LIVES VS. LIVELIHOODS: THE IMPACT OF THE GREAT RECESSION ON MORTALITY AND WELFARE *

Amy Finkelstein
Matthew J. Notowidigdo
Frank Schilbach
Jonathan Zhang

April 18, 2025

Abstract

We leverage spatial variation in the severity of the Great Recession across the United States to examine its impact on mortality and explore the quantitative implications. 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 reduced air pollution appears 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.

JEL: E3 - Prices, Business Fluctuations, and Cycles, I1 - Health

*Finkelstein: MIT and NBER, afink@mit.edu; Notowidigdo: Chicago Booth and NBER, noto@chicagobooth.edu; Schilbach: MIT and NBER, fschilb@mit.edu; Zhang: Duke and NBER, jonathan.zhang@duke.edu. We are grateful to Pat Collard, Abigail Joseph, Angelo Marino, Wesley Price, Enzo Profili, Steven Shi, Samuel Wolf, Carine You, and Tracy Zhou for excellent research assistance. We thank Daron Acemoglu, Jonathan Colmer, Steve Cicala, Raj Chetty, Peter Ganong, Emir Kamenica, Pete Klenow, Jing Li, Adriana Lleras-Muney, Lee Lockwood, David Molitor, Tim Moore, Julian Reif, Chris Ruhm, Hannes Schwandt, Jesse Shapiro, Robert Topel, Danny Yagan, six anonymous referees, Larry Katz (the editor) and participants at many seminars for helpful comments, and we thank the Chicago Booth Healthcare Initiative (Notowidigdo) for funding.

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.

We find that the Great Recession substantially reduced mortality. 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 persist for at least 10 years, although the point estimates become less precise and statistically insignificant over time. 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. These estimates imply that the Great Recession provided one in twenty-five 55-year-olds with an extra year of life.

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 appear across many causes of death, including cardiovascular disease, motor vehicle accidents, liver disease, and suicide; no cause of death experiences a statistically significant increase in mortality, and we estimate a precise zero for cancer mortality, the second largest cause of death. We find 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.

Several pieces of evidence suggest that the primary driver of the mortality declines are externalities from reduced aggregate economic activity, holding constant own employment or consumption. First, averted deaths are concentrated in the elderly population—who experienced little if any direct income effects from the Great Recession-induced local labor market decline. Second, we find a quantitatively important role for a particular external channel—recession-induced declines in air pollution; like the mortality declines, recession-induced pollution declines persist throughout our study period and may be able to explain at least 20 percent and potentially all of the recession-induced mortality declines. By contrast, we find little evidence for other mechanisms discussed in the literature: a key direct (i.e., non-externality) mechanism, whereby reduced labor market activity frees up time for beneficial health behaviors (as in Ruhm 2000, 2005), and for two other external channels: reduced spread of infectious disease (as in Adda 2016), or improved quality of nursing home care (as in Stevens et al. 2015).

The recession-induced mortality declines are quantitatively important for estimates of the welfare effects of recessions. Extending the Krebs (2007) model of the consumption-based welfare cost of facing a lifetime risk of recessions, we find that accounting for pro-cyclical mortality substantially reduces the welfare cost of recessions. For example, accounting for pro-cyclical mortality reduces the willingness to pay to avoid future recessions by more than half 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. Willingness to pay to avoid future recessions declines even more dramatically at older ages. Viewed through the lens of our stylized macro model, recessions may even be welfare-improving for the elderly, who benefit from mortality reductions while exhibiting limited consumption responses to recessions. Lastly, endogenous mortality also has important distributional implications: because the mortality declines from recessions are concentrated entirely among those with a high school degree or less, endogenous mortality substantially mitigates—and at older ages even reverses—the regressive nature of recessions that is found when focusing exclusively on consumption.

These findings come with some important caveats. First, our design will not pick up any aggregate impacts of the Great Recession, for example, any nationwide mortality impacts from the stock market collapse (see e.g., McInerney, Mellor and Nicholas (2013)), or any nationwide increase in malaise. 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 fully 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. Fourth, although we analyze the 10-year impact of the

Great Recession shock, our analysis does not measure impacts at even longer time horizons, which may be very different (see e.g., Schwandt and Von Wachter (2020)). Finally, while we view our welfare analysis as a useful way to benchmark the magnitude of our mortality estimates, our analysis falls far short of a comprehensive analysis of the welfare impacts of recessions; it does not incorporate other potential channels for welfare impacts such as reduced job satisfaction, subjective well-being, and public resources for education, or the career costs of recessions for new labor market entrants that have been highlighted in other work (e.g., Akerlof et al. 1988; Kahn 2010; Oreopoulos, Von Wachter and Heisz 2012; Jackson, Wigger and Xiong 2021). These 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.

This 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, Philipson and Soares 2005; Murphy and Topel 2006; Hall and Jones 2007; Jones and Klenow 2016; Brouillette, Jones and Klenow 2021). There has been relatively less attention, however, to incorporating cyclical fluctuations in health into welfare analyses of business cycles.[1]

We also contribute to a much larger empirical literature on the relationship between the economy and health. A considerable body of evidence suggests that improvements in the economy are good for health, based on which one might expect that recessions increase mortality. There is a well-documented negative relationship between income and mortality within countries, across countries, and over time (e.g., Cutler, Deaton and Lleras-Muney 2006; Costa 2015; Chetty et al. 2016; Cutler, Huang and Lleras-Muney 2016), although the causal evidence of the impact of income on mortality is limited and mixed (Dobkin and Puller 2007; Evans and Moore 2012; Cesarini et al. 2016). 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, Dorn and Hanson 2019).

However, the existing empirical work on the relationship between recessions and mortality raises questions about what to expect for the Great Recession. For the decades before the Great Recession, a series of papers starting with the influential paper of Ruhm (2000) have documented

[1] Two exceptions are Edwards (2009) who extends Lucas (1987) to allow for cyclical mortality, and Egan, Mulligan and Philipson (2014) who contrast fluctuations in GDP to fluctuations in mortality-adjusted GDP. They reach different conclusions.

a negative contemporaneous association between area unemployment rates and mortality in area-year panel data both in the US (e.g., Ruhm 2000; Miller et al. 2009; Stevens et al. 2015), and in Canada and several European countries (Neumayer 2004; Granados 2005; Buchmueller, Jusot and Grignon 2007; Ariizumi and Schirle 2012). However, in the decades before the Great Recession, 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, Huang and Lleras-Muney (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 (Currie, Duque and Garfinkel 2015; Currie and Tekin 2015; Strumpf et al. 2017; Seeman et al. 2018; Cutler and Sportiche 2022; Salinari and Benassi 2022; Lamba and Moffitt 2023).When we surveyed over 300 experts in spring 2023 on the impact of the Great Recession on the U.S. mortality rate, 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 estimate, and 82 percent provided a prediction larger than the upper bound of our 95 percent confidence interval (Appendix A).

Our empirical approach follows Bartik (1991), Blanchard and Katz (1992), and especially Yagan (2019) in exploiting regional differences in exposure to a large, aggregate economic shock. We complement existing work, which analyzes the relationship between an area's mortality rate and its contemporaneous unemployment rate, by controlling for area and year fixed effects. Relative to this literature, we offer several innovations. First, our use of a single, spatially differentiated shock allows us to examine 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, Beach and Hanlon (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, such as increased access to or generosity of disability insurance or unemployment insurance.

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.

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 US 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, gender, and education. The population data provide annual, county-level population estimates by single year of age, race, ethnicity, and gender.

Second, we use mortality records from a 20 percent random sample of all Medicare enrollees aged 65+ in the US from 2003 to 2016. The enrollee-level panel data contain information on ZIP Code of residence each year, date of death (if deceased), and demographic variables such as race, ethnicity, gender, and annual enrollment in Medicaid (a proxy for low income). Unfortunately, we do not observe the cause of death. However, 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 any diagnoses 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. Observing mortality and the population denominator in the same data 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. Assigning individuals to their pre-recession locations 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, Beach and Hanlon 2022). Third, we can use the (lagged) data on enrollee health conditions to analyze heterogeneous impacts on mortality by health status, 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 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 focus primarily on fine particulate matter (PM2.5), measured in micrograms per cubic meter (μg/m^3). Using granular, annual data on PM2.5 concentration from van Donkelaar et al. (2020), we construct county-year measures of PM2.5 that cover 99.3% of (population-weighted) counties in the U.S. The authors generate estimates of PM2.5 by combining ground-level pollution monitor measurements from the EPA's Air Quality System (AQS) database with observations of visual occlusion from satellite images to produce estimates of PM2.5 for virtually the entire U.S. We discuss these data—which have recently been used in several studies of pollution as an input or output (e.g., Jha and Nauze 2022; Gould et al. 2023; Molitor, Mullins and White 2023)—in more depth in Appendix B.3. For counties that also have AQS measures of PM2.5, the van Donkelaar et al. (2020) and AQS measures produce similar findings (Appendix C.9).

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 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 US to measure nursing home staffing as well as other characteristics such as patient volume and composition. Third, we draw on restricted-use (state-level) data from the Health and Retirement Survey for 2002-2014—a nationally representative, bi-annual survey of older adults—to examine self-reported measures of formal and informal care received by 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 $SHOCK_c$ measures the economic impact of the Great Recession on area c, $\mathbb{1}(Year_t)$ is an indicator for 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 cluster our standard errors at the local area c. The coefficients of interest are the β_t's; they measure impacts on the outcome y_{ct} in year t across areas differentially impacted by the Great Recession. 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 areas in the US (Appendix Figure A.1), we weight each area-year by its 2006 population, as in prior work 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.[2] 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.[3]

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

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

[2] Specifically, we add one to the mortality rate to avoid taking logs of zeros, although in practice we never need to do so for the aggregate CZ-level analysis. Even when we disaggregate by cause of death or various demographics, mortality rates of zero are extremely rare. Our main results are very similar if we instead estimate a Poisson specification for age-adjusted mortality rates, as recommended by Chen and Roth (2024); see Appendix C.6.

[3] We calculate the age-adjusted mortality rate in a CZ by averaging over the mortality rate in each of 19 age bins within the CZ, weighting each age bin by the national share of the population in that age bin in 2000. This approach 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+.

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 pre-trends in the event study results. Of course, finding similar mortality trends before the Great Recession in areas that are differentially impacted does not guarantee that these areas would have been on similar trends in the absence of the Great Recession, and this assumption becomes less plausible the further out in time we go past the Great Recession.

Measuring the Great Recession Shock. Our empirical strategy relies on the large spatial variation in the economic impact of the Great Recession. This strategy has been previously leveraged to study the impact of the Great Recession on outcomes such as employment (Yagan 2019; Rinz 2022), time use (Aguiar, Hurst and Karabarbounis 2013), consumption (Mian, Rao and Sufi 2013), and educational attainment (Charles, Hurst and Notowidigdo 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 Ia 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 saw an average 2.9 percentage-point increase in the unemployment rate, compared to a 6.7 percentage-point increase in the highest quartile. Especially hard-hit areas 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 Midwest manufacturing states 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 shocks and can be parameterized in different ways. We therefore examine four different measures: unemployment rate, EPOP ratio, log GDP per capita, and log house prices. The spatial variation in the 2007-2009 shock as measured by these variables is highly, but imperfectly, correlated (Appendix Figure A.2). In the national time series (Appendix Figure A.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. Figure Ib documents the wide variation in age-adjusted mortality rates across CZs in 2006, immediately before the Great Recession. Mortality rates were particularly high in the Southeastern United States and low in the Western United States. Figure Ic 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 II plots age-adjusted mortality rates from 2003 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 hard-hit ones, creating a gap in age-adjusted mortality rates that persists through the end of the series in 2016.

The aggregate slowdown in mortality declines after the Great Recession shown in Figure II is an important reminder that our empirical strategy captures only differential mortality declines across local labor markets that are differentially affected by the Great Recession. In other words, we are estimating the impact of differential local labor market shocks produced by the Great Recession, not the overall impact of the Great Recession. The slowdown in the aggregate mortality decline in Figure II could reflect changes in determinants of mortality unrelated to the Great Recession such as the rate of progress in medical technologies, but it could also reflect aggregate impacts of the Great Recession on mortality that would not be captured by our empirical strategy. This limitation is the well-known "missing intercept" problem for macro-economic counterfactuals.[4]

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 are shown in Appendix D.

[4] As one suggestive way to gauge how large this missing intercept might be, Appendix Figure A.5 plots a time series of nationwide log mortality and unemployment from 1969 to 2019, residualized on a linear time trend and then standardized. Appendix Table A.1 displays coefficients from a time-series regression of log mortality on unemployment from 1969-2019, controlling for either a linear or a quadratic time trend; these indicate an even larger negative relationship than we find below when exploiting the spatial variation in the impact of the Great Recession.

3.1 Overall Mortality Estimates

Figure III shows results from estimating equation (1) for log age-adjusted mortality, with the β_{2006} coefficient normalized to zero. Places harder hit by the Great Recession experienced an immediate and pronounced decline in log age-adjusted mortality, which then remained 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 A.4). The slightly positive pre-trend in the mortality estimates from 2003 through 2006 (also visible in Figure II) indicates that before 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 finding 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) and Appendix Figure A.4). The opposite-signed pre-trend in the mortality estimates also suggests that by measuring the mortality impact of the Great Recession relative to 2006, we may be underestimating the extent of recession-induced mortality declines, if the pre-trend reflects unobserved forces that would have continued in the absence of the Great Recession.

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. From 2010 to 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. Compared to the shorter-run estimates, the longer-run estimates are much less precise and are only marginally significant ($p = 0.08$ for 2010-2016, compared to $p = 0.001$ for 2007-2009); however, we cannot reject that the two estimates are identical ($p = 0.78$).[5]

The Great Recession on average increased local area unemployment by about 4.6 percentage points between 2007 and 2009. An increase in the local area unemployment rate of this magnitude thus reduces average mortality by 2.3 percent per year, with effects persisting for at least ten years. This decline is equivalent to the average, two-year secular mortality improvement over the half-century before the Great Recession (see Appendix Figure A.10 and also Ma et al. (2015)). Based on the standard population life table, the ten-year estimates suggest that 1 in 25 of 55-year-olds gained an extra year of life from this sized local shock (Appendix Table A.2).

[5]Although there is work looking at lagged impacts of unemployment on mortality (e.g., Ruhm 2000), 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 economic impact*. In Appendix C.1, we show that a larger initial economic shock continued to translate into larger mortality declines in 2010-2016, both in areas with below-median economic recoveries from 2010-2016 and in areas with above-median recoveries. However, like our overall estimates of mortality declines in Figure III, these 2010-2016 estimates also lack precision, and the two areas' estimated impacts in 2010-2016 are not statistically distinguishable from zero, or from each other.

3.2 Unpacking the Overall Mortality Decline

Mortality rates vary substantially across demographic groups and reflect several underlying causes (Appendix Table A.3).[6] 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 several 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). In this section, we examine the nature of the mortality decline across causes of death and various demographics and briefly explore impacts on morbidity. Because the patterns are often similar in the 2007-2009 period and the 2010-2016 period, we focus most of the discussion on the 2007-2009 period, where we have greater precision. We frequently summarize the average estimates; all underlying event studies are shown in Appendix D.

By cause of death. Figure IVa shows the estimated 2007-2009 mortality impacts for each of the top 11 causes of death (arranged in descending order of prevalence in 2006) and a final residual category for all other causes (Appendix Figure A.7a does the same for estimated 2010-2016 impacts). Because the underlying mortality rates differ greatly by cause, Figure IVb combines these estimates with 2006 cause-specific mortality rates to report the share of the recession-induced 2007-2009 mortality reduction accounted for by each cause of death.

Cardiovascular disease accounts for both the largest share of deaths and the largest share of the estimated total reduction in deaths. 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). Since cardiovascular disease accounted for over one-third of total mortality in 2006, the estimate implies that nearly half (48 percent) of the deaths averted by the Great Recession would have been caused by cardiovascular disease. By contrast, while their percentage mortality reductions are large and statistically significant, 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.[7]

Most other point estimates in Figure IVa also indicate mortality declines, and no cause of death experiences a statistically significant increase in mortality. Several other causes of death—lower respiratory disease, influenza/pneumonia, kidney 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, which is the second largest cause of

[6] We use the top 11 causes of death in 2006 from the Department of Vital Statistics' List of 39 Selected Causes of Death, and group all remaining causes into a single residual category. See Appendix B for more detail.

[7] Given the large (22.5 percent) share of deaths in the residual category, we also analyzed an alternative, standard cause-of-death grouping into 10 mutually exclusive categories and yields a much smaller (3.5 percent) share of deaths in the residual category. The two approaches code many causes similarly, so the results are quite similar. We discuss the alternative coding, how it compares to our baseline, and the results in more detail in Appendix C.2.

death, 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.

Figure V displays the full event-study estimates from 2003 to 2016 for cardiovascular disease, cancer, motor vehicle accidents, suicide, liver disease, and homicide (event studies for the remaining causes of death are in Appendix Figure A.8). The effects on cardiovascular and liver mortality appear persistent, with long-run (2010-2016) estimates similar to short-run (2007-2009) estimates, but with larger standard errors. By contrast, the effects on mortality from motor vehicle accidents have entirely dissipated by 2016, while the modest decline in suicide due to the Great Recession over the 2007-2009 period 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 effect is striking given state-year panel estimates that increases in unemployment are associated with contemporaneous *increases* in suicides (Ruhm 2000; Harper et al. 2015), and may reflect recession-induced reductions in pollution as we discuss below.

Not surprisingly in light of the recession-induced declines in both suicides and deaths from liver disease, the Great Recession reduced "deaths of despair" (Case and Deaton 2015, 2017, 2021)—deaths from suicide, liver disease, and drug poisonings—in the 2010-2016 period. A one-percentage-point increase in the 2007-2009 unemployment rate is associated with a 1.4 percent (standard error = 0.63) decline in deaths of despair from 2010-2016 (Appendix Figure A.11a). Consistent with this, 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 more exposed to import competition from China experienced an increase in deaths of despair primarily among working-age populations.

By age. Figure VI displays 2007-2009 mortality declines for each age group, indicating that the Great Recession is associated with quantitatively and statistically similar percentage reductions in mortality rates across all (adult) age groups. The point estimates in Panel (a) are broadly similar across age groups, with many statistically significant. While the point estimates are larger at younger ages, they are also quite imprecise. Longer-term 2010-2016 estimates, as displayed in Figure A.7b, display similar trends. When we aggregate into larger age groups, we are unable to reject the hypothesis that the average percentage decline in mortality across the years 2007-2009 is the same for ages 25-64 and for 65+ ($p = 0.30$).[8]

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 propor-

[8] By contrast, we can reject that the percentage decline in mortality for 0-24-year-olds is the same as either the percentage decline for 25-64-year-olds ($p = 0.01$) or for 65+-year-olds ($p = 0.03$).

tional to their 72.5 percent share of total mortality in 2006. The slightly larger percentage decline in mortality rates for 0-24-year-olds seen in panel (a) has little quantitative significance for the total mortality declines, given the very low baseline mortality rate of this age group.

By education. Strikingly, the entire recession-induced mortality decline is concentrated among those with a high school degree or less (Panel (a) of Figure VII). Specifically, among those age 25 and over, we compare impacts separately for the roughly half of the population with a high school degree or less to those with more than a high school degree.[9] 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 within age groups (Appendix Figure A.43). Second, 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.[10] Third, given potential concerns that the differential impacts by education might reflect differences across areas with different education shares, we confirmed that there is little variation in the share of a state's population with a high school degree or less, and little correlation between the state-level Great Recession shock and the education share.[11] 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 (a proxy for low-income) in the prior year (Appendix Figure A.44).

[9] Due to data limitations explained in more detail in Appendix C.3, this analysis is conducted at the state rather than CZ level, is limited to individuals ages 25 and older, and excludes a few states with missing data. As shown in that Appendix, these restrictions have little impact on our estimates.

[10] When we dis-aggregate the lower education sample into those with less than a high school degree and those with exactly a high school degree, we see declines in both subgroups (Appendix Figure A.42), although the estimates become much noisier and statistically insignificant for these sub-groups.

[11] The (population-weighted) mean state has 52 percent of the population with a high school degree or less, and the 10-90 range is only 0.46 to 0.58. The correlation between the state-level Great Recession shock and the share with a high school degree or less is 0.16, and not statistically significantly different from zero. Expanding our analysis to allow for calendar year effects to vary with the share of the state's population with a high school degree or less in 2006 yields unchanged results (see Appendix Section C.6, and especially Appendix Figure A.18).

By gender and by race/ethnicity. We find no evidence of differential mortality impacts by gender, with nearly identical estimates for males and females (Figure VII Panel (b)). 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 (Figure VII Panel (c)).

Health status of marginal lives saved. When examining mortality effects over short time horizons—such as a day or three days—a natural question is whether they reflect a meaningful change in mortality over longer horizons, or merely a slight re-timing of deaths, a phenomenon often referred to as "mortality displacement" or "harvesting." Researchers tend to investigate this possibility by studying 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 study effects at the annual level that persist over 10 years.

Nevertheless, for our welfare analysis in Section 5, it matters whether the remaining life expectancy of the marginal lives saved by the Great Recession differs from that of the typical decedent of the same age. 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. 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 (see Appendix C.4 for more detail).

Morbidity. 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 with low mortality (see Appendix Table A.3). The focus on mortality therefore raises the possibility that we are missing important non-mortality health effects at younger ages that might eventually 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 mortality increases.

In the spirit of Ruhm (2003), we therefore explore, where feasible, the impact of the Great Recession on measures of morbidity. We sign each measure so that—like mortality—higher values indicate 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: (i) health that is less than very good, (ii) any days in the last month with poor mental health, (iii) ever been diagnosed with diabetes, and (iv) currently have asthma. Since we cannot observe commuting zones in the BRFSS, we estimate equation (1) at the state level.[12]

[12]We show in Appendix C.6 that our baseline mortality estimates (Figure III) are unchanged when switching from

Figure VIII shows evidence that the Great Recession reduced morbidity. Panel (a) shows the results for the measures of self-reported morbidity individually and for the average treatment effects, created by taking the simple average of treatment effects across the measures. The Great Recession caused a statistically significant 1.26 percent reduction (standard error = 0.47) of the morbidity index over the 2007-2009 period and a 1.19 percent reduction (standard error = 0.51) over the entire 2007-2016 period. This morbidity reduction reflects declines in each measure 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 0.98 percent (standard error = 0.59) 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 1.37 percent (standard error = 1.13) decline in the share who report themselves as having asthma. The declines in average morbidity are similar across age groups (18-45, 46-64, and 65+), although 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.

3.3 Investigating Sensitivity to Population Changes: Medicare Panel Data

If recessions affect the size or composition of the local population in a way that is not captured by our population measures, such impacts could bias the estimated relationship between recessions and mortality. Arthi, Beach and Hanlon (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.[13] This finding 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 the estimated population declines driving our findings is that we estimate a precise zero for declines in cancer mortality, the second leading cause of death (Figure IV). If estimated declines in the mortality rate simply reflected unmeasured declines in population, we would expect to see declines in mortality for all major causes of death.[14]

To directly explore the sensitivity of our findings to unmeasured population changes, we turn to

the commuting zone to the state level for analysis.

[13]See Appendix Figure A.12 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 2024). We also show in Appendix C.5 that population composition based on gender, race, and education does not change in areas that are more vs. less impacted by the Great Recession (Appendix Figure A.13) and that predicted mortality —based on gender, race, and education—does not change in areas that are more vs. less impacted by the Great Recession (Appendix Figure A.14.)

[14]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.

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, Gentzkow and Williams 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.

We begin by showing Gompertz estimates for the sample of Medicare enrollees we observe in 2003 and follow forward, using their yearly location. Specifically, we estimate:

$$\log(m_{it}(a)) = \rho a + \beta_t[SHOCK_{c(i,t)} * \mathbf{1}(Year_t)] + \alpha_{c(i,t)} + \gamma_t + \epsilon_{it}. \tag{3}$$

Once again, γ_t are year fixed effects, and we cluster standard errors at the CZ level.

Table I row 1 (and Appendix Figure A.15a) shows estimates based on yearly location. The 2007-2009 estimate indicates that a one-percentage-point increase in the local area unemployment rate reduces the annual mortality rate by 0.51 percent (standard error = 0.16), which is nearly identical to our baseline estimate in Figure III.[15]

We then report results from estimating the "reduced-form" impact of the Great Recession based on individuals' location in 2003:

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

The key distinction is that 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. Measuring location pre-recession alleviates concerns about potential contamination from differential population flows into or out of areas that experience different shocks. We continue to find a statistically significant decline in mortality from an increase in the unemployment rate (Table I, row 2 and Appendix Figure A.15b). In the 2007-2009 period, a one-percentage-point increase in the local area unemployment rate reduces the annual 2-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:

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

[15]For the 65+ population, our baseline analysis using equation (1) in the CDC data (as displayed in Figure VI) looks similar to results from estimating equation (1) using the 65+ Medicare repeated cross-sectional data and using a subsample of Medicare enrollees whom we can observe in 2003 and follow forward (see Appendix Figure A.17).

The first stage is large (Table I, row 3 and Appendix Figure A.15c), 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 (Table I, row 4 and Appendix Figure A.15d) when we use the $\hat{v}_{it}$ residuals from equation (5) as an additional regressor in the following equation:

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

The identifying assumption behind this control function approach is that while a person's 2003 location of residence may directly affect 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, Gentzkow and Williams (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. The control function estimated mortality effect from 2007-2009 of -0.37 (standard error = 0.17) is smaller in absolute value—but not statistically distinguishable from—the estimate based on yearly residence in row 1. This difference may reflect the presence of unmeasured population declines in areas harder hit by the Great Recession. Finally, Table I, row 5 (Appendix Figure A.16) shows estimates based on yearly location (i.e., estimating equation (3)), limited to the 88 percent of the sample who does not move CZ from their 2003 location; these estimates are also quite similar to the estimates based on year residence for the full sample (row 1).

Additional sensitivity analyses. In Appendix C.6, we explore the sensitivity of our baseline mortality estimate in Figure III to several alternative specifications. These include (i) the geographic unit of analysis (CZ vs. state vs. county), (ii) our choices regarding functional form for both the dependent variable and the key independent $SHOCK_c$ variable, and (iii) the sample of CZs included in the analysis (to confirm, for example, that our findings do not spuriously reflect impacts of the geographically-concentrated fracking boom that occurred during our time period). The results are quite stable across these alternatives. Several additional analyses lend support to the assumption in our baseline specification that the log mortality rate is *linear* in the size of the shock; for example, the estimated impacts are similar whether estimated based on CZs that experienced an above-average or below-average unemployment shock. Since the average shock to the unemployment rate during the Great Recession was much higher than a typical recession, this linearity increases our confidence that our mortality findings may generalize to more "typical" recessions.

4 Mechanisms

Recessions might reduce mortality via several channels. We group them 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 on health.[16] Internal and external effects have different implications for the welfare consequences of our findings. External health benefits from reduced economic activity would suggest that the negative welfare effects from reduced income and consumption are mitigated by positive welfare effects from improved health. In contrast, the welfare implications of mortality reductions from internal effects would be less clear-cut, and depend in part on whether individuals engage in privately optimal behavior. Our findings strongly point to external effects as the primary driver of the recession-induced 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, which 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. 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).

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 (Appendix C.8 and especially Appendix Figure A.20).[17] Second, the time pattern of the mortality reductions—an immediate decline that does not grow larger over time (recall Figure III)—is not consistent with an important role for changes in health behaviors; we would expect changes in exercise, diet, or smoking to impact mortality with a lag and to grow over time as health capital improves.[18]

[16]We use the term external effects rather than externalities to indicate a broader set of health effects from factors other than individual-level behavioral responses. Of course, 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—likely reflect a mix of both internal effects (single car accidents) and external effects (multi-car accidents).

[17]Consistent with our findings, other work using the same empirical strategy has similarly found little evidence of Great Recession-induced employment declines for the elderly. For example, (Rinz 2022) finds much more modest and short-lived declines in elderly employment compared to impacts at younger ages.

[18]For example, studies of the impact of smoking cessation on mortality find that effects grow gradually over a 10-

We find little direct evidence of a substantive role for internal effect. We do not find a statistically significant impact of the Great Recession on self-reported health behaviors (Figure VIII, Panel (b)) either individually or pooled 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, that they did not receive a flu shot in the past year, or that they are currently overweight or obese. That said, while imprecise, some of the point estimates are consistent with potentially large improvements in certain health behaviors such as smoking and exercise, which might ultimately translate into important health improvements.[19] We also find no evidence of a substantively or statistically significant impact on healthcare use among the elderly, measured in the Medicare data by physician visits, ER visits, or total expenditures (Appendix Figure A.21).[20] 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 IV and Appendix Figure A.11b). However, the combined decline in mortality that may be due to health-harmful consumption 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 air pollution (Chay and Greenstone 2003; Heutel and Ruhm 2016), increases in the quality of healthcare (Stevens et al. 2015), and reductions in the spread of infectious disease (Adda 2016). We find evidence consistent with a quantitatively important role for recession-induced reductions in air pollution—which can explain at least one-fifth and potentially a much larger share of the recession-induced mortality declines—but little support for a role for the latter two classes of external effects.

Reduction in air pollution. To examine the impact of the Great Recession on air pollution and the extent to which this channel is responsible for the reduction in mortality, we conduct our analysis at the county level. County-level analysis provides a better measure of a person's exposure

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).

[19] For example, we estimate that on average over the 2007-2009 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 0.8 percent (standard error = 0.6 percent). Interestingly, although statistically insignificant, the point estimates are often similar in magnitude to those found in Ruhm (2000). Appendix Table A.4 shows this more clearly by estimating the specification in levels and reporting the comparable estimates from Ruhm (2000).

[20] 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. This increase in the rate of inpatient admissions may reflect compositional changes, as elderly individuals who would have died are now alive and at risk of hospitalization.

to pollution than CZ-level analysis; 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:

$$y_{ct} = \beta_t[SHOCK_{cz(c)} * \mathbb{1}(Year_t)] + \alpha_c + \gamma_t + \varepsilon_{ct}, \tag{7}$$

where c now denotes county, cz denotes commuting zone, and $SHOCK_{cz(c)}$ is defined identically as in equation (1). Figure IXa confirms that our estimates of the impact of the Great Recession on mortality remain very similar to our baseline results in Figure III when we estimate equation (7) at the county level using the age-adjusted log mortality rate as the dependent variable.

Counties that were harder hit by the Great Recession also experienced larger declines in pollution, with these declines persisting through the end of our study period (Figure IXb). Following the recent air pollution literature (e.g., Deryugina et al. 2019; Dedoussi et al. 2020; Currie, Voorheis and Walker 2023), we focus on PM2.5 (in μg/m^3) as the dependent variable when estimating equation (7). A one-percentage-point increase in the CZ level unemployment rate from 2007-2009 is associated with an average reduction of PM2.5 from 2007-2009 of 0.14 micrograms per cubic meter (μg/m^3) (standard error = 0.039), and from 2010-2016 of 0.20 (standard error = 0.055); to put that in perspective, the average 0.18 μg/m^3 decline from 2007-2016 represents a 1.7 percent decline relative to the 10.5 μg/m^3 population-weighted national average level of PM2.5 in 2006. Consistent with existing work showing that recessions decrease air pollution (e.g., Chay and Greenstone 2003; 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 Figure IXb 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 in 2007—is consistent with a large existing literature indicating impacts of (contemporary) pollution on (contemporary) mortality (see, e.g., Graff Zivin and Neidell 2013; Currie et al. 2014, for reviews). Second, both mortality declines and PM2.5 declines persist to the end of our study period. Third, 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, Mullins and White 2023), all areas where we found statistically significant mortality declines (recall Figure IV). Fourth, the recession-induced mortality declines are concentrated in the half of the population with a high school degree or less, consistent with less educated and lower-income individuals being disproportionately exposed to greater levels of air pollution both overall (Bell and Ebisu 2012; Hajat, Hsia and O'Neill

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. Three complementary approaches suggest that pollution is a quantitatively important channel behind the estimated mortality declines. First, combining 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, a back-of-the-envelope calculation suggests 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 the mortality estimates used from Deryugina et al. (2019). This calculation 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 (see details in Appendix Section C.10).

Second, to more directly gauge the quantitative importance of the pollution channel, we use the fact that while counties that were harder hit by the Great Recession on average experienced a larger decline in pollution (Figure IXb), there is substantial heterogeneity in this relationship (Figure IXc). 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, Mogstad and Rønning 2021). Specifically, we estimate:

$$y_{ct} = \beta_t[SHOCK_{cz(c)} * \mathbb{1}(Year_t)] + \phi_t[PM2.5\_SHOCK_c * \mathbb{1}(Year_t)] + \alpha_c + \gamma_t + \varepsilon_{ct}, \qquad (8)$$

where y_{ct} is the log age-adjusted mortality rate, $SHOCK_{cz(c)}$ is defined identically as in equation (7), 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).[21]

Figure IXd shows the estimates of β_t from equation (8). Controlling for the pollution shock attenuates the estimated impact of the Great Recession on mortality from 2007-2009 by about 20 percent, from a one-percentage-point increase in unemployment reducing mortality by 0.50 percent (Figure IXa) to 0.39 percent (Figure IXd).[22]

[21] We parameterize $PM2.5\_SHOCK_c$ as the negative 2006 to 2010 change because this change is highly correlated with $SHOCK_{cz(c)}$ (Figure IXc), while other parameterizations such as the 2006-2009 change in PM2.5 or the 2006-2016 change are much less highly correlated, thereby leaving little room for PM2.5 as a mediator. Using measures of changes in PM 2.5 that are not highly correlated with the Great Recession shock seemed contrary to the spirit of the mediation exercise, which is designed to quantify in our setting how the estimated impact of the Great Recession on mortality may be mediated by the estimated impact of the Great Recession on pollution.

[22] Appendix C.9 shows similar results when we focus on the subset of counties where we can measure PM 2.5 in both the EPA monitor data and the baseline data used in Panels (b) and (d) of Figure IX. Using the EPA data, we find no significant impacts of the Great Recession on other pollutants, specifically carbon monoxide and ozone.

Third, to isolate exogenous variation in the PM2.5 shock—and to avoid potential downward bias due to classical measurement error in the PM2.5 shock—we also estimate an instrumental variables version of equation (8). We instrument for a county's PM2.5 shock using the CZ-level Great Recession economic shocks in upwind neighboring counties outside of the county's CZ (see Appendix C.11 for more detail). Consistent with measurement error in the PM 2.5 variable, recession-induced pollution declines now appear to have a greater role in explaining the recession-induced mortality declines. Whereas with the OLS analysis, the recession-induced pollution declines explain about 20 percent of the recession-induced mortality declines from 2007-2009, they appear potentially able to explain them entirely in the IV analysis.[23]

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

Improved quality of nursing home care for the elderly. Tighter labor markets may result in improved quantity and quality of healthcare workers. Such changes seem 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. Given widespread concerns about worker shortages in these sectors (e.g., Geng, Stevenson and Grabowski 2019; Grabowski, Gruber and McGarry 2023), increased availability of direct care workers could in turn have meaningful health benefits for the elderly. Indeed, Stevens et al. (2015) provide 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 X(a) shows results from re-estimating equation (1) in the Medicare data, separately for the 7 percent of the population that was in a nursing home in any given year or the previous year and the 93 percent that was 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

[23] The possibility that recession-induced declines in pollution may explain the entirety of recession-induced declines in mortality is broadly consistent with the evidence in Chay and Greenstone (2003), who use geographic variation in reductions in air pollution caused by the 1981/82 recession to assess the impact of air pollution on infant mortality. Their analysis differs from ours in several ways, including their pollution measure—total suspended particulate (TSP) levels, which is a super-set of our air pollution measure of PM2.5 particles—their focus on infant mortality, and their exclusion restriction that the only way the recession affected infant mortality was via effects on pollution. With these caveats in mind, we can apply their headline estimate—a 1-percent reduction in TSP results in a 0.35 percent decline in the infant mortality rate—to our setting. Since we estimate a 1.5 percent reduction in PM 2.5, based on their estimate, we would expect a 0.52 percent decline in mortality, which is nearly identical to our baseline estimate.

or previous year have much higher mortality rates—this 7 percent of the elderly accounts for 32 percent of their annual deaths. 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.[24] 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.7, 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, although the results are fairly noisy.[25]

5 Welfare Consequences of Recessions with Endogenous Mortality

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. To do so, we augment Krebs (2007)'s calibrated model of the welfare cost of facing a lifetime of possible recessions to allow mortality to also vary with the business cycle; this extension allows us to gauge the quantitative importance of our estimates of endogenous mortality on a "'standard" calibration of the welfare cost of recession risk. Our augmentation follows existing work that incorporates changes in life expectancy into welfare analyses (e.g., Becker, Philipson and Soares 2005; Jones and Klenow 2016) by assuming that gains in life expectancy represent improvements in well-being.

5.1 Model

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

$$U(c(t), m(t)) = \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t S(m(t)) u(c(t)) \right] \tag{9}$$

where $c(t)$ is the agent's consumption in period t, $m(t)$ is the mortality rate (allowed to vary over the life-cycle), and β is the agent's subjective discount rate. The cumulative survival rate

[24] For example, the point estimates suggest that for every one-percentage-point increase in the local area unemployment rate 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.

[25] 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 before the Great Recession, and annual, state-level information on vehicle miles traveled is inconsistently reported and of questionable reliability (Federal Highway Administration 2014).

$S(m(t)) = \prod_{\tau=0}^{\tau=t}(1-m(\tau))$ 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., $T = \sum_{t=0}^{\infty} S(m(t))$.

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

$$u(c) = b + \frac{c^{1-\gamma}}{1-\gamma}, \tag{10}$$

where b governs the willingness to pay for additional years of life. Assuming that $\beta = 1$ and that consumption is constant over time, the value of a statistical life-year (VSLY) is given by:

$$\text{VSLY} = \frac{U(c,m)/u'(c)}{T} = bc^{\gamma} - \frac{c}{\gamma - 1}, \tag{11}$$

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 we assume that consumption always equals income in each period ($c(t) = y(t)$ for all t); i.e., there is no saving, borrowing, or insurance.[26]

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 and the probability of a recession ($\omega = L$) given by $1 - \pi_H$. 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:

$$y_{t+1} = (1+g)(1+\theta_{t+1})(1+\eta_{t+1})y_t \tag{12}$$

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:

$$\eta_{t+1} = \begin{cases} -d^{\omega} & \text{with probability } p^{\omega} \\ \frac{p^{\omega} d^{\omega}}{1-p^{\omega}} & \text{with probability } 1 - p^{\omega} \end{cases} \tag{13}$$

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

[26] In Krebs (2007), the agent choosing consumption equal to income each period is derived as an equilibrium outcome. We instead assume $c(t) = y(t)$ at the outset to make it as easy as possible to compare our results to the original results in Krebs (2007). Based on one of our referees' comments, we conjecture that $c(t) = y(t)$ is also an equilibrium outcome in our extended model as long as the borrowing rate and lending rate differ due to exogenous financial intermediation costs (and the resulting interest rate spread is sufficiently large), and the intertemporal elasticity of substitution for consumption is sufficiently small. In this case, the agent will find it too costly to borrow when young to smooth consumption.

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, 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:

$$\underbrace{\mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t S(m^{\omega}(t))u((1+\Delta^{dm})y(t))\right]}_{\text{Expected Lifetime Utility with Stochastic Aggregate State}} = \underbrace{\mathbb{E}_0^{\omega=H}\left[\sum_{t=0}^{\infty}\beta^t S(m^{\omega=H}(t))u(y(t))\right]}_{\text{Expected Lifetime Utility without Recessions}}, \tag{14}$$

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 VI—that a recession lowers the mortality rate by a constant percentage across all age groups. Thus:

$$m^L(t) = (1 + dm) \cdot m^H(t) \tag{15}$$

for all t, and recall from our empirical estimates that dm (the percentage change in mortality caused by a recession) is negative. [27]

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 E.1 that, if we set $p^H = 0$ and take a first-order approximation of the formula for Δ^{dT}, we obtain:

$$\Delta^{dT} \approx \Delta - dT\left(\frac{\text{VSLY}}{c} + \frac{1}{\gamma - 1}\right). \tag{16}$$

[27] In this setup, when $\omega = H$ for all time periods, lifetime consumption risk is reduced (since income shocks are larger and more likely in recessions compared to normal times), and lifetime mortality is increased. Following Krebs (2007), mean consumption growth remains the same when recessions are eliminated; life expectancy decreases when recessions are eliminated because $dm < 0$. A natural extension would be to allow mean consumption growth to increase when recessions are eliminated.

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.[28] 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 as a share of annual consumption in the normal state ($VSLY/c$) plus an adjustment factor $1/(\gamma - 1)$.[29] This result implies that no matter how costly the recession is in terms of labor earnings, there always exists a value of the VSLY (given a change in life expectancy 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 (16) 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. Next, recall our empirical findings of (roughly) equi-proportional impacts on the mortality rate across ages. Using the population mortality rates from the 2007 SSA life tables used in the calibration below, recessions produce larger percentage gains in life expectancy (dT) at older ages (see Appendix Table A.2). 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.[30]

5.2 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 calibration 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. We

[28] The additive separability—which we will find is a fairly 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.

[29] Intuitively, the adjustment factor comes from the fact that if $\gamma > 1$ and $b = 0$, then $VSLY < 0$, which perversely implies that individuals are willing to pay to reduce life expectancy. In Appendix E.2, we derive exact analytical results and a similar approximation formula for the full dynamic model developed. We find a similar approximation formula that includes an additional term coming from the income and consumption dynamics in the full model.

[30] For additional intuition, note that a proportional change in mortality rates has a larger relative impact on survival rates at higher (compared to lower) mortality rates. As a result, a given percentage decline in mortality rates across the age distribution leads to larger percentage gains in life expectancy (dT) at older ages.

ignore potential recession-induced morbidity improvements (see Figure VIII), which would further mitigate the welfare losses associated with reduced consumption. [31]

We report results for VSLYs that correspond to two, five, or eight times annual consumption at age 35 (which is normalized to 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 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 (11) for each value of γ assuming annual consumption of $c = \$50k$. 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 E.3.

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 aged 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 (14), we numerically simulate the economy for a large number of individuals ($N = 1,000$).[32]

5.3 Results

Baseline results. Figure XIa shows our baseline estimates of the welfare cost of recessions for people starting at different ages between 35 and 75, with and without accounting for endogenous mortality. 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. 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 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

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

[32] To increase the accuracy of our simulations, we carry out 200 independent simulations and calculate Δ^{dm} by solving equation (14) numerically in each simulation, and then calculate the simple average across the 200 simulations for each value of Δ^{dm} that we report in our figures and tables.

annual consumption to 0.91 percent (a decline of 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 1.15 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 A.5). 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.

Heterogeneity by education. Recessions tend to more adversely impact consumption among those with less education (see, e.g., Guvenen, Ozkan and Song 2014; Mian and Sufi 2016). The heterogeneous mortality impacts of the recession by education (shown in Section 3) provide a countervailing force that mitigates this regressive nature of recessions. To study this through the lens of our model, we allow both the economic and mortality impacts of recessions to vary with education based on our empirical estimates of the mortality effects of recessions by education, as well as calibrated education-specific mortality rates and education-specific job displacement probabilities and earnings losses conditional on displacement (see Appendix E.4 for more details).

Accounting for the differential endogenous mortality by education mitigates—and ultimately reverses—the regressivity of recessions under exogenous mortality (Figure XIb). For those with more than a high school degree, the welfare effects with exogenous and endogenous mortality are nearly identical, since we estimate effectively no mortality impacts of recessions for this group. For those with a high school education or less, the welfare cost of recessions with exogenous mortality is substantially higher than for those with more education, reflecting the greater economic impact on the less educated group. However, accounting for endogenous mortality reduces the welfare cost of recessions for those with a high school education or less; as individuals age, the impact of endogenous mortality for the less educated becomes so large that it closes and ultimately reverses the finding under exogenous mortality that recessions are more costly for those with less education. With exogenous mortality, the welfare cost of recessions for those with a high school degree or less is about five times as large as it is for those with more than a high school degree between ages 35 and 55. However, with endogenous mortality, the welfare costs of recessions converge for the two education groups by about age 50, and after that are less costly for those with less education.

Accounting for retirement. The welfare analysis thus far has made the (extreme) assumption that the economic impacts of recessions are the same at all ages. This assumption is unlikely to be true. Indeed, in the context of the Great Recession's local labor market shocks, the evidence suggests much smaller (or perhaps even no) economic impacts for the elderly (see e.g., Rinz (2022) as well as Appendix Figure A.20). To assess the potential importance of this heterogeneity in economic impacts by age, Figure XIc displays welfare analyses under a different (extreme) assumption of no impact of recessions on income for agents aged 65 and over, i.e., everyone at this age is retired and on a fixed income. Once again, the figure displays results for $\gamma = 2$ and the value of b that corresponds to a VSLY of \$250k, while Appendix Table A.6 shows results for a range of assumptions about risk aversion and the value of a statistical life-year.

