rate increased by 4.6 percentage points between 2007 and 2009, our estimates imply 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 for at least 10 years. To put this in perspective, these estimates imply that the Great Recession provided one in twenty five 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 economic 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.

We explore heterogeneity in the mortality impacts of the Great Recession by cause of death and by demographics. 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 demographic groups. They also appear across all major causes of death except for cancer mortality—the second largest cause of death—for which we estimate a precise null effect. We find roughly equi-proportional impacts (i.e., similar percentage reductions in mortality rates) across gender, race/ethnicity, and age groups. However, because mortality is so much higher among the elderly, about three-quarters of the overall mortality reduction comes from averted 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 half of the estimated mortality declines due to the Great Recession.

Before incorporating these findings into welfare analysis, we investigate potential mechanisms behind the recession-induced mortality declines. To the extent that these declines reflect externalities from reduced aggregate economic activity on health, holding constant own employment or consumption, they may mitigate the negative welfare effects of recession-induced consumption changes. The evidence points to such externalities as the primary driver behind our estimates. The concentration of averted deaths in the elderly population—who did not experience any direct income effects from the Great Recession-induced local labor market decline—is one important indication. Moreover, we detect no evidence of a key direct mechanism discussed in the literature, whereby reduced labor market activity frees up time for beneficial health behaviors (as in Ruhm 2000, 2005). We do, however, find a quantitatively important role for a particular external channel—recession-induced declines in air pollution—which we estimate can explain over one-third of the recession-induced mortality declines. We do not, however, find evidence for a role for two other external channels that have been discussed in the literature: reduced spread of infectious disease (as in Adda 2016), or improved quality of nursing home care (as in Stevens et al. 2015).

To assess the quantitative importance of mortality declines for the welfare consequences of recessions, we conduct two types of exercises. First, we examine how they alter standard welfare analyses of recessions that are based solely on their impacts on consumption. To do so, we extend the Krebs (2007) model of the consumption-based welfare cost of facing a lifetime risk of recessions to incorporate our estimates of pro-cyclical mortality. Our results suggest that accounting for endogenous mortality substantially reduces the welfare cost of recessions. For example, for a 45-year-old with a coefficient of relative risk aversion of two and a value of a statistical life-year of five times annual consumption, we estimate that accounting for recession-induced mortality declines reduces their willingness to pay to avoid future recessions by more than half. At older ages, the willingness to pay to avoid future recessions declines even more dramatically, and starting around age 55 recessions become welfare-improving.

Second, we focus specifically on the Great Recession and examine how its welfare implications are affected by our mortality estimates. We estimate the impact of the Great Recession on consumption using the same spatial variation in its severity that we use to estimate its impact on mortality. We then use the consumption and mortality estimates to assess the welfare implications of a local labor market shock of the size of the Great Recession with and without accounting for mortality impacts. Accounting for endogenous mortality not only lowers the overall welfare cost of the Great Recession (for example by about 25 percent for a 55-year-old using the parameterization described above) but also has important distributional implications. Specifically, a welfare analysis of the Great Recession that focused solely on local economic impacts would suggest that its welfare costs were larger for those with less education; however, accounting for the mortality effects that are concentrated entirely among those with a high school degree or less substantially mitigates—and at older ages even reverses—that conclusion.

These findings come with some important caveats. First, our design will not pick up any nationwide impacts of the Great Recession. Our estimates thus exclude, for example, any mortality impacts from the nationwide collapse of the stock market, or any nationwide increase in malaise.[1] In this sense, our estimates may be more applicable to the more "typical" local recessions studied in the literature than to aggregate, national downturns. Relatedly, our design does not capture impacts of the Great Recession that are spatially differentiated but not perfectly correlated with local labor market declines, such as declines in house prices, or declines in air pollution that may originate from declines in local labor markets but impact other areas due to wind patterns. Second, while the Great Recession helps identify the impact of local area recessions on mortality, those impacts may not generalize to other, particularly milder, recessions; that said, we do not find evidence of a non-linear relationship between the size of the economic shock and the mortality decline. Third, our analysis focuses primarily on mortality impacts, yet recessions may also have important morbidity impacts, particularly for those at younger ages with very low mortality. Our limited evidence indicates that the Great Recession also caused roughly equi-proportional morbidity reductions across ages, suggesting that our focus on mortality may underestimate the extent of recession-induced health improvements. Finally, although we analyze the 10-year impact of the Great Recession shock, our analysis does not measure impacts at even longer time horizons.[2] 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.

Our paper extends the macroeconomics 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 macroeconomics 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 health into welfare analyses of business cycles.[3]

Our findings also contribute to a much larger empirical literature on the relationship between

[1] 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.

[2] For example, Schwandt and Von Wachter (2020) find that a temporarily higher state unemployment rate at the age of labor market entry (ages 16 to 22) is associated with long-run declines in earnings and increased mortality several decades later.

[3] Two 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.

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 countries, across countries, and over time (e.g. Cutler et al. 2006; Costa 2015; Chetty et al. 2016; Cutler et al. 2016), although the causal evidence of the impact of income on mortality is limited and mixed.[4] There is also evidence that job loss increases mortality (Sullivan and Von Wachter 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) have documented a negative contemporaneous association between area unemployment rates and mortality in area-year panel data. This relationship appears both in the US (e.g. Ruhm 2000; Miller et al. 2009; Stevens et al. 2015), as well as in Canada (Ariizumi and Schirle 2012) and several European countries (Neumayer 2004; Granados 2005; Buchmueller et al. 2007). However, this work focused on the decades before the Great Recession, and over those decades the relationship between local unemployment and mortality weakened in the US (McInerney and Mellor 2012; Ruhm 2015). Moreover, studying almost three dozen countries over 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] When we surveyed over 300 experts in spring 2023 on the likely impact of the Great Recession on the U.S. mortality rate, we found that 50 percent of respondents predicted that the Great Recession would increase mortality, and only 27 percent predicted a decrease; moreover, 93 percent of respondents provided a predicted impact on mortality larger than our (negative) point

[4]For example, Cesarini et al. (2016) find no impact from lottery winnings on adults' mortality up to 10 years later while 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.

[5]In the time-series, Seeman et al. (2018) find that blood pressure and blood glucose levels worsened for adults during the Great Recession, and Lamba and Moffitt (2023) find that pain increased. Yet when examining the relationship between health and the area unemployment rate using two-way fixed effect models, Currie et al. (2015) find that between 2003 and 2010, increases in the state's annual unemployment rate worsened contemporaneous physical and mental health of disadvantaged women, but may have improved the health of more advantaged women, while Strumpf et al. (2017) find that between 2005 and 2010, increases in a metropolitan area's annual unemployment rate decreased contemporaneous mortality. When measuring the Great Recession by its impact on the housing market, Currie and Tekin (2015) estimate that increases in neighborhood foreclosure rates from 2005 to 2010 increased 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.

estimate, and 82 percent provided a prediction larger than the upper bound of our 95 percent confidence interval. Appendix A provides more detail on the survey and its results.

Our empirical approach follows in the spirit of Bartik (1991), Blanchard and Katz (1992), and especially Yagan (2019) in exploiting the fact that different areas of the country had very different exposure to a large, aggregate economic shock. This 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. Second, as emphasized by Arthi et al. (2022), a key limitation to the existing literature is the potential for contamination from unobserved migration in response to recessions. For some of our analyses, we 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 endogenous migration or unmeasured changes in the local population. Third, our empirical approach helps isolate the causal impacts of recessions from potential confounding factors that could both increase the local unemployment rate and also directly affect health.[6]

The rest of our paper proceeds as follows. Section 2 presents our data and empirical strategy. Section 3 presents our empirical estimates of mortality impacts. Section 4 investigates potential mechanisms behind these results. Section 5 explores their implications for the welfare analysis of recessions. Section 6 provides a brief conclusion.

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. Our primary analysis is across Commuting Zones (CZs), which are a standard aggregation of counties that partition the United States into 741 areas designed to approximate local labor markets; we also perform some analyses at the county or state level. We briefly describe our main data sources here, and Appendix B provides more detail on the underlying data sources and variable construction.

[6]Examples of potential confounds include increased access to disability insurance, increased unemployment insurance generosity, or increases in the minimum wage; for each, there is evidence both that they may increase unemployment and that they may improve health (Autor and Duggan 2003; Gelber et al. 2017; Johnston and Mas 2018; Kuka 2020; Flinn 2006; Ruffini 2022).

Mortality. We use two major sources of mortality data. First, following Ruhm (2016), we construct mortality rates by combining death records from the restricted-use mortality microdata from the Centers for Disease Control and Prevention (CDC) on the universe of U.S. mortality events from 2003 to 2016 (National Center for Health Statistics 2023) with population data from the National Cancer Institute's Surveillance Epidemiology and End Results (SEER) program. For each decedent, we observe county of residence, exact date of death, cause of death, 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.

Second, we use mortality records from a 20 percent random sample of all 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); unfortunately, we do not observe the cause of death in the Medicare data. These data are available for all Medicare enrollees. In addition, for the approximately three-quarters of the elderly who are enrolled in Traditional Medicare, we also observe detailed, annual information about their healthcare use—including doctor visits, hospital admissions, and nursing home stays—and whether they were diagnosed with one of 20 chronic conditions in the last year, such as lung cancer, diabetes, or depression. We analyze two primary Medicare samples: a panel of 2003 Medicare enrollees ages 65-99 in 2003, and a repeated cross section of individuals ages 65-99 each year, often further restricted to individuals who were enrolled in Traditional Medicare in the prior or current year.

The Medicare data offer several advantages over the CDC mortality data, albeit for the 65 and older 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 data in which the numerator (deaths) and the denominator (population) 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 allows us to define a cohort of individuals based on their initial location and follow them over time. This allows us to address a concern with many existing estimates of pro-cyclical mortality that results may be confounded by endogenous migration in response to economic shocks (Blanchard and Katz 1992; Arthi et al. 2022). Third, we can use the (lagged) data on enrollee health conditions to analyze heterogeneous impacts on mortality by pre-existing health, which is not recorded in the CDC data. Finally, we use the Medicare data to analyze the impact of the Great Recession on the consumption of healthcare and estimate heterogeneous impacts by whether the individual lives in a nursing home.

Economic indicators. We use publicly available local economic indicators to trace the Great Recession across areas and years from 2003-2016. We construct the CZ-year unemployment rate and employment-to-population (EPOP) ratio using data from the Bureau of Labor Statistics' Local

Area Unemployment Statistics, and CZ-year real GDP per capita using data from the Bureau of Economic Analysis. For the sub-sample of counties for which it is available, we construct a CZ-level annual house price index from the Federal Housing Finance Agency's yearly House Price Index (HPI) public release. We obtain state-level annual data on total household expenditures on (durable and non-durable) goods and services from the Personal Consumption Expenditures (PCE) surveys published by the Bureau of Economic Analysis; we use the PCE Index to adjust all expenditures to 2012 dollars and divide state-level annual expenditures by the SEER population data to obtain a measure of state-year real consumption per capita. We use data from the Current Population Survey to measure state-year earnings and income in the overall working-age population, as well as by education and age.

Air pollution. 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. As in other recent papers studying air pollution (e.g. Deryugina et al. 2019; Dedoussi et al. 2020; Currie et al. 2023; Heo et al. 2023) we focus primarily on fine particulate matter (PM2.5), 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 recession-induced air pollution on mortality, we therefore limit our analysis to the approximately two-thirds of (population-weighted) counties which have a pollution monitor in 2006 and in 2010. 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).[7]

Other outcomes. We draw on several additional data sources to probe 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) to examine the impacts of the Great Recession on self-reported health, health behaviors, and health insurance coverage at the state level (the finest geographic information available). Second, we use facility-level administrative data from annual certification inspections of all nursing home facilities across the United States to

[7]We explored addressing this by using PM2.5 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 but sparser EPA monitor data.

measure the impact of the Great Recession on a range of nursing home staffing measures as well as other characteristics such as patient volume and composition. 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 at the state level (the finest geographic information available) on self-reported measures of formal and informal care received for individuals 65 and older.

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 economic 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 area and year fixed effects, respectively, and ε_{ct} is the error term. We estimate equation (1) using OLS, and we cluster our standard errors at the local area c. 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 unless indicated otherwise), we omit the interaction with the shock variable in 2006 so that all β_t coefficients are relative to 2006. Because population varies greatly across different areas in the US (Appendix Figure OA.1), we weight each area-year by its 2006 population, as in prior literature examining effects of recessions on mortality (e.g. Ruhm 2000, 2015).

Also following this prior literature, we define our main outcome variable y_{ct} to be the log age-adjusted mortality rate in area c and year t.[8] For sufficiently low annual individual mortality rates, this specification is an approximation to a parametric individual-level survival model in which the individual's log odds of dying are given by the right-hand side of equation (1). 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, so that our analysis is not affected by different secular trends in mortality across age groups.[9]

[8] Specifically, we add one to the mortality rate to avoid taking logs of zeros, although in practice this is never binding for the aggregate CZ-level analysis. Even when we dis-aggregate by cause of death or various demographics, mortality rates of zero are rare. The age group with the largest share of (population-weighted) CZs with zero deaths in a CZ-year is ages 5-14, with a share of zero deaths of 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. Our main results are very similar if we instead estimate a Poisson specification for age-adjusted mortality rates, as recommended by Chen and Roth (forthcoming); see the sensitivity analysis in Section 3.3.

[9] We calculate the age-adjusted mortality rate in a CZ by averaging over the mortality rate in each of 19 age bins

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 an area-year-group outcome, $\mathbb{1}(Group_g)$ are indicators for sub-groups, α_{cg} are area-group fixed effects, γ_{tg} are year-group fixed effects, and ε_{ctg} is the error term.

For both estimating equations, the key identifying assumption is that there are no shocks to mortality that coincide exactly with the timing of the Great Recession and are correlated with the size of the local area economic 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 economic impact of the Great Recession. This has been previously 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 educational attainment (Charles et al. 2018). Following Yagan (2019), in our baseline specification we parameterize the impact of the Great Recession on area c (i.e., $SHOCK_c$) as the percentage point change in the CZ unemployment rate between 2007 and 2009. 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 mortality rate) associated with a one-percentage-point increase in the unemployment rate from 2007 to 2009 in that CZ.

Figure 1a shows the spatial variation in this baseline measure of $SHOCK_c$. The median (population-weighted) CZ experienced a 4.6 percentage point increase in the unemployment rate. Virtually every CZ in the country experienced an increase in unemployment between 2007 and 2009. Yet some areas were much harder hit than others: the bottom quartile of CZs experienced an average 2.9-percentage-point increase in the unemployment rate, compared to a 6.7-percentage-point increase in the highest quartile. 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). However, in practice, all recessions—including the Great Recession—are multi-faceted economic shocks and can be parameterized in different ways. We therefore examine four different measures of the Great Recession: unemployment rate, EPOP ratio, log GDP per capita, and log

within the CZ, weighting each age bin by the national share of the population in that age bin in 2000. This is in the spirit of Ruhm (2000), who controls for the share of the population in various age groups. The 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+.

house prices. The spatial variation in the 2007-2009 shock as measured by these different variables is highly, but imperfectly, correlated (Appendix Figure OA.2). In the national time series (Appendix Figure OA.3) they all flatten out between 2006 and 2007 and then worsen through 2009; however, the national aggregate trends in the 2010-2016 period look fairly different across these indicators, which is why we also consider other measures of the Great Recession besides the unemployment rate in Section 3.

Mortality Patterns Across Areas. 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 Southeastern United States and low in the Western United States. Figure 1c shows no correlation between the magnitude of the 2007-2009 Great Recession shock in each CZ and its 2006 (age-adjusted) mortality rate.

Mortality Patterns Across Areas Over Time. 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 persists through the end of the series in 2016.

3 Mortality Impacts of the Great Recession

We present estimated mortality impacts overall and across different sub-populations and causes of death. After presenting initial event study results, for most of the subsequent analyses in the paper we summarize the average event study estimates for the 2007-2009 and 2010-2016 periods for ease of exposition; the underlying event studies for all such results are shown in Appendix D.

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. Places 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. The immediate impact of the Great

Recession on mortality in 2007 is consistent with economic indicators also beginning to deteriorate in 2007 in harder-hit areas (Appendix Figure OA.4). The slightly positive pre-trend in the mortality estimates from 2003 through 2006 (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 opposite-signed pre-trend is consistent with our findings that recessions reduce mortality, as areas that were subsequently harder hit by the Great Recession experienced a relative rise in economic indicators in the preceding years (see Yagan (2019) as well as Appendix Figure OA.4). The opposite-signed pre-trend in the mortality estimates also suggests that by measuring the mortality impact of the Great Recession relative to the mortality level in 2006, we may be underestimating the extent of the recession-induced mortality declines.

The point estimates imply that a one-percentage-point increase in the local area unemployment rate between 2007 and 2009 was associated with a 0.50 percent (standard error = 0.15) decline in the area's annual age-adjusted mortality rate in 2007-2009 relative to its 2006 level. Over the next seven years (2010-2016), a one-percentage-point increase in the unemployment rate between 2007 and 2009 was associated with a 0.58 percent (standard error = 0.34) decline in the annual, age-adjusted mortality rate relative to 2006; we cannot reject that the estimates for the two time periods are identical ($p = 0.78$).

The Great Recession on average increased local area unemployment by 4.6 percentage points between 2007 and 2009, implying that an increase in the local area 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. For a 55-year-old facing the standard population life table, these estimates suggest that 1 in 25 of them gained an extra year of life from this sized local shock (see Appendix Table OA.1). As another benchmark, the mortality declines from the average Great Recession shock are equivalent to the average, two-year secular mortality improvement over the half-century prior to the Great Recession.[10] 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 (e.g., Ruhm 2015; Stevens et al. 2015). To investigate possible lagged impacts of economic downturns on subsequent mortality, we exploit spatial variation not only in the initial labor market impact of the Great Recession but also in the labor market recovery, conditional on the initial impact. Specifically, we estimate:

[10] Over the half-century preceding the Great Recession, average annual age-adjusted mortality declined by 1.1 percent per year (see Appendix Figure OA.5 and also Ma et al. (2015)).

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

where $\mathbb{1}\left(Recovery_{H(c)}\right)$ is an indicator that CZ c has an above-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. Because the unemployment rate is a notoriously challenging measure of recovery—as worker exit from the labor force can produce a decline in unemployment without any corresponding increase in the employment-to-population ratio—we measure the recovery by the change in the area's EPOP ratio between 2010-2016, rather than the change in the area's unemployment rate.[11] 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 ratio. Using the EPOP ratio instead of the unemployment rate for the measurement of $SHOCK_c$ in equation (1) produces very similar results to our baseline specification (see Appendix Figure OA.6). Estimation of equation (3) thus 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). The above- vs. below-median recovery CZs (conditional on the size of the initial shock) are distributed fairly evenly across the United States (Appendix Figure OA.8) and display no systematic relationship with pre-recession demographic characteristics (Appendix Table OA.2).

The top two panels of Figure 4 show the results of estimating equation (3) using the EPOP ratio as the dependent variable. While in above-median recovery CZs (Panel b) the EPOP ratio has returned to the pre-recession level by 2016, 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 one-percentage-point decline in the EPOP ratio associated with a 0.4 percent decline in mortality. Strikingly, however, 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, while the below-median places have only partly recovered.[12] The fact that we continue to see lower mortality in areas even once they have experienced a complete recovery is suggestive of lagged mortality effects of the initial economic downturn.

[11] For example, 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 remain substantially below their 2006 levels (Appendix Figure OA.3). The same phenomenon appears when comparing more vs. less affected areas (Appendix Figure OA.4).

[12] Over the 2010-2016 period the below-median recovery places experience an approximately 20 percent larger mortality decline (relative to 2006) than the above-median recovery places, although these declines are not statistically significantly different from each other (or from zero).

3.2 Unpacking the Overall Mortality Decline

Mortality rates vary substantially across demographic groups and reflect several underlying causes (Appendix Table OA.3). In 2006, the elderly (65 and older) accounted for almost three-quarters of deaths, although they were only 12 percent of the population; individuals with a high school degree or less comprise about half (52 percent) of the population but account for 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 causes (Figure 5) and demographic groups (Figures 6 and 7). Because the patterns are largely the same in the 2007-2009 period and the 2010-2016 period, we focus our discussion primarily on the 2007-2009 period where we have greater precision.

By cause of death. Figure 5 indicates mortality declines due to the Great Recession for essentially all major causes of death, with the important exception of cancer. Panel (a) reports the estimates for each of the top 11 causes of death (arranged in descending order of prevalence in 2006) as well as a final residual category for all other causes. Most of the point estimates indicate declines, and several are statistically significant; no cause of death experiences a statistically significant increase in mortality. For the 2007-2009 period, we estimate that a one-percentage-point increase in the 2007-2009 local area unemployment reduces the mortality rate from cardiovascular disease by 0.65 percent (standard error = 0.21), from motor vehicle accidents by 1.7 percent (standard error = 0.56), and from liver disease by 1.1 percent (standard error = 0.43).[13] Several other causes of death—lower respiratory disease, influenza/pneumonia, kidney disease, liver disease, and homicides—experience a percentage decline in their mortality rate similar to or larger than that of cardiovascular disease, but these declines are not statistically significant. For cancer deaths, we estimate a precise null effect of 0.02 percent (standard error = 0.11), which we interpret as reassuring that our results are picking up the causal impact of the Great Recession, rather than spurious factors correlated with the size of the Great Recession shock.

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 decline (standard error = 0.5) 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); it may reflect recession-induced reductions in pollution as we discuss in Section 4 below. Not surprisingly in light of the recession-induced declines in both suicides and deaths from liver disease in the 2010-2016 period, we also find that the Great

[13]Interestingly, the event studies in Appendix Figures OA.19 and OA.20 suggest that effects on mortality from motor vehicle accidents have entirely dissipated by 2016, while effects on cardiovascular and liver mortality are more persistent.

Recession 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 poisonings (accidental or unknown-intent)—in the 2010-2016 period. Specifically, 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 (see Appendix Figure OA.11a). Consistent with this finding, Case and Deaton (2017) note that there is no evidence of deaths of despair rising during the Great Recession, and interpret deaths of despair arising not from declines in income per se but rather from a more prolonged impact of cumulative disadvantage. However, our findings contrast with Pierce and Schott (2020)'s result that areas of the US more exposed to import competition from China experienced an increase in deaths of despair.

Figure 5 Panel (b) combines the 2007-2009 point estimates on mortality declines for each cause of death in Panel (a) 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 percent of 2006 mortality, and so their contributions to the total recession-induced mortality decline are only 6.9 percent and 2.6 percent, respectively.

By age. Figure 6 indicates mortality declines due to the Great Recession for each age group, with many statistically significant. The point estimates are also broadly similar; while they appear to be larger for younger population groups, the estimates at younger ages are quite imprecise (see Panel (a)). When we aggregate into larger age groups, we are unable to reject the hypothesis that the average percentage decline in mortality across the years 2007-2016 is the same for ages 25-64 and for 65+ (p-value 0.76). In other words, it appears that the Great Recession is associated with quantitatively and statistically similar percentage reductions in mortality rates across all (adult) age groups.[14]

Panel (b) combines 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. The elderly account for the majority—74.3 percent—of deaths averted by the Great Recession, roughly proportional to their 72.5 percent share of total mortality in 2006.

By education. Strikingly, the entire recession-induced mortality decline is concentrated among those with a high school degree or less (Panel (a) of Figure 7). Specifically, among those age 25 and over, we compare impacts separately for the roughly half of the population with a high school

[14] By contrast, we can reject that the percentage decline in mortality for 0-24-year-olds is the same as either other age group (p-value 0.004 for 25-64-year-olds and 0.013 for 65+-year-olds). Note, however, that the slightly larger percentage decline in mortality rates for 0-24-year-olds has little quantitative significance for the total mortality declines, given the very low baseline mortality rate of this age group.

degree or less to those with more than a high school degree.[15] The point estimates indicate that in 2007-2009, a one-percentage-point increase in the local unemployment rate is associated with a statistically significant 0.80 percent (standard error = 0.26) decline in the mortality rate for those with high school or less, compared to a statistically insignificant 0.014 percent (standard error = 0.54) increase for those with more than high school. Although the mortality impacts by education are not statistically distinguishable ($p = 0.12$) in 2007-2009, they are statistically distinguishable ($p < 0.01$) in 2010-2016 (the point estimate is -1.48 (standard error = 0.69) for those with less education compared to 0.48 (standard error = 0.75) for those with more), as well as for the entire 2007-2016 period ($p < 0.01$; the point estimate is -1.3 (standard error = 0.56) for those with less education compared to 0.34 (standard error = 0.68) for those with more education).

We performed several additional checks and analyses on these results by education. First, since the education distribution differs by age, we confirmed that the impact of the Great Recession is confined to those with high school education or less even when we look within age groups (Appendix Figure OA.23). Second, we show that when we further disaggregate the higher education sample into those with some college and those with college or more, there is no evidence of mortality declines in either subgroup (Appendix Figure OA.16). Finally, consistent with mortality impacts that are concentrated among those with less education, we also find in the Medicare data that the mortality impacts on the elderly are much larger among the approximately 12 percent of the population on Medicaid in the prior year (Appendix Figure OA.24).

By gender and by race/ethnicity. Panels (b) and (c) of Figure 7 show results by gender and race/ethnicity. There is no evidence of differential mortality impacts by gender, with nearly identical estimates for males and females. And while recession-induced mortality declines appear to be more pronounced for non-White population groups (with particularly large point estimates for Hispanic individuals), we cannot reject equal impacts across groups in any time period.

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 whether they reflect a meaningful change in mortality over a longer horizon, or merely a slight re-timing of deaths, a phenomenon often referred to as "mortality displacement" or "harvesting." Researchers tend to investigate this 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 over 10 years.

Nevertheless, for our welfare analysis of pro-cyclical mortality in Section 5, it is important to consider how the remaining life expectancy of the marginal lives saved by the Great Recession

[15] Due to data limitations explained in more detail in Appendix C.1, this analysis is conducted at the state rather than CZ level, is limited to individuals age 25 and older, and excludes a few states with missing data. We show in the Appendix that these restrictions have little impact on our estimates.

differs from the remaining life expectancy of infra-marginal people of that age. To examine this, closely following Deryugina et al. (2019), we use the Medicare data to develop an auxiliary model of mortality as a function of individual demographics and health conditions at the beginning of the year. We use this model to predict counterfactual, remaining life expectancy for each individual in each year and analyze the impact of the Great Recession on life-years lost. We find that the marginal life saved (when predicting life expectancy based on age, demographics, and chronic conditions) has only a statistically insignificant six percent lower counterfactual remaining life expectancy than a typical decedent of the same age. Appendix C.2 describes our analysis in more detail.

Morbidity. Like most of the literature in health economics, we focus on mortality as a measure of health 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.3). 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 (see Appendix Figure OA.32). This raises the possibility that we are missing important non-mortality health effects at younger ages that might only translate into mortality effects decades later. These longer-run mortality impacts need not be beneficial; for those who are entering the labor market (ages 16-22) during a recession, Schwandt and Von Wachter (2020) find long-run negative mortality impacts.

Therefore, in the spirit of Ruhm (2003), we explore, where feasible, the impact of the Great Recession on measures of morbidity. We sign each measure so that—like mortality—higher values are indicative of worse health. Specifically, we analyze the impact of the Great Recession on the log share of respondents in the BRFSS with the following self-reported morbidity measures: health that is less than very good, any days in the last month with poor mental health, ever been diagnosed with diabetes, currently have asthma, are overweight or obese, or are obese. Since we cannot observe commuting zone in the BRFSS, we estimate equation (1) at the state level and show below that our baseline mortality estimates (Figure 3) are essentially unchanged when switching from the commuting zone to the state level for analysis.

Panel (a) of Figure 8 shows the results for these six different measures of self-reported morbidity individually, as well as the average treatment effects across the measures. We estimate a statistically significant negative average treatment effect on our six morbidity measures of -0.96 percent (standard error = 0.37) over the 2007-2009 period and of -1.06 percent (standard error = 0.46) over the entire 2007-2016 period. This reflects declines in each of the individual measures of morbidity, although none of them is individually statistically significant. For example, in the 2007-2009 period, 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 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. The declines in average morbidity remain when we look separately at effects for ages 18-45, 46-64, and 65+, although they are only statistically significant for the two younger age groups. Overall, we interpret these results as suggestive that morbidity is also pro-cyclical, with roughly similar magnitudes across age groups.[16]

3.3 Sensitivity Analysis

3.3.1 Population flows

If recessions affect the size or composition of the local population in a way that is not captured by our population measures, 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, areas that were harder hit by the Great Recession experienced a relative decline in (measured) population, primarily reflecting an increase in the share of the population that is 65 and over.[17] This raises the concern that what looks like fewer people dying in harder-hit areas might in fact reflect fewer people 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 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.[18]

To directly explore the sensitivity of our findings to unmeasured population changes, we turn to the individual-level panel data for the Medicare population. We analyze a panel of 2003 Medicare enrollees aged 65-99 in 2003 and examine how the estimated mortality impact of the Great Recession is affected by fixing their location at their 2003 location compared to allowing it to vary each year as it (implicitly) can in the preceding analyses using the death certificate data. 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. Once again, we focus our discussion primarily on the 2007-2009 results where we have greater precision.

Table 1 summarizes the results. In the first row, we estimate the "reduced-form" impact of the

[16]We discuss Panels (b) and (c) of Figure 8 in Section 4 below.

[17]See Appendix Figure OA.9 and also Yagan (2019). The 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 forthcoming).

[18]Of course, this logic presumes that migration rates are similar for individuals with different comorbidities. 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 in that year. 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.

Great Recession based on individuals' location in 2003:

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

Once again, γ_t are year fixed effects, and we cluster standard errors at the CZ 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 individuals' 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. The 2007-2009 period estimate indicates that a one-percentage-point increase in the local area unemployment rate reduces 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 the 2003 location and the contemporary location. To account for this, 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 = 0.003) in 2007-2009; therefore, not surprisingly, the reduced form is only slightly smaller than the control function estimate we find when we use the $\hat{v}_{it}$ residuals from equation (5) as an additional 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 place of residence has on mortality as in Finkelstein et al. (2021)—the Great Recession shock experienced by the place a person lives in 2003 only affects their mortality through its correlation with the Great Recession shock experienced by the place they live in later years.

To further assess the impact of accounting for potential non-random re-sorting of the population across CZs that is correlated with the Great Recession shock, we compare the estimates from the control function approach in equation (6) with estimates based on 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 from 2007-2009 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 1 indicates that estimating equation (7) on the sub-sample of 88 percent of beneficiaries that do not move CZs between 2003 and 2016 increases the magnitude of the point estimate slightly to -0.56 (standard error = 0.18).

3.3.2 Additional sensitivity analysis

We also explored the sensitivity of our estimates to a number of alternative specifications. Table 2 summarizes the findings. The first row replicates our baseline estimates from estimating equation (1), as shown in Figure 3; subsequent rows present one-off deviations from this baseline. We continue to focus our discussion primarily on the 2007-2009 period estimates where we have greater precision. These results are quite stable.

Geographic unit. Estimates are very similar when we re-estimate equation (1) at the state level or county level instead of the CZ level (Panel A). For example, for the 2007-2009 period, our baseline estimate is that a one-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 = 0.10).

Functional form. Estimates are also very similar across functional form choices (Panel B). If we replace the dependent variable with the age-adjusted mortality rate in levels in year t, we obtain very similar results. For example, for the 2007-2009 period, we estimate that a one-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 what happens if we estimate our specification with a Poisson regression using the age-adjusted mortality rate in levels as the outcome. Specifically, we estimate:

$$y_{ct} = \exp(\beta_t[SHOCK_c * \mathbb{1}(Year_t)] + \alpha_c + \gamma_t), \tag{8}$$

where all variables are defined as in equation (1). The 2007-2009 estimate of -0.45 percent (standard error = 0.14) is very similar to our baseline result.

Sample of CZs. Results are robust to dropping various subsets of CZs from the analysis (Panel C). A particular concern is that the fracking boom occurred during our time period of interest and was concentrated in particular geographic areas—such as parts of Texas, Oklahoma, North Dakota, Colorado, Pennsylvania, and West Virginia—where it may have had direct impacts on economic activity and mortality (Bartik et al. 2019). Reassuringly, the results are robust to omitting the 56 CZs (representing about nine percent of the population) that include any county defined as "treated" by fracking in the Bartik et al. (2019) analysis of the impacts of fracking. To further probe concerns that different parts of the country may be experiencing different other shocks or secular trends, the next row shows results when we allow each of the year fixed effects to differ across each of the nine census divisions. The estimated 2007-2009 average impacts are somewhat attenuated to -0.38 percent (standard error = 0.14), but still show statistically significant mortality declines.[19] Finally, because population is very right-skewed across CZs (see Appendix Figure OA.1), the penultimate row of Panel C confirms the robustness of our results to dropping the ten most populous CZs.

Linearity in Shock. Our baseline specification assumes that the log mortality rate is linear in the size of the shock to the unemployment rate. This is a substantive as well as statistical assumption. The average shock during the Great Recession was much higher than in a typical recession; if mortality effects are linear in the size of the shock, this would increase our confidence that our mortality findings generalize to more "typical" recessions.

We therefore undertook four additional analyses to assess whether it is a reasonable approximation to assume linearity of mortality impacts in the size of the economic shock; the last three are described in more detail in Appendix C.3. First, the last row of Table 2 Panel C shows that the baseline results are essentially unaffected if we drop the top and bottom decile of CZs by the size of the shock. Second, we found that the estimated effects of a one-percentage-point increase in the Great Recession shock are similar when we allow the effects to vary based on whether the CZ experienced an above- or below-average shock. Third, when 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 find that the impacts on mortality are increasing monotonically in the quartile of shock, although these effects are not perfectly linear in the average size of the shock by quartile. Finally, when we plot the relationship between the (population-weighted) average $SHOCK_c$ in each ventile of the $SHOCK_c$ distribution and the average change in the log mortality rate between 2006 and several post-periods, we find that the relationship is roughly linear, albeit fairly noisy.

4 Possible mechanisms

There are several potential channels through which recessions might reduce mortality. We group them conceptually into internal effects—whereby an individual's reduced employment or consumption reduces her own mortality—and external effects, which hold constant one's own employment and consumption and include any externalities from reduced aggregate economic activity

[19] CZs are assigned to states (and resulting Census Divisions) according to the state with the plurality of the CZ population. To further probe sensitivity to the set of CZs, Appendix Table OA.4 presents results when each of the nine census divisions is dropped in turn.

on health.[20]

Internal and external effects have potentially different implications for the welfare consequences of our findings. Positive external health benefits from reduced economic activity would suggest that recessions may have positive welfare effects that mitigate their negative welfare effects from reduced income and consumption, while the welfare implications of mortality reductions that arise from internal effects would be less clear-cut.[21] Our findings strongly point to external effects as the primary driver of the recession-inducted mortality reductions, motivating our final section in which we examine their implications for the welfare consequences of recessions.

4.1 Internal Effects

There are two main channels for internal effects discussed in the literature. First, 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, 2005). 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.[22] Second, recession-induced consumption declines could improve health by decreasing health-harmful consumption such as alcohol, illegal drugs, and cigarettes (Ruhm 1995; Carpenter and Dobkin 2009; Evans and Moore 2012). However, we do not find evidence of a quantitatively important role for internal effects in driving recession-induced mortality reductions.

Two features of our findings in Section 3 are inconsistent with internal effects as the primary driver of the estimated mortality declines. First, three-quarters of the mortality reduction comes from a reduction in elderly deaths, a group whom we estimate did not experience any direct income effects from Great Recession-induced local labor market declines (see Appendix Figure OA.44). Second, the time pattern of the mortality reductions—an immediate decline that does not grow larger over time (recall Figure 3)—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

[20] We use the term external effects rather than externalities to indicate a broader set of health effects that come from factors other than individual-level behavioral responses. Of course, there are some channels, such as the reduction in motor vehicle fatalities which we find was responsible for about seven percent of the total recession-induced mortality decline, which likely reflects a mix of both internal effects (single car accidents) and external effects (multi-car accidents).

[21] Specifically, if the recession-induced mortality reductions were the result of optimizing agents choosing to use some of their increased leisure time or decreased consumption to invest in beneficial health behaviors or reduce their consumption of mortality-increasing goods (such as alcohol), then, by the usual envelope theorem arguments, the mortality reductions would not, to first order, be relevant for welfare analysis. 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), then recession-induced changes in behavior could be welfare-improving.

[22] 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).

and to grow over time as health capital improves.[23]

Moreover, when we look directly for evidence of internal effects, we find no evidence of a substantive role for these channels. We find no evidence of a statistically significant impact of the Great Recession on self-reported health behaviors (Figure 8, Panel B) either individually or when we pool them to improve statistical power. Specifically, we examine the impact on the log share of individuals in the area who report that they currently smoke, that they smoke daily, that they currently drink, that they have consumed more than five drinks in one sitting in the past month, that they have not exercised within the past 30 days, or that they did not receive a flu shot in the past year.[24] We also find no evidence of a substantively or statistically significant impact of the Great Recession on healthcare use among the elderly, measured in the Medicare data by physician visits, ER visits, or total expenditures (Appendix Figure OA.10).[25] 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.11b), but combined this accounts for less than seven percent of the total reduction in mortality.

4.2 External Effects

We explore three main potential sources of positive external health effects from recessions suggested by prior literature: reductions in the spread of infectious disease (Adda 2016), increases in the quality of healthcare (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 classes of external effects, but evidence consistent with a quantitatively important role for recession-induced reductions in air pollution in explaining over one-third of the recession-induced mortality declines.

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

[23] 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).

[24] For example, we estimate that on average over the 2007-2016 period, a one-percentage-point increase in state unemployment from 2007-2009 decreases the share smoking by 1.2 percent (standard error 0.9 percent), increases the share excessively drinking by 0.6 percent (standard error 0.6), and decreases the share not exercising by 1.5 percent (standard error = 1.2 percent). Interestingly, although statistically insignificant, the point estimates are often similar in magnitude to those found in Ruhm (2000). Appendix Table OA.5 shows this more clearly by estimating the specification in levels and reporting the comparable estimates from Ruhm (2000).

[25] 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 per percentage-point increase in $SHOCK_c$) in the 2010-2016 period. Some of this may reflect compositional changes as elderly individuals who would have died are now at risk of hospitalization.

Improved quality of nursing home care for the elderly. Tighter labor markets may result in improved quantity and quality of healthcare workers. This seems particularly likely for direct care workers providing home care and nursing home care for the elderly, which does not require much formal training and may therefore be relatively elastically supplied.[26] Given widespread concerns about worker shortages in these sectors (e.g., Geng et al. 2019; Grabowski et al. 2023), this in turn could have meaningful health benefits for the elderly. Indeed, Stevens et al. (2015) provides evidence from state-year panel data from 1978-2006 that increases in the unemployment rate are associated with increases in the quantity and quality of nursing home staff, and that deaths in nursing homes are particularly responsive to the state unemployment rate; similarly, using county-year panel data, Konetzka et al. (2018) and Antwi and Bowblis (2018) find that the quality of nursing home staffing is counter-cyclical.

However, we do not find any evidence for this channel (Figure 9). Panel A shows results from re-estimating equation (1) in the Medicare data, separately for the 7 percent of the population that were in a nursing home in any given year or the previous year and the 93 percent that were not. A one-percentage-point increase in the unemployment rate from the Great Recession reduced mortality rates by the same 0.5 percent for each group. Individuals who were in a nursing home in the current or previous year have much higher mortality rates—this 7 percent of the elderly accounts for 32 percent of their annual deaths—placing an upper bound on the potential role of improved nursing home care in contributing to recession-induced mortality declines among the elderly of about 32 percent. However, panel B shows no 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.[27] Panel C also shows no evidence of an impact of the Great Recession on nursing home occupancy rates or resident characteristics. Finally, in Appendix Section C.4, we find no evidence of an impact of the Great Recession on whether elderly individuals receive more home healthcare either from a professional or from a spouse, child or relative.[28]

Reduction in Air Pollution. To examine the impact of the Great Recession on air pollution and the extent to which air pollution is responsible for the reduction in mortality, we conduct our

[26]Recession-induced declines in the price of elderly care may be part of a larger phenomenon of recession-induced price declines which could have health benefits. For example, Stroebel and Vavra (2019) find that retail prices declined more in areas that were harder hit by the Great Recession's housing bust.

[27]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 insignificant 0.11 percent (standard error = 0.22) decrease in direct care hours per resident-day during 2007-2009 and a 0.09 percent decrease (standard error = 0.24) from 2010-2016. By contrast, Stevens et al. (2015) estimate that every one-percentage-point increase in the state-year unemployment rate increases employment in a nursing home by three percent.

[28]Another potential channel for improved quality of care could be recession-induced decreases in motor vehicle traffic and hence reduced ambulance transport times. There is evidence that increased congestion increases ambulance transport times and increases the 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 questionable reliability (Federal Highway Administration 2014).

analysis at the county level in order to get a better measure of a person's exposure to pollution than we would if we measured pollution at the CZ-level; we continue to measure the Great Recession shock at the CZ level since the local labor market is the more suitable area for the impact of that shock, and we continue to cluster our standard errors at the CZ level.

