The Welfare Cost of Recessions When Recessions are Good for Your Health: Evidence from the Great Recession

Amy Finkelstein Matthew J. Notowidigdo Frank Schilbach Jonathan Zhang*

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Abstract

We leverage spatial variation in the severity of the Great Recession across the United States to estimate its impact on health and explore implications for the welfare consequences of recessions. We estimate that the Great Recession reduced the average, age-adjusted mortality rate by 2.3 percent per year, with effects persisting at least 10 years. The effects appear across demographic groups and causes of death, with the elderly responsible for about three-quarters of the total mortality reduction. Incorporating our estimates of recession-induced mortality declines into the standard analysis of the welfare costs of recessions substantially reduces their welfare impact, particularly at older ages where recessions may even be welfare-improving.

****PRELIMINARY AND INCOMPLETE!****
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*Finkelstein: MIT and NBER, afink@mit.edu; Notowidigdo: Chicago Booth and NBER, noto@chicagobooth.edu; Schilbach: MIT and NBER, fschilb@mit.edu; Zhang: McMaster, jonathanzhang@mcmaster.ca. We are grateful to Pat Collard, Angelo Marino, Wesley Price, and Enzo Profili for excellent research assistance, and to the Chicago Booth Healthcare Initiative (Notowidigdo) for funding.

1 Introduction

People hate recessions. Macro-economists debate their welfare costs (e.g. Lucas 1987, 2003; Krebs 2007). Health economists have found that, in the 1970s and 1980s, they have been good for health (e.g. Ruhm 2000, 2003, 2005; Stevens et al. 2015), although perhaps not in the subsequent two decades Ruhm (2015). In this paper, we leverage the spatial variation in the severity of the Great Recession across the U.S. to provide new empirical evidence on the impact of recessions on health, and to explore its 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, we estimate that the age-adjusted mortality rate fell by 0.5 percent per year. Like the employment reductions from the Great Recession previously documented by Yagan (2019) using this same strategy, these mortality reductions show up immediately and persist for at least 10 years. Since average unemployment increased by 4.6 percentage points between 2007 and 2009, our estimates imply that the Great Recession decreased mortality rates by 2.3 percent per year for 10 years. To put this into perspective, this annual mortality reduction from the Great Recession is over two times the 1 percent per year average annual age-adjusted secular mortality decline over the half-century preceding the Great Recession.[1]

Great-Recession-induced declines in mortality appear across demographic groups and across causes of death; they are not limited to a particular subset of the population or sources of mortality. Indeed, the recession-induced mortality declines are roughly similar (in percentage terms) by gender, by race/Hispanic origin, and across age groups, including prime-age workers, younger individuals, and the elderly. Because the mortality rate is so much higher among the elderly, however, our finding of an equi-proportional reduction in mortality across age groups implies that most of the Great-Recession-averted-deaths were among the elderly (i.e., those ages 65+); we estimate that about three-quarters of the mortality reduction comes from reduced deaths among the elderly, roughly the same as their share of pre-recession mortality. The single largest cause of death in 2006 was cardiovascular mortality, which accounted for about one-third of deaths and about two-fifths of the estimated mortality declines due to the Great Recession. We briefly explore potential mechanisms, with the evidence thus far not consistent with mortality declines driven by improved health behaviors (as in Ruhm (2000)) or improved quality of nursing home care (as in Stevens et al. (2015)).

In the final part of the paper, we explore the implications of our estimated mortality effects of the Great Recession for the welfare consequences of recessions in general and the Great Recession in particular. To do so, we extend the Krebs (2007) model of the welfare cost of recessions to allow for mortality to also vary with recessions. Our results suggest that accounting for endogenous mortality

[1] Authors' calculations using CDC data available here: `https://www.cdc.gov/nchs/data-visualization/mortality-trends/index.htm`. See also Ma et al. (2015).

effects substantially reduces standard estimates of the welfare cost of recessions. For example, with a coefficient of relative risk aversion of 2 and a value-of-a-statistical life year of $\$250,000$, we estimate that the welfare costs of recessions are 1.5 percent of average annual consumption for a 45-year-old if mortality is assumed to be exogenous to aggregate economic conditions, but are 55 percent lower—only 0.68 percent of consumption, once we account for the mortality benefits of recessions. We also find that the reduction in the welfare cost of recessions from endogenous mortality is increasing in age, due to our finding of a constant proportional reduction in mortality caused by the Great Recession and mortality rates that increase in age. Combined with a more limited impact of recessions on the consumption of the elderly, our results imply that recessions may even be welfare-enhancing for the elderly.

Naturally, our analysis comes with important caveats. First, our design will not pick up any impacts of the Great Recession that are not correlated with local labor market impacts. These include, for example, the nationwide collapse of the stock market, or any nationwide increase in malaise.[2] Second, while the Great Recession is helpful in identifying the impact of recessions on mortality, those impacts may not generalize to other, particularly more mild, recessions. Third, our analysis so far has focused only on mortality impacts; we hope to expand to morbidity impacts going forward.

Our paper relates to literatures in both health economics and macroeconomics. Starting with the influential paper of Ruhm (2000), a series of papers in health economics used panel data at the local area-by-year level to analyze the relationship between an area's mortality rate (or other health measures) and the area's contemporary unemployment rate (or other measures of local macroeconomic conditions), controlling for area and year fixed effects.[3] We extend this literature by employing a different empirical strategy that exploits a large aggregate economic shock with differential exposure across areas (in the spirit of Bartik (1991); Blanchard et al. (1992); Yagan (2019)).[4] Relative to the existing state-year panel analysis, our approach may help isolate the causal impacts of recessions from potential confounding factors that could simultaneously increase local unemployment and also directly affect health.[5] Our use of a single (spatially-differentiated)

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

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

[4] Mostly closely related to our approach, Cutler and Sportiche (2022) examine the impact of the Great Recession on the mental health of pre-retirement adults (ages 51-61) in the Health and Retirement Survey by exploiting geographic variation in the extent of house price declines during the Great Recession. They find no average impact on mental health in this population.

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

shock also helps us more easily identify the temporal pattern of effects.