As expected, relative to the baseline results in Figure XIa which ignore retirement and assume the same income process for all ages, welfare costs of recessions are now lower because income is unaffected by recessions starting at age 65. With exogenous mortality, welfare costs of recessions are now (mechanically) zero starting at age 65. With endogenous mortality, recessions now become welfare improving around age 50 rather than around 55 when we ignore retirement. Indeed, in a model with endogenous mortality and retirement, eliminating recession risk at age 55 reduces welfare by about 0.52 percent of average annual consumption, and eliminating it at age 65 reduces welfare by about 2.12 percent of average annual consumption.

Accounting for mortality effects of job displacement. Lastly, we extend our model to allow for job displacements to increase mortality among the displaced and we calibrate the extended model to match the empirical results in Sullivan and Von Wachter (2009) who find large effects of job displacements on mortality for high-tenure workers (see Appendix E.5 for more detail).[33] The welfare cost of recessions is about twice as large for workers who are ever displaced compared to workers who are never displaced, and the gap in welfare costs of recessions between endogenous and exogenous mortality is larger for workers who are never displaced compared to the gap for all workers in our baseline model calibration. Intuitively, this is because our baseline mortality estimates are *net* of any countervailing mortality increases caused by job displacements, so once we account for the mortality effects of job displacements, recessions must cause even larger mortality reductions for non-displaced workers to match our main empirical results. One implication is that any recession that triggers an unusually large number of job displacements of high-tenure workers is likely to have smaller reductions (or potentially even increases) in mortality in the aggregate compared to our Great Recession estimates.[34]

[33] In contrast to previous analyses that consider ex-ante differences in welfare costs across workers with different characteristics, we now compare the *ex-post* welfare costs of workers who are displaced vs. not displaced.

[34] We have followed Krebs (2007) in modeling recessions as being associated with increases in rates of job displacement. However, if instead recessions are primarily driven by reductions in the job-finding rate rather than by increases in the job-separation rate as documented by (Shimer 2012), then the recession-induced reductions in mortality documented above may not be netting out substantial increases in mortality from job displacement of the kind documented in Sullivan and Von Wachter (2009).

6 Conclusions

We examined the impact of the Great Recession on mortality and explored its implications for the welfare consequences of recessions. We find evidence of pro-cyclical mortality driven largely by the external health effects of reduced local 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.

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 (and similar mechanisms behind them) from other economic shocks such as natural resource booms and busts (Black, McKinnish and Sanders 2005; Feyrer, Mansur and Sacerdote 2017), adoption of industrial robots (Acemoglu and Restrepo 2020), the North American Free Trade Agreement (Choi et al. 2024), and increased import competition from China (Autor, Dorn and Hanson 2013).

References

Acemoglu, Daron and Pascual Restrepo, "Robots and Jobs: Evidence from US Labor Markets," *Journal of Political Economy*, 2020, *128* (6), 2188–2244.

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

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

Akerlof, George A, Andrew K Rose, Janet L Yellen, Laurence Ball, and Robert E Hall, "Job switching and job satisfaction in the US labor market," *Brookings papers on economic activity*, 1988, *1988* (2), 495–594.

Antwi, Yaa Akosa and John R Bowblis, "The Impact of Nurse Turnover on Quality of Care and Mortality in Nursing Homes: Evidence from the Great Recession," *American Journal of Health Economics*, 2018, *4* (2), 131–163.

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

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

Autor, David, David Dorn, and Gordon Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–2168.

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

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

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

Bell, Michelle and Keita Ebisu, "Environmental Inequality in Exposures to Airborne Particulate Matter Components in the United States," *Environmental Health Perspectives*, 2012, *120* (12), 1699–1704.

Black, Dan, Terra McKinnish, and Seth Sanders, "The Economic Impact of the Coal Boom and Bust," *The Economic Journal*, 2005, *115* (503), 449–476.

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

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

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

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

Burton, Anne M. and Travis Roach, "Negative Externalities of Temporary Reductions in Cognition: Evidence from Particulate Matter Pollution and Fatal Car Crashes," *Working Paper*, 2023.

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

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

_ **and** _ , "Mortality and Morbidity in the 21st Century," *Brookings Papers on Economic Activity*, 2017, pp. 397–476.

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

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

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

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

Chen, Jiafeng and Jonathan Roth, "Logs with zeros? Some problems and solutions," *The Quarterly Journal of Economics*, 2024, *139* (2), 891–936.

Chernozhukov, V., I. Fernández-Val, and A. Galichon, "Improving Point and Interval Estimators of Monotone Functions by Rearrangement," *Biometrika*, 2009, *96* (3), 559–575.

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

Choi, Jiwon, Ilyana Kuziemko, Ebonya Washington, and Gavin Wright, "Local economic and political effects of trade deals: Evidence from NAFTA," *American Economic Review*, 2024, *114* (6), 1540–1575.

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

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

Feyrer, James, Erin T Mansur, and Bruce Sacerdote, "Geographic Dispersion of Economic Shocks: Evidence from the Fracking Revolution," *American Economic Review*, 2017, *107* (4), 1313–1334.

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

Foster, Ann C., "Beyond the Numbers: Consumer Expenditures Vary by Age," https://www.bls.gov/opub/btn/volume-4/pdf/consumer-expenditures-vary-by-age.pdf 2015.

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

Gould, Carlos F, M Lorena Bejarano, Brandon De La Cuesta, Darby W Jack, Samuel B Schlesinger, Alfredo Valarezo, and Marshall Burke, "Climate and health benefits of a transition from gas to electric cooking," *Proceedings of the National Academy of Sciences*, 2023, *120* (34), e2301061120.

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

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

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

Guvenen, Fatih, Serdar Ozkan, and Jae Song, "The Nature of Countercyclical Income Risk," *Journal of Political Economy*, 2014, *122* (3), 621–660.

Hajat, Anjum, Ana V Diez-Roux, Sara D Adar, Amy H Auchincloss, Gina S Lovasi, Marie S O'Neill, Lianne Sheppard, and Joel D Kaufman, "Air Pollution and Individual and Neighborhood Socioeconomic Status: Evidence from the Multi-Ethnic Study of Atherosclerosis (MESA)," *Environmental Health Perspectives*, 2013, *121* (11–12), 1325–1333.

_ **, Charlene Hsia, and Marie S O'Neill**, "Socioeconomic Disparities and Air Pollution Exposure: A Global Review," *Current Environmental Health Reports*, 2015, *2*, 440–450.

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

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

Hershbein, Brad and Bryan A Stuart, "The Evolution of Local Labor Markets After Recessions," *American Economic Journal: Applied Economics*, 2024, *16* (3), 399–435.

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

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

Jackson, C Kirabo, Cora Wigger, and Heyu Xiong, "Do school spending cuts matter? Evidence from the Great Recession," *American Economic Journal: Economic Policy*, 2021, *13* (2), 304–335.

Jbaily, Abdulrahman, Xiaodan Zhou, Jie Liu, Ting-Hwan Lee, Leila Kamareddine, Stéphane Verguet, and Francesca Dominici, "Air Pollution Exposure Disparities Across US Population and Income Groups," *Nature*, 2022, *601*, 228–233.

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

Jha, Akshaya and Andrea La Nauze, "US Embassy air-quality tweets led to global health benefits," *Proceedings of the National Academy of Sciences*, 2022, *119* (44), e2201092119.

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

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

Kahn, Lisa B, "The long-term labor market consequences of graduating from college in a bad economy," *Labour economics*, 2010, *17* (2), 303–316.

Kawachi, Ichiro, Graham A. Colditz, Meir J. Stampfer, Walter C. Willett, JoAnn E.

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

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

Konetzka, R Tamara, Karen B Lasater, Edward C Norton, and Rachel M Werner, "Are recessions good for staffing in nursing homes?," *American Journal of Health Economics*, 2018, *4* (4), 411–432.

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

Krusell, Per, Toshihiko Mukoyama, Ayşegül Şahin, and Anthony A Smith Jr, "Revisiting the Welfare Effects of Eliminating Business Cycles," *Review of Economic Dynamics*, 2009, *12* (3), 393–404.

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

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

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

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

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

McInerney, Melissa and Jennifer M Mellor, "Recessions and Seniors' Health, Health Behaviors, and Healthcare Use: Analysis of the Medicare Current Beneficiary Survey," *Journal of Health Economics*, 2012, *31* (5), 744–751.

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

Mian, Atif and Amir Sufi, "Who Bears the Cost of Recessions? The Role of House Prices and Household Debt," *Handbook of Macroeconomics*, 2016, *2*, 255–296.

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

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

Molitor, David, Jamie T Mullins, and Corey White, "Air Pollution and Suicide in Rural and Urban America: Evidence from Wildfire Smoke," *Proceedings of the National Academy of Sciences*, 2023, *120* (38), e2221621120.

Monras, Joan, "Economic Shocks and Internal Migration," 2020. Working Paper, https://joanmonras.weebly.com/uploads/7/6/7/9/76790475/spatial_mobility_joan_monras_v19.pdf.

Mons, Ute, Aysel Müezzinler, Carolin Gellert, Ben Schöttker, Christian C. Abnet, Martin Bobak, Lisette de Groot, Neal D. Freedman, Eugène Jansen, Frank Kee et al., "Impact of Smoking and Smoking Cessation on Cardiovascular Events and Mortality Among Older Adults: Meta-analysis of Individual Participant Data from Prospective Cohort Studies of the CHANCES Consortium," *BMJ*, 2015, *350*, h1551.

Murphy, Kevin M and Robert H Topel, "The Value of Health and Longevity," *Journal of*

Political Economy, 2006, *114* (5), 871–904.

National Center for Health Statistics, "Deaths (Mortality) - Multiple Cause of Death, States, and all Counties, 2003-2016, as compiled from data provided by the 57 vital statistics jurisdictions through the Vital Statistics Cooperative Program," 2023.

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

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

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

Oreopoulos, Philip, Till Von Wachter, and Andrew Heisz, "The short-and long-term career effects of graduating in a recession," *American Economic Journal: Applied Economics*, 2012, *4* (1), 1–29.

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

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

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

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

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

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

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

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

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

Salinari, Giambattista and Federico Benassi, "The long-term effect of the Great Recession on European mortality," *Journal of Population Research*, 2022, *39* (3), 417–439.

Schwandt, Hannes and Till Von Wachter, "Socio-Economic Decline and Death: The Life-Cycle Impacts of Recessions for Labor Market Entrants," *National Bureu of Economic Research Working Paper No:26638*, 2020.

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

Shimer, Robert, "Reassessing the ins and outs of unemployment," *Review of Economic Dynamics*, 2012, *15* (2), 127–148.

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

Stiglitz, Joseph E, Amartya Sen, Jean-Paul Fitoussi et al., "Report by the Commission on the Measurement of Economic Performance and Social Progress," 2009. https://ec.europa.eu/eurostat/documents/8131721/8131772/Stiglitz-Sen-Fitoussi-Commission-report.pdf.

Strumpf, Erin C, Thomas J Charters, Sam Harper, and Arijit Nandi, "Did the Great

Recession Affect Mortality Rates in the Metropolitan United States? Effects on Mortality by Age, Gender and Cause of Death," *Social Science & Medicine*, 2017, *189*, 11–16.

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

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

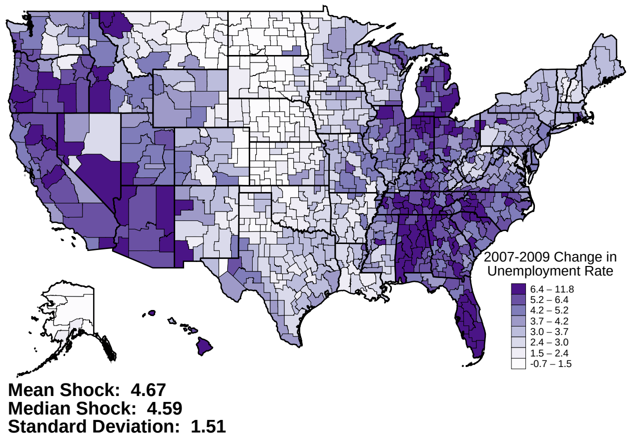
van Donkelaar, Aaron, Melanie S. Hammer, Liam Bindle, Michael Brauer, Jeffery R. Brook, Michael J. Garay, N. Christina Hsu, Olga V. Kalashnikova, Ralph A. Kahn, Colin Lee, Robert C. Levy, Alexei Lyapustin, Andrew M. Sayer, and Randall V. Martin, "Monthly Global Estimates of Fine Particulate Matter and Their Uncertainty," *Environmental Science & Technology*, 2020, *55* (22), 15287–15300.

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

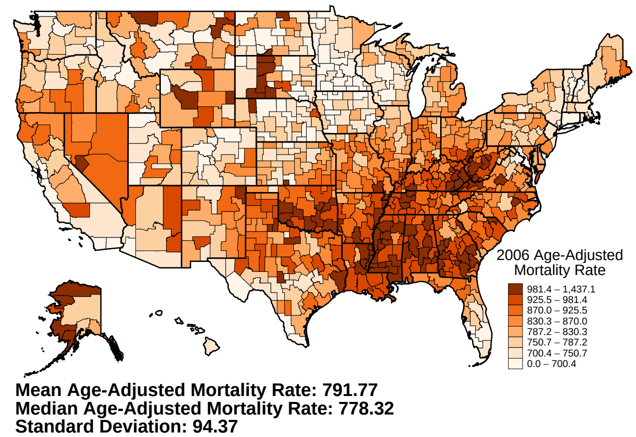
Figures

Figure I: Geographic Patterns and Correlation of Unemployment and Mortality

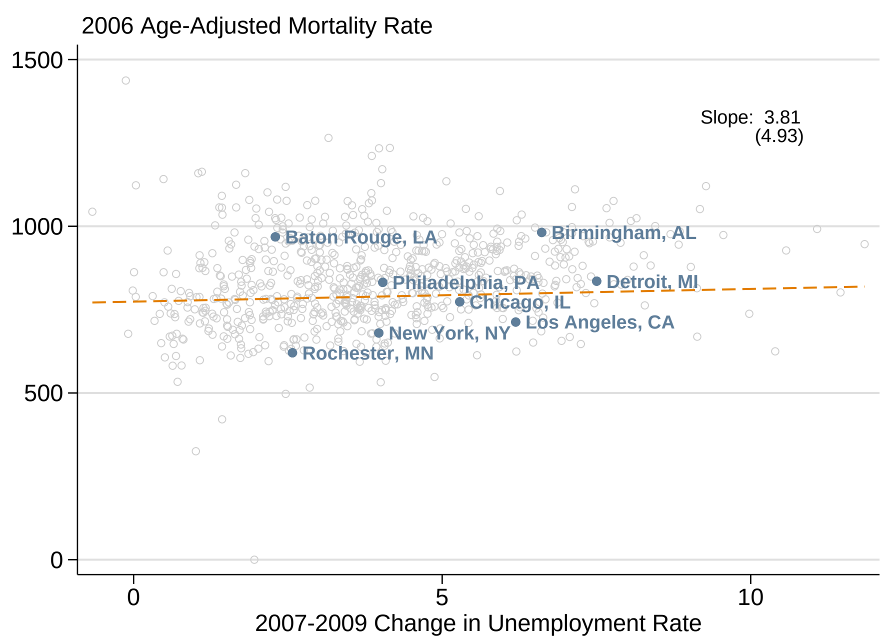
(a) 2007-2009 Change in Unemployment Rate



(b) 2006 Age-Adjusted Mortality Rate

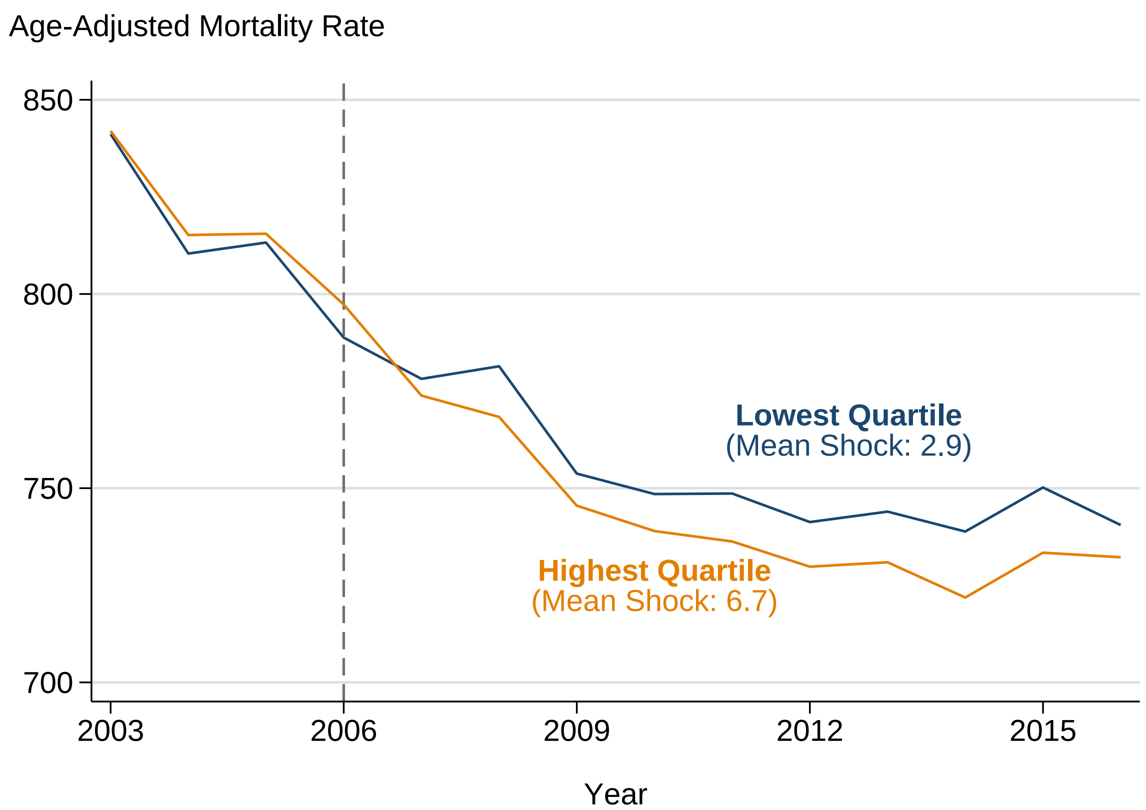


(c) Correlation of Pre-Recession Mortality Rates and Shock



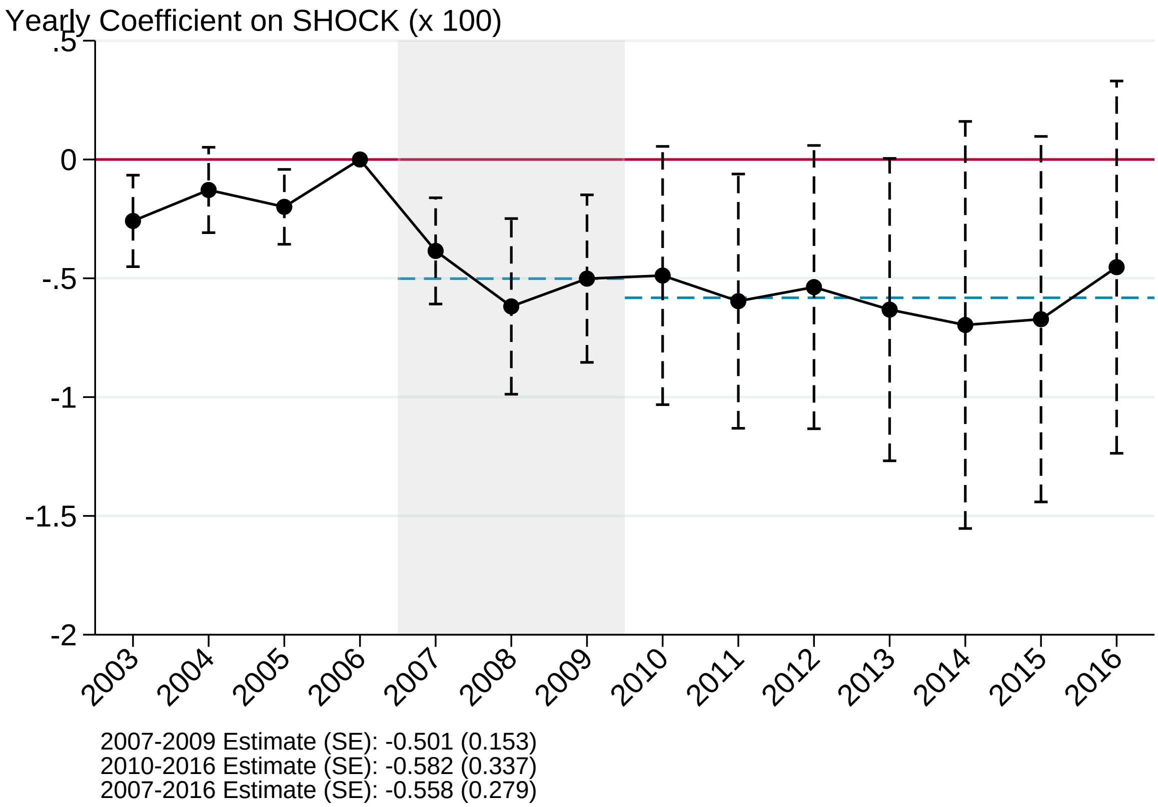
Notes: Figure Ia displays a heat map of the unemployment shock, i.e., the change in CZ unemployment rates from 2007-2009, binned into octiles. Figure Ib displays a heatmap of 2006 CZ age-adjusted mortality rates per 100,000. The 2006 CZ population-weighted mean and standard deviation of the unemployment shock and mortality rate are reported in the lower left-hand corner of each figure. Figure Ic 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 II: 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.

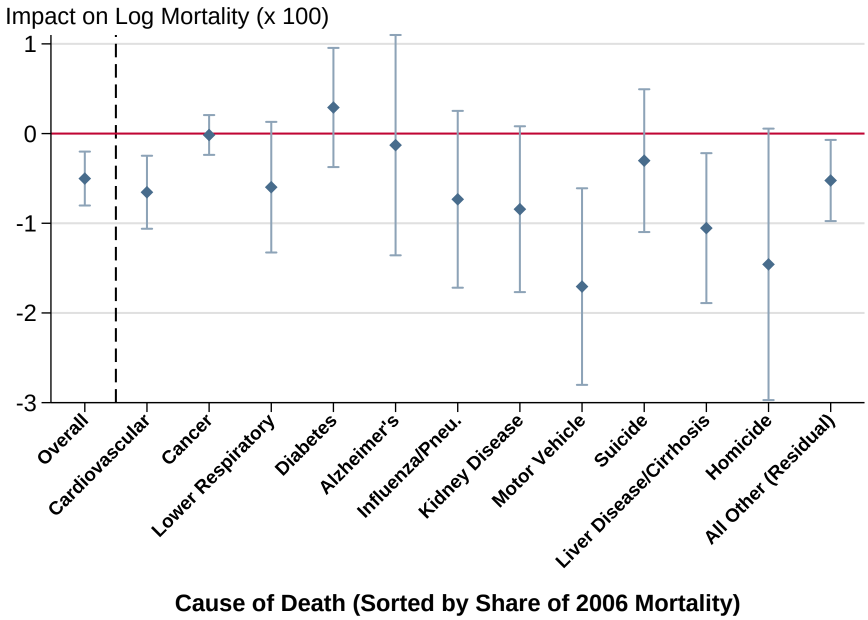
Figure III: Impact of Shock on Log Mortality



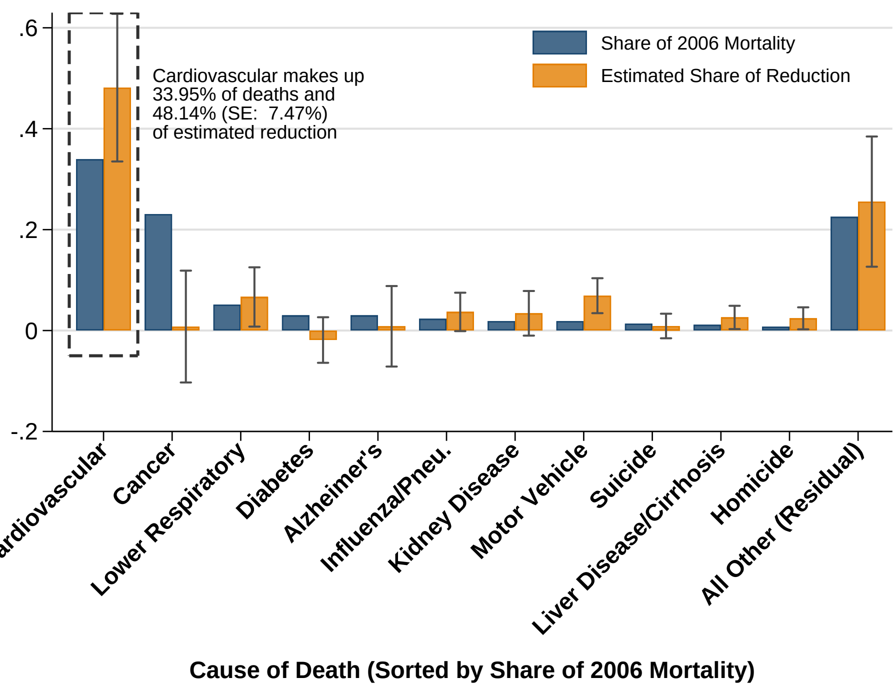
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000, and $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Observations are weighted by CZ population in 2006. Horizontal blue dashed lines 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. The area shaded in gray corresponds to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs.

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

(a) 2007-2009 Pooled Estimates



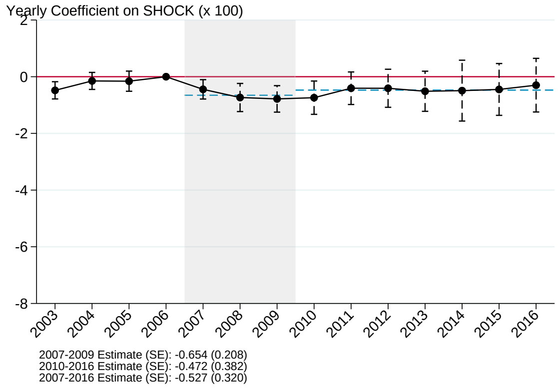
(b) 2007-2009 Decomposition



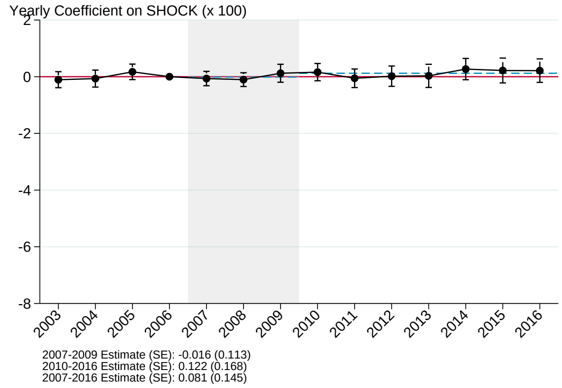
Notes: Figure IVa displays the group-specific average of 2007-2009 coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted CZ mortality rate per 100,000, groups g are defined as the 11 most common causes of death in the ICD10 39-group classification (presented in order 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. Analogous 2010-2016 estimates can be found in Appendix Figure A.7. Figure IVb 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 IVa). The blue bars indicate each cause of death's share of 2006 mortality. The orange bars present the implied share of the mortality decline accounted for by a given cause of death. To construct these orange bars, 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 estimated death reductions across all causes. Note that the implied "overall" mortality reduction from this exercise is -0.46%, very close to our estimate from Figure III of -0.50%. 95% confidence intervals for these estimates, clustered by CZ, are shown as vertical lines. N=741 CZs.

Figure V: Impact of Shock on Log Mortality, by Cause of Death: Selected Event Studies

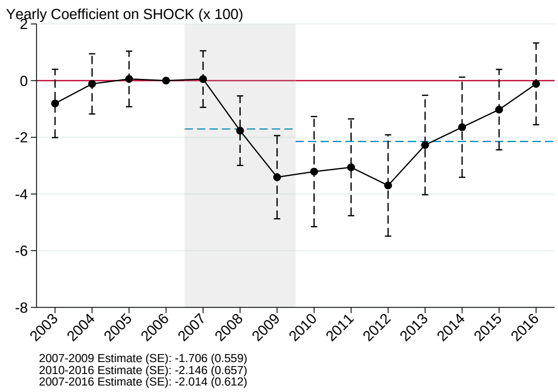
(a) Cardiovascular Disease



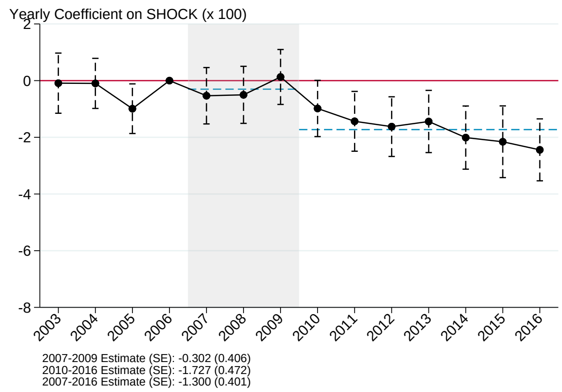
(b) Cancer



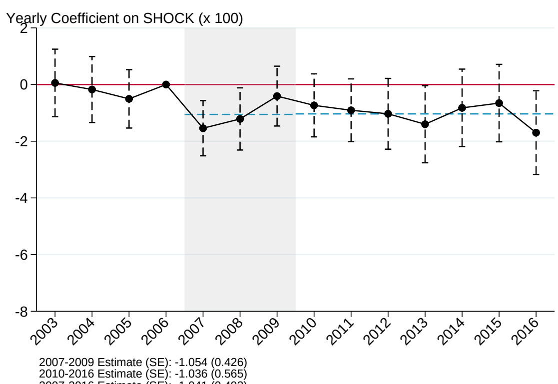
(c) Motor Vehicle Accidents



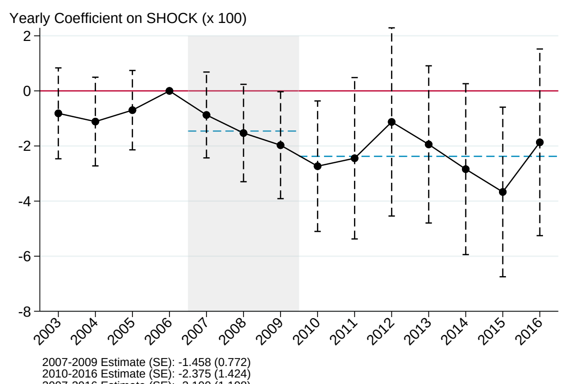
(d) Suicide



(e) Liver Disease/Cirrhosis



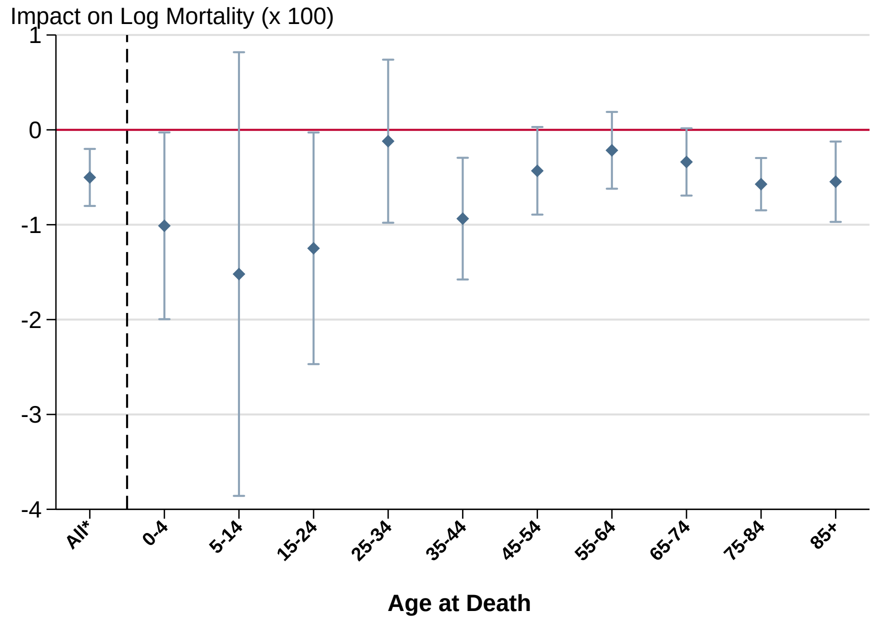
(f) Homicide



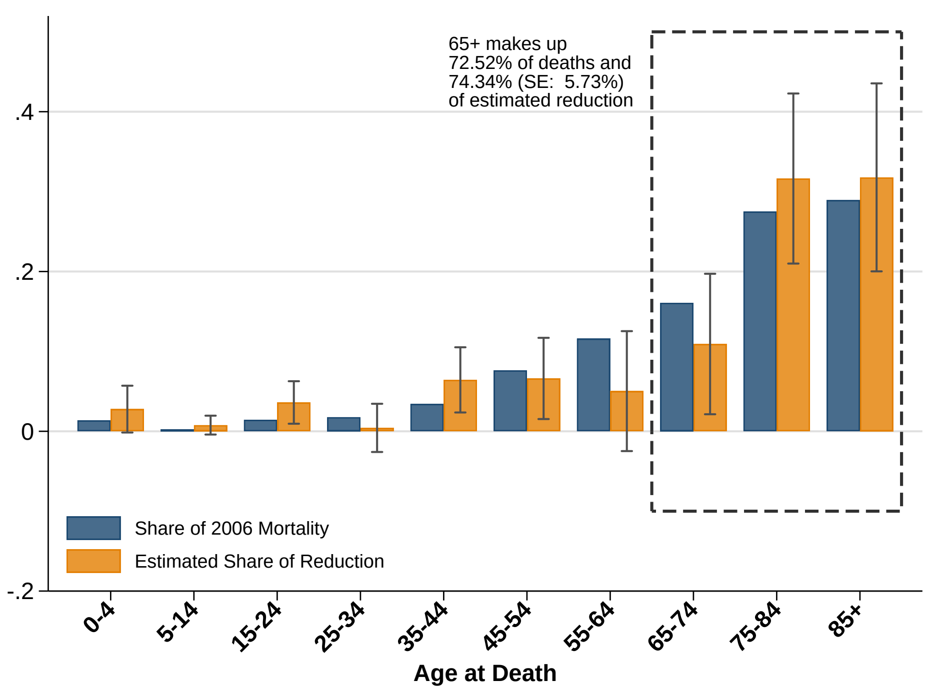
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted CZ mortality rate per 100,000, and g indicates 12 cause of death categories (six of which are displayed here; the remaining six are displayed in Figure A.8). $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Figure Va displays effects on the log mortality rate from cardiovascular disease; Figure Vb from cancer; Figure Vc from motor vehicle accidents; Figure Vd from suicide; Figure Ve from liver disease; and Figure Vf from homicide. 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs.

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

(a) 2007-2009 Pooled Estimates



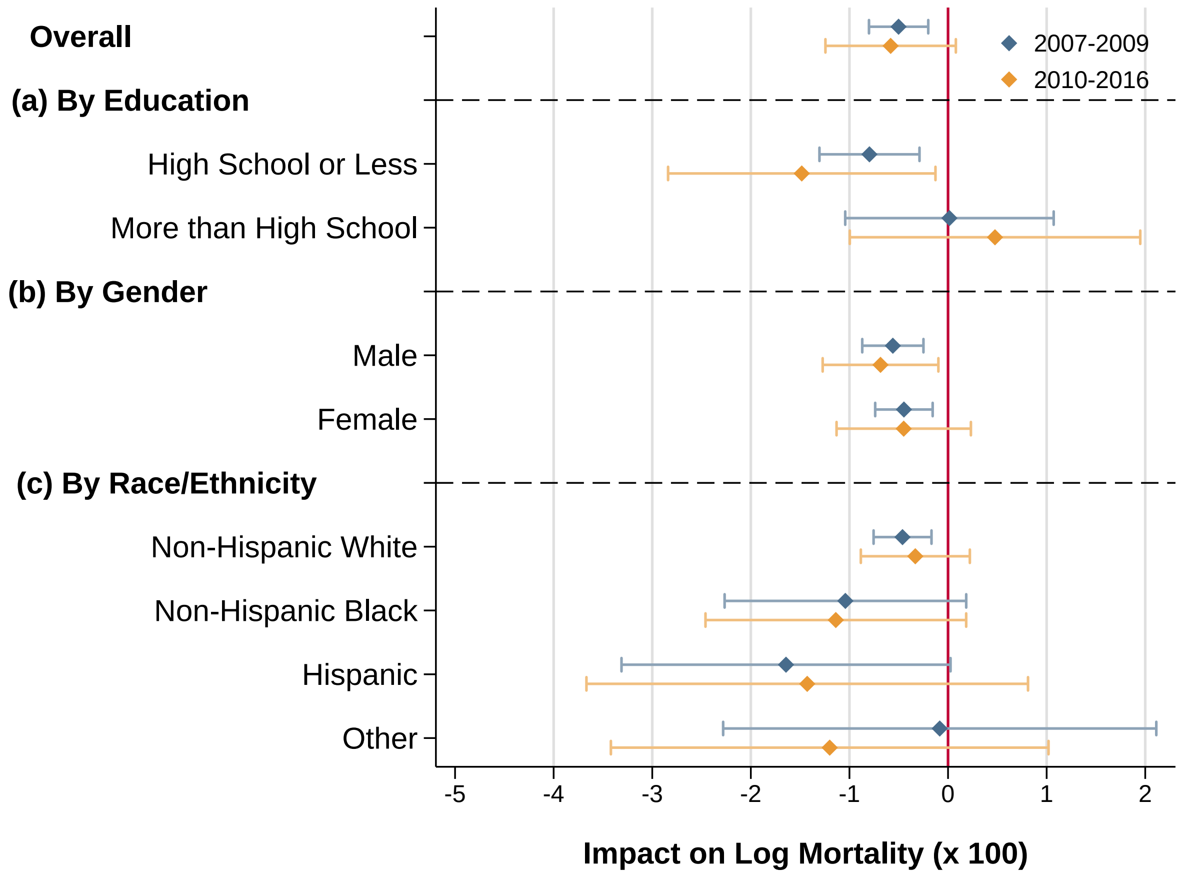
(b) 2007-2009 Decomposition



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

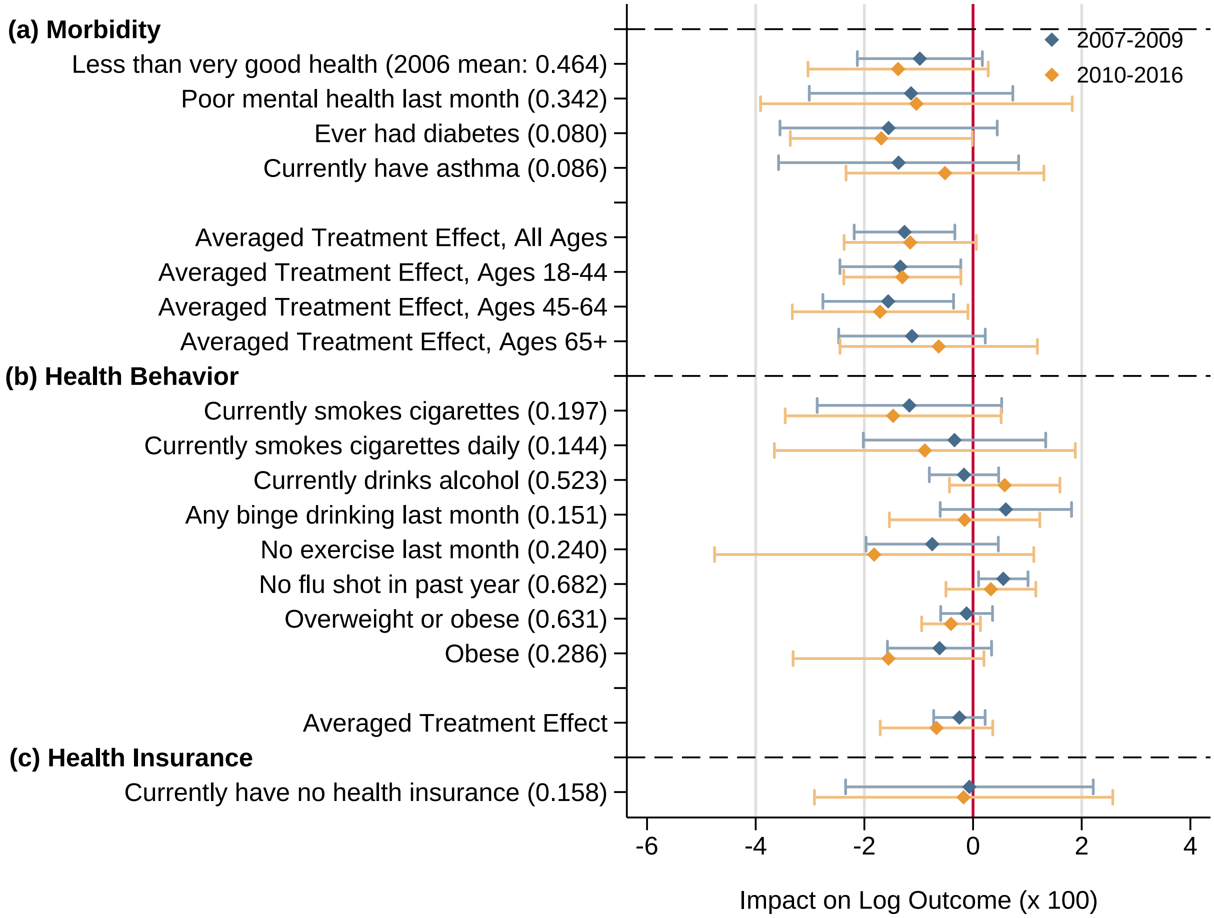
Notes: This figure displays the group-specific average of 2007-2009 coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log CZ mortality rate per 100,000 for a given age group, without any age adjustment, and groups g are defined by 10 age groups. Observations are weighted by CZ population 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. Analogous 2010-2016 estimates can be found in Appendix Figure A.7. Figure VIb 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 VIa). The blue bars indicate each age group's share of 2006 mortality. The orange bars present the implied share of the mortality decline accounted for by a given age group. To construct these orange bars, we multiply each estimated age group reduction in 2007-2009 by the number of deaths from that age group in 2006 and divide by the sum of estimated death reductions across all age groups. Note that the implied "overall" mortality reduction from this exercise is -0.50%, matching our estimate from Figure III of -0.50%. 95% confidence intervals for these estimates, clustered by CZ, are shown as vertical lines. N=741 CZs.

Figure VII: Impact of Shock on Log Mortality, by Education, Gender 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, gender, 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 gender 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 gender, and N=434 CZs (96% of the total 2006 population) for estimates by race. Note that calculating age-adjusted separately for each racial group requires a CZ to have at least one person of each race in all 19 age bins in all years of our sample period. This requirement drops smaller, less diverse CZs but keeps the larger ones, hence most of the 2006 population is still covered despite dropping so many CZs.