We first estimate:

$$y_{ct} = \beta_t[SHOCK_{cz(c)} * \mathbb{1}(Year_t)] + \alpha_c + \gamma_t + \varepsilon_{ct}, \tag{9}$$

where c now denotes county, cz denotes commuting zone, and $SHOCK_{cz(c)}$ is defined identically as in equation (1). Panel (a) of Figure 10 confirms that our estimates of the impact of the Great Recession on mortality remain very similar to our baseline results when we conduct the analysis at the county level in the restricted set of counties for which we have pollution monitor data. Specifically, it shows the result of estimating equation (9) using the age-adjusted log mortality rate as the dependent variable and limiting to the restricted set of counties.

Panel (b) of Figure 10 shows that counties that were harder hit by the Great Recession also experienced larger declines in pollution. Specifically, it shows the results of estimating equation (9) using PM2.5 levels (in μg/m^3) as the dependent variable. We find that a one-percentage-point increase in the CZ level unemployment rate from 2007-2009 is associated with an average reduction of PM2.5 of 0.16 micrograms per cubic meter (μg/m^3) (standard error = 0.04) from 2007-2009, representing a 1.3 percent decline relative to the 12 μg/m^3 national average level of PM2.5 in 2006.[29] Consistent with existing work showing that recessions decrease air pollution (e.g., Heutel 2012; Feng et al. 2015; Heutel and Ruhm 2016), this finding likely reflects recession-induced declines in major sources of air pollution such as industrial activity, electricity generation, and transportation.

Qualitatively, several pieces of evidence are consistent with the recession-induced pollution decline shown in Panel (b) driving at least some of the recession-induced mortality declines. First, the time pattern of the effects—with both PM2.5 and mortality declines showing up immediately 2007—is 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; Currie et al. 2014, for reviews). Second, the causes of death that are affected are also consistent with a pollution channel. PM2.5 is understood to affect mortality by reaching deep into the lungs and being absorbed by the bloodstream. This can impair cardiovascular function (EPA 2004) and—perhaps more surprisingly—increase motor vehicle mortality (Burton and Roach 2023), and also reduce mental health and increase rates of suicide (Jia et al. 2018; Persico and Marcotte 2022; Molitor et al. 2023), all areas where we found statistically significant mortality declines (recall Figure 5). Third, our finding that the mortality declines are concentrated in the half of the population with a high school degree or less is consistent with evidence that less educated and lower-income individuals are disproportionately exposed to greater levels of air pollution both overall (Bell and Ebisu 2012;

[29] Appendix C.6 shows no impacts on other pollutants.

Hajat et al. 2015; Jbaily et al. 2022) as well as within cities (e.g., Hajat et al. 2013).

Assessing the quantitative importance of recession-induced pollution declines for recession-induced mortality declines is more challenging. However, we pursue two complementary approaches that are both suggestive of pollution being a quantitatively important channel behind the estimated mortality declines. First, we combine existing estimates from Deryugina et al. (2019) of the impact of daily PM2.5 exposure on elderly mortality with our estimates of the impact of an increase in the unemployment rate on the levels of PM2.5 to make a back-of-the-envelope calculation that the recession-induced pollution declines can explain about 17 to 35 percent of the 2007-2009 total recession-induced mortality declines, depending on which mortality estimates we use from Deryugina et al. (2019). This back-of-the-envelope calculation (described in more detail in Appendix Section C.7) imposes the assumption that one year of increased exposure to PM2.5 has 365 times the impact on mortality as one day of increased exposure; as we discuss, this assumption is surely heroic but the sign of any bias is unclear.

Second, to more directly gauge the quantitative importance of the pollution channel, we take advantage of the fact that while counties that were harder hit by the Great Recession on average experienced a larger decline in pollution (Figure 10 Panel b), there is substantial heterogeneity in this relationship (Figure 10 Panel c). We therefore examine how much the estimated impact of the Great Recession on mortality changes when we control for changes in pollution; 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, this mediation analysis allows us to estimate the importance of the pollution channel (see, e.g., MacKinnon et al. 2002; Fagereng et al. 2021). Specifically, we estimate:

$$y_{ct} = \beta_t[SHOCK_{cz(c)} * \mathbb{1}(Year_t)] + \phi_t[PM2.5\_SHOCK_c * \mathbb{1}(Year_t)] + \alpha_c + \gamma_t + \varepsilon_{ct}, \tag{10}$$

where y_{ct} is the log age-adjusted mortality rate, $SHOCK_{cz(c)}$ is defined identically as in equation (9), and $PM2.5\_SHOCK_c$ denotes the negative 2006 to 2010 change in PM2.5 levels in county c (with positive numbers reflecting a decline).

Panel (d) of Figure 10 shows the estimates of β_t from equation (10). We find that controlling for the pollution shock attenuates the estimated impact of the Great Recession on mortality from 2007-2009 by 37 percent, from a one-percentage-point increase in unemployment reducing mortality by 0.52 percent (see Panel a) to 0.33 percent (see Panel d).

Panels (a) and (b) of Figure 10 also suggest that the recession-induced pollution declines may have not only an instantaneous but also a lagged impact on mortality. Panel (a) indicates that in areas harder hit by the Great Recession, mortality remains at a constant, lower level through 2016. However, Panel (b) shows that pollution starts rising in harder-hit areas 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." This suggests that any role for pollution in contributing to recession-induced mortality declines in later years would be via a (lagged) effect of reduced pollution on later mortality declines. Unfortunately, the lag structure whereby declines in exposure to pollution today may translate into health improvements in later periods is not well understood. However, the literature showing impacts of in-utero and early child pollution exposure on later life outcomes (Currie et al. 2014) is consistent with current pollution exposure having lagged mortality effects, as is the evidence that prior cigarette smoking can lead to lung cancer many years after the smoking has ceased (Kristein 1984; Islami et al. 2015).

5 Welfare Consequences of Recessions

To assess the quantitative importance of the estimated recession-induced mortality declines, we consider how incorporating these mortality declines affects the welfare consequences of recessions. We follow the approach in the existing literature that incorporates changes in life expectancy into welfare analyses (e.g., Becker et al. 2005; Jones and Klenow 2016) by assuming that gains in life expectancy represent improvements in well-being. We undertake two main exercises. First, we augment Krebs (2007)'s calibrated model of the welfare cost of facing a lifetime of possible recessions to we allow mortality to also vary with the business cycle; this allows us to gauge the quantitative importance of our estimates of endogenous mortality on a 'standard' calibration of the welfare cost of recession risk. In our second exercise, we focus specifically on the Great Recession and examine how endogenous mortality affects its welfare consequences. To do so, we exploit the same spatial variation in the labor market impacts of the Great Recession that we used to estimate its mortality impact to also directly estimate its impact on consumption; we then compare calibrations of a model of the welfare cost of the Great Recession based solely on consumption effects to one that also incorporates mortality effects.

5.1 Impacts of Endogenous Mortality on 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:

$$U(c(t), m(t)) = \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t S(m(t)) u(c(t)) \right] \tag{11}$$

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

$$u(c) = b + \frac{c^{1-\gamma}}{1-\gamma}, \tag{12}$$

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

$$\text{VSLY} = \frac{U(c,m)/u'(c)}{T} = bc^{\gamma} - \frac{c}{\gamma - 1}, \tag{13}$$

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. Our model of recessions and income processes follows Krebs (2007) exactly. The aggregate state $\omega \in \{L, H\}$ affects the agent's stochastic income process and is drawn each period, with the probability of a normal state ($\omega = H$) given by π_H.

Income in period $t = 0$ is normalized to 1, and evolves according to a stochastic process which allows for two types of persistent income shocks:

$$y_{t+1} = (1+g)(1+\theta_{t+1})(1+\eta_{t+1})y_t \tag{14}$$

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:

$$\eta_{t+1} = \begin{cases} -d^{\omega} & \text{with probability } p^{\omega} \\ \frac{p^{\omega}d^{\omega}}{1-p^{\omega}} & \text{with probability } 1 - p^{\omega} \end{cases} \tag{15}$$

The p^H and p^L values correspond to the approximate job separation rates during normal times and a recession, respectively, and the d^{ω} values likewise correspond to the average earnings loss from job displacement, with $p^L > p^H$ and $d^L > d^H$. In other words, both the risk of job loss and the reduction in income conditional on job loss are 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.

Welfare Cost of Recessions. Again following Krebs (2007), we define the welfare cost of recessions Δ^{dm} as the amount the representative agent would need to be paid,[30] 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 $\omega = H$ for all time periods:

$$\underbrace{\mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t S(m^{\omega}(t))u((1+\Delta^{dm})y(t))\right]}_{\text{Expected Lifetime Utility with Stochastic Aggregate State}} = \underbrace{\mathbb{E}_0^{\omega=H}\left[\sum_{t=0}^{\infty}\beta^t S(m^{\omega=H}(t))u(y(t))\right]}_{\text{Expected Lifetime Utility without Recessions}}, \tag{16}$$

where $m^{\omega}(t)$ is age-specific mortality risk in state ω (potentially endogenous to the aggregate state). If mortality is exogenous, then $m^{\omega=H}(t) = m^{\omega=L}(t) = m(t)$, and the expression above simplifies to the expression in Krebs (2007), using 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:

$$m^L(t) = (1 + dm) \cdot m^H(t) \tag{17}$$

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

Intuition for the impacts of endogenous mortality: simplified model. To build intuition for how endogenous mortality will affect the welfare cost of recessions, consider a simplified version of the above model in which the aggregate state $\omega \in \{L, H\}$ is drawn once and for all at $t = 0$. 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 C.8 that if we set $p^H = 0$ and take a first-order approximation of the formula for Δ^{dT} we obtain:

$$\Delta^{dT} \approx \Delta - dT\frac{\text{VSLY}}{c}. \tag{18}$$

This formula 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.[31] The second term shows that an endogenous increase in life expectancy reduces the willingness to pay to avoid a recession by the percentage change in life expectancy dT times the value of this additional lifespan ($VSLY$)

[30] We sometimes refer to this as willingness to pay rather than willingness to accept; for small amounts, these are equivalent in a neoclassical model.

[31] The additive separability—which we will find is a good approximation of the full model—indicates that we do not have to incorporate any potential correlation within individuals between consumption declines and mortality changes, such as those implied by the Sullivan and Von Wachter (2009) evidence that job loss itself increases mortality.

as a share of annual consumption in the normal state. It also indicates that no matter how costly the 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 willingness to pay for nature to draw the recession state.

The approximation formula allows us to anticipate that endogenous mortality will have a greater impact on the welfare costs of recessions at older ages. To see this, note that equation (18) 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. Our empirical findings that the mortality rate declines during a recession by the same percentage amount across ages, together with the population mortality rates from the 2007 SSA life tables that we will use in the calibration below, imply that recessions produce larger percentage gains in life expectancy (dT) at older ages (see Appendix Table OA.1). For example, at age 35, remaining life expectancy is 44 years, and the Great Recession increases life expectancy by 0.037 percent, while at age 65, remaining life expectancy is 18 years and the Great Recession increases life expectancy by 0.36 percent, i.e., by ten times as much.[32]

5.1.2 Calibration and Results

Calibration. We use the 2007 SSA mortality tables to calculate age-specific, unisex mortality rates for mortality in "normal" times (the $m^H(t)$ vector) and set $m^H(t) = 1$ starting at age 100. We choose a higher discount factor ($\beta = 0.99$) compared to $\beta = 0.96$ 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 similar to Krebs (2007). For the mortality effect of a recession, we set $dm = -0.015$ for all ages. This is based on an average 3.1 percentage point increase in the unemployment rate in a typical recession, combined with our estimates in Section 3 that a one-percentage-point increase in unemployment causes a 0.5 percent decline in the mortality rate and that this percent decline was quantitatively and statistically similar across ages in the age range we are modeling.[33]

[32]For additional 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 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 (dm) produces larger percentage gains in life expectancy (dT) for higher $m(0)$, i.e., at older ages.

[33]As discussed in Section 3.2, conditional on age, the marginal death averted has only about six percent lower counterfactual remaining life expectancy than a typical decedent, a difference sufficiently small (and statistically

We report results for VSLYs that correspond to two, five, or eight times annual consumption at age 35 (which is one by assumption). At an annual consumption of $\$50k$ (roughly average expenditure for consumer units in the 2013 CEX (Foster 2015)), these correspond to a VSLY of $\$100k$, $\$250k$, or $\$400k$, respectively. The high end of the range is based on several different sources described in Kniesner and Viscusi (2019). The low end of the range follows the assumed $\$100k$ VSLY made by e.g., Cutler (2005) and Cutler et al. (2022), and is also similar to the baseline VSLY in Hall and Jones (2007). Given an assumption for the VSLY, we compute the implied b in equation (13) for each value of γ assuming annual consumption of $c = \$50k$. Note that because of the assumed average annual growth in consumption ($g = 0.02$), the VSLY in the model calibration will also grow with age, however for ease of exposition we refer to them by the assumed value corresponding to consumption of $\$50k$. We discuss our calibration of mortality and the VSLY in more detail in Appendix C.9.

Finally, for our calibration of the income process we follow Krebs (2007) exactly: 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, and 2.5. To calibrate equation (16), we numerically simulate the economy for a large number of individuals ($N = 1,000$).[34]

Results. Figure 11 shows our estimates of the welfare cost of recessions for people starting at different ages between 35 and 75, with and without accounting for endogenous mortality.[35] The figure shows results for $\gamma = 2$ and the value of b that corresponds to a VSLY of $\$250k$. With exogenous mortality, we find that a 35-year-old would be willing to pay 2.36 percent of average annual consumption for the rest of their lives to avoid the risk of all future recessions.[36] This willingness to pay declines monotonically with age since older people have fewer years remaining and hence fewer periods in which they risk recession-induced consumption declines.

Accounting for endogenous mortality lowers the welfare cost of recession at all ages and, as anticipated by the simplified model, more so at older ages. For a 35-year-old, accounting for endogenous mortality lowers the welfare cost of recessions from 2.36 percent of average annual

insignificant) that we do not account for it in our welfare analysis.

[34]We choose $N = 1,000$. To increase the accuracy of our simulations, we carry out 1,000 independent simulations and calculate Δ^{dm} by solving equation (16) numerically in each simulation, and then calculate the simple average across the 1,000 simulations for each value of Δ^{dm} that we report in our figures and tables.

[35]As mentioned, Schwandt and Von Wachter (2020) 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.

[36]This is very close to 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. Without these differences, we replicate his estimates.

consumption to 1.63 percent, a decline of 0.73 percentage points (or about 30 percent), while for a 45-year-old, endogenous mortality lowers the welfare cost of recessions from 2.00 percent of average annual consumption to 0.91 percent (about 55 percent). Starting at around age 55, accounting for endogenous mortality makes recessions welfare improving. At age 65, for example, eliminating recession risk *reduces* welfare by about 1.2 percent of average annual consumption.

Although these qualitative patterns are fairly robust, the specific numbers are naturally sensitive to our assumptions about risk aversion and the value of a statistical life-year (see Appendix Table OA.6). Intuitively, welfare costs of recessions are increasing in the assumed level of risk aversion (γ), and the impact of endogenous mortality on these welfare costs is increasing in the assumed value of a statistical life-year. Under exogenous mortality, the welfare cost of recessions for a 35-year-old ranges from 1.74 percent of average annual consumption for risk aversion of 1.5 to 3.09 percent with risk aversion of 2.5. Holding risk aversion constant at $\gamma = 2$, accounting for endogenous mortality lowers the welfare cost of a recession for a 35-year-old by 0.30 percentage points for a VSLY of \$100k and by 1.16 percentage points for a VSLY of \$400k.[37]

5.2 Impacts of Endogenous Mortality on Welfare Analysis of Great Recession

We now turn from considering how endogenous mortality affects welfare analysis of eliminating a lifetime of recession risk to considering how it affects the welfare analysis of eliminating the Great Recession. Specifically, we assume that a labor market shock of the size of the Great Recession occurs at $t = 0$ and that after 10 years the economy reverts back to the no-recession state until the end of life. We maintain the same utility function as before, but rather than using Krebs (2007)'s calibration of a stochastic income process and the assumption that consumption is the same as income, we now directly estimate the effect of the Great Recession on consumption, which allows us to capture partial insurance to income shocks (Blundell et al. 2008). We also depart from the representative agent framework to allow the economic and mortality impacts of the Great Recession to vary across groups of individuals (j) based on education, since we found large differences in the mortality impacts of the Great Recession by education. We define $j \in \{HS, C, A\}$ to correspond to the two education groups in our empirical analysis—high degree or less (HS) and some college education or more (C)—or to an aggregate group (A) which encompasses both.

We define the welfare cost of the Great Recession ($\Delta^{dm}_{j,GR}$) for individuals in education group j as the amount they would need to be paid, as a percentage of their average annual consumption, to be indifferent between experiencing the Great Recession and experiencing an otherwise similar

[37] As anticipated by the simplified model, Appendix Table OA.6 also shows that the welfare cost of recessions with endogenous mortality is well-approximated by the welfare cost of recessions with exogenous mortality and an additively separable term based on the welfare impact of the recession-induced mortality decline. Specifically, at a given age, the difference in welfare costs of recessions with exogenous mortality (column 1) and endogenous mortality under an assumed VSLY is essentially constant as we vary γ, because it affects the welfare cost of recessions under exogenous mortality but not the endogenous mortality adjustment.

economy which stays in state $\omega = H$:

$$\sum_{t=0}^{\infty} \beta^t S(m_j^{\omega}(t))u((1 + \Delta_{j,GR}^{dm})c_j^{\omega}(t)) = \sum_{t=0}^{\infty} \beta^t S(m_j^{\omega=H(t)})u(c_j^{\omega=H}(t)) \tag{19}$$

The right-hand side of equation (19) corresponds to the lifetime utility of an individual in education group j when the aggregate state is always $\omega = H$ (no recessions). The left-hand side is the lifetime utility of an individual experiencing the Great Recession, which is modeled as experiencing the aggregate state of $\omega = L$ for $0 \leq t \leq 9$ and $\omega = H$ after that.[38] Except for mortality and consumption, our calibration of all other parameters follows our previous choices.

We define mortality $m_j^{\omega}(t) = m_j^H(t) \cdot (1 + dm_j \cdot \mathbb{1}(\omega = L))$ where dm_j denotes the percentage decline in the mortality rate from the Great Recession from group j. For our full population analysis, we continue to use the 2007 SSA mortality tables for $m^H(t)$, and we assume $dm_A = -0.023$, which comes from our empirical estimate that a one-percentage-point increase in unemployment causes a 0.5 percent decline in the mortality rate and the average increase in unemployment during the Great Recession of 4.6 percentage points. For our analyses by education, we assume $dm_{HS} = -0.037$ and $dm_C = 0.0006$ for those with more than high school ($j = C$), which we get from our estimates in Figure 7 multiplied by 4.6 as above. We also adjust our baseline age-specific mortality rates up for those with high school education or less and down 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 percent higher remaining life expectancy at age 25 than those with a high school education or less.[39] Finally, we normalize consumption in state $\omega = H$ to be one and we define the consumption path $c_j^{\omega}(t) = 1 + dc_j(t) \cdot \mathbb{1}(\omega = L)$, i.e., we assume no consumption impacts of the Great Recession after 10 years, which is as long as we allow for mortality effects.

5.2.1 The Impacts of the Great Recession on Consumption

To estimate the impact of the Great Recession on consumption ($dc_j(t)$), we use the same spatial variation that we used to estimate the impact of the Great Recession on mortality.[40] Thus, our estimates of both economic and mortality impacts reflect the differential impact of the Great

[38] Unlike the previous set of calibration results, the results based on equation (19) have no uncertainty since all individuals within an education group j are assumed to experience the same consumption path. We focus on this simpler model for the Great Recession to be able to focus directly on the trade-off between consumption declines and mortality reductions.

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

[40] 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. 2012; 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. In closely related exercises, 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.

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).

Figure 12 shows the results from estimating equation (1) with log per capita consumption as the dependent variable; we conduct this analysis at the state level due to data availability. On average over the 2007-2016 period, a one-percentage-point increase in the state unemployment rate from 2007-2009 is associated with a 1.2 percent decline in personal consumption expenditures per capita (standard error = 0.34). 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. In the welfare analysis below, we use the point estimates for the 2007-2016 period multiplied by 4.6 to calibrate $dc_j(t)$ for $0 \leq t \leq 9$.

Since we are unable to directly estimate the impacts of the Great Recession on consumption separately by education group, we arrive at consumption effects by education by proceeding in two steps; Appendix C.5 describes the analyses and results in more detail. We first use state-level earnings data from the Current Population Survey to estimate the effects of the Great Recession on earnings by education group. The earnings impacts of the Great Recession are about three times larger for those with high school education or less compared to those with some college or more; this is consistent with other studies of the distributional nature of the economic impact of recessions (see, e.g., Guvenen et al. 2014; Mian and Sufi 2016). To translate these estimated earnings impacts by education into consumption effects by education ($dc_j(t)$), we scale our estimates of group-specific earnings effects by the ratio of our estimated effects on consumption to our estimated effects on earnings in the full population.[41] For the full sample, a one-percentage-point increase in the unemployment rate from 2007-2009 is associated with a 1.7 percent (standard error = 0.48) decline in earnings over the 2007-2016 period. Consistent with the presence of substantial—albeit incomplete—insurance against income shocks (as in Blundell et al. 2008), this estimated 1.7 percent decline in earnings is larger than our estimated 1.2 percent decline in consumption (see Figure 12).

5.2.2 Welfare Results

Figure 13 shows our estimates of the welfare costs of the Great Recession by age and education group, under the baseline assumptions of $\gamma = 2$ and VSLY of \$250k; Appendix Table OA.7 shows results for other assumptions about γ and VSLY. Panel (a) shows results for exogenous mortality. For a 35-year-old With exogenous mortality, we find that that the Great Recession imposed an average welfare cost of about 1.61 percent of average annual consumption. This welfare cost rises

[41] This may cause us to underestimate the extent to which the economic impact of the Great Recession is regressive since the consumption response to a given earnings shock may be larger for those who have less education (Blundell et al. 2008).

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. Welfare costs are also substantially higher for the less educated; at age 35 we estimate that the welfare cost of the Great Recession is more than twice as large for those with a high school degree or less (2.89 percent of average annual consumption) than those with more than a high school degree (1.23 percent of average annual consumption).

Panel (b) shows that accounting for endogenous mortality reduces the welfare cost of the Great Recession at all ages but, as anticipated by the stylized model in equation (18), reduces this welfare cost substantially more at older ages. For a 35 year-old, accounting for endogenous mortality reduces the welfare cost of the Great Recession by about 9 percent (from 1.61 percent of average annual consumption to 1.47 percent). However, for a 55-year-old, endogenous mortality reduces the welfare cost of the Great Recession by about 25 percent (from 2.39 percent of average annual consumption to 1.80 percent).

Accounting for the differential endogenous mortality by education mitigates—and ultimately reverses—the regressivity of the Great Recession under exogenous mortality, as illustrated in Panel (c). For those with more than a high school degree, the welfare effects with exogenous and endogenous mortality are indistinguishable, since we estimate effectively no mortality impacts of the Great Recession for this group. For those with a high school education or less, accounting for endogenous mortality reduces the welfare cost of the Great Recession. As individuals age, the impact of endogenous mortality for the less educated group becomes so large that it closes and ultimately reverses the finding under exogenous mortality that the Great Recession is more costly for those with less education. With exogenous mortality, the welfare cost of the Great Recession for those with a high school degree or less is about twice as large, at all ages, as it is for those with more than a high school degree. However, with endogenous mortality, the welfare costs of the Great Recession converge for the two education groups by about age 65, and after that are less costly for those with less education.

Finally, we note that this analysis of the Great Recession has made the (extreme) assumption that the economic impacts are the same at all ages. In practice, however, we find no impact on the income of those 65 and over (see Appendix Figure OA.44). Appendix Figure OA.17 therefore shows welfare analysis of the Great Recession under the other (extreme) assumption that Great-Recession induced consumption declines are limited to those under 65.[42] With exogenous mortality, the welfare costs are now zero by construction starting at age 65. With endogenous mortality, a

[42]We scale up our estimate of $dc_{i,t}$ for ages under 65 (and $t \leq 9$) to reflect the fact that we are assuming the impact on consumption is zero for the 12.6 percent of the population that (according to the SEER data from 2007) was 65 and older. Importantly, as with all our other analyses, this ignores any nationwide impacts of the Great Recession, such as the decline in asset prices which has been found to impose disproportionate welfare losses on older cohorts relative to younger ones (Glover et al. 2020). However, it is consistent with the time series evidence that, unlike younger individuals, older individuals experienced little change in consumption during the Great Recession (see Malmendier and Shen (2024) Figure 1).

local labor market shock of the size of the Great Recession becomes welfare-*improving* starting around age 60, although as we have emphasized throughout, these analyses reflect the differential impact of the Great Recession across local labor markets and may therefore be more appropriate for the 'typical' recessions we analyzed in the previous sub-section.

6 Conclusions

We examined 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, and that this is driven largely by the external health effects of reduced economic activity; recession-induced pollution declines appear to be a quantitatively important mechanism. 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, recessions may be welfare-improving for older people.

These findings naturally come with some caveats. In particular, our estimates do not incorporate any national impacts of the Great Recession. For example, they do not capture any mortality impacts that operate through the nationwide 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 suggest important trade-offs between economic activity and mortality, adding to the growing literature suggesting that GDP is an incomplete proxy for welfare (e.g., Stiglitz et al. 2009; Jones and Klenow 2016). Our results also highlight the importance of considering the link between changes in economic activity and mortality when evaluating the welfare consequences of recessions or of potential public policies designed to blunt their impacts. They also raise important questions for further work about whether we would find similar mortality impacts from other economic shocks such as natural resource booms and busts (Black et al. 2005; Feyrer et al. 2017), adoption of industrial robots (Acemoglu and Restrepo 2020), and increased import competition from China (Autor et al. 2013).

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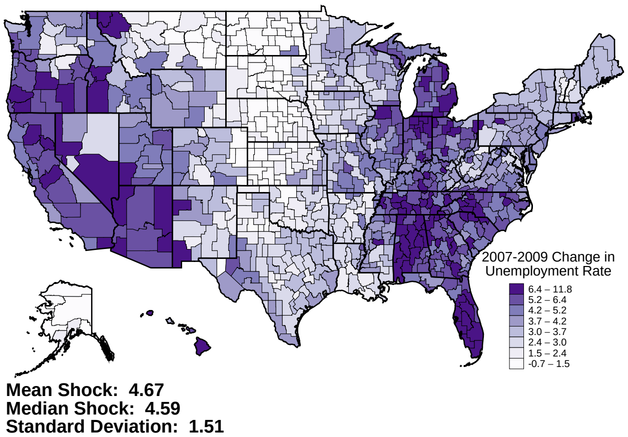
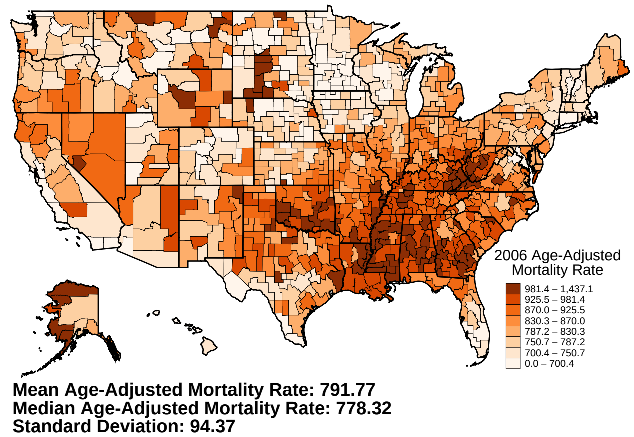
Figures

Figure 1: Geographic Patterns and Correlation of Unemployment and Mortality

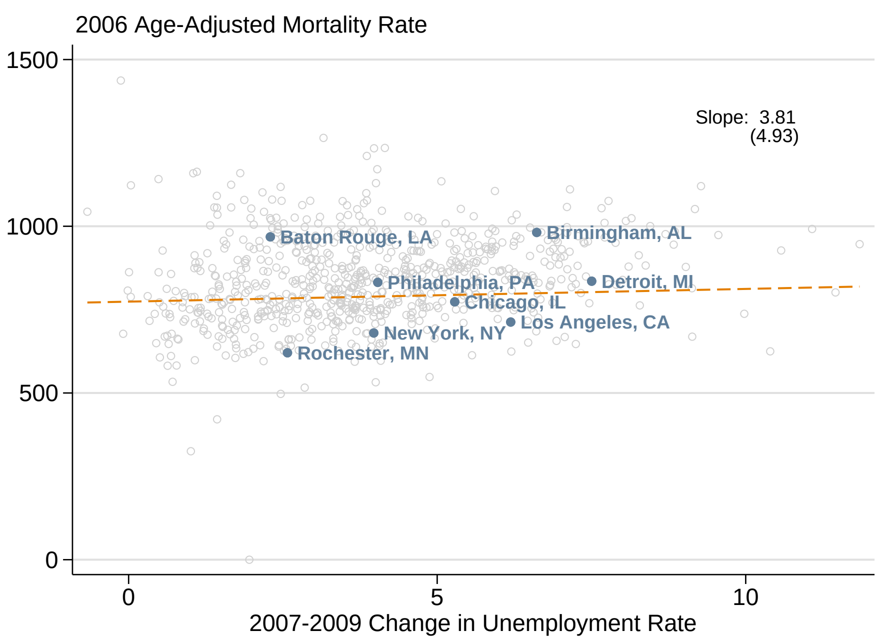
(a) 2007-2009 Change in Unemployment Rate



(b) 2006 Age-Adjusted Mortality Rate

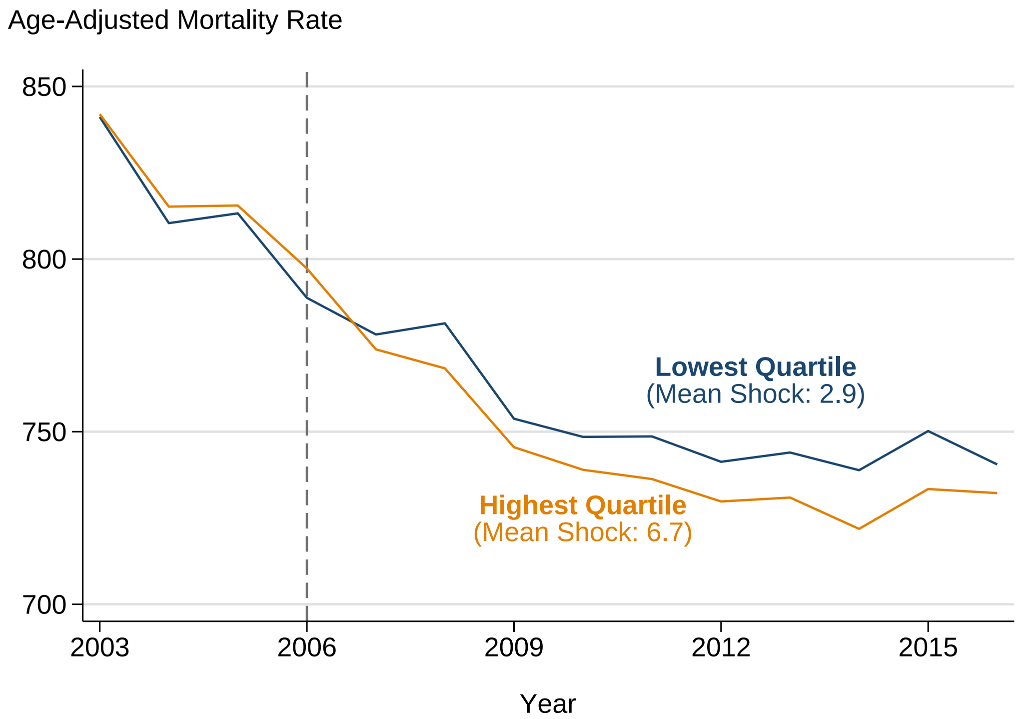


(c) Correlation of Pre-Recession Mortality Rates and Shock



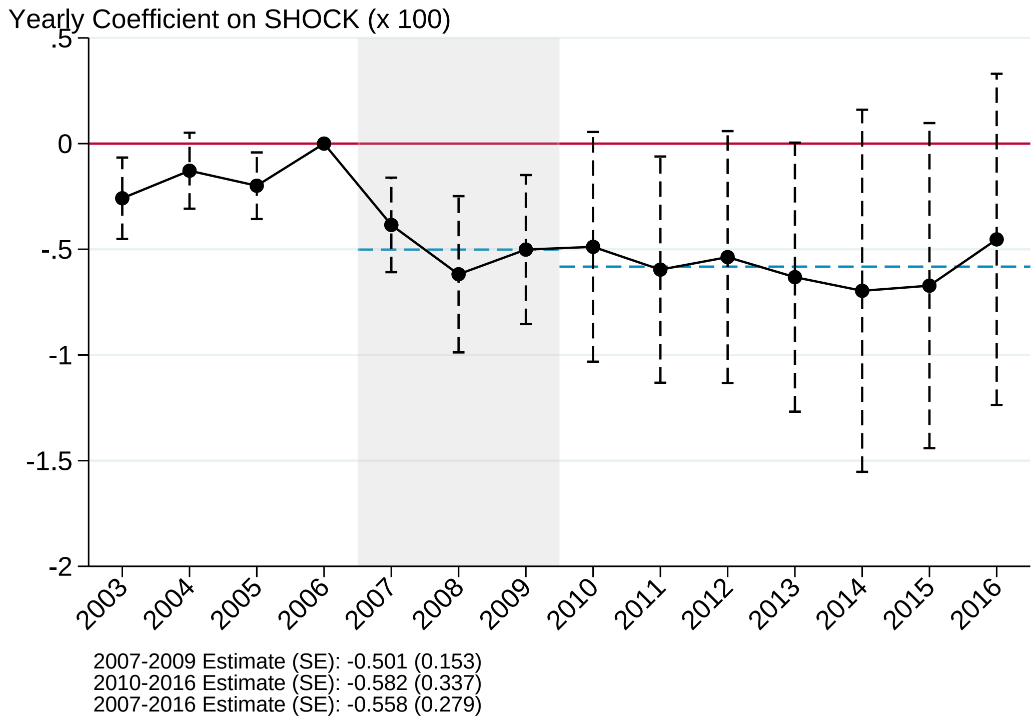
Notes: Figure 1a displays a heat map of the unemployment shock, i.e., the change in CZ unemployment rate from 2007-2009, binned into octiles. Figure 1b displays a heatmap of 2006 CZ age-adjusted mortality rates per 100,000. The 2006 CZ population-weighted mean and standard deviation of the unemployment shock and mortality rate are reported in the lower left-hand corner of each figure. Figure 1c displays a scatterplot of the 2006 age-adjusted CZ mortality rate against the 2007-2009 change in CZ unemployment rate, with each circle representing one CZ. The linear fit between the 2006 mortality rate and the 2007-2009 change in the unemployment rate, weighted by the 2006 population, 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. N=741 CZs.

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



Notes: This figure displays trends in the (population-weighted) mean age-adjusted CZ mortality rate per 100,000 from 2003 to 2016. Mean mortality among CZs in the highest (population-weighted) quartile of the Great Recession unemployment shock is displayed in orange; the mean among the lowest (population-weighted) quartile of CZs is displayed in blue. Weights throughout are the 2006 CZ population. N=473 CZs in total, 125 CZs in the top quartile, and 348 CZs in the bottom quartile.

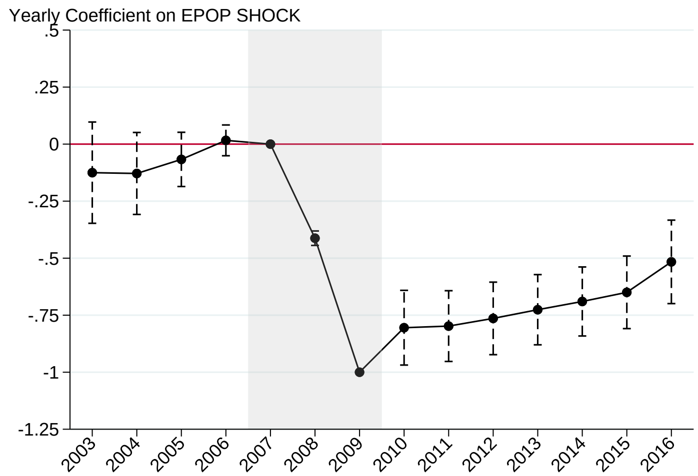
Figure 3: Impact of Shock on Log Mortality



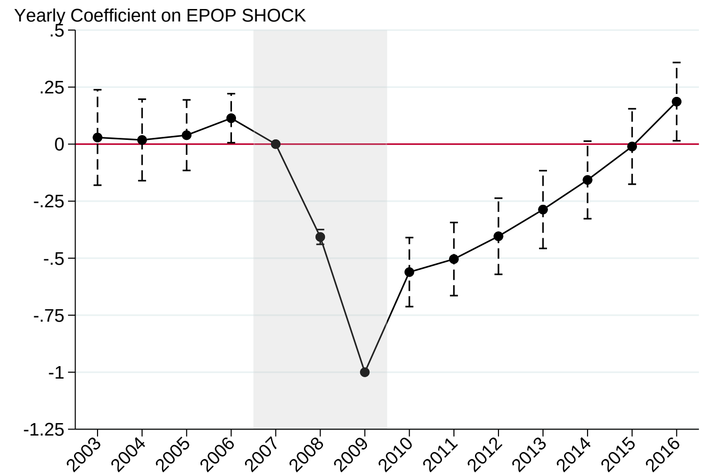
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000, and $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Observations are weighted by CZ population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs.