The findings from the existing literature also raise questions about what to expect for the impact of the Great Recession on mortality. On the one hand, for the decades before the Great Recession, there is widespread evidence of a negative association between cross-area unemployment rates and mortality in the US (Ruhm 2000; Stevens et al. 2015; Miller et al. 2009) and in other countries (see e.g. Neumayer (2004) for Germany, Granados (2005) for Spain, Buchmueller et al. (2007) for France, and Ariizumi and Schirle (2012) for Canada).[6] However, the relationship between local unemployment and mortality in the US appears to have weakened over time and to have disappeared by 2010 (Ruhm 2015).[7]

Our paper extends the macro-economics literature on the welfare cost of business cycles (see e.g. Lucas (1987); Krebs (2007)) to incorporate our estimates of endogenous mortality over the business cycle. Our approach is in the spirit of existing work in macro-economics that has incorporated secular improvements in health into welfare comparisons across countries and welfare analyses of economic growth within and across countries (e.g. Nordhaus (2003); Becker et al. (2005); Murphy and Topel (2006); Hall and Jones (2007); Jones and Klenow (2016); Brouillette et al. (2021)). There has been relatively less attention, however, on incorporating cyclical fluctuations in health into welfare analyses of business cycles.[8]

2 Data and Empirical Strategy

2.1 Data

We use two major sources of data to study the mortality impacts of the Great Recession. First, following Ruhm (2016), we use death counts from the restricted-use mortality microdata from the Centers for Disease Control and Prevention, combined with population data—the denominator in constructing mortality rates—from the National Cancer Institutes Surveillance Epidemiology and End Results (SEER) program.[9] The mortality data encompass the universe of mortality events in the United States from 2003 to 2016 at the event level. For each decedent, we observe the county

health (Flinn 2006; Ruffini 2021), or changes in other labor market institutions which have been shown to affect unemployment (Nickell 1998; Holmes 1998) and might directly affect health as well.

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

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

[9] These mortality data are in turn derived from state death certificates which in turn are completed by physicians, coroners, medical examiners, and funeral directors. (Office of Disease Prevention and Health Promotion (n.d.))

of residence and county of death, the exact date of death, the cause of death,[10] and demographic information including age in years, race, ethnicity, sex, and education.[11] The SEER population data provide annual, county-level population estimates by single year of age, race, ethnicity, and sex.[12]

Our second major source of mortality data comes from the universe of Medicare enrollees aged 65+ in the United States from 2003 to 2014. The enrollee-level panel data contain information on zip code of residence and date of death (if any), along with demographic variables such as age, race, ethnicity, sex, and enrollment in Medicaid (a proxy for low income). The death records that we use in the Medicare data come primarily from the Social Security administration.[13] These data are available for both Traditional Medicare enrollees and Medicare Advantage enrollees. In addition, for the approximately three-quarters of the elderly who are enrolled in Traditional Medicare for all of 2002, we also observe detailed information about their healthcare use and about their health diagnoses.[14] Specifically, we observe doctor visits, emergency room visits, inpatient hospitalizations, and nursing home stays; we also observe annual indicators capturing the presence of 20 specific chronic conditions that the patient could have been diagnosed for, such as lung cancer, diabetes, or depression.[15]

The Medicare data offer several advantages over the CDC mortality data. First, they provide a well-defined population denominator in which mortality can be directly observed. This addresses the well-known challenge with most other US mortality data in which the numerator (mortality) and the denominator (deaths) come from different datasets; this creates concerns about consistency

[10]For cause of death, we use the ICD10 codes for the "underlying cause of death" variable. This gives a single, mutually exclusive cause of death.

[11]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), omits certain demographics such as education, and suppresses mortality information for cells with less than 10 deaths; this threshold can prevent the publication of county data for groups with low mortality rates (e.g. younger individuals), or small population shares (e.g. less common causes of death or demographic groups). We confirmed that we can replicate our aggregate findings in the public-use data. For information on how to apply for the microdata, data see `https://www.cdc.gov/nchs/nvss/nvss-restricted-data.html`.

[12]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.

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

[14]Medicare Advantage is a program in which private insurers receive capitated payments from the government in return for providing Medicare beneficiaries with health insurance. Insurance claims (and hence health care utilization measures or health measures which are based on diagnoses recorded by physicians) are not available for enrollees in Medicare Advantage. However, the Medicare data do contain demographic and mortality information for both traditional Medicare and Medicare Advantage enrollees.

[15]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.

between the two sources, as well as potential mis-estimation of the denominator during intercensal years (Currie and Schwandt 2016). Second, the individual-level panel nature of the Medicare data allow us to define a cohort of individuals based on their initial location and follow them over time so that we can confirm that our results are not confounded by (potentially endogenous) migration in response to economic shocks (Arthi et al. 2022; Blanchard et al. 1992). Third, this same panel feature allows us to leverage the detailed data on health conditions available in the Medicare data to analyze heterogeneous impacts on mortality by health as well as other demographics. Finally, we can use health and healthcare utilization measures to analyze the impact of the Great Recession on healthcare utilization (a potential channel for health effects) and non-mortality health measures. The primary disadvantage of the Medicare data is that they are limited to the elderly, although as we will see below, the vast majority of the mortality reduction that we estimate occurs among the elderly.[16] Another disadvantage of the Medicare data is that we have not been able to obtain the cause of death data for this population.

We restrict our analysis to mortality events among US residents of 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. In our baseline Medicare data analysis, we restrict to individuals who are 65-99 in 2003 so that we can follow a fixed cohort over time.[17]

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. We employ slightly different specifications depending on whether we are analyzing repeated cross-sections in the CDC data or individual-level panel Medicare data.

Analysis of repeated cross sections. Our main estimating equation is:

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

where $SHOCK_c$ is a measure of the impact of the Great Recession on area c, $\mathbb{1}(Year_t)$ is an indicator for calendar year, α_c and γ_t are location and year fixed effects respectively, and ϵ_{ct} is the error term. The coefficients of interest are the β_t's; they measure differential impacts on the outcome y_{ct} in year t across areas differentially impacted by the Great Recession. In this equation (and across this paper), we omit the interaction with the shock variable in 2006 so that all coefficients are relative to 2006, and we cluster our standard errors at the local area c.

[16] The data also contain information on under 65 Medicare enrollees, in particular recipients of Social Security Disability Income (SSDI), but we exclude these individuals from our analysis since both the number and composition of SSDI recipients change during recessions (Carey et al. 2022).