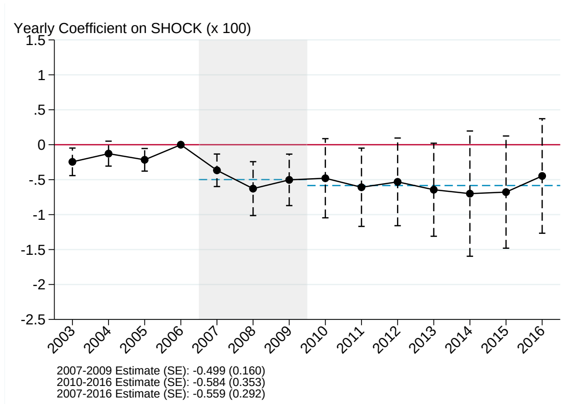
Figure VIII: Impact of Shock on Log Self-Reported Health and Health Behaviors



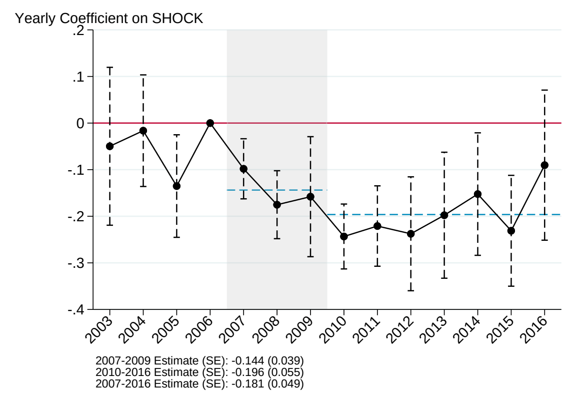
Notes: This figure displays the average of 2007-2009 and 2010-2016 coefficients β_t from equation (1), where the outcome y_{ct} is the log share of respondents in each state who report the various rows' health conditions or health behaviors in the 2003-2016 BRFSS. Appendix B.4 provides more details on 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 outcome (in levels, not logs) 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 IX: Impact of Shock on Log Mortality and Pollution

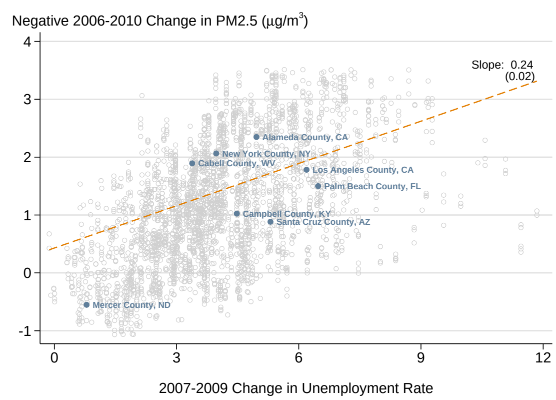
(a) Log Age-Adjusted Mortality Rate



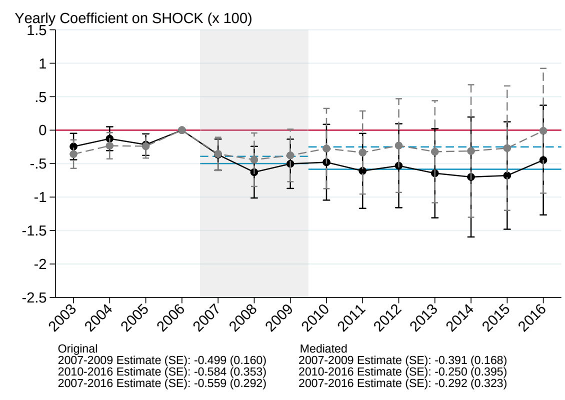
(b) PM2.5 Levels ($\mu g/m^3$)



(c) Unemployment and PM2.5 Shock Correlation

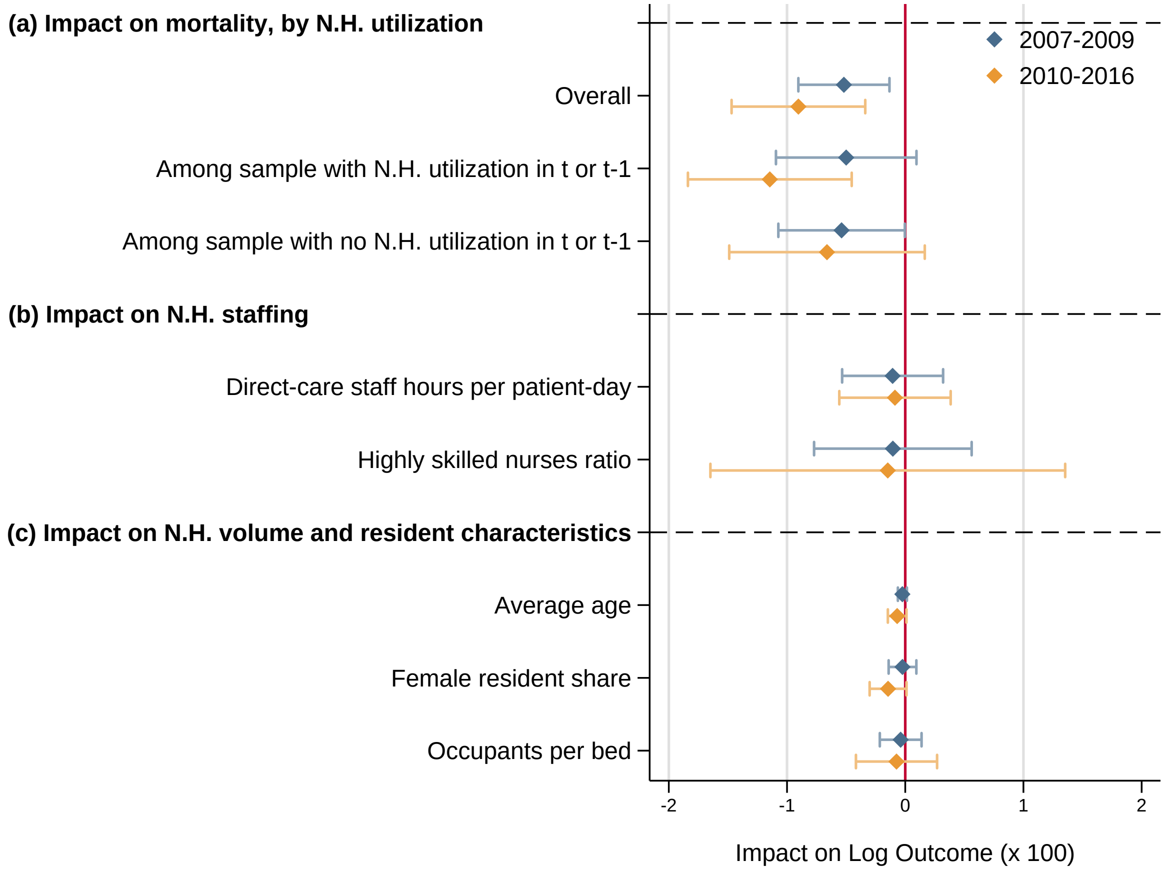


(d) Log Mortality, Mediating for PM2.5 Shock



Notes: Figures IXa and IXb display the yearly coefficients β_t from equation (7), where the outcome y_{ct} is the log age-adjusted county mortality rate per 100,000 (Figure IXa) or the annual county PM2.5 level (Figure IXb), and $SHOCK_c$ is the 2007-2009 CZ change in unemployment rate. Figure IXc scatters 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 IXd displays the yearly coefficients β_t from equation (8) in grey, where the outcome y_{ct} remains the same. β_t is the coefficient on the 2007-2009 change in the CZ unemployment rate interacted with calendar year when mediating for the negative 2006-2010 change in PM2.5 interacted with calendar year. The unmediated coefficients β_t from Figure IXa are plotted in black for reference. All analyses are restricted to the 3,107 counties (representing 99.3% of the US population) for which we observe PM2.5 satellite data 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 the mediated coefficients from 2007-2009 and 2010-2016 (and solid lines show the original coefficient averages from Figure IXa for reference). 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 IXa and IXd for ease of interpretation. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. The areas shaded in gray in Figures IXa, IXb, and IXd correspond to the timing of the Great Recession, adopting the NBER's business cycle dating.

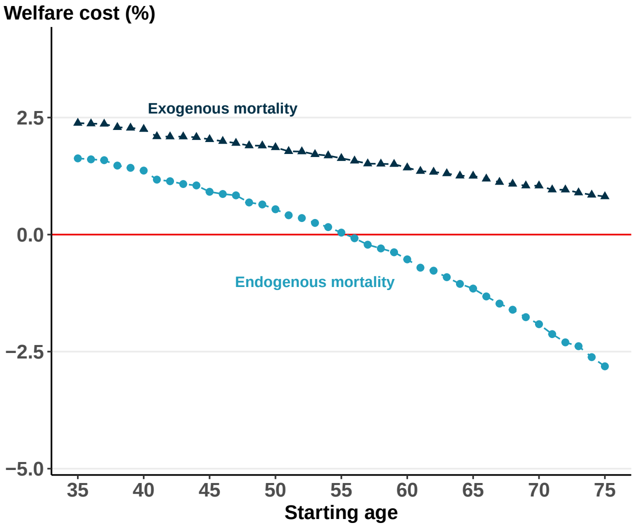
Figure X: Impact of Shock on Log Characteristics of Nursing Home Care



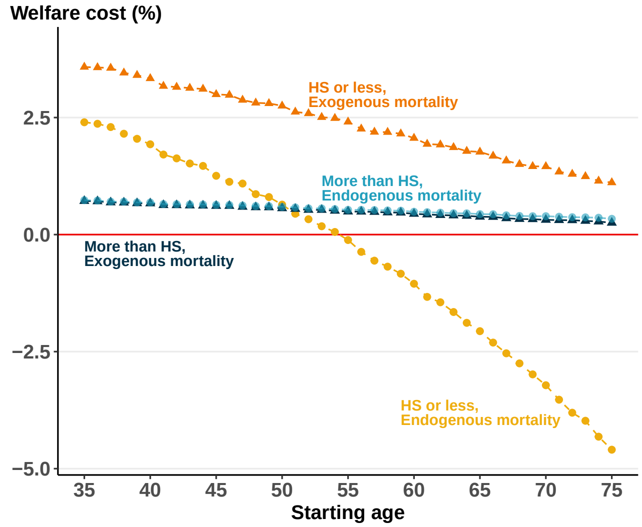
Notes: This figure displays the average of 2007-2009 and 2010-2016 coefficients β_{tg} from equation (2) (Panel (a)) and coefficients β_t from equation (1) (Panels (b) and (c)), where outcomes y_{ctg} and y_{ct} include several facets of nursing home care. Panel (a) measures the log (non age-adjusted) mortality rate per 100,000 separately among individuals who did and did not utilize nursing home care in the current or previous year, as well as across the whole sample of nursing home utilizers and nursing home non-utilizers. Panels (b) and (c) draw from a range of data sources that originally measure outcomes at the nursing home 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 number 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 nursing home'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 nursing home utilization and one not associated with nursing home utilization in every year. N=716 CZs (covering 99.8% of the overall 2006 population) in Panels (b) and (c), with the sample of CZs limited to those with at least one nursing home.

Figure XI: Impact of Endogenous Mortality on Welfare Costs of Recessions

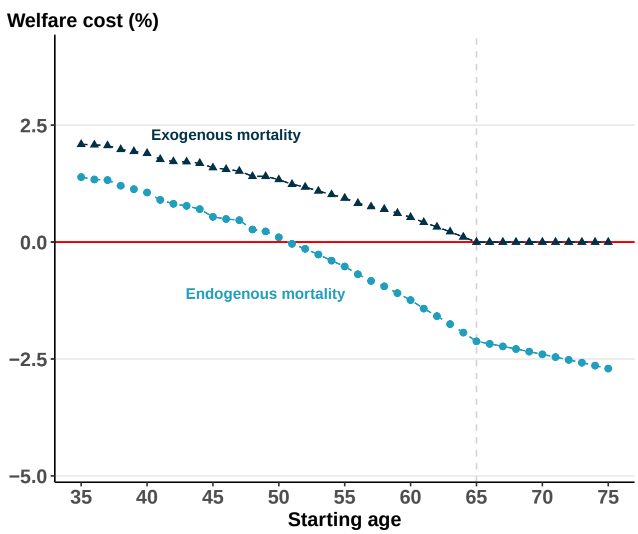
(a) Baseline



(b) By Education



(c) With Retirement (No Income Variation After Age 65)



Notes: This figure displays the welfare cost of recessions, based on equation (14), at various ages under exogenous and endogenous mortality, assuming $\gamma = 2$ and b corresponding to a $VSLY$ of \$250k. The 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. Because the true target function is monotonically decreasing in age, we rearrange the non-monotonic estimates following Chernozhukov, Fernández-Val and Galichon (2009) to improve efficiency. Figure XIa shows results for our baseline simulation. Figure XIb displays results when we allow for different income and mortality impacts of recessions for different education groups: those with a High School (HS) diploma or less and those with more than a HS diploma. Figure XIc shows results when we incorporate retirement by assuming there is no income variation for agents ages 65 and above.

Tables

Table I: Sensitivity to Current vs. 2003 Location

Regression Specification	2007-2009 Period Estimate	2010-2016 Period Estimate	2007-2016 Period Estimate
Yearly Residence (β_t, eq. 3)	-0.513	-0.533	-0.527
	(0.161)	(0.241)	(0.210)
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 (Non-Movers) (β_t, eq. 3)	-0.559	-0.666	-0.634
	(0.179)	(0.244)	(0.218)

Notes: This table displays the point estimates 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. 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 equSCation (6) for the control function specification and from equation (3) 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 A.7. The event studies for rows 1, 2, and 4 can be found in Figure A.15, the event study for row 3 can be found in Figure A.15c, and the event study for row 5 can be found in Figure A.16. N = 6,634,999 in all rows, except for the last row where we limit to non-movers, where N = 5,838,592.

ONLINE APPENDIX:

LIVES VS. LIVELIHOODS: THE IMPACT OF THE GREAT RECESSION ON MORTALITY AND WELFARE

Amy Finkelstein
Matthew J. Notowidigdo*
Frank Schilbach
Jonathan Zhang

April 18, 2025

*Notowidigdo: noto@chicagobooth.edu; 5807 S Woodlawn Ave, Chicago, IL 60637.

Table of Contents

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 of 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 A.6 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.[1]

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 2024). 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.[2]

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

[1] 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.

[2] 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, Miller and Molitor 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 institutions, 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 with, such as lung cancer, diabetes, or depression.[3]

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 A.7. 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 A.8. Summary statistics for each of these samples can be found in Appendix Table A.9. In addition, Appendix Figure A.17 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 our repeated cross-section of Medicare beneficiaries (N=13,705,511) and our panel of 2003 beneficiaries who are then followed forward through 2016 (N=6,634,999).

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, and 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/`).[4] 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

[3] 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.

[4] 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`

directly from the replication package in Yagan (2019), who calculates annual CZ unemployment rates in 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, Doerner and Larson (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

For our primary measure of PM2.5, we use the granular, annual data on PM2.5 concentration levels from van Donkelaar et al. (2020). The authors generate estimates of PM2.5 by feeding observations of visual occlusion from satellite images into a chemical transport model, and combining the predictions with ground-level pollution monitor measurements from the EPA's Air Quality System (AQS) database using a Geographic Weighted Regression model. These data have recently been used by economists studying such topics as the impact of pollution on suicide (Molitor, Mullins and White 2023) and the impact on air pollution of US embassy air-quality tweets (Jha and Nauze 2022) or of transitioning from gas to electric cooking (Gould et al. 2023). They have also been used to construct a national Census-linked individual-level dataset of pollution exposure (Voorheis et al. 2023).

The estimates from van Donkelaar et al. (2020) are extremely granular, generated over a 0.01 degree by 0.01 degree grid (roughly 1 km at the equator), and we use the annual frequency mean PM2.5 estimates for North America. Thanks to the high granularity, we are able to assign each grid block to a Census

Block Group and weight the grid blocks in a county by their 2010 Census population when averaging PM2.5 to the county level. Doing the same aggregation for every year of our sample period, we construct a county-year level PM2.5 data set that covers 99.3% of (population-weighted) counties in the U.S.

As a check on the van Donkelaar et al. (2020) measures of PM2.5, as well as to be able to look at other air pollutants, we also use data on air pollution obtained directly 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. Although the EPA monitor data are commonly used to measure air pollution (e.g., Isen, Rossin-Slater and Walker 2017; Deryugina et al. 2019; Alexander and Schwandt 2022), they are limited in several respects for our purposes. First, 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, Voorheis and Walker 2023). Second, a well-known limitation is that the pollution monitoring network is sparse (Fowlie, Rubin and Walker 2019). Indeed, to study the impact of the Great Recession on air pollution or the impact of recession-induced air pollution on mortality using the EPA data, we limit our analysis to the approximately two-thirds of (population-weighted) counties which have a pollution monitor in 2006 and in 2010. Moreover, even when monitors exist in counties, they are unlikely to be representative of the whole county, both because pollution can vary a lot within a county and because there is evidence that monitors are endogenously placed to avoid the worst-polluting spots (Grainger and Schreiber 2019). Reassuringly, we show in Appendix C.9 below that, when we limit to counties in which both satellite and EPA measures of PM2.5 are available, results look very similar.

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.[5]

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

[5] 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.

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 A.10 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 focus 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), with their instrumental activities of daily living (IADLs), or with 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.

C Additional Details on Empirical Analyses

C.1 Lag Structure of the Impact of the Economy on Mortality

Although there is work looking at lagged impacts of unemployment on mortality (e.g., Ruhm 2000), 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 try 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:

$$y_{ct} = \sum_{q \epsilon \{L,H\}} \beta_{qt}[SHOCK_c * \mathbb{1}(Year_t) * \mathbb{1}\left(Recovery_{q(c)}\right)] + \alpha_c + \gamma_t + \epsilon_{ct}, \tag{17}$$

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.[6] For symmetry, we also measure the initial economic shock ($SHOCK_c$) in equation (17) 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 A.22). Estimation of equation (17) 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 A.23). 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 A.24) and display no systematic relationship with pre-recession demographic characteristics (Appendix Table A.11).

The top two panels of Figure A.25 show the results of estimating equation (17) 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.

The results for 2010-2016 are more puzzling. Qualitatively, we see similar mortality declines persist 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. Lagged mortality impacts of past economic declines could potentially explain the persistent mortality results in the above-median areas. However, we would also expect *larger* (in absolute value) mortality declines in the below-median recovery areas; consistent with this, the point estimates

[6] 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 A.3). The same phenomenon appears when comparing more vs. less affected areas (Appendix Figure A.4).

indicate that over the 2010-2016 period, the below-median recovery places do experience an approximately 20 percent larger mortality decline (relative to 2006) than the above-median recovery places. However, like the overall analysis in Figure III, the estimated 2010-2016 mortality declines are not statistically significant in either the above- or below-median recovery areas (nor are they statistically distinguishable from each other). The imprecision of the results therefore admits a range of possibilities, making firm conclusions difficult.

C.2 Mortality Impacts by Cause of Death

Our baseline analysis by cause of death examines the 11 most common causes of death in the ICD10 39-group classification and groups all other deaths into the residual category. Since this residual comprises roughly a quarter of 2006 deaths, as well as a quarter of the estimated 2007-2009 mortality reduction, we also examined results for an alternative cause of death categorization with a smaller residual. The alternative definition uses the top 10 most common causes of death as given by the ICD10 chapters (which approximately correspond to disease of various body systems) classification system and groups the rest into a residual category that now comprises only 3.5% of 2006 deaths.

Table A.12 displays the confusion matrix for the two different classifications of causes of deaths. It shows a generally very close correspondence between the baseline and alternative cause of death categories; the exceptions are the alternative category of respiratory disease, which encompasses both the lower respiratory disease and influenza/pneumonia baseline causes, and the alternative category of external causes, which encompasses the motor vehicle accident, suicide, and homicide baseline causes; one of the reasons we prefer our baseline specification is that it breaks out these—very different—external causes. However, Table A.12 also shows the advantage of these alternative cause of death categories: most of our baseline residual is allocated to one of the alternative causes.

Figure A.9 displays both the share of 2006 deaths each alternative category comprised and each category's share of the 2007-2009 mortality reduction (analogous to Figure IVb for the baseline cause of death categories).

Table A.13 shows the 2007-2009, 2010-2016, and 2007-2016 estimates for mortality reduction by baseline cause of death, and Table A.14 shows the same thing by alternative cause of death. The causes in Table A.14 are ordered to be roughly analogous to the order of causes in Table A.13 (ex. Cardiovascular disease is the first cause in Table A.13, and circulatory diseases is the first cause in Table A.14), but as described above, the baseline and alternative causes of death do not exactly map one to one.

C.3 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 A.42a, which estimates our main specification at the state-level using 47 states, the 2007-2009 period estimate is -0.66 (standard error = 0.25), which is very similar to the corresponding estimate of -0.62 (standard error = 0.25) using all 50 states and the District of Columbia and all ages in Table A.15.

C.4 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.4.1 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 gender, the Medicare data contain measures of individual health conditions derived from health diagnoses recorded in claims data.[7]

To estimate remaining life expectancy, we follow the standard approach in the literature (e.g., Olshansky and Carnes 1997; Finkelstein, Gentzkow and Williams 2021; Chetty et al. 2016), and adopt a

[7]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.

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:

$$log(m_{it}(a)) = \rho a + \psi X_{i(t-1)} + \epsilon_{it} \tag{18}$$

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, gender), 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 (18) 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:

$$LE_{it} = \int_{A_o}^{\infty} \exp\left[\frac{e^{\psi X_{i(t-1)}}}{\rho} * (e^{\rho a} - e^{\rho A_0})\right] da. \tag{19}$$

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 A.47). 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.4.2 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 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

$$\text{LYL}_{ct} = 100,000 \times \frac{\sum_{i \in S_{ct}} \text{LYL}_{it}}{|S_{ct}|}, \tag{20}$$

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 A.16 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 5 percent (to 0.54 percent); none of these differences are statistically distinguishable.

The analysis in Appendix Table A.16 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 A.17 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.5 Assessing Potential Demographic Changes Associated with the Great Recession

We examined whether changes in the demographic composition of the population associated with the timing and magnitude of the Great Recession Shock could spuriously drive findings of recession-induced mortality declines. A priori, we considered this unlikely since areas that were harder hit by the Great Recession experienced an increase in the age of the population (Appendix Figure A.12), and no substantive changes in population composition by race, gender, or education (Appendix Figure A.13).

However, to further investigate other potential demographic changes correlated with mortality rates, we use data from the National Health Interview Survey (NHIS) from 2003-2016, which contains information on individuals' year of death, gender, race, and education, to estimate a logistic regression that predicts an individual's probability of death in a given year based on those demographic characteristics. Since all of these variables are also available in the American Community Survey (ACS), we use the estimates from this regression to generate a predicted mortality rate for every person-year in the ACS from 2003-2016, and then aggregate this predicted mortality measure to the state-year level. Figure A.14a shows that there is dispersion in our predicted state-year mortality rate.

Figure A.14b shows the estimates of the impact of the Great Recession from equation (1) on both the log mortality rate (dashed gray line) and the log predicted mortality rate (black line); both analyses are run at the state-year level rather than the CZ-year level because we are only able to generate predicted mortality at the state level. Unlike the recession-induced decline in actual mortality, Figure A.14b shows no impact of the Great Recession on predicted mortality, suggesting that any changes in demographic composition associated with the Great Recession shock are unlikely to contribute to the estimated mortality declines in more impacted areas.[8]

C.6 Additional Sensitivity Analysis

We explored the sensitivity of our baseline estimates in Figure III to a number of alternative specifications. Table A.15 summarizes the findings. The first row replicates our baseline estimates from estimating equation (1), as shown in Figure III; 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:

$$y_{ct} = \exp(\beta_t[SHOCK_c * \mathbb{1}(Year_t)] + \alpha_c + \gamma_t), \tag{21}$$

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 con-

[8] Figures A.14c and A.14d show, respectively, the resultant dispersion in state-year predicted mortality and the impact of the Great Recession on predicted mortality, when we also include age as a predictor in the mortality prediction equation. We prefer not to use age as a predictor since our main outcome is the *age-adjusted* mortality rate and, since, as noted, the increase in age in areas harder hit by the Great Recession biases against our finding of a recession-induced mortality increase. However, for completeness we also include a version of this analysis with age as an additional predictor. Not surprisingly, predicted mortality is now *rising* in areas that were harder hit by the Great Recession.

centrated 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 differentially experiencing 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.[9] Finally, because population is very right-skewed across CZs (see Appendix Figure A.1), the penultimate row of Panel (c) confirms the robustness of our results to dropping the ten most populous CZs.

Measurement of Shock. We explored the sensitivity of our results to measuring the Great Recession shock by the change in the area's employment-to-population (EPOP) ratio between 2007 and 2009 (Panel (d)), rather than the change in the unemployment rate as done by Yagan (2019) in his analysis of the Great Recession and in prior analyses of the relationship between recessions and mortality (e.g., Ruhm 2000, 2003, 2005; Stevens et al. 2015). 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 A.22)

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. First, the last row of Table A.15 Panel (c) shows that the baseline results are somewhat larger (in absolute value) if we drop the top and bottom decile of CZs by the size of the shock.

Second, 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 (17), 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 A.30; consistent with the linearity assumption, we find very similar estimated impacts of the shock in both sub-samples.

Third, we 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

$$y_{ct} = \sum_{j=2}^{4} \beta_t^{(j)} \left[SHOCKQ_c^{(j)} * \mathbb{1}(Year_t) \right] + \alpha_c + \gamma_t + \epsilon_{ct}, \tag{22}$$

[9] 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 A.18 presents results when each of the nine census divisions is dropped in turn.

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 A.27. 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.

Fourth, Appendix Figure A.28 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).

Fifth and finally, Appendix Figure A.29 displays our main event study where $SHOCK_c$ is the *percent* unemployment change from 2007-2009 relative to the 2007 unemployment rate, rather than the 2007-2009 unemployment shock in percentage points. Under this alternative nonlinear functional form, we continue to see negative coefficients post-2007, with a 2007-2009 period effect of -0.026 (SE = 0.005) and a 2010-2016 period effect of -0.044 (SE = 0.009). These estimates imply a similar effect size to our main specification.[10]

Endogenous migration. Section 3.3 examines the sensitivity of our main results to endogenous migration, using Medicare panel data to examine the impact of the GR shock while assigning individuals to either their yearly CZ of residence or their CZ of residence in 2003; these results are presented in Table I and Figures A.15 and A.16. However, these results all adopt an individual-level Gompertz specification, in contrast to our primary CZ-level two-way fixed effects model. Therefore, as an additional robustness check, we first apply our main specification in equation (1) to Medicare panel data, collapsing individuals to CZs using their yearly CZ of residence. Figure A.17 shows the results from applying this specification to the elderly population in the CDC data (panel (a)) and the elderly population in the Medicare data (panel (b)), indicating that the analysis is not affected by the change in data.

We then adopt a revised specification which instead applies the GR shock corresponding to individuals' 2003 CZ of residence. Specifically, we estimate:

$$\widetilde{\text{SHOCK}}_{c(i,t)} = \sum_{I_{c,t}} \frac{\text{SHOCK}_{c(i,2003)}}{N_{ct}} \tag{23}$$

$$y_{ct} = \beta_t[\widetilde{\text{SHOCK}}_{c(i,t)} * \mathbb{1}(Year_{c(i,t)})] + \alpha_{c(i,t)} + \gamma_t + \varepsilon_{c(i,t)} \tag{24}$$

where $c(i,t)$ refers to an individual's yearly CZ of residence, $I_{c,t}$ is the set of individuals living in CZ c in year t, $c(i,2003)$ refers to an individual's 2003 CZ of residence, and N_{ct} is the sample size for a given CZ-year. $\widetilde{\text{SHOCK}}_{c(i,t)}$ therefore represents the mean 2003 CZ shock experienced by individuals in

[10]Specifically, the mean population-weighted CZ has a 2007 unemployment rate of 4.76 percent; therefore, for the typical CZ, a 1 percentage point increase in unemployment is equivalent to a $1/4.76 = 21$ percent increase. Thus, a 0.026 percent decrease in mortality from a 1 percent increase in unemployment roughly implies a $0.026 * 21 = 0.546$ percent decrease in mortality from a 1 percentage point unemployment increase. This is quite similar to our main specification estimate of -0.501.

a given CZ-year. Equation (24) in effect represents the CZ-level impact of a GR shock using 2003 CZ of residence, while still applying fixed effects based on yearly CZ. This equation can therefore be understood as a supplementary check for endogenous migration.

Figure A.17 panels (c) and (d) present event studies following this specification, using first the yearly CZ (panel (c)) and then the 2003 CZ (panel (d)).[11] Results look similar, suggesting that our results are not meaningfully impacted by endogenous migration.

Heterogeneity by state-level educational attainment. In Appendix Figure A.42, we first show that our main effect is heterogeneous by education level, with large negative effects among those with a high school degree or less and null effects among those with more than high school. However, one may worry that these results may be driven by the fact that the areas more or less impacted by the Great Recession may have systematically more or less educated populations. This may in turn spark broader concerns about confounding trends biasing our results.

To test directly for this phenomenon, we adopt an alternative specification in which we allow for year fixed effects to vary by state-level educational attainment. Specifically, we estimate:

$$y_{ct} = \beta_t[SHOCK_c * \mathbb{1}(Year_t)] + \alpha_c + \gamma_t + \theta_t[x_{s,2006} * \mathbb{1}(Year_t)] + \varepsilon_{ct}, \tag{25}$$

where $x_{s,2006}$ is the proportion of individuals in 2006 aged 25+ in a given state with a high school education or less, and this proportion is interacted with state fixed effects. Recall that all education-related results are presented at the state level, as this is the level at which we have education data.

Figure A.18 presents event studies both under our main specification in equation (1) and using equation (25). The two event studies are highly similar, indicating that our main education findings are driven by within-state variation rather than between-state variation.

C.7 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.[12] 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 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):

$$y_{it} = \beta_t[SHOCK_{s(i,t)} * \mathbb{1}(Year_t)] + \alpha_{s(i,t)} + \gamma_t + \epsilon_{it}, \tag{26}$$

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 $s(i,t)$.

[11] Note that the panel (c) and (d) results are based on the sub-sample of Medicare enrollees in panel (b) whom we can observe in 2003 and follow forward, while the panel (b) results use the repeated cross-section of Medicare data without requiring they be present in the data in 2003.

[12] 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.

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:

$$ln\left(\frac{P(y_{it}=1)}{1-P(y_{it}=1)}\right) = \beta_t[SHOCK_{s(i,t)} * \mathbb{1}(Year_t)] + \alpha_{s(i,t)} + \gamma_t + \epsilon_{it}. \tag{27}$$

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

We estimate the regression 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,[13] and cluster standard errors at the state level.

Appendix Figure A.31 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.8 Income, by age, in the CPS

We leverage individual-level data in the CPS on income and age to estimate the impact of the Great Recession on income by age. We estimate both our standard OLS analysis of the impact of the Great Recession (equation 1) at the state-year level, and also an individual-level Poisson regression of the impact of the Great Recession with the following Poisson regression:

$$y_{it} = \exp\left(\beta_t\left[\text{SHOCK}_{s(i,t)} \times \mathbb{1}(Year_t)\right] + \alpha_{s(i,t)} + \gamma_t + \delta_{e(i,t)} + \eta_{a(i,t)} + \sigma_{g(i)}\right), \tag{28}$$

where y_{it} denotes income 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. The individual-level analysis allows us to reduce noise by including demographic controls; specifically, we include 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 degree, or PhD. The coefficients of interest are the estimates of β_t. We estimate equation (28) using the survey weights provided by the CPS and cluster standard errors at the state level.

Appendix Figure A.20 shows the results. Panels (b), (d), and (f) display the estimates of β_t from estimating the individual-level Poisson equation (28), where the outcome is income for all individuals aged 25+, income for individuals aged 25-54, and income for individuals aged 65+. Panels (a), (c), and (e) show analogous results from estimating equation (1) by OLS for the state-year outcome log average income for individuals in the relevant age group. Reassuringly, the results look similar using either approach but, as expected, the estimates with the individual-level specification are noticeably more precise. 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)).

[13] 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. live in a nursing home), live outside the United States, or are out of the HRS age range have weights of zero.

C.9 Impacts of the Great Recession PM2.5 and on Other Pollutants Using EPA Monitor Data

Figure A.32 shows that the satellite measures of PM2.5 and the EPA monitor measures produce similar findings when we limit to the overlap counties. Unlike the results using satellite data from the full country (Figure IXb) which indicate that counties harder hit by the Great Recession experience a persistent decline in PM2.5 levels through the end of our study period, Figure A.32a shows that using the EPA monitor data, counties that were harder hit by the Great Recession experienced declines in PM 2.5 through 2010, after which pollution levels began to increase and by 2016 had returned to pre-recession levels. Reassuringly, the discrepancy between these two findings appears driven by the limited set of counties for which EPA monitor data is available; Figure A.32b, which uses satellite data but only in the sample of counties covered by the pollution monitor data, displays a similar pattern of an initial decline in PM2.5 in harder-hit counties, followed by a return to pre-recession levels by the end of the sample period. Not surprisingly, therefore, controlling for the PM2.5 shock has a similar mediating effect on impact of the Great Recession shock on mortality using either the EPA monitor data or the satellite data in the same counties (Figures A.32c and A.32d).

We also used the EPA monitor data to explore the impact of the Great Recession on other pollutants, as Heutel and Ruhm (2016) also find significant roles for decreased carbon monoxide (CO) and ozone (O_3) in explaining countercyclical mortality, in addition to decreased PM2.5. We found no effects of the Great Recession on either carbon monoxide or ozone. 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 524 counties (comprising 64.4 percent of the 2006 population) for PM2.5, 179 counties (comprising 44.1 percent of the 2006 population) for CO, 730 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 A.33 shows the results from estimating equation (7) 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 (8) using the 2006-2010 change in a different pollutant as the mediating factor, it has little impact on our estimates of the impact of the Great Recession on mortality (see Appendix Figure A.34). 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 about one-third for the 2007-2009 period, which is quite similar to the mediating effect we find for PM 2.5 alone in the same sample (see Appendix Figure A.33, panel (b)).

(see Appendix Figure A.35).

C.10 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 EPA (2004), Graff Zivin and Neidell (2013), and Currie et al. (2014) for reviews, or Deryugina et al. (2019) for more recent work.[14] 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 to pollution when it persists over a longer period of time; Barreca, Neidell and Sanders (2021) find evidence consistent with the latter.

These issues notwithstanding, 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 IXb that a one-percentage-point increase in the unemployment rate is associated with an average annual PM2.5 reduction of 0.14 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.

C.11 Instrumenting for PM2.5 exposure with Wind Direction

We estimate an alternative version of the pollution mediation analysis in Figure IXd, in which we instrument for the PM2.5 that a county is exposed to with the extent that they are downwind from commuting zones with substantial economic shocks from the Great Recession. Recall that commuting zones which experience a larger decline in unemployment from the Great Recession experience larger declines in PM 2.5 (see Figure IXb). The idea behind the instrument is that counties that are downwind of commuting zones that experience a large economic shock from the Great Recession may experience declines in pollution that are independent from the economic consequences of the Great Recession in the counties' own commuting zone. Prior work has used variation in wind direction as an instrument for both short-term

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

variation in pollution exposure (Deryugina et al. 2019) and long-term exposure to pollution (Anderson 2020).[15]

Construction of wind instrument. We first confirm that a persistent, time-invariant wind direction exists for each county. To do so, we calculate annual measures of the prevailing wind in each county using 2003-2016 monthly data over a 0.25 degree by 0.25 degree grid of the entire United States; we obtained the raw prevailing wind data as grid-month averages from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) data set.[16] To aggregate up geographically to the county level, we map the center of each grid square to the Census Block Group (CBG); we weight each square by 2010 population when averaging to the county-month level. We then take a simple average of prevailing wind direction across months to obtain an annual, county-level measure of prevailing wind. Figure A.36 confirms that there is a persistent wind direction. Specifically, it plots the county's wind direction (as defined by the angle θ) in year t, against the wind direction in $t-1$; the correlation is quite high. In what follows, we therefore use a single, time-invariant measure of the prevailing wind direction into each county, based on the average of the county-year measures during our 2003-2016 study period.

To construct the wind instrument, we follow Anderson (2020) and define a cone 45 degrees wide on both sides of the destination county's prevailing wind direction, extended outwards for a radius of 500 miles;[17] any neighboring counties whose centers fall within this cone are defined as upwind of the destination county.[18] We use the simple average of the CZ-level Great Recession shock in all upwind counties as instruments for the PM2.5 shock of the destination county. We exclude from the group of upwind counties any counties that share a CZ with the destination county and, due to data availability, we only consider Great Recession shocks for U.S. counties that fall within our defined cone and do not account for recession-induced changes in pollution in Canadian or Mexican regions that also fall within a cone.

Figure A.37 illustrates examples of our instrument. The prevailing direction vector points towards the destination county and extends outward 500 miles from the destination county. The quarter-circle region defined as upwind is a cone that extends 45 degrees in either direction of the prevailing wind direction. Any counties whose centers fall within the defined upwind region are classified as upwind counties, and are highlighted in yellow.

First stage and placebo test. We define the counties $\kappa \in K(c)$ to be the set of counties that are upwind of county c and are not in the same commuting zone as county c, with $N_{K(c)}$ denoting the number

[15] An alternative to using wind direction as an instrument would be to use an integrated assessment model such as the AP3 model (see Hollingsworth et al. (2022) for a recent paper taking this approach). The AP3 model captures emissions transportation over long distances but requires as inputs measures of emissions of individual pollutants. Since our analysis uses overall PM 2.5 pollution measures rather than emissions of individual pollutants, we use the wind instrument approach instead to predict downwind pollution changes. To the extent that our wind instrument approach does not capture all of the downwind effects that would be captured in the AP3 model, we will understate the overall role of pollution in explaining our mortality results.

[16] Data can be downloaded at: https://cds-beta.climate.copernicus.eu/datasets/reanalysis-era5-single-levels-monthly-means?tab=overview. In the raw data, wind direction is given as a u vector, the strength of wind along the east-west axis, and a v vector, the strength of wind along the north-south axis. After aggregating to the (time-invariant) county level, basic trigonometry allows us to convert the u and v vectors into a wind direction angle ranging from 0 to 360 degrees, where north is 0 degrees and south is 180 degrees.

[17] The 500 mile cutoff is ad hoc; we chose it to maximize the strength of the first stage.

[18] We calculate the coordinates of each county's center by averaging the coordinates of each Census Block Group within the county, weighting by 2010 population.

of counties in set $K(c)$ The first stage estimating equation is therefore:

$$PM2.5_{ct} = \rho_t \left[\left(\frac{1}{N_{K(c)}} \sum_{\kappa \in K(c)} SHOCK_{cz(\kappa)} \right) * \mathbb{1}(Year_t) \right] + \beta_t [SHOCK_{cz(c)} * \mathbb{1}(Year_t)] + \alpha_c + \gamma_t + \epsilon_{ct}, \quad (29)$$

where $PM2.5_{ct}$ is the level of PM2.5 in a county-year for the destination county c, $SHOCK_{cz(c)}$ is the CZ-level Great Recession shock in county c, while $SHOCK_{cz(\kappa)}$ is the CZ-level Great Recession shock in some upwind county κ. ρ_t are the coefficients of the instrument, β_t are the coefficients on the destination county's own Great Recession shock, and α_c and γ_t denote county and year fixed effects, respectively.

Since the wind direction data is not sufficiently granular to contain at least one observation in each county, we are able to define the wind instrument for 2,982 of the 3,107 counties (94.8 percent of the population-weighted counties) analyzed in Figure IXb). Figure A.38a shows the first stage relationship between the instrument and PM 2.5 levels; specifically, it displays the coefficients ρ_t from equation (29).

To verify that wind is the actual channel for the instrument's power, and that the Great Recession shocks of other, non-upwind, neighboring counties would not be equally effective instruments for the destination county's PM2.5 shock, we run a placebo test in equation (30) where we add a placebo instrument in addition to the real instrument. The placebo instrument has the exact same definition as the real instrument, but with the prevailing wind direction rotated 90 degrees clockwise. A new cone is drawn out from the placebo prevailing wind direction, also 45 degrees on both sides and 500 mile radius, and $K'(c)$ is the set of placebo upwind counties comprised of individual counties κ'. Everything else is defined the same as in equation (29).

$$PM2.5_{ct} = \rho_t \left[\left(\frac{1}{N_{K(c)}} \sum_{\kappa \in K(c)} SHOCK_{cz(\kappa)} \right) * \mathbb{1}(Year_t) \right] + \eta_t \left[\left(\frac{1}{N_{K'(c)}} \sum_{\kappa' \in K'(c)} SHOCK_{cz(\kappa')} \right) * \mathbb{1}(Year_t) \right] + \beta_t [SHOCK_{cz(c)} * \mathbb{1}(Year_t)] + \alpha_c + \gamma_t + \epsilon_{ct} \quad (30)$$

Note that while rotating the prevailing wind direction 180 degrees would be an intuitive choice of placebo, wind actually tends to blow along an axis, sometimes reversing direction, so a 90 degree rotation is a truer placebo than a 180 degree rotation (NOAA 2017).

Figures A.38b and A.38c show the results of the placebo test: the estimates of ρ_t and η_t from equation (30) respectively. Estimates of ρ_t remain very similar in the placebo test, while estimates of η_t, the placebo instrument, are insignificant. This supports the contention that our wind instrument captures PM2.5 declines, and that these declines are driven by changes in economic activity in specifically upwind counties.

IV mediation analysis. For the IV version of the mediation analysis in equation (8), we estimate a more parsimonious version of equation (8) in which we replace the interaction of each shock with year fixed effects with the interaction of each shock with either a single indicator $POST$ variable for years 2007-2016, or—in an alternative specification—with two indicator variables for the years 2007-2009 ($POST1$) and the years 2010-2016 ($POST2$). We do this to increase the power of the first stage.

Specifically, we estimate:

$$y_{ct} = \beta[SHOCK_{cz(c)} * POST] + \alpha_c + \gamma_t + \epsilon_{ct} \tag{31}$$

and a mediated version:

$$y_{ct} = \beta[SHOCK_{cz(c)} * POST] + \phi[PM2.5\_SHOCK_c * POST] + \alpha_c + \gamma_t + \epsilon_{ct} \tag{32}$$

or analogs in which the single indicator $POST$ is replaced by two separate indicators for $POST1$ and $POST2$.

Table A.19 shows the results. Columns (1) and (2) of Table A.19 show that the results from estimating equations (31) and (32) look very similar to the more flexible specifications seen, respectively in Panels (a) and (d) of Figure IX.[19] As we saw previously, the OLS mediation analysis suggests that controlling for pollution reduces the recession-induced mortality declines by about 20 percent in 2007-2009, from an estimated impact of a 1 percentage point increase in unemployment on mortality of -0.530 percent (standard error = 0.155) in column 1 to an estimated impact of -0.425 percent (standard error = 0.161) in column 2 once the PM2.5 shock is controlled for. The role of recession-induced declines in PM2.5 in mediating the impact of the Great Recession on mortality becomes, if anything, more pronounced when we instrument for the pollution shock with upwind economic shocks in column (3). The IV analysis in column 3 indicates that controlling for the PM 2.5 shock essentially obliterates the impact of unemployment on mortality in 2007-2009, with the point estimate now a statistically insignificant -0.022 (standard error = 0.31). A similar pattern appears for the 2010-2016 estimates or the pooled 2007-2016 estimates. The substantially larger mediating impact of pollution in the IV analysis is consistent with the extensive discussions in the literature of the potential for substantial measurement error in PM2.5 (Fowlie, Rubin and Walker 2019; Grainger and Schreiber 2019; Currie, Voorheis and Walker 2023).

[19] Note that the estimates in column (1) and (2) differ slightly from the average of the pooled coefficients in Figure IXa and IXd, respectively, because the sample here is the *subsample* of 2,982 counties (from the original 3,107) for which we have the data necessary to construct the wind instrument.

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:** Figures V and A.8 show results for the 11 most common causes of death, plus a residual category for all other deaths.
- **Deaths of despair:** Figure A.11a shows results for deaths of despair, while Figures Vd, Ve, and A.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:** Figures A.40 and A.41 show results for different age groups.
- **By education:** Figure A.42 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 further to those with less than high school, exactly high school, some college but no four-year degree, and a four-year college degree or more.
- **By education, by age:** Figure A.43 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:** Figure A.44 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:** Figure A.45 disaggregates results by Non-Hispanic White, Non-Hispanic Black, Hispanic, and Other populations.
- **By gender:** Figure A.46 disaggregates results by gender.
- **Health status of marginal life saved:** Figure A.47 shares average predicted counterfactual remaining life expectancy among decedents under a range of controls, and Tables A.16 and A.17 estimate the impact of $SHOCK_c$ on life-years lost under these counterfactual life expectancies.
- **Morbidity:** Figures A.48 and A.49 show impacts on measures of morbidity from the BRFSS.
- **Motor vehicle mortality by age:** Figure A.52 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, motor vehicle accidents account for a much larger share of the recession-induced mortality declines. 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:** Figure A.16 shows results restricting to non-movers in the Medicare panel data. Figures A.17 and A.19 confirm 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, and that results look similar when assigning individuals to CZs based on their 2003 CZ of residence rather than their yearly CZ of residence.

- **Sensitivity to geography:** Figure A.26 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:** Figure A.27 shows results under alternative functional forms.

- **Linearity:** Figure A.28 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 Figure A.30 adopts a modified version of equation (17), 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:**. Figures A.50, and A.51 show results for self-reported health behaviors in the BRFSS.

- **Utilization of health services:** Figure A.21 examines utilization of health services among the Medicare population.