Figure 4: Impact of Shock by Subsequent Recovery

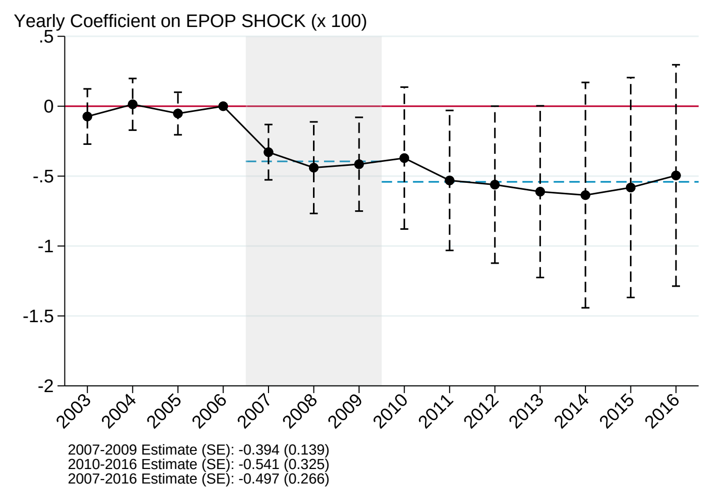
(a) Impacts on **EPOP** for **Below-Median Recovery** CZs



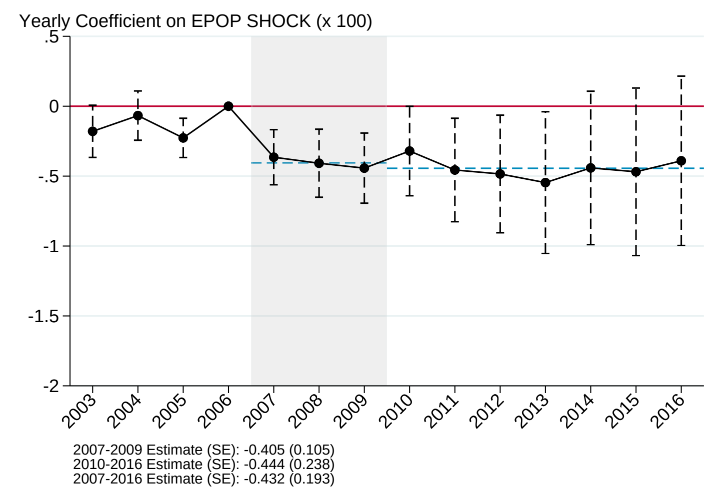
(b) Impacts on **EPOP** for **Above-Median Recovery** CZs



(c) Impacts on **Log Mortality** for **Below-Median Recovery** CZs



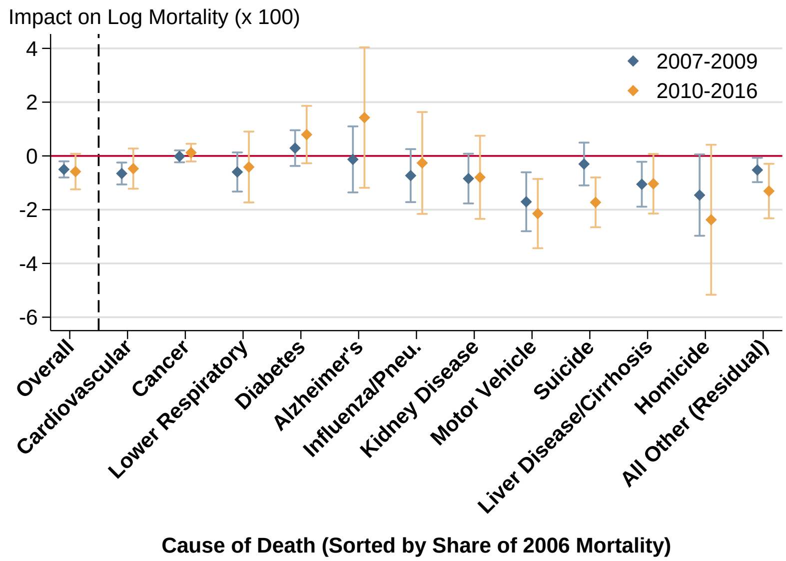
(d) Impacts on **Log Mortality** for **Above-Median Recovery** CZs



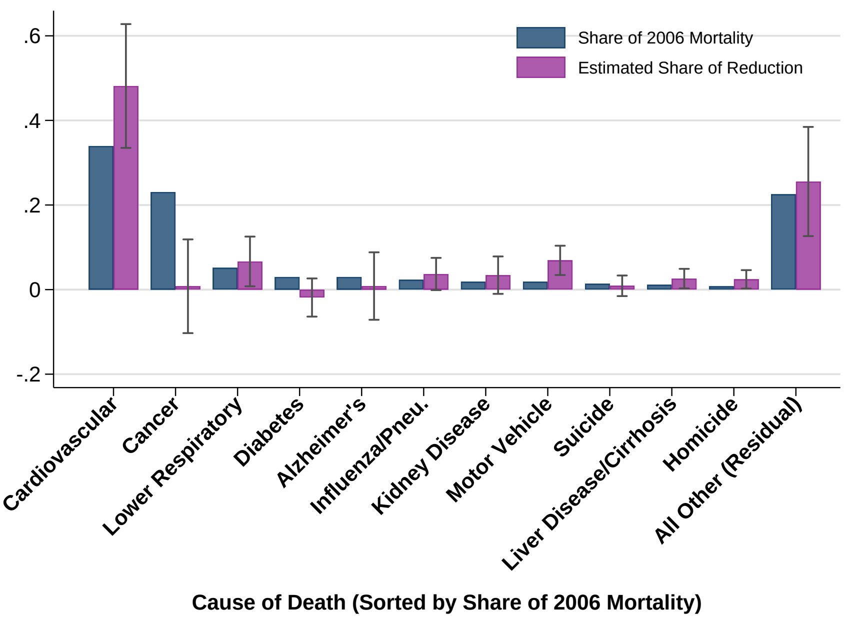
Notes: This figure displays the yearly coefficients β_{qt} from equation (3). Figures 4a and 4c display the estimates for below-median recovery CZs—i.e., $\mathbb{1}\left(Recovery_{L(c)}\right)$ is an indicator that the CZ has a below-median 2010-2016 EPOP recovery among CZs in the same decile of $SHOCK_c$—while Figures 4b and 4d display the estimates for above-median recovery CZs—i.e., $\mathbb{1}\left(Recovery_{H(c)}\right)$ is an indicator that CZ c has an above-median 2010-2016 EPOP recovery rate among CZs in the same decile of $SHOCK_c$. In figures 4a and 4b, the outcome y_{ct} is the EPOP; in figures 4c and 4d, the outcome y_{ct} is the log age-adjusted mortality rate per 100,000. Throughout this figure, $SHOCK_c$ refers to the 2007-2009 CZ change in EPOP. Observations are weighted by CZ population in 2006. The coefficients in Figures 4a and 4b are normalized to zero in 2007 instead of 2006 so that the 2009 estimate is mechanically negative one. The coefficients, standard errors, and confidence intervals in Figures 4c and 4d are multiplied by 100 throughout for ease of interpretation, and horizontal blue dashed lines in those figures indicate the point estimate for the average of coefficients from 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, 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 Shock on Log Mortality, by Cause of Death

(a) Pooled Estimates



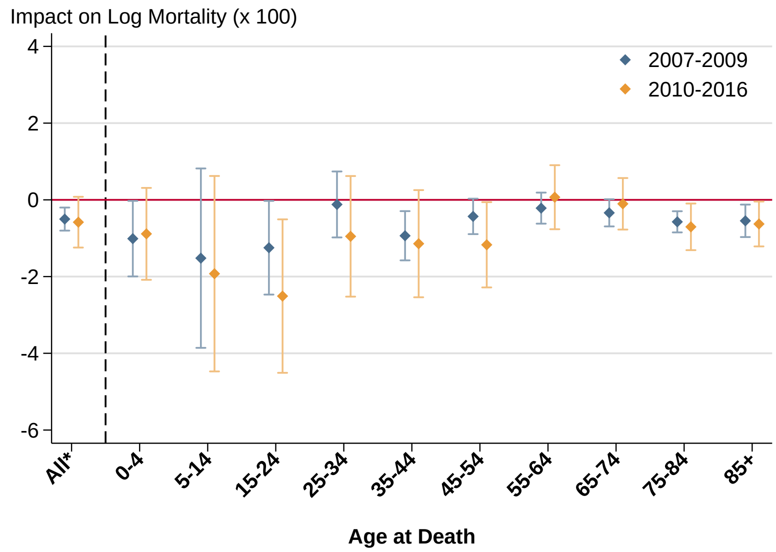
(b) 2007-2009 Decomposition



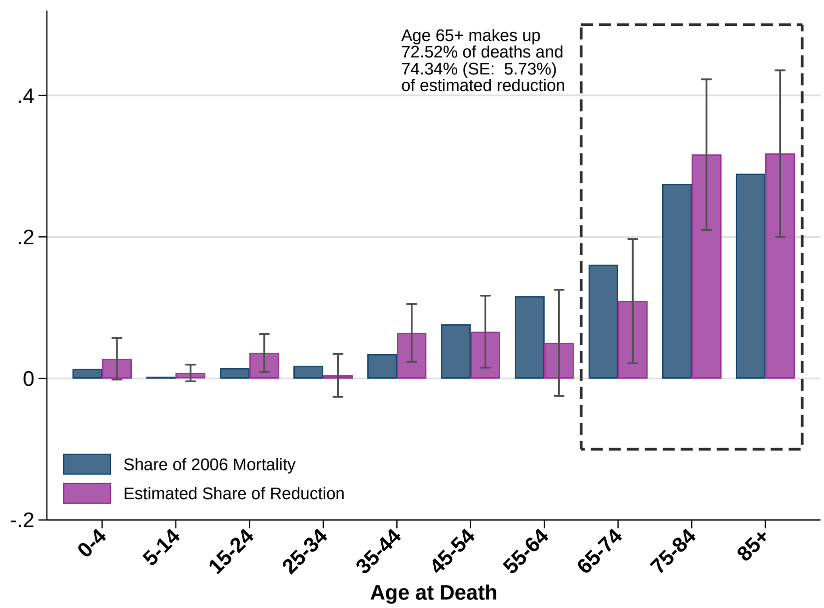
Notes: Figure 5a displays the group-specific average of 2007-2009 and 2010-2016 coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted CZ mortality rate per 100,000, groups g are defined as the 11 most common causes of death in the ICD10 39-group classification (presented in order of decreasing prevalence), and the final category is a residual category which captures all other mortality. Observations are weighted by CZ population in 2006. Coefficients and confidence intervals are multiplied by 100 throughout for ease of interpretation. 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. the 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 -0.50%. 95% confidence intervals for these estimates, clustered by CZ, are shown as vertical lines. N=741 CZs.

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

(a) Pooled Estimates



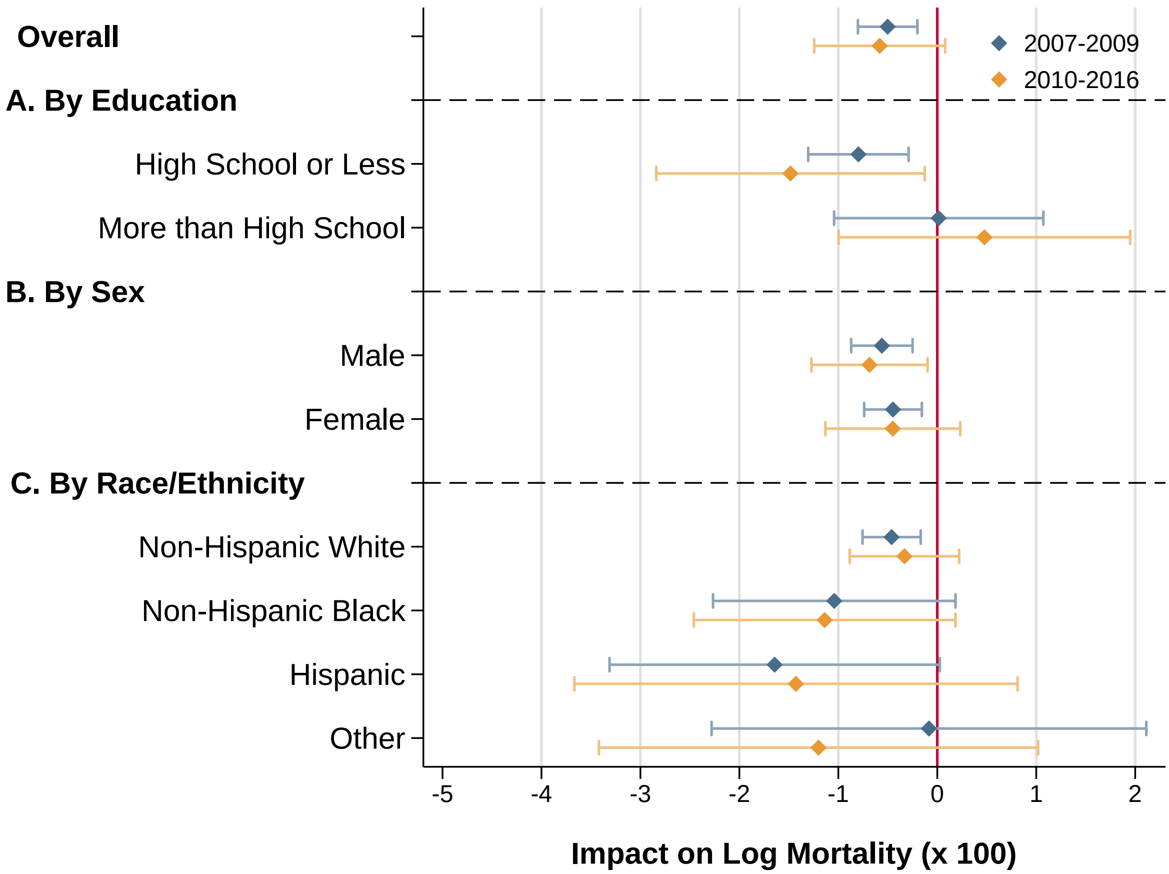
(b) 2007-2009 Decomposition



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

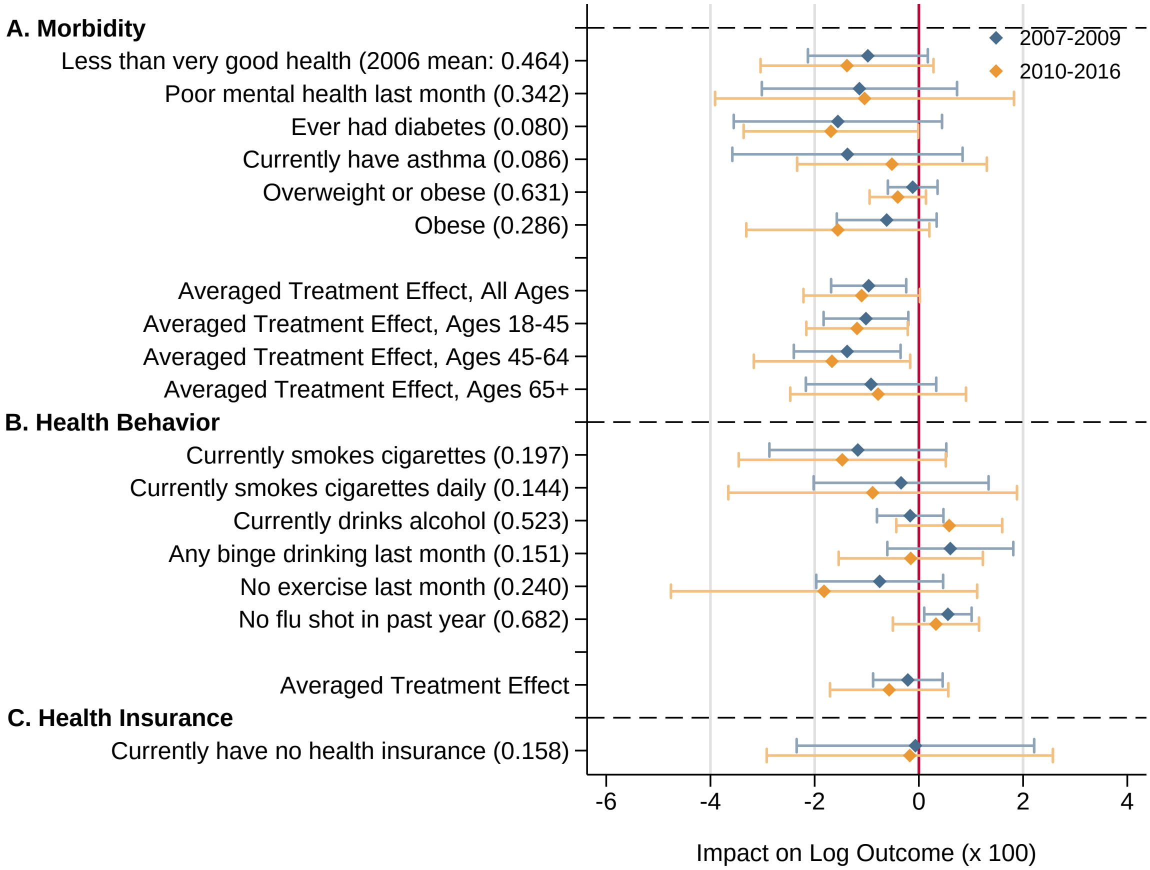
Notes: This figure displays the group-specific average of 2007-2009 and 2010-2016 coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log CZ mortality rate per 100,000 for a given age group, without any age adjustment, and groups g are defined by 10 age groups. Observations are weighted by CZ population in 2006. Coefficients and confidence intervals are multiplied by 100 throughout for ease of interpretation. 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. the estimate from Figure 6a). The blue bars indicate each age group'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 Shock on Log Mortality, by Education, Sex and Race



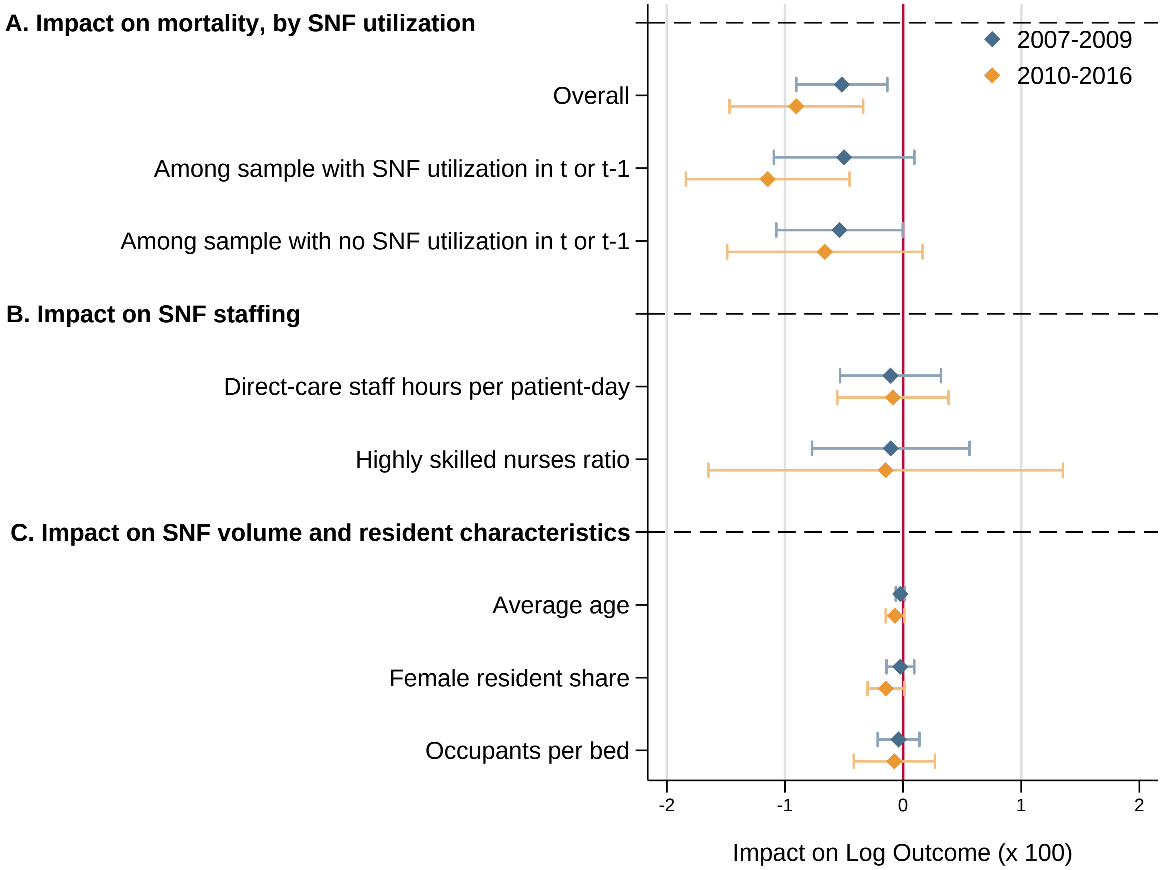
Notes: This figure displays the group-specific average of 2007-2009 and 2010-2016 coefficients β_{tg} from equation (2), where the outcome y_{ctg} is log age-adjusted mortality rate per 100,000 and groups g are defined by education, sex, and race categories. The top row replicates the baseline estimates 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. Coefficients and confidence intervals are multiplied by 100 for ease of interpretation. Period estimates are displayed as diamonds; horizontal bars indicate 95% confidence intervals, clustered at the CZ level. N=741 CZs for "overall" estimates. N=47 states for estimates by education. N=739 CZs (>99.9% of the total 2006 population) for estimates by sex, and N=434 CZs (96% of the total 2006 population) for estimates by race.

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



Notes: This figure displays the average of 2007-2009 and 2010-2016 coefficients β_t from equation (1), where the outcome y_{ct} is the log share of respondents in each state who report the various rows' health conditions or health behaviors in the 2003-2016 BRFSS. Appendix B.4 provides more details on the sample and variable definitions. The averaged treatment effects are the average of the coefficients for each measure of health or health behavior, either for the sample as a whole or separately by age group as indicated. State averages are generated as the mean value of individual reports in a given state, weighted by BRFSS survey weights. Estimates are therefore all estimated at the state level, weighting by 2006 state population. Period estimates are displayed as diamonds; horizontal bars indicate 95% confidence intervals, clustered at the state level. Coefficients, standard errors, and confidence intervals are multiplied by 100 for ease of interpretation. The population average of each (exponentiated) outcome in 2006 is noted in parentheses next to each variable label (i.e., 2006 population-weighted means of each state estimate). N=51 states.

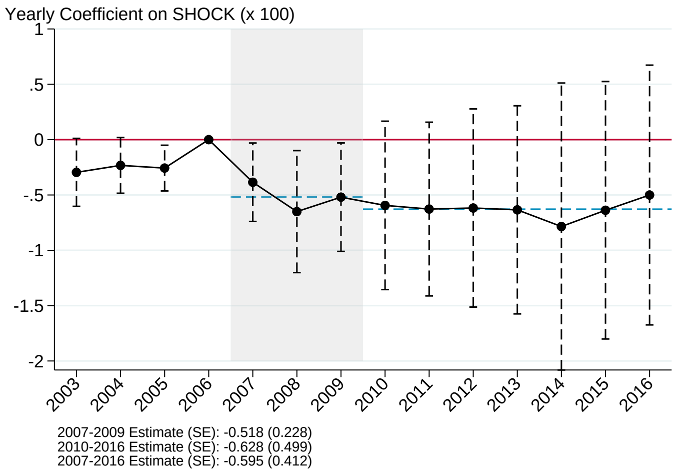
Figure 9: Impact of Shock on Log Characteristics of SNF Care



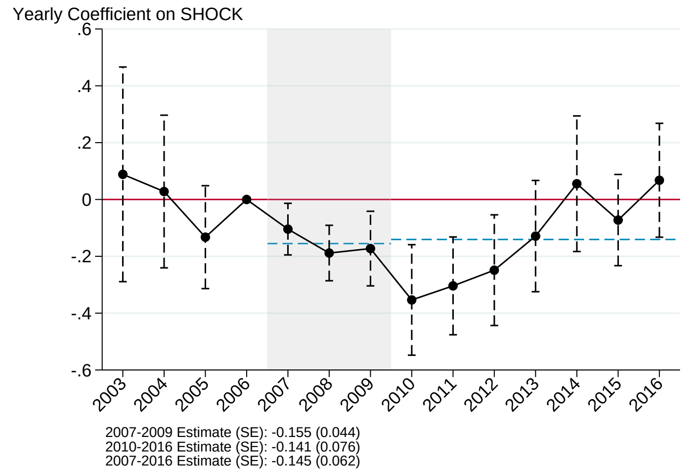
Notes: This figure displays the average of 2007-2009 and 2010-2016 coefficients β_{tg} from equation (2) (in Panel A) and coefficients β_t from equation (1) (in Panels B and C), where outcomes y_{ct} and y_{ctg} include several facets of SNF care. Panel A measures log (non age-adjusted) mortality rate per 100,000 among individuals who did and did not utilize SNF care in the current or previous year, as well as across the whole sample of SNF utilizers and SNF non-utilizers. Panels B and C draw from a range of data sources that originally measure outcomes at the SNF level. 'Direct-care staff hours' is defined as the sum of the hours worked by registered nurse, licensed practical nurse, and certified nursing assistant staff per resident-day. 'Highly skilled nurses ratio' is the ratio of registered nurse full-time equivalents divided by the number of registered nurse + licensed practical nurse full-time equivalents in nursing homes. These and other outcomes in Panels B and C are then aggregated to the CZ level, weighting by each SNF's total number of beds, before being logged. All impacts are therefore estimated at the CZ level, weighting by 2006 CZ population. Coefficients, standard errors, and confidence intervals are multiplied by 100 for ease of interpretation. Point estimates are displayed as diamonds; vertical bars indicate 95% confidence intervals, clustered at the CZ level. N=733 CZs (covering >99.9% of the 2006 Medicare population) in Panel A, with the sample of CZs limited to those with at least one beneficiary associated with SNF utilization and one not associated with SNF utilization in every year. N=716 CZs (covering 99.8% of the overall 2006 population) with at least one SNF in Panels B and C.

Figure 10: Impact of Shock on Log Mortality and Pollution

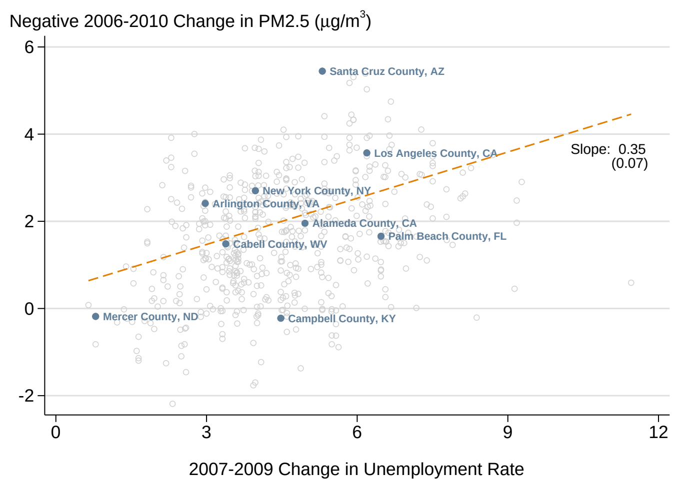
(a) Log Age-Adjusted Mortality Rate



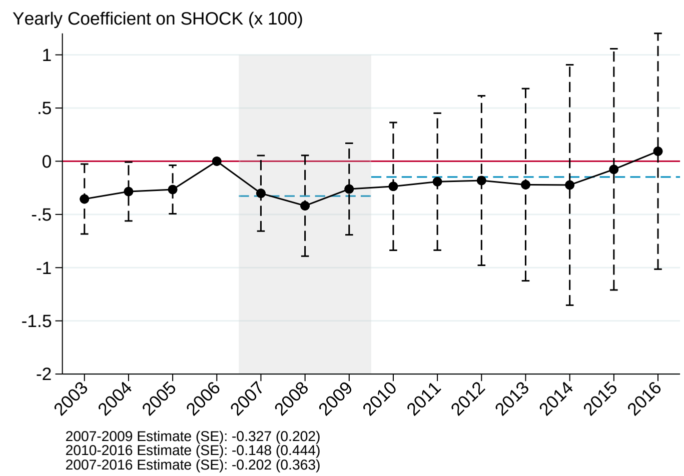
(b) PM2.5 Levels ($\mu g/m^3$)



(c) Correlation of Unemployment and PM2.5 Shocks

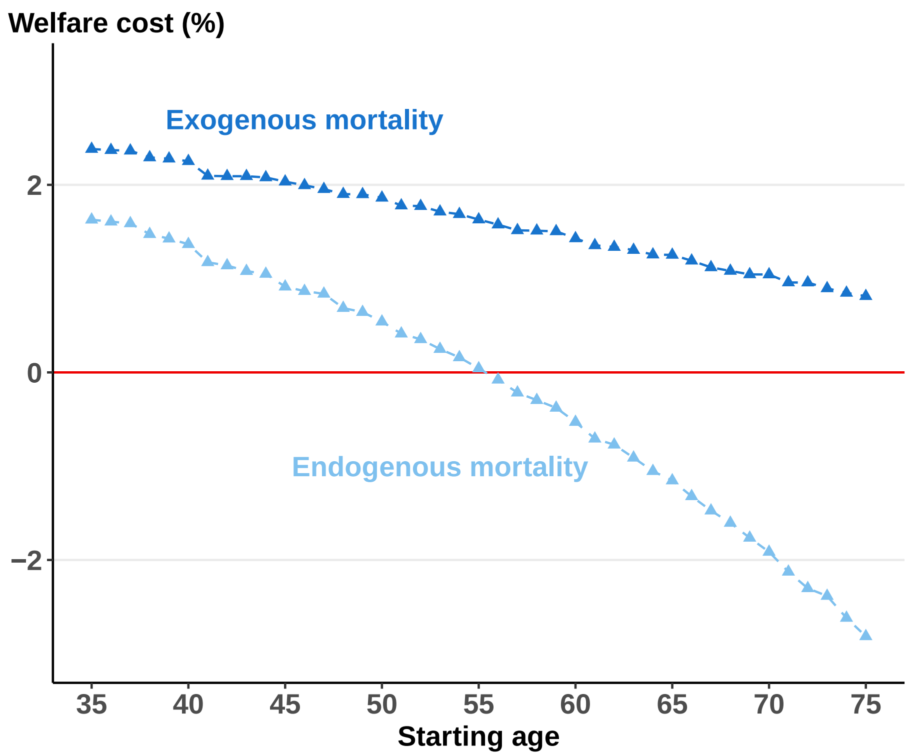


(d) Log Mortality, Controlling for PM2.5 Shock



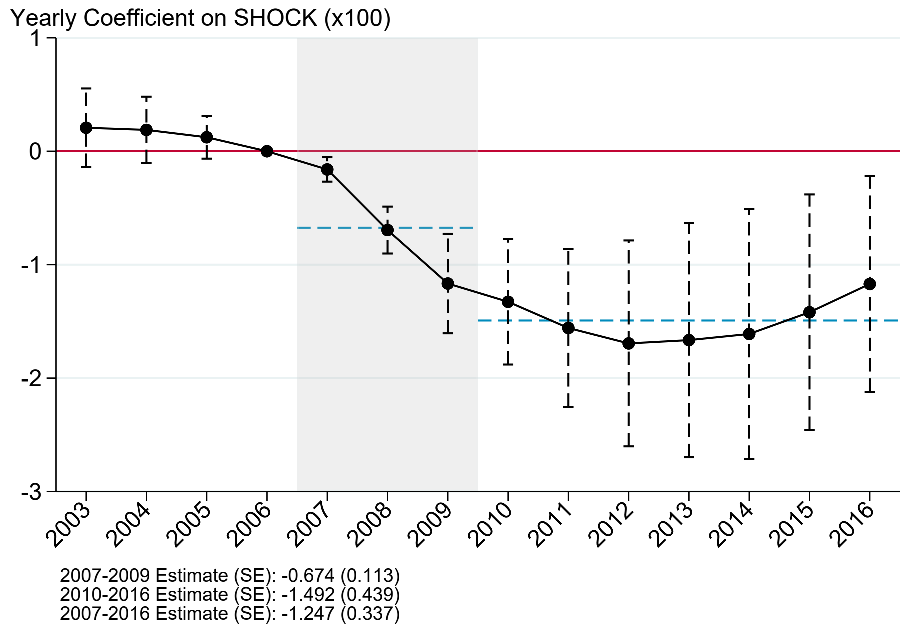
Notes: Figures 10a and 10b display the yearly coefficients β_t from equation (9), where the outcome y_{ct} is the log age-adjusted county mortality rate per 100,000 (Figure 10a) or the annual county PM2.5 level (Figure 10b), and $SHOCK_c$ is the 2007-2009 CZ change in unemployment rate. Figure 10c scatters the the negative 2006-2010 change in the county PM2.5 level against the 2007-2009 change in its CZ's unemployment rate. 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. Figure 10d displays the yearly coefficients β_t from equation (10), where the outcome y_{ct} is the log age-adjusted county mortality rate per 100,000. β_t is the coefficient on the 2007-2009 change in the CZ unemployment rate interacted with calendar year when controlling for the negative 2006-2010 change in PM2.5 interacted with calendar year. All analyses are restricted to the 542 counties (representing 64.4% of the US population) for which we observe a PM2.5 monitor in both 2006 and 2010, and observations are weighted by county population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 in Figures 10a and 10d for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient.

Figure 11: Welfare Costs of Recessions by Age



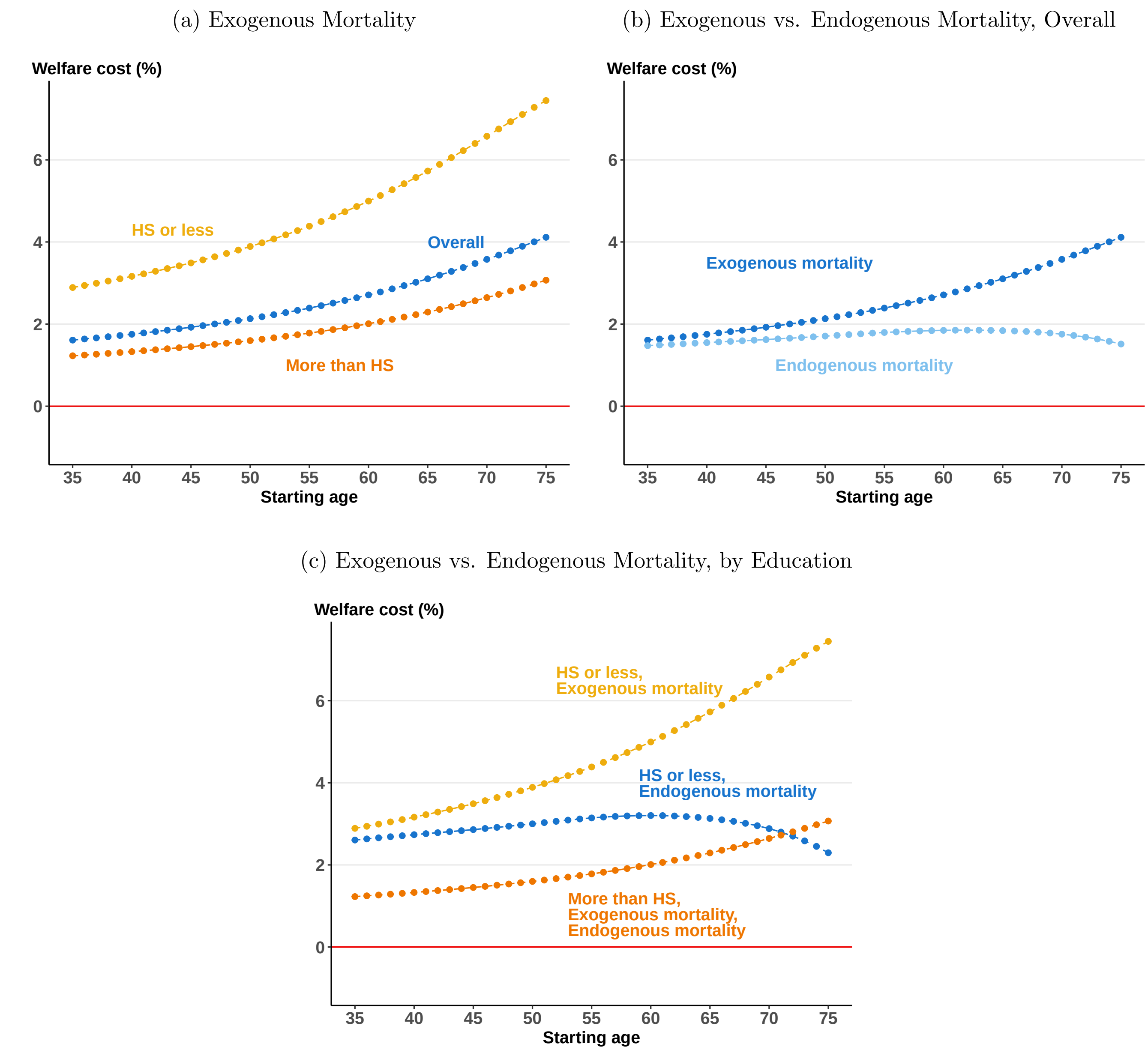
Notes: This figure displays the welfare cost of recessions, based on equation (16), at various ages under exogenous and endogenous mortality. This welfare cost is the amount an individual would need to be paid to accept the stochastic aggregate state relative to an otherwise similar economy that stays in the non-recession state for all time periods, measured as a percentage of average annual consumption. These estimates assume $\gamma = 2$, and b corresponding to a $VSLY$ of $\$250k$. Because the true target function is monotonically decreasing in age, we rearrange the non-monotonic estimates following Chernozhukov et al. (2009) to improve efficiency.

Figure 12: Impact of Shock on Consumption



Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log state personal consumption expenditure per capita, inflation-adjusted to 2012 dollars, and $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. Observations are weighted by 2006 state population. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the state level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=51 states.

Figure 13: Welfare Costs of the Great Recession by Age



Notes: This figure displays the 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 a HS diploma, based on equation (19). 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: 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)	-0.348	-0.269	-0.293
	(0.157)	(0.233)	(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)	-0.370	-0.326	-0.339
	(0.165)	(0.251)	(0.223)
Yearly Residence (β_t, eq. 7)	-0.513	-0.533	-0.527
	(0.161)	(0.241)	(0.210)
Yearly Residence (Non-Movers) (β_t, eq. 7)	-0.559	-0.666	-0.634
	(0.179)	(0.244)	(0.218)

Notes: This table displays the point estimate and standard errors (in parentheses) of coefficients from various individual-level Gompertz hazard models of $\log(m_{it}(a))$: the log mortality rate at age a. Table displays the average of yearly coefficients from 2007-2009, 2010-2016, and 2007-2016, respectively. Estimates are based on coefficients π_t^{FS} from equation (4) for the reduced form specification, on coefficients π_t^{FS} from equation (5) for the first stage regression where the dependent variable is the shock experienced in a given year, and on coefficients β_t from equation (6) for the control function specification and from equation (7) for yearly residence specifications. $SHOCK_c$ is defined as the 2007-2009 CZ change in the unemployment rate. Standard errors are clustered at the CZ level, except for the standard errors from estimating the control function specification 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. Coefficients and standard errors are multiplied by 100 throughout for ease of interpretation. The sample is all 2003 Medicare beneficiaries, subject to the restrictions in Appendix Table OA.8. N = 6,634,999 in all rows, except for the last row where we limit to non-movers, where N = 5,838,592.

Table 2: Sensitivity Analysis of Impact of Shock on Log Mortality

	(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)
Implied Percent Change	-0.470	-0.498	-0.489
Poisson	-0.453	-0.482	-0.473
	(0.139)	(0.295)	(0.245)
Panel C: Sample			
Drop CZs With High Fracking Activity	-0.464	-0.504	-0.492
	(0.157)	(0.348)	(0.287)
Add Census-Division-by-Year Effects	-0.384	-0.339	-0.353
	(0.135)	(0.277)	(0.229)
Drop 10 Most Populous CZs	-0.516	-0.624	-0.592
	(0.103)	(0.195)	(0.163)
Drop Top/Bottom Decile of Shocked CZs	-0.785	-1.037	-0.961
	(0.264)	(0.676)	(0.546)

Notes: This table displays estimates of one-off deviations from equation (1), which estimates the impact of the 2007-2009 CZ unemployment shock ($SHOCK_c$) on the log age-adjusted mortality rate per 100,000 (y_{ct}). Columns (1), (2), and (3) display the point estimate and standard error (in parentheses) for the average of yearly coefficients β_t from 2007-2009, 2010-2016, and 2007-2016, respectively. 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. In Panel B, the implied percent change is computed by dividing the coefficients obtained from estimating the specification with the mortality rate in levels as the outcome by the average age-adjusted mortality rate across CZs in 2006, weighted by the 2006 population. In the first row of Panel C, we estimate equation (1) for the 685 CZs (out of 741 total) that are do not contain counties with high potential for fracking as defined by Bartik et al. (2019), which represent 91% of the 2006 population; for more information, see Section 3.3. In the last row, we estimate this equation omitting the top and bottom (population-weighted) deciles of shocked CZs, leaving 393 CZs remaining. All estimates except those in Panel A are weighted by 2006 CZ population, 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. Coefficients and standard errors are multiplied by 100 throughout for ease of interpretation. N=741 for CZ analysis; N=51 for state analysis; N=3,101 for county analysis.

Appendices

A 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 (now known as X) 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 on the magnitude of the change in the aggregate U.S. unemployment rate during the Great Recession (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 percent self-identified as health economists, 20 percent as macro-economists, and 25 percent as other economists or researchers. Approximately 84 percent of respondents identified as faculty or post-doctoral researchers. Of the 354 responses, 317 responses provided a guess for the magnitude of change.

Results. Figure OA.18 shows the distribution of the direction of change in mortality rates predicted by respondents in the analysis sample. Panel (a) indicates that nearly half of all respondents predicted an increase in mortality, while Panel (c) shows differences in the predicted direction of change by age group. Panel (d) shows heterogeneity in predictions by respondent subfield: macroeconomists are more likely to predict an increase than health economists.

Panel (b) describes the distribution of the predicted direction and magnitude of change in the cumulative distribution function (with answers below the 5th percentile and above the 95th percentile trimmed from the figure for visual clarify, though these respondents are included in the following statistics). We find that 93 percent of the respondents provided a predicted impact on mortality larger than our (negative) point estimate, and 82 percent provided a prediction above the upper bound of our 95 percent confidence interval.

B Data

Throughout, we restrict our analysis to people in the 50 states and the District of Columbia from 2003 to 2016.[43]

B.1 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.htm`.

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 ten deaths; this threshold can prevent the publication of county-level 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 compute mortality rates using the CDC microdata, we use population data from the National Cancer Institute's 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.

To measure cause of death, 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.

Medicare data. We use the Medicare data to analyze mortality for a 20 percent random sample of the near-universe of Americans 65 and older.[44]

We observe death records, annual zip code of residence, and demographic variables for all Medicare enrollees, regardless of whether they are enrolled in Traditional Medicare or Medicare Advantage. 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 healthcare

[43] In the CZ-level analyses, we exclude eight counties in Alaska (five of which did not exist until 2014) because it is not straightforward to map them to CZs; these counties account for less than 0.006 percent of the population.

[44] 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).

utilization measures or health measures which are based on diagnoses recorded by physicians) are not available for enrollees in Medicare Advantage.

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 in this file can be found in Jarosek (2022). The Social Security Administration in turn receives death reports directly from sources "including family members, funeral homes, financial institutional, postal authorities, States and other Federal agencies" (Social Security Administration 2023).

For the approximately three-quarters of the elderly who are enrolled in Traditional Medicare, we also observe detailed information about their healthcare use and 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.[45]

We analyze two primary Medicare samples. First, we analyze a panel of 2003 Medicare enrollees aged 65-99 in 2003; we make a few other minor sample restrictions described in Appendix Table OA.8. We use this enrollee-level panel to explore the sensitivity of our findings to accounting for potentially endogenous movements of individuals across areas. Second, we analyze a repeated cross section of individuals aged 65-99 each year, often further restricting to individuals who were enrolled in Traditional Medicare in the previous or current year; again, we make a few other minor sample restrictions described in Appendix Table OA.9. Summary statistics for each of these samples can be found in Appendix Table OA.10. In addition, Appendix Figure OA.34 illustrates that the estimates of the impact of the Great Recession on mortality for the 65+ population are similar when using Medicare data as when using CDC mortality data, and are also similar across the various Medicare samples we analyze.