[17] Appendix Table A.7 presents more detail on how each sample restriction affects the sample size in the Medicare data.

Our baseline analysis follows Yagan (2019) for the definition of the local labor market as well as the measure of the Great Recession's impact. Specifically, we use Commuting Zones (CZs) as our geographic unit of analysis (c). CZs are a standard aggregation of counties that partition the United States into 741 areas that are designed to approximate labor markets. Again following Yagan (2019), we measure the impact of the Great Recession on area c (which we denote by $SHOCK_c$) as the difference between the 2009 unemployment rate in the CZ and the 2007 unemployment rate in that CZ. Thus β_t captures the percent change in the mortality rate in CZ c and year t (relative to that CZ's 2006 average mortality rate) associated with a one-percentage-point increase in the unemployment rate from 2007 to 2009 in that CZ. Since population varies widely across CZs (Appendix Figure A.4), we weight each CZ-year observation by its 2006 population.[18]

Our main outcome variable y_{ct} is the log age-adjusted mortality rate in area c and year t, defined as the share of the population in area c and year t at the beginning of year t who die during year t.[19,20] Our analysis of the log mortality rate follows the prior literature on the impacts of recessions on mortality (Ruhm 2000, 2015); in addition, as we will show below, modeling the impact of the Great Recession as a proportional shock to mortality fits the data well.

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

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

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

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

Analysis of individual-level panel data. The Medicare data allow us to expand beyond the repeated cross-sectional analysis to individual-level panel data, so that we can fix potentially time-varying individual characteristics – such as location – in a pre-recession base year. We therefore

[18] This is consistent Yagan (2019)'s prior analysis analyzing the impact of spatial variation of the Great Recession on labor market outcomes, as well as with the prior literature examining effects of recessions on mortality rates (e.g. Ruhm 2000, 2015).

[19] More specifically we add 1 to the mortality rate to avoid taking logs of zeroes. Although this is very rare in the aggregate data, it becomes non-trivial when we start disaggregating by age and cause of death.

[20] 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. Specifically, we calculate the age-adjusted mortality rate in a CZ by averaging over the mortality rate in each of the 19 age bins (roughly equally-sized five-year age bins) within the CZ, weighting by the national share of the population in each age bin in 2000. This is in the spirit of Ruhm (2000) who controls for the share of the population in various age groups.

define a cohort of Medicare enrollees in a base year and track their mortality over time. As is standard in the literature (e.g. Olshansky and Carnes (1997); Chetty et al. (2016); Finkelstein et al. (2021)), we adopt a Gompertz specification for the age-mortality gradient in which the log of the mortality rate for individual i in year t ($\log(m_{it})$) is linear in age a_{it}:

$$\log(h_{it}(a)) = \rho a + \beta_t[SHOCK_{c(i,2003)} * \mathbf{1}(Year_t)] + \alpha_{c(i,2003)} + \gamma_t + \epsilon_{it} \tag{3}$$

Once again, the coefficients of interest are the β_t's; these capture differential changes in the log mortality rate across areas differentially impacted by the Great Recession. Once again, we omit the interaction with the shock variable in 2006, so that all coefficients are relative to 2006. Once again, $\alpha_{c(i,2003)}$ and γ_t are location and year fixed effects, respectively. However we now measure both the location fixed effects $\alpha_{c(i,2003)}$ and the Great Recession shock $SHOCK_{c(i,2003)}$ based on the enrollees' location in 2003. This alleviates concerns about potential contamination from differential population flows into or out of areas that experience different shocks. Once again, we cluster the standard errors at the Commuting Zone level.

3 Mortality Impacts of the Great Recession

3.1 Descriptive Statistics

Spatial variation in the Great Recession. Our empirical strategy relies on the large spatial variation in the impact of the Great Recession. This has been previously documented and leveraged to study the impact of the Great Recession on outcomes such as employment (e.g. Yagan (2019); Rinz (2022), and time use (Aguiar et al. 2013). Following Yagan (2019), we parameterize the local area impact of the Great Recession by the percentage point change in the Commuting Zone's (CZ) unemployment rate between 2007 and 2009.

Figure 1 shows the spatial variation in this shock across CZs. The Great Recession was a nationwide shock: the Figure illustrates that virtually every CZ in the country experienced an increase in the unemployment rate. Across (population-weighted) CZs, there was a median 4.6 percentage point increase in the unemployment rate between 2007 and 2009, with a cross-CZ standard deviation of 1.5. Yet some areas were much harder hit than others; the bottom quartile of CZs experienced an average increase in the unemployment rate of 2.9 percentage points, compared to an increase of 6.7 percentage points in the highest quartile of CZs. Areas that were especially hard hit include the so-called 'sand states' of Florida, Arizona Nevada and parts of California – where the pre-recession housing and construction booms were concentrated – and the manufacturing states in the Midwest such as Michigan, Indiana and Ohio. By contrast, most of Texas, Oklahoma, Kansas, Nebraska and the Dakotas were relatively unscathed.

Our use of the unemployment rate to parameterize the Great Recession follows the approach of the existing state-year panel literature analyzing the relationship between recessions and mortality (e.g. Ruhm 2000, 2003, 2005; Stevens et al. 2015). However, an alternative way to parameterize the Great Recession shock to utilize the spatial variation in house price declines and housing net worth during the Great Recession, as documented by e.g. Mian et al. (2013).[21] Not surprisingly, these measures are highly but imperfectly correlated (see Appendix Figure A.2).In addition, it is important to keep in mind that Yagan (2019) shows that areas that experienced larger unemployment rate increases in 2007-2009 saw their unemployment rates decline in the later years of his study period (2010-2015), but their employment rates remained depressed at 2009 levels throughout his study period. This suggests that mortality impacts in later years may reflect the ongoing employment declines.

Mortality patterns. Table 1 presents summary statistics on US mortality in 2006. The elderly (65 and older) account for almost three-quarters of those deaths, although they are only 12 percent of the population. The two most common causes of (age-adjusted) deaths are cardiovascular disease (34 percent of deaths) and malignant neoplasms - i.e. cancer - (23 percent). Relative to non-Hispanic Whites, mortality rates are higher for Non-Hispanic Blacks and lower for Hispanics.