- **Nursing home care:** Figure A.53 examines the effect of $SHOCK_c$ on mortality separately by individuals' nursing home utilization, while Figures A.54 and A.55 examine nursing home characteristics.

- **Informal care provision:** Figure A.31 examines the effect of $SHOCK_c$ on measures of informal care provision recorded in the HRS.

- **Pollution:** Figures A.33, A.34, and A.35 examine the mediation effects of other pollutants on our main results.

E Additional Details on Welfare Analyses

E.1 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:

$$\mathbb{E}[U(c,m)]^{\text{normal}} = p^H * T * u((1-d^H)c) + (1-p^H) * T * u(c) \tag{33}$$

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

$$\mathbb{E}[U(c,m)]^{\text{recession}} = p^L * T * u((1-d^L)c) + (1-p^L) * T * u(c) \tag{34}$$

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

$$\mathbb{E}[U((1+\Delta)c,m)]^{recession} = \mathbb{E}[U(c,m)]^{normal} \tag{35}$$

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:

$$\Delta = \left(\frac{p^H(1-d^H)^{(1-\gamma)} + (1-p^H)}{p^L(1-d^L)^{(1-\gamma)} + (1-p^L)} \right)^{1/(1-\gamma)} - 1 \tag{36}$$

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.[20] The welfare cost of the recession is independent of b, the parameter which governs the VSLY, and of 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.[21]

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:

$$\mathbb{E}[U]^{\text{normal}} = p^H * T * u((1-d^H)c) + (1-p^H) * T * u(c) \tag{37}$$

$$\begin{aligned} \mathbb{E}[U]^{\text{recession}} &= p^L * T(1+dT) * u((1-d^L)c) \\ &\quad +(1-p^L) * T(1+dT)u(c) \end{aligned} \tag{38}$$

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

[20] The expression is also increasing in $p^L - p^H$ and $d^L - d^H$ for all $0 < d^L < 1$ and $0 < d^H < 1$.

[21] 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}):

$$\Delta^{dT} = \left(\frac{-dT * b/\tilde{u}(c) + p^H(1-d^H)^{(1-\gamma)} + (1-p^H)}{(1+dT)(p^L(1-d^L)^{(1-\gamma)} + (1-p^L))} \right)^{1/(1-\gamma)} - 1 \tag{39}$$

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 (39) is valid for any value of dT and it simplifies to the expression for Δ in equation (36) if $dT = 0$.[22]

We can build further intuition by setting $p^H = 0$ and then taking a first-order approximation around the left-hand side of equation (39) at $\Delta^{dT} = 0$, which leads to the following expression:

$$1 + (1-\gamma) * \Delta^{dT} \approx \frac{-dT * b + \tilde{u}(c)}{(1+dT) * (p^L * (1-d^L)^{(1-\gamma)}\tilde{u}(c) + (1-p^L)\tilde{u}(c))} \tag{40}$$

$$\Delta^{dT} \approx \Delta - dT\left(\frac{\text{VSLY}}{c} + \frac{1}{\gamma - 1}\right) \tag{41}$$

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.[23]

E.2 Analytical Results for the Full Model

In the main text, we report simulation results of our model extending Krebs (2007) to allow for recessions to have mortality effects. The main reason we focus on the simulation results (rather than analytical results) is to be able to use realistic age-specific mortality rates which allow the welfare effects of recessions with endogenous mortality to vary by age.

In this section, we derive analytical results for the full model to show that the intuition from the simplified welfare model above carries through to our full model. To derive an analytical solution to our model, we make the following simplifying assumptions: we set $\beta = 1$, and we assume that the mortality rate $1 - q^S$ depends on the aggregate state but not age. We also continue to assume hand-to-mouth consumption so that consumption equals income each period.

In this setup, our goal is to solve for Δ, which is implicitly defined as follows:

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

[22] To see this, note that the $-dT * b\tilde{u}(c)$ 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.

[23] The derivation uses the fact that the per-period utility function $u(c) = \tilde{u}(c) + b$ implies $VSLY = bc^\gamma - c/(\gamma - 1)$, which can be re-written as follows:

$$\begin{aligned} VSLY &= bc^\gamma - c/(\gamma-1) \\ VSLY/c + 1/(\gamma-1) &= b * c^{(\gamma-1)} \\ VSLY/c + 1/(\gamma-1) &= b/\tilde{u}(c)/(1-\gamma) \end{aligned}$$

This expression shows that b needs to be "sufficiently large" to ensure that $VSLY/c$ is positive, which is necessary for individuals to prefer lower mortality rates.

As in the simplified model, we define $u(c) \equiv \tilde{u}(c) + b$, and we use this definition to re-arrange as follows:

$$\mathbb{E}_0\left[\sum_{t=0}^{\infty}(q^S)^t(\tilde{u}((1+\Delta)y(t))+b)\right] = \mathbb{E}_0^{S=H}\left[\sum_{t=0}^{\infty}(q^H)^t(\tilde{u}(y(t))+b)\right]$$

$$\mathbb{E}_0\left[\sum_{t=0}^{\infty}(q^S)^t(\tilde{u}((1+\Delta)y(t)))\right] + \mathbb{E}_0\left[\sum_{t=0}^{\infty}(q^S)^t(b)\right] = \mathbb{E}_0^{S=H}\left[\sum_{t=0}^{\infty}(q^H)^t(\tilde{u}(y(t)))\right] + \mathbb{E}_0^{S=H}\left[\sum_{t=0}^{\infty}(q^H)^t(b)\right]$$

We next define $T \equiv \mathbb{E}_0\left[\sum_{t=0}^{\infty}(q^S)^t\right]$, $T^{S=H} \equiv \mathbb{E}_0\left[\sum_{t=0}^{\infty}(q^H)^t\right]$, and $dT = T - T^{S=H}$, so that $dT > 0$ implies that eliminating recessions reduces mortality. We then have the following:

$$\mathbb{E}_0\left[\sum_{t=0}^{\infty}(q^S)^t(\tilde{u}((1+\Delta)y(t)))\right] + dT * b = \mathbb{E}_0^{S=H}\left[\sum_{t=0}^{\infty}(q^H)^t(\tilde{u}(y(t)))\right]$$

Following the derivations in Krebs (2007), we have the following expressions:

$$\mathbb{E}_0\left[\sum_{t=0}^{\infty}(q^S)^t(\tilde{u}((1+\Delta)y(t)))\right] = \frac{\tilde{u}((1+\Delta)y_0)}{1-\overline{q}\mathbb{E}_0[(1+g)^{(1-\gamma)}(1+\theta)^{(1-\gamma)}(1+\eta)^{(1-\gamma)}]}$$

$$\mathbb{E}_0^{S=H}\left[\sum_{t=0}^{\infty}(q^H)^t(\tilde{u}(y(t)))\right] = \frac{\tilde{u}(y_0)}{1-q^H\mathbb{E}_0[(1+g)^{(1-\gamma)}(1+\theta)^{(1-\gamma)}(1+\eta)^{(1-\gamma)}]}$$

where $\overline{q} = \pi^L * q^L + \pi^H * q^H$. Substituting in these expressions gives the following:

$$\frac{(1+\Delta)^{(1-\gamma)}}{1-\overline{q}\mathbb{E}_0[(1+g)^{(1-\gamma)}(1+\theta)^{(1-\gamma)}(1+\eta)^{(1-\gamma)}]} + dT * b/\tilde{u}(y_0) = \frac{1}{1-q^H\mathbb{E}_0^{S=H}[(1+g)^{(1-\gamma)}(1+\theta)^{(1-\gamma)}(1+\eta)^{(1-\gamma)}]}$$

Note that if $dT = 0$ and $q^L = q^H = q$, then we have the following:

$$(1+\Delta)^{(1-\gamma)} = \frac{1-q\mathbb{E}_0[(1+g)^{(1-\gamma)}(1+\theta)^{(1-\gamma)}(1+\eta)^{(1-\gamma)}]}{1-q\mathbb{E}_0^{S=H}[(1+g)^{(1-\gamma)}(1+\theta)^{(1-\gamma)}(1+\eta)^{(1-\gamma)}]}$$

$$\Delta = \left(\frac{1-q\mathbb{E}_0[(1+g)^{(1-\gamma)}(1+\theta)^{(1-\gamma)}(1+\eta)^{(1-\gamma)}]}{1-q\mathbb{E}_0^{S=H}[(1+g)^{(1-\gamma)}(1+\theta)^{(1-\gamma)}(1+\eta)^{(1-\gamma)}]}\right)^{\frac{1}{1-\gamma}} - 1$$

which is the same expression as in Krebs (2007), setting $\beta = q$.

To simplify the expression when $dT > 0$, we use the fact that $(VSLY/c) * (1-\gamma) - 1 = b/\tilde{u}(c)$. We then go back to the above expression for Δ and substitute. We also define $\lambda \equiv (1-\overline{q}\mathbb{E}_0[(1+g)^{(1-\gamma)}(1+\theta)^{(1-\gamma)}(1+\eta)^{(1-\gamma)}])/(1-q^H)$. We then have the following expression for Δ^{dT} (which we label as Δ^{dT} following the simplified model in the previous section and to distinguish from the Δ defined in Krebs (2007)):

$$\boxed{(1+\Delta^{dT})^{(1-\gamma)} = \frac{1-\overline{q}\mathbb{E}_0[(1+g)^{(1-\gamma)}(1+\theta)^{(1-\gamma)}(1+\eta)^{(1-\gamma)}]}{1-q^H\mathbb{E}_0^{S=H}[(1+g)^{(1-\gamma)}(1+\theta)^{(1-\gamma)}(1+\eta)^{(1-\gamma)}]} - \frac{dT}{T^{S=H}} * \lambda * ((VSLY/y_0) * (1-\gamma) - 1)}$$

As in the previous section, if we take a first-order approximation around $\Delta^{dT} = 0$, then we get $1 + (1-\gamma) * \Delta^{dT}$ on the left-hand side, which gives the following approximation formula:

$$\boxed{\Delta^{dT} \approx \Delta - \frac{dT}{T^{S=H}} * \lambda * \left(\frac{VSLY}{y_0} + \frac{1}{\gamma - 1}\right)}$$

The formula above is similar to the approximation formula in E.1 except for the additional λ term which is a necessary adjustment since the full model has a dynamic income process. The two boxed formulas show analytically that the welfare cost of recessions in the full model is approximately "separable" in the welfare cost coming from endogenous mortality.

E.3 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 mortality tables separately 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 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 $dm = -0.015$.

- **VSLY** We report results for a VSLY of \$100k, \$250k, and \$400k.[24] 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.

[24]We calculate the value of b given an assumed value of γ for each $VLSY$ value, and we report these values in Table A.20.

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.

E.4 Welfare Analysis by Education

Consider two educational groups where $e = \ell$ refers to individuals with a high school (HS) diploma or less and $e = h$ to individuals with more than a HS diploma. We have heterogeneity by education through three main channels in our welfare analysis: mortality rates $m_e(t)$, mortality effects dm_e, and income effects (which are jointly defined by the probability of being displaced d_e^ω and the displacement shock p_e^ω, where $\omega \in \{L, H\}$. Below we discuss how we estimate or calibrate each of these parameters.

- **Mortality rates by education** We allow mortality rates to vary by education, calibrating them based on Meara, Richards and Cutler (2008) so that the remaining life expectancy at age 25 is 14.1% higher for those with more than a high school degree.[25] Specifically, we use our unisex mortality rates, given by a population-weighted average of SSA gender-specific rates, and adjust it for education using the following algorithm: First, guess some $x \in (0, 1)$. Second, for each age a define $m_a^\ell = (1 + x)m_a$ and $m_a^h = (1 - x)m_a$, where m_a is the mortality rate at that age from the unisex table. Third, using these mortality rates and the methodology described in Appendix C.4.1, compute the remaining life expectancy at each age. Fourth, choose x such that the remaining life expectancy at age 25 is 14.1% higher for those with less than a high school degree.

- **Mortality effects by education** In Section 3, we report that a 1 percentage point increase in the local unemployment rate is associated with a statistically significant 0.80 percent (standard error = 0.26) decline in the 2007-2009 mortality rate for those with a high school education or less, compared to a statistically significant 0.014 percent (standard error = 0.54) increase in the mortality rate for those with more than a high school education. We use these estimates to calibrate the welfare effects of recessions by education by imposing that the ratios of the mortality effects in a typical recession relative to our estimated mortality effects during the Great Recession are the same by education.

  Specifically, we set up a system of two equations with two unknowns: the typical recession mortality effects for each education group e: $dm_{e=\ell}$ and $dm_{e=h}$. Define ζ_e as the population share for educational group.

$$\begin{cases} dm = \zeta_{e=\ell} dm_{e=\ell} + (1 - \zeta_{e=\ell}) dm_{e=h} \\ \frac{dm_{e=\ell}}{dm^{GR}_{e=\ell}} = \frac{dm_{e=h}}{dm^{GR}_{e=h}} \end{cases}$$

  The first equation states that the overall mortality effect of a typical recession is given by the population-share-weighted average of the mortality effects by education. The second equation states that the ratio of the mortality effects (of a typical recession relative to the Great Recession) is the same by education group. We estimate in the CPS that 68 percent of the population has a high school degree or less, and 32 percent has at least some college education, so we set $\zeta_{e=\ell} = 0.68$ and $\zeta_{e=h} = 0.32$.[26] As noted in Section 5, we calibrate the mortality effect of a typical recession

[25] This number comes from Exhibit 1 of Meara, Richards and Cutler (2008), which shows that, in 2000, remaining life expectancy at 25 was 56.6 years for those with more than HS and 49.6 years for those with a HS diploma or less, a difference of 14.1%.

[26] Note that our analysis in this section pools CPS data from 1976-2007, which means that we re-estimate the population shares by education group for this longer time period. The population shares indicate lower average levels of education than for the population in the Great Recession sample because of secular trends in educational attainment in the US during the last several decades.

to be $dm = -0.015$ based on our baseline empirical estimates that a 1 percentage point increase in unemployment is associated with a 0.5 percent decline in the mortality rate, combined with the average 3.1 percentage point increase in the unemployment rate in a typical recession. Our Great Recession estimates are $dm^{GR}_{e=\ell} = -0.0367$ and $dm^{GR}_{e=h} = 0.0006$ Using these estimates, we solve the two-equation system and find $dm_{e=\ell} = -0.023$ and $dm_{e=h} = 0.0004$.

- **Job displacement effects by education** To calibrate the welfare effects of recessions by education, we also need to calibrate education-group-specific job displacement parameters and education-group-specific change in income conditional on job displacement parameters. Existing evidence from Farber (2017) using the CPS Displaced Worker Supplement finds larger percentage reductions in income for workers with lower levels of education. Workers with lower levels of education also have higher unemployment rates in both recessions and normal times, partly due to higher job separation rates. As a result, we calibrate separate job displacement and income change (conditional on job displacement) parameters for the two education groups (i.e., separate p^S_e and d^S_e parameters for each education group in each aggregate state).

  To do this, we first calibrate the education-specific job displacement probabilities p^S_e. We estimate the education-group-specific average unemployment rate by state S ($\overline{v}^S_e$) using data from the CPS from 1976 to 2007; we use the recession years within this time period to estimate $\overline{v}^L_e$ and the non-recession years to estimate $\overline{v}^H_e$ (based on the recession years defined by the NBER). This gives us estimates $\overline{v}^L_{e=\ell} = 0.095$, $\overline{v}^H_{e=\ell} = 0.083$, $\overline{v}^L_{e=h} = 0.041$, and $\overline{v}^H_{e=h} = 0.038$.

  Next, we assume that the ratios of unemployment rates by education (in state S) are the same as the ratio of the p^S_e job displacement probabilities needed in the model calibration. We also assume that the overall job displacement probability p^S is equal to the education-group-weighted average of the education-group-specific job displacement probabilities. This leads to the following two-equation system, which is defined for each aggregate state:

$$\begin{cases} p^S = \zeta_{e=\ell} p^S_{e=\ell} + (1 - \zeta_{e=\ell}) p^S_{e=h} \\ \frac{\overline{v}^S_{e=\ell}}{\overline{v}^S_{e=h}} = \frac{p^S_{e=\ell}}{p^S_{e=h}} \end{cases}$$

  Following Krebs (2007), we have $p^L = 0.05$ and $p^H = 0.03$, which when combined with the estimates above allows us to solve for the four unknown parameters: $p^L_{e=\ell} = 0.061$, $p^L_{e=h} = 0.027$, $p^H_{e=\ell} = 0.037$, and $p^H_{e=h} = 0.016$.

  The last set of parameters are the changes in income conditional on displacement, which we also want to allow to vary by education group and aggregate state (d^S_e). To calibrate these values, we use estimates of the earnings losses for full-time displaced workers by education from Table 2 in Farber (2017). We average the education categories (using population weights) to match our two broad education categories, and this gives us the average decline in income from job displacement by education (averaged across labor market states). To get state-specific estimates by education, we solve the following two-equation system for each aggregate state:

$$\begin{cases} d^S = \zeta_{e=\ell} d^S_{e=\ell} + (1 - \zeta_{e=\ell}) d^S_{e=h} \\ \frac{d^S_{e=h}}{d_{e=h}} = \frac{d^S_{e=\ell}}{d_{e=\ell}} \end{cases} \tag{42}$$

As with the mortality effects and the job displacement probabilities, the two equations assume a common ratio by education group and impose that the overall average income decline by state is equal to the education-group-weighted average income decline. Given the $d^L = 0.21$ and $d^H = 0.09$ values from Krebs (2007) and the Farber (2017) estimates, we calculate $d^L_{e=\ell} = 0.233$, $d^L_{e=h} = 0.161$, $d^H_{e=\ell} = 0.100$, and $d^H_{e=h} = 0.069$.

This gives us all of the parameters needed to calibrate the welfare model separately by education group.

E.5 Incorporating Mortality Effects of Job Displacement

Sullivan and Von Wachter (2009) find that job displacements substantially increase mortality. Our finding that the increase in unemployment from the Great Recession reduces mortality is a *net* result, which can mask the increase in mortality for the subset of people who lose their job. In our baseline welfare model calibrations, we do not allow for job displacements to affect mortality. This section describes how we adapt our model to accommodate this result by allowing for separate effects of recessions on mortality for those who do or do not experience job displacement, in order to incorporate the results in Sullivan and Von Wachter (2009).

Since Sullivan and Von Wachter (2009) find that mortality increases significantly for displaced workers with high tenure, we add a new state variable to our model so that agents have tenure ($\tau \in \{\ell, h\}$) drawn independently (across our simulated cross section of individuals each period), with the per-period probability of high tenure given by $p^{\tau=h}$. We define D to be an indicator that equals one at or after the first time a worker is displaced with high tenure. Mortality rates are affected by job displacement (for high-tenure workers only) and by the aggregate state (as in the baseline model) as follows: $m^L = (1 + dm^{L'}) * (1 + dm^{D=1}) * m^H$, where $dm^{L'} < 0$ is the overall "gross" effect of recessions and $dm^{D=1} > 0$ is the persistent effect of high-tenure job displacement on mortality.

To calculate $dm^{L'}$ and $dm^{D=1}$, we impose the condition that the ratio of expected mortality in the recession state and the normal state in this new model is the same as in our baseline model calibration. In other words, given a calibrated value for the displacement effect $dm^{D=1} > 0$, we set the "gross" mortality effect of recessions $dm^{L'} < 0$ so that the *net* impact of recessions on mortality remains the same as in the baseline model. More specifically, Sullivan and Von Wachter (2009) estimate that high-tenure displaced workers between age 35 and 50 lose around 1.5 years of life expectancy. Using the framework described above and the survival function in our main calibration, this is equivalent to a high-tenure displacement effect on mortality of $dm^{D=1} = 0.21$. Defining high-tenure as at least 6 years of tenure and using data from the CPS Displaced Workers Supplement, we find that the probability of being at or after the first high-tenure displacement probability in any period is given by 0.25, which allows us to calculate a gross recession effect on mortality of $dm^{L'} = -0.035$. This is 2.3 times larger than the dm^L used in our baseline calibration, which indicates how the large estimated mortality effects in Sullivan and Von Wachter (2009) indirectly affect the welfare cost of recessions for the "never displaced" workers according to our model (i.e., recessions benefit them 2.3 times as much as the average worker in our baseline calibration).

To see how this affects our welfare analysis, we calibrate this extended model allowing for mortality effects of job displacement, and we break out the workers who are "ever displaced" and "never displaced." Figure A.39a reports the mortality cost of a job displacement as a percentage of average annual consumption. This welfare cost is defined as the willingness to accept an economy where job displacements affect mortality (i.e., $dm^{D=1} = 0.21$) relative to an economy where job displacements do not affect mortality (i.e., $dm^{D=1} = 0$), holding constant the income and consumption consequences of job displacement (following Krebs (2007)). The large welfare effects therefore come entirely from the large effects of job displacement on mortality risk.

The second panel (Figure A.39b) shows the welfare cost of recessions for the "ever displaced" and "never displaced" workers under exogenous and endogenous mortality. Given the Sullivan and Von Wachter (2009) age restrictions, we assume that only workers between ages 35 and 50 can experience the large mortality effects of a high-tenure job displacement. The results show that the welfare cost of recessions is about twice as large for the ever-displaced workers compared to never displaced workers, and the gap between the welfare costs with endogenous and exogenous mortality is larger for the never displaced workers compared to our baseline calibration; this follows mechanically from the fact that $dm^{L'}$ is larger in magnitude than the dm^{L} used in our baseline calibration.

One implication of these results is that any recession that triggers an unusually large number of job displacements of high-tenure workers is likely to have smaller reductions (or even increases) in mortality in the aggregate as compared to our Great Recession estimates. Put another way, the mortality increases from job displacements in Sullivan and Von Wachter (2009) are substantially larger in magnitude than the overall mortality decreases that we estimate across the entire population. Interestingly, there is existing evidence in macroeconomics that recessions are primarily driven by reductions in the job finding rate rather than by increases in the job separation rate (Shimer 2012). This would make it much easier to simultaneously explain our results alongside the results in Sullivan and Von Wachter (2009). The Krebs (2007) model we use assumes that job displacement increases during recessions (and in our extension, we assume that this increase in displacement probability is the same (proportionally) for high and low tenure workers), but if in fact recessions are not associated with an increase in job displacement, the two findings may not be related.

Appendix References

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

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

Autor, David, David Dorn, and Gordon Hanson, "The China Syndrome: Local Labor Market Effects of Import Competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–2168.

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

Bartik, Alexander W, Janet Currie, Michael Greenstone, and Christopher R Knittel, "The Local Economic and Welfare Consequences of Hydraulic Fracturing," *American Economic Journal: Applied Economics*, 2019, *11* (4), 105–155.

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

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

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

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

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

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

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

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

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

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

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

Farber, Henry S., *"Employment, Hours, and Earnings Consequences of Job Loss: US Evidence from the Displaced Workers Survey," Journal of Labor Economics, 2017, 35 (S1), S235 – S272.*

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

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

Gould, Carlos F, M Lorena Bejarano, Brandon De La Cuesta, Darby W Jack, Samuel B Schlesinger, Alfredo Valarezo, and Marshall Burke, *"Climate and health benefits of a transi-*

tion from gas to electric cooking," Proceedings of the National Academy of Sciences, 2023, 120 (34), e2301061120.

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

Grainger, Corbett and Andrew Schreiber, *"Discrimination in Ambient Air Pollution Monitoring?," AEA Papers and Proceedings, 2019, 109, 277–282.*

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

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

Hollingsworth, Alex, Taylor Jaworski, Carl Kitchens, and Ivan J Rudik, *"Economic Geography and the Efficiency of Environmental Regulation," Working Paper 29845, National Bureau of Economic Research March 2022.*

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

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

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

Jha, Akshaya and Andrea La Nauze, *"US Embassy air-quality tweets led to global health benefits," Proceedings of the National Academy of Sciences, 2022, 119 (44), e2201092119.*

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

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

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

LTCFocus, *"Data Download," urlhttps://ltcfocus.org/data 2023.*

Meara, Ellen R, Seth Richards, and David Cutler, *"The Gap Gets Bigger: Changes in Mortality and Life Expectancy, by Education, 1981–2000," Health Affairs, 2008, 27 (2), 350–360.*

Molitor, David, Jamie T Mullins, and Corey White, *"Air Pollution and Suicide in Rural and Urban America: Evidence from Wildfire Smoke," Proceedings of the National Academy of Sciences, 2023, 120 (38), e2221621120.*

Mommaerts, Corina and Yulya Truskinovsky, *"The Cyclicality of Informal Care," Journal of health economics, 2020, 71, 102306.*

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

NOAA, *"Flight Environment: Prevailing Winds," 2017. https://www.weather.gov/source/zhu/\protect\penalty\z@ZHU_Training_Page/winds/Wx_Terms/Flight_Environment.htm.*

Office of Disease Prevention and Health Promotion, *"National Vital Statistics System - Mortality (NVSS-M)," 2024. https://health.gov/healthypeople/objectives-and-data/data-sources-and-methods/data-sources/national-vital-statistics-system-mortality-nvss-m.*

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

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

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

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

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

Shimer, Robert, *"Reassessing the ins and outs of unemployment," Review of Economic Dynamics,* *2012, 15 (2), 127–148.*

Social Security Administration, *"Requesting SSA's Death Information," url-https://www.ssa.gov/dataexchange/request˙dmf.html 2023.*

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

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

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

van Donkelaar, Aaron, Melanie S. Hammer, Liam Bindle, Michael Brauer, Jeffery R. Brook, Michael J. Garay, N. Christina Hsu, Olga V. Kalashnikova, Ralph A. Kahn, Colin Lee, Robert C. Levy, Alexei Lyapustin, Andrew M. Sayer, and Randall V. Martin, *"Monthly Global Estimates of Fine Particulate Matter and Their Uncertainty," Environmental Science & Technology, 2020, 55 (22), 15287–15300.*

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

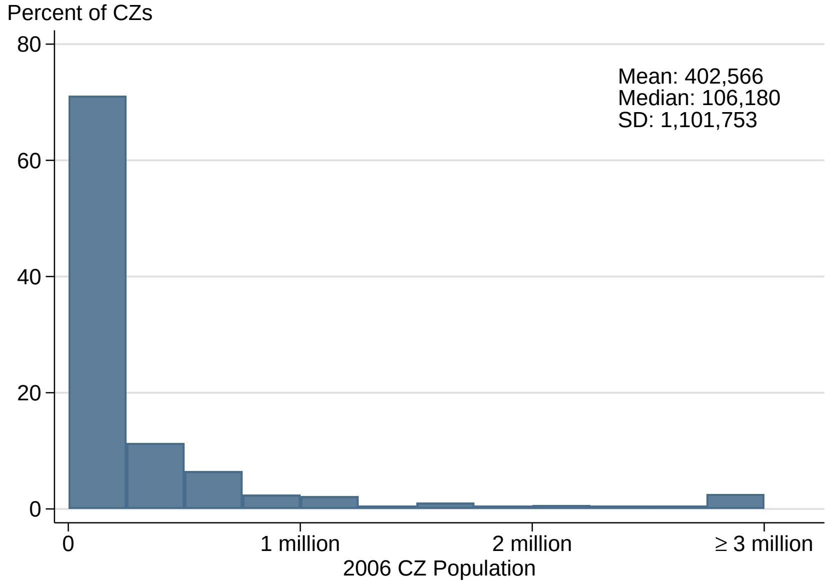
Voorheis, John, Jonathan Colmer, Kendall Houghton, Eva Lyubich, Mary Munro, Cameron Scalera, and Jennifer Withrow, *"Building the Prototype Census Environmental Impacts Frame," Center for Economic Studies (CES) Working Paper Series, 2023.*

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

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

F Appendix Figures

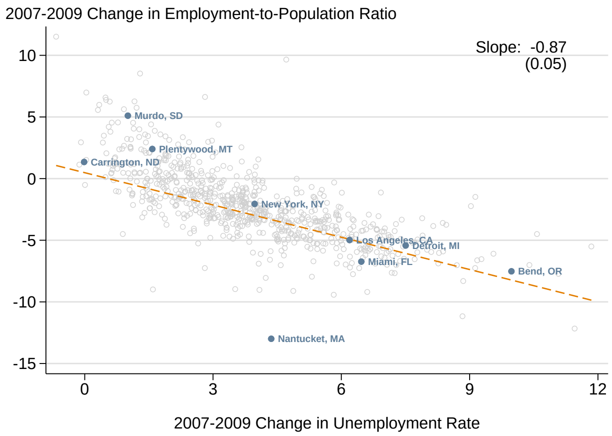
Figure A.1: 2006 Commuting Zone Population



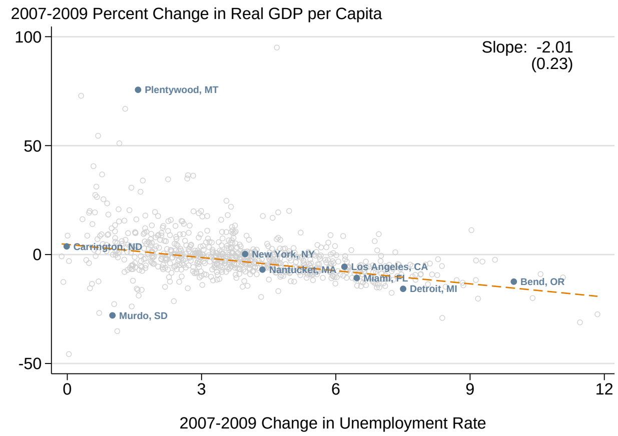
Notes: This figure displays a histogram of 2006 CZ populations, in bins of 250,000. For visualization purposes, CZs with populations larger than three million are binned to three million. Descriptive statistics in the upper right-hand corner are reported for the full distribution. N=741 CZs.

Figure A.2: Correlation of Alternative Great Recession Shocks

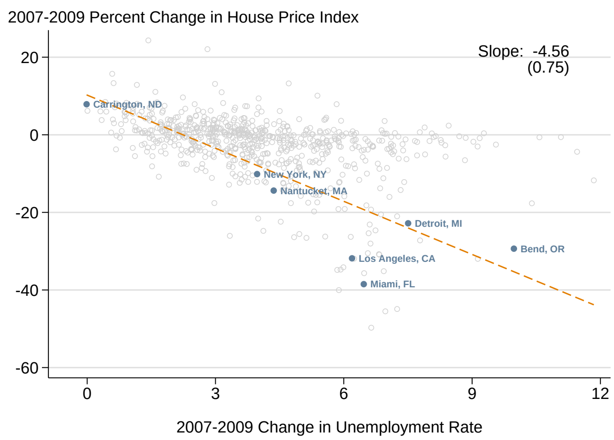
(a) 2007-09 Employment-to-Population Change



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



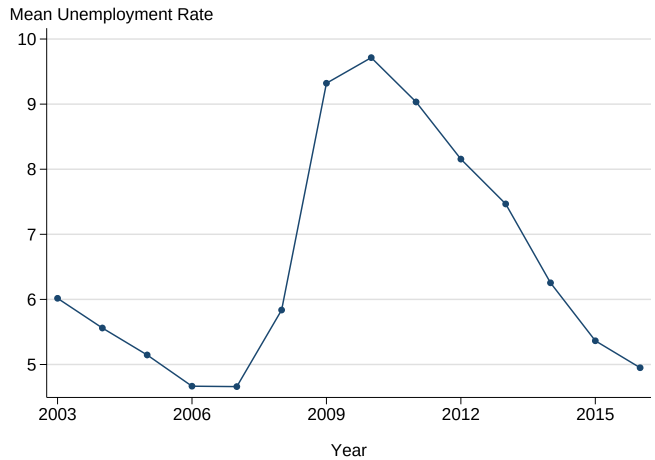
(c) 2007-09 House Price Index Percent Change



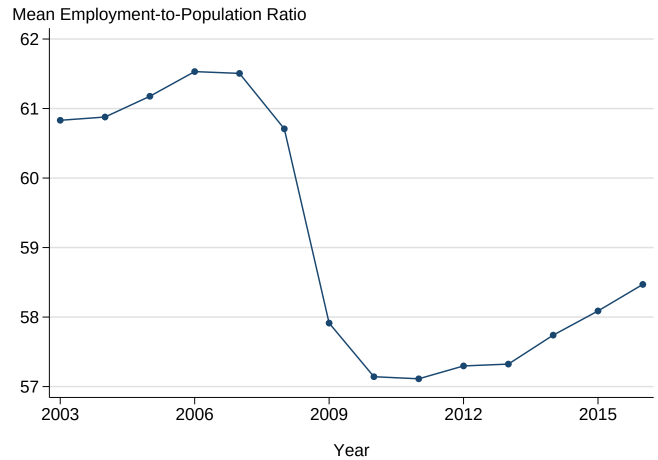
Notes: This figure displays scatterplots of measures of shocks associated with the Great Recession. Figure A.2a plots the 2007-2009 change in the CZ employment-to-population ratio against the 2007-2009 change in the CZ unemployment rate. Figure A.2b plots the change in CZ real GDP per capita (in thousands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

Figure A.3: Time Series of Economic Indicators

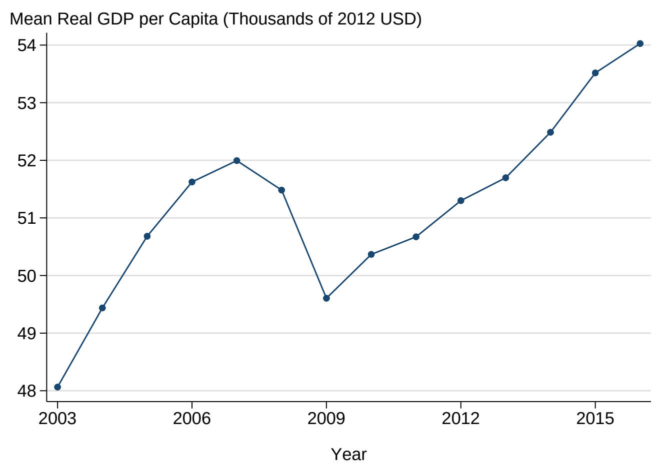
(a) Unemployment Rate



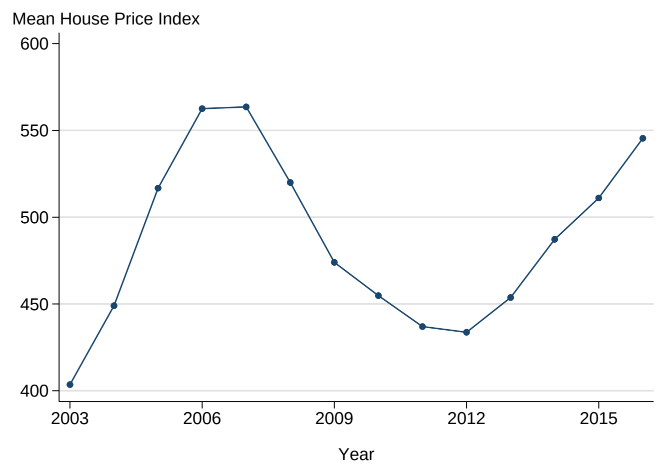
(b) Employment-to-Population Ratio



(c) Real GDP per Capita

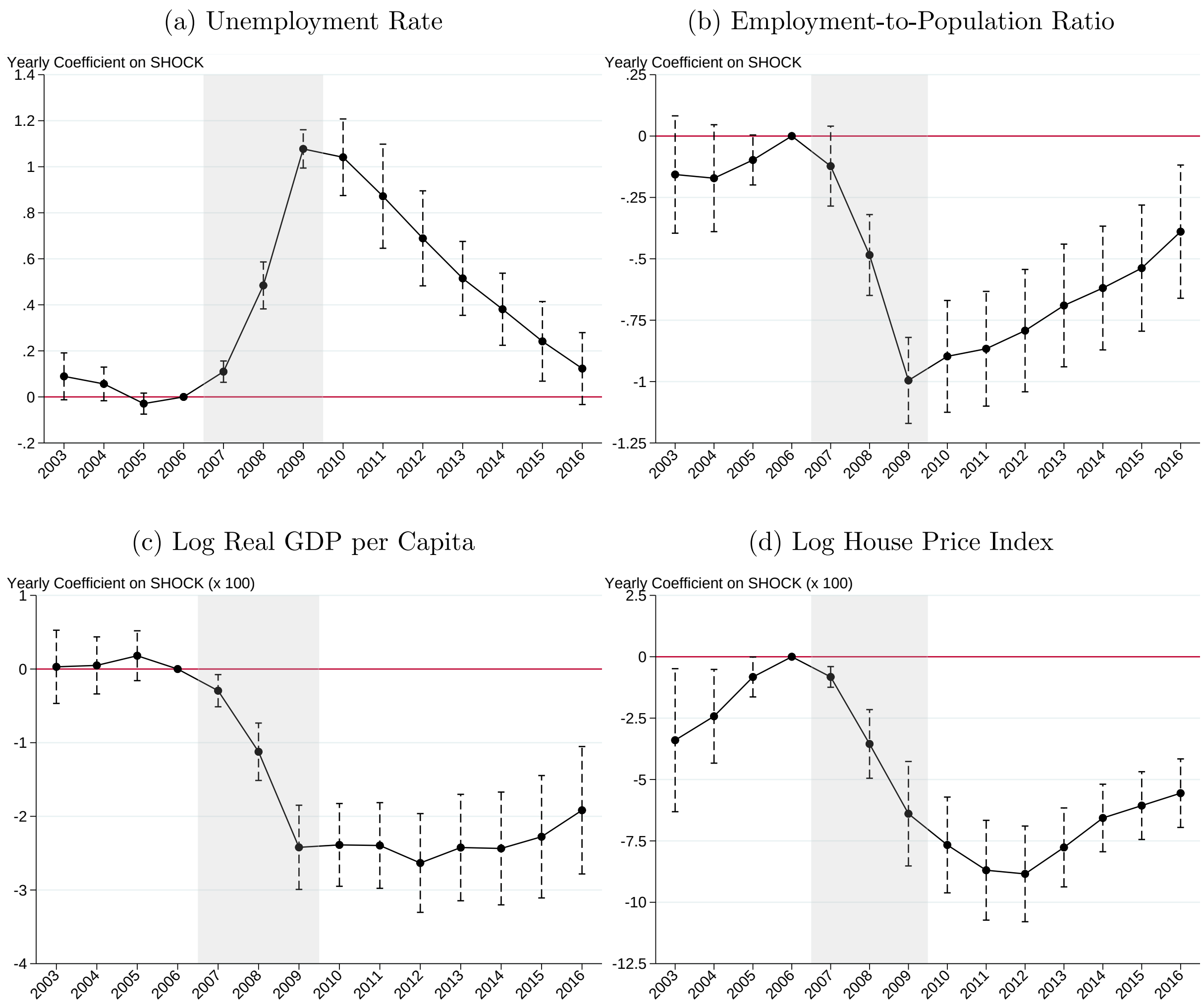


(d) House Price Index



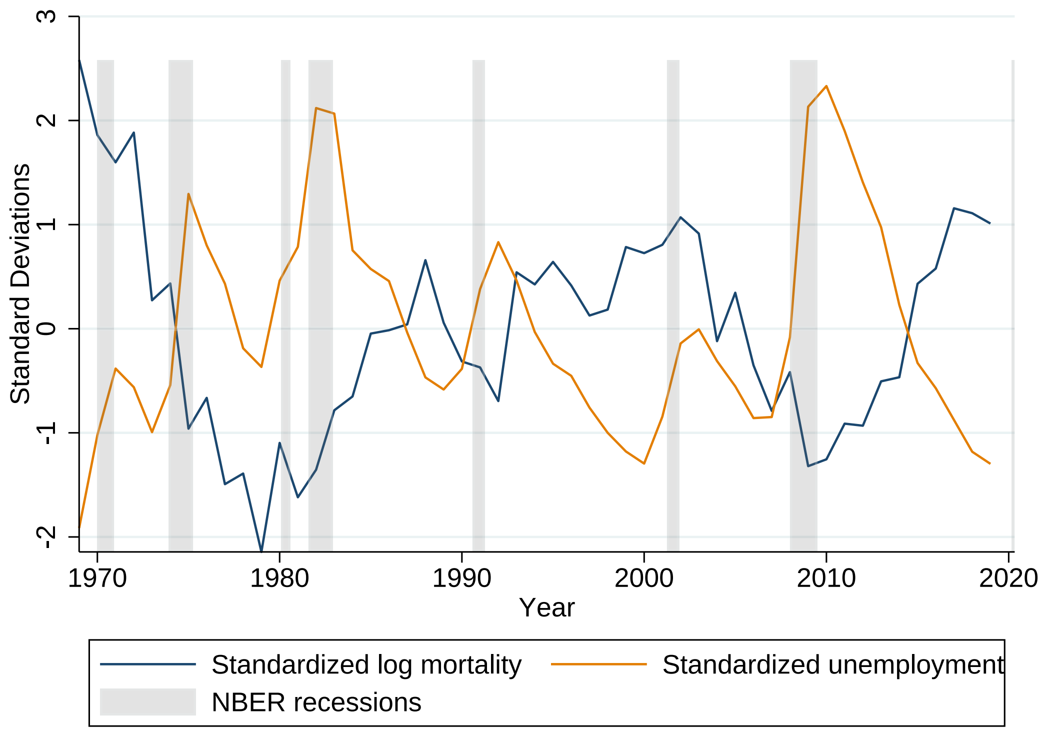
Notes: This figure displays yearly means of CZ-level measures of the Great Recession, weighted by 2006 CZ population. Figure A.3a plots the unemployment rate; Figure A.3b plots the employment-to-population ratio; Figure A.3c plots real GDP per capita (in thousands of 2012 chained USD); and Figure A.3d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

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



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 A.4a), employment-to-population ratio (Figure A.4b), log real GDP per capita (in thousands of 2012 chained USD; Figure A.4c), or the log house price index (Figure A.4d). Coefficients, standard errors, and confidence intervals in Figures A.4c and A.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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs in Figures A.4a and A.4b; in Figures A.4c and A.4d, N=740 CZs and N=684 CZs, respectively, for which we have complete data from 2003-2016.

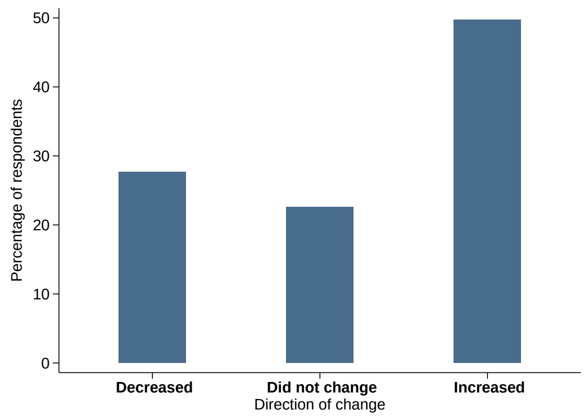
Figure A.5: Time Series of Unemployment and Mortality



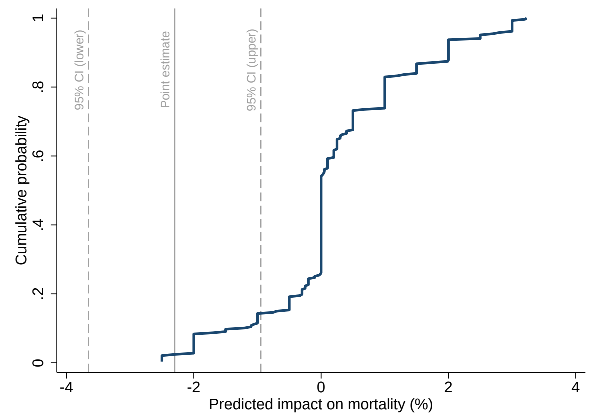
Notes: This figure displays, for all years from 1969 to 2019, yearly nationwide log age-adjusted mortality (in blue) and unemployment (in red). Both of these variables are first residualized on a linear time trend, and yearly residuals are then standardized and displayed in standardized (SD) units. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. Yearly mortality is derived from NCHS data which has been aggregated to the national level, while yearly unemployment is taken directly from national CPS data. N=51 years.