B.2 Economic Data

We obtain monthly data on the county-level unemployment rate and counts of employment from the Bureau of Labor Statistics' Local Area Unemployment Statistics (LAUS, available at `https://www.bls.gov/lau/`). Following Yagan (2019), we construct CZ-year estimates of the unemployment rate in each month by summing the number of unemployed individuals across all counties in each CZ-month and taking the average across all months in a year, then dividing by the annual population (for ages 16+) in that CZ from the Census (available at `https://www2.census.gov/programs-surveys/popest/datasets/2010-2019/counties/asrh/`).[46] Similarly, to construct CZ-year estimates of the employment-to-population (EPOP) ratio, we sum the monthly employment counts across counties within a CZ and then average the monthly employment counts across months within a year; we transform these annual CZ employment counts into estimates of the CZ-year EPOP ratio using the same annual counts of CZ-level population aged 16+ from the Census as the denominator.

For our baseline $SHOCK_c$ measure in equation (1), we also follow Yagan (2019) and measure it as the percentage point change in the CZ unemployment rate between 2007 and 2009. We obtain this directly from the replication package in Yagan (2019), who calculates annual CZ unemployment rates in

[45] 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.

[46] 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`

the manner we do above—i.e. 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.

We obtain annual county-year real GDP from the Bureau of Economic Analysis (see the CAGDP1 time series at https://apps.bea.gov/regional/downloadzip.cfm). We aggregate this to the CZ-year level by summing the real GDP and population for all counties within a CZ, then dividing to obtain real GDP per capita for that year. For a sub-sample of counties for which it is available, we also obtain annual county-year house pricing data from the Federal Housing Finance Agency's yearly House Price Index (HPI) public release. This data release is available at https://www.fhfa.gov/DataTools/Downloads/Pages/House-Price-Index-Datasets.aspx. 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.

State-level household total consumption expenditures on (durable and non-durable) goods and services are from the Personal Consumption Expenditures (PCE) surveys published by the Bureau of Economic Analysis. 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.

Finally, 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) as well as income (overall and by age 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. To match the yearly structure of our data, we use the CPS survey results from March of each year. We measure individual annual earnings, adjusted to 2015 dollars using the CPI. We also measure inflation-adjusted individual annual income (censoring negative values to be zero); individual income includes wage income, retirement income, unemployment insurance, and business and farm income (see https://cps.ipums.org/cps-action/variables/INCTOT#comparability_section).

B.3 Air Pollution Data

We obtain data on air pollution from the EPA's Air Quality System (AQS) database (available at https://www.epa.gov/aqs). 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. We limit our analysis to the approximately two-thirds (population-weighted) of counties for which we have a pollution monitor in both 2006 and 2010; Appendix Figure OA.15 shows a map of these counties.

B.4 BRFSS Data

The Behavioral Risk Factor Surveillance Survey is an annual telephone survey administered to approximately 400,000 individuals aged 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 healthcare 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.)

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.

BRFSS Variable Definitions. Our analyses examine several BRFSS measures of self-reported health, health behavior, and healthcare. 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 as 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 healthcare coverage, including health insurance, prepaid plans such as HMOs, or government plans such as Medicare?" This question is asked of all respondents.

Appendix Table OA.11 shows the means of these various outcomes overall and separately by age group.

B.5 Nursing home data

We use the Online Survey Certification and Reporting (OSCAR) and Certification and Survey Provided Enhanced Reporting (CASPER) databases to measure nursing home staffing. In particular, we use the data compiled by the Shaping Long-Term Care in America Project at Brown University (LTCFocus 2023), which compiles the OSCAR/CASPER data with aggregate facility-level measures from CMS's Minimum Data Set (MDS). These are facility-level administrative data obtained from certification inspections of nursing homes; they are the same data that were previously used by Stevens et al. (2015) to study the impact of recessions on the quantity and quality of nursing home staffing. We take CZ-level means of each measure, weighting facility observations by that facility's total number of beds in that year. We then take the log of these CZ-level aggregates before proceeding with analysis. In particular, we measure:

- The number of nursing home staff hours. We observe the number of direct care staff hours per resident-day, where direct care workers include registered nurses, licensed practical nurses, and certified nursing assistants.
- The skill mix of nursing home staff hours, defined as the ratio of registered nurse full-time equivalents divided by the number of registered nurse and licensed practical nurse full-time equivalents in nursing homes.
- The volume of nursing home patients, measured by the occupancy rate (occupants per bed).
- The average age of nursing home residents.
- The share of residents that are female.

B.6 Health and Retirement Study Data

Data and Sample The Health and Retirement Study (HRS) 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.

HRS Variable Definitions We analyze four measures of home care in the HRS. First, we examine 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, henceforth referred to as "helpers". We also examine separate indicators for whether respondents report any paid helpers, unpaid helpers, or 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 percent of the 2006 sample reports any help in the past month, 16 percent of the sample reports any unpaid helpers, and 4 percent of the sample reports any paid helpers.

C Additional Details on Specific Analyses

C.1 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. We also limit our analysis to individuals aged 25 and over so that we can observe completed education.

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, some college, and college or more), 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 allows us to produce a state-year panel of age-adjusted mortality rates for each education bin, which we use to conduct our analysis.

Note, however, that the education level is missing for a small share (4.5 percent) 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 percent 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 percent 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 percent.

These sample restrictions do not meaningfully affect our results. As seen in Figure OA.16a, which estimates our main specification at the state-level using 47 states, the 2007-2009 period estimate is -0.56 (standard error = 0.26), which is very similar to the corresponding estimate of -0.62 (standard error = 0.25) using all 50 states and the District of Columbia and all ages in Table 2.

C.2 Health Status of Marginal Life Saved

To analyze the health status of the marginal life saved, we closely follow 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 can therefore 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.

C.2.1 Predicting Remaining Life Expectancy

The rich, detailed information on individual demographics and health conditions in the Medicare data allows 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.[47]

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:

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

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.27). If we assume that decedents would have had the remaining life expectancy of the average Medicare enrollee, we predict their counterfactual remaining life expectancy to be 11 years. Accounting for age—i.e. that the typical Medicare decedent is older than the typical Medicare enrollee—reduces that counterfactual remaining life expectancy by about 30 percent, to 7.9 years. Further accounting for demographics and chronic health conditions reduces counterfactual remaining life expectancy by another 20 percent, to 6.5 years.

C.2.2 Analyzing decline in life-years lost

We define life-years lost for each individual in the data at the beginning of the year to be zero 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 then re-estimate equation (1) with the dependent variable now the log number of

[47] 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.

life-years lost in CZ c and year t per hundred thousand beneficiaries. Specifically, we define life-years lost per hundred thousand beneficiaries (LYL_{ct}) as

$$\text{LYL}_{ct} = 100,000 \times \frac{\sum_{i \in S_{ct}} \text{LYL}_{it}}{|S_{ct}|} \tag{22}$$

where LYL_{it} is the life-years lost for individual i in year t and S_{ct} represents the set of beneficiaries living in CZ c during year t.

The key object 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. Appendix Table OA.12 shows the results from re-estimating equation (1) for the dependent variable log life-years lost ($\log(\text{LYL}_{ct})$). For comparison, Column (1) shows the results where the dependent variable is the log of the (non age-adjusted) mortality rate per 100,000; it indicates that a one-percentage-point increase in the unemployment rate reduces the mortality rate by 0.6 percent. As expected, we see in Column (2) that estimating equation (1) with log life-years lost as the dependent variable yields very similar results to Column (1) if we assume that decedents have the same remaining life expectancy of the average Medicare enrollee. In particular, Column (2) suggests that a one-percentage-point increase in the unemployment rate reduces the life-years lost in a CZ by about 0.62 percent. Columns (3) through (5) explore how this changes as we incorporate richer covariates into our prediction of counterfactual remaining life expectancy among decedents. Column (3) shows that accounting for age reduces the estimate of life-years lost by about 8 percent to 0.57 percent. Accounting for differences in demographics and health conditions further reduces the estimate of life-years lost by about another 6 percent (to 0.54 percent); none of these differences are statistically distinguishable.

The analysis in Appendix Table OA.12 suggests that the Great Recession-induced mortality reductions came from individuals who had only slightly lower counterfactual life expectancy than typical *decedents* of the same age; since we are comparing how the percent change in life-years lost varies across sets of controls, we are effectively normalizing by the 'typical' decline in life-years due to mortality or, in other words, to decedents. We can also ask whether the marginal life saved has substantially lower life expectancy than a typical Medicare *enrollee* of the same age. To do this, we re-estimate equation (1) with the level of life-years lost (LYL_{ct}) as the dependent variable. Table OA.13 shows the results. 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 in the set of beneficiaries covered by Traditional Medicare in the previous year. 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 across all Medicare enrollees in this sample (11 years), we obtain a decline in life-years lost of 326 per 100,000 beneficiaries (that is, 326 life-years gained). Incorporating age reduces the decline in life-years lost substantially, to 212 (column 3) or by about 35 percent. Further incorporating demographic and health covariates reduces the decline in life-years lost by another 20 percent, to 167; in other words, the marginal life saved has about 80 percent the remaining life expectancy of a typical Medicare enrollee of the same age, when modeling life expectancy off of age, demographics, and chronic conditions. This is not surprising as the decedent population in general has a lower remaining life expectancy than the general population.

C.3 Probing the assumed linearity of the impact of the recession shock.

We undertook a number of additional analyses (that we summarized but did not report in the main text) to examine our baseline assumption that mortality impacts are linear in the size of the economic shock. We describe them in more detail here. As in the main sensitivity analysis, we focus our discussion primarily on the estimated average impacts from 2007-2009.

We allowed the impact of the shock to vary based on whether the CZ experienced an above- or below-average shock. Under the assumed linearity, we should find the same impact of the shock on both sub-samples. To examine this, we adopt a modified version of equation (3), with $Recovery_{q(c)}$ substituted for an indicator of whether a CZ experienced an above or below (population-weighted) median CZ 2007-2009 unemployment shock. The results are shown in Appendix Figure OA.38; consistent with the linearity assumption, we find very similar estimated impacts of the shock in both sub-samples.

We also relaxed 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. Specifically, we estimate

$$y_{ct} = \sum_{j=2}^{4} \beta_t^{(j)} \left[SHOCKQ_c^{(j)} * \mathbb{1}(Year_t) \right] + \alpha_c + \gamma_t + \epsilon_{ct} \tag{23}$$

where $SHOCKQ_c^{(j)}$ is an indicator for the jth quartile 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 $\beta_t^{(4)}$. The results are shown in Appendix Figure OA.36. We find that the impacts on mortality are increasing monotonically in the quartile of shock, although these effects are not perfectly linear in the average size of the shock by quartile. 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, Appendix Figure OA.37 plots the relationship between the (population-weighted) average of $SHOCK_c$ in each ventile of the CZ-shock distribution against the average change (for CZs in that ventile) in the log mortality rate between 2006 and its average across several post-period years: 2007-2009, 2010-2016, and 2007-2016. The relationship is noisy but looks roughly linear. This provides some support for the linear specification in equation (1).

C.4 Impacts on Paid and Unpaid Home Care (HRS)

We examined informal care provision, as this might increase in tight labor markets when adult children have lower opportunity costs of time.[48] We therefore turn to the Health and Retirement Survey (HRS) to estimate impacts of the Great Recession on the elderly's receipt of paid or unpaid home care. The data and variables are described in more detail in Appendix B.6.

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

[48] Mommaerts and Truskinovsky (2020) find evidence using a state-year panel that informal care provided by adult children is counter-cyclical, but it appears to be offset by the pro-cyclicality of spousal informal care, with no overall effect on the amount of informal care received by the elderly.

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):

$$y_{it} = \beta_t[SHOCK_{s(i,t)} * \mathbb{1}(Year_t)] + \alpha_{s(i,t)} + \gamma_t + \epsilon_{it} \tag{24}$$

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, with helpers defined as anyone assisting with activities of daily living, instrumental activities of daily living, or finances), we instead estimate a logistic regression model of the form:

$$ln\left(\frac{P(y_{it}=1)}{1-P(y_{it}=1)}\right) = \beta_t[SHOCK_{s(i,t)} * \mathbb{1}(Year_t)] + \alpha_{s(i,t)} + \gamma_t + \epsilon_{it} \tag{25}$$

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,[49] and cluster standard errors at the state level.

Appendix Figure OA.39 displays the results. It shows no evidence of an impact of the Great Recession on any of the measures of receipt of paid home care or receipt of unpaid home care.

C.5 Analysis of Impacts on Earnings and Income in the CPS

As noted in Section 5.2.1, we are unable to obtain estimated impacts on consumption separately by education. To calibrate impacts on consumption by education, we therefore instead estimate impacts on *earnings* for individuals ages 25 and older by education in the Current Population Survey, and then scale these education-specific earnings impacts by the ratio of impacts on consumption and impacts on earnings for both education groups combined to obtain estimates of impacts on *consumption* by education.

For the earnings estimates, we could simply estimate equation (1) at the state level for the outcome log average earnings. However, when we do so, the results are quite noisy. We therefore leverage the availability of individual-level data in the CPS to obtain more precise estimates of the effect on earnings for model calibration. Since earnings equal zero for many individuals, we estimate the proportional impact of the Great Recession with the following Poisson regression:

$$y_{it} = \exp\left(\beta_t\left[\text{SHOCK}_{s(i,t)} \times \mathbb{1}(Year_t)\right] + \alpha_{s(i,t)} + \gamma_t + \delta_{e(i,t)} + \eta_{a(i,t)} + \sigma_{g(i)}\right) \tag{26}$$

where y_{it} denotes earnings for individual i in year t; $\text{SHOCK}_{s(i,t)} \times \mathbb{1}(Year_t)$, $\alpha_{s(i,t)}$, and γ_t are defined just as in equation (1), where $s(i,t)$ gives the state individual i lives in during year t. To reduce noise, we also include demographic controls, specifically fixed effects for the individual's detailed education category ($\delta_{e(i,t)}$), age ($\eta_{a(i,t)}$), and gender ($\sigma_{g(i)}$). The educational categories we include are none, grades 1-4, grades 5-6, grades 7-8, grade 9, grade 10, grade 11, grade 12 (no diploma), high school, some college, Associate's degree (vocational), Associate's degree (academic), Bachelor's degree, Master's degree, professional school

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

degree, or PhD. The coefficients of interest are the estimates of β_t. We estimate equation (26) using the survey weights provided by the CPS and cluster standard errors at the state level.

Appendix Figure OA.43 shows the results. Panels (b), (d), and (f) display the estimates of β_t from estimating the individual-level Poisson equation (26), where the outcome is the earnings for all individuals aged 25+, earnings for individuals aged 25+ with a HS degree or less, and earnings for individuals aged 25+ with more than a HS degree, respectively. Panels (a), (c), and (e) show analogous results from estimating the equation (1) by OLS for the state-year outcomes log average earnings for all individuals aged 25+, the log average earnings for individuals aged 25+ with a HS degree or less, and the log average earnings for individuals aged 25+ with more than a HS degree, respectively. Reassuringly, the results look similar using either approach but, as expected, the estimates with the individual specification are noticeably more precise.

We estimate that the earnings impacts of the Great Recession are about two times larger for those with a high school education or less. On average over the 2007-2016 period, we find that a one-percentage-point increase in the unemployment rate from 2007-2009 is associated with a 1.8 percent (standard error = 0.48) decline in earnings (Panel b). Panels (d) and (f) show the estimated earnings declines separately by education. We estimate that a one-percentage-point increase in the unemployment rate reduced average annual earnings by 2.8 percent for those with a high school degree or less, compared to a 1.5 percent decline in average annual earnings for those with more than a high school degree. This is consistent with other studies of the distributional nature of the economic impact of recessions (e.g. Guvenen et al. 2014; Mian and Sufi 2016).

Appendix Figure OA.44 shows an analogous set of results for income for individuals ages 25 and older overall, 25-64, and 65 and older, both from estimating the individual-level Poisson equation (26) in Panels (b), (d), and (f) and from estimating the state-year OLS equation (1) in Panels (a), (c) and (e). Again, the results are similar across specifications but more precise with the individual level specification. We find that the recession-induced income reductions are limited to individuals ages 25-64 (Panel d); we find no evidence of recession-induced income declines for the 65 and older population (Panel f).

C.6 Impacts of the Great Recession on other pollutants

In addition to our finding in the main text that PM2.5 declines in areas harder hit by the Great Recession (see Figure 10), Heutel and Ruhm (2016) also find significant roles for decreased carbon monoxide (CO) and ozone (O_3) in explaining countercyclical mortality. We therefore explored impacts on those pollutants, but found no effects. We summarize the results here.

Due to limitations in the number of counties for which EPA monitor data is available for these pollutants, we focus our analysis on two samples for each pollutant: (1) the sample consisting of all counties for which we can measure the change in pollution between 2006 and 2010 for that specific pollutant and (2) the sample consisting of all counties for which we can measure this change for all three pollutants. These samples consist of 542 counties (comprising 64.4 percent of the 2006 population) for PM2.5, 229 counties (comprising 44.1 percent of the 2006 population) for CO, 751 counties (comprising 70.7 percent of the 2006 population) for O_3, and 137 counties (comprising 39.0 percent of the 2006 population) for the overlap sample.

Appendix Figure OA.40 shows the results from estimating equation (9) with different pollutants as the dependent variable. In the left hand column we show results for the maximum sample of counties that we have for that pollutant, and in the right hand column for the overlap sample of counties where we observe all three pollutants. As previously seen, we find that areas more exposed to the Great Recession shock experience declines in PM2.5 (Panels a and b). However, we find no evidence of recession-induced changes in carbon monoxide (Panels c and d) or in ozone (Panels e and f). Not surprisingly, therefore, if we run the mediation analysis in equation (10) using the 2006-2010 change in a different pollutant as the mediating factor, it has little impact of our estimates of the impact of the Great Recession on mortality (see Appendix Figure OA.41). As expected, therefore, when we include all three pollutants' changes between 2006-2010 interacted with year fixed effects as potential mediators, we find that it reduces the estimated impact of a one-percentage-point increase in the unemployment rate on mortality by 34.2 percent for the 2007-2009 period, which is nearly identical to the result mediating for PM2.5 alone of 36.9 percent (see Appendix Figure OA.42).

C.7 Gauging the impact of estimated pollution reductions on mortality

We use the evidence from the existing quasi-experimental literature on the impact of air pollution on mortality to perform a back-of-the-envelope calculation of what size mortality declines we would expect from our estimate of the recession-induced pollution decline. A key challenge for this exercise is that we estimate a multi-year pollution decline, while the literature 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), Graff Zivin and Neidell (2013), and Currie et al. (2014) for reviews, or Deryugina et al. (2019) for more recent work).[50] Moreover, it is a priori unclear whether the impact of a prolonged change in pollution exposure will be proportional, larger, or smaller than a temporary change. A persistent change might have proportionally smaller effects if harvesting is a primary driver of the short-run impacts, or it might have proportionally larger effects if impacts 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.

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 pollution 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. Deryugina et al. (2019) estimate that a one 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). We make 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. Under this assumption, our estimate in Figure 10b that a one-percentage-point increase in the unemployment rate is associated with an average annual PM2.5 reduction of 0.16 micrograms per cubic meter over 2007-2009 suggests that the pollution declines associated with a one-percentage-point increase in unemployment would cause a decline in elderly deaths of between 4 and 8 deaths per 100,000, depending on whether we use their three-day window estimates or their one-month window estimates. 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 2007-2009 total estimated recession-induced mortality decline.

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

C.8 Simplified Welfare Model

We consider a simplified version of the model in Section 5 in which the aggregate state $\omega \in \{L, H\}$ 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:

$$\mathbb{E}[U(c,m)]^{\text{normal}} = p^H * T * u((1-d^H)c) + (1-p^H) * T * u(c) \tag{27}$$

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

$$\mathbb{E}[U(c,m)]^{\text{recession}} = p^L * T * u((1-d^L)c) + (1-p^L) * T * u(c) \tag{28}$$

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

$$\mathbb{E}[U((1+\Delta)c,m)]^{recession} = \mathbb{E}[U(c,m)]^{normal} \tag{29}$$

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:

$$\Delta = \left(\frac{p^H(1-d^H)^{(1-\gamma)} + (1-p^H)}{p^L(1-d^L)^{(1-\gamma)} + (1-p^L)}\right)^{1/(1-\gamma)} - 1 \tag{30}$$

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.[51] 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.[52]

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:

$$\mathbb{E}[U]^{\text{normal}} = p^H * T * u((1-d^H)c) + (1-p^H) * T * u(c) \tag{31}$$

$$\begin{aligned}\mathbb{E}[U]^{\text{recession}} &= p^L * T(1+dT) * u((1-d^L)c) \\ &\quad + (1-p^L) * T(1+dT)u(c)\end{aligned} \tag{32}$$

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

[51] The expression is also increasing in $p^L - p^H$ and $d^L - d^H$, as well.

[52] 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 (holding p^L constant) we have Δ going to ∞, implying that the agent is not willing to accept any amount of consumption to accept the recession state as the earnings consequences of job displacement grow large, as in Krebs (2007).

mortality (Δ^{dT}):

$$\Delta^{dT} = \left(\frac{-dT * b/\tilde{u}(c) + p^H(1-d^H)^{(1-\gamma)} + (1-p^H)}{(1+dT)(p^L(1-d^L)^{(1-\gamma)} + (1-p^L))} \right)^{1/(1-\gamma)} - 1 \tag{33}$$

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 (33) is valid for any value of dT and it simplifies to the expression for Δ in equation (30) if $dT = 0$.[53]

We can build further intuition by setting $p^H = 0$ and then taking a first-order approximation around the left-hand side of equation (33), which leads to the following expression:

$$1 + (1-\gamma) * \Delta^{dT} \approx \frac{-dT * b + \tilde{u}(c)}{(1+dT) * (p^L * (1-d^L)^{(1-\gamma)}\tilde{u}(c) + (1-p^L)\tilde{u}(c))} \tag{34}$$

$$\Delta^{dT} \approx \Delta - dT\frac{\text{VSLY}}{c} \tag{35}$$

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.

C.9 Calibrations for Welfare Analysis of Adapted Krebs (2007) Model

- **Mortality in "normal" times** For mortality in "normal" times, we use the 2007 SSA mortality tables to calculate age-specific mortality rates for the $m^H(t)$ vector. 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 $m(a) = s^m(a) * m^m(a) + (1 - s^m(a)) * m^f(a)$.

- **Mortality decline from a typical recession** To calibrate the mortality decline from a typical recession, we estimate that a typical recession produces a 3.1-percentage-point increase in the unemployment rate. We arrive at this estimate by 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/`). From this, 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). We then combine this unemployment rate increase with our our estimates in Section 3 that a one-percentage-point increase in unemployment causes a 0.5 percent decline in the mortality rate to calibrate the mortality decline from a typical recession of $dm = -0.015$.

[53] 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.

- **VSLY** We report results for a VSLY of \$100k, \$250k, or \$400k. 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 $\text{VSLY} = r * \text{VSL}/(1-(1+r)^{-L})$, 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.

D Compilation of Event Studies

In Section 3.2, we summarize the results from some mortality event studies in terms of the average estimated effects across years, particularly as they pertain to heterogeneity in mortality declines across groups and causes of death. We also refer to additional mortality analyses not presented in the main text. Here we present the underlying event studies behind these results:

- **Cause of death:** Appendix Figures OA.19 and OA.20 show results for the 11 most common causes of death, plus a residual category for all other deaths.
- **Deaths of despair:** Appendix Figure OA.11a shows results for deaths of despair, while Appendix Figures OA.20c, OA.20d, and OA.11b show the results for each of the three components of deaths of despair: suicide, liver disease, and drug poisonings (accidental or unknown).
- **By age:** Appendix Figures OA.21 and OA.22 show results for different age groups.
- **By education:** Appendix Figure OA.16 shows results by education. It shows results 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. It also disaggregates the results for those with more than a high school degree, showing results separately for the 22 percent of the population with some college and the 29 percent with a college degree or more.
- **By education, by age:** Appendix Figure OA.23 confirms that the finding that the Great Recession is confined to those with a high school education or less persists even when we look within age groups.
- **By Medicaid status:** Appendix Figure OA.24 shows results using the Medicare cross-sectional data for the elderly by whether or not individuals were enrolled in Medicaid during the previous year.
- **By race:** Appendix Figure OA.25 disaggregates results by Non-Hispanic White, Non-Hispanic Black, Hispanic, and Other populations.
- **By sex:** Appendix Figure OA.26 disaggregates results by sex.
- **Health status of marginal life saved:** Appendix Figure OA.27 shares average predicted counterfactual remaining life expectancy among decedents under a range of controls, and Appendix Tables OA.12 and OA.13 estimate the impact of $SHOCK_c$ on life-years lost under these counterfactual life expectancies.
- **Morbidity** Appendix Figures OA.28 and OA.29 show impacts on measures of morbidity from the BRFSS.
- **Motor vehicle mortality by age** Appendix Figure OA.32 shows results for motor vehicle mortality by age groups, as well as the share of the total mortality decline for various age groups that can be accounted for by declines in motor vehicle mortality. 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 seven percent 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. 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.

In Section 3.3, we summarize the results from various event studies in terms of the average estimated effect of the Great Recession on mortality across years, particularly with regard to sensitivity analyses. Here we present the underlying event studies behind these results:

- **Sensitivity to fixing population location in 2003:** Appendix Figure OA.33 shows results fixing baseline residence in the Medicare panel data. Appendix Figure OA.34 confirms that our overall mortality estimates look similar among the Medicare sample to our main specification which uses CDC data to estimate mortality across all age groups.

- **Sensitivity to geography:** Appendix Figure OA.35 shows results changing the level of geography to counties and states rather than CZs, as well as dropping certain CZs from the sample (including especially populous CZs and CZs with significant fracking activity).

- **Sensitivity to functional form:** Appendix Figure OA.36 shows results under alternative functional forms.

- **Linearity:** Appendix Figure OA.37 plots the (population-weighted) average of $SHOCK_c$ in each ventile of the CZ-shock distribution against the within-ventile average change in log mortality, while Appendix Figure OA.38 adopts a modified version of equation (3), with $Recovery_{q(c)}$ substituted for an indicator for whether a CZ experienced an above or below (population-weighted) median unemployment shock, and displays separate event studies for above- and below-median CZs.

In Section 4 we summarize results from various event studies, particularly regarding potential mechanisms for mortality declines. Here we present the underlying event studies behind these results.

- **Self-reported health behaviors:**. Appendix Figures OA.30, and OA.31 show results for self-reported health behaviors and health measures.

- **Utilization of health services:** Appendix Figure OA.10 examines utilization of health services among the Medicare population.

- **SNF care:** Appendix Figure OA.12 examines the effect of $SHOCK_c$ on mortality separately by individuals' SNF utilization, while Figures OA.13 and OA.14 examine SNF characteristics.

- **Informal care provision:** Appendix Figure OA.39 examines the effect of $SHOCK_c$ on measures of informal care provision recorded in the HRS.

- **Pollution:** Appendix Figures OA.40, OA.41, and OA.42 examine the mediation effects of other pollutants on our main results.

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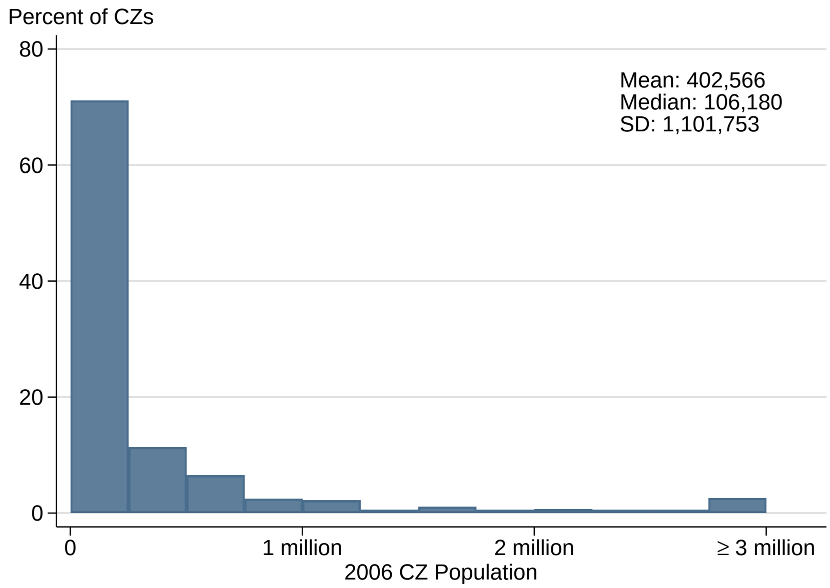
E Appendix Figures

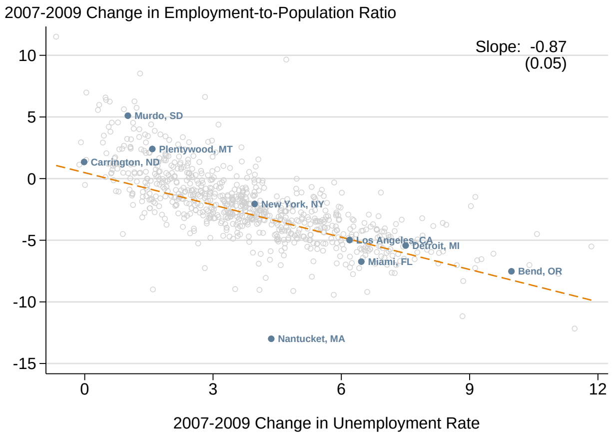
Figure OA.1: 2006 Commuting Zone Population



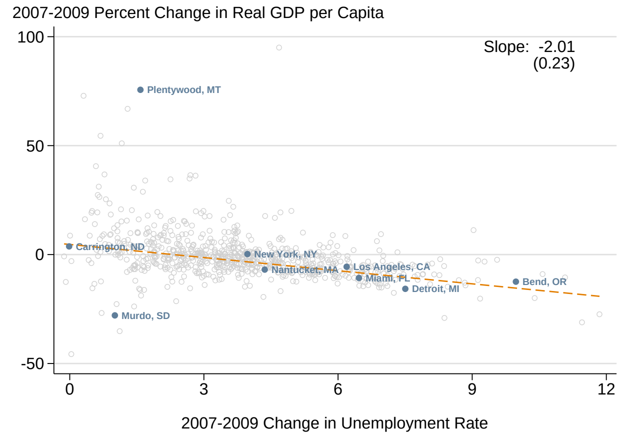
Notes: This figure displays a histogram of 2006 CZ populations, in bins of 250,000. For visualization purposes, CZs with populations larger than three million are binned to three million. Descriptive statistics in the upper right-hand corner are reported for the full distribution. N=741 CZs.

Figure OA.2: Correlation of Alternative Great Recession Shocks

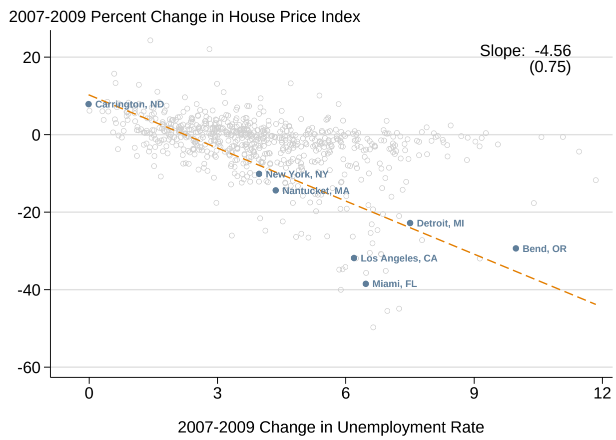
(a) 2007-09 Employment-to-Population Change



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



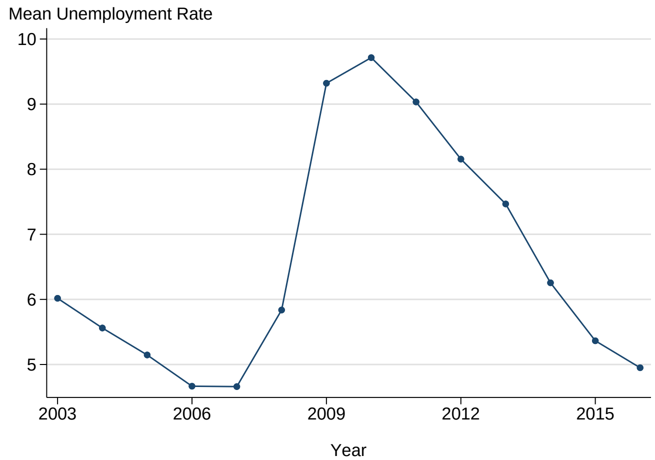
(c) 2007-09 House Price Index Percent Change



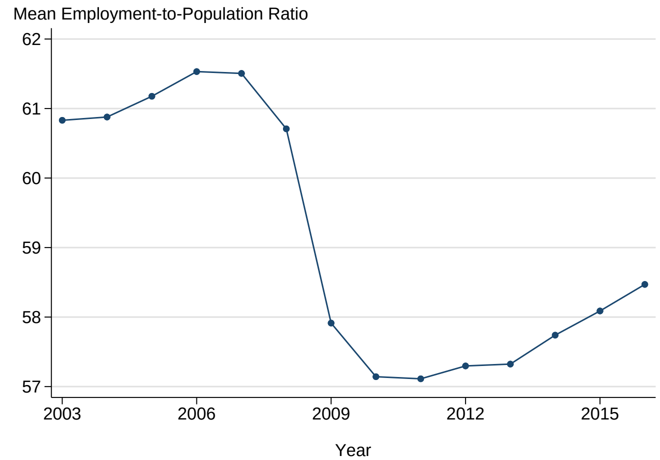
Notes: This figure displays scatterplots of measures of shocks associated with the Great Recession. Figure OA.2a plots the 2007-2009 change in the CZ employment-to-population ratio against the 2007-2009 change in the CZ unemployment rate. Figure OA.2b plots the change in CZ real GDP per capita (in thousands of 2012 chained USD) against the same unemployment rate shock, and Figure OA.2c plots the 2007-2009 change in the CZ annual house price index against the unemployment rate shock. N=741 CZs in Figure OA.2a; in Figures OA.2b and OA.2c, N=740 CZs and N=684 CZs, respectively, for which we have complete data from 2003-2016.

Figure OA.3: Time Series of Economic Indicators

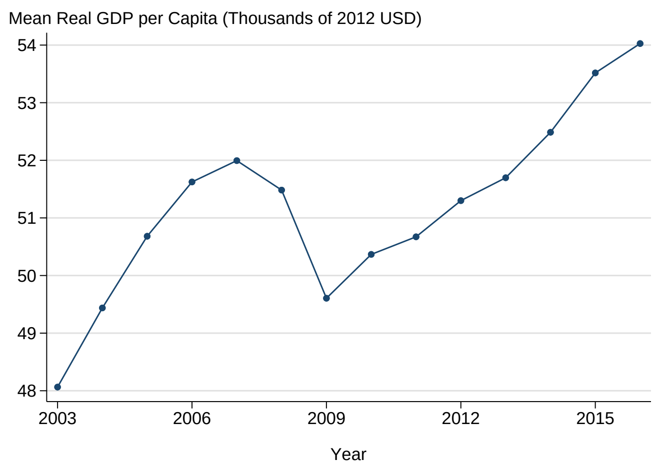
(a) Unemployment Rate



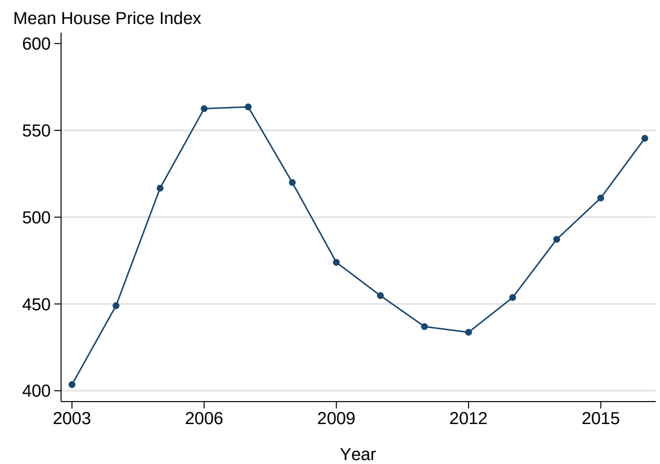
(b) Employment-to-Population Ratio



(c) Real GDP per Capita



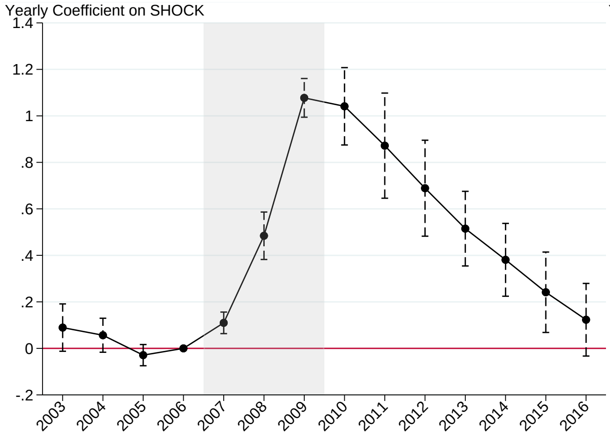
(d) House Price Index



Notes: This figure displays yearly means of CZ-level measures of the Great Recession, weighted by 2006 CZ population. Figure OA.3a plots the unemployment rate; Figure OA.3b plots the the employment-to-population ratio; Figure OA.3c plots real GDP per capita (in thousands of 2012 chained USD); and Figure OA.3d plots the annual house price index. N=741 CZs in Figures OA.3a and OA.3b; in Figures OA.3c and OA.3d, N=740 CZs and N=684 CZs, respectively, for which we have complete data from 2003-2016.

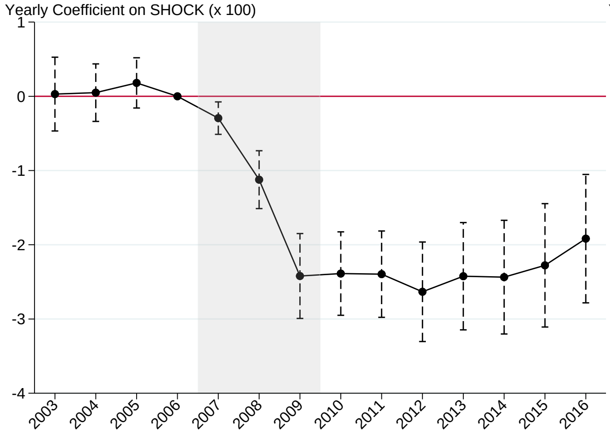
Figure OA.4: Impact of Shock on Measures of the Great Recession

(a) Unemployment Rate

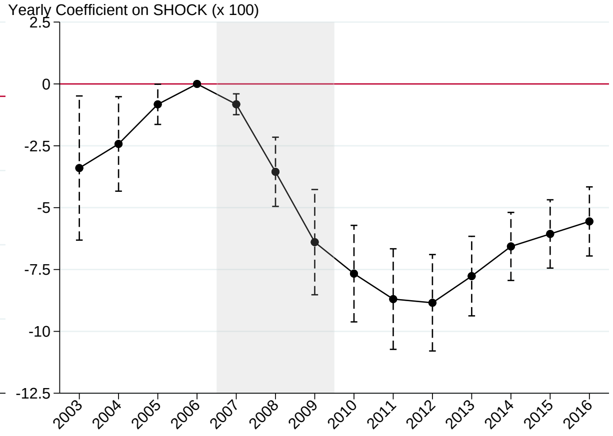


(b) Employment-to-Population Ratio

(c) Log Real GDP per Capita

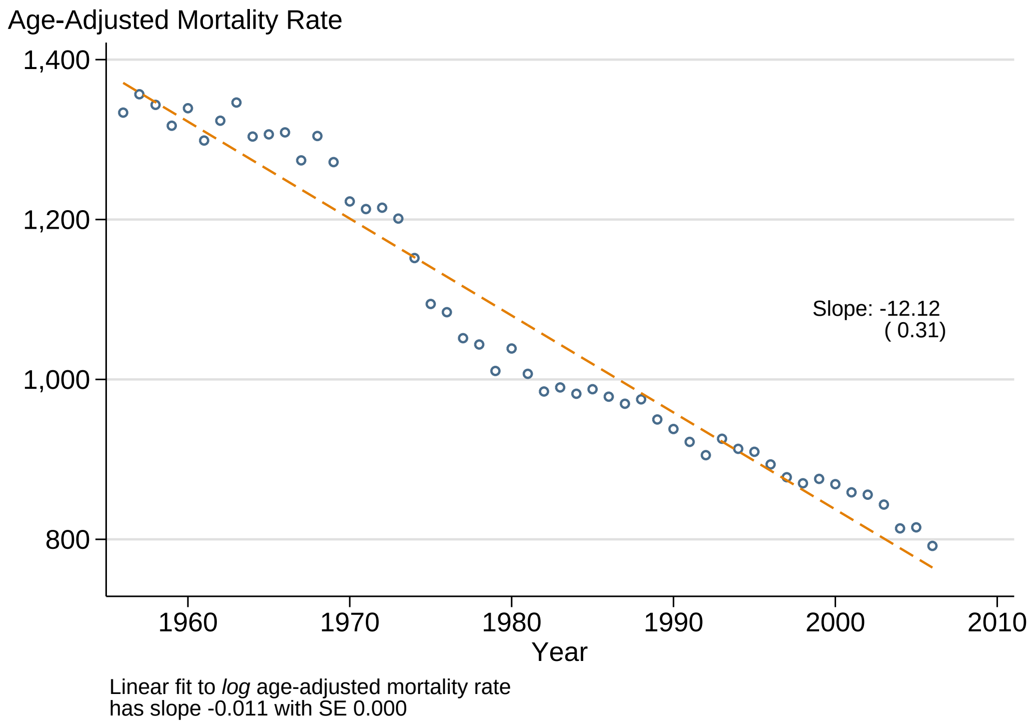


(d) Log House Price Index



Notes: This figure displays the yearly coefficients β_t from equation (1), where $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate, and the outcome y_{ct} is either the CZ unemployment rate (Figure OA.4a), employment-to-population ratio (Figure OA.4b), log real GDP per capita (in thousands of 2012 chained USD; Figure OA.4c), or the log house price index (Figure OA.4d). Coefficients, standard errors, and confidence intervals in Figures OA.4c and OA.4d are multiplied by 100 for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs in Figures OA.4a and OA.4b; in Figures OA.4c and OA.4d, N=740 CZs and N=684 CZs, respectively, for which we have complete data from 2003-2016.