Mortality rates vary widely across the United States (e.g. Chetty et al. (2016); Finkelstein et al. (2021). Figure 2a documents the variation in age-adjusted mortality rates across CZs in 2006, immediately prior to the Great Recession.[22] Mortality rates were particularly high in the South-Eastern United States and low in the Western United States.[23] However there is no correlation between the magnitude of the 2007-2009 Great Recession shock in the CZ and its 2006 (age-adjusted) mortality rate; Figure 2b shows that a 1 percentage point higher Great Recession shock is associated with a statistically insignificant 3.8 per 100,000 higher 2006 mortality rate (95 percent confidence interval is -5.9 to 13.5).

Figure 3 provides a preliminary look at how changes in mortality correlate with areas more or less hard hit by the Great Recession. We plot age-adjusted mortality rates from 1999 through 2016 for the CZs in the lowest quartile of the 2007-2009 unemployment shock (mean unemployment shock of 2.9 percentage points) and the CZs in the highest quartile (mean unemployment shock of 6.7 percentage points). Both exhibit decreasing mortality over this study period. Their mortality rates are indistinguishable in 2003 and by 2006 the CZs that will be harder hit by the Great Recession have, if anything, experienced a relative increase in mortality.[24] After 2006, however, there is an

[21]This is the recession measurement used by Cutler and Sportiche (2022) in studying the impact of the Great Recession on the mental health of 51- to 61-year-olds.

[22]The (population-weighted) standard deviation across CZs of 94 deaths per 100,000 is over 10 percent of the mean mortality rate of 792 deaths per 100,000.

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

[24]As we discuss in more detail below, this is consistent with our findings that recessions reduce mortality and Yagan (2019)'s findings that the areas that were subsequently harder hit by the Great Recession experienced a relative rise

immediate and pronounced decline in age-adjusted mortality in the harder-hit CZs relative to the less harder-hit ones, creating a gap in age-adjusted mortality rates that persist through the end of the series in 2016.

3.2 Mortality Estimates

Overall mortality. Figure 4 shows the results from estimating equation (1) for log age-adjusted mortality, with the coefficient on β_{2006} normalized to zero. Starting in 2007, we see an immediate and pronounced decline in log age-adjusted mortality rate in areas that are harder hit by the Great Recession. The estimates imply that in the first three years, a one-percentage point greater decline in the unemployment rate from the Great Recession is associated with a 0.5 percent (standard error = 0.15) decline in the age-adjusted mortality rate.[25] The mortality decline is essentially constant over our 10-year study period, i.e. places that were hardest hit by the recession enjoyed reduced mortality for at least ten years. Given that the Great Recession on average increased unemployment by 4.6 percentage points between 2007 and 2009, these results suggest that the Great Recession reduced average mortality by 2.3 percent per year, for at least ten years.

To put these numbers in perspective, we can compare them to the secular declines in mortality and to the impact of health insurance on mortality. Over the half-century preceding the Great Recession, average annual age-adjusted mortality declined by 1.1 percent per year.[26] The mortality benefits from the Great Recession are thus equivalent to the mortality declines achieved over a two-decade period. Goldin et al. (2021) estimate that each adidtional month of insurance coverage provided under the Affordable Care Act to previously uninsured 45-64 year olds reduces their two-year mortality rate by 0.18 percentage points, or equivalently by 0.18 percent relative to their average two-year mortality rate of 1 percent in this population. Thus, our estimates imply that a one percentage point increase in local area unemployment is roughly as good for mortality as an average 2-3 month increase in insurance coverage.

In addition to the magnitudes, the time patterns in Figure 4 are noteworthy in several respects. First, they are broadly consistent with the time pattern of impacts of the Great Recession local shocks on employment estimated by Yagan (2019). In particular, Yagan (2019) estimates that the local shocks caused employment to decline starting in 2007, reaching its nadir in 2009, and remained at this depressed level through the end of his 2015 study period (see Figure 4a of his

in employment in the preceding years).

[25] This point estimate is in fact the same as Ruhm (2000)'s finding of the relationship between the state unemployment rate and the annual mortality rate over the 1970s and 1980s, but substantially larger than what Ruhm (2015) finds for this relationship in later periods, including those covering the Great Recession; there, he cannot reject the null hypothesis that total mortality is unrelated to macro-economic conditions. For example, for the 1991-2010 period, Ruhm (2015) estimates that a one percentage point increase in state-year unemployment is associated with a statistically insignificant 0.10 percent (standard error = 0.10) decline in the mortality rate.

[26] Appendix Figure A.3 shows that age-adjusted mortality declined from about 1,334 per hundred thousand in 1956 to 792 (i.e. 0.79 percent) per 100,000 in 2006, an average annual mortality decline of 1.1 percent. See also Ma et al. (2015).

paper, reproduced in our Appendix Figure A.1). Our estimate of a persistent, 10-year reduction in the annual mortality rate from the Great Recession should be interpreted in light of its persistent, 10-year reduction in the employment rate. Second, Figure 4 suggests that prior to the Great Recession, areas that were subsequently harder hit were experiencing a slight relative increase in mortality; this is consistent with the evidence from Yagan (2019) that these areas were experiencing a relative rise in employment prior to the Great Recession. Second, there is evidence of a positive pre-trend in which areas that were subsequently hit harder by the Great Recession are experiencing a relative rise in mortality in the years leading up to it. As noted in our discussion of Figure 3 above, this is consistent with our finding that the Great Recession reduces mortality and the finding of Yagan (2019) reproduced in Appendix Figure A.1) that areas that were subsequently harder hit by the Great Recession were experiencing a relative rise in employment prior to the Great Recession. Finally, the time pattern of mortality impacts is more suggestive of some types of mechanisms by which recessions reduce mortality than others, a point we will return to in more detail below.