Figure A.6: Expert Survey on Predicted Direction of Change in Mortality

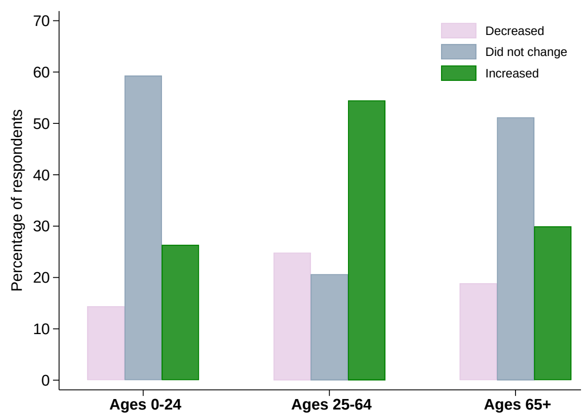
(a) Overall Prediction



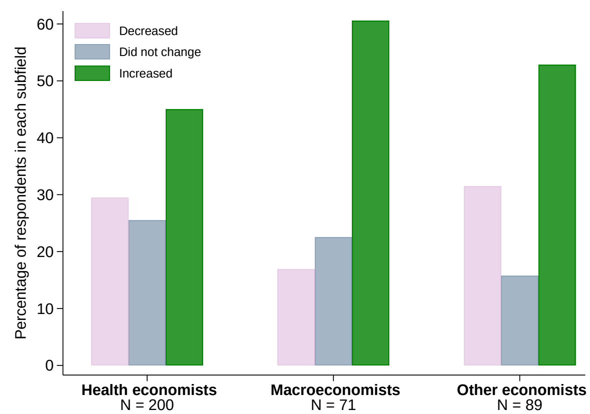
(b) Predicted Change in Mortality, Empirical CDF



(c) Prediction by Age Bin



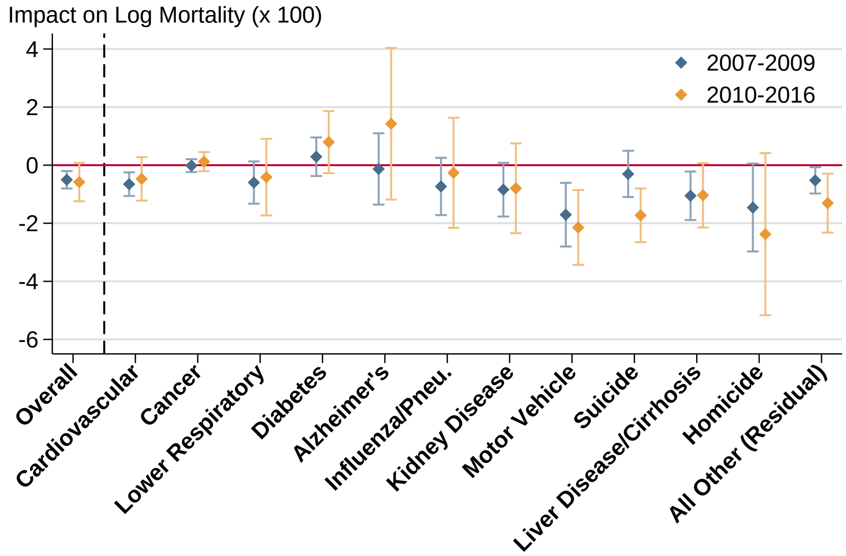
(d) Prediction by Respondent Subfield



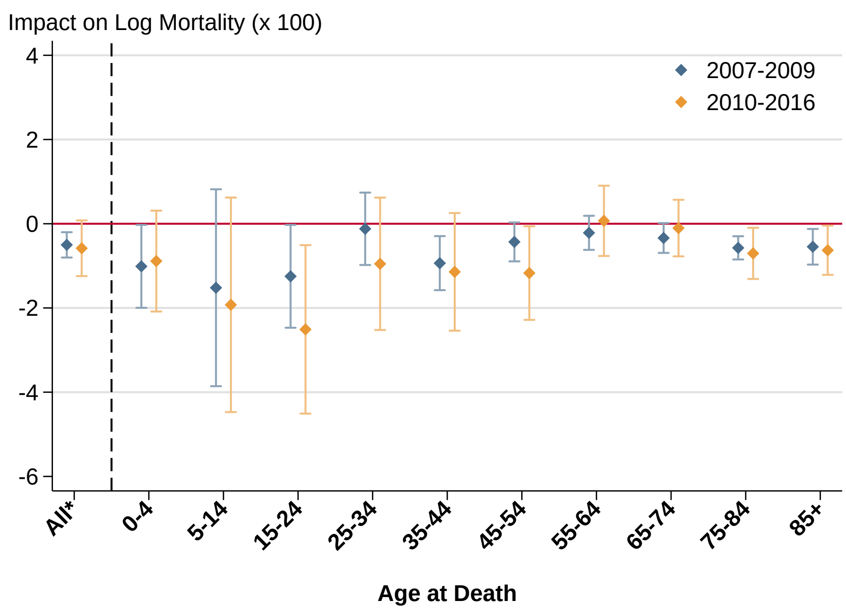
Notes: This figure shows results of an expert survey eliciting predictions about the impact of the Great Recession on mortality. Figures show the predicted direction of change in the U.S. mortality rate overall (A.6a), for each of the three age bins appearing in the survey (A.6c), and by respondent subfield (A.6d). Figure A.6b 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 A.7: Impact of Shock on Log Mortality, by Cause of Death and Age

(a) Pooled Estimates: Cause of Death



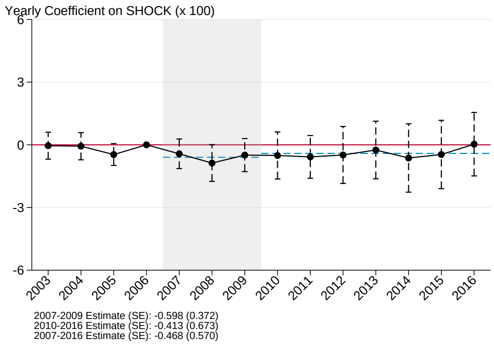
(b) Pooled Estimates: Age



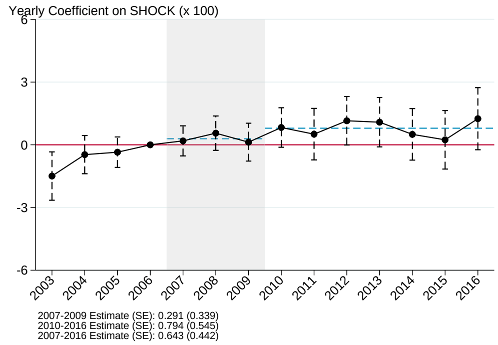
Notes: Figure A.7a displays the group-specific average of 2007-2009 and 2010-2016 coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted CZ mortality rate per 100,000, groups g are defined as the 11 most common causes of death in the ICD10 39-group classification (presented in order of decreasing prevalence), and the final category is a residual category which captures all other mortality. In Figure A.7b, groups g are instead defined by 10 age groups. In both figures, 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. N=741 CZs.

Figure A.8: Impact of Shock on Log Mortality, by Cause of Death: Supplementary Event Studies

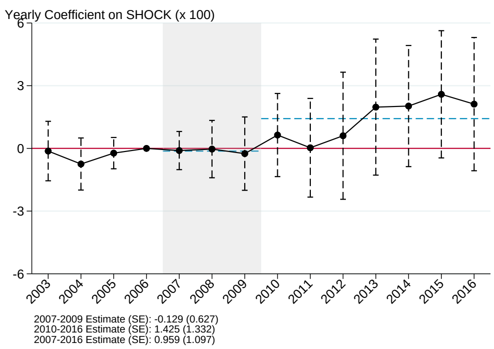
(a) Chronic Lower Respiratory Disease



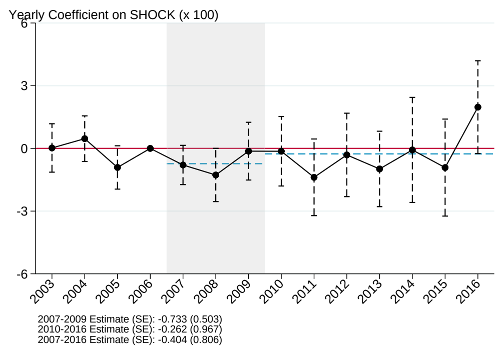
(b) Diabetes



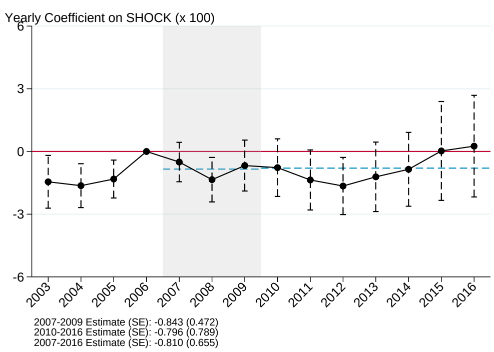
(c) Alzheimer's Disease



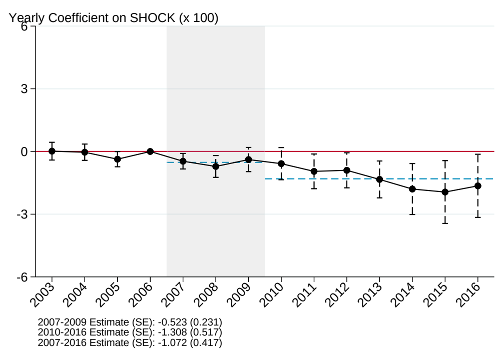
(d) Influenza/Pneumonia



(e) Kidney Disease

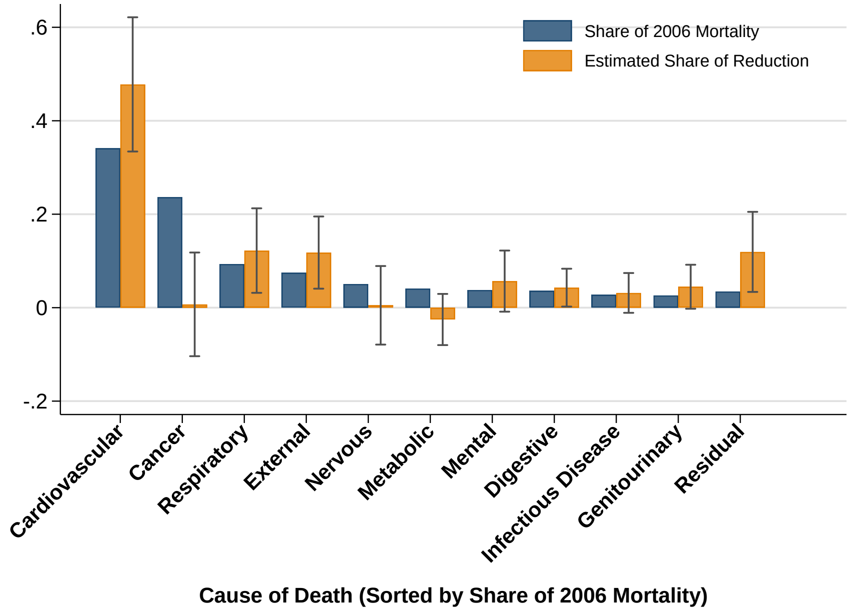


(f) All Other Causes (Residual)



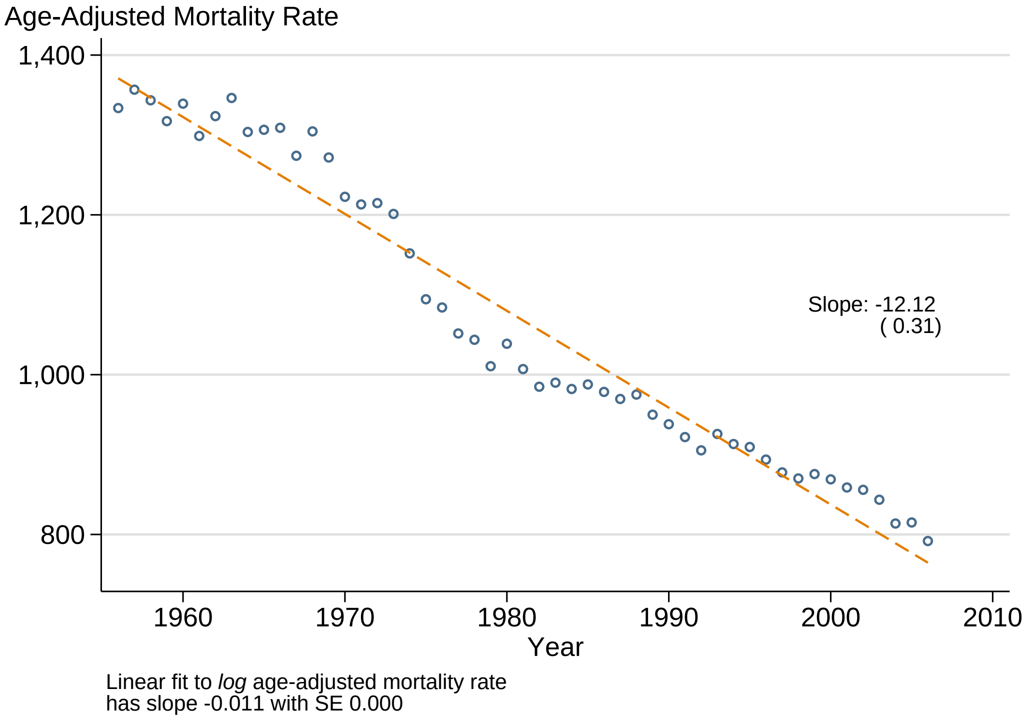
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted CZ mortality rate per 100,000, and g indicates 12 cause of death categories (six of which are displayed here; the remaining six are displayed in Figure V). $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Figure A.8a displays effects on the log mortality rate from chronic lower respiratory disease; Figure A.8b from diabetes; Figure A.8c from Alzheimer's disease; Figure A.8d from influenza or pneumonia; Figure A.8e from kidney disease; and Figure A.8f from all other causes of death not described elsewhere in Figures V or A.8. 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs.

Figure A.9: Impact of GR Shock on Log Mortality, by Alternative Cause of Death



Notes: Figure A.9 decomposes the contribution of 10 cause-of-death categories plus a residual category to the overall estimated 2007-2009 pooled reduction in mortality. These alternative categories were created to leave fewer deaths in the residual category than the baseline cause of death classification used in Figure IVb, and this figure is analogous to Figure IVb but for the alternative cause of death categories. These 10 categories are defined as the 10 most common ICD10 chapters/disease categories (out of 20 chapters, presented in order of descending prevalence, and then with the residual at the end), and they are an exhaustive and mutually exclusive categorization of 2006 deaths. The blue bars indicate each cause of death's share of 2006 mortality. The orange 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" mortality reduction from this exercise is -0.46%, very close to our estimate from Figure III of -0.50% and even closer to the baseline version of this exercise in IVb of also -0.46%. 95% confidence intervals for these estimates, clustered by CZ, are shown as vertical lines. N=741 CZs.

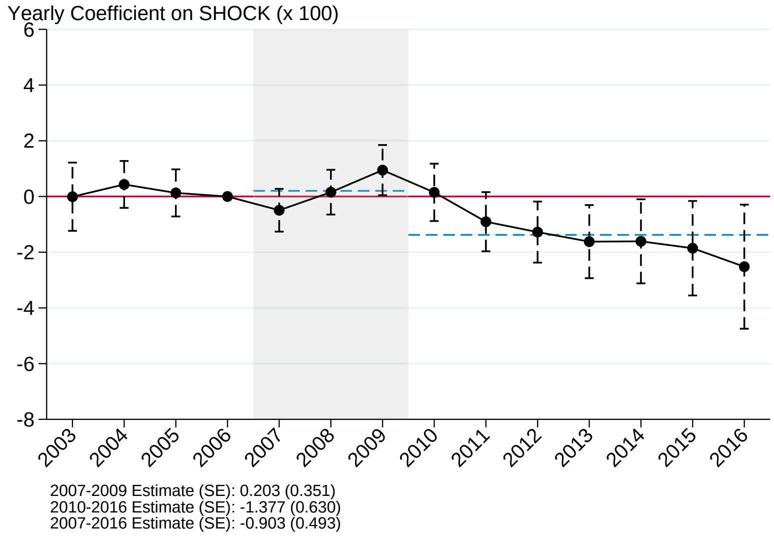
Figure A.10: Age-Adjusted Mortality Rates in the United States, 1956-2006



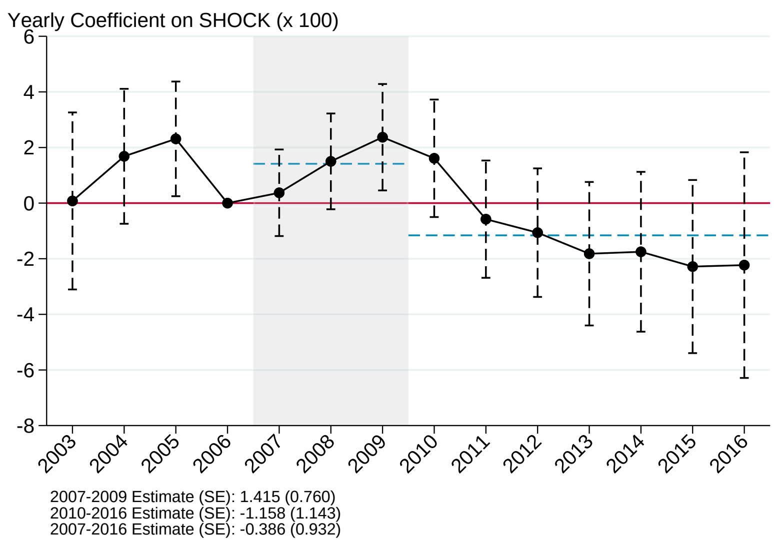
Notes: This figure reports trends in the age-adjusted mortality rate per 100,000 in the United States from 1956-2006. Data are drawn from the National Center for Health Statistics, "Mortality Trends in the United States, 1900-2018." The dashed line represents a linear fit of the age-adjusted mortality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

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

(a) Suicides, Liver Disease, and Drug Poisonings



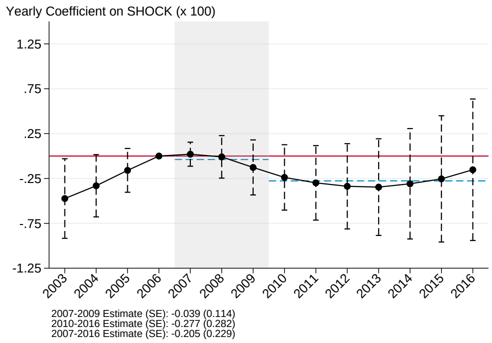
(b) Drug Poisonings Only



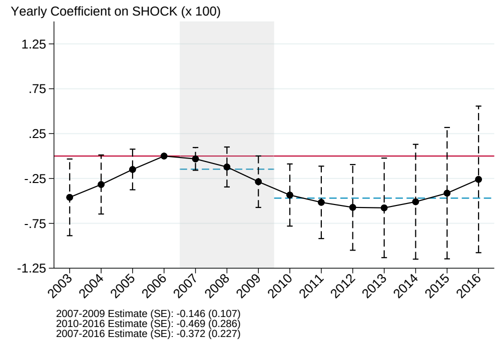
Notes: This figure plots the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000 from suicides, liver disease, and drug poisonings (Figure A.11a) or accidental and unknown-intent drug poisonings only (Figure A.11b); note that Figures Vd and Ve 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs.

Figure A.12: Impact of Shock on Population, by Age

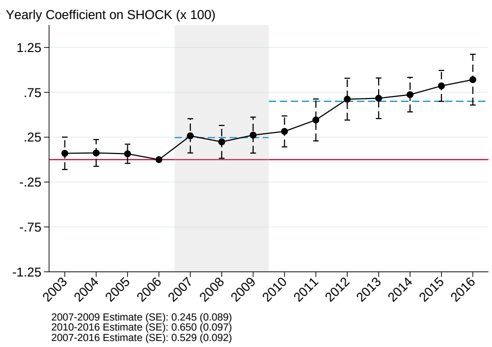
(a) Log Total Population



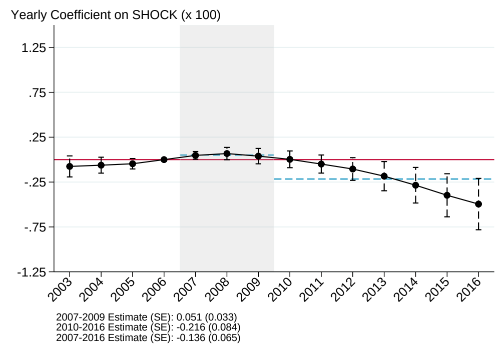
(b) Log Population Aged 25-64



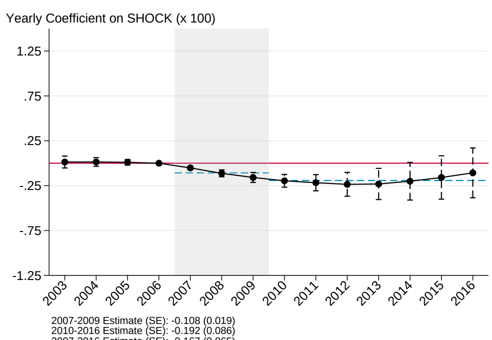
(c) Log Median Age



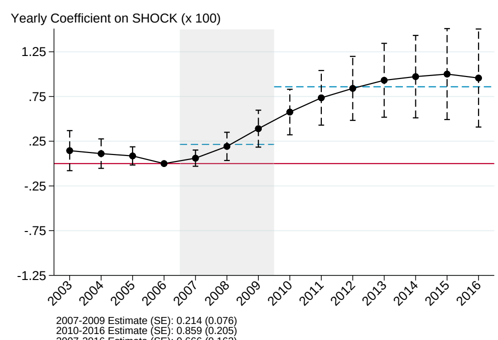
(d) Log Share $<$ 25 Years Old



(e) Log Share 25-64 Years Old



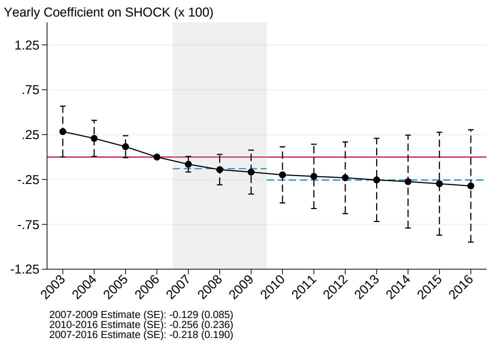
(f) Log Share $\geq$ 65 Years Old



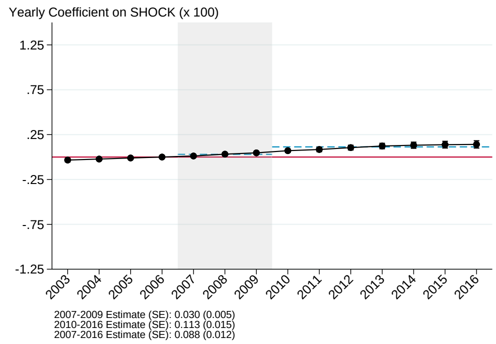
Notes: These figures display yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log annual total CZ population (Figure A.12a); the log annual CZ population aged 25-64 (Figure A.12b); the log median CZ age (Figure A.12c); the log share of the CZ population under age 25 (Figure A.12d); the log share of the CZ population aged 25-64 (Figure A.12e); and the log share of the CZ population aged 65+ (Figure A.12f). 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs.

Figure A.13: Impact of Shock on Population, by Demographic Characteristics

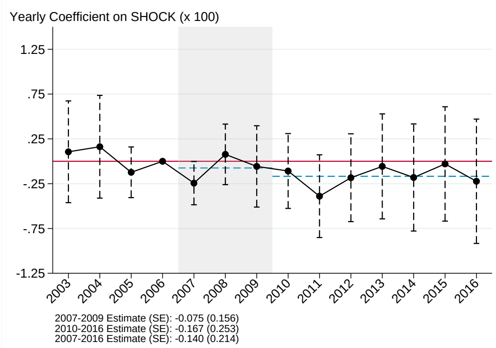
(a) Log Share White



(b) Log Share Female



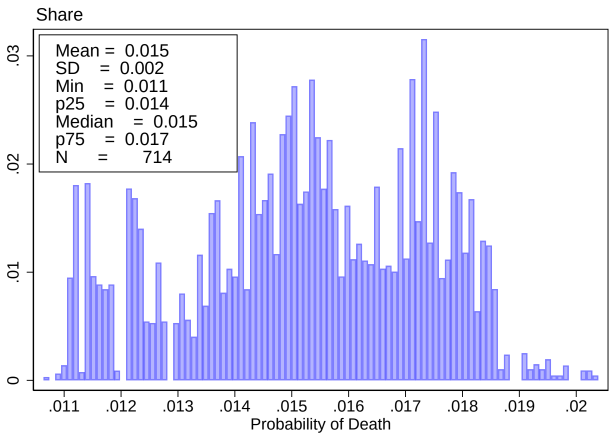
(c) Log Share More than High School Education



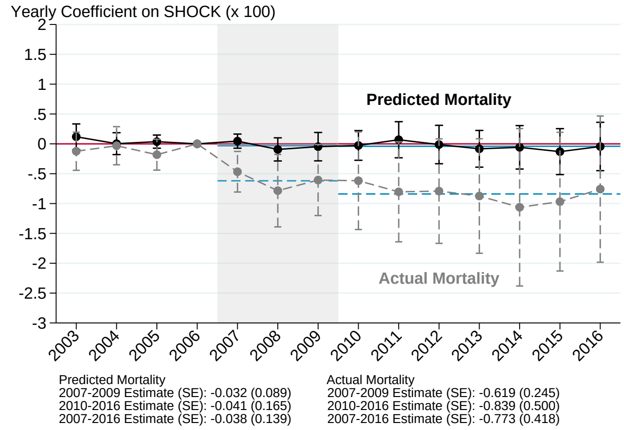
Notes: These figures display yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log share of the CZ population that is white (Figure A.13a); the log share of the CZ population that is female (Figure A.13b); and the log share of the state population with more than a high school education (Figure A.13c). In Figures A.13a and A.13b, $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate, and in Figure A.13c, $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. (We only observe education data at the state level.) Observations are weighted by CZ (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 CZ (state) level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs (51 states).

Figure A.14: Impact of Shock on Log Predicted Mortality

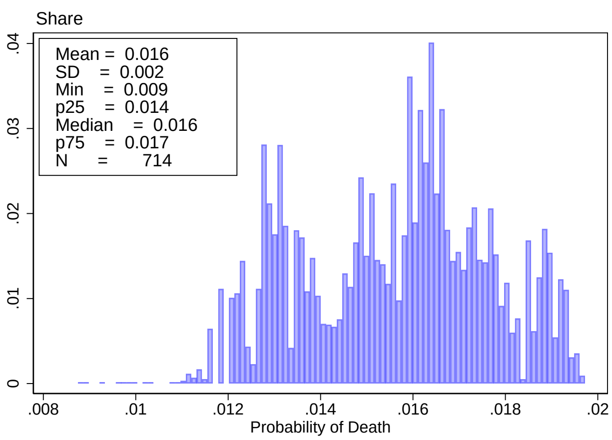
(a) State-Year Predicted Mortality



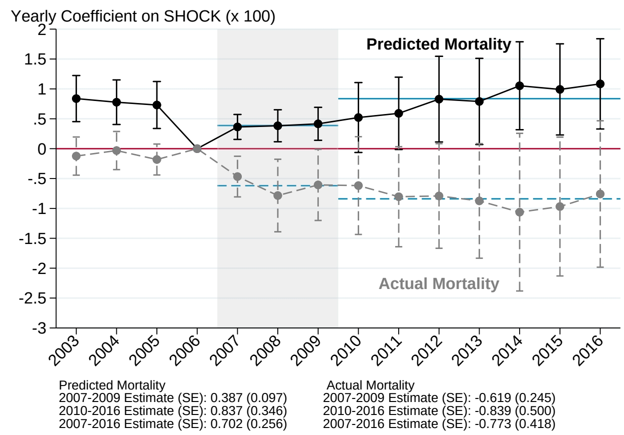
(b) Actual vs. Predicted Mortality



(c) State-Year Predicted Mortality, Including Age



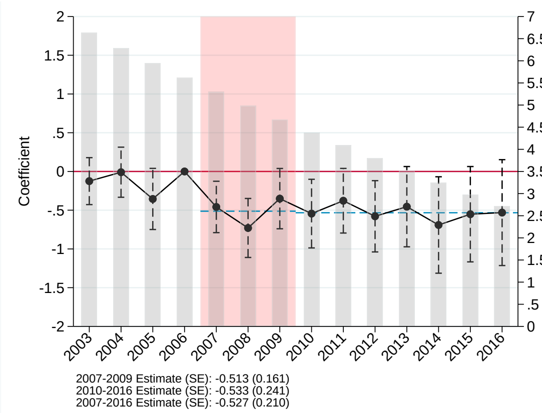
(d) Actual vs. Predicted Mortality, Including Age



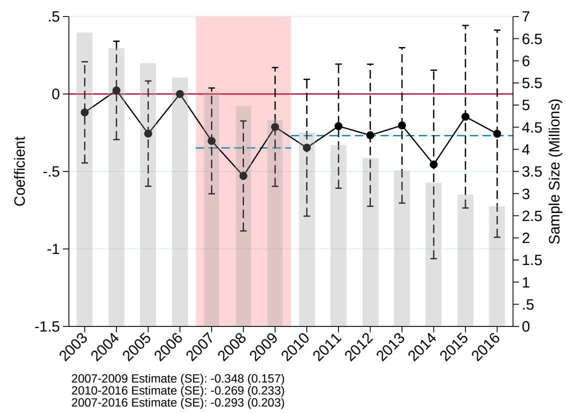
Notes: Figure A.14a shows the (population-weighted) distribution of state-year predicted mortality rates for all 50 states plus D.C. from 2003-2016, based on the individual's gender, race, and education. Appendix Section C.5 provides more detail on how we construct this predicted mortality measure. Figure A.14b displays estimates of β_t from estimating equation (1) at the state-year level with two different outcomes: the actual age-adjusted log mortality rate in each state-year (in gray), and the predicted log mortality rate in each state-year (in black). Figures A.14c and A.14d show the same, only also including age as an additional predictor of mortality. Vertical dashed lines denote 95% confidence intervals. For the actual mortality rate, these are constructed using heteroskedasticity-robust standard errors clustered at the state level. For the predicted mortality rate, these are constructed using a two-step bootstrap method with 500 bootstraps, first resampling the training data used to predict mortality on a sample of individuals, and then resampling the resulting average predicted mortality rates at the state level via the block bootstrap. The regressions are weighted by each state's (total) population in 2006. The area shaded in gray in Figure A.14b corresponds to the timing of the Great Recession, adopting the NBER's business cycle dating. N=51 states.

Figure A.15: Impact of Shock on Mortality Hazard Rate: Sensitivity to Yearly vs. Baseline Residence

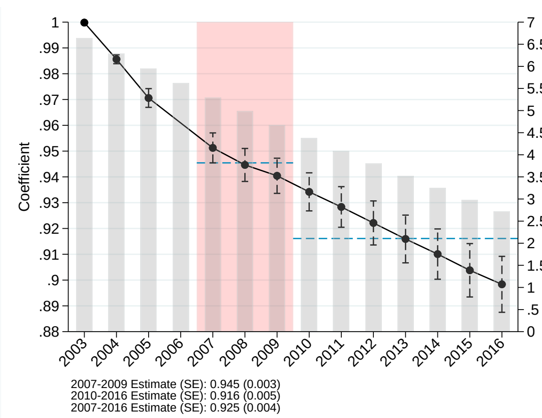
(a) Yearly Residence (Full Sample)
(β_t, equation (3))



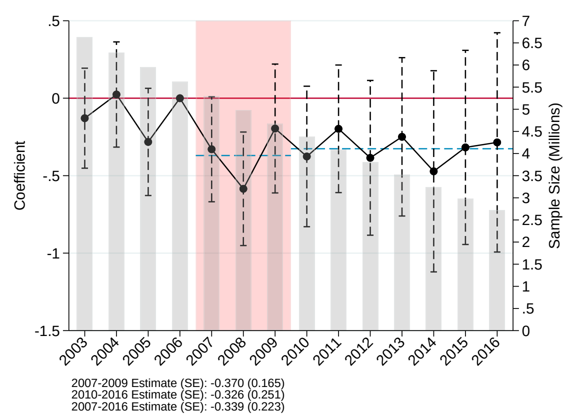
(b) 2003 Residence (Reduced Form)
(π_t^{RF}, equation (4))



(c) 2003 Residence (First Stage)
(π_t^{FS}, equation (5))

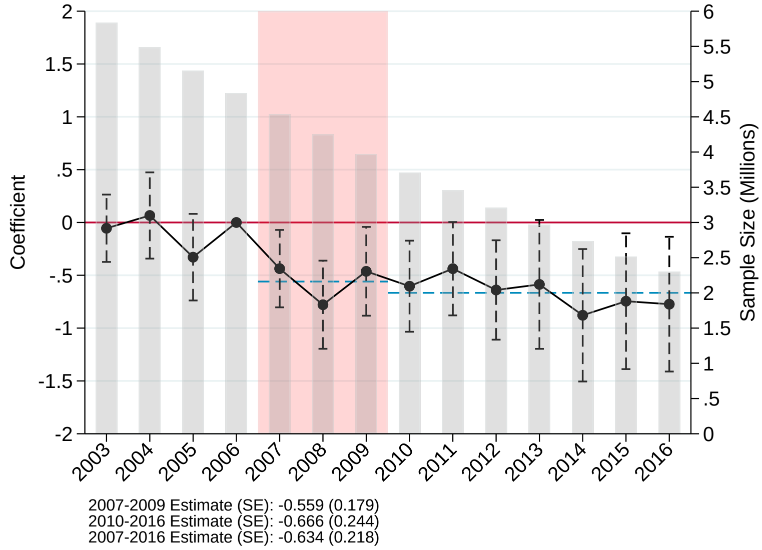


(d) Control Function (β_t, equation (6))



Notes: This figure displays yearly coefficients β_t from equation (3) (Figure A.15a), π_t^{RF} from equation (4) (Figure A.15b), π_t^{FS} from equation (5) (Figure A.15c), and β_t from equation (6) (Figure A.15d), with outcome $log(m_{it}(a))$ defined as the log of the individual-level mortality hazard rate at age a. In Figure A.15a, individuals are assigned their yearly residence, while in Figure A.15b, individuals are assigned their 2003 CZ of residence. Figure A.15c's outcome is 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. The sample reflects a panel of 2003 Medicare beneficiaries, subject to the restrictions in Table A.7. 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. 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. The areas shaded in red correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=6,634,999 beneficiaries.

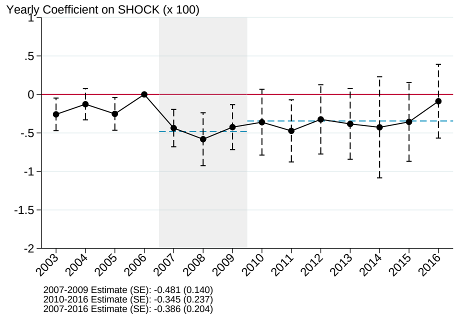
Figure A.16: Impact of Shock on Mortality Hazard Rate: Among Non-Movers



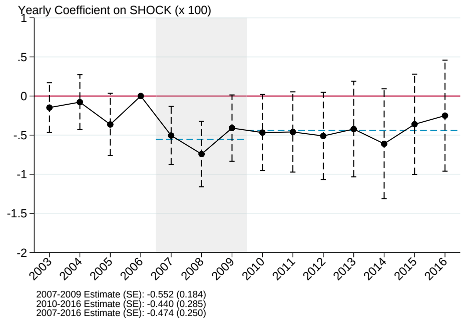
Notes: This figure displays yearly coefficients β_t from equation (3), with outcome $log(m_{it}(a))$ defined as the log of the individual-level mortality hazard rate at age a. Individuals are assigned their yearly CZ of residence. The sample reflects a panel of 2003 Medicare beneficiaries, subject to the restrictions in Table A.7, while further restricting to non-movers. 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. Gray bars indicate the sample size by year (which is reduced each year due to mortality); scale is determined by the secondary y-axis. The areas shaded in red correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=5,841,523 non-moving beneficiaries.

Figure A.17: Impact of Shock on Log Mortality, Among Medicare Samples

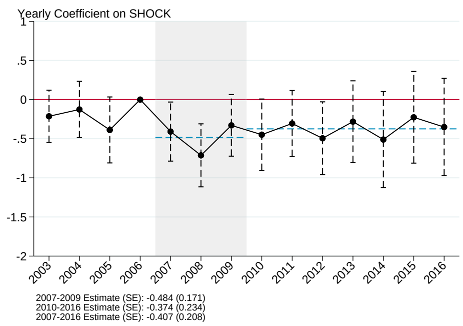
(a) Impact on 65+ in the CDC Data



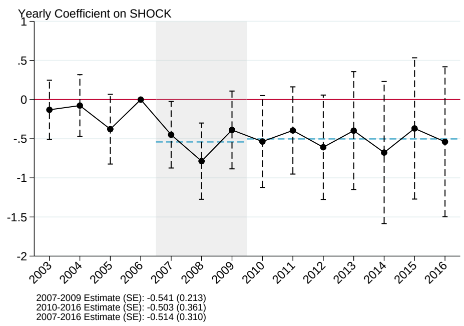
(b) Medicare Repeated Cross Section



(c) Medicare Panel



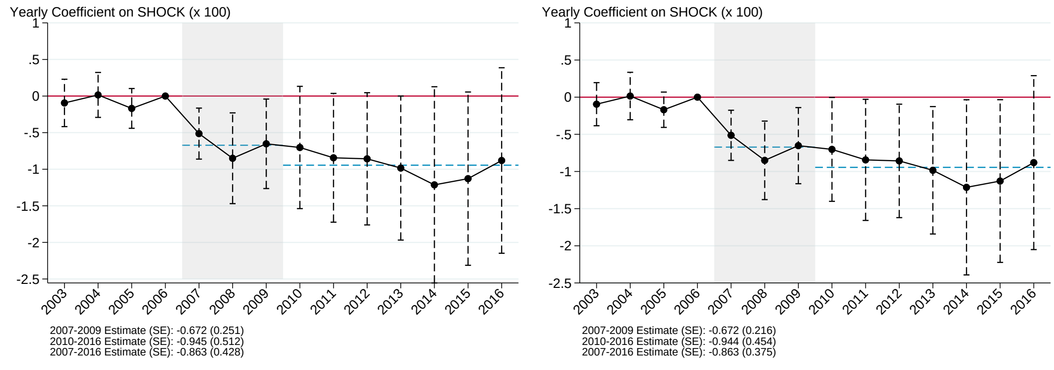
(d) Medicare Panel: 2003 CZ Shocks



Notes: This figure displays the yearly coefficients β_t from equation (1) (Figures A.17a, A.17b, and A.17c) or equation (24) (Figure A.17d), where the outcome y_{ct} is logged but non-age-adjusted CZ mortality rate per 100,000, and $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Figure A.17a 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 sample. Figure A.17b uses a repeated cross-section while restricting to beneficiaries based on Table A.8, resulting in a total sample of 13,705,511 unique individuals. Figures A.17c and A.17d use a panel of 2003 Medicare Beneficiaries who are then followed through 2016, adopting the restrictions in Table A.7, resulting in a total sample of 6,634,999 unique individuals; note that this is a strict subsample of Figure A.17b's repeated cross-section. 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. The areas shaded in red correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. 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 A.18: Impact of Shock on Log Mortality, Including Education-by-Year Fixed Effects

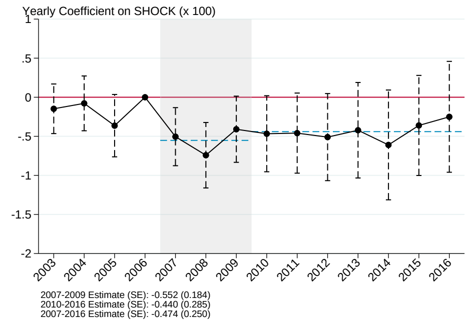
(a) Main Specification (b) Education-by-Year FEs



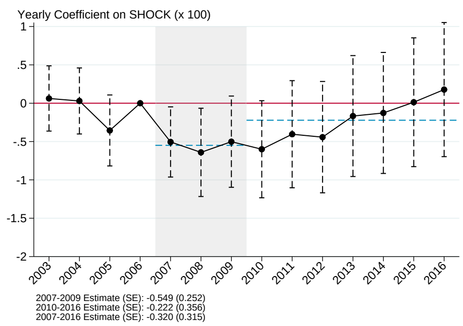
Notes: This figure displays the yearly coefficients β_t from equation (1) (Figure A.18a) and equation (25) (Figure A.18b), where the outcome y_{ct} is the log age-adjusted state mortality per 100,000 for individuals aged 25+. $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. Observations 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.3 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=47 states.

Figure A.19: Impact of Shock on Log Mortality, Among Repeated Cross Section Sub-Samples

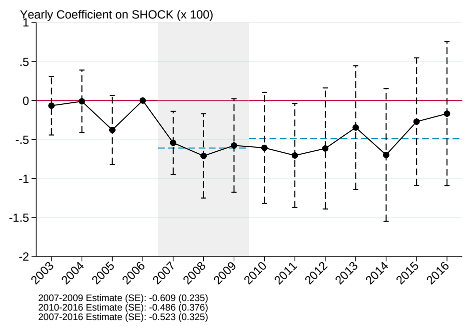
(a) Medicare Repeated Cross Section (overall)



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



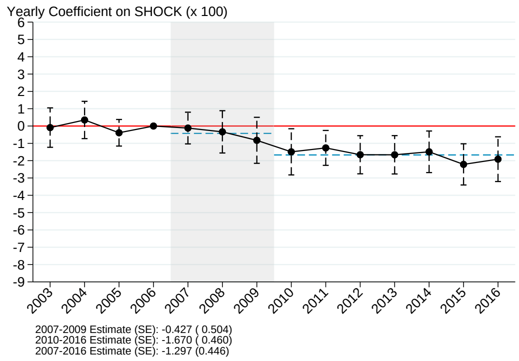
(c) Medicare Repeated Cross Section (TM in $t-1$)



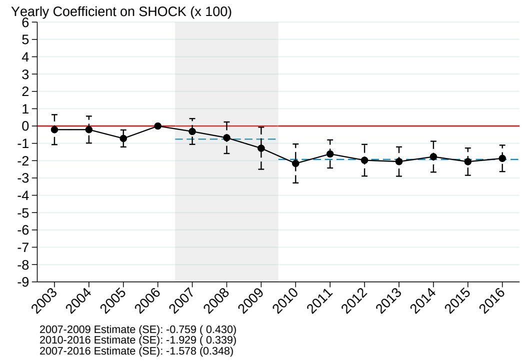
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the logged but not age-adjusted CZ mortality rate per 100,000, and $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. All panels use variants of the Medicare Repeated Cross Section sample, which restricts to beneficiaries based on Table A.8. Figure A.19a uses the primary Repeated Cross Sample; Figure A.19b restricts attention to the set of Medicare enrollees who were covered by Traditional Medicare (TM) in every month of the current year, while Figure A.19c 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. 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 A.20: Impact of Shock on Income, By Age

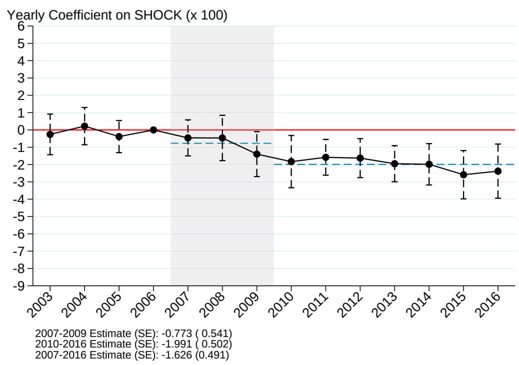
(a) All Individuals (State-Level OLS)



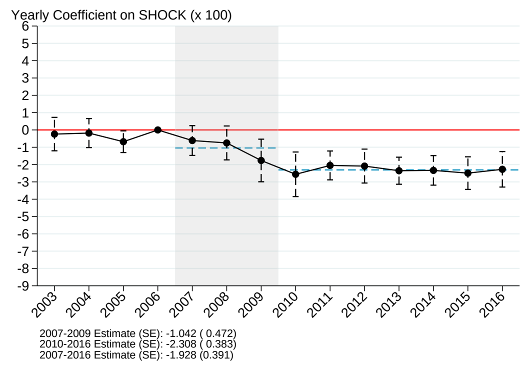
(b) All Individuals (Person-Level Poisson)



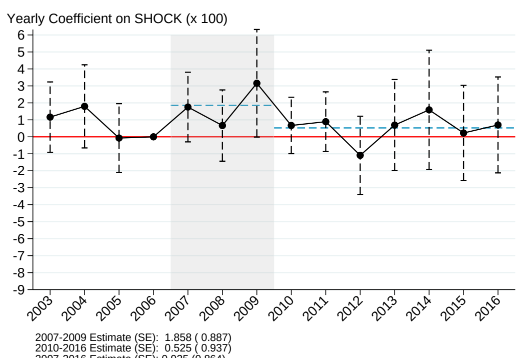
(c) 25-64 (State-Level OLS)



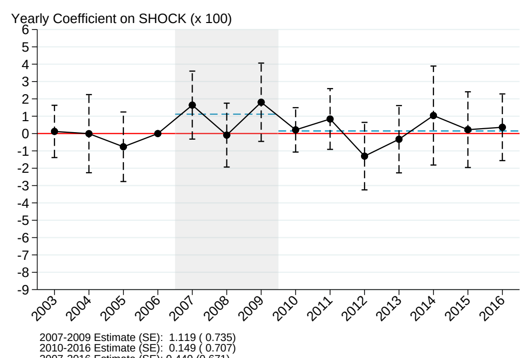
(d) 25-64 (Person-Level Poisson)



(e) 65+ (State-Level OLS)



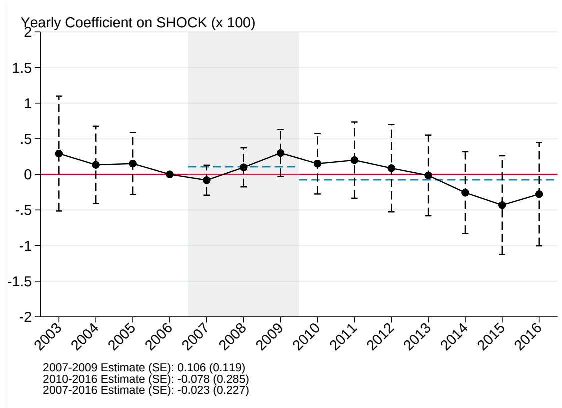
(f) 65+ (Person-Level Poisson)



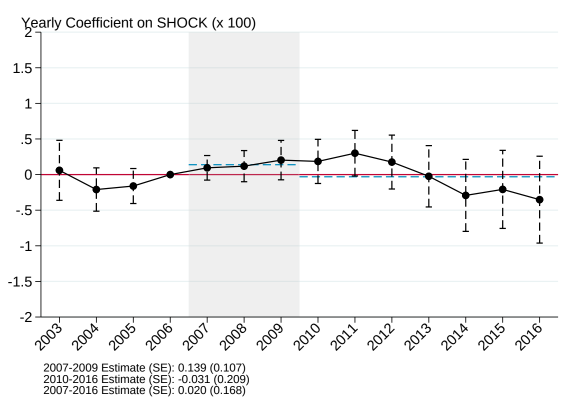
Notes: Figures A.20a, A.20c, and A.20e display the yearly coefficients β_t from equation (1) estimated at the state level via OLS, with the outcome y_{ct} defined as the log average state income for individuals aged 25+ in different age groups, per the Current Population Survey (CPS). Observations are weighted by state population in 2006. Figures A.20b, A.20d, and A.20f display the yearly coefficients β_t from equation (28) 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=714 state-years in Figures A.20a, A.20c, and A.20e; N=1,788,643 person-years in Figure A.20b; N=781,637 person-years in Figure A.20d; and N=1,007,006 person-years in Figure A.20f.