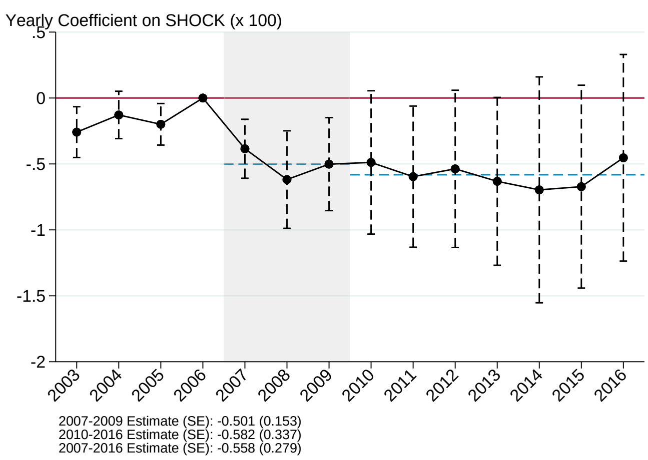
Figure OA.5: Age-Adjusted Mortality Rates in the United States, 1956-2006



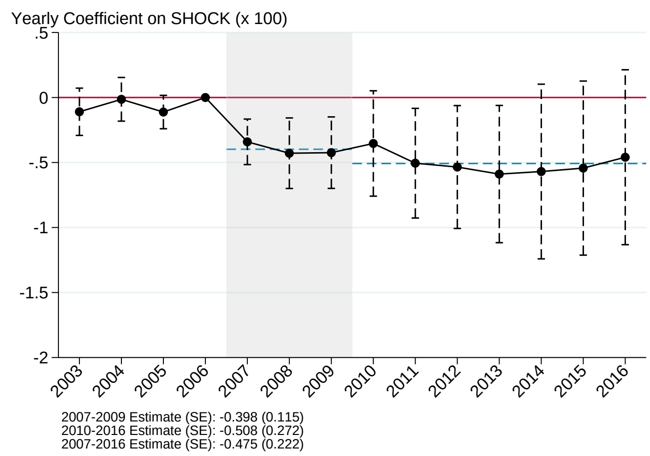
Notes: This figure reports trends in the age-adjusted mortality rate per 100,000 in the United States from 1956-2006. Data are drawn from the National Center for Health Statistics, "Mortality Trends in the United States, 1900-2018." The dashed line represents a linear fit of the age-adjusted mortality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

Figure OA.6: Impact of Unemployment vs. Employment-to-Population Shocks on Log Mortality

(a) Unemployment Shock (Baseline)

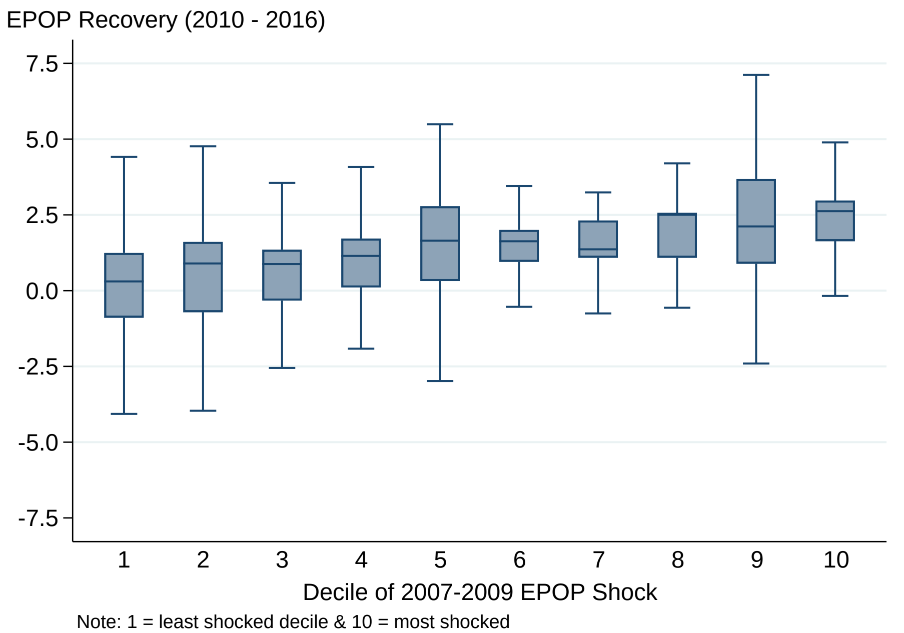


(b) EPOP Shock



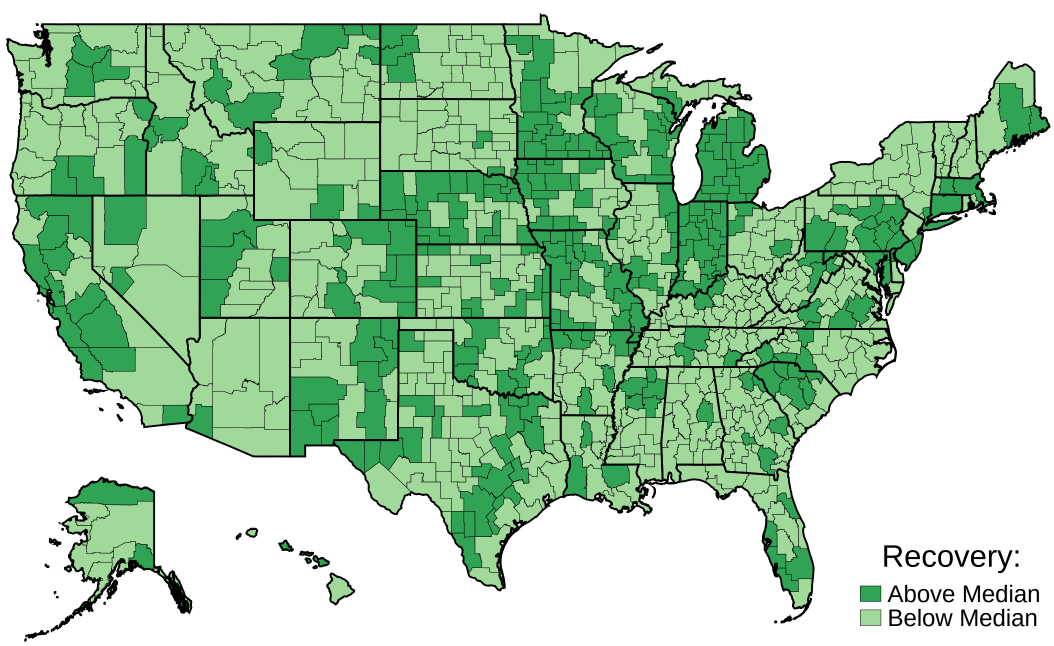
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000, and $SHOCK_c$ is defined as the 2007-2009 change in CZ unemployment rate (Figure OA.6a) or the negative 2007-2009 CZ change in the employment-to-population (EPOP) ratio (Figure OA.6b). Observations are weighted by CZ population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs.

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



Notes: This figure displays the distribution across CZs of the 2010-2016 change in employment-to-population (EPOP) ratio, by population-weighted decile of 2007-2009 EPOP shock. EPOP is defined as monthly 16+ employment divided by yearly 16+ population, and EPOP shock is defined as the negative of the 2007-2009 change in EPOP. CZs are weighted by 2006 population aged 16+. N=741 CZs.

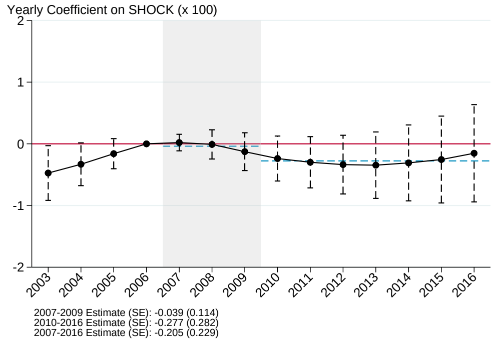
Figure OA.8: Map of CZs By Employment-to-Population Recovery, Conditional on Shock



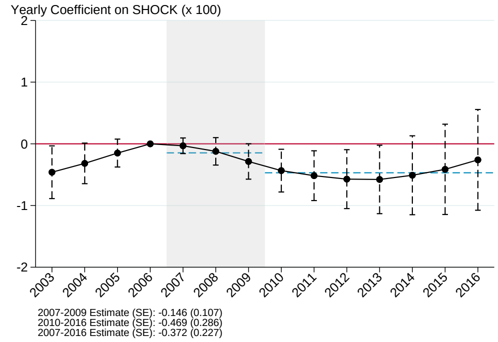
Notes: This figure maps CZs based on whether they have above or below median recovery rates as measured by the 2010-2016 change in the CZ employment-to-population (EPOP) ratio, conditional on the population-weighted decile of the initial 2007-2009 CZ EPOP shock. The deciles and medians for each decile are computed weighting each CZ by its 2006 population aged 16+. N=741 CZs; 460 CZs are below-median recovery, and 281 CZs are above-median recovery.

Figure OA.9: Impact of Shock on Population

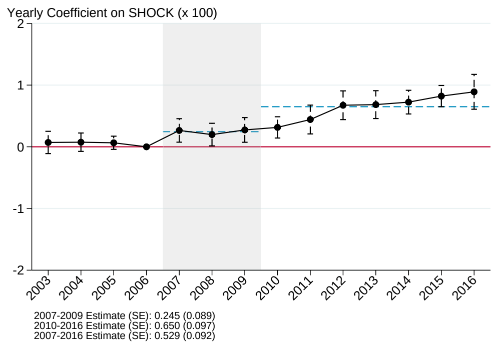
(a) Log Total Population



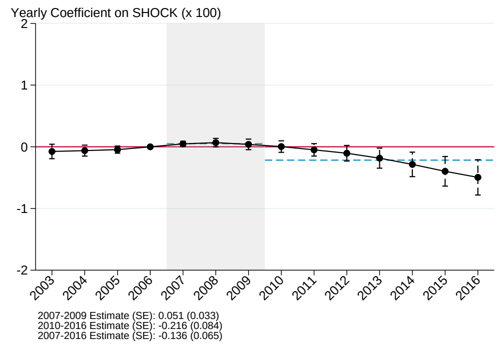
(b) Log Population Aged 25-64



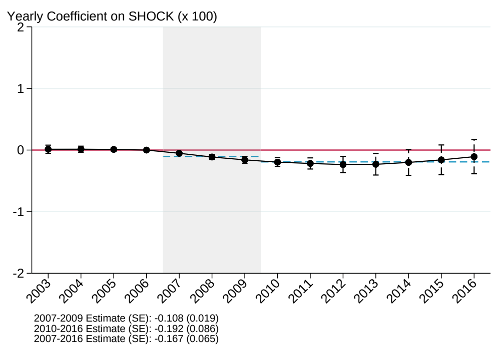
(c) Log Median Age



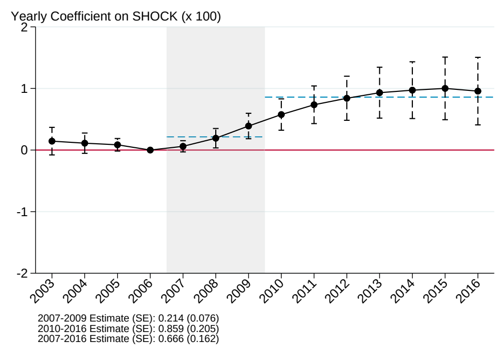
(d) Log Share $<$ 25 Years Old



(e) Log Share 25-64 Years Old



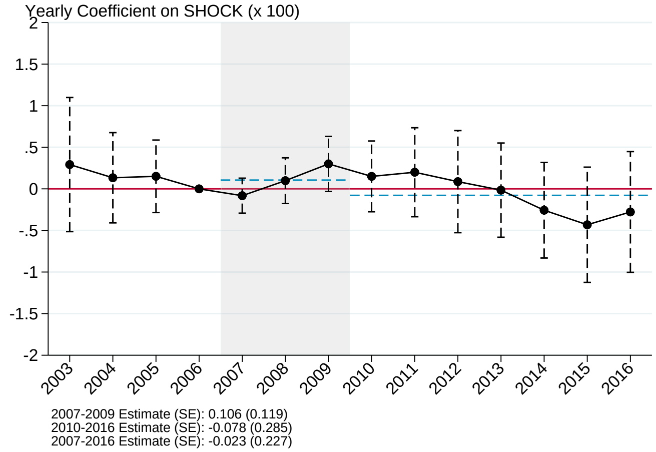
(f) Log Share $\geq$ 65 Years Old



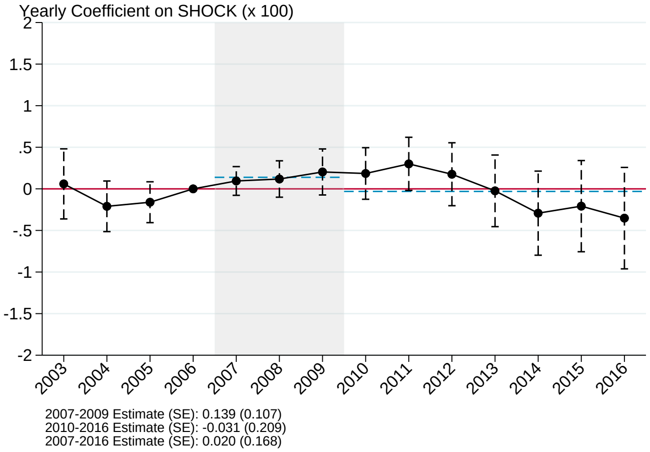
Notes: These figures display yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log annual total CZ population (Figure OA.9a); the log annual CZ population aged 25-64 (Figure OA.9b); the log median CZ age (Figure OA.9c); the log share of the CZ population under age 25 (Figure OA.9d); the log share of the CZ population aged 25-64 (Figure OA.9e); and the log share of the CZ population aged 65+ (Figure OA.9f). In all cases, $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Observations are weighted by CZ population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs.

Figure OA.10: Impact of Shock on Medicare Healthcare Utilization Measures

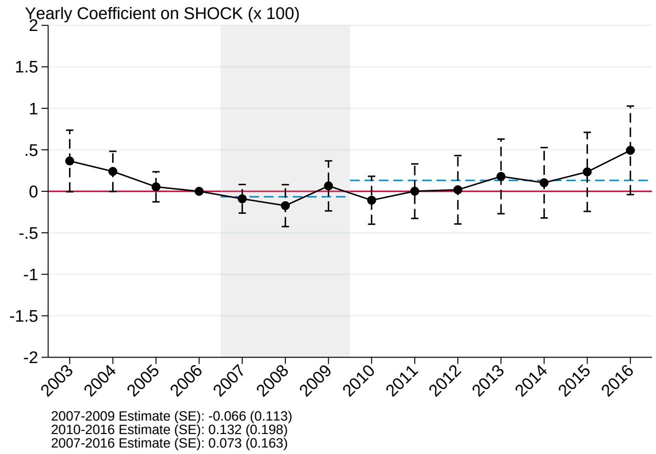
(a) Log Total Expenditure



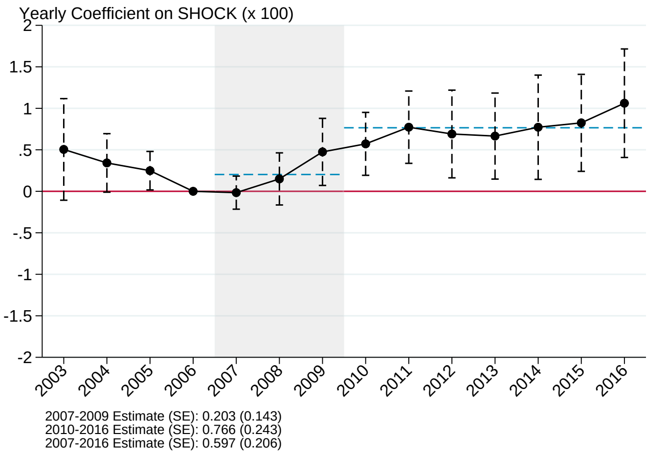
(b) Log Physician Visits



(c) Log Patient Share with ER Visit



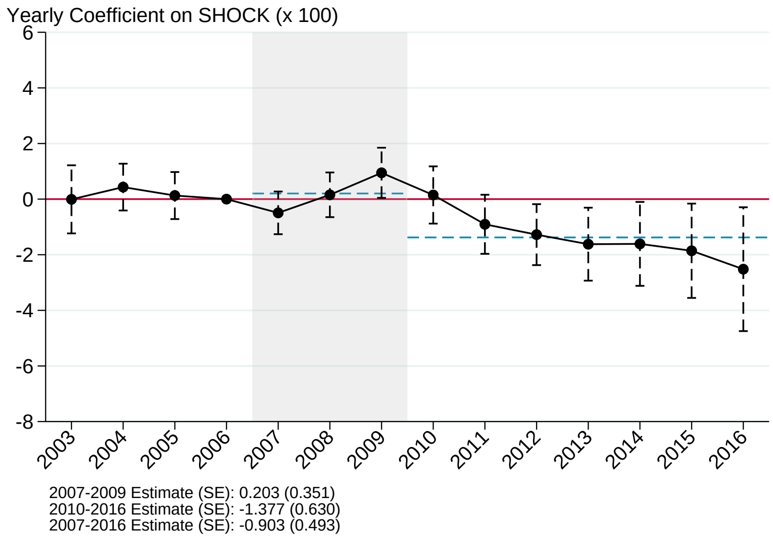
(d) Log Patient Share with Inpatient Admission



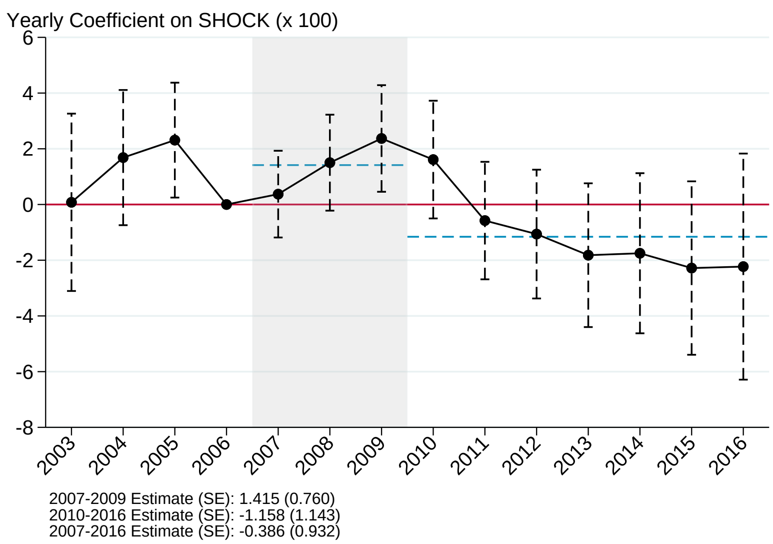
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is defined as the log of various healthcare utilization measures in CZ c and year t, and $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Each individual is assigned their yearly CZ of residence, and CZ-year utilization measures are constructed as the average of their patient-year measures. We utilize the Repeated Cross Section sample, with beneficiaries subject to the restrictions in Table OA.9. Patient-years are further restricted to those that were enrolled in TM in the current year (TM in year t) and did not die during the year. Observations are weighted by CZ population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. N=738 CZs for which we observe individuals on Medicare from our 20% MBSF sample in each year.

Figure OA.11: Impact of Shock on Log Mortality From "Deaths of Despair"

(a) Suicides, Liver Disease, and Drug Poisonings



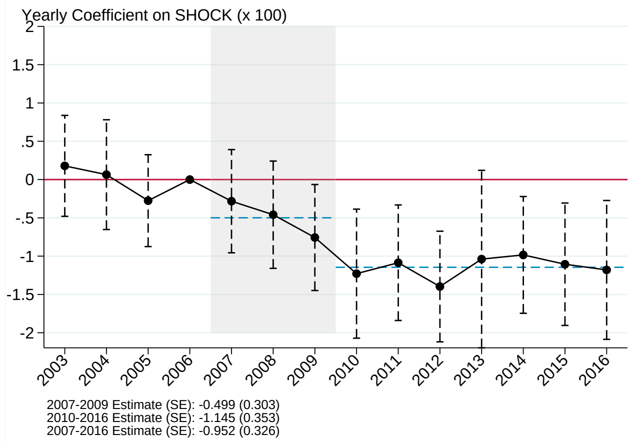
(b) Drug Poisonings Only



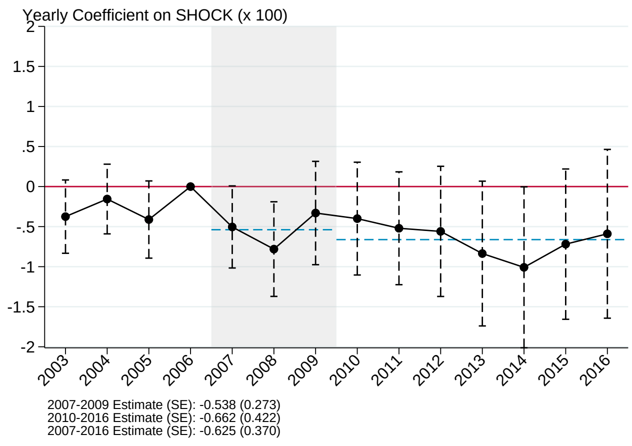
Notes: This figure plots the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000 from suicides, liver disease, and drug poisonings (Figure OA.11a) or accidental and unknown-intent drug poisonings only (Figure OA.11b). (Within Figure OA.20, Figures OA.20c and OA.20d share results for suicide and liver disease, respectively.) $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs.

Figure OA.12: Impact of Shock on Log Mortality by SNF Use

(a) SNF use in t or $t-1$



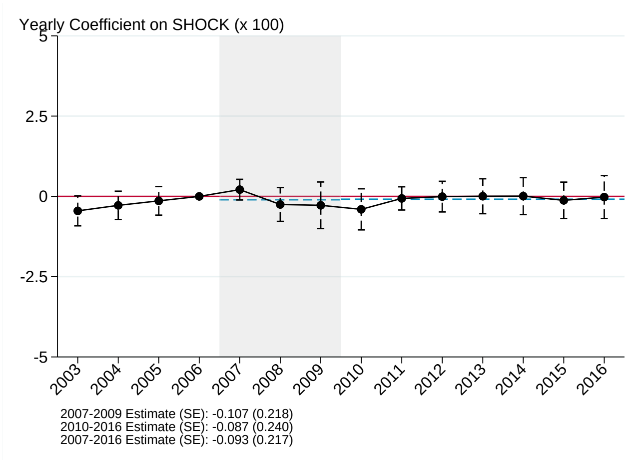
(b) No SNF use in t or $t-1$



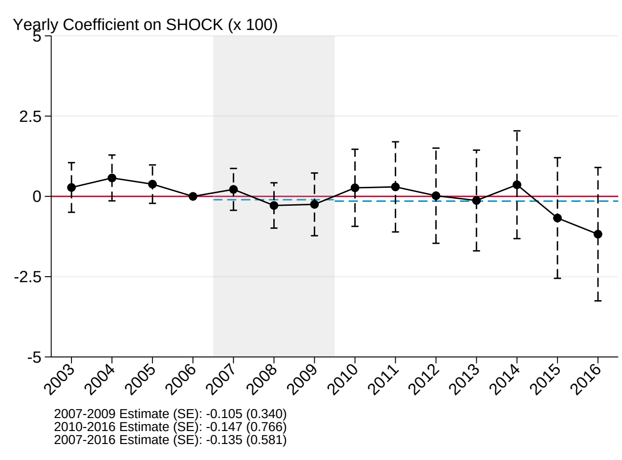
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000 and $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Figure OA.12a aggregates CZ-level mortality for individuals who utilized SNF care in a given year or the year prior. Figure OA.12b aggregates CZ-level mortality for individuals who did not utilize SNF care in a given year or the year prior. Each individual is assigned their yearly CZ of residence. We utilize the Repeated Cross Section sample, with beneficiaries subject to the restrictions in Table OA.9. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=733 CZs (covering >99.9% of Medicare 2006 population) with at least one beneficiary associated with SNF utilization and one not associated with SNF utilization in every year.

Figure OA.13: Impact of Shock on Nursing Home Staffing

(a) Log Direct-Care Staff Hours Per Resident-Day



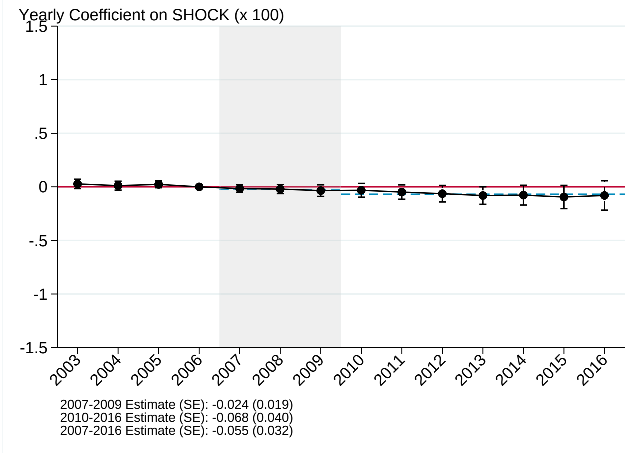
(b) Log Highly Skilled Nurses Ratio



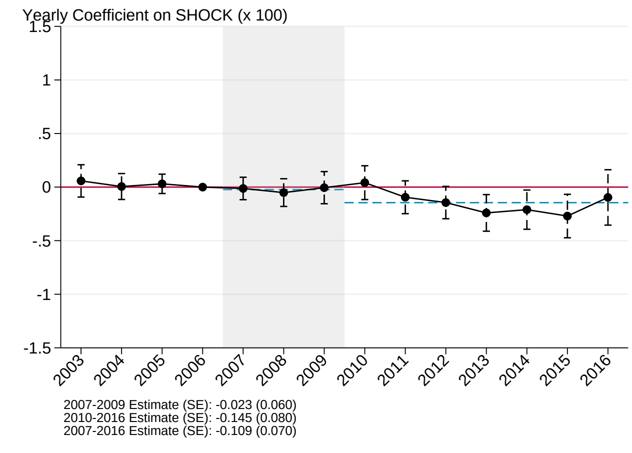
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} includes two CZ-level measures of nursing home staffing and $SHOCK_c$ is the 2007-2009 change in CZ unemployment rate. In Figure OA.13a, the outcome y_{ct} is defined as the sum of the hours worked by registered nurse, licensed practical nurse, and certified nursing assistant staff per resident-day during the two weeks prior to the annual OSCAR survey. In Figure OA.13b, the outcome y_{ct} is the log of the ratio of registered nurse full-time equivalents divided by the number of registered nurse and licensed practical nurse full-time equivalents in nursing homes. In both instances, we take a CZ-level mean of these SNF-level observations, weighted by the total beds in each SNF, and then take the log of this CZ-level statistic. 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, alongside a 2007-2016 period estimate). Facility observations are weighted by 2006 CZ population from the SEER, and standard errors are clustered at the CZ level. N=716 CZs (covering 99.8% of overall 2006 population) which contain at least one SNF.

Figure OA.14: Impact of Shock on Nursing Home Volume and Resident Characteristics

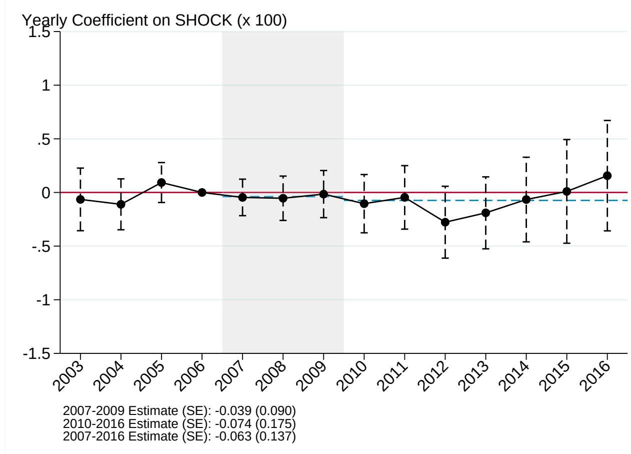
(a) Log Average Age



(b) Log Female Resident Share

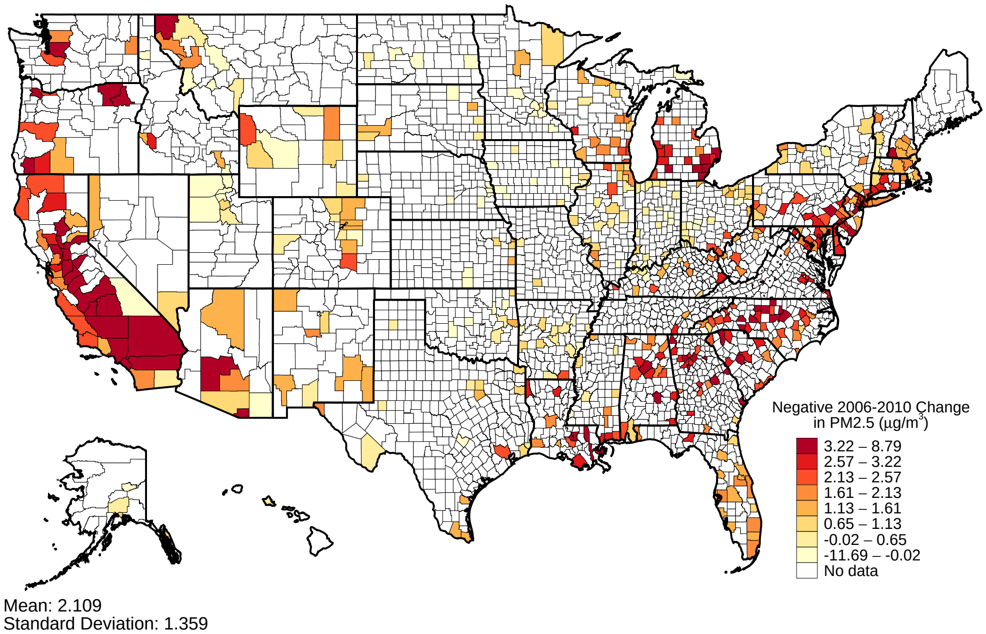


(c) Log Occupants per Bed



Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} includes three CZ-level measures of nursing home characteristics and $SHOCK_c$ is the 2007-2009 change in CZ unemployment rate. In Figure OA.14a, the outcome y_{ct} is the log average age of residents across facilities in each CZ; in Figure OA.14b, the outcome y_{ct} is the log CZ-level mean share of facility residents who are female; and in Figure OA.14c, the outcome y_{ct} is the log CZ-level mean number of occupants per facility bed. In each case, we take a CZ-level mean of these SNF-level observations, weighted by the total beds in each SNF, and then take the log of this CZ-level statistic. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=716 CZs (covering 99.8% of overall 2006 population) which contain at least one SNF.

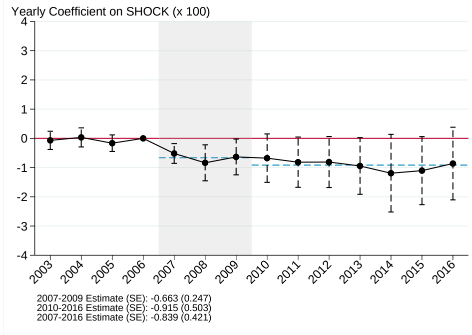
Figure OA.15: Heatmap of PM2.5 Shock



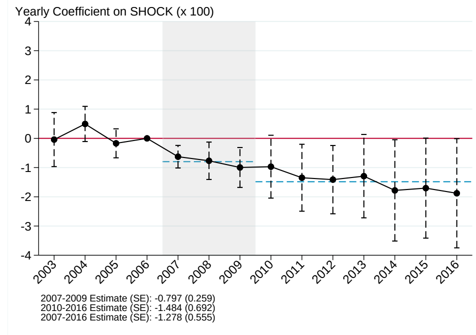
Notes: This figure displays a heatmap of the negative 2006-2010 change in PM2.5 (measured in $\mu g/m^3$) for all counties with observed PM2.5 levels in those two years. County colors are assigned according to population-weighted octiles, with cutpoints noted in the figure legend. Population-weighted mean and standard deviation are noted in the bottom left corner. N=542 counties.

Figure OA.16: Impact of Shock on Log Mortality, by Education

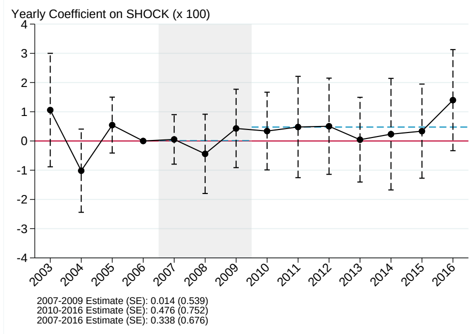
(a) Overall



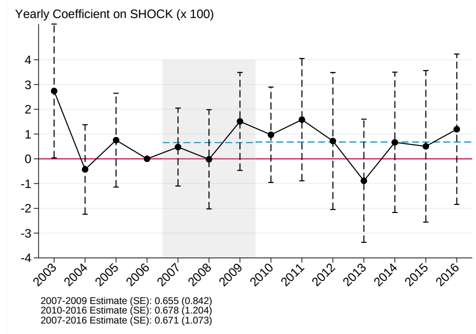
(b) HS or Less



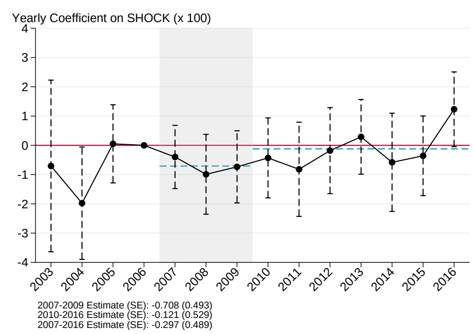
(c) More Than HS



(d) Some College

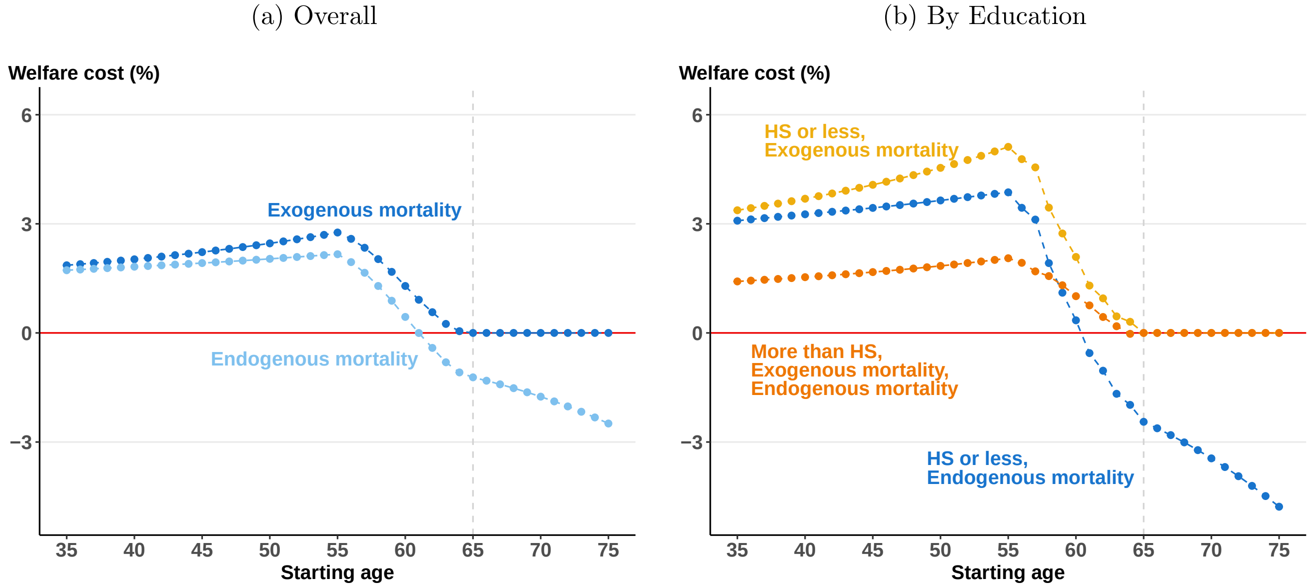


(e) College or More



Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted state mortality per 100,000 for individuals aged 25+, and g indicates a range of different education level groups. $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. Figure OA.16a examines all individuals aged 25+, and Figures OA.16b and OA.16c subdivide the sample into the approximately 52 percent with a high school diploma or less (OA.16b) and the approximately 48 percent with more than a HS diploma (OA.16c). Lastly, Figures OA.16d and OA.16e further subdivide those with more than a high school diploma into the approximately 45 percent with some college education but no four-year degree (OA.16d), and the approximately 55 percent with a four-year college degree or more (OA.16e). Observations are weighted by state population in 2006. Georgia, New York, Rhode Island, and South Dakota are excluded from the sample due to missing data issues (see Appendix C.1 for details). Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the state level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=47 states.

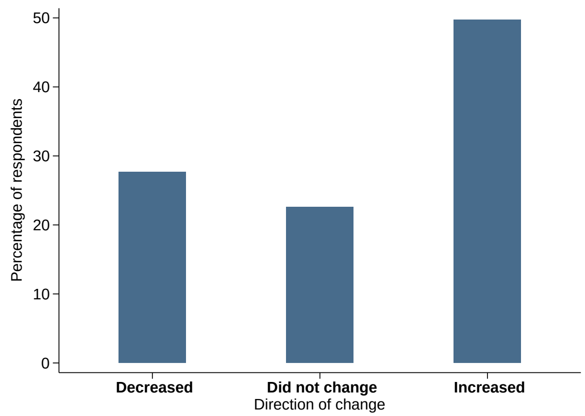
Figure OA.17: Welfare Costs of the Great Recession by Age, Assuming No Consumption Impacts on the Elderly



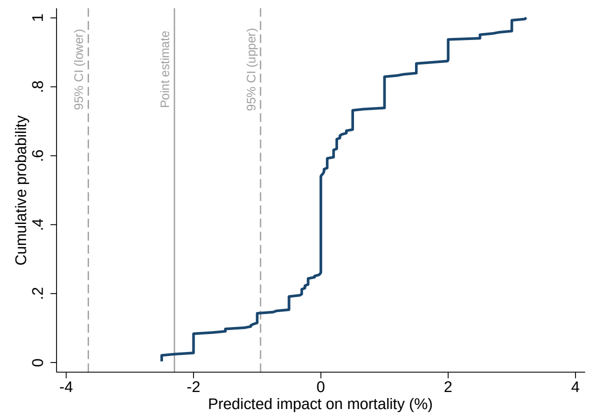
Notes: This figure displays the welfare cost of the Great Recession at various ages under exogenous and endogenous mortality regimes, assuming that there are no consumption impacts for individuals age 65 or older. Figure OA.17a displays overall results, while Figure OA.17b separately examines those with a high school diploma or less, and those with more than a HS diploma, following equation (19). The estimates use group-specific consumption and mortality effects of the Great Recession, as well as group-specific mortality rates. The welfare cost is measured as a percentage of average annual consumption. These estimates use $\gamma = 2$ and b corresponding to a $VSLY$ of \$250k.