Results by cause of death and demographic group. Mortality declines from the Great Recession appear for essentially all major causes of death, with the important exception of cancer where there is no impact. Table 2 summarizes these findings; Appendix Figures A.12, and A.13 report the underlying event studies.[27] Column 1 reports, for each cause of death, its share of (age-adjusted) total deaths in 2006, column 2 reports our estimates of the impact of the Great Recession by cause of death from estimating equation 2, and column 3 combines the estimates to calculate the contribution to the total mortality decline accounted for by each cause of death. Although results often lack precision, there is no evidence of increases in mortality for any cause, and many of the mortality declines are statistically significant. We estimate a statistically significant impact of the Great Recession on cardiovascular disease – the largest cause of death - that can account for about 41 percent of the reduction in mortality; this is only slightly larger than its share of 2006 mortality (34 percent). By contrast, we estimate a precise null effect for cancer-related deaths, even though it is the second largest cause of death, accounting for 23 percent of 2006 mortality.[28] We also estimate statistically significant declines in mortality from motor vehicle accidents (1.9 percent of deaths but 7.2 percent of the mortality reduction) and cirrhosis/liver disease (1.1 percent of deaths but 2.4 percent of the mortality reduction). We find statistically insignificant declines in suicides and increases in accidental poisonings.[29] The disease-specific estimates remain roughly constant

[27]We focus in this table on the 2007-2009 period where we have more power, but Appendix Table A.4 shows that results are similar for the 2010-2016 period or the pooled 2007-2016 period.

[28]The next two largest causes of death are chronic lower respiratory disease (5 percent) and diabetes (3 percent); we estimate a statistically insignificant decline in chronic lower respiratory disease mortality that accounts for 6 percent of the mortality reduction and a statistically insignificant increase in diabetes deaths that would reduce the mortality decline by 1.8 percent.

[29]This contrasts with state-year panel estimates of the relationship between state-level unemployment and suicide rates which found that increases in unemployment are associated with increases in suicide mortality (Ruhm 2000; Harper et al. 2015)

through the 2010-2014 period, although the precision worsens (see Appendix Figure A.5).

Figure 5 summarizes mortality impacts of the Great Recession by gender, by race/Hispanic background, and by age; once again, we report the underlying event studies in Appendix Figures A.8, A.9, A.10, and A.11.[30] There is no evidence of differential mortality impacts by gender, with nearly identical estimates for males and females. While the mortality declines due to the Great Recession appear to be more pronounced for non-white population groups (with particularly large point estimates for Hispanic individuals), we cannot reject equal impacts across population groups. Similarly, Figure 5b shows little evidence of heterogeneous impacts on the log mortality rate across age groups. While the decline in log mortality rates appears to be larger for younger population groups, these estimates are quite imprecise, and we cannot reject equality of impacts across age groups.

Our results imply that the elderly (individuals 65 and older) account for the majority of the deaths averted by the Great Recession. Indeed, we estimate (see Appendix Table A.3) that the elderly accounted for 74.3 percent of the 2007-2009 reductions in deaths, which is roughly proportional to their 72.5 percent share of total mortality in 2006. This finding is similar to that of Stevens et al. (2015) who found that in state-year panel data, estimates of reduced deaths associated with increases in the local unemployment rate were also concentrated in the elderly. One source of mortality where the elderly are under-represented, however, is motor vehicle accidents. They constitute only 15 percent of deaths from motor vehicle accidents, while 15-24 year olds account for one-quarter and 25-64 year olds account for over half. Appendix Table A.6 shows no evidence of mortality declines due to motor vehicle accidents for the elderly, which is consistent with recessions not affecting their driving patterns. By contrast, it shows roughly proportional effects for all other age groups.

Impacts on elderly mortality by health status. Using Medicare data, we can also examine the impact of the Great Recession on mortality by health status. This analysis is, by necessity, limited to the elderly population which, as we have seen, accounts for three-quarters of the estimated mortality decline. The Medicare data offer two unique advantages for examining heterogeneity by health. First, they contain detailed measures of enrollee health derived from the health diagnoses recorded in their claims data. Second, the ability to follow individuals in a panel allows us to examine the impacts of the Great Recession based on health in a base year, without having to worry that contemporaneous health measures could themselves be affected by the Great Recession.[31]

[30] Appendix Tables A.1 and A.2 report the underlying estimates for different time periods as well as for the pooled time period.

[31] 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.

We focus primarily on the three-quarters of the overall Medicare sample that is on Traditional Medicare and for whom, as explained in Section 2, we therefore can observe additional measures of health. Relative to the overall Medicare sample, the Traditional Medicare sample is slightly older (average age of 76.3 in 2003 compared to 75.6) and slightly more likely to be enrolled in Medicaid in 2003 (15 percent compared to 12 percent).

We estimate the Gompertz proportional hazard model in equation (3) for various groups. The results are shown in Figures 6 and summarized in Table 3. Figure 6 shows mortality estimates for the full sample of elderly Medicare enrollees in 2003 (panel a) and the subset who were enrolled in Traditional Medicare in 2003 (panel b). Both show a pronounced and statistically significant decline in the mortality rate associated with the Great Recession. The estimates suggest that in the 2007-2009 period, a 1 percentage point increase in the area's unemployment rate was associated with a statistically significant average annual mortality decline of 0.32 percent (standard error = 0.16) in the full sample and 0.28 percent (standard error = 0.15) in the Traditional Medicare subsample. Note that these estimates are not directly comparable to our analyses of the impacts on mortality for the 65+ in the death certificate data. In those data, our study population comprises individuals who are 65 and over *each year*. In the Medicare data, by contrast, our study population is a fixed cohort of individuals who is 65 and over in 2003; this also means that (as can be seen in Figure 6) the sample size declines each year due to mortality, and the confidence intervals on the point estimates therefore also widen in later years.

These findings raise the natural question to which extent these effects are concentrated in relatively frail individuals with high baseline mortality rates, so that the effects mostly reflect slight changes in the timing of mortality rather than larger changes in life expectancy or overall population health. This so-called "mortality displacement" or "harvesting" possibility is particularly a concern when examining mortality effects over very short time horizons—such as a day or 3 days—-and researchers investigate this by looking at longer time horizons such as a month (see e.g. Deryugina et al. (2019)). We are less concerned about this when looking at effects at the annual level that persist out 10 years. However, we will soon be providing heterogeneity analysis of mortality effects by underlying health, as well as analyses of health care utilization and non mortality health measures. Stay tuned!