Figure A.21: Impact of Shock on Medicare Healthcare Utilization Measures

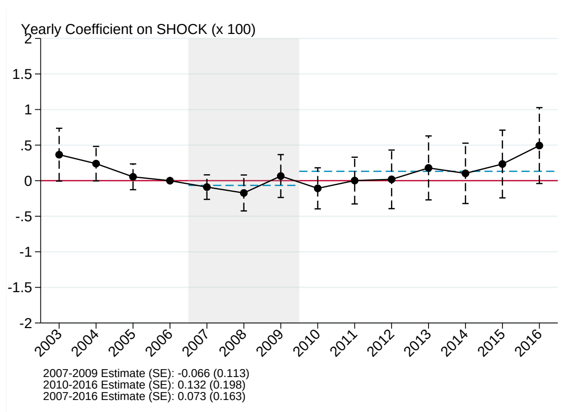
(a) Log Total Expenditure



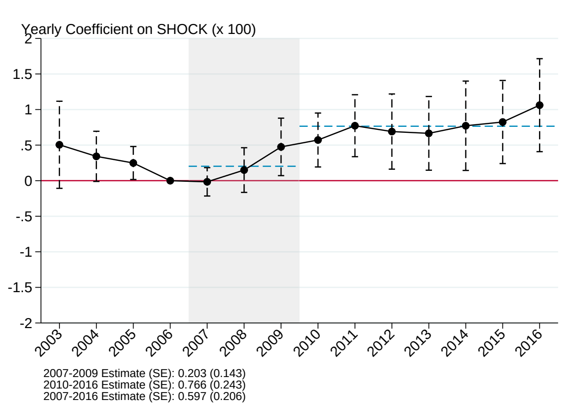
(b) Log Physician Visits



(c) Log Patient Share with ER Visit



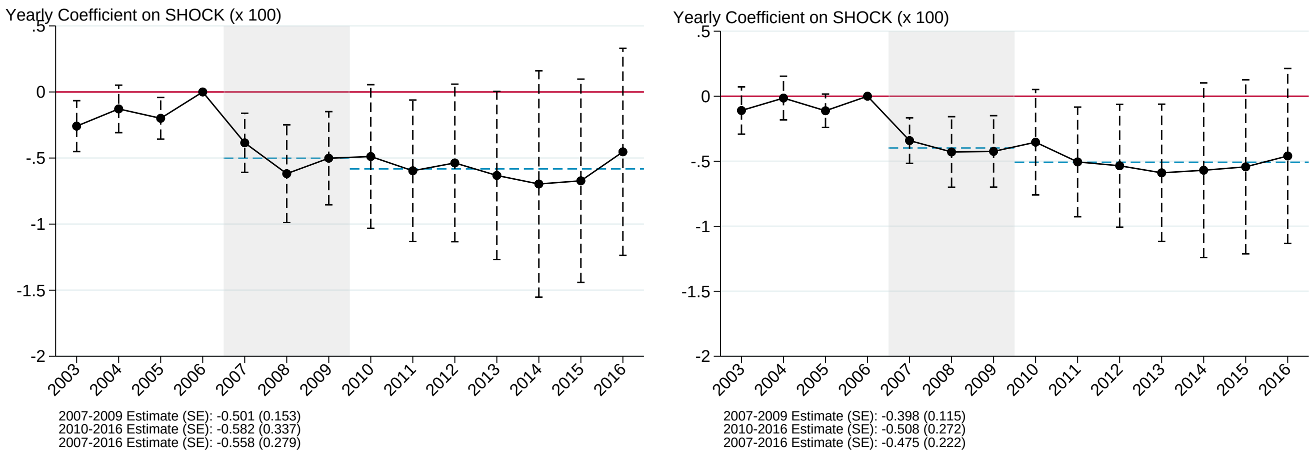
(d) Log Patient Share with Inpatient Admission



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 A.8. Patient-years are further restricted to those that were enrolled in Traditional Medicare 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=738 CZs for which we observe individuals on Medicare from our 20% MBSF sample in each year.

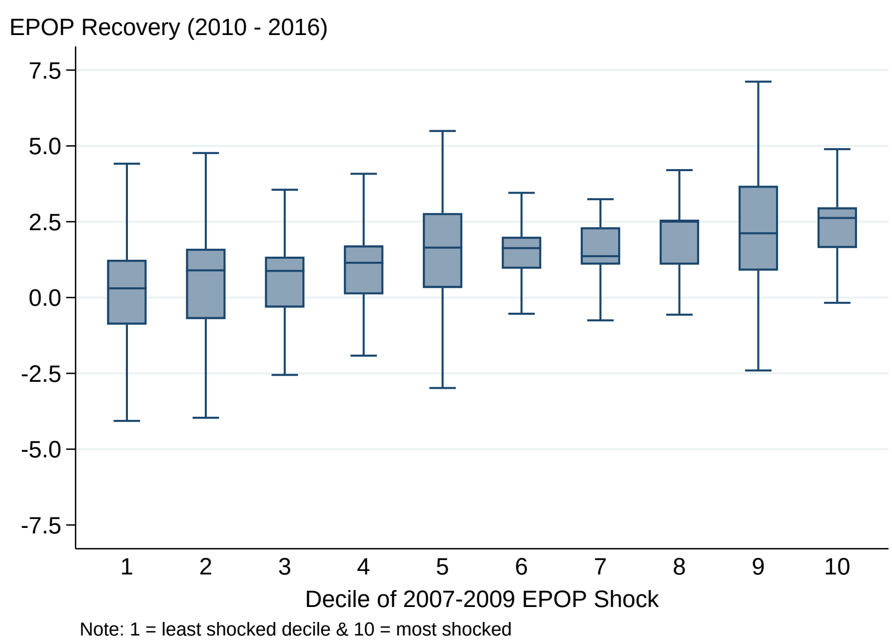
Figure A.22: Impact of Unemployment vs. Employment-to-Population Shocks on Log Mortality

(a) Unemployment Shock (Baseline) (b) EPOP Shock



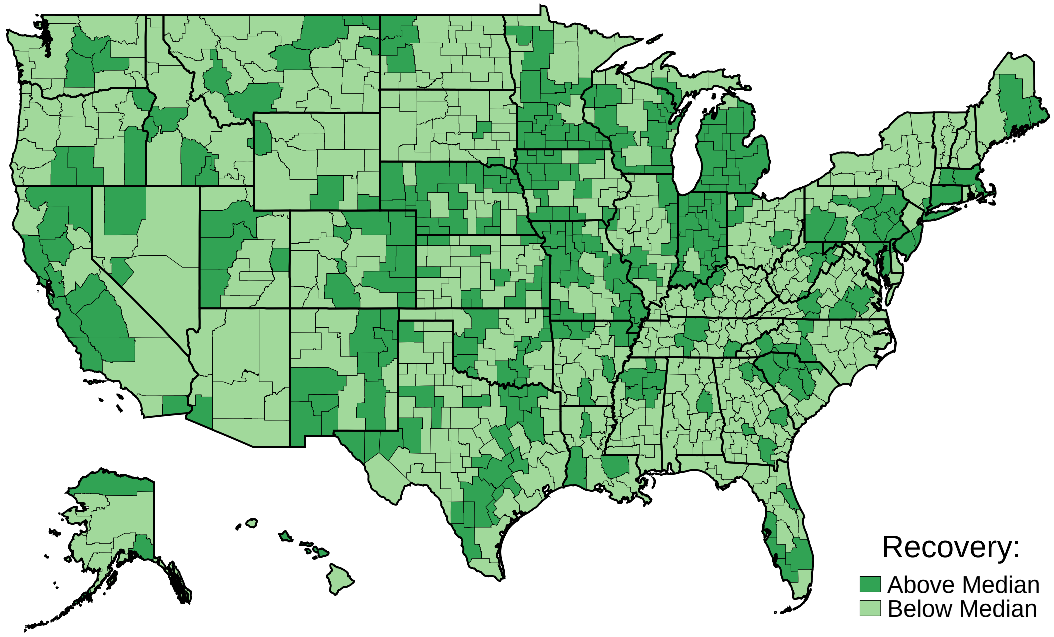
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000, and $SHOCK_c$ is defined as the 2007-2009 change in CZ unemployment rate (Figure A.22a) or the negative 2007-2009 CZ change in the employment-to-population (EPOP) ratio (Figure A.22b). 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs.

Figure A.23: 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.

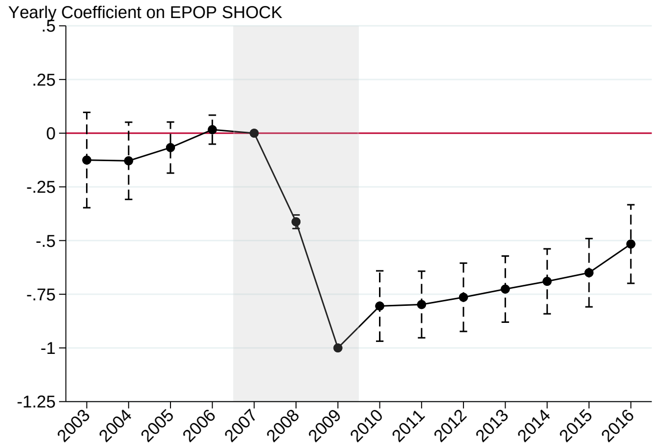
Figure A.24: Map of CZs By Employment-to-Population Recovery, Conditional on Shock



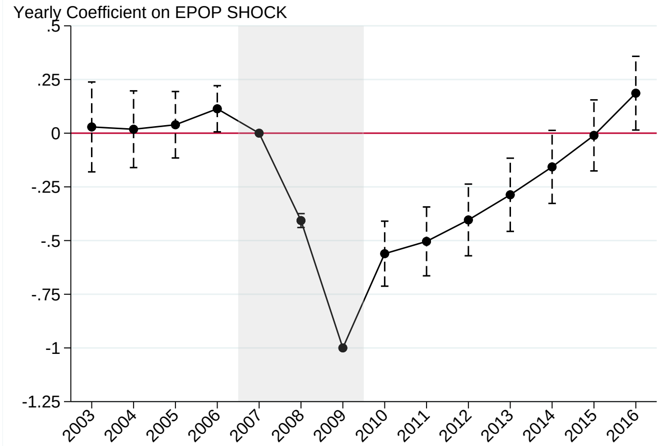
Notes: This figure maps CZs based on whether they have above or below median recovery rates as measured by the 2010-2016 change in the CZ employment-to-population (EPOP) ratio, conditional on the population-weighted decile of the initial 2007-2009 CZ EPOP shock. The deciles and medians for each decile 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 A.25: Impact of Shock by Subsequent Recovery

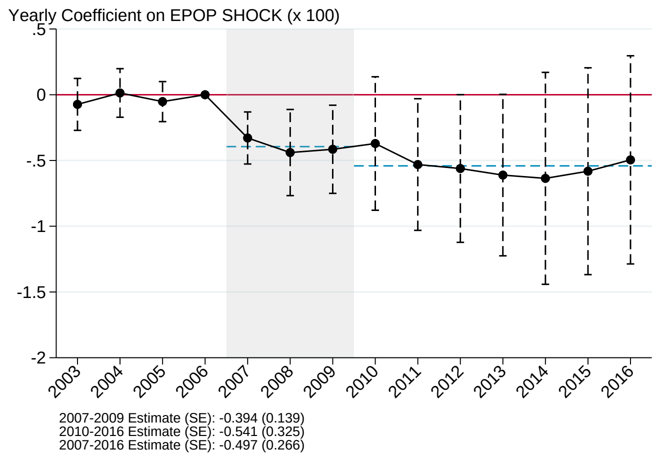
(a) Impacts on **EPOP** for **Below-Median Recovery** CZs



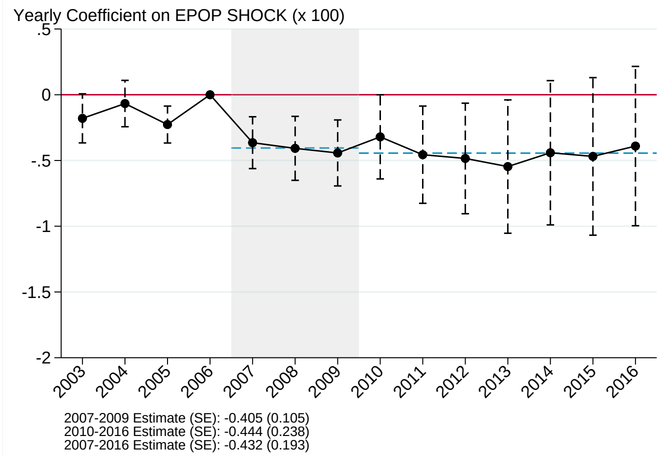
(b) Impacts on **EPOP** for **Above-Median Recovery** CZs



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



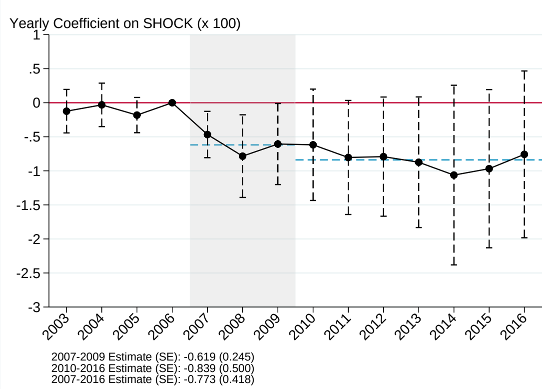
(d) Impacts on **Log Mortality** for **Above-Median Recovery** CZs



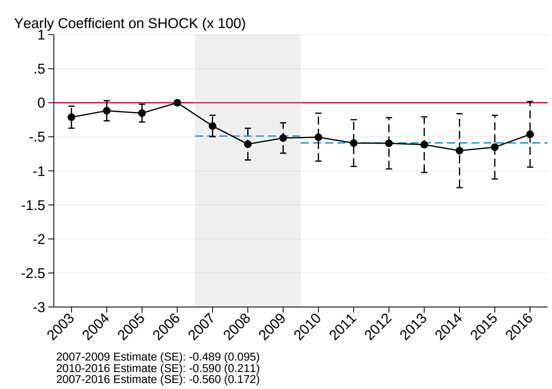
Notes: This figure displays the yearly coefficients β_{qt} from equation (17). Figures A.25a and A.25c display the estimates for below-median recovery CZs—i.e. coefficients on $\mathbb{1}\left(Recovery_{L(c)}\right)$—while Figures A.25b and A.25d display the estimates for above-median recovery CZs—i.e., coefficients on $\mathbb{1}\left(Recovery_{H(c)}\right)$. In figures A.25a and A.25b, the outcome y_{ct} is the EPOP; in figures A.25c and A.25d, 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 A.25a and A.25b 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 A.25c and A.25d 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs in total; 460 are below-median recovery, and 281 are above-median recovery.

Figure A.26: Sensitivity to Geography and Sample

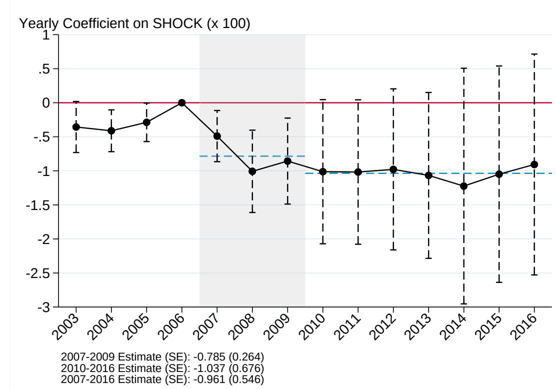
(a) State Level Analysis



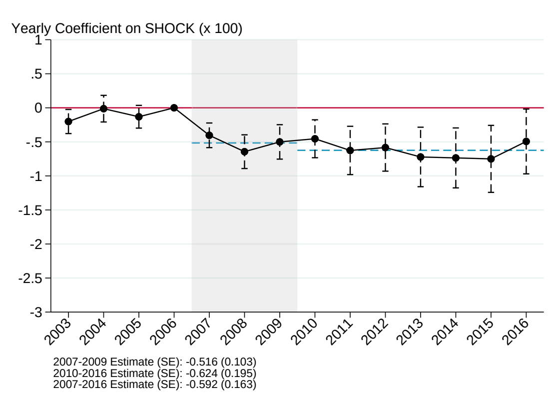
(b) County Level Analysis



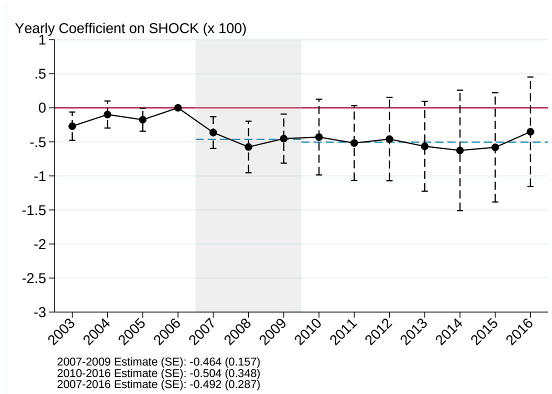
(c) Drop Top/Bottom Decile of Shocked CZs



(d) Drop 10 Most Populous CZs



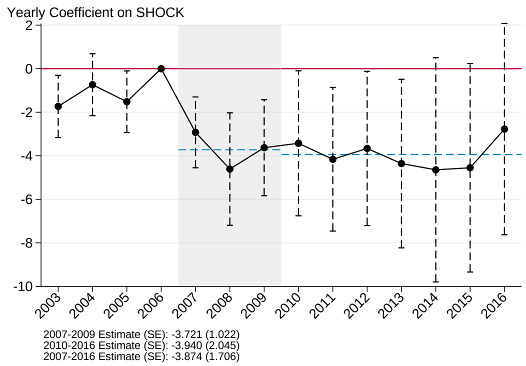
(e) Drop High-Fracking CZs



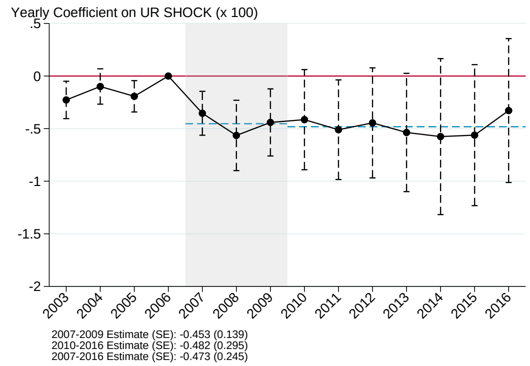
Notes: This figure displays the yearly coefficients β_t from equation (1), where outcome y_{ct} is the log age-adjusted mortality rate per 100,000, and $SHOCK_c$ is the 2007-2009 change in the unemployment rate. Figure A.26a defines y_{ct} and $SHOCK_c$ at the state level, and Figure A.26b defines y_{ct} and $SHOCK_c$ at the county level. Figure A.26c drops the top and bottom 2006 population-weighted deciles of shocked CZs, while defining y_{ct} and $SHOCK_c$ at the CZ level. Figure A.26d 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 Francisco, CA) while defining y_{ct} and $SHOCK_c$ at the CZ level. Figure A.26e 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=51 states in Figure A.26a; N=3,131 counties in Figure A.26b; N=393 CZs in Figure A.26c; N=731 CZs in Figure A.26d; and N=685 CZs in Figure A.26e.

Figure A.27: Sensitivity to Functional Form

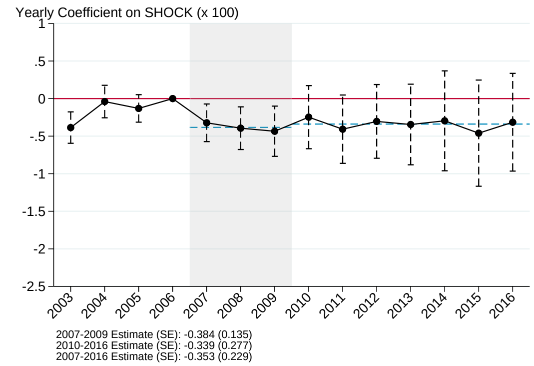
(a) Mortality Rate in Levels



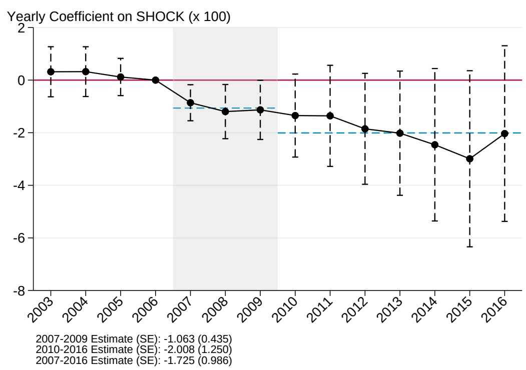
(b) Poisson Specification



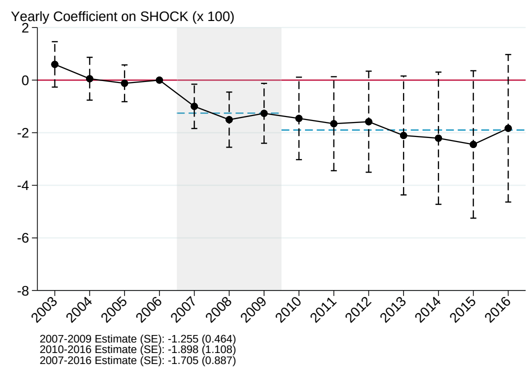
(c) Add Census-Division-by-Year Fixed Effects



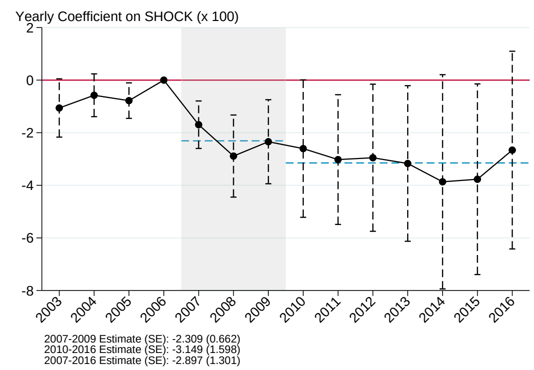
(d) SHOCK Quartiles: Second Quartile



(e) SHOCK Quartiles: Third Quartile



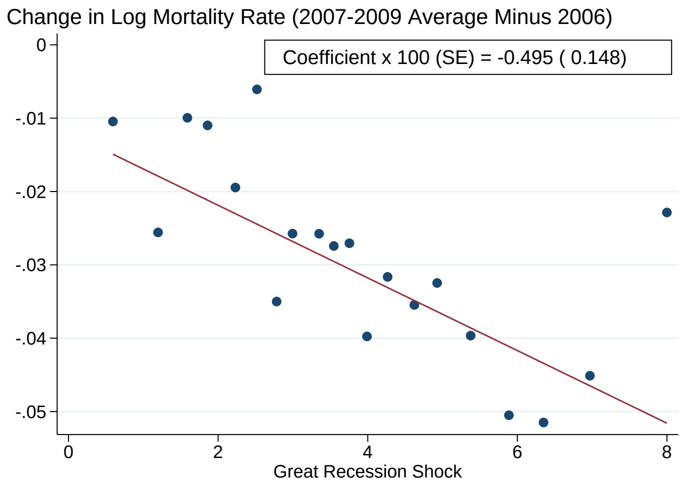
(f) SHOCK Quartiles: Fourth Quartile



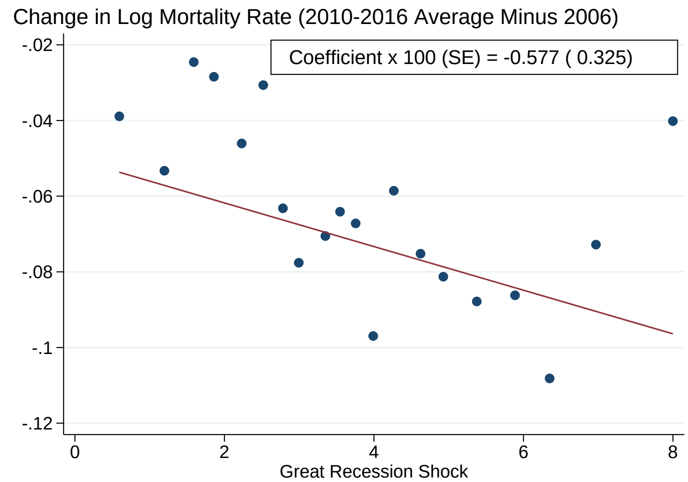
Notes: Figure A.27a displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the age-adjusted CZ mortality rate per 100,000; in all other figures, it is the log age-adjusted CZ mortality rate per 100,000. In Figure A.27b, we estimate the Poisson specification in equation (21), instead of equation (1). In Figure A.27c, 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 A.27d, A.27e, and A.27f, we replace the linear $SHOCK_c$ variable with indicators for the quartile of the shock, and we estimate equation (22), 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 A.27a. Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs.

Figure A.28: Non-Parametric Check of Linearity Assumption

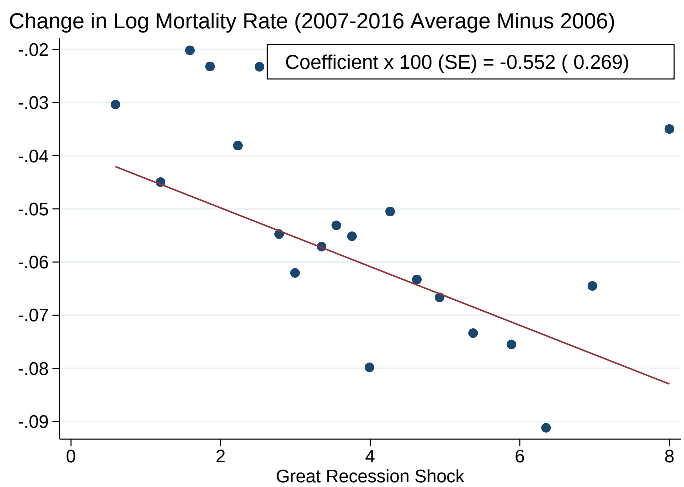
(a) Change in Log Mortality, 2006 vs 2007-09 Average, by GR Shock



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

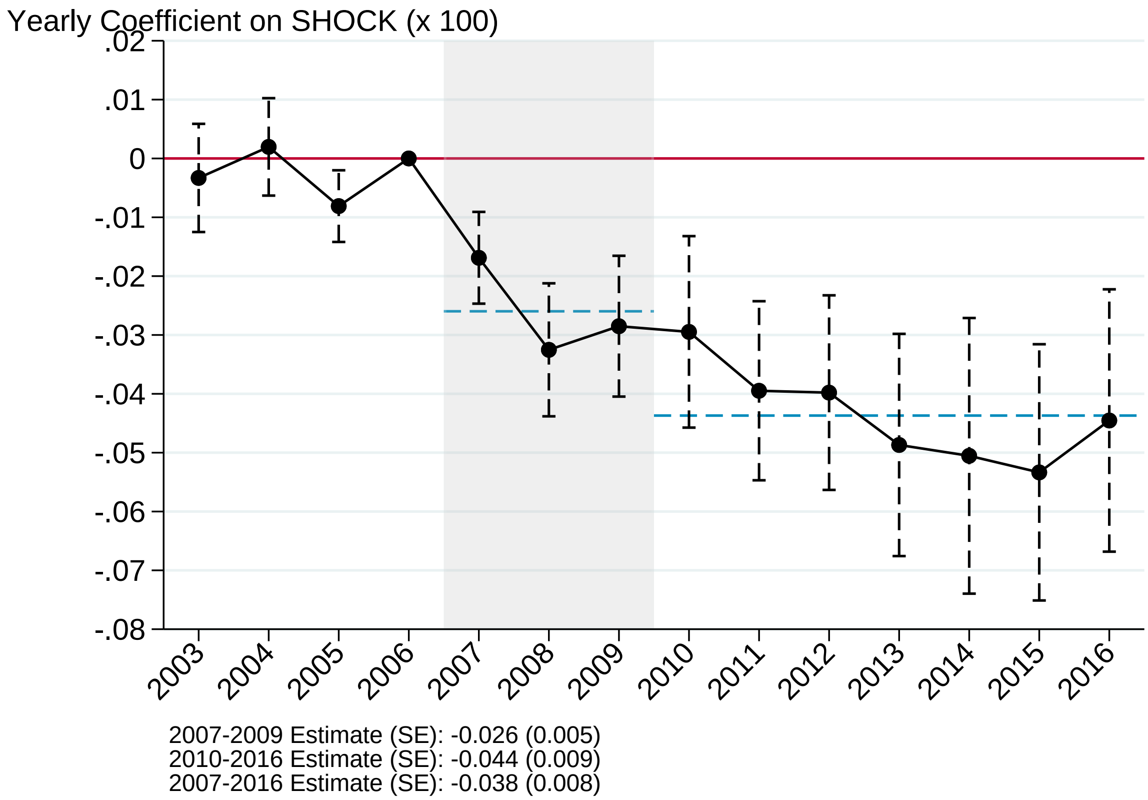


(c) Change in Log Mortality, 2006 vs 2007-16 Average, by GR Shock



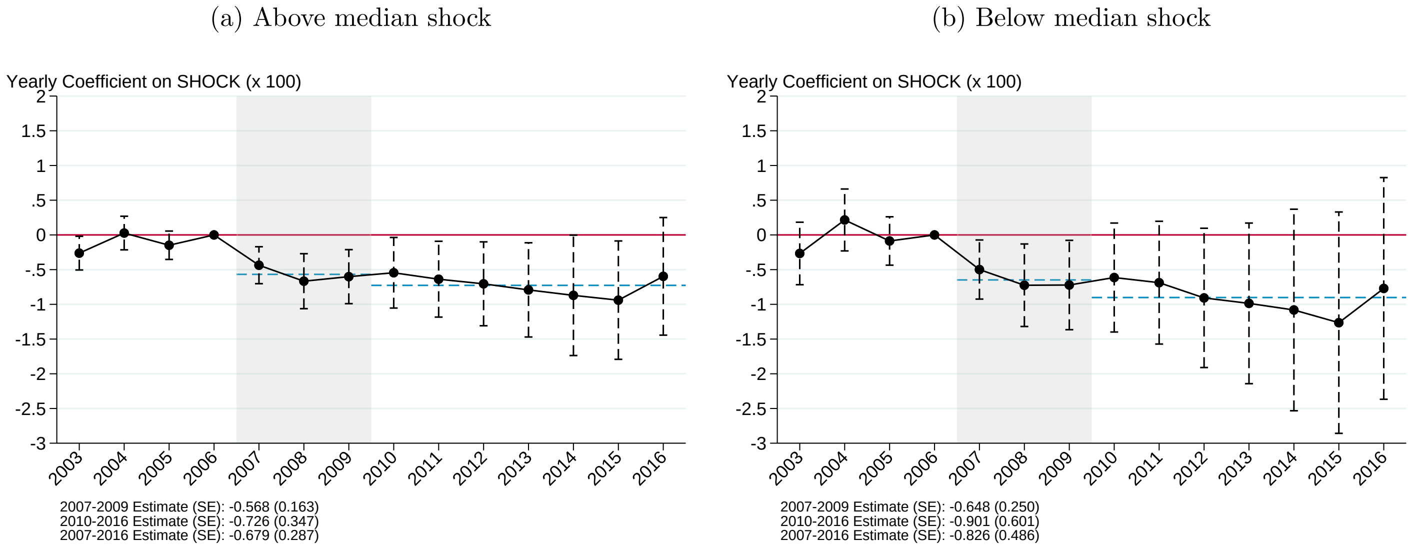
Notes: This figure plots the 2006 population-weighted average difference in the log age-adjusted CZ mortality rate per 100,000 between various post periods and a fixed 2006 pre-period. This is plotted against the population-weighted average CZ unemployment shock in each ventile of the unemployment shock 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. The area shaded in gray corresponds to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs.

Figure A.29: Impact of Shock in Percent 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 *percent* change in unemployment from 2007 to 2009, relative to the 2007 unemployment level. 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs.

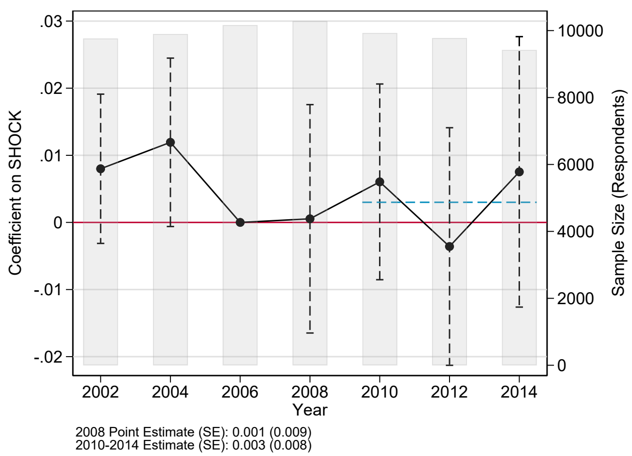
Figure A.30: Impact of Shock on Log Mortality, By Size of Shock



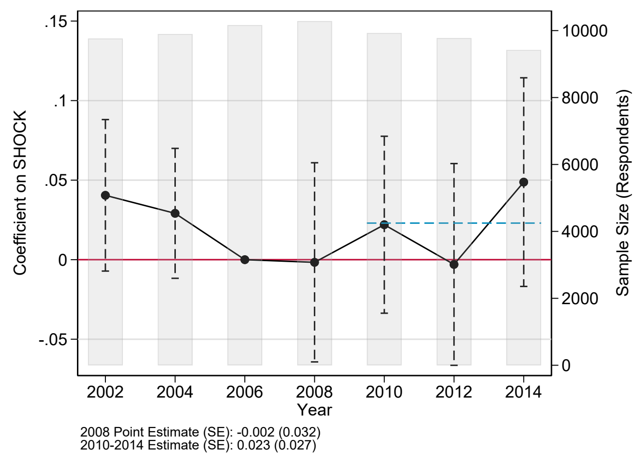
Notes: This figure displays the yearly coefficients β_{qt} from a modified version of equation (17), with $Recovery_{q(c)}$ substituted for an indicator for whether a CZ experienced an above or below median population-weighted 2007-2009 unemployment shock. The outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000, and $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Figure A.30a plots estimates among above-median unemployment shock CZs, and Figure A.30b 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 A.31: Impact of Shock on Measures of Care in the HRS

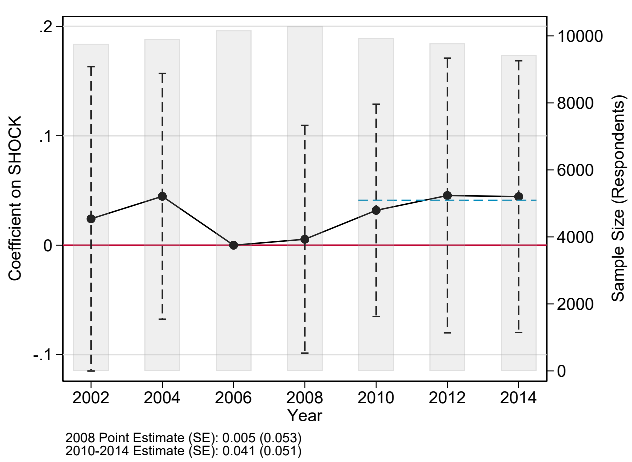
(a) Number of Helpers in the Past Month



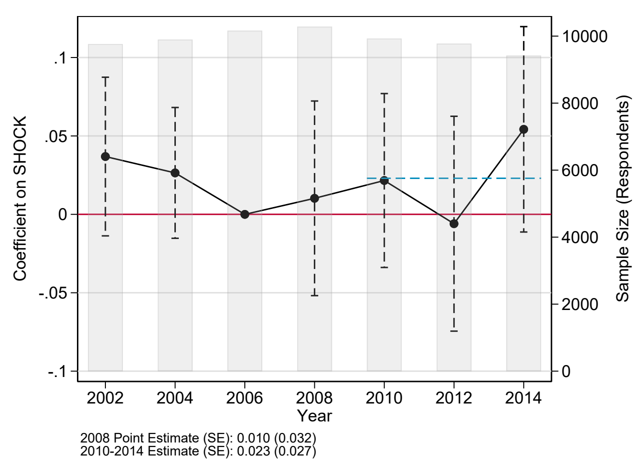
(b) Any Helpers in the Past Month



(c) Any Paid Helpers in the Past Month



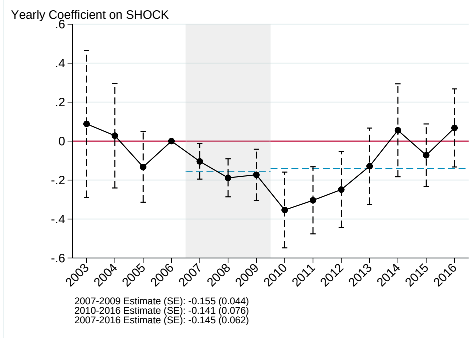
(d) Any Unpaid Helpers in the Past Month



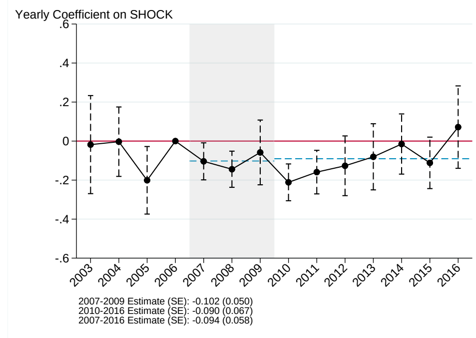
Notes: This figure displays the yearly coefficients β_t from equations (26) and (27), where the outcome y_{it} is either the number of helpers reported by the respondent (Figure A.31a, using equation 26), or a binary indicator for any reported helpers, any reported paid helpers, and any reported unpaid helpers (Figures A.31b, A.31c, and A.31d), all run as logistic regressions with equation (27). 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 A.32: Mediating for Air Pollution, Compare Monitor and Satellite Data

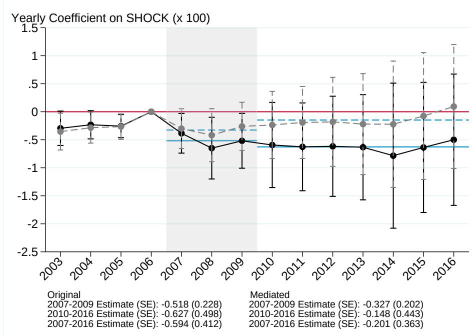
(a) Monitor Data PM2.5



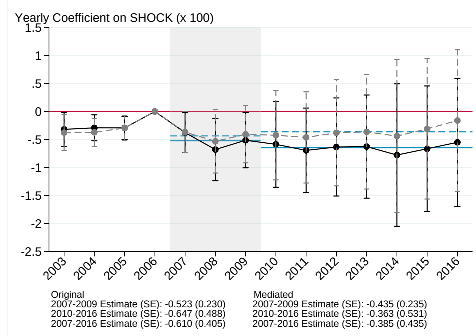
(b) Satellite Data PM2.5



(c) Monitor Data Mediation



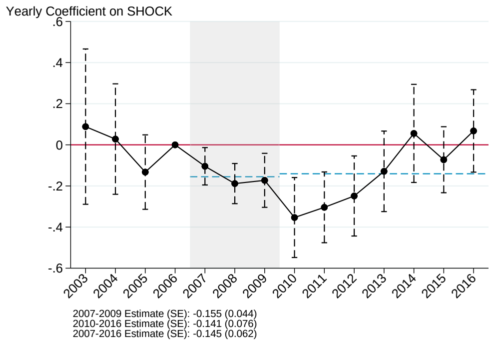
(d) Satellite Data Mediation



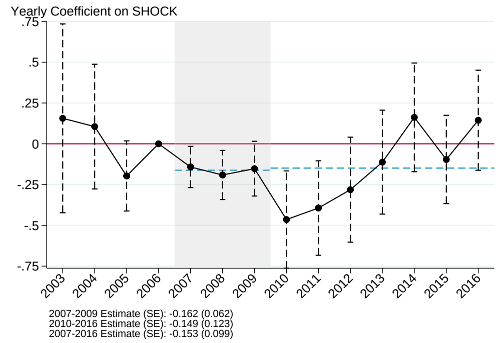
Notes: This figure compares the results of PM2.5 mediation using pollution monitor data and satellite data in only the subsample of U.S. counties for which pollution monitor data exists in both 2006 and 2010. Figures A.32a and A.32b display the yearly coefficients β_t from equation (7), where the outcome y_{ct} is the county-year level of PM2.5 (measured in $\mu g/m^3$), and $SHOCK_{cz(c)}$ is the 2007-2009 change in the CZ unemployment rate for a given county's corresponding CZ (analogous to Figure IXb). Figures A.32c and A.32d display the yearly coefficients β_t in equation (7) (in black, solid) and equation (8) (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 (analogous to Figure IXd). 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 (7) (equation 8). These estimates (and corresponding standard errors) are reported in the lower left-hand (right-hand) corner for equation (7) (equation 8). Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=524 counties for the pollution monitor data sample (64.4% of total U.S. 2006 population), and N=519 counties for the satellite data in counties covered by pollution monitors sample (63.9% of total U.S. 2006 population).