Figure OA.18: Expert Survey on Predicted Direction of Change in Mortality

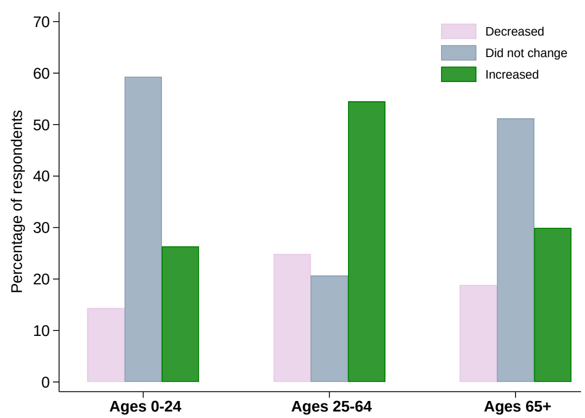
(a) Overall Prediction



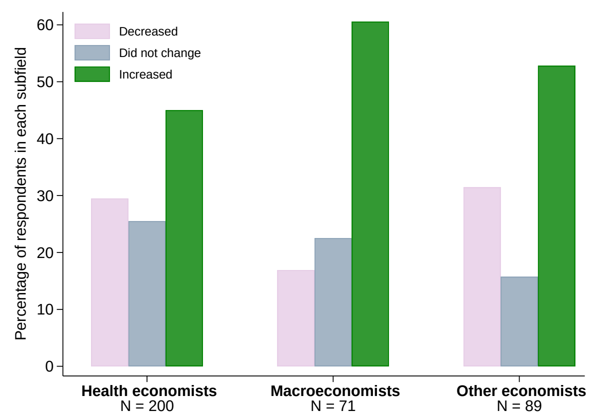
(b) Predicted Change in Mortality, Empirical CDF



(c) Prediction by Age Bin



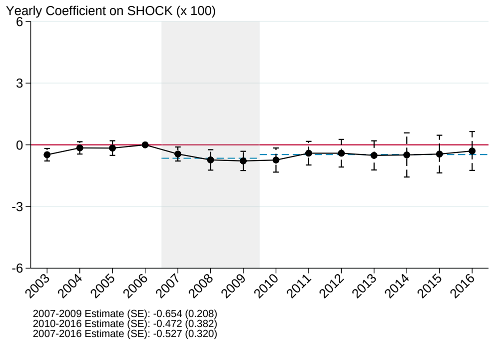
(d) Prediction by Respondent Subfield



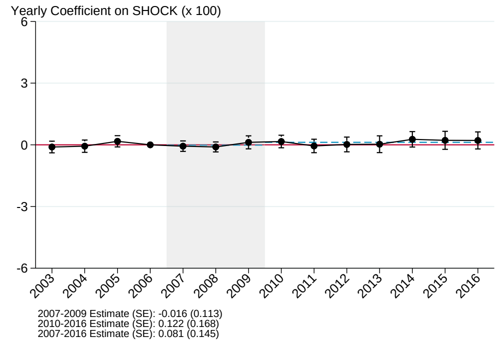
Notes: This figure shows results of an expert survey eliciting predictions about the impact of the Great Recession on mortality. Figures show the predicted direction of change in the U.S. mortality rate overall (OA.18a), for each of the three age bins appearing in the survey (OA.18c), and by respondent subfield (OA.18d). Figure OA.18b 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 (3.23%) percentiles 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 7th percentile of the untrimmed sample. The dashed vertical lines indicate the bounds for the confidence interval; the upper bound (−0.95%) of our confidence interval is the 18th percentile of the untrimmed responses. N=354 respondents.

Figure OA.19: Impact of Shock on Log Mortality, by Cause of Death I

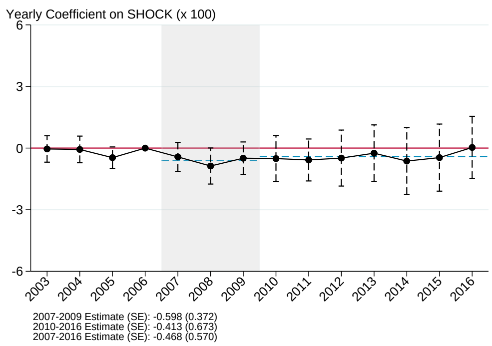
(a) Cardiovascular Disease



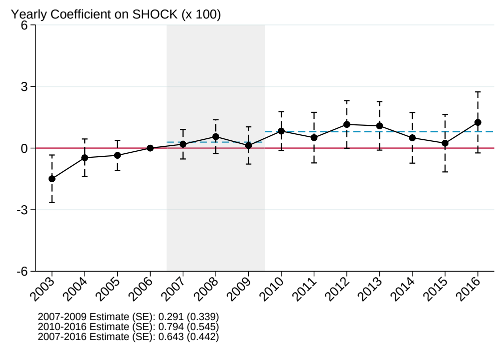
(b) Cancer



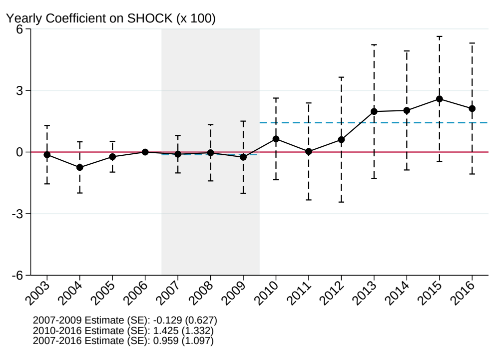
(c) Chronic Lower Respiratory Disease



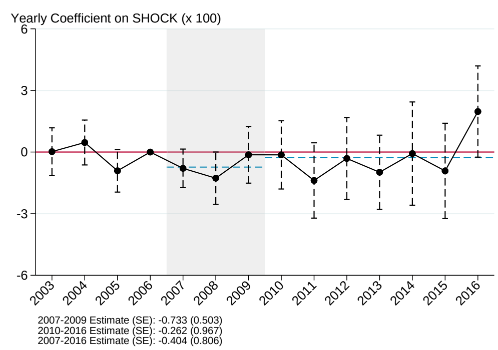
(d) Diabetes



(e) Alzheimer's Disease



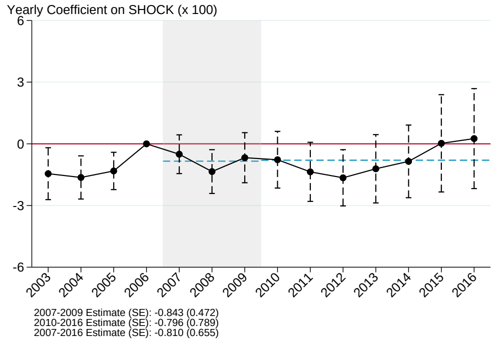
(f) Influenza/Pneumonia



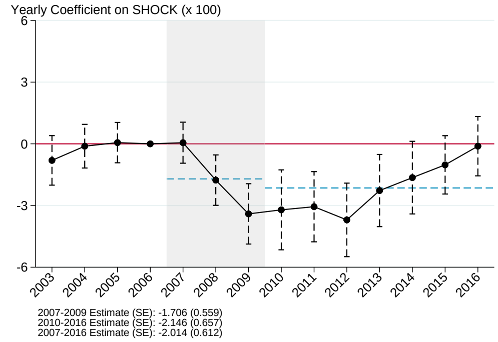
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted CZ mortality rate per 100,000, and g indicates 12 cause of death categories (six of which are displayed here; the remaining six are displayed in Figure OA.20). $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Figure OA.19a displays effects on the log mortality rate from cardiovascular disease; Figure OA.19b from cancer; Figure OA.19c from chronic lower respiratory disease; Figure OA.19d from diabetes; Figure OA.19e from Alzheimer's disease; and Figure OA.19f from influenza or pneumonia. Observations are weighted by CZ population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs.

Figure OA.20: Impact of Shock on Log Mortality, by Cause of Death II

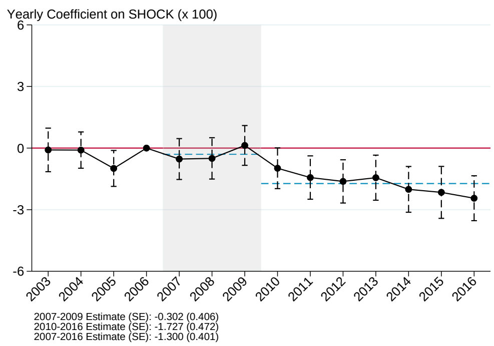
(a) Kidney Disease



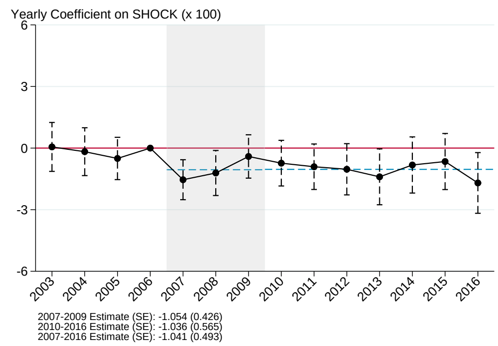
(b) Motor Vehicle Accidents



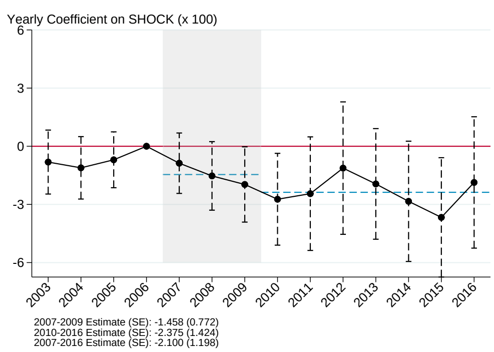
(c) Suicide



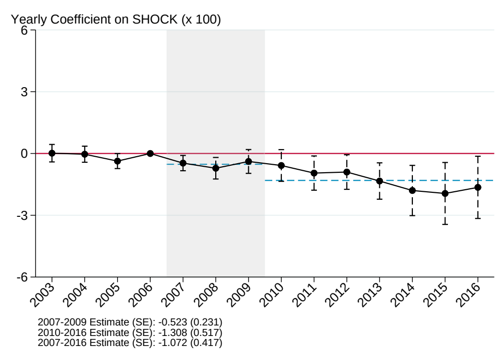
(d) Liver Disease/Cirrhosis



(e) Homicide



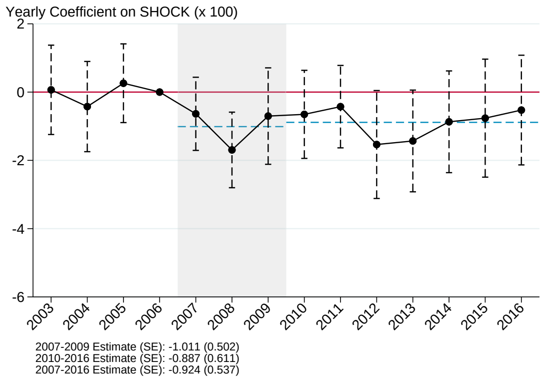
(f) All Other Causes (Residual)



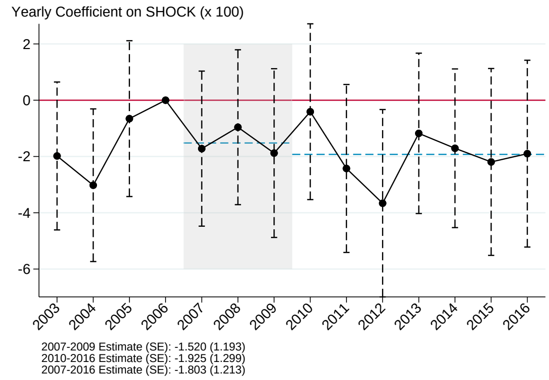
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted CZ mortality rate per 100,000, and g indicates 12 cause of death categories (six of which are displayed here; the remaining six are displayed in Figure OA.19). $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Figure OA.20a displays effects on the log mortality rate from kidney disease; Figure OA.20b from motor vehicle accidents; Figure OA.20c from suicide; Figure OA.20d from liver disease; Figure OA.20e from homicide; and Figure OA.20f from all other causes of death not described elsewhere in Figures OA.19 or OA.20. Observations are weighted by CZ population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs.

Figure OA.21: Impact of Shock on Log Mortality, by Age Group: Age 0-54

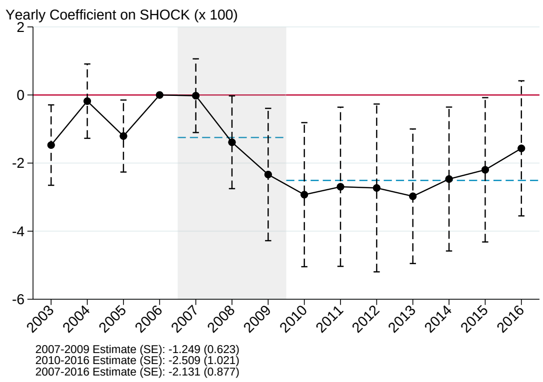
(a) Age 0-4



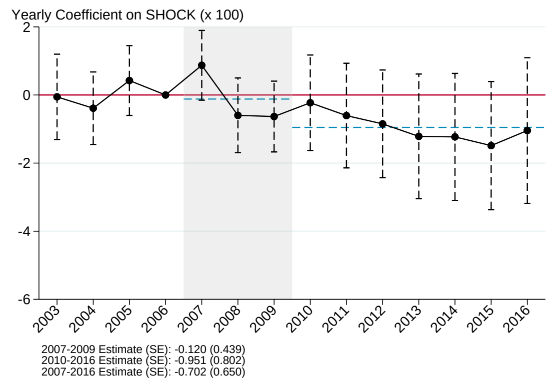
(b) Age 5-14



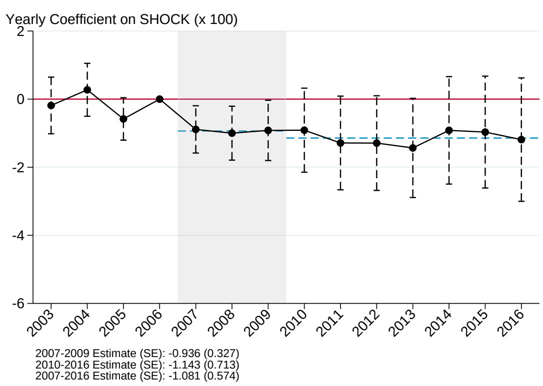
(c) Age 15-24



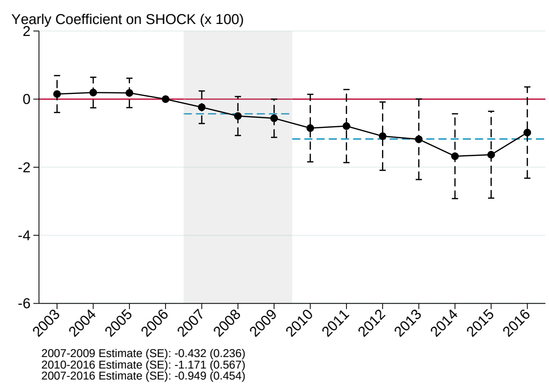
(d) Age 25-34



(e) Age 35-44



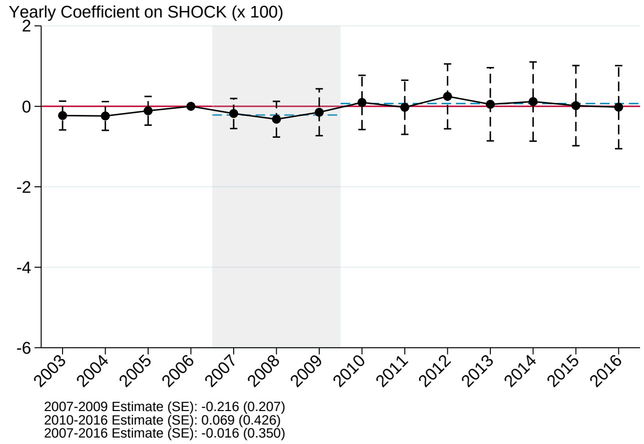
(f) Age 45-54



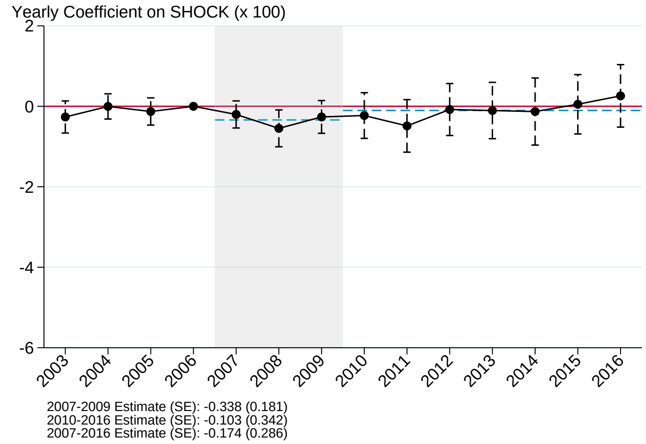
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is log age-adjusted CZ mortality rate per 100,000, and g indicates 10 age groups (six of which are displayed here; the remaining four are displayed in Figure OA.22). $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Observations are weighted by CZ population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs.

Figure OA.22: Impact of Shock on Log Mortality, by Age Group: Age 55+

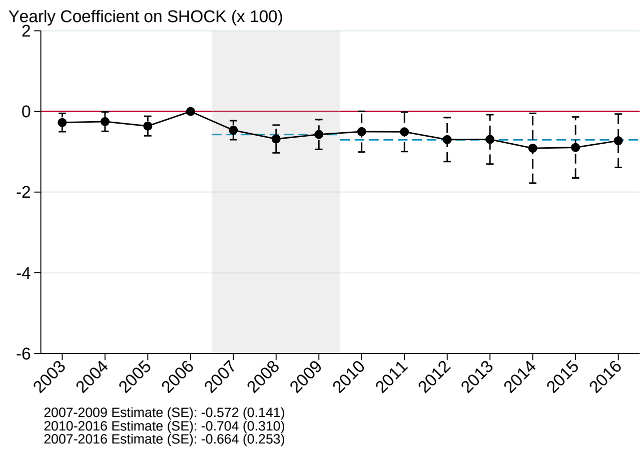
(a) Age 55-64



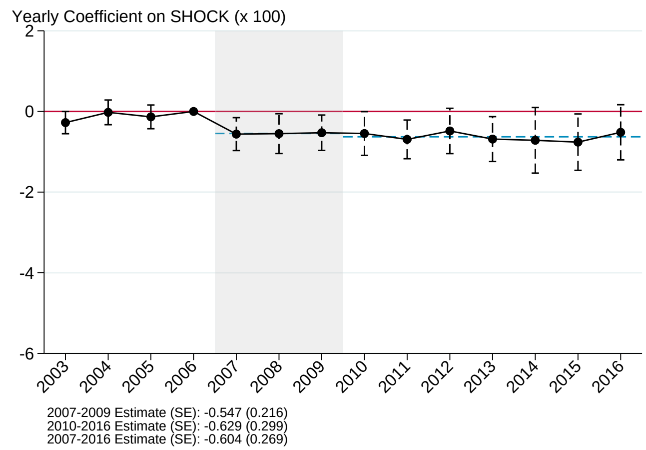
(b) Age 65-74



(c) Age 75-84



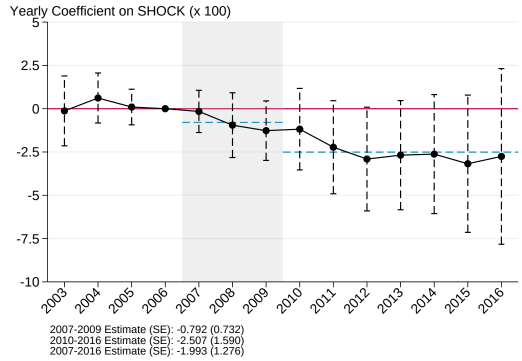
(d) Age 85+



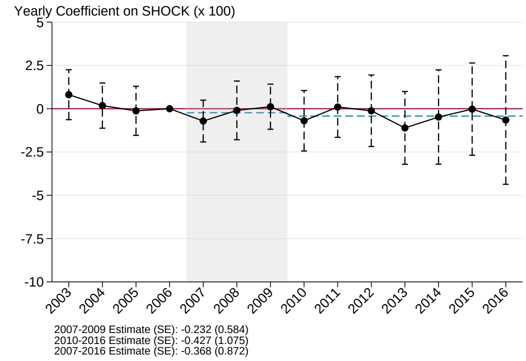
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is log age-adjusted CZ mortality rate per 100,000, and g indicates 10 age groups (four of which are displayed here; the remaining six are displayed in Figure OA.21). $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Observations are weighted by CZ population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs.

Figure OA.23: Impact of Shock on Log Mortality, by Education and Age

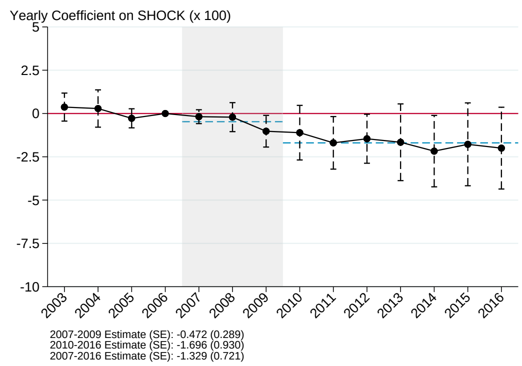
(a) HS or Less, 25-44 Year-Olds



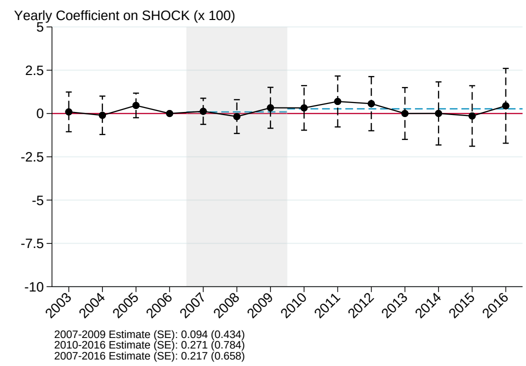
(b) More Than HS, 25-44 Year-Olds



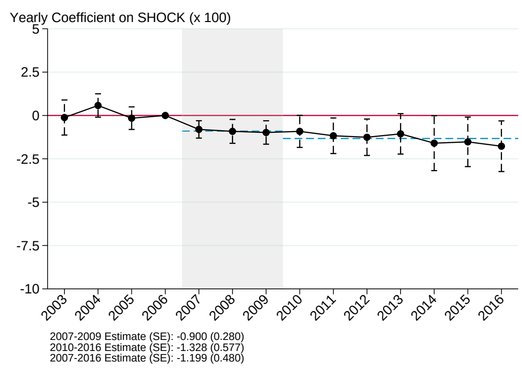
(c) HS or Less, 45-64 Year-Olds



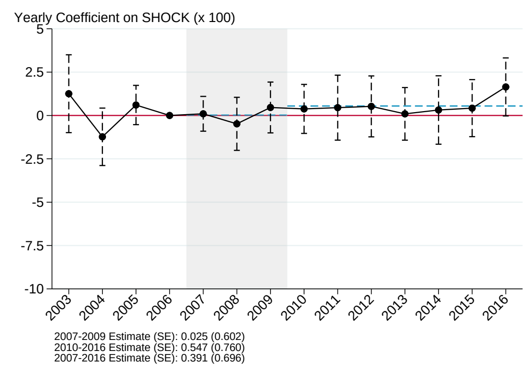
(d) More Than HS, 45-64 Year-Olds



(e) HS or Less, 65+ Year Olds



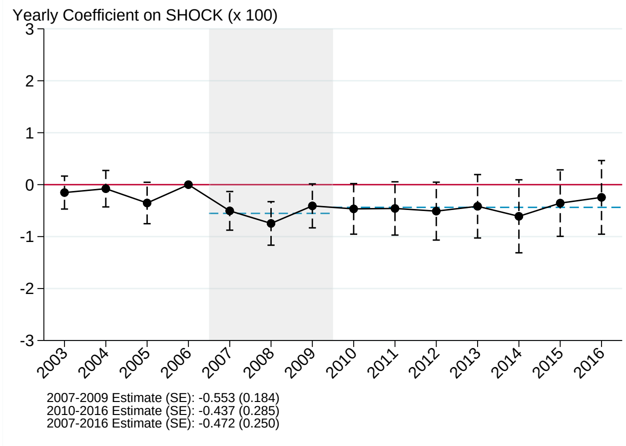
(f) More Than HS, 65+ Year Olds



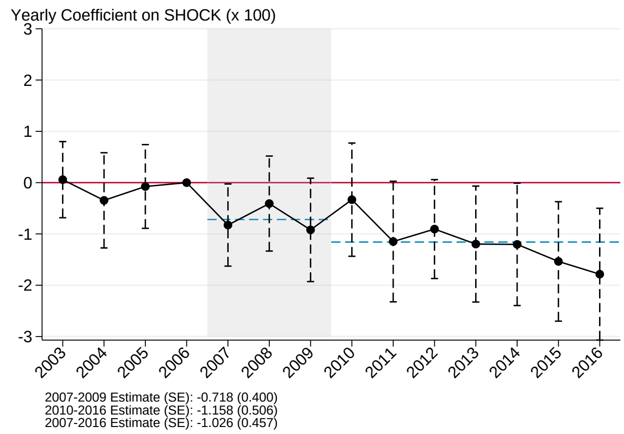
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted state mortality rate per 100,000, and g indicates six education/age bin combinations. $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. Observations are weighted by state population in 2006. Georgia, New York, Rhode Island, and South Dakota are excluded from the sample due to missing data issues (see Appendix C.1 for details). Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the state level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=47 states.

Figure OA.24: Impact of Shock on Log Mortality Among Elderly, by Medicaid Status

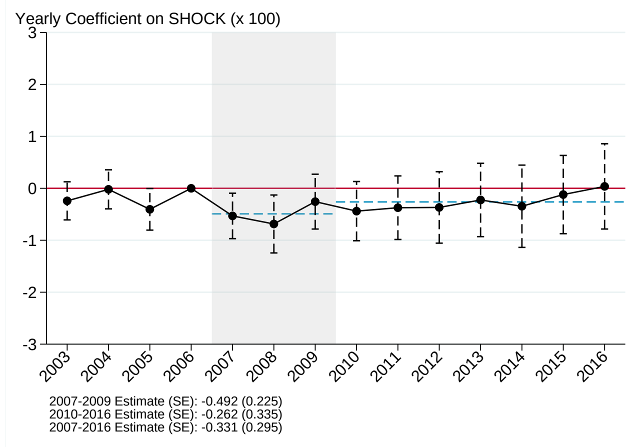
(a) Overall Medicare 65+ sample



(b) Medicaid in year $t-1$



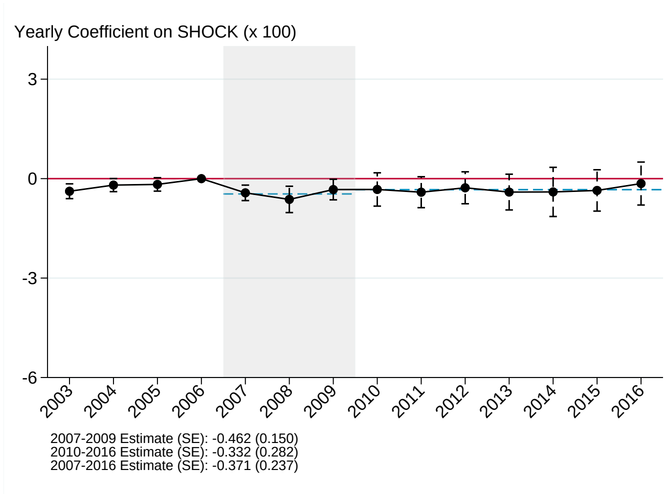
(c) No Medicaid in year $t-1$



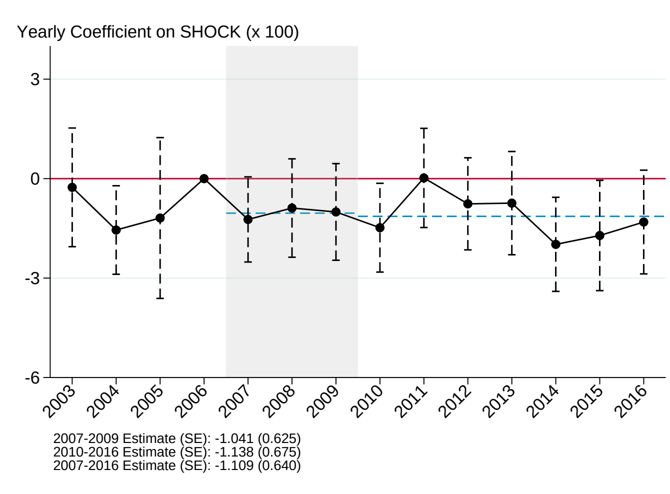
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log (non age-adjusted) CZ mortality rate per 100,000, and g indicates whether individuals were recently on Medicaid. $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. The sample for this figure is individuals aged 65+ whom we observe in the Medicare cross-sectional data, the sample restrictions for which are displayed in rows (1) through (8) of Table OA.9. Figure OA.24a shows results among all individuals, Figure OA.24b shows results among all individuals who were on Medicaid at some point during the previous year, and Figure OA.24c shares results among individuals who were not on Medicaid in the previous year. Observations are weighted by CZ population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=736 CZs that observe at least one Medicaid recipient and at least one non-recipient in each year between 2003 and 2016.

Figure OA.25: Impact of Shock on Log Mortality, by Race/Ethnicity

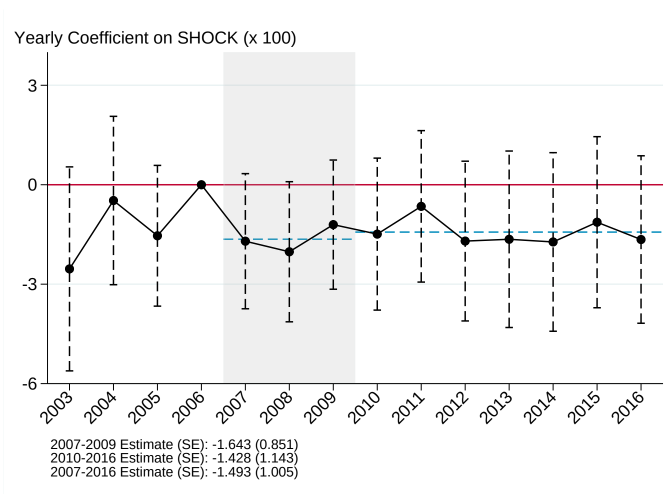
(a) Non-Hispanic White



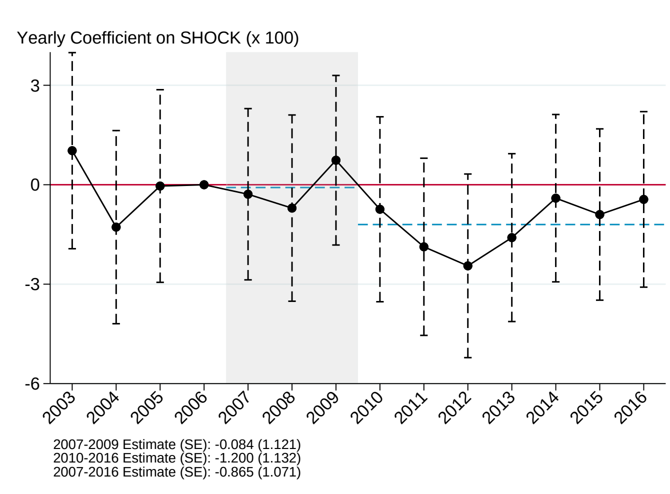
(b) Non-Hispanic Black



(c) Hispanic



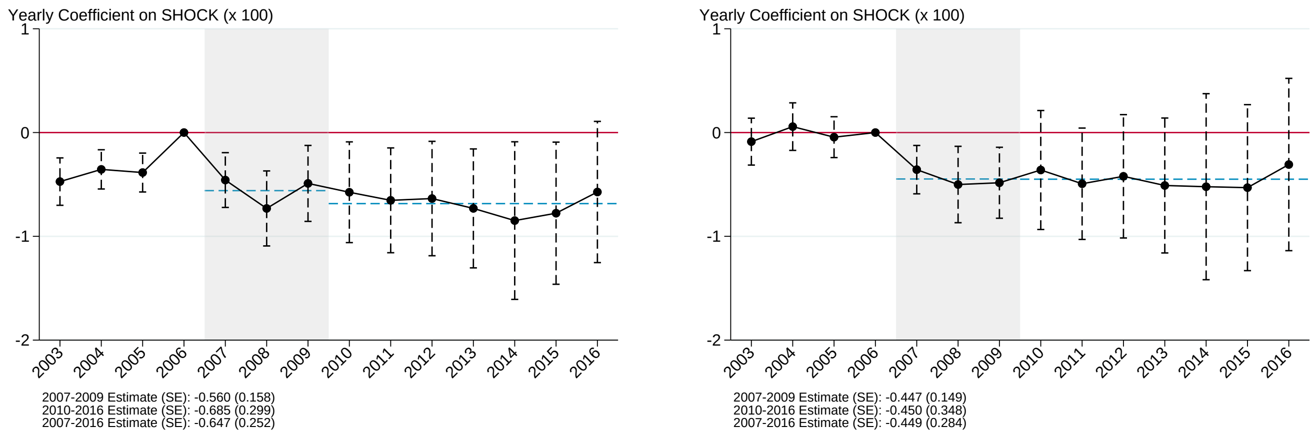
(d) Other



Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted CZ mortality rate per 100,000, and g indicates a range of racial groups. $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=434 CZs for which we can calculate age-adjusted mortality for each CZ/year/race cell pertaining to the CZ, which requires at least one observation of an individual in each age bucket for each race/year within a CZ. These 434 CZs make up 96% of the total 2006 population.

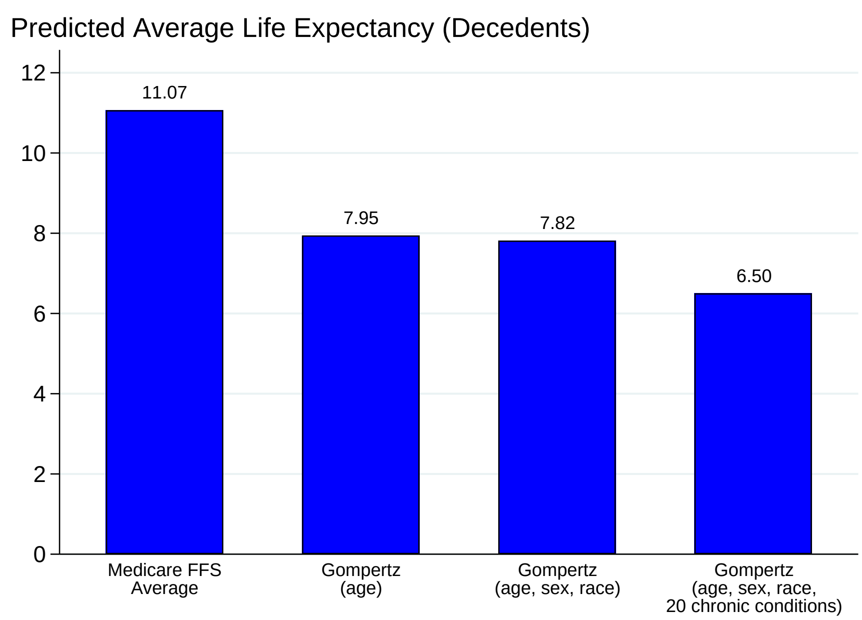
Figure OA.26: Impact of Shock on Log Mortality Rate, by Sex

(a) Male (b) Female



Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted CZ mortality rate per 100,000, and g indicates gender groups. $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=739 CZs for which we can calculate age-adjusted mortality for each CZ/year/gender cell pertaining to the CZ, which requires at least one observation of an individual in each age bucket for each gender/year within a CZ. These 739 CZs make up over 99.9% of the total 2006 population.

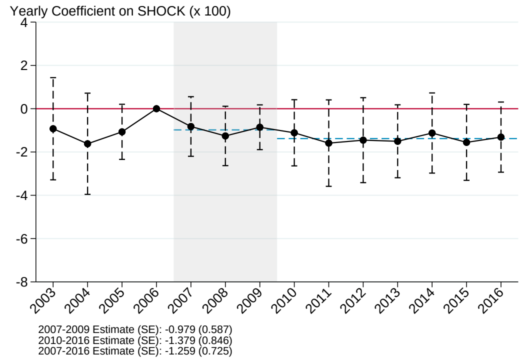
Figure OA.27: Average, Counterfactual Predicted Remaining Life Expectancy of Decedents



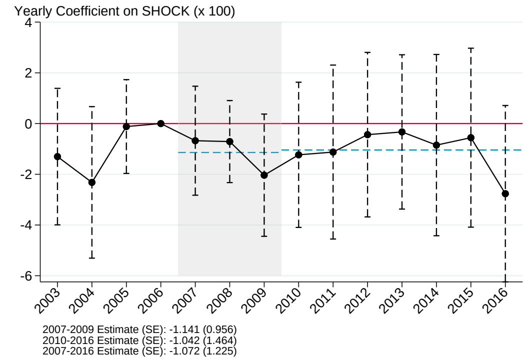
Notes: This figure displays the average predicted counterfactual remaining life expectancy at the start of the year for Medicare beneficiaries who subsequently die within the year. Remaining life expectancy is determined as of January 1 of a given year, and is estimated as per equation (20), using a 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 (TM in $t-1$) sample. This sample restricts patient-years as per Table OA.9, further restricting beneficiaries to those enrolled in TM in the previous year. N=3,714,177 patient-years.

Figure OA.28: Impact of Shock on Self-Reported Health in the BRFSS

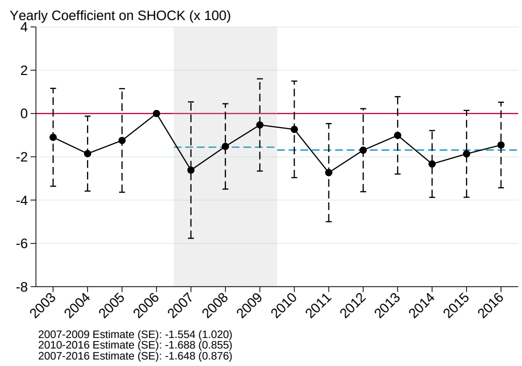
(a) Log share less than very good health



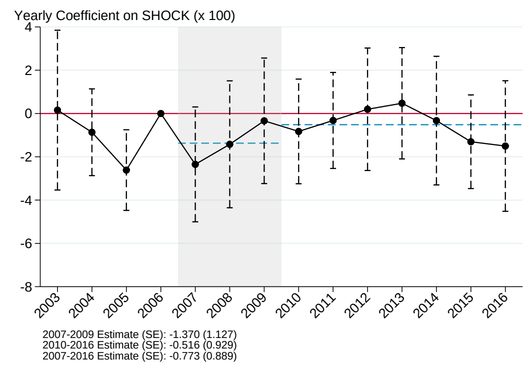
(b) Log share poor mental health last month



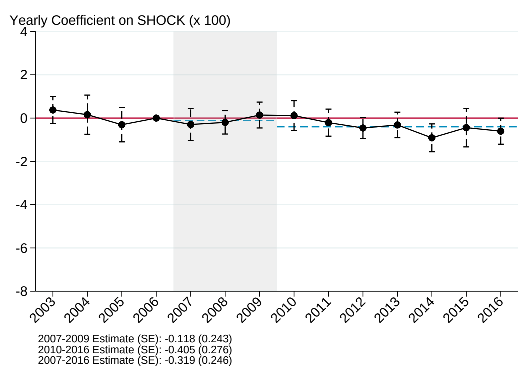
(c) Log share ever had diabetes



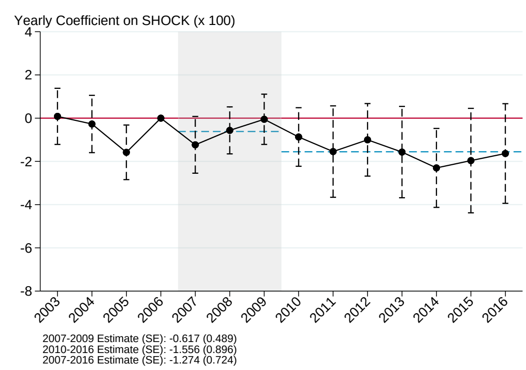
(d) Log share with asthma



(e) Log share overweight or obese



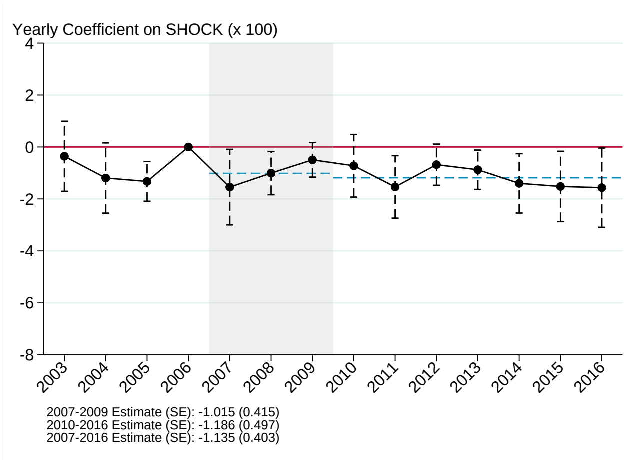
(f) Log share obese



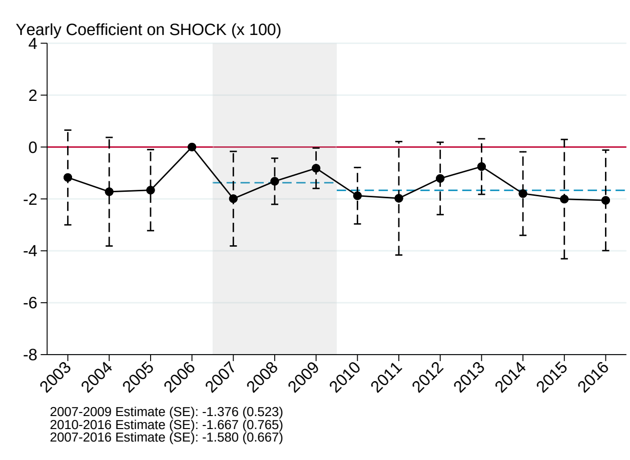
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the share of the state population with a range of health characteristics. These shares are calculated as the mean of respondent-level BRFSS variables (weighted according to BRFSS survey weights). Variable construction is described in further detail in Appendix B.4. $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. Observations are weighted by state population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the state level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=51 states.