3.3 Sensitivity analysis

Population flows. A central concern with our estimates using the death certificate data—and of similar analyses in the literature on the impacts of recessions on mortality—is the potential for recessions to affect population in-flows and out-flows and to thus create measurement error in the mortality rate that is correlated with the recession's impacts. If recessions affect the size or composition of the local population, this could bias the estimated relationship between the recession and mortality. For example, if local area recessions caused (unmeasured) exit of relatively unhealthy populations, this could produce a spurious relationship between mortality improvements and the impact of the Great Recession. Heightening these concerns is the fact that in measuring the mortality rate the numerator comes from a different source (death certificate data) than the population denominator (SEER population data), and that the latter is based partly on interpolations.

Our analysis of the Medicare panel data above is valuable for alleviating concerns that the mortality impacts of the Great Recession are spurious artifacts of unmeasured population changes. There, we were able to fix the sample based on its location in 2003 and estimate a 'reduced-form' impact of the Great Recession based on the shock experienced by the individual's 2003 Commuting Zone.

To get a sense of the potential for confounding effects of unmeasured population changes at other ages, we also examined the impact of the recession on (measured) population magnitude and composition. Appendix Table A.5 summarizes the results.[32]They indicate that areas that were harder hit by the recession experienced a relative decline in population, and in particular in the prime age population (ages 25-64) in the years following the Great Recession.[33] As a result, the Great Recession caused a statistically significant increase in the population's median age of about 0.20 percent per year (standard error = 0.03), primarily reflecting an increase in the share of the population that is 65 and over.[34] It also caused a small decline in the female share of the population (0.09 percent (standard error = 0.01) and in the share white (0.22 percent, standard error = 0.19). These findings suggest that—at least on the observable dimensions of age, gender, and race—any population changes due to the Great Recession should likely bias against our findings of mortality declines due to the Great Recession, as people who are younger, female, or white tend to have below-average mortality rates.

In the Medicare data, we can more directly explore the sensitivity of our findings to differential population changes. To account for the potential for non-random re-sorting of the population across Commuting Zones that is correlated with the Great Recession shock the CZ experiences, we estimate a control function model with the shock the person would have experienced based on their CZ in 2003 as the excluded instrument in the mortality model. In particular, we estimate the first-stage equation relating the shock a person would have experienced each year based on her

[32]The underlying event studies are shown in Appendix Figures A.6 and A.7.

[33]Yagan (2019) similarly documents relative population declines in areas harder hit by the recession.Appendix Figure A.6 shows that areas that were harder hit by the Great Recession experienced a relative increase in population in the years before it hit, consistent with the Mian and Sufi (2014) finding that the Great Recession hit harder in areas that had experienced local housing booms.

[34]Existing research suggests that this compositional change primarily reflects a decline in in-migration of prime-age workers to areas particularly affected by the Great Recession, rather than an increase in out-migration (Yagan 2019; Monras 2020).

current location to the shock that she would have experienced based on her 2003 location:[35]

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

and then use the the $\hat{v_{it}}$ residuals from equation (4) as a regressor in the following equation:

$$log(h_{it}(a)) = \rho a + \beta_t[SHOCK_{c(i,t)} * \mathbf{1}(Year_t)] + \alpha_{c(i,2003)} + \gamma_t + \phi\hat{v_{it}} + \epsilon_{it} \tag{5}$$

The identifying assumption is that while a person's 2003 location of residence may have a direct effect on their mortality (reflecting a combination of systematic variation in unobserved health determinants across the elderly in different CZs as well as any direct impact of where you live on your mortality as in Finkelstein et al. (2021)), the Great Recession shock experienced by the place they live in 2003 only affects their mortality through its correlation with the Great Recession shock experienced by the place they live in later years. We compute standard errors by performing a Bayesian bootstrap of the two-stage procedure with 450 repetitions so that first-stage residuals are redrawn for every re-weighted sample.

We can then compare the control function estimates from equation (5) to those from the type of OLS analysis we must do when we do not have access to panel data:

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

The results are summarized in Panel B of Table 3, and the underlying event studies are show in Appendix Figure A.14. We find that the first stage is quite large, with an average coefficient of 0.95 (standard error = 0.03) in 2007-2009; not surprisingly therefore the 2007-2009 reduced form of -0.32 percent (standard error = 0.16) is only slightly smaller than the control function estimate of -0.34 (standard error = 0.17). Somewhat more surprisingly – given that we expected the relative aging of places more strongly hit by the Great Recession to bias against estimates of mortality improvements from the Great Recession – the OLS analysis estimates of the Great Recession impact are larger, with a point estimate of -0.48 (standard error = 0.16).

3.4 Possible mechanisms

The finding that health is counter-cyclical is, at first glance, puzzling. A priori, recessions could be expected to reduce health and increase mortality by lowering income and hence overall consumption, and/or by increasing stress, risky alcohol and drug consumption, or suicides. Consistent with this, the existing evidence indicates that job loss increases mortality (Sullivan and Von Wachter 2009), and reduced economic prospects have been found to be associated with "deaths of despair" (Case

[35] As in equation (1), in equations (4) and (5) we omit the interaction with yearly location and 2003 location shock variables in 2006, so that all coefficients are relative to 2006.

and Deaton 2021). In addition, counties exposed to greater import competition and thus job loss from trade liberalization with China experienced 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 (Dorn et al. 2019). There are also well-known positive gradients between income and health and between education and health, and some evidence that these relationships are causal.[36]

Despite this, there are a number of potential explanations why recessions might reduce mortality. We find it useful to group them into internal effects – whereby an individual's reduced employment or consumption reduces her own mortality – and external effects, or externalities from reduced aggregate economic activity on health, holding constant own employment or consumption. Naturally these have potentially very different implications for the welfare consequences of our estimates. Positive health externalities from reduced economic activity suggest that recessions may have positive welfare effects that mitigate the negative welfare effects from reduced consumption that economists have estimated (e.g. Krebs (2007)). However, mortality reductions that arise from internal effects are less clear cut. In a rational agent model in which affected individuals choose to use some of their increased leisure time to produce more health, there may be no welfare consequences of the health effects by the usual envelope theorem argument; of course, if individuals are engaged in privately sub-optimal health behaviors such as smoking or medication non-adherence (e.g. Gruber and Köszegi (2001)), recession-induced changes in behavior could be welfare improving.