Figure A.33: Impact of Shock on Air Pollution Measures

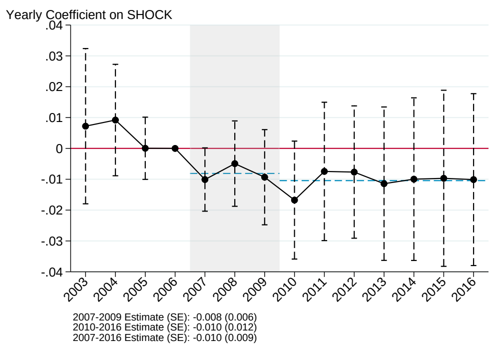
(a) Effect on PM2.5 (All Counties)



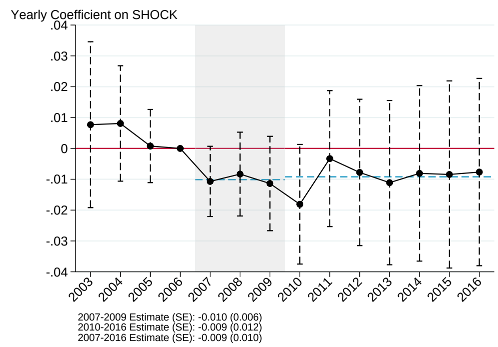
(b) Effect on PM2.5 (Overlap Sample)



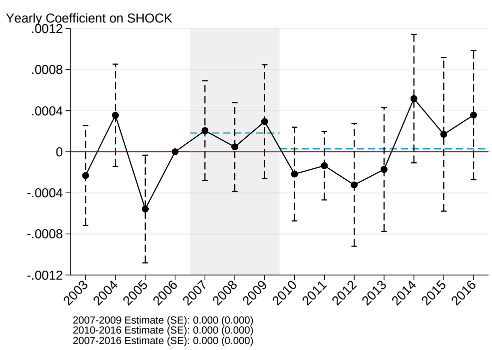
(c) Effect on CO (All Counties)



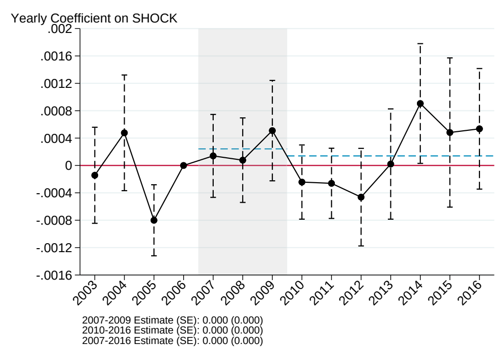
(d) Effect on CO (Overlap Sample)



(e) Effect on O_3 (All Counties)



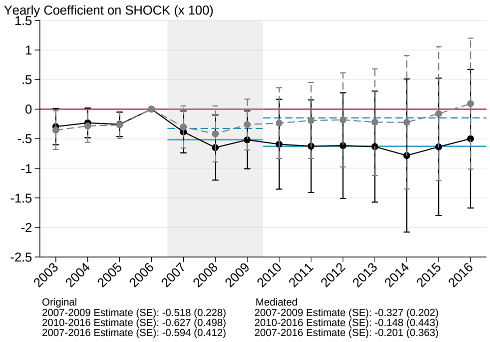
(f) Effect on O_3 (Overlap Sample)



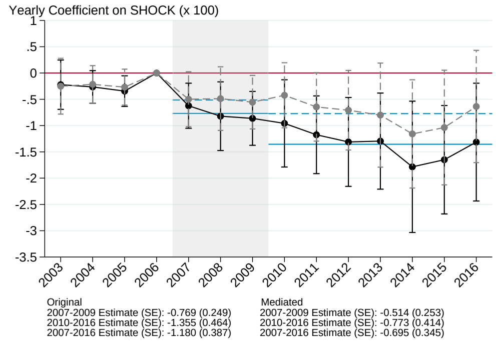
Notes: This figure displays the yearly coefficients β_t from equation (7), where the outcome y_{ct} is the county-year level of various pollutants (measured in $\mu g/m^3$), and $SHOCK_{cz(c)}$ is the 2007-2009 change in the CZ unemployment rate for a given county's corresponding CZ. In Figures A.33a, A.33c, and A.33e, analysis is restricted to the counties in which we observe monitors for the mediated pollutant in both 2006 and 2010 (524 counties representing 64.4% of the 2006 population in Figure A.33a, 179 counties representing 44.1% of the 2006 population in Figure A.33c, and 730 counties representing 70.7% of the 2006 population in Figure A.33e). In Figures A.33b, A.33d, and A.33f, 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating.

Figure A.34: Mediating For Air Pollution: Multiple Measures

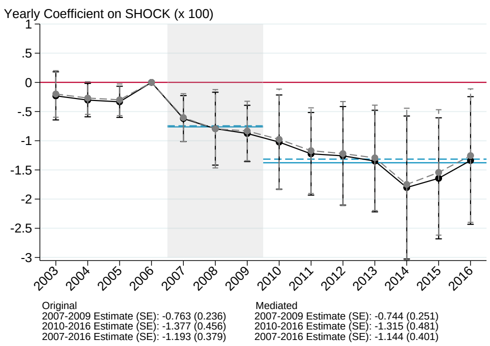
(a) Mediating for PM2.5 (All Counties)



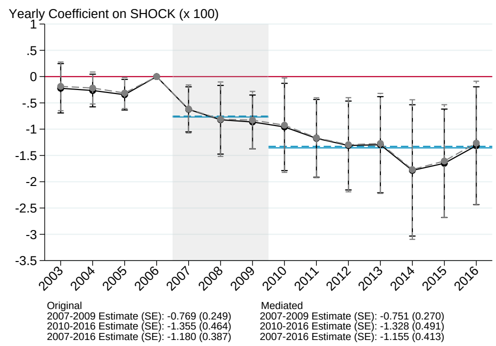
(b) Mediating for PM2.5 (Overlap Sample)



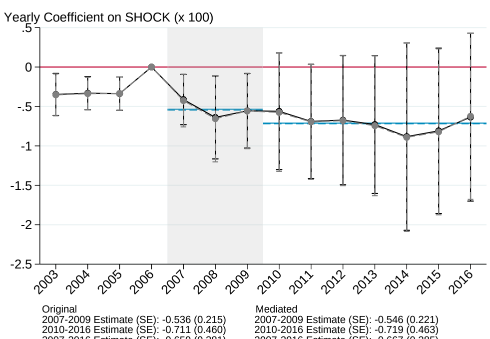
(c) Mediating for CO (All Counties)



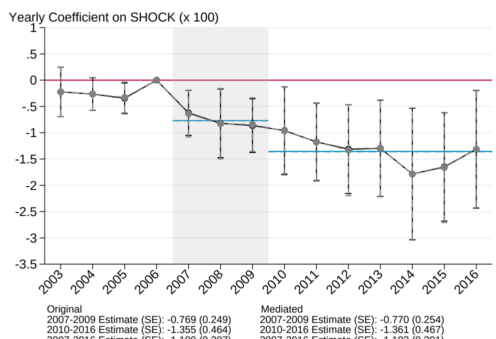
(d) Mediating for CO (Overlap Sample)



(e) Mediating for O_3 (All Counties)

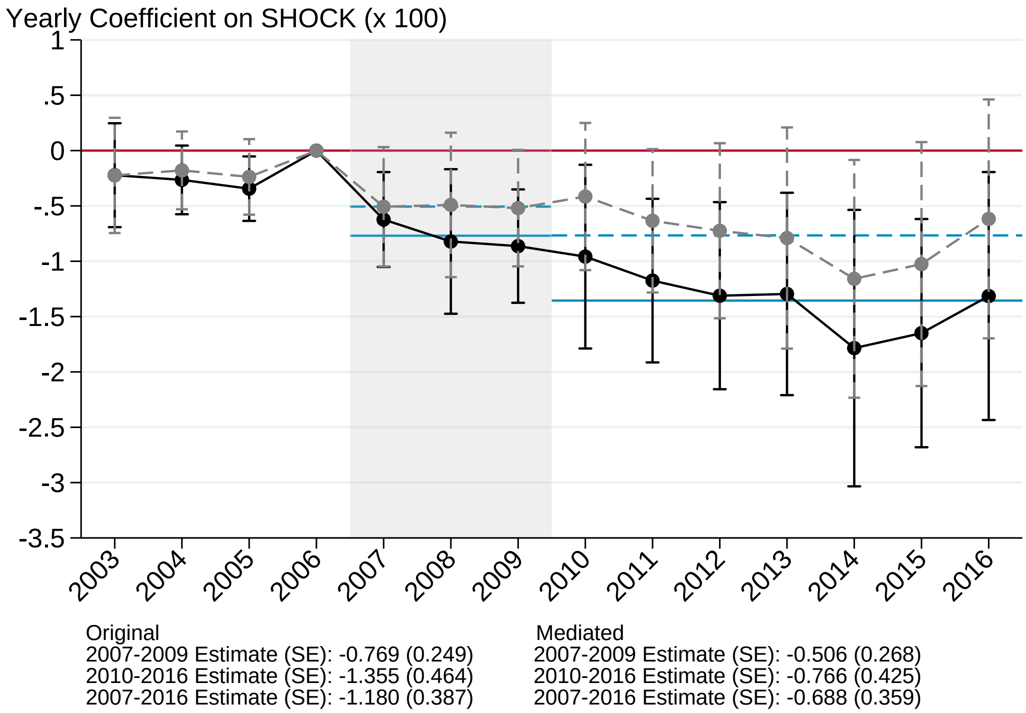


(f) Mediating for O_3 (Overlap Sample)



Notes: This figure displays the yearly coefficients β_t in equations (7) (in black, solid) and (8) (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 A.34a, A.34c, and A.34e, analysis is restricted to the counties in which we observe monitors for the mediated pollutant in both 2006 and 2010 (524 counties representing 64.4% of the 2006 population in Figure A.34a, 179 counties representing 44.1% of population in Figure A.34c, and 730 counties representing 70.7% of population in Figure A.34e). In Figures A.34b, A.34d, and A.34f, analysis is restricted to the 137 counties representing 39.0% of the 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 (7) (equation 8). These estimates (and corresponding standard errors) are reported in the lower left-hand (right-hand) corner for equation (7) (equation 8). Standard errors are clustered at the CZ level, and dashed vertical lines indicate 95% confidence intervals. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating.

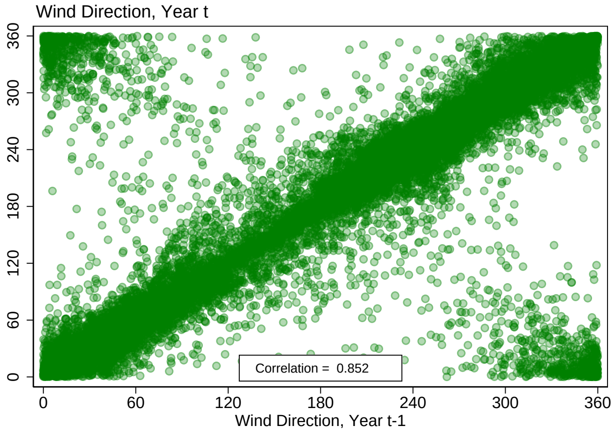
Figure A.35: Impact of Shock on Log Mortality, Mediating for PM2.5, CO, and O_3



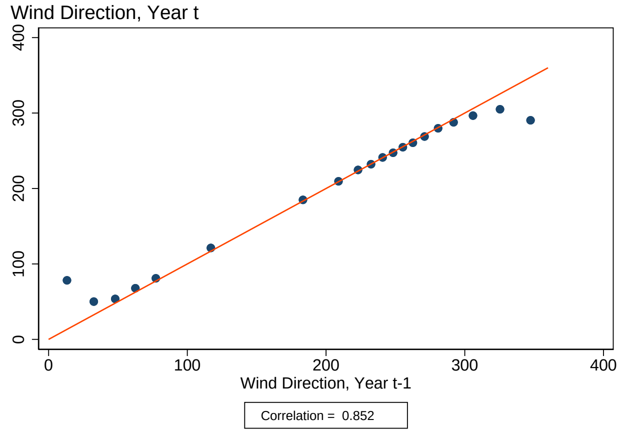
Notes: This figure displays the yearly coefficients β_t in equations (7) (in black, solid) and (8) (in gray, dashed), where the outcome y_{ct} is the log age-adjusted county mortality rate per 100,000, and $SHOCK_{cz(c)}$ is the 2007-2009 change in the CZ unemployment rate for a given county's corresponding CZ. The vector of controls in equation (8) 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 (7), while horizontal blue dashed lines indicate the same for equation (8). These estimates (and corresponding standard errors) are reported in the lower left-hand corner for equation (7) and lower right-hand corner for equation (8), 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 area shaded in gray corresponds to the timing of the Great Recession, adopting the NBER's business cycle dating. N=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 A.36: Prevailing Wind Direction Across Years

(a) Scatter



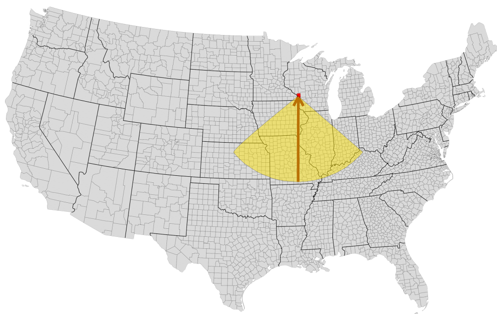
(b) Bin Scatter



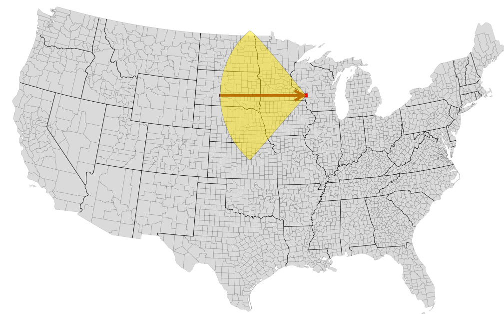
Notes: Prevailing wind direction is defined as the direction from which wind blows most frequently into the destination county, and ranges from 0 to 360 degrees. North is 0 degrees, and south is 180 degrees. County-year prevailing wind direction is calculated using monthly data over a 0.25 degree by 0.25 degree grid from the European Centre for Medium-Range Weather Forecasts (ECMWF) Reanalysis v5 (ERA5) data set. To aggregate up to the county level, the center of each grid square is mapped to the Census Block Group (CBG) it falls in, and the squares are weighted by 2010 population when averaging to the county-month level. A simple average of prevailing wind direction over months aggregates to county-year. The correlation between a county's prevailing wind direction in a given year and the preceding year is quite strong, suggesting that a persistent, time-invariant prevailing wind direction exists for counties. Note that the actual correlation is even higher than the reported 0.852, since the geometry of a circle means that 0 and 360 degrees are the same, as seen in the clustering in the top left and bottom right corners of Figure A.36a: i.e., a county with a prevailing wind direction last year of 355 degrees and 5 degrees this year would have the same amount of consistency in prevailing wind direction as a county with a prevailing wind direction of 45 degrees last year and 55 degrees this year, because the difference across years is 10 degrees in both cases.

Figure A.37: Definition of Upwind Counties Illustration

(a) Southern Wind (True Direction)



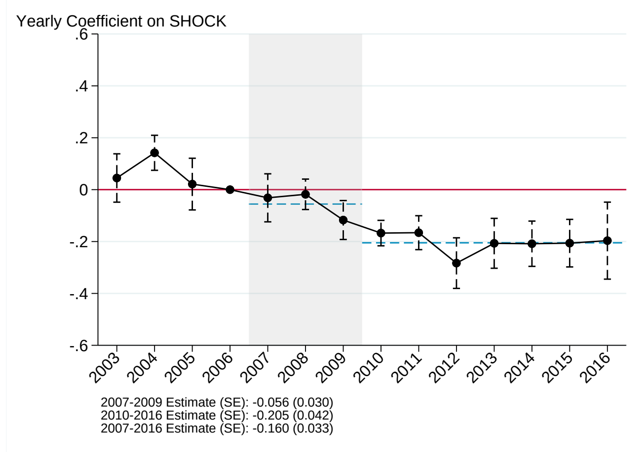
(b) Western Wind (Placebo Direction)



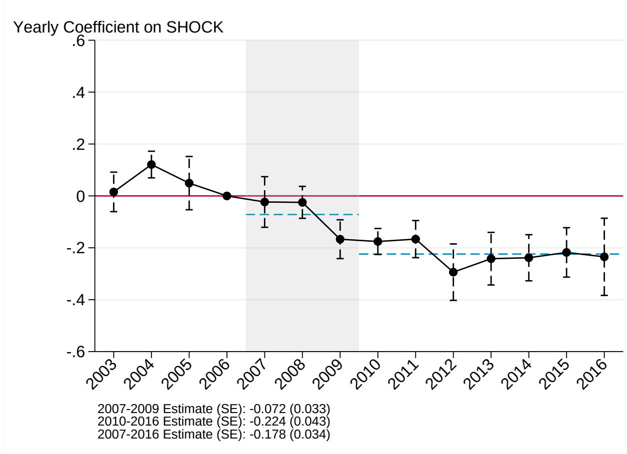
Notes: Our wind direction instrument uses the CZ-level Great Recession shocks of upwind counties to instrument for the PM2.5 shock of the destination county. Following Anderson (2020), we define a cone 45 degrees wide on both sides of the destination county's prevailing wind direction and extend outwards for a radius of 500 miles. Any neighboring counties whose centers fall within this cone are defined as upwind to the destination county. The yellow cone in Figure A.37a shows the counties that would be counted as upwind if the prevailing wind to the destination county (in red) came from the south, and the yellow cone in Figure A.37b shows the counties that would be counted as upwind in the placebo instrument for that same county (i.e. true prevailing wind direction and corresponding 500-mile radius cone are rotated 90 degrees clockwise).

Figure A.38: Wind Direction Instrument First Stage and Placebo

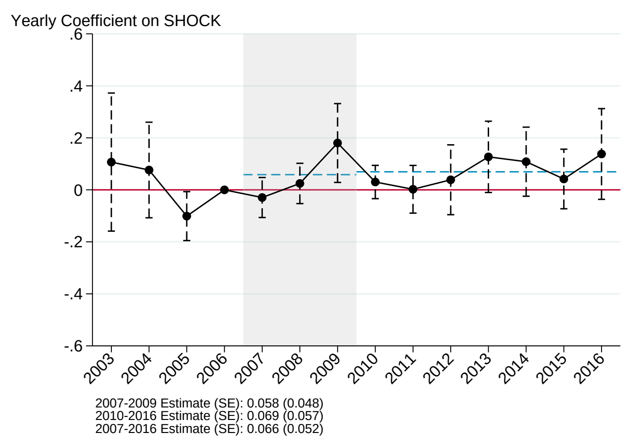
(a) First Stage



(b) Placebo Test: True Instrument



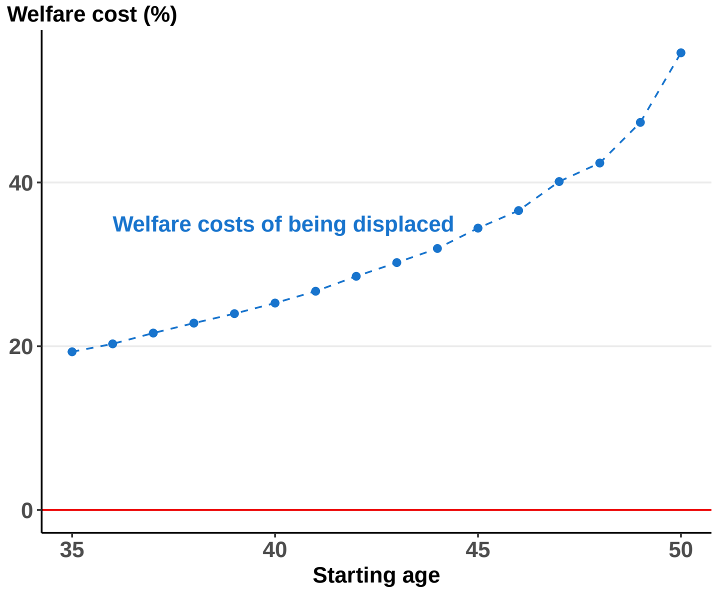
(c) Placebo Test: Placebo Instrument



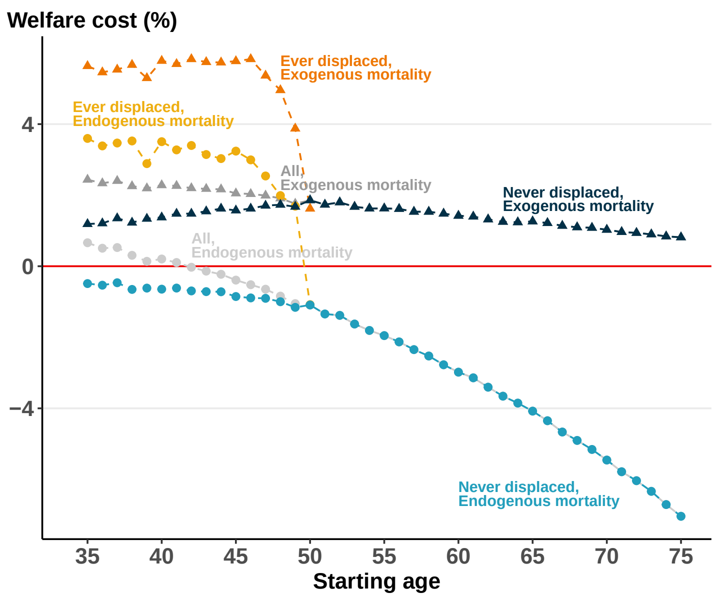
Notes: Figure A.38a plots estimates of ρ_t from equation (29). Figures A.38b and A.38c plot estimates of ρ_t and η_t respectively from equation (30). These regressions are weighted by 2006 county population. In Figures A.38a and A.38b, $SHOCK$ is the average 2007-2009 change in the CZ-level unemployment rate of upwind (but not same-CZ) neighboring counties. In Figure A.38c, $SHOCK$ is the average 2007-2009 change in the CZ-level unemployment rate of a group of not-upwind (and not same-CZ) neighboring counties: take the cone region that defines upwind counties, rotate it 90 degrees clockwise around the center of the destination county, and take all counties whose centers fall within the new cone as the placebo upwind counties. Satellite data is used for the annual measures of PM2.5 levels. 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 county level, and dashed vertical lines indicate 95% confidence intervals on each coefficient. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=2,983 counties.

Figure A.39: Allowing for Mortality Effects of Job Displacements

(a) Direct Welfare Cost of the Mortality Effects of Job Displacements



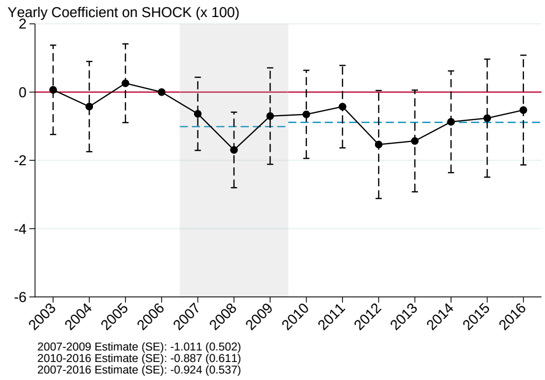
(b) Welfare Cost of Recessions Allowing for Mortality Effects of Job Displacements



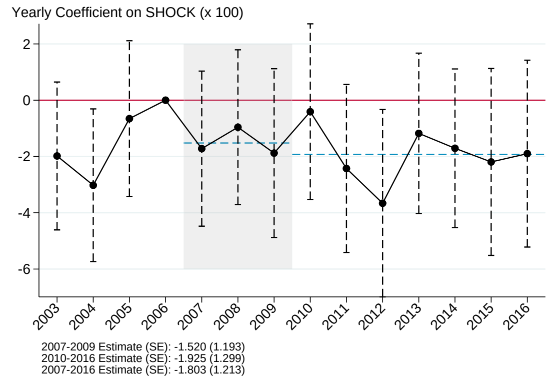
Notes: This figure displays calibration results from an extended version of our model based on equation (14) at various ages by allowing for job displacements to have mortality effects based on the estimates in Sullivan and Von Wachter (2009) for high-tenure workers. Figure A.39a shows the welfare cost of job displacements coming from mortality effects. Figure A.39b shows results analogous to Figure XIa, separating out the workers who are ever displaced and never displaced for ages 35 through 50.

Figure A.40: Impact of Shock on Log Mortality, by Age Group: Ages 0-54

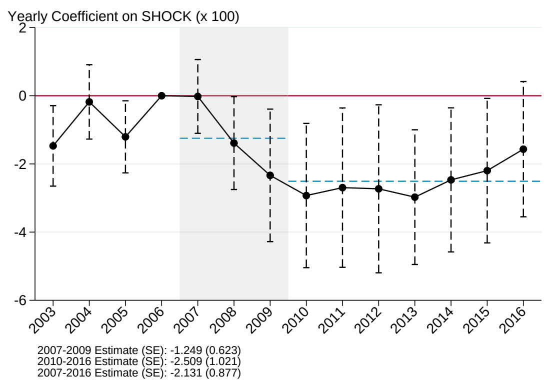
(a) Ages 0-4



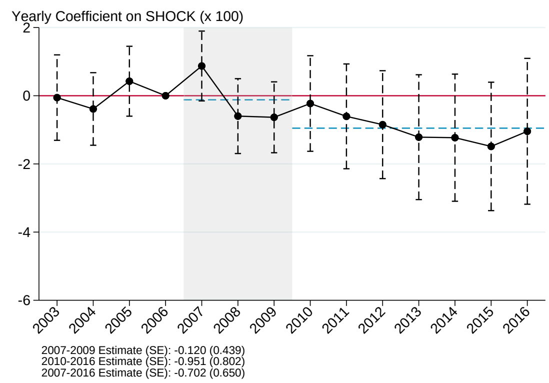
(b) Ages 5-14



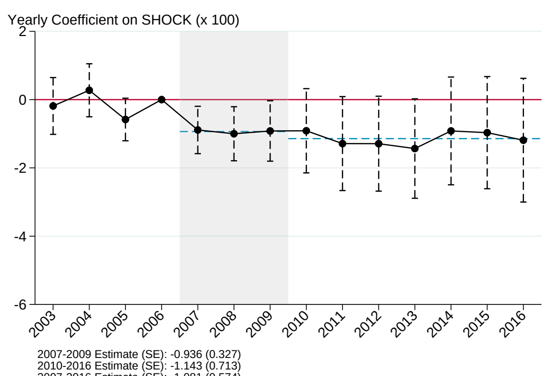
(c) Ages 15-24



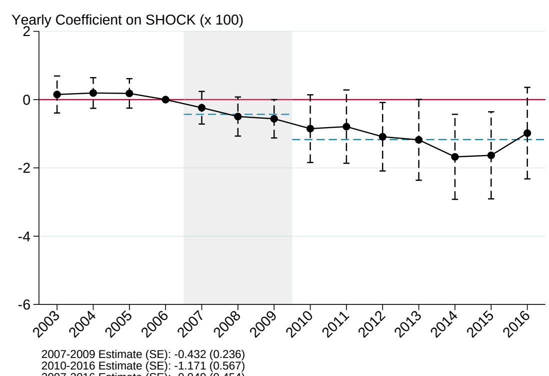
(d) Ages 25-34



(e) Ages 35-44



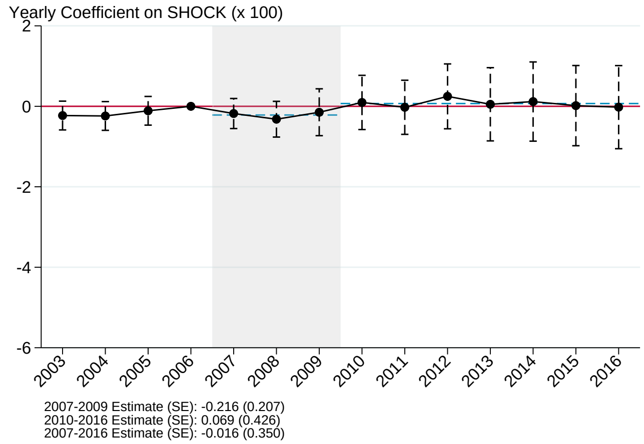
(f) Ages 45-54



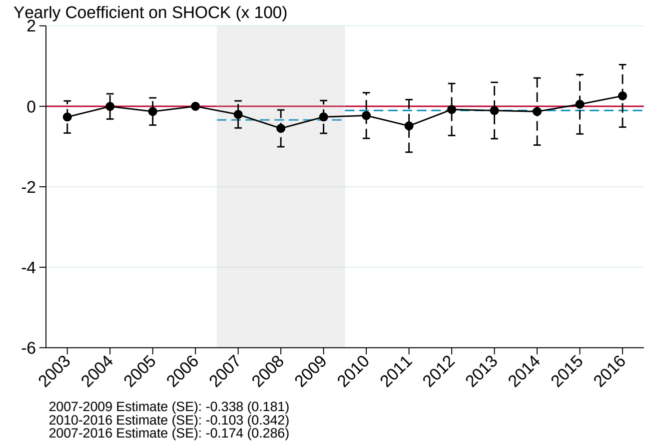
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is log age-adjusted CZ mortality rate per 100,000, and g indicates 10 age groups (six of which are displayed here; the remaining four are displayed in Figure A.41). $SHOCK_c$ is the 2007-2009 change 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs.

Figure A.41: Impact of Shock on Log Mortality, by Age Group: Ages 55+

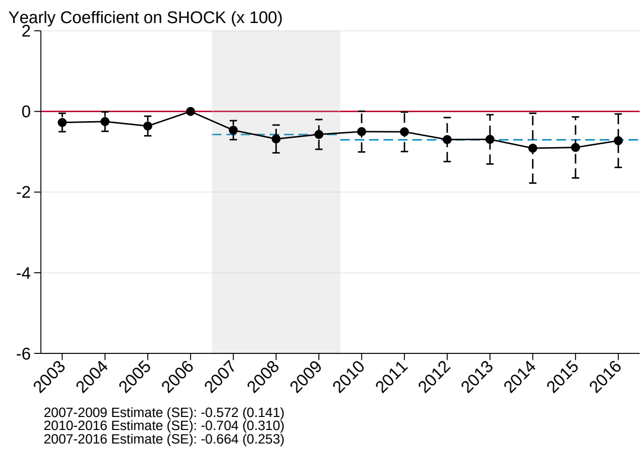
(a) Ages 55-64



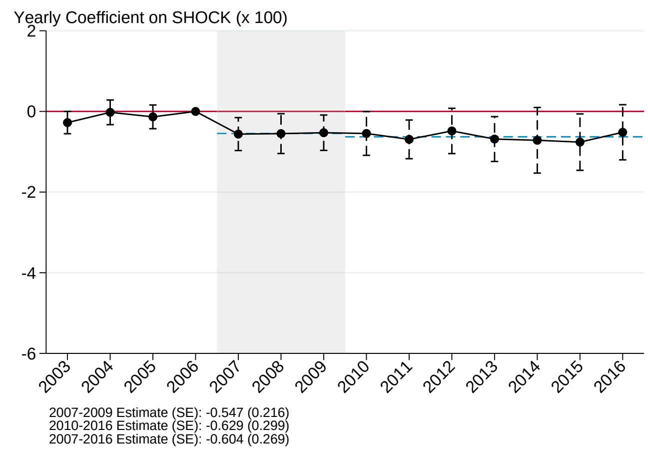
(b) Ages 65-74



(c) Ages 75-84



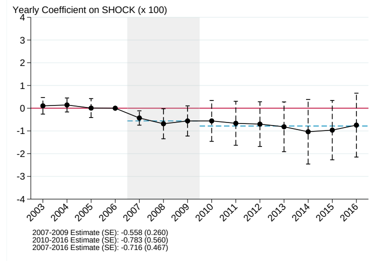
(d) Ages 85+



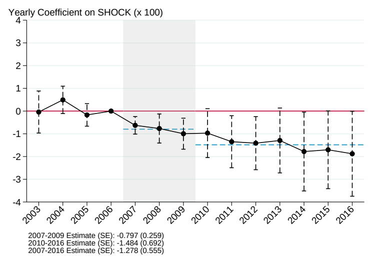
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is log age-adjusted CZ mortality rate per 100,000, and g indicates 10 age groups (four of which are displayed here; the remaining six are displayed in Figure A.40). $SHOCK_c$ is the 2007-2009 change 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=741 CZs.

Figure A.42: Impact of Shock on Log Mortality, by Education

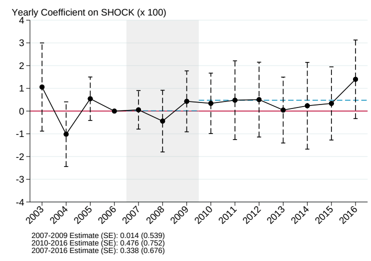
(a) Overall



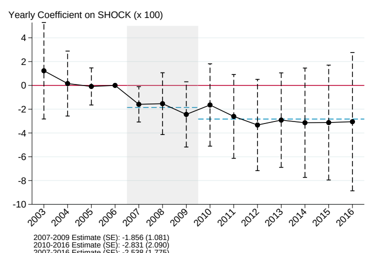
(b) HS or Less



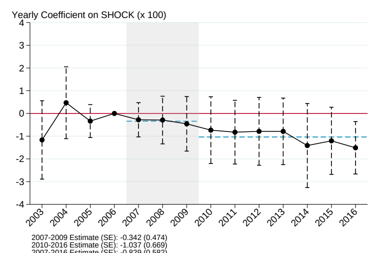
(c) More Than HS



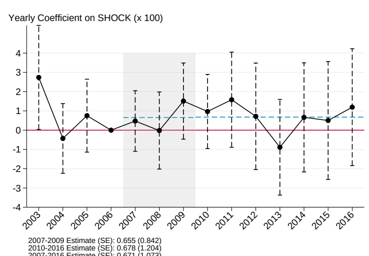
(d) Less than HS



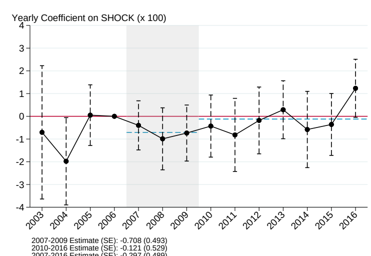
(e) Exactly HS



(f) Some College



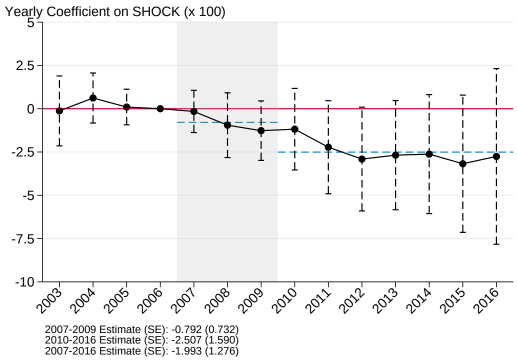
(g) College or More



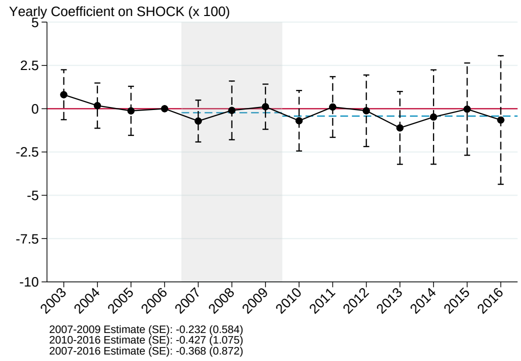
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted state mortality per 100,000 for individuals aged 25+, and g indicates a range of different education level groups. $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. Figure A.42a examines all individuals aged 25+, and Figures A.42b and A.42c subdivide the sample into the approximately 52 percent with a high school diploma or less (A.42b) and the approximately 48 percent with more than a HS diploma (A.42c). Lastly, Figures A.42d, A.42e, A.42f, and A.42g further subdivide those with less than a high school diploma (12% of our sample), exactly a high school diploma (36%), some college education but no four-year degree (22%), and a four-year college degree or more (30%). 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.3 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=47 states.

Figure A.43: Impact of Shock on Log Mortality, by Education and Age

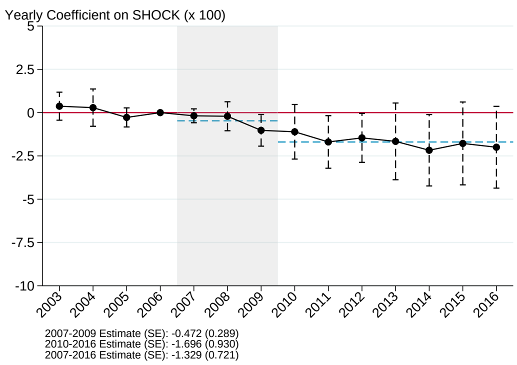
(a) HS or Less, 25-44 Year-Olds



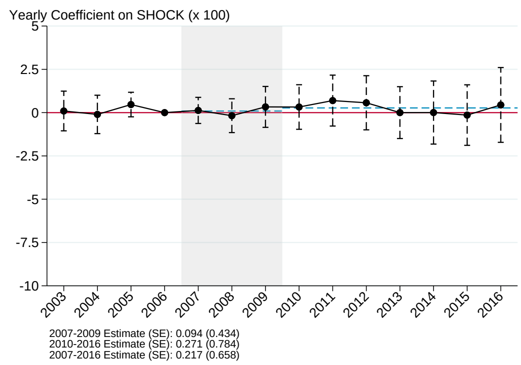
(b) More Than HS, 25-44 Year-Olds



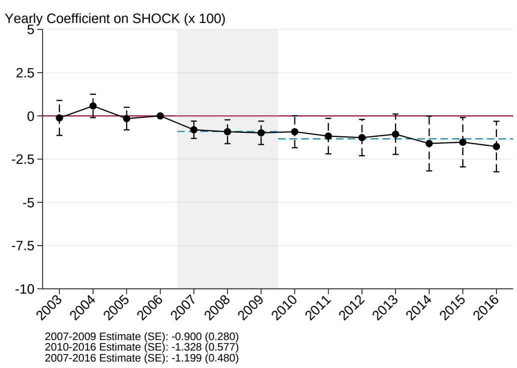
(c) HS or Less, 45-64 Year-Olds



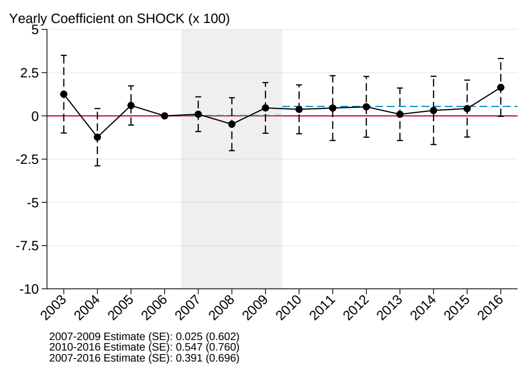
(d) More Than HS, 45-64 Year-Olds



(e) HS or Less, 65+ Year-Olds



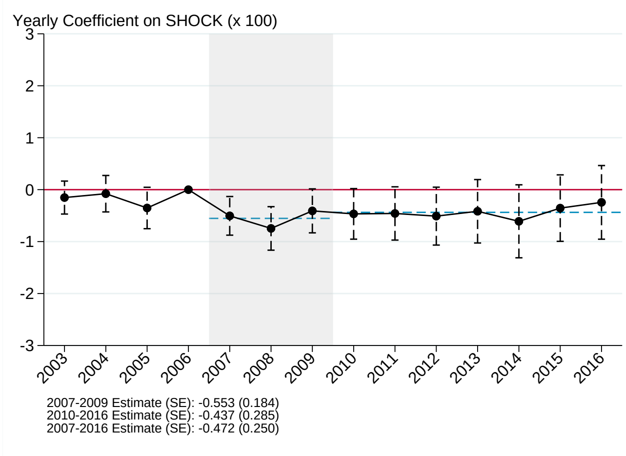
(f) More Than HS, 65+ Year-Olds



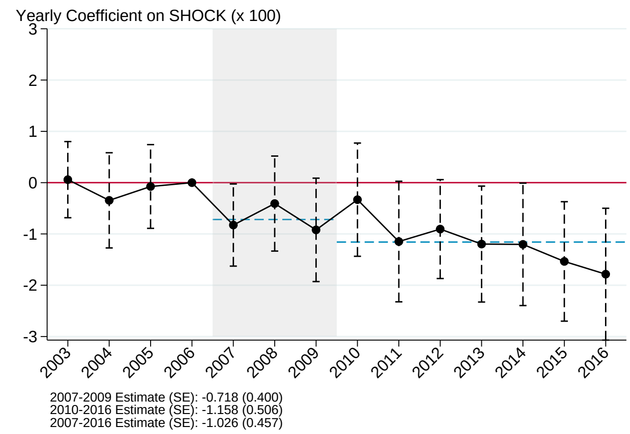
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted state mortality rate per 100,000, and g indicates six education/age bin combinations. $SHOCK_c$ is the 2007-2009 change in the state unemployment rate. Observations are weighted 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.3 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=47 states.

Figure A.44: Impact of Shock on Log Mortality Among Elderly, by Medicaid Status

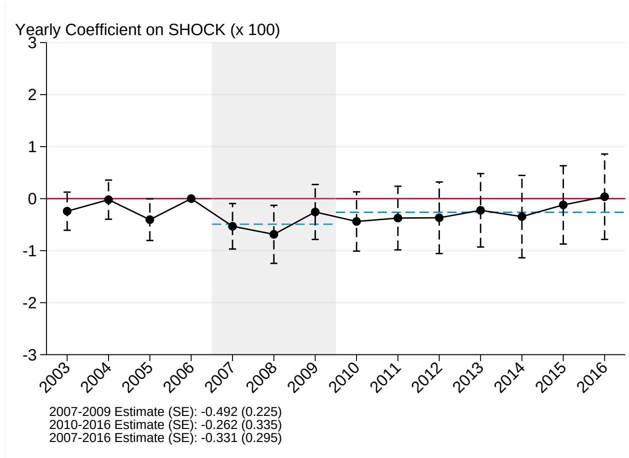
(a) Overall Medicare 65+ sample



(b) Medicaid in year $t - 1$



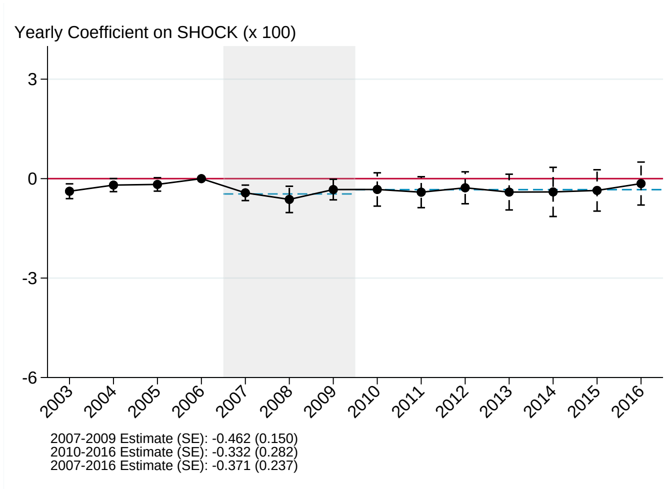
(c) No Medicaid in year $t - 1$



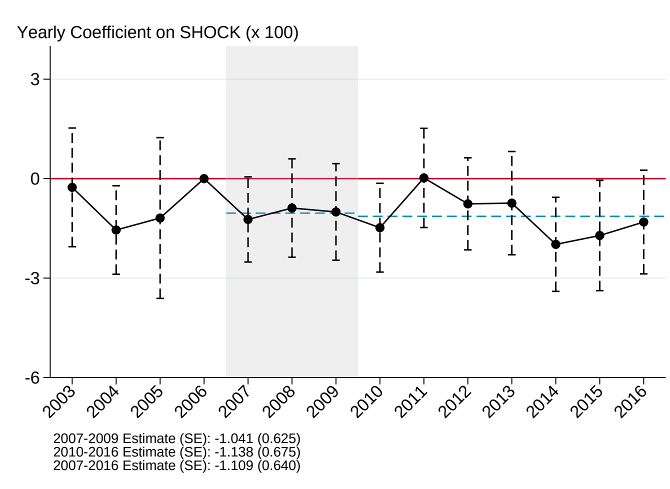
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log (non age-adjusted) CZ mortality rate per 100,000, and g indicates whether individuals were recently on Medicaid. $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. The sample 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 A.8. Figure A.44a shows results among all individuals, Figure A.44b shows results among all individuals who were on Medicaid at some point during the previous year, and Figure A.44c 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=736 CZs that observe at least one Medicaid recipient and at least one non-recipient in each year between 2003 and 2016.