Figure OA.29: Average Impact of Shock on Health Measures in the BRFSS, By Age

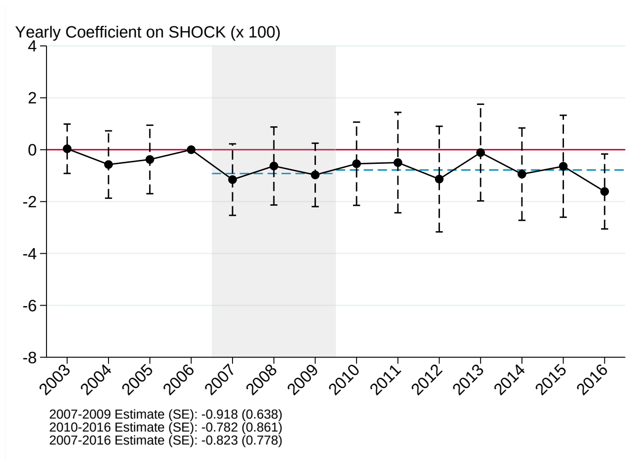
(a) Ages 18-45



(b) Ages 45-64



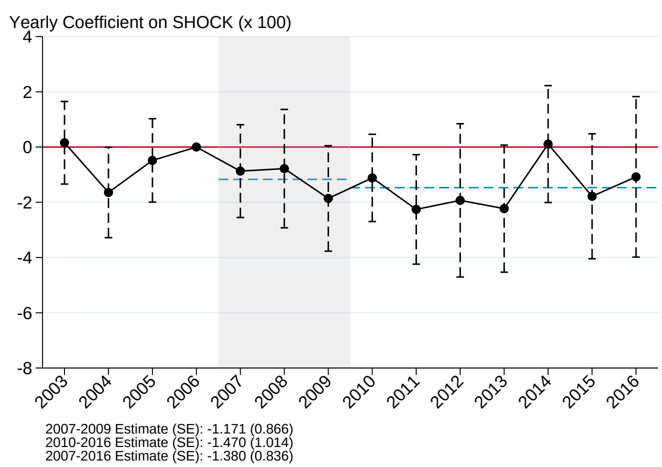
(c) Ages 65+



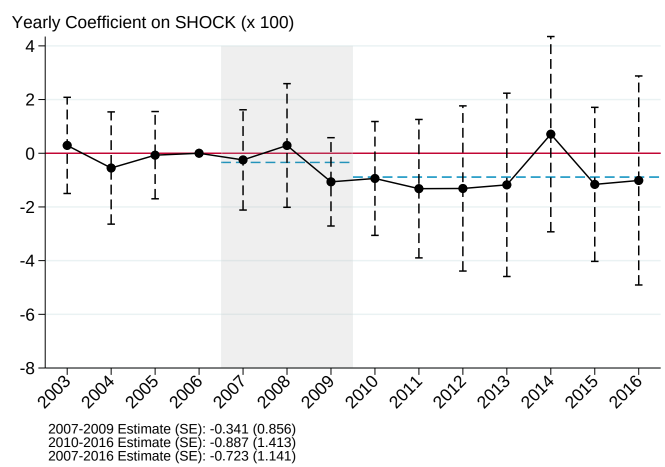
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the mean share of the state population with a range of health characteristics, and g indicates three age categories. These shares are calculated as the mean of respondent-level BRFSS variables (weighted according to BRFSS survey weights). The average effect on health measures is then computed as the average event study coefficient in each year across each measure of health and health behavior. Variable construction is described in further detail in Appendix Section B.4. $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. Observations are weighted by state population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the state level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=51 states.

Figure OA.30: Impact of Shock on Health Behavior in the BRFSS

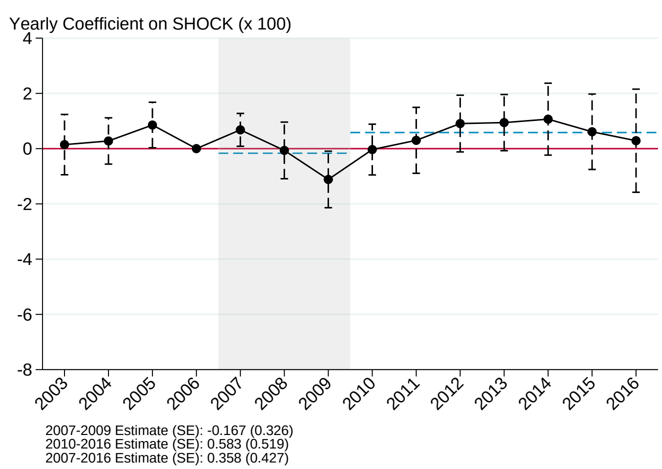
(a) Log share who currently smoke



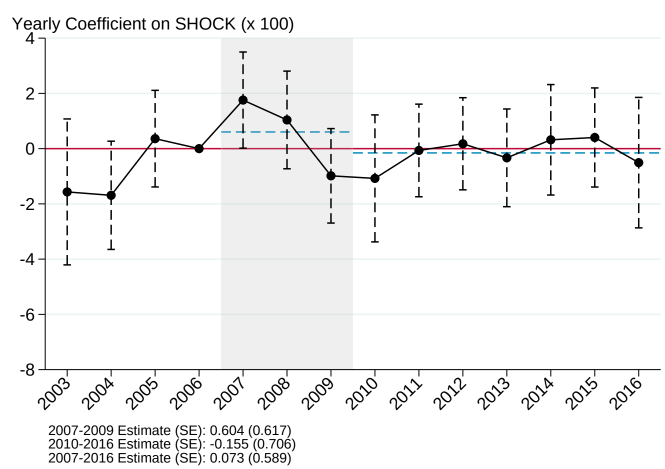
(b) Log share who smoke daily



(c) Log share who currently drink alcohol



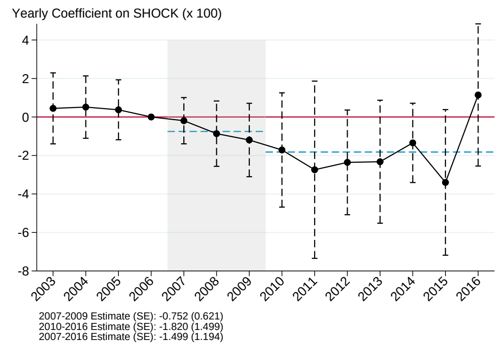
(d) Log share binge drinking last month



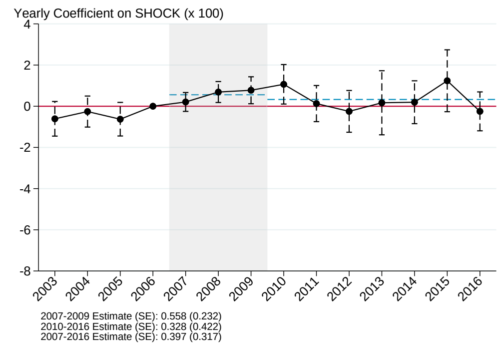
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the share of the state population exhibiting a range of health behaviors. These shares are calculated as the mean of respondent-level BRFSS variables (weighted according to BRFSS survey weights). Variable construction is described in further detail in Appendix B.4. $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. Observations are weighted by state population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the state level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=51 states.

Figure OA.31: Impact of Shock on Health Behavior and Healthcare in the BRFSS

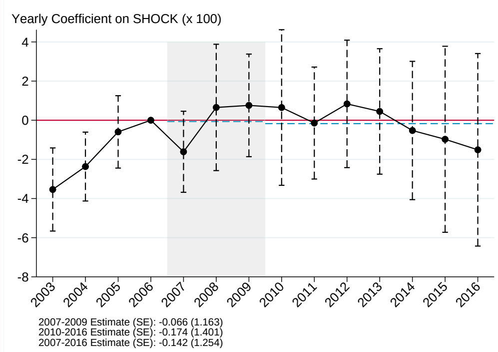
(a) Log share who did not exercise last month



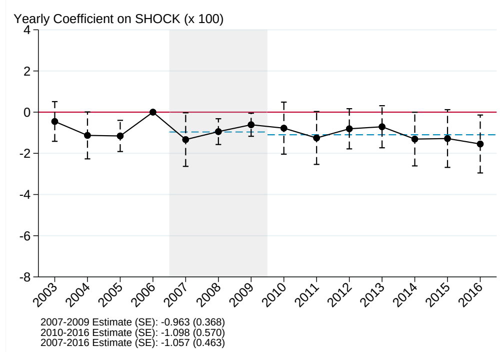
(b) Log share who did not have a flu shot last year



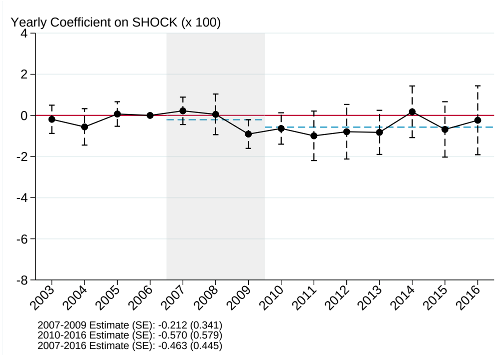
(c) Log share who do not currently have health insurance



(d) Average effect on health measures



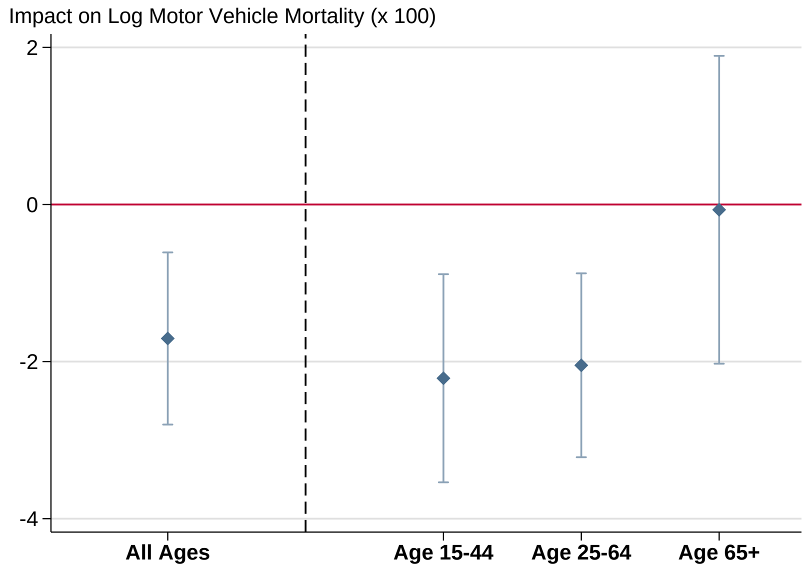
(e) Average effect on health behaviors



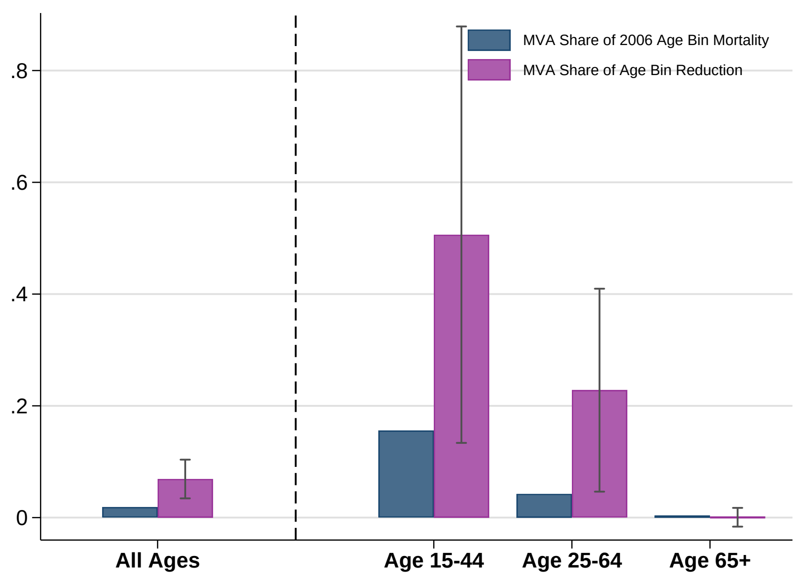
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the share of the state population with a range of health measures and behaviors. These shares are calculated as the mean of respondent-level BRFSS variables (using BRFSS survey weights). The average effect on health measures and health behaviors is computed as the average event study coefficient in each year across each measure of health and health behavior. Variable construction is described in further detail in Appendix B.4. $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. Observations are weighted by state population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the state level, and dashed vertical lines indicate 95% confidence intervals. N=51 states.

Figure OA.32: Impact of Shock on Log Motor Vehicle Mortality, By Age

(a) 2007-2009 impact of unemployment shock on log motor vehicle mortality



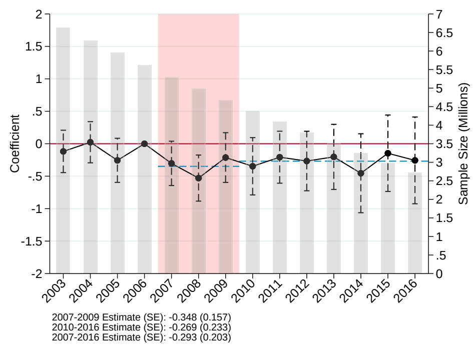
(b) Share of age group mortality reductions attributable to reductions in motor vehicle deaths



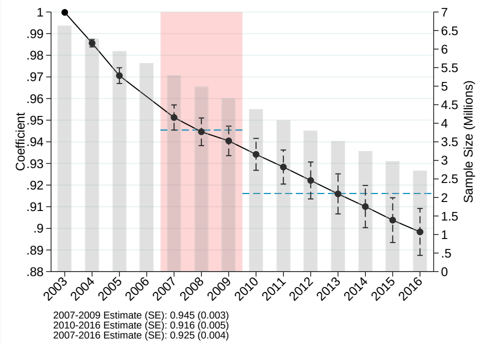
Notes: Figure OA.32a displays the group-specific average of 2007-2009 coefficients β_{tg} from equation (2), where the outcome is log age-adjusted CZ mortality rate from motor vehicle accidents, and groups g are defined as age groups. Observations are weighted by CZ population in 2006. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Point estimates are displayed as diamonds; vertical bars indicate 95% confidence intervals, clustered at the CZ level. Figure OA.32b decomposes the contribution of motor vehicle mortality to the overall estimated 2007-2009 pooled reduction in mortality, separately by age group. The blue bars indicate the share of 2006 mortality attributable to motor vehicle accidents. The purple bars present the implied share of the mortality decline accounted for by motor vehicle accidents. To construct these, we multiply the motor vehicle accident cause-of-death reduction in 2007-2009 by the number of deaths from motor vehicle accidents 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 lines. N=741 CZs.

Figure OA.33: Sensitivity to Yearly vs. Baseline Residence

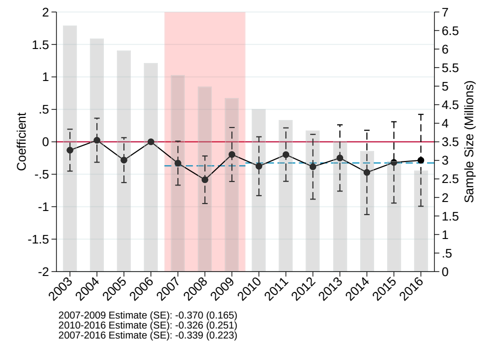
(a) 2003 Residence (Reduced Form) (π_t^{RF}, equation (4))



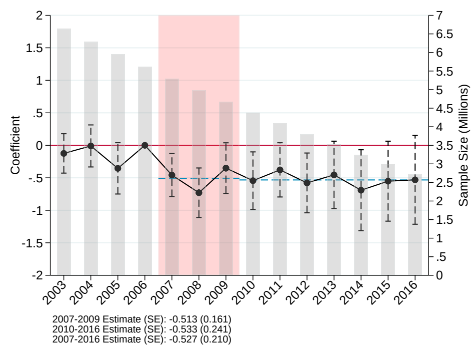
(b) First Stage (π_t^{FS}, equation (5))



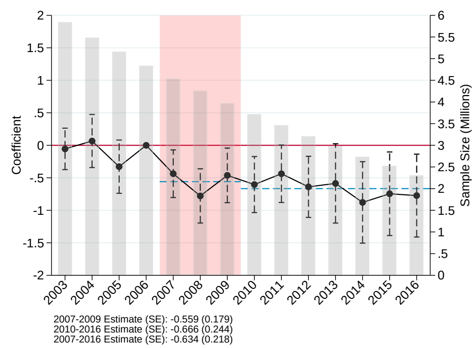
(c) Control Function (β_t, equation (6))



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



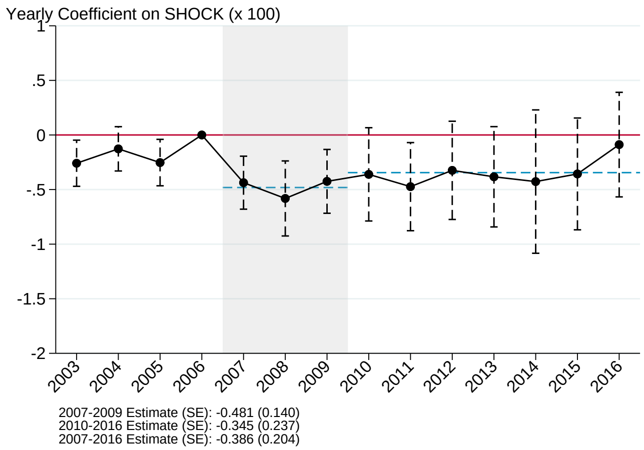
(e) Yearly Residence (Non-Movers) (β_t, equation (7))



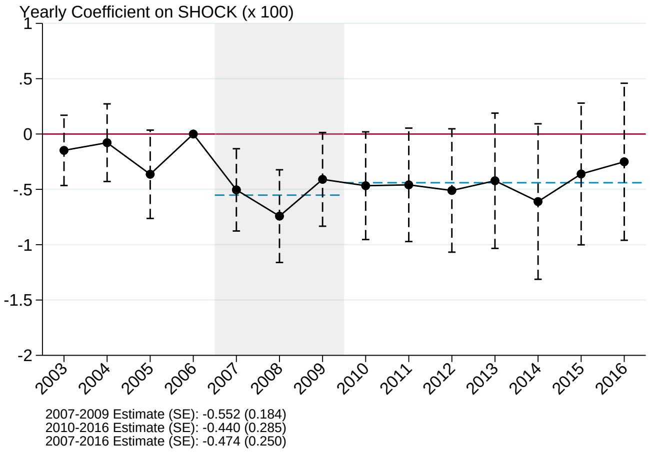
Notes: This figure displays yearly coefficients π_t^{RF} from equation (4) (Figure OA.33a), as well as β_t from equation (6) (Figure OA.33c) and equation (7) (Figures OA.33d and OA.33e), with outcome $log(m_{it}(a))$ defined as the log of the individual-level mortality hazard rate at age a. The figure also displays coefficients π_t^{FS} from equation (5) (Figure OA.33b), with outcome defined as the sum of the interactions of $SHOCK_c$ based on yearly CZ of residence and year dummies, where $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. In Figures OA.33b, OA.33c, OA.33d, and OA.33e, individuals are assigned their yearly CZ of residence, while in Figure OA.33a individuals are assigned their 2003 CZ of residence. The sample reflects a panel of 2003 Medicare beneficiaries, subject to the restrictions in Table OA.8. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. In Figures OA.33b, OA.33c, OA.33d, and OA.33e, coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. Control function standard errors are calculated via a Bayesian bootstrap procedure with 500 repetitions. 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=6,634,999 beneficiaries. N(non-movers)=5,841,523.

Figure OA.34: Impact of Shock on Log Mortality, Among Medicare Samples

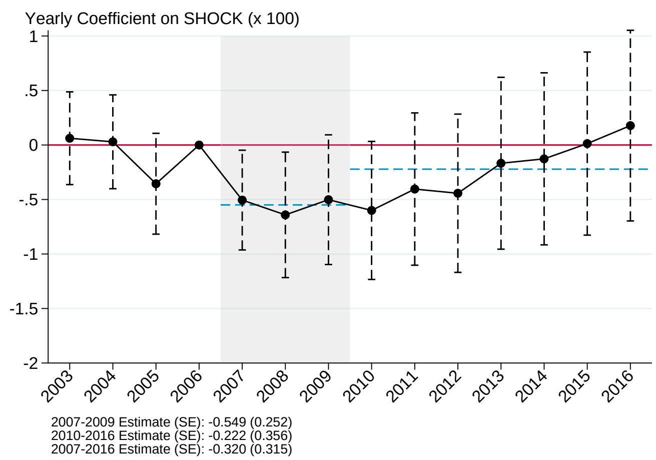
(a) Impact on 65+ Mortality Rate in the CDC Data



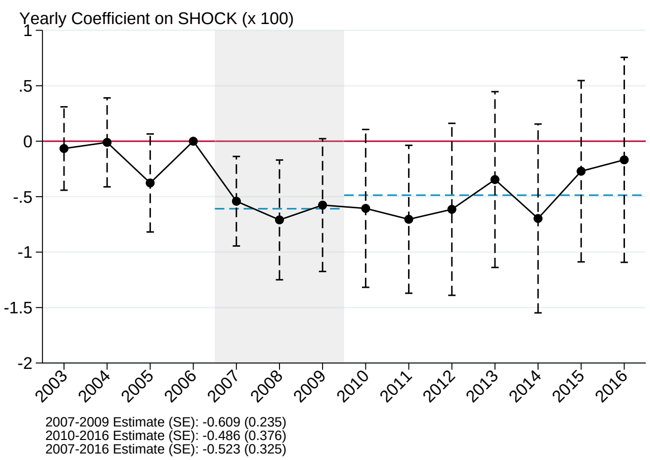
(b) Medicare Repeated Cross Section



(c) Medicare Repeated Cross Section (TM in t)



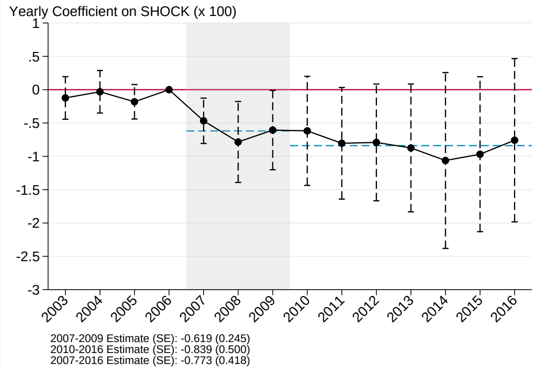
(d) Medicare Repeated Cross Section (TM in $t-1$)



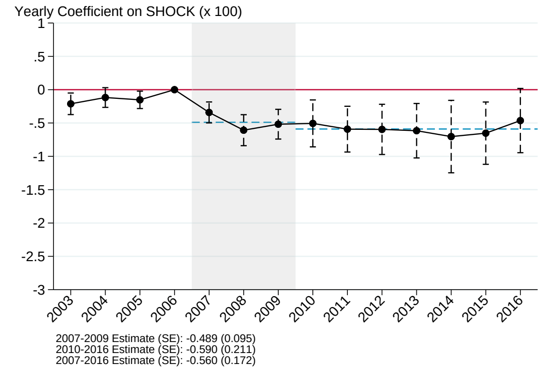
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the non-logged and non age-adjusted CZ mortality rate per 100,000, and $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Figure OA.34a shows results of estimating equation (1) with the outcome as the 65+ mortality rate using the CDC data. The remaining figures use variants of the Medicare Repeated Cross Section sample, which restricts to beneficiaries based on Table OA.9. Figure OA.34b uses the primary Repeated Cross Sample; Figure OA.34c restricts attention to the set of Medicare enrollees who were covered by Traditional Medicare (TM) in every month of the current year, while Figure OA.34d restricts to those covered by TM in every month of the previous year. Observations are weighted by CZ population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs in the CDC data; N=738 CZs in the Medicare data in which we observe individuals on Medicare from our 20% sample in each year.

Figure OA.35: Sensitivity to Geography and Sample

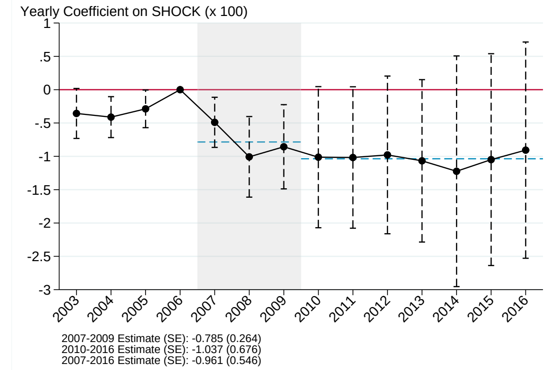
(a) State Level Analysis



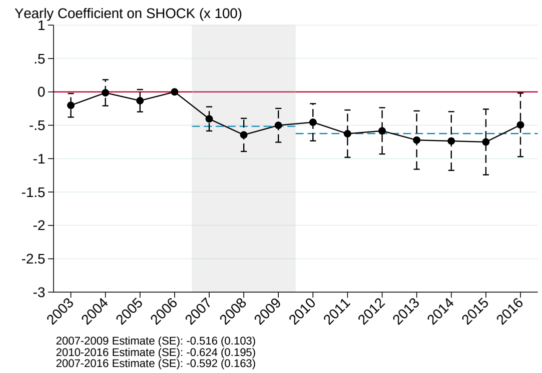
(b) County Level Analysis



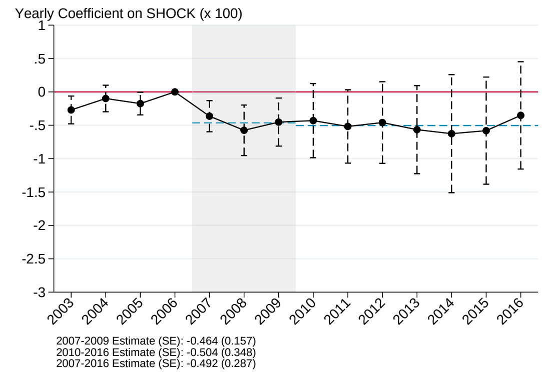
(c) Drop Top/Bottom Decile of Shocked CZs



(d) Drop 10 Most Populous CZs



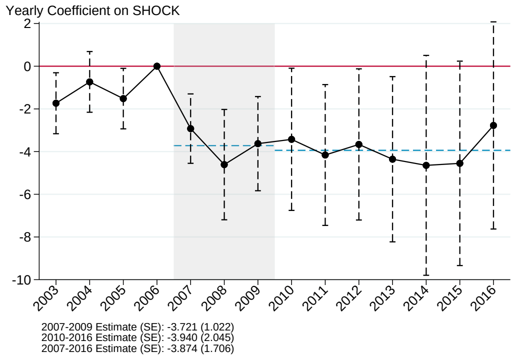
(e) Drop High-Fracking CZs



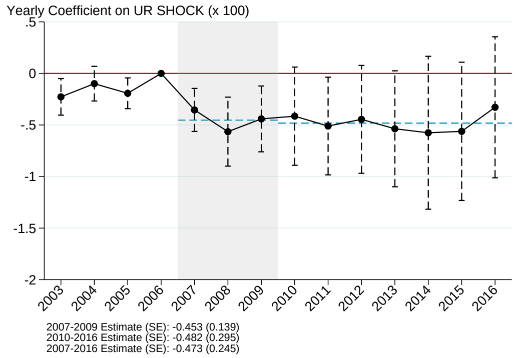
Notes: This figure displays the yearly coefficients β_t from equation (1), where outcome y_{ct} is the log age-adjusted mortality rate per 100,000, and $SHOCK_c$ is the 2007-2009 change in the unemployment rate. Figure OA.35a defines y_{ct} and $SHOCK_c$ at the state level, and Figure OA.35b defines y_{ct} and $SHOCK_c$ at the county level. Figure OA.35c drops the top and bottom 2006 population-weighted deciles of shocked CZs, while defining y_{ct} and $SHOCK_c$ at the CZ level. Figure OA.35d 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) while defining y_{ct} and $SHOCK_c$ at the CZ level. Figure OA.35e drops the 56 CZs that overlap with a county containing a top-quartile shale play, as defined in Bartik et al. (2019), while defining y_{ct} and $SHOCK_c$ at the CZ level. Observations are weighted by state, county, or CZ population in 2006 according to the levels described. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the state, county, or CZ population in 2006 according to the levels described, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=51 states in Figure OA.35a; N=3,131 counties in Figure OA.35b; N=393 CZs in Figure OA.35c; N=731 CZs in Figure OA.35d; and N=685 CZs in Figure OA.35e.

Figure OA.36: Sensitivity to Functional Form

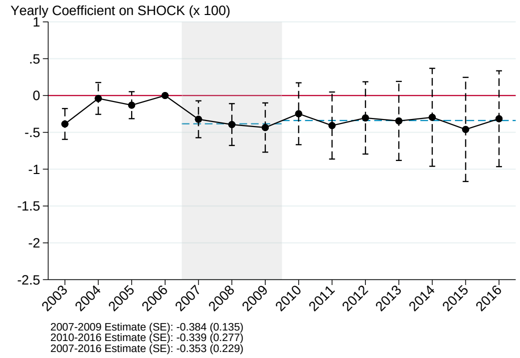
(a) Mortality Rate in Levels



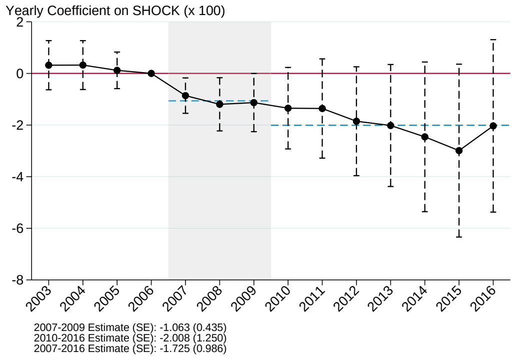
(b) Poisson Specification



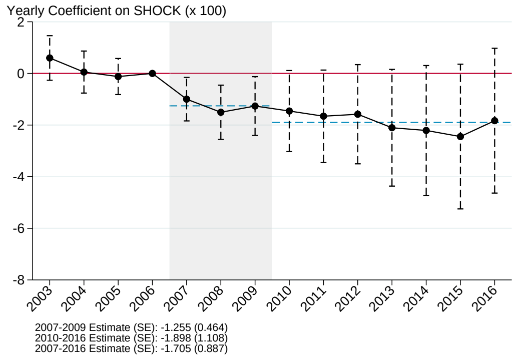
(c) Add Census-Division-by-Year Fixed Effects



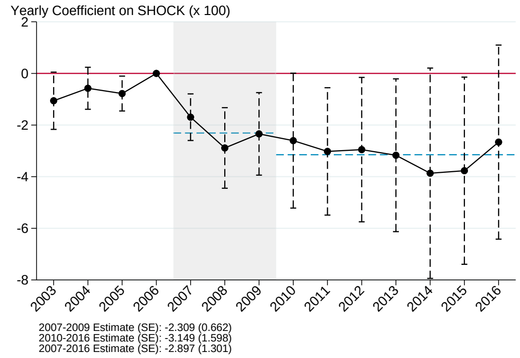
(d) SHOCK Quartiles: Second Quartile



(e) SHOCK Quartiles: Third Quartile



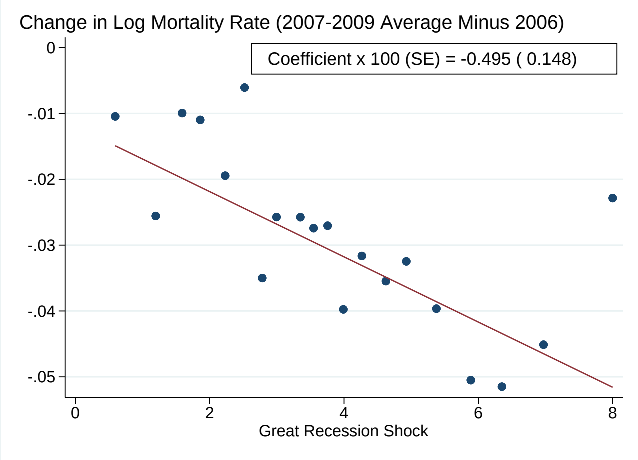
(f) SHOCK Quartiles: Fourth Quartile



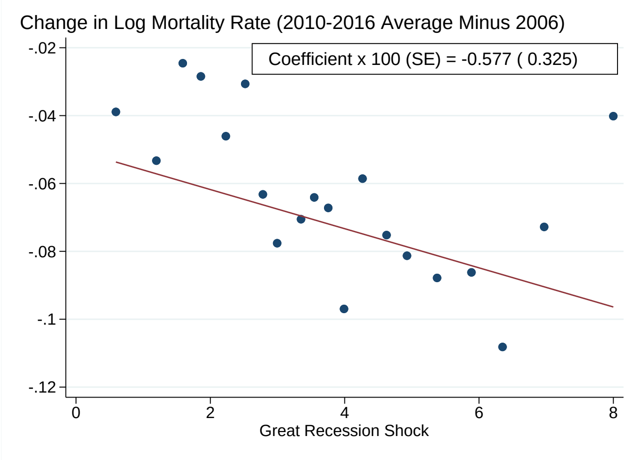
Notes: Figure OA.36a displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the age-adjusted CZ mortality rate per 100,000; in all other figures, it is the log age-adjusted CZ mortality rate per 100,000. In Figure OA.36b, we estimate the Poisson specification in equation (8), instead of equation (1). In Figure OA.36c, we add Census-Division-by-year fixed effects for the 9 Census Divisions and 14 years of the sample to equation (1). $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate in these three figures. In Figures OA.36d, OA.36e, and OA.36f, we replace the linear $SHOCK_c$ variable with indicator for the quartile of the shock, and we estimate the equation (23), where $SHOCKQ_c^{(j)}$ is an indicator for the jth quartile of the 2006 population-weighted CZ unemployment rate shock; we omit the first 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 observations are weighted by CZ population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation, except in Figure OA.36a. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs.

Figure OA.37: Non-Parametric Check of Linearity Assumption

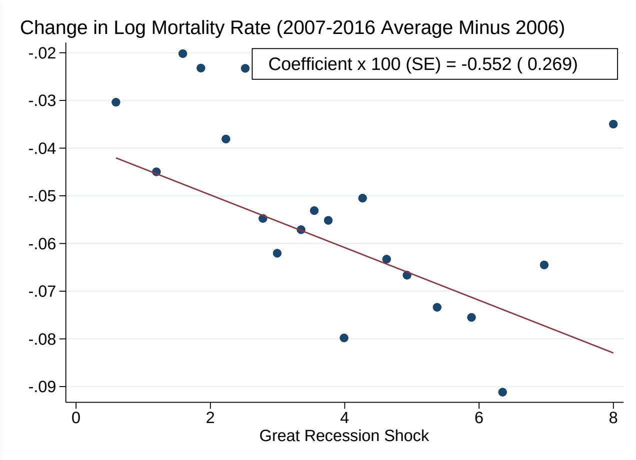
(a) Change in Log Mortality, 2006 vs 2007-09 Average, by GR Shock



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



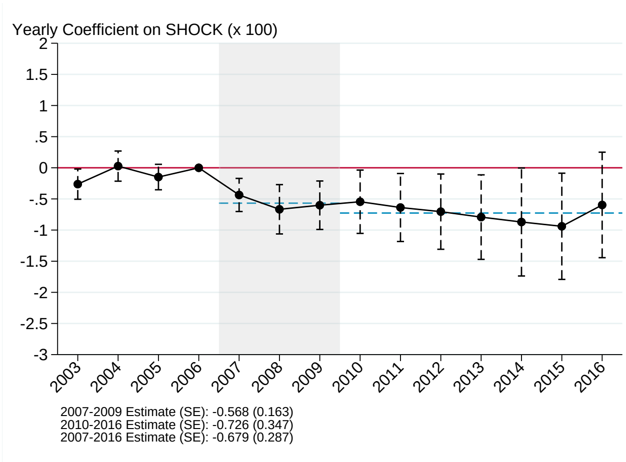
(c) Change in Log Mortality, 2006 vs 2007-16 Average, by GR Shock



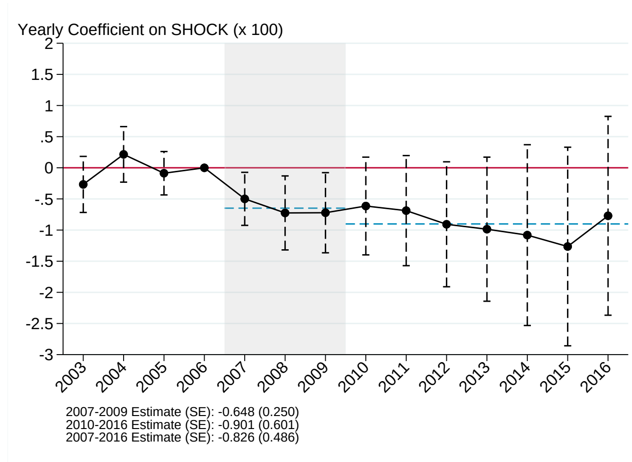
Notes: This figure plots the 2006 population-weighted average difference in the log age-adjusted CZ mortality rate per 100,000 between various post periods and a fixed 2006 pre-period. This is plotted against the population-weighted average CZ unemployment shock in each ventile of the unemployment shock distribution. The line of best fit is plotted in red, computed on the underlying sample of all CZs (weighting by each CZ's 2006 population). The coefficient and robust standard error are displayed in the top right corner of each figure. N=741 CZs.

Figure OA.38: Impact of Shock on Log Mortality, By Size of Shock

(a) Above median shock



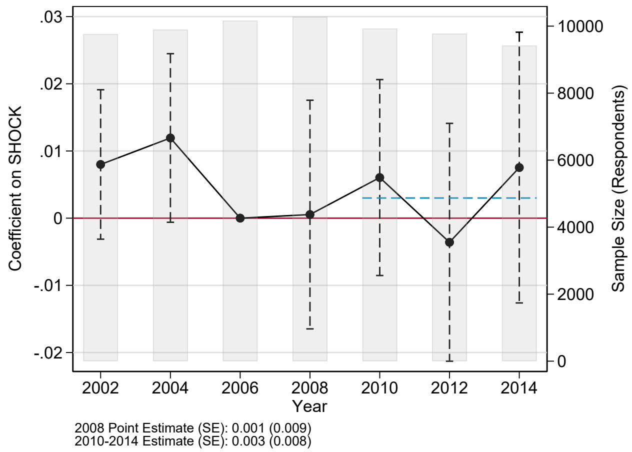
(b) Below median shock



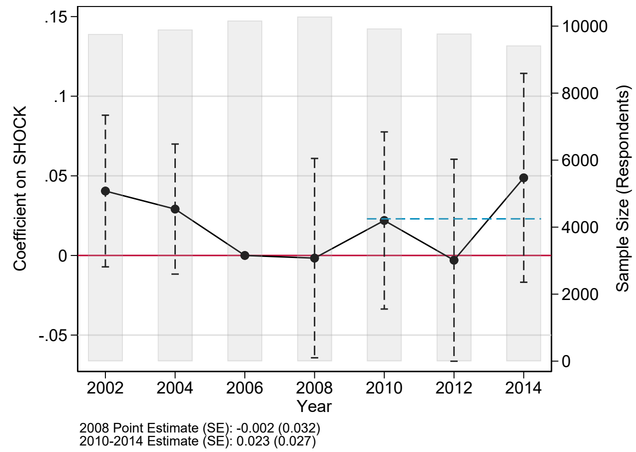
Notes: This figure displays the yearly coefficients β_{qt} from a modified version of equation (3), with $Recovery_{q(c)}$ substituted for an indicator for whether a CZ experienced an above or below median population-weighted 2007-2009 unemployment shock. The outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000, and $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Figure OA.38a plots estimates among above-median unemployment shock CZs, and Figure OA.38b plots estimates among below-median unemployment shock CZs. Observations are weighted by CZ population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=741 CZs: 246 with an above-median shock, and 495 with a below-median shock.