There are two main channels for internal effects discussed in the literature. One channel is that with their increased non-labor time, the newly unemployed may have more time for self-care. This may improve health by reducing stress (Ruhm 2000; Brenner and Mooney 1983) or improving health behaviors (Ruhm 2000). Under this scenario, we might expect to see improved diet, increased exercise, and increased smoking cessation—which was the mechanism behind the procyclical mortality effects emphasized in the original work by Ruhm (2000) — as well as potentially increased use of medical care, although presumably losses in health insurance associated with employment losses and reductions in income would cut against that. A second channel is that declines in consumption —which can occur both among those directly affected in the labor market as well as through overall wealth declines accompanying a recession —could improve health by decreasing health-harmful consumption such as alcohol and cigarettes (Carpenter and Dobkin 2009; Evans and Moore 2012; Ruhm 1995).

Several pieces of indirect evidence mitigate against the likelihood of these internal channels. First, the time pattern of the mortality reductions is not consistent with a major role for changes in health behaviors. Figure 4 showed an immediate, contemporaneous relationship between declines in local area employment and declines in mortality that does not grow further over time. However, an explanation based on changes in exercise, diet, or smoking would be expected to impact mortality

[36] Cesarini et al. (2016) provide evidence of a causal effect of income on improving health; Lleras-Muney (2022) reviews the literature of the causal effect of education on health, noting that results vary across contexts and studies.

with a lag, and to grow over time as health capital improves.[37] By contrast, an immediate mortality decline is consistent with a role for pollution—which has been found to decline immediately during a recession and for which changes can impact mortality not only within a year but even within days (Chay and Greenstone 2003; Deryugina et al. 2019).[38] Second, the cause-specific mortality estimates suggest a relatively small role for changes in health behavior. While we do estimate a statistically significant decline in mortality from cirrhosis of the liver, this accounts for less than 3 percent of the total reduction in mortality, and we detect no statistically significant effects on homicides, accidental poisonings, or suicides.[39] Finally, the fact that three-quarters of the mortality reduction comes from a reduction in elderly deaths, a group whom we estimate did not experience any direct income or employment effects from the Great Recession, also mitigates against internal effects as the primary driver of the estimated mortality declines. In on-going work we are trying to directly examine the impact of the Great Recession on various health behaviors.

We also explore two main potential sources of positive health externalities from recessions: increases in the quality of health care and reductions in pollution. Consistent with the former, Stevens et al. (2015) suggest that cyclical fluctuations in the quality of nursing home staff contribute to improvements in elderly health during recessions. An existing body of evidence also indicates that recessions decrease pollution (e.g. Heutel 2012; Heutel and Ruhm 2016; Feng et al. 2015) and that pollution increases mortality, with effects that occur instantaneously (see e.g. Currie et al. (2014) and Graff Zivin and Neidell (2013) for reviews; examples of more recent papers include Deryugina et al. (2019) and Ebenstein et al. (2017)). This suggests that recession-induced pollution reductions may be an important channel for procyclical mortality. Indeed, Chay and Greenstone (2003) and Heutel and Ruhm (2016) provide direct evidence that recession-induced changes in pollution affect infant mortality and total mortality, respectively.[40] Our preliminary results below show no evidence in support of the hypothesis that recessions improve health by improving the quality of nursing home care received; we hope to have additional results on this and on the pollution channel in the near feature.

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

[38]It is worth noting that house price declines began in 2006, about a year before the labor market declines, see e.g. Figure 1 of Dastrup and Ellen (2012). It may therefore be possible for some of the mortality effects caused by the Great Recession to also show up earlier.

[39]We estimate a statistically significant decline in deaths from motor vehicle accidents that accounts for about 7 percent of the total mortality reduction. Declines in motor vehicle fatalities may consist of both direct effects (single-car fatal accidents) and external effects (multi-car fatal accidents).

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

Quality of nursing home care for the elderly. Recessions may have positive external effects on the quality of health care arising through tighter labor markets and hence improved quantity and quality of health care workers, particularly relatively low-skilled, direct care workers where there are widespread concerns about shortages. It is also possible that informal care provided by adult children could increase with tighter labor markets. Stevens et al. (2015) emphasize this channel, with evidence from state-year panel data from 1978-2006 that staffing levels at nursing homes rise with the state unemployment rate and deaths of the elderly residing in nursing homes decline.

We find no evidence in support of the hypothesis that improvements in nursing home staffing and quality of care were a contributor to the impact of the Great Recession on mortality. To examine the impact on nursing home staffing, we follow Stevens et al. (2015) and use OSCAR/CASPER facility-level administrative data from annual certification inspections of nursing facilities across the United States.[41] We analyze data from 2003 through 2016, covering a range of nursing home staffing measures and other characteristics.

Figure 7 shows little evidence of an increase in nursing home staffing where the Great Recession hit harder. Specifically, we examine direct care hours per resident day; direct care staff hours include the number of hours worked by a registered nurse, licensed practical nurse, or certified nursing assistant in the two weeks prior to the measurement date.[42] In 2006, the average facility (weighted by beds) provided 3.3 direct care hours per resident day. The point estimates suggest that for every 1 percentage point increase in the local area unemployment during the Great Recession, there is a statistically and substantively insignificant 0.95 percent (standard error = 0.49) increase in direct care hours per resident day during 2007-2009, and 0.54 percent (standard error = 0.28) from 2010 - 2016.[43] We also find no evidence of an impact of the Great Recession on nursing home occupancy rates or resident characteristics (Appendix Figure A.15). In the absence of any obvious impacts of the Great Recession on the composition of nursing home occupants, we also examined the impact of the Great Recession on elderly deaths in nursing homes. Using the panel Medicare data, we find that the Great Recession reduced the hazard rate of dying among the elderly with no recent or current nursing home use (Appendix Figure A.16b but not among the elderly with recent or current nursing home use.

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

[42] LTCFocus verifies staffing data via comparison to previous values for the same facility, and assigns new values that are "implausible" (e.g. a ratio of 3:1 CNAs to beds) as missing or imputes them from prior data.

[43] By contrast, Stevens et al. (2015) estimate that every 1 percentage point increase in the state-year unemployment rate increases total-full time employment in a nursing home by 3 percent, with increases in nurses, certified aides, and other occupations.