Figure A.45: Impact of Shock on Log Mortality, by Race/Ethnicity

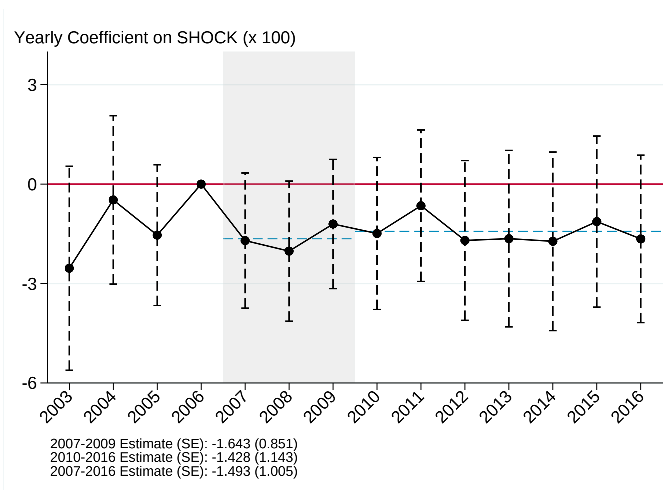
(a) Non-Hispanic White



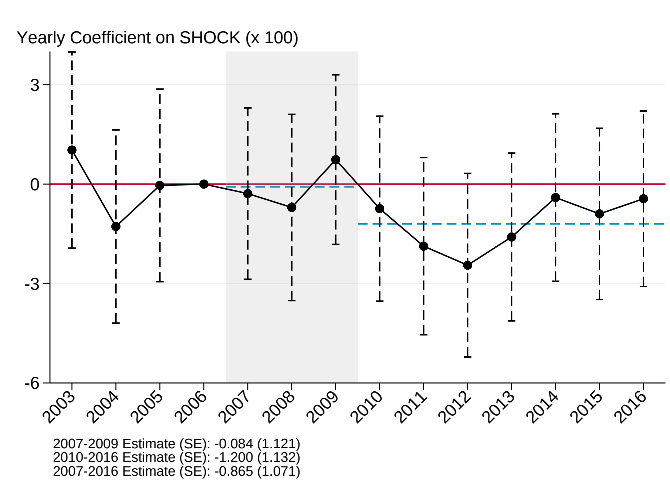
(b) Non-Hispanic Black



(c) Hispanic



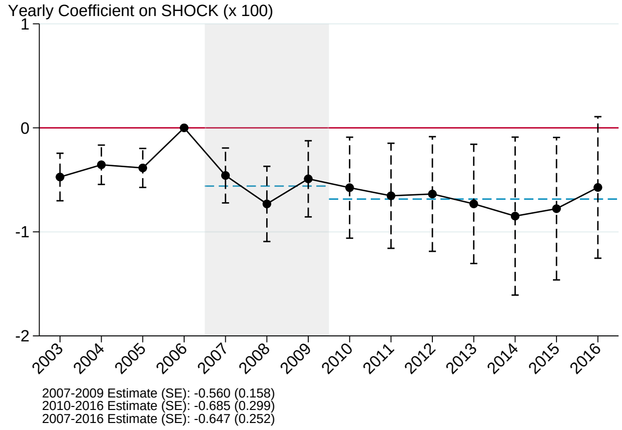
(d) Other



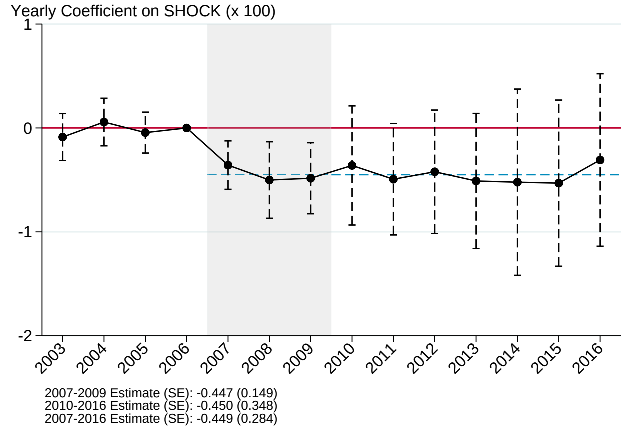
Notes: This figure displays the yearly coefficients β_{tg} from equation (2), where the outcome y_{ctg} is the log age-adjusted CZ mortality rate per 100,000, and g indicates a range of racial groups. $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Horizontal blue dashed lines indicate 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. 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 A.46: Impact of Shock on Log Mortality Rate, by Gender

(a) Male

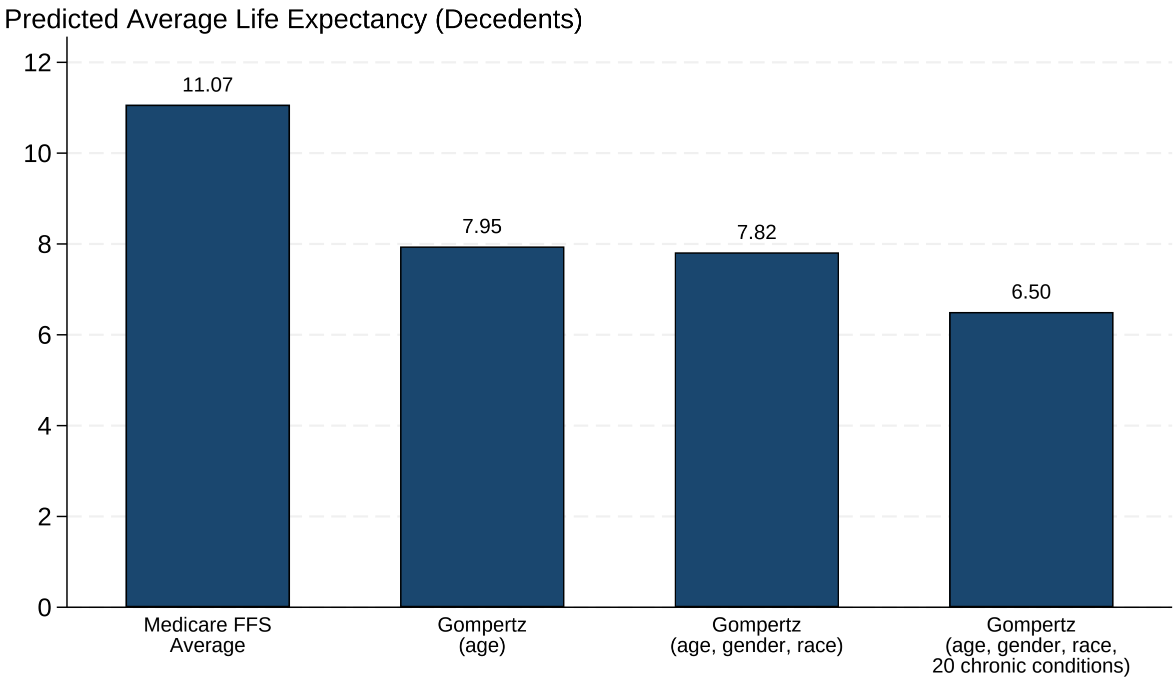


(b) Female



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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. 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.

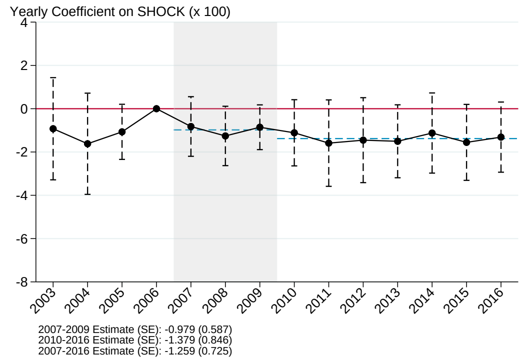
Figure A.47: Average, Counterfactual Predicted Remaining Life Expectancy of Decedents



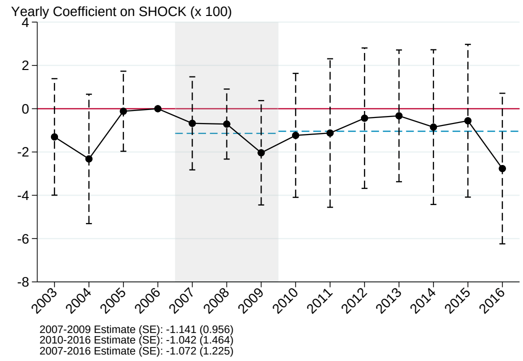
Notes: This figure displays the average predicted counterfactual remaining life expectancy at the start of the year for Medicare beneficiaries who subsequently die within the year. Remaining life expectancy is determined as of January 1 of a given year, and is estimated as per equation (18), using a 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 A.8, further restricting beneficiaries to those enrolled in Traditional Medicare in the previous year. N=3,714,177 patient-years.

Figure A.48: Impact of Shock on Self-Reported Health Measures in the BRFSS

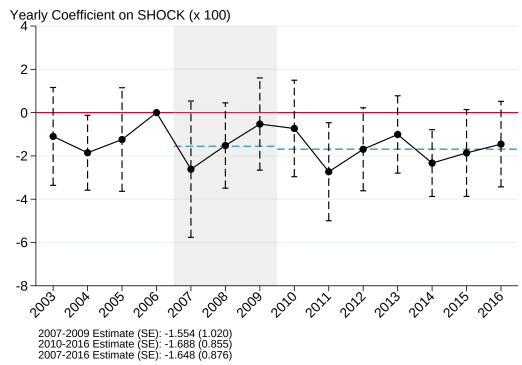
(a) Log share less than very good health



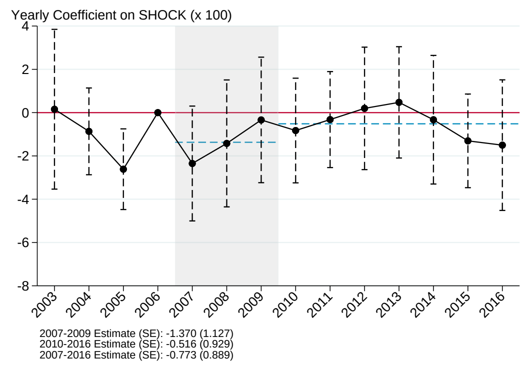
(b) Log share poor mental health last month



(c) Log share ever had diabetes



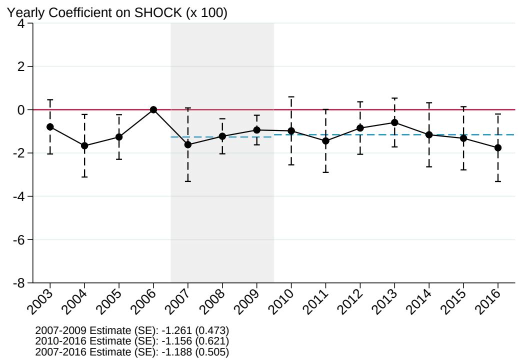
(d) Log share with asthma



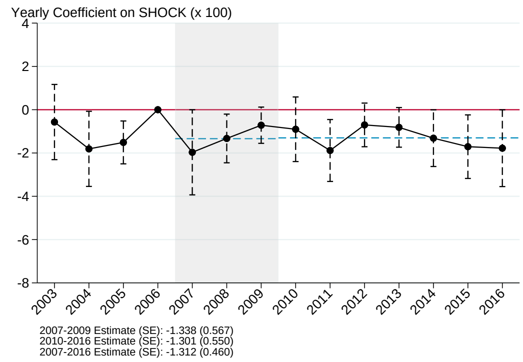
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the share of the state population with a range of health characteristics. These shares are calculated as the mean of respondent-level BRFSS variables (weighted according to BRFSS survey weights). Variable 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=51 states.

Figure A.49: Average Impact of Shock on Health Measures in the BRFSS, By Age

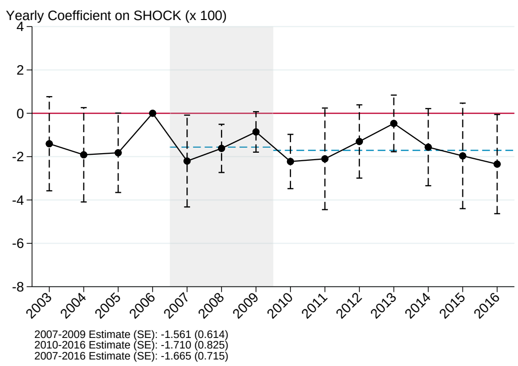
(a) All ages



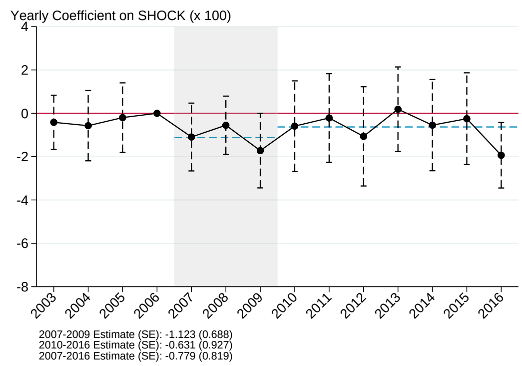
(b) Ages 18-44



(c) Ages 45-64



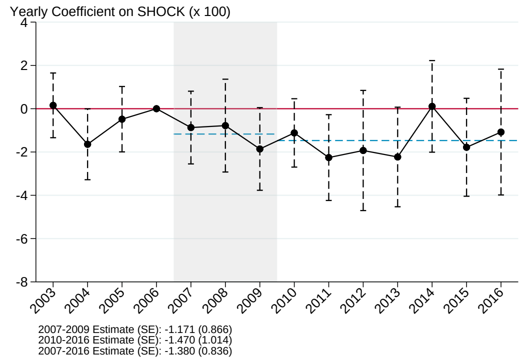
(d) Ages 65+



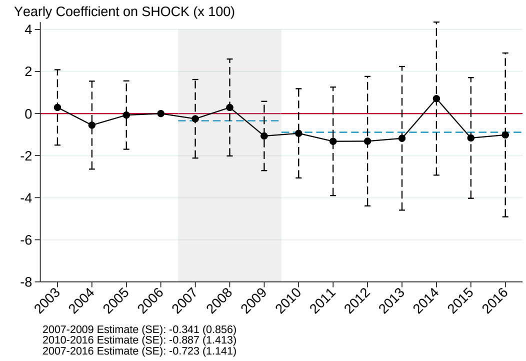
Notes: This figure displays the yearly average event study coefficients across estimated event study coefficients for four different self-reported health measures, as summarized in panel (a) of Figure VIII. We average the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log share of the state-level population with the health measure in question. This is done both overall and within three distinct age groups. 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=51 states.

Figure A.50: Impact of Shock on Health Behavior in the BRFSS I

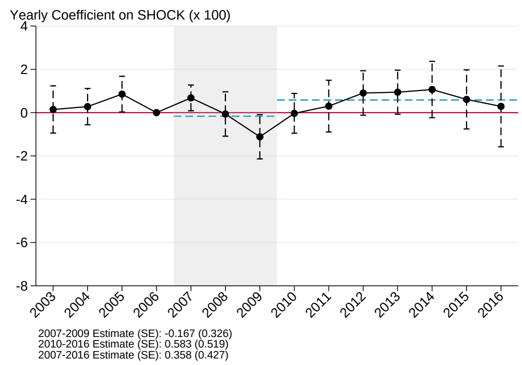
(a) Log share who currently smoke



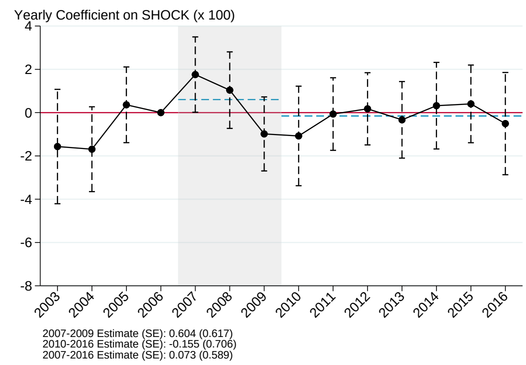
(b) Log share who smoke daily



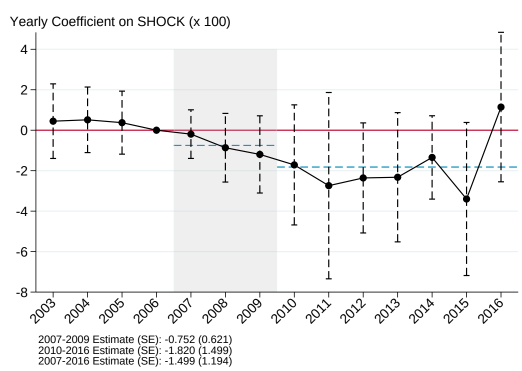
(c) Log share who currently drink alcohol



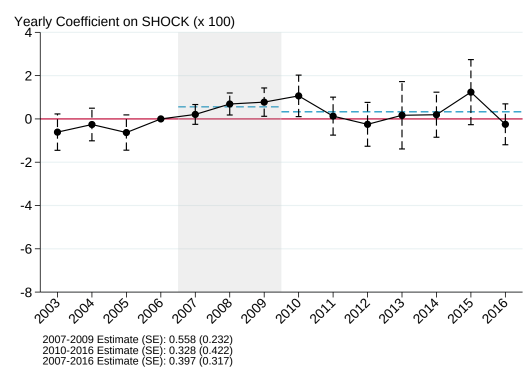
(d) Log share binge drinking last month



(e) Log share who did not exercise last month



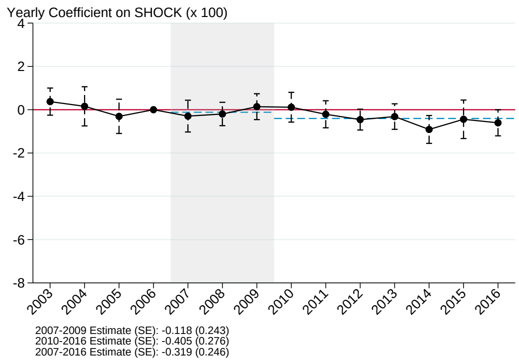
(f) Log share who did not have a flu shot last year



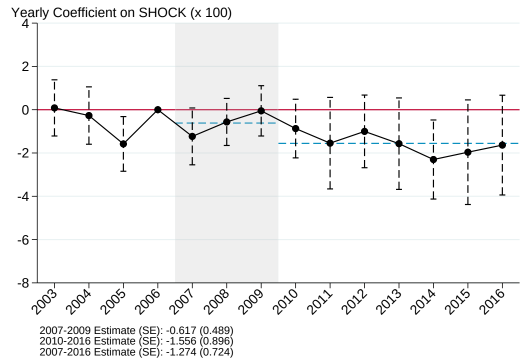
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the share of the state population exhibiting a range of health behaviors. These shares are calculated as the mean of respondent-level BRFSS variables (weighted according to BRFSS survey weights). Variable 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=51 states.

Figure A.51: Impact of Shock on Health Behavior in the BRFSS II

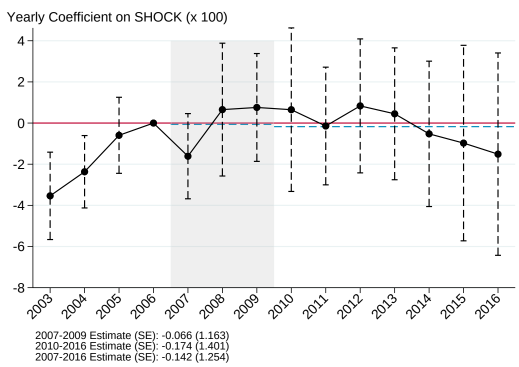
(a) Log share overweight or obese



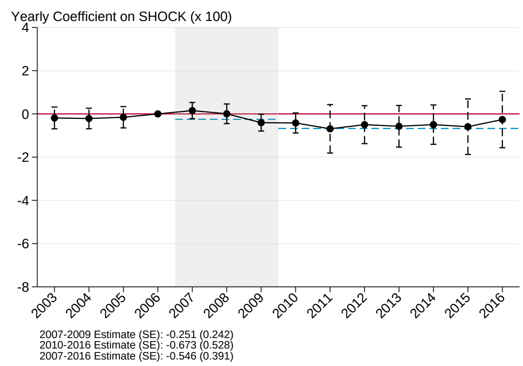
(b) Log share obese



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



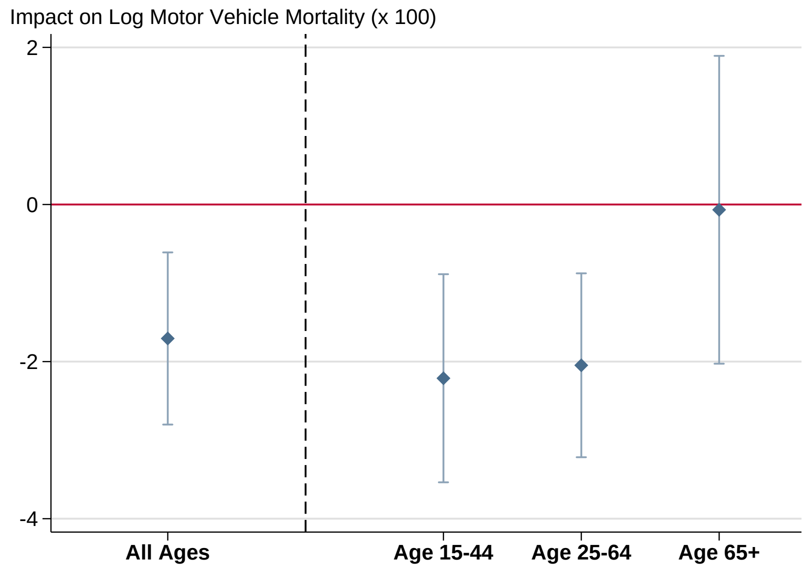
(d) Average effect on health behaviors



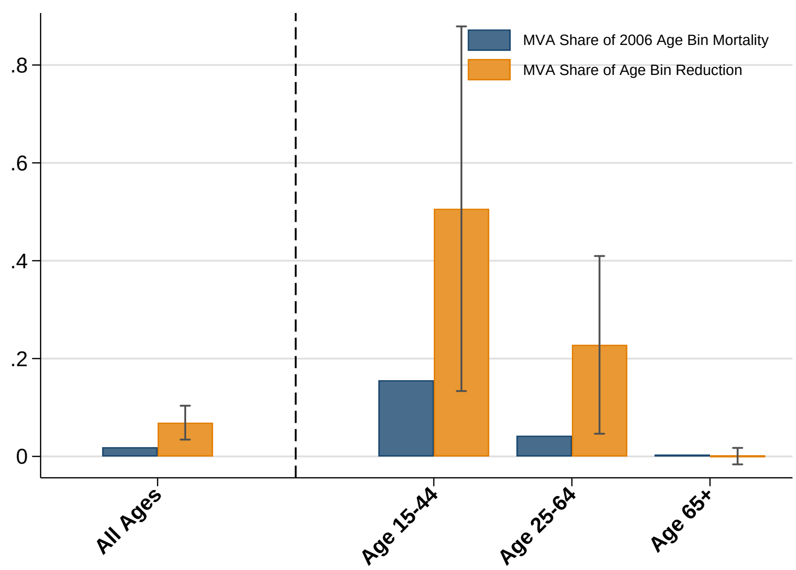
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the share of the state population with a range of health behaviors and health insurance status. These shares are calculated as the mean of respondent-level BRFSS variables (using BRFSS survey weights). 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. Panel (d) displays the yearly average event study coefficients across estimated event study coefficients for the different health behaviors, as summarized in panel (b) of Figure VIII. 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=51 states.

Figure A.52: Impact of Shock on Log Motor Vehicle Mortality, By Age

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



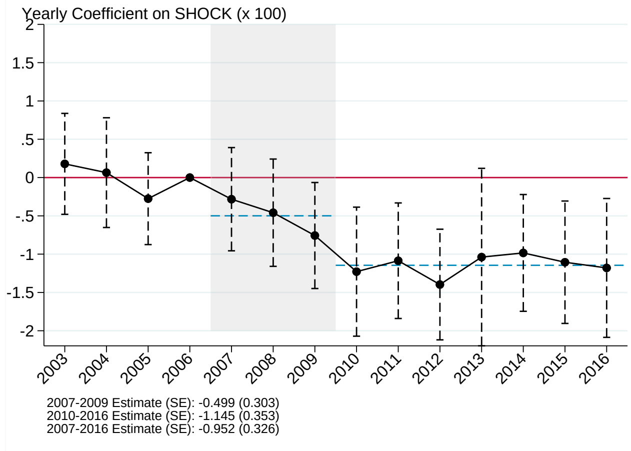
(b) Share of age group mortality reductions attributable to reductions in motor vehicle deaths



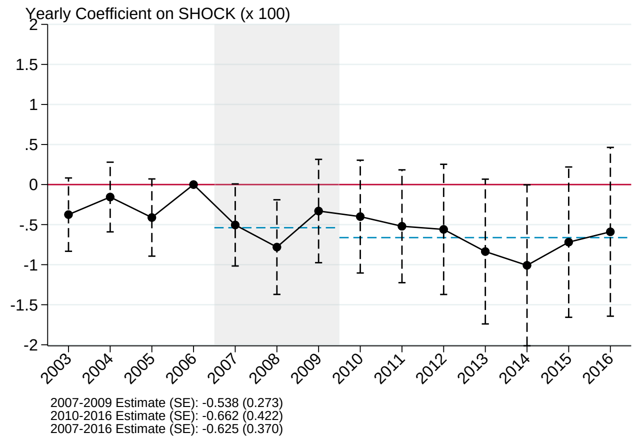
Notes: Figure A.52a displays the group-specific average of 2007-2009 coefficients β_{tg} from equation (2), where the outcome is log age-adjusted CZ mortality rate from motor vehicle accidents, and groups g are defined as age groups. Observations are weighted by CZ population in 2006. Coefficients, standard 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 A.52b 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 orange 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 A.53: Impact of Shock on Log Mortality by Nursing Home Use

(a) Nursing home use in t or $t-1$



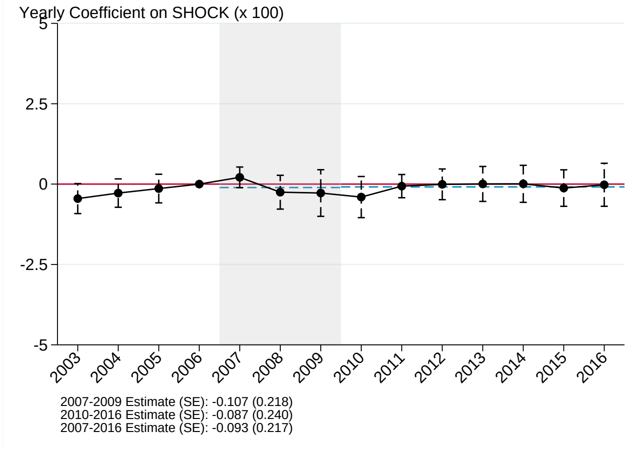
(b) No nursing home use in t or $t-1$



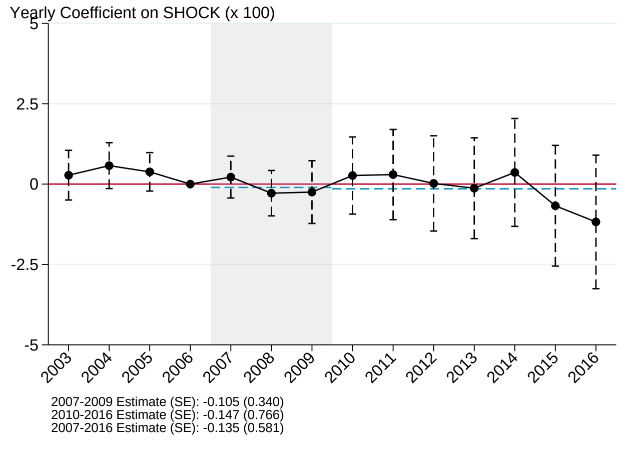
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000 and $SHOCK_c$ is the 2007-2009 change in the CZ unemployment rate. Figure A.53a aggregates CZ-level mortality for individuals who utilized nursing home care in a given year or the year prior. Figure A.53b aggregates CZ-level mortality for individuals who did not utilize nursing home 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 A.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. 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=733 CZs (covering >99.9% of Medicare 2006 population) with at least one beneficiary associated with nursing home utilization and one not associated with nursing home utilization in every year.

Figure A.54: Impact of Shock on Nursing Home Staffing

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



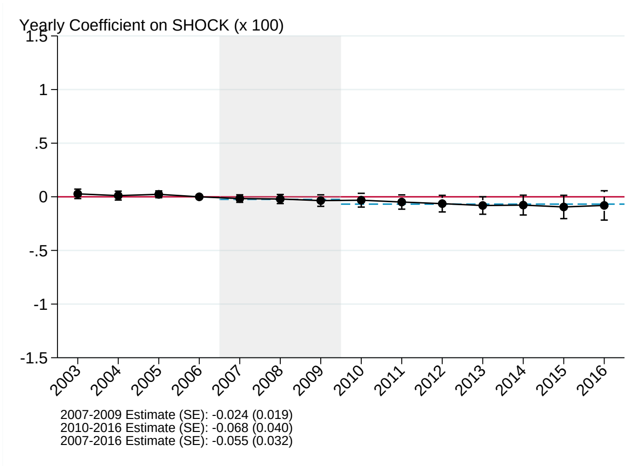
(b) Log Highly Skilled Nurses Ratio



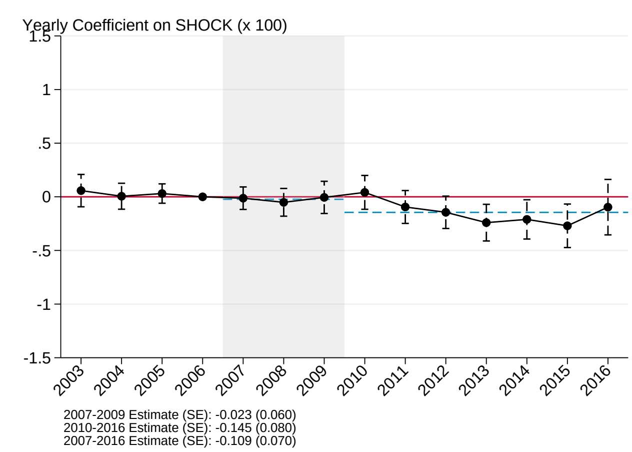
Notes: This figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} includes two CZ-level measures of nursing home staffing and $SHOCK_c$ is the 2007-2009 change in CZ unemployment rate. In Figure A.54a, the outcome y_{ct} is defined as the sum of the hours worked by registered nurse, licensed practical nurse, and certified nursing assistant staff per resident-day during the two weeks prior to the annual OSCAR survey. In Figure A.54b, the outcome y_{ct} is the log of the number of registered nurse full-time equivalents divided by the number of registered nurse + licensed practical nurse full-time equivalents in nursing homes. In both instances, we take a CZ-level mean of these nursing home-level observations, weighted by the total beds in each nursing home, 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=716 CZs (covering 99.8% of overall 2006 population) which contain at least one nursing home.

Figure A.55: Impact of Shock on Nursing Home Volume and Resident Characteristics

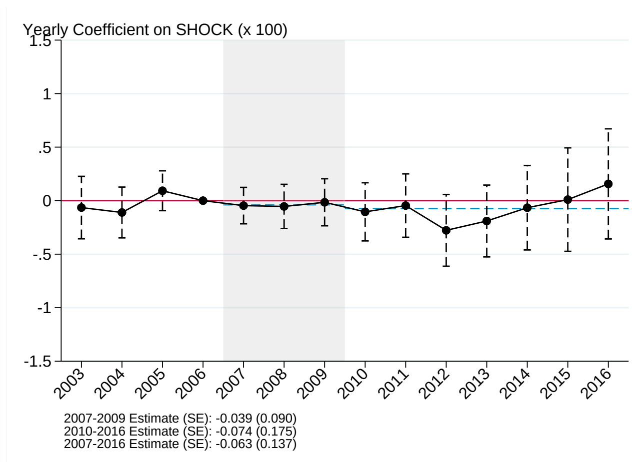
(a) Log Average Age



(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 A.55a, the outcome y_{ct} is the log average age of residents across facilities in each CZ; in Figure A.55b, the outcome y_{ct} is the log CZ-level mean share of facility residents who are female; and in Figure A.55c, 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 nursing home-level observations, weighted by the total beds in each nursing home, 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. The areas shaded in gray correspond to the timing of the Great Recession, adopting the NBER's business cycle dating. N=716 CZs (covering 99.8% of overall 2006 population) which contain at least one nursing home.

G Appendix Tables

Table A.1: Time Series Estimates of Relationship between National Log Mortality Rate and National Unemployment

	Time series estimates				GR effect: 2007-2009
	(1)	(2)	(3)	(4)	(5)
U_t	-1.108 (0.137)	-1.057 (0.113)	-0.724 (0.193)	-0.642 (0.192)	-0.501 (0.153)
Time control	Linear	Quadratic	Linear	Quadratic	
Estimation method	OLS	OLS	GLS	GLS	

Notes: This table uses annual, nationwide data from 1969 to 2019 to estimate the time-series relationship between the national log mortality rate and the national unemployment rate. The table employs the same data sources as in Appendix Figure A.5, with mortality data taken from the NCHS and aggregated to the national level, and unemployment data taken directly from national CPS data. Columns (1) and (3) control for a linear time trend while columns (2) and (4) control for a quadratic time trend. Columns (1) and (2) report results from OLS estimation with heteroskedasticity-robust standard errors. Columns (3) and (4) report results from GLS estimation. Finally, for comparison, Column (5) reproduces the 2007-2009 GR effect from our main specification in equation 1, as can be found in Figure III. N=51 years in Columns (1)-(4); N=741 CZs in Column 5.

Table A.2: Impact of the Great Recession on Life Expectancy by Age

Age	Mortatilty rate (per 100,000)	Life Expectancy (without recession)	Life Expectancy (with recession)	Change in life expectancy: Percent increase	Change in life expectancy: 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 E.3). 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 A.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 A.4: 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	0.2396	-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 gender. 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 A.5: 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 (14), 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.

Table A.6: Welfare Costs of Recessions by Age With Retirement

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

Notes: This table displays the welfare cost of recessions, based on equation (14), at various ages under exogenous and endogenous mortality, for various assumptions about risk aversion (γ) and the value of a statistical life-year ($VSLY$). Retirement is modeled as no income variation for agents aged 65 or over. 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.

Table A.7: 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
(2) 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, applied sequentially, 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 A.8: 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, applied sequentially 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 A.7, 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 A.9: Medicare Patient-Year Sample Demographic Summary Statistics

	All 2003 Beneficiaries (1)	Repeated Cross Section (2)	Repeated Cross Section (TM in $t-1$) (3)	Repeated Cross Section (TM in t) (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 A.7. The "Repeated Cross Section" sample draws beneficiaries in every year during the 2003-2016 period, subject to the restrictions in Table A.8. "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 A.10: 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
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
Overweight or obese	0.631	0.630	0.700	0.636
Obese	0.286	0.294	0.331	0.249
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 A.11: 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	$36,869
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, Dorn and Hanson (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 A.12: Baseline vs Alternative Cause of Death Category Cross Tabulations (Percents)

	Circ.	Canc.	Resp.	Meta.	Nerv.	Geni.	Ext.	Dig.	Ment.	Infect.	Res.
Cardio.	33.95	0	0	0	0	0	0	0	0	0	0
Canc.	0	23.08	0	0	0	0	0	0	0	0	0
L. Resp.	0	0	5.13	0	0	0	0	0	0	0	0
Diab.	0	0	0	2.99	0	0	0	0	0	0	0
Alzh.	0	0	0	0	2.99	0	0	0	0	0	0
Flu/Pn.	0	0	2.32	0	0	0	0	0	0	0	0
Kidn.	0	0	0	0	0	1.87	0	0	0	0	0
MVA	0	0	0	0	0	0	1.87	0	0	0	0
Suic.	0	0	0	0	0	0	1.37	0	0	0	0
Liv.	0	0	0	0	0	0	0	1.14	0	0	0
Hom.	0	0	0	0	0	0	0.77	0	0	0	0
Res.	0.16	0.58	1.89	1.10	2.08	0.75	3.48	2.48	3.78	2.76	3.47

Notes: This table displays the cross tabulations between the baseline cause of death categories (rows) and alternative cause of death categories (columns). The values sum up to 100 percent of all deaths in 2006. Categories were abbreviated for spacing reasons. Written out for the baseline categories, from top to bottom, they are: Cardiovascular, Cancer, Lower Respiratory, Diabetes, Alzheimer's, Influenza/Pneumonia, Kidney Disease, Motor Vehicle Accident, Suicide, Liver Disease, Homicide, and Residual. Written out for the alternative categories, from left to right, they are: Circulatory Diseases, Cancer, Respiratory Diseases, Metabolic Diseases, Nervous Diseases, Genitourinary Diseases, External Causes, Digestive Diseases, Mental Disorders, Infectious Diseases, and Residual. Baseline causes are presented top to bottom in order of decreasing prevalence, and then the residual at the end. Alternative causes are presented in the order most analogous to the baseline causes, although the mapping is not exactly one to one. Almost all alternative cause of death categories consist of one of the baseline causes of death and a share of the baseline cause of death residual.

Table A.13: Impact of GR Shock on Mortality, by Baseline Cause of Death

	(1) 2007-2009 Period Estimate	(2) 2010-2016 Period Estimate	(3) 2007-2016 Period Estimate
Cardiovascular	-0.654	-0.472	-0.527
	(0.216)	(0.396)	(0.332)
Cancer	-0.016	0.122	0.081
	(0.117)	(0.175)	(0.150)
Lower Respiratory	-0.598	-0.413	-0.468
	(0.386)	(0.698)	(0.591)
Diabetes	0.291	0.794	0.643
	(0.352)	(0.566)	(0.458)
Alzheimer's	-0.129	1.425	0.959
	(0.650)	(1.383)	(1.138)
Influenza/Pneumonia	-0.733	-0.262	-0.404
	(0.522)	(1.003)	(0.836)
Kidney Disease	-0.843	-0.796	-0.810
	(0.489)	(0.819)	(0.680)
Motor Vehicle Accident	-1.706	-2.146	-2.014
	(0.580)	(0.682)	(0.635)
Suicide	-0.302	-1.727	-1.300
	(0.421)	(0.490)	(0.416)
Liver Disease	-1.054	-1.036	-1.041
	(0.443)	(0.587)	(0.512)
Homicide	-1.458	-2.375	-2.100
	(0.801)	(1.477)	(1.243)
Residual	-0.523	-1.308	-1.072
	(0.240)	(0.537)	(0.433)

Notes: This table displays the group-specific average of 2007-2009 (Column (1)), 2010-2016 (Column (2)), and 2007-2016 (Column (3)) 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. Standard errors are clustered at the CZ level.

Table A.14: Impact of GR Shock on Mortality, by Alternative Cause of Death

	(1) 2007-2009 Period Estimate	(2) 2010-2016 Period Estimate	(3) 2007-2016 Period Estimate
Circulatory Diseases	-0.650	-0.476	-0.528
	(0.216)	(0.397)	(0.333)
Cancer	-0.014	0.093	0.061
	(0.115)	(0.173)	(0.149)
Respiratory Diseases	-0.606	-0.613	-0.611
	(0.372)	(0.696)	(0.591)
Metabolic Diseases	0.287	0.429	0.387
	(0.295)	(0.505)	(0.400)
Nervous Diseases	-0.046	0.923	0.632
	(0.407)	(0.799)	(0.661)
Genitourinary Diseases	-0.793	-0.779	-0.783
	(0.397)	(0.558)	(0.470)
External Causes	-0.730	-1.968	-1.596
	(0.347)	(0.812)	(0.649)
Digestive Diseases	-0.550	-0.711	-0.663
	(0.285)	(0.421)	(0.352)
Mental Disorders	-0.697	-2.807	-2.174
	(0.520)	(1.108)	(0.901)
Infectious Diseases	-0.530	-1.116	-0.940
	(0.446)	(0.954)	(0.782)
Residual	-1.596	-1.697	-1.667
	(0.509)	(0.652)	(0.535)

Notes: This table displays the group-specific average of 2007-2009 (Column (1)), 2010-2016 (Column (2)), and 2007-2016 (Column (3)) 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 10 most common ICD10 chapters/disease categories (out of 20 chapters, presented in order closest to being analogous to the order of the baseline cause of death categories in Table A.13), 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. Standard errors are clustered at the CZ level.

Table A.15: 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)
Panel (d): Shock definition			
Substitute UE shock for EPOP shock	-0.398	-0.508	-0.475
	(0.115)	(0.272)	(0.222)

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 III. In Panel (a), we estimate equation (1) at the state and county level, with 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 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 Appendix Section C.6. In the last row, we estimate this equation omitting the top and bottom (population-weighted) deciles of shocked CZs, leaving 393 CZs remaining. In Panel (d), we estimate equation (1), where $SHOCK_c$ is defined as the negative 2007-2009 CZ change in the employment-to-population (EPOP) ratio, rather than the 2007-2009 change in CZ unemployment rate. 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.

Table A.16: 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 + Gender + Race (TM in $t-1$)	Age + Gender + 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 A.8), 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}; see Appendix C.4 for more details on how this is defined and constructed. 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 A.17: 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 + Gender + Race (TM in $t-1$)	Age + Gender + 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 A.8), 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}; see Appendix C.4 for more details on how this is defined and constructed. 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.

Table A.18: 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 III. 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 A.19: Effect of GR Shock on Unemployment, Mediated by Uninstrumented and Instrumented Pollution

	(1) Unmediated	(2) Mediated (OLS)	(3) Mediated (IV)
Panel (a): Two Post Periods			
$\text{SHOCK}_{cz(c)} * \mathbb{1}(2007-2009)$	-0.529	-0.424	-0.022
	(0.155)	(0.161)	(0.311)
$\text{PM2.5\_SHOCK}_c * \mathbb{1}(2007-2009)$		-0.417	-2.027
		(0.152)	(1.034)
$\text{SHOCK}_{cz(c)} * \mathbb{1}(2010-2016)$	-0.705	-0.400	0.038
	(0.330)	(0.362)	(0.646)
$\text{PM2.5\_SHOCK}_c * \mathbb{1}(2010-2016)$		-1.221	-2.973
		(0.309)	(2.187)
First Stage F-Statistic			9.484
Panel (b): One Post Period			
$\text{SHOCK}_{cz(c)} * \mathbb{1}(2007-2016)$	-0.652	-0.407	0.020
	(0.274)	(0.297)	(0.541)
$\text{PM2.5\_SHOCK}_c * \mathbb{1}(2007-2016)$		-0.980	-2.689
		(0.250)	(1.822)
First Stage F-Statistic			14.226

Notes: Columns (1), (2), and (3) display point estimates and standard errors (in parentheses). Column (1) displays estimates from equation (31), and Column (2) and Column (3) display estimates from equation (32). Column (1) estimates the impact of the 2007-2009 CZ-level Great Recession unemployment shock ($SHOCK_{cz(c)}$) on the log age-adjusted mortality rate per 100,000 (y_{ct}). Columns (2) and (3) estimate the impact of the same unemployment shock on the same measure of mortality, but mediating for the impact of a PM2.5 pollution shock (negative 2006-2010 change in PM2.5 levels). Column (2) displays the estimates when using OLS and each county's own PM2.5 shock, and Column (3) displays the estimates when instrumenting for each county's PM2.5 shock with the Great Recession shocks of upwind counties. All estimates are weighted by 2006 CZ population, with standard errors clustered at the CZ level. Coefficients and standard errors are multiplied by 100 throughout for ease of interpretation. N = 2,982 counties. Note that the unmediated estimates in Column (1) differ somewhat from the estimates in Figure IXa because this analysis uses only 2,982/3,107 of the counties included in that analysis, due to the lack of wind direction data in some of those counties.

Table A.20: $VSLY$ Parameters for Welfare Costs of Recessions Calibrations

	(1)	(2)	(3)
Panel (a): Values of b used in calibrations			
$\gamma = 1.5$	3.563	6.236	8.909
$\gamma = 2$	2.381	4.762	7.143
$\gamma = 2.5$	1.885	4.007	6.128
Panel (b): Implied subsistence consumption			
$\gamma = 1.5$	0.315	0.103	0.050
$\gamma = 2$	0.420	0.210	0.140
$\gamma = 2.5$	0.500	0.303	0.228
VSLY	\$100k	\$250k	\$400k

Notes: This table reports the values of the b parameter in the Hall and Jones (2007) utility function that are used in the model calibrations. The values of the $VSLY$ parameter are set to be two, five, and eight times average annual consumption. We solve for b using equation (11) by setting average annual consumption to be $c = 1.26$, which is the average annual consumption in the simulated model starting at age 35, normalizing initial consumption to 1. The top panel of the table reports the values of each parameter used in the model calibrations, and the bottom panel reports the implied subsistence consumption floor, defined as $((\gamma - 1) * b)^{1/(1-\gamma)}$ and expressed as a share of consumption.