Figure OA.39: Impact of Shock on Measures of Care in the HRS

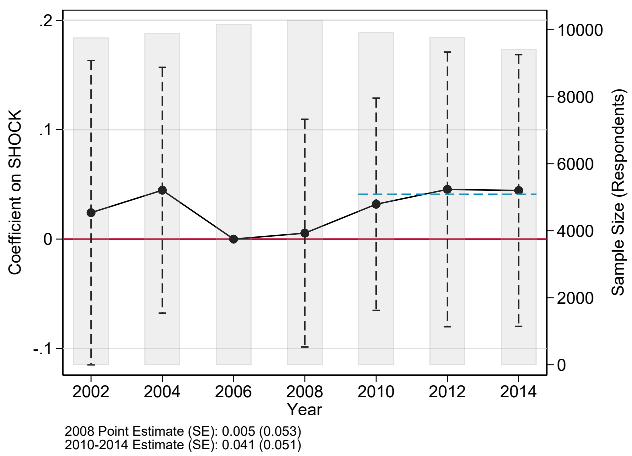
(a) Number of Helpers in the Past Month



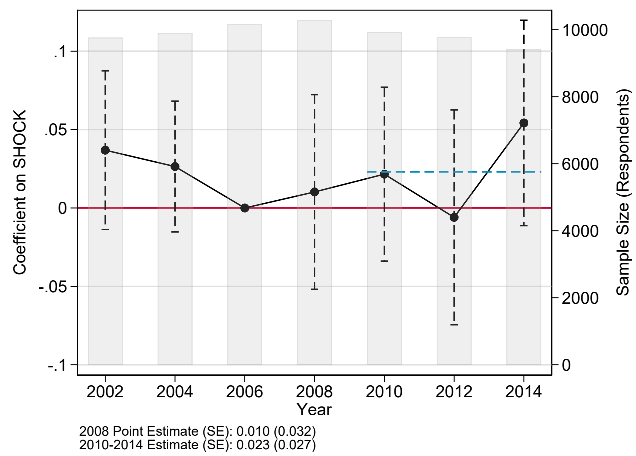
(b) Any Helpers in the Past Month



(c) Any Paid Helpers in the Past Month



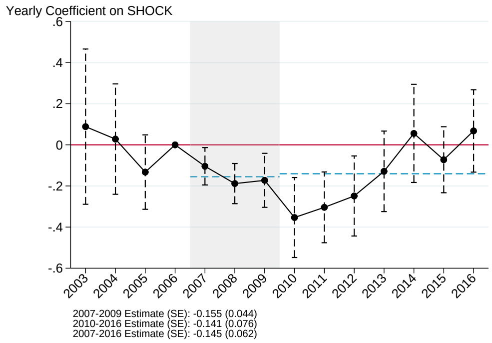
(d) Any Unpaid Helpers in the Past Month



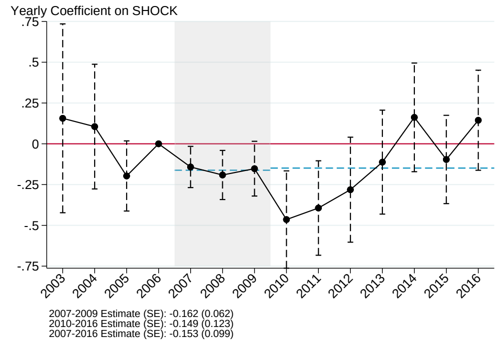
Notes: This figure displays the yearly coefficients β_t from equations (24) and (25), where the outcome y_{it} is either the number of helpers reported by the respondent (Figure OA.39a, using equation 24), or a binary indicator for any reported helpers, any reported paid helpers, and any reported unpaid helpers (Figures OA.39b, OA.39c, and OA.39d), all run as logistic regressions with equation (25). In all cases, $SHOCK_{s(i,t)}$ is the 2007-2009 change in the state unemployment rate. Observations are weighted by the HRS respondent weights. 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. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 2010-2014. These estimates (and corresponding standard errors) are reported in the lower left-hand corner, along with the point estimate for 2008. Standard errors are clustered at the state level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=9,750 respondents in 2006.

Figure OA.40: Impact of Shock on Air Pollution Measures

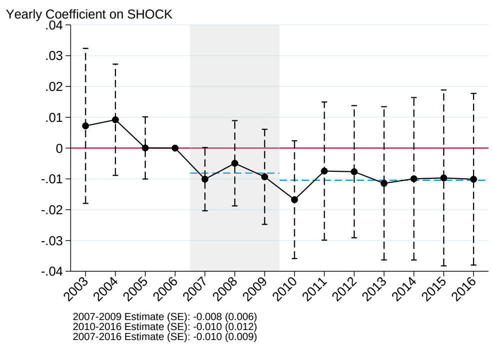
(a) Effect on PM2.5 (All Counties)



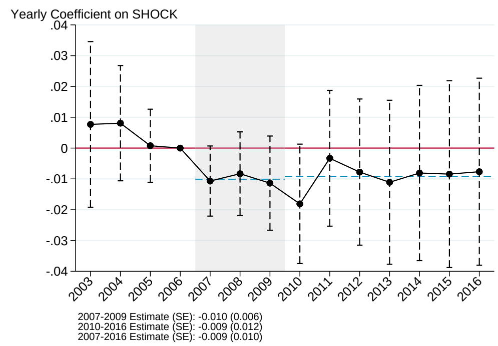
(b) Effect on PM2.5 (Overlap Sample)



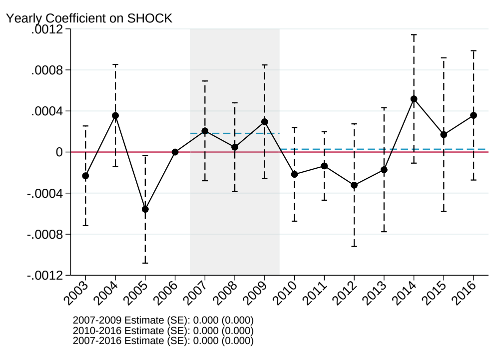
(c) Effect on CO (All Counties)



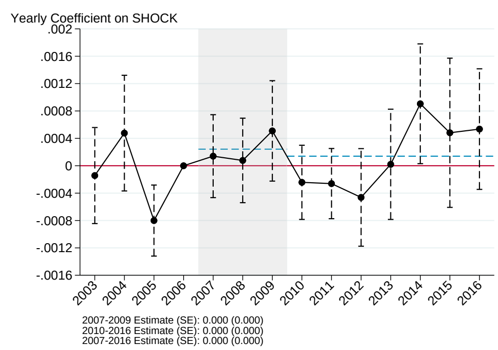
(d) Effect on CO (Overlap Sample)



(e) Effect on O_3 (All Counties)



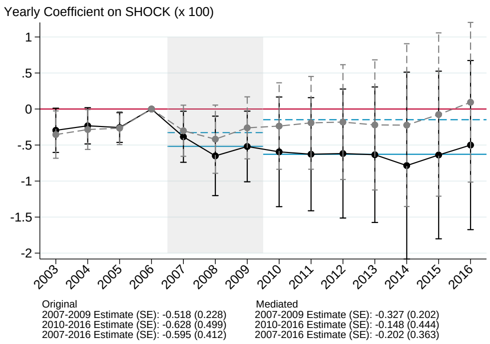
(f) Effect on O_3 (Overlap Sample)



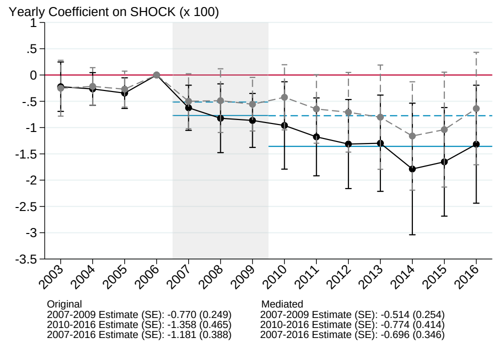
Notes: This figure displays the yearly coefficients β_t from equation (9), where the outcome y_{ct} is the county-year level of various pollutants (measured in $\mu g/m^3$), and $SHOCK_{cz(c)}$ is the 2007-2009 change in the CZ unemployment rate for a given country's corresponding CZ. In Figures OA.40a, OA.40c, and OA.40e, analysis is restricted to the counties in which we observe monitors for the mediated pollutant in both 2006 and 2010 (542 counties representing 64.4% of the 2006 population in Figure OA.40a, 229 counties representing 44.1% of the 2006 population in Figure OA.40c, and 751 counties representing 70.7% of the 2006 population in Figure OA.40e). In Figures OA.40b, OA.40d, and OA.40f, analysis is restricted to the 137 counties representing 39.0% of the 2006 population in which we observe a PM2.5, CO, and O_3 monitor in both 2006 and 2010. Observations are weighted by county population in 2006. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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, and dashed vertical lines indicate 95% confidence intervals on each coefficient.

Figure OA.41: Mediating For Air Pollution: Multiple Measures

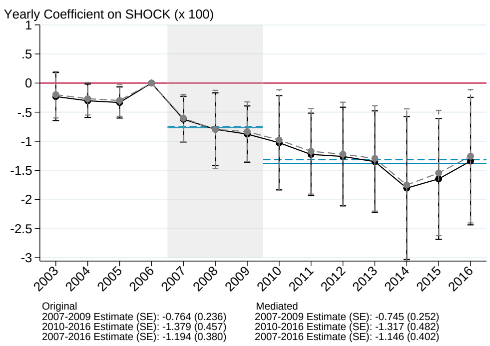
(a) Mediating for PM2.5 (All Counties)



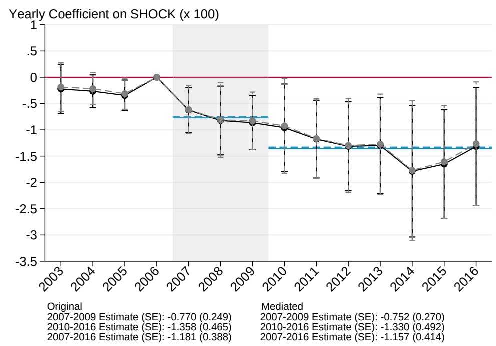
(b) Mediating for PM2.5 (Overlap Sample)



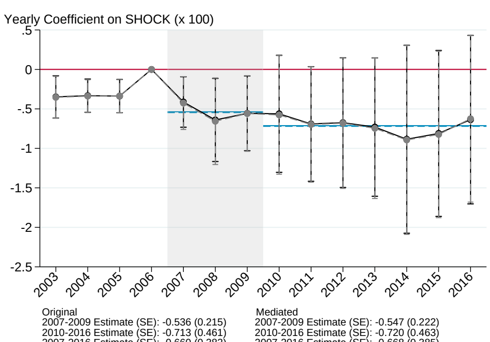
(c) Mediating for CO (All Counties)



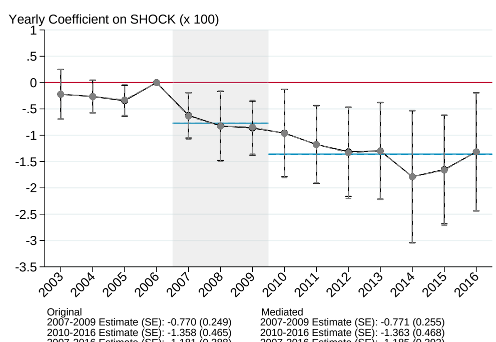
(d) Mediating for CO (Overlap Sample)



(e) Mediating for O_3 (All Counties)

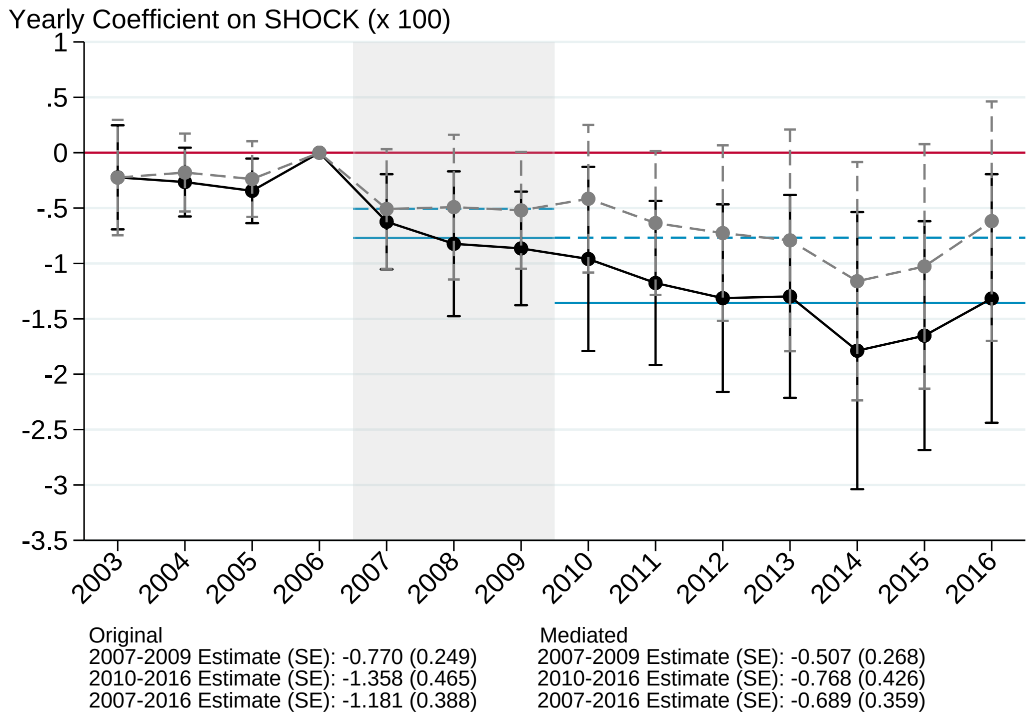


(f) Mediating for O_3 (Overlap Sample)



Notes: This figure displays the yearly coefficients β_t in equations (9) (in black, solid) and (10) (in gray, dashed), where the outcome y_{ct} is the log age-adjusted county mortality rate per 100,000, and $SHOCK_{cz(c)}$ is the 2007-2009 change in the CZ unemployment rate for a given county's corresponding CZ. In Figures OA.41a, OA.41c, and OA.41e, analysis is restricted to the counties in which we observe monitors for the mediated pollutant in both 2006 and 2010 (542 counties representing 64.4% of the 2006 population in Figure OA.41a, 229 counties representing 44.1% of population in Figure OA.41c, and 751 counties representing 70.7% of population in Figure OA.41e). In Figures OA.41b, OA.41d, and OA.41f, analysis is restricted to the 137 counties representing 39.0% of population in which we observe a PM2.5, CO, and O_3 monitor in both 2006 and 2010. Observations are weighted by county population in 2006. Horizontal blue solid (dashed) lines indicate the point estimate for the average of coefficients from 2007-2009 and 2010-2016 for equation (9) (equation 10). These estimates (and corresponding standard errors) are reported in the lower left-hand (right-hand) corner for equation (9) (equation 10). Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals.

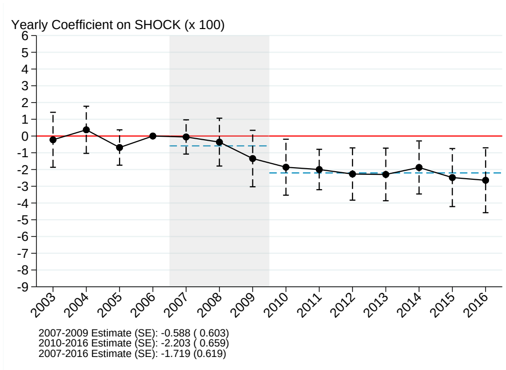
Figure OA.42: Impact of Shock on Log Mortality, Mediating for PM2.5, CO, and O_3



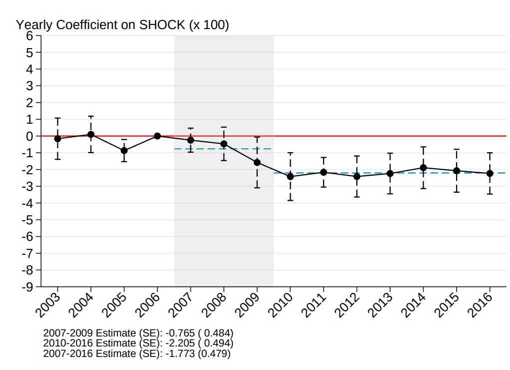
Notes: This figure displays the yearly coefficients β_t in equations (9) (in black, solid) and (10) (in gray, dashed), where the outcome y_{ct} is the log age-adjusted county mortality rate per 100,000, and $SHOCK_{cz(c)}$ is the 2007-2009 change in the CZ unemployment rate for a given county's corresponding CZ. The vector of controls in equation (10) includes the 2006-2010 change in PM2.5, CO, and O_3, each interacted with year fixed effects. Observations are weighted by county population in 2006. Horizontal blue solid lines indicate the point estimate for the average of coefficients from 2007-2009 and 2010-2016 for equation (9), while horizontal blue dashed lines indicate the same for equation (10). These estimates (and corresponding standard errors) are reported in the lower left-hand corner for equation (9) and lower right-hand corner for equation (10), along with the corresponding estimate for the entire 2007-2016 period. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. The sample is 137 counties representing 39.0% of population in which we observe a PM2.5, CO, and O_3 monitor in both 2006 and 2010.

Figure OA.43: Impact of Shock on Earnings, By Education

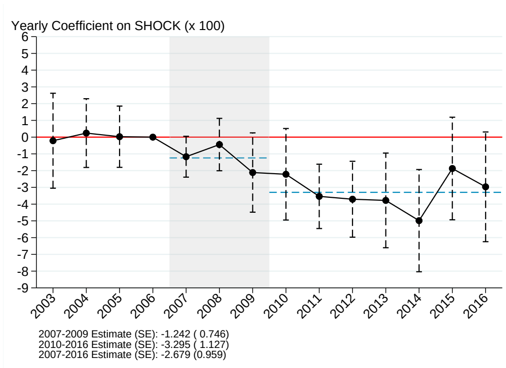
(a) All Individuals (State-Level OLS)



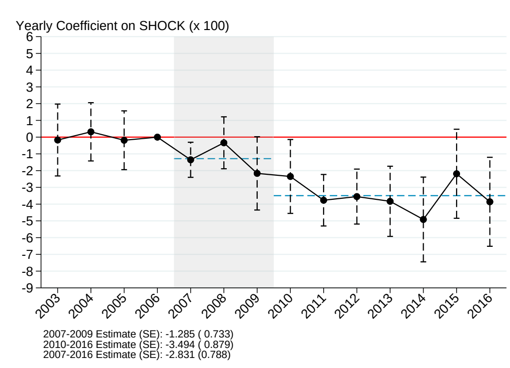
(b) All Individuals (Person-Level Poisson)



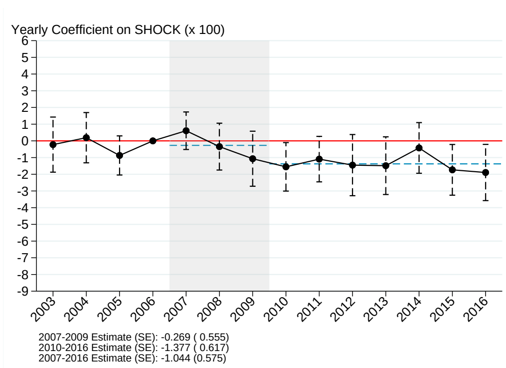
(c) HS or Less (State-Level OLS)



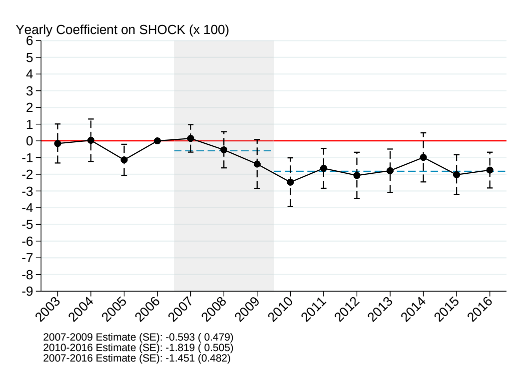
(d) HS or Less (Person-Level Poisson)



(e) More than HS (State-Level OLS)



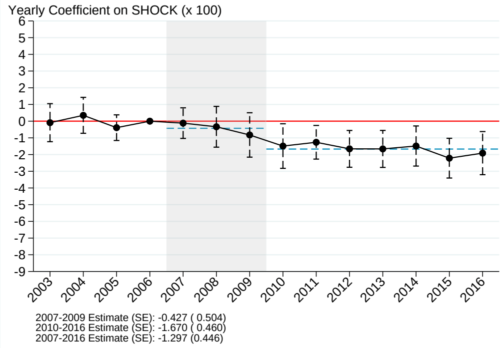
(f) More than HS (Person-Level Poisson)



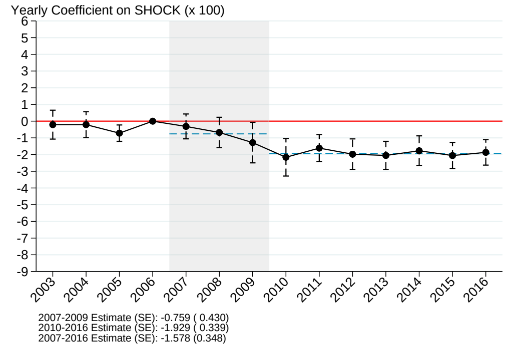
Notes: Figures OA.43a, OA.43c, and OA.43e display the yearly coefficients β_t from equation (1) estimated at the state level via OLS, with the outcome y_{ct} defined as the log average state earnings for individuals aged 25+ with various levels of education, per the Current Population Survey (CPS). Observations are weighted by state population in 2006. Figures OA.43b, OA.43d, and OA.43f display the yearly coefficients β_t from equation (26) estimated via Poisson regression, where the outcome y_{it} is individual-level earnings for those aged 25+ with various levels of education. These regressions are weighted by the CPS survey weights for each individual in each year. In all cases, $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the state level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=714 state-years in Figures OA.43a, OA.43c, and OA.43e; N=1,788,643 person-years in Figure OA.43b; N=781,637 person-years in Figure OA.43d; and N=1,007,006 person-years in Figure OA.43f.

Figure OA.44: Impact of Shock on Income, By Age

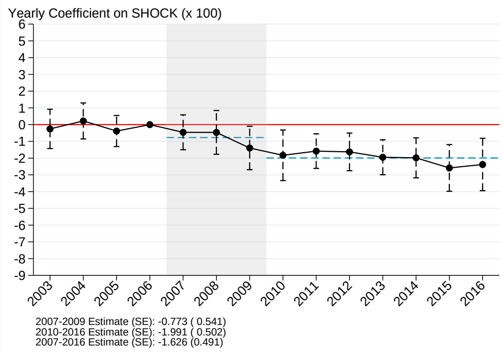
(a) All Individuals (State-Level OLS)



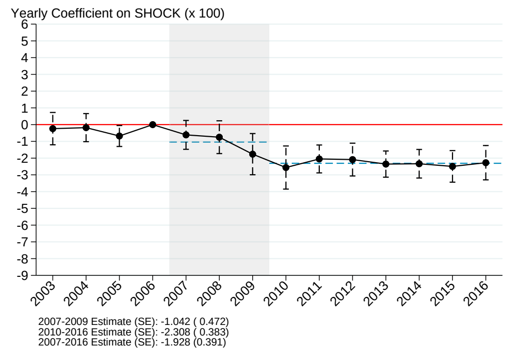
(b) All Individuals (Person-Level Poisson)



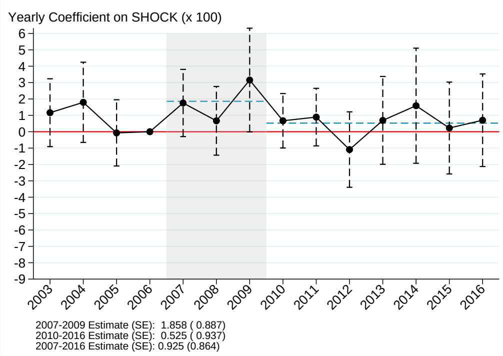
(c) 25-64 (State-Level OLS)



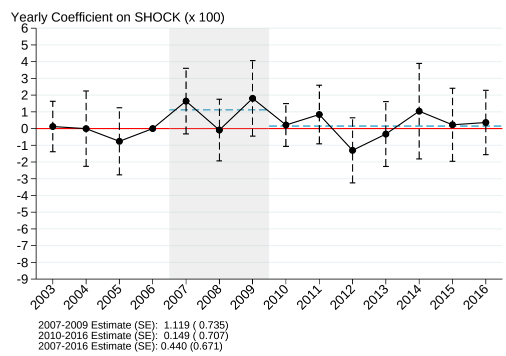
(d) 25-64 (Person-Level Poisson)



(e) 65+ (State-Level OLS)



(f) 65+ (Person-Level Poisson)



Notes: Figures OA.44a, OA.44c, and OA.44e display the yearly coefficients β_t from equation (1) estimated at the state level via OLS, with the outcome y_{ct} defined as the log average state income for individuals aged 25+ in different age groups, per the Current Population Survey (CPS). Observations are weighted by state population in 2006. Figures OA.44b, OA.44d, and OA.44f display the yearly coefficients β_t from equation (26) estimated via Poisson regression, where the outcome y_{it} is individual-level income for those aged 25+ in different age groups. These regressions are weighted by the CPS survey weights for each individual in each year. In all cases, $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 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. Coefficients, standard errors, and confidence intervals are multiplied by 100 throughout for ease of interpretation. Standard errors are clustered at the state level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. N=714 state-years in Figures OA.44a, OA.44c, and OA.44e; N=1,788,643 person-years in Figure OA.44b; N=781,637 person-years in Figure OA.44d; and N=1,007,006 person-years in Figure OA.44f.

F Appendix Tables

Table OA.1: Impact of the Great Recession on Life Expectancy by Age

Age	Mortality Rate (per 100,000)	Life Expectancy (without recession)	Life Expectancy (with recession)	Change in life expectancy	
				Percent increase	Years increase
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	1,385	18.004	18.069	0.359%	0.065
75	3,388	11.068	11.154	0.778%	0.086

Notes: This table translates our empirical estimates into the implications of the Great Recession for life expectancy at various ages. Column (1) displays unisex mortality rates by age based on the 2007 SSA mortality tables (see Appendix Section C.9). Column (2) translates these mortality rates into remaining life expectancy. Column (3) considers how this remaining life expectancy would change if mortality rates declined by 2.3 percent for 10 years and then returned to normal, corresponding to a 4.6 percentage point unemployment shock that lasts for ten years. Columns (4) and (5) report the percentage difference in life expectancy and the years difference in life expectancy, respectively, between column (3) and column (2). 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. For each gender, life expectancy is obtained as the sum over each age x of the share of individuals of that gender that die at age x multiplied by the number of years lived since age A.

Table OA.2: Average Characteristics of CZs, By Recovery

	Average in CZs With Recovery:	
	Below Median	Above Median
Share 25+ With More Than HS Degree (2006)	0.472	0.475
Income 25+ (2006)	\$35,165	\$36,868
Share Living in Urban Areas (1990)	0.683	0.713
Share Working in Manufacturing (2000)	0.160	0.162
PM2.5 (2006)	11.4	11.8

Notes: This table displays 2006 population-weighted average characteristics of CZs based on whether they have above or below median 2010-2016 recovery rates as measured by the change in the employment-to-population (EPOP) ratio, conditional on deciles of the 2007-2009 EPOP shock. The deciles of the EPOP shock and the median recovery for each shock decile are constructed from 2006 population-weighted CZ distributions. The share of individuals living in urban areas in 1990 is from the 1990 Census, and the share of employees working in manufacturing in 2000 is from Autor et al. (2013), who in turn calculate it using the 2000 Census. The 2006 level of PM2.5 (measured in $\mu g/m^3$) is obtained from the EPA's Air Quality Survey. N=460 CZs below the median recovery and 281 CZs above the median recovery. These sample sizes are lower for the share living in urban areas (420 and 266 CZs, respectively), the share working in manufacturing (446 and 276 CZs, respectively) and PM2.5 (222 and 114 CZs, respectively) due to missing data.

Table OA.3: Descriptive Statistics: 2006 Mortality

Group	Share of Population	Number of Deaths	Mortality Rate per 100,000	Share of Deaths
Full Population*	1.00	2,426,023	790.28	1.00
Age Bins				
0-4 years	0.07	33,157	166.33	0.01
5-14 years	0.14	6,149	15.16	0.00
15-24 years	0.14	34,886	81.44	0.01
25-34 years	0.13	42,950	109.04	0.02
35-44 years	0.14	83,042	192.08	0.03
45-54 years	0.15	185,029	427.59	0.08
55-64 years	0.11	281,397	881.59	0.12
65-74 years	0.06	390,089	2,032.10	0.16
74-84 years	0.04	667,335	5,097.46	0.28
85+ years	0.02	701,989	14,430.00	0.29
Gender*				
Male	0.49	1,201,760	945.62	0.50
Female	0.51	1,224,263	668.58	0.50
Race*				
Non-Hispanic White	0.67	1,947,877	787.63	0.80
Non-Hispanic Black	0.13	287,796	1,027.73	0.12
Hispanic	0.15	132,968	608.72	0.05
Non-Hispanic Other	0.06	57,382	503.88	0.02
Education*†				
HS or Less	0.52	1,536,814	1,243.46	0.70
More than HS	0.48	611,009	982.18	0.28
Cause of Death*				
Cardiovascular Disease	.	823,701	267.39	0.34
Cancer	.	559,875	182.08	0.23
Chronic Lower Respiratory Disease	.	124,578	41.04	0.05
Diabetes	.	72,448	23.57	0.03
Alzheimer's Disease	.	72,432	23.49	0.03
Influenza/Pneumonia	.	56,323	18.32	0.02
Kidney Disease	.	45,343	14.79	0.02
Motor Vehicle Accidents	.	45,301	15.00	0.02
Suicide	.	33,292	10.98	0.01
Liver Disease/Cirrhosis	.	27,550	8.76	0.01
Homicide	.	18,553	6.20	0.01
All Other Causes (Residual)	.	546,627	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 among the entire population.
Notes: This table displays 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.4: 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: This 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. All estimates are weighted by 2006 CZ population as estimated from the SEER, with standard errors clustered at the CZ level.

Table OA.5: Period Estimates of Effects on 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: This table displays estimates of effects on 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 (1), where the outcome y_{ct} is the share of state c'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 2006 state 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.6: Welfare Costs of Recessions by Age

	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: This table displays the welfare cost of recessions, based on equation (16), at various ages under exogenous and endogenous mortality, for various assumptions about risk aversion (γ) and the value of a statistical life-year ($VSLY$). This welfare cost is the amount an individual would need to be paid to accept the stochastic aggregate state relative to an otherwise similar economy that stays in the non-recession state for all time periods, measured as a percentage of average annual consumption. A 10-year duration of the Great Recession is considered, followed by a period without recessions until the end of life.

Table OA.7: Welfare Costs of the Great Recession by Age and Education

Mortality	Exogenous			Endogenous								
Education	All	$\leq$ HS	$>$ HS	All	$\leq$ HS	$>$ HS	All	$\leq$ HS	$>$ HS	All	$\leq$ HS	$>$ HS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A. Starting age 35												
$\gamma = 1.5$	1.59	2.82	1.21	1.53	2.70	1.22	1.44	2.50	1.22	1.34	2.30	1.22
$\gamma = 2$	1.61	2.89	1.23	1.56	2.79	1.23	1.47	2.61	1.23	1.39	2.43	1.23
$\gamma = 2.5$	1.63	2.97	1.24	1.59	2.87	1.24	1.51	2.71	1.24	1.44	2.55	1.25
Panel B. Starting age 45												
$\gamma = 1.5$	1.90	3.41	1.44	1.77	3.14	1.44	1.56	2.70	1.44	1.35	2.26	1.45
$\gamma = 2$	1.92	3.49	1.45	1.81	3.26	1.45	1.62	2.86	1.46	1.43	2.47	1.46
$\gamma = 2.5$	1.95	3.58	1.47	1.85	3.37	1.47	1.68	3.02	1.47	1.51	2.67	1.48
Panel C. Starting age 55												
$\gamma = 1.5$	2.36	4.29	1.76	2.12	3.77	1.77	1.69	2.89	1.78	1.28	2.03	1.78
$\gamma = 2$	2.39	4.38	1.78	2.17	3.92	1.78	1.80	3.14	1.79	1.42	2.38	1.80
$\gamma = 2.5$	2.42	4.48	1.80	2.22	4.07	1.80	1.89	3.38	1.81	1.56	2.70	1.82
Panel D. Starting age 65												
$\gamma = 1.5$	3.07	5.62	2.27	2.54	4.52	2.28	1.65	2.69	2.30	0.77	0.92	2.32
$\gamma = 2$	3.10	5.73	2.29	2.63	4.75	2.30	1.84	3.13	2.32	1.06	1.56	2.33
$\gamma = 2.5$	3.13	5.83	2.31	2.72	4.97	2.32	2.01	3.53	2.33	1.32	2.14	2.35
VSLY	-	-	-	\$100k	\$100k	\$100k	\$250k	\$250k	\$250k	\$400k	\$400k	\$400k

Notes: This table displays the welfare cost of recessions, based on equation (16), at various ages under exogenous and endogenous mortality, for various assumptions about risk aversion (γ) and the value of a statistical life-year ($VSLY$). This welfare cost is the amount an individual would need to be paid to accept the stochastic aggregate state relative to an otherwise similar economy that stays in the non-recession state for all time periods, measured as a percentage of average annual consumption. We measure the costs separately for individuals with a High School (HS) diploma or less, and individuals with more than a HS diploma. The estimates use group-specific consumption and mortality effects of the Great Recession, as well as group-specific mortality rates. A 10-year duration of the Great Recession is considered, followed by a period without recessions until the end of life.

Table OA.8: Medicare Beneficiary Sample Restrictions (All 2003 Medicare Beneficiaries)

	Number of Beneficiaries (2003)
(1) Unique beneficiaries in the 2003 Medicare beneficiary 20% sample	8,624,883
Exclude beneficiaries that are:	
(3) Younger than 65 or older than 99 in 2003	6,912,995
(4) Living overseas or in US territories in at least one year	6,753,774
(5) Observed with incomplete data (gaps, inconsistent age/death information, etc.)	6,637,939
(6) Not matched with a commuting zone in at least one year	6,634,999
(7) Number of beneficiaries	**6,634,999**

Notes: This table displays the impact of each of our restrictions on the sample size of 2003 Medicare beneficiaries. We begin in Row (1) 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, and does not require that individuals were enrolled in Parts A & B for all months in 2003 (to allow for beneficiaries who entered Medicare in 2003). In Row (7), we display the final sample used for analyses of all 2003 beneficiaries, after the full set of restrictions are applied.

Table OA.9: Medicare Beneficiary Sample Restrictions (2003-2016 Repeated Cross Section)

	Number of Beneficiaries
(1) Unique 2001-2016 beneficiaries in the 20% Denominator data sample	18,400,912
(2) Exclude beneficiaries that are:	
(3) Younger than 65 or older than 99 in a given year	15,092,828
(4) Living overseas or in US territories in at least one year	14,709,778
(5) Observed with incomplete data (gaps, inconsistent age/death information, etc.)	14,412,941
(6) Not matched with a commuting zone in at least one year	14,406,146
(7) Not observed from 2003 onwards	13,705,511
(8) Number of beneficiaries	**13,705,511**
(9) Number of beneficiaries on TM in t-1	**10,170,053**
(10) Number of beneficiaries on TM in t	**10,587,653**

Notes: This table displays the impact of each of our restrictions on the sample size of Medicare beneficiaries for the 2003-2016 Repeated Cross Section sample. The Repeated Cross Section Sample, in contrast to the sample laid out in Table OA.8, does not require that individuals were on Medicare in 2003, but rather takes a sample of individuals between 2003-2016 who meet a set of criteria in each individual year. We begin in Row (1) with a 20 percent sample of all 2001-2016 Medicare patient-years, based on the Medicare Master Beneficiary Summary File (MBSF). The total sample after all restrictions are applied is displayed in Row (8). Row (9) shares the total number of unique beneficiaries after imposing some additional restrictions: namely, that individuals are on Traditional Medicare (as judged by Medicare Part B) for each month of the previous year, and not on Medicare Advantage for any month of the previous year. Row (10) concludes by sharing the number of unique individuals who met both of these qualifications in the current year, rather than the previous year.

Table OA.10: Medicare Patient-Year Sample Demographic Summary Statistics

	All 2003 Beneficiaries	Repeated Cross Section	Repeated Cross Section (TM in $t-1$)	Repeated Cross Section (TM in t)
	(1)	(2)	(3)	(3)
Share female	0.59	0.56	0.58	0.57
Share white	0.87	0.85	0.87	0.87
Mean age	78.81	74.84	75.88	75.34
Share in age group				
65-74	0.28	0.54	0.49	0.51
75-84	0.51	0.33	0.36	0.34
85+	0.21	0.13	0.15	0.14
Share movers	0.14	0.12	0.12	0.12
Share enrolled in Medicaid	0.13	0.13	0.14	0.14
Share enrolled in Medicare Advantage	0.24	0.26	0.03	0.00
Mortality rate (per 100,000)	6,482	4,692	5,322	5,191
Number of patients	6,634,999	13,705,511	10,170,053	10,587,653
Number of patient-years	64,185,293	106,076,652	69,784,414	72,788,077

Notes: This table displays summary statistics on four Medicare patient-year samples: All 2003 Beneficiaries, Repeated Cross Section, Repeated Cross Section (TM in $t-1$), and Repeated Cross Section (TM in t). The All 2003 Beneficiaries sample represents a panel of 2003 Medicare beneficiaries, subject to the restrictions in Table OA.8. The Repeated Cross Section sample draws beneficiaries in every year during the 2003-2016 period, subject to the restrictions in Table OA.9. Repeated Cross Section (TM 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; Repeated Cross Section (TM in t) does the same for the current year.

Table OA.11: Average Share of Individuals With BRFSS Health Measures and Health Behaviors in 2006, By Age

	Age Group			
	Overall	Under 45	45-64	65+
Panel A: Health				
Less than very good health	0.464	0.432	0.487	0.624
Poor mental health last month	0.342	0.373	0.328	0.189
Ever had diabetes	0.080	0.059	0.115	0.189
Currently have asthma	0.086	0.087	0.089	0.079
Overweight or obese	0.631	0.630	0.700	0.636
Obese	0.286	0.294	0.331	0.249
Panel B: Health Behavior				
Currently smokes cigarettes	0.197	0.219	0.206	0.085
Currently smokes cigarettes daily	0.144	0.160	0.156	0.064
Currently drinks alcohol	0.523	0.551	0.535	0.383
Any binge drinking last month	0.151	0.175	0.117	0.033
No exercise last month	0.240	0.223	0.251	0.323
No flu shot in past year	0.682	0.754	0.671	0.324
Panel C: Health Insurance				
Currently has no health insurance	0.158	0.186	0.128	0.019

Notes: This table displays the average share of individuals across all states, within various age groups, with each of several health measures and health behaviors, per the BRFSS. State-level averages are weighted by the BRFSS sample weights, while the average across states is weighted by the population of each state in 2006.

Table OA.12: Impact of 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 + Sex + Race (TM in $t-1$)	Age + Sex + Race + 20 Chronic Conditions (TM in $t-1$)
	(1)	(2)	(3)	(4)	(5)
Great Recession Shock	-0.609	-0.622	-0.573	-0.565	-0.540
	(0.235)	(0.229)	(0.238)	(0.238)	(0.233)
Mean Mortality Rate (per 100,000)	5,307.0	NA	NA	NA	NA
Mean LYL per Decedent	NA	11.07	7.95	7.82	6.50
Observations	738	738	738	738	738

Notes: This table displays the average of 2007-2009 coefficients β_t from equation (1). The analysis is conducted in the 65+ population in the Medicare data (see Table OA.9), further limited to the sub-sample of patient-years in 2003-2016 enrolled in Traditional Medicare (TM) in year $t-1$. In Column (1), the outcome y_{ct} is the log of the (non age-adjusted) CZ-year mortality rate per 100,000. 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. Each individual is assigned their yearly CZ of residence. $SHOCK_c$ is defined as the 2007-2009 change in the CZ unemployment rate. Observations are weighted by CZ population in 2006. Standard errors are clustered at the CZ level and reported in parentheses below each period estimate. Coefficients and standard errors are multiplied by 100 throughout for ease of interpretation. 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.13: Impact of 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 + Sex + Race (TM in $t-1$)	Age + Sex + Race + 20 Chronic Conditions (TM in $t-1$)
	(1)	(2)	(3)	(4)	(5)
Great Recession Shock	-29.5	-326.3	-212.6	-208.0	-166.9
	(12.0)	(128.0)	(94.1)	(93.6)	(77.4)
Mean Mortality Rate (per 100,000)	5,307.0	NA	NA	NA	NA
Mean LYL per Decedent	NA	11.07	7.95	7.82	6.50
Observations	738	738	738	738	738

Notes: This table displays the average of 2007-2009 coefficients β_t from equation (1). The analysis is conducted in the 65+ population in the Medicare data (see Table OA.9), further limited to the sub-sample of patient-years in 2003-2016 enrolled in Traditional Medicare (TM) in year $t-1$. In Column (1), the outcome y_{ct} is the (non age-adjusted) CZ-year mortality rate per 100,000. In the life-years lost regressions in Columns (2)-(5), the dependent variable is the CZ-year level life-years lost per 100,000 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. Each individual is assigned their yearly CZ of residence. $SHOCK_c$ is defined as the 2007-2009 change in the CZ unemployment rate. Observations are weighted by CZ population in 2006. Standard errors are clustered at the CZ level and reported in parentheses below each period estimate. CZs are restricted to those with at least one beneficiary in every year in the 2003-2016 period, which restricts to 738 CZs.