4 Welfare Consequences of Recessions

Our estimated effects of the Great Recession on mortality risk have implications for the welfare consequences of recessions. In an influential paper, Lucas (1987) argues that the welfare costs of recessions are negligible when viewed through the lens of a standard representative-agent model with uninsurable idiosyncratic labor market risk. The welfare costs of recessions can be an order of magnitude larger, however, when carefully accounting for the long-term earnings losses of displaced workers (Krebs 2007). We build on the Krebs (2007) model to study the welfare cost of recessions when recessions are "good for your health," by allowing for endogenous mortality using the welfare approach in Jones and Klenow (2016) to value changes in mortality risk alongside changes in earnings.

4.1 Basic Model

We begin with a basic model that simplifies the economic environment and illustrates the main intuition behind our results. The basic model is a discrete-time, infinite-horizon, representative-agent model. Subsequently, the full dynamic model incorporates age-specific mortality rates, state-dependent and state-independent persistent income shocks, stochastic beginning and ending of recessions, and retirement.

Utility. The representative agent's expected lifetime utility is given by:

$$U(c(t), m(t)) = \mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t S(m(t)) u(c(t)) \right] \tag{7}$$

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

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

$$u(c) = b + \frac{c^{1-\gamma}}{1-\gamma}, \tag{8}$$

where b governs the willingness to pay for additional years of life. The value of a statistical life-year (VSLY) is given by VSLY $= \frac{U(c,m)/u'(c)}{T} = bc^{\gamma} - \frac{c}{\gamma-1}$, which implies that the VSLY is increasing in c if $\gamma > 1$ (Hall and Jones 2007). The agent receives income $y(t)$ when alive, and, as in Krebs (2007), we assume that consumption always equals income in each period ($c(t) = y(t)$ for all t); i.e., there is no savings, borrowing, or insurance.

Recessions. There is an aggregate state $S \in \{L, H\}$ that is drawn once and for all at $t = 0$. The aggregate state determines the earnings risk faced by the agent during their lifetime. There is only one source of earnings risk in the basic model, which is the instantaneous probability of job displacement at $t = 0$, which depends on the aggregate state as follows:

- $S = H$ *(Normal state).* In this state, the agent faces probability p^H of job displacement at $t = 0$ (and only at that time). Job displacement leads to an immediate and persistent reduction in income from y to $(1 - d^H)y$, where $0 < d^H < 1$. Since we assume the agent is engaging in hand-to-mouth consumption, this reduction in income leads to a reduction in consumption from c to $(1 - d^H)c$.
- $S = L$ *(Recession).* In this state, there is an increase in the probability of job displacement at $t = 0$ from p^H to p^L ($> p^H$), and the reduction in income (and consumption) conditional on job displacement is also larger, decreasing consumption from c to $(1 - d^L)c$, where $d^L > d^H$.

In this model, the welfare cost of a recession is thus determined by the greater probability of job loss ($p^L > p^H$) and the larger reduction in income conditional on job loss ($d^L > d^H$).

Welfare cost of a recession with exogenous mortality. We begin by assuming mortality is exogenous and does not depend on the aggregate state. Given this assumption, 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:

$$\mathbb{E}[U(c, m)]^{\text{normal}} = p^H * T * u((1 - d^H)c) + (1 - p^H) * T * u(c) \tag{9}$$

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

$$\mathbb{E}[U(c, m)]^{\text{recession}} = p^L * T * u((1 - d^L)c) + (1 - p^L) * T * u(c) \tag{10}$$

Following Krebs (2007), we calculate the welfare cost of a recession as the representative agent's willingness to pay to avoid the recession state, calculated as a percentage of their average annual consumption. This involves solving for Δ such that[44]

$$\mathbb{E}[U((1 + \Delta)c, m)]^{recession} = \mathbb{E}[U(c, m)]^{normal} \tag{11}$$

[44]Technically Δ denotes the willingness to accept rather than the willingness to pay, but for small amounts these are equivalent.

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:

$$\Delta = \left(\frac{p^H (1-d^H)^{(1-\gamma)} + (1-p^H)}{p^L (1-d^L)^{(1-\gamma)} + (1-p^L)} \right)^{1/(1-\gamma)} - 1 \tag{12}$$

This expression is increasing in p^L (the probability of job displacement in a recession) and d^L (the reduction in consumption in a recession), as expected. The welfare cost of the recession is independent of b, the parameter which governs the VSLY, or life expectancy T. Since life expectancy is assumed to be independent of the aggregate state, neither it nor the VSLY affects the agent's willingness to pay to avoid the recession state.[45]

Welfare cost of recession with endogenous mortality. We now extend the basic model to allow for the agent's mortality risk to vary with the aggregate state. For simplicity, we assume that the aggregate state affects mortality risk as follows: in the normal state, life expectancy is T, while in the recession state, life expectancy is $T(1+dT)$.[46] This leads to the following expressions for expected lifetime utility in the two states:

$$\mathbb{E}[U]^{\text{normal}} = p^H * T * u((1-d^H)c) + (1-p^H) * T * u(c) \tag{13}$$

$$\begin{aligned}\mathbb{E}[U]^{\text{recession}} &= p^L * T(1+dT) * u((1-d^L)c) \\ &\quad + (1-p^L) * T(1+dT)u(c)\end{aligned} \tag{14}$$

Using the above expressions, we can solve for the welfare cost of a recession in the case with endogenous mortality (Δ^{dT}):

$$(1+\Delta^{dT})^{(1-\gamma)} = \frac{-dT * b/\tilde{u}(c) + p^H * (1-d^H)^{(1-\gamma)} + (1-p^H)}{(1+dT) * (p^L * (1-d^L)^{(1-\gamma)} + (1-p^L))} \tag{15}$$

$$\Delta^{dT} = \left(\frac{-dT * b/\tilde{u}(c) + p^H (1-d^H)^{(1-\gamma)} + (1-p^H)}{(1+dT)(p^L (1-d^L)^{(1-\gamma)} + (1-p^L))} \right)^{1/(1-\gamma)} - 1 \tag{16}$$

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 (16) is valid for any value of

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

[46] This assumes that the effect of a recession on mortality risk is the same regardless of whether or not the agent experiences a job displacement. This is another simplification that we will eventually relax in the calibration of the full dynamic model.

dT and it simplifies to the expression for Δ in equation (12) if $dT = 0$.[47]

We can build further intuition by setting $p^H = 0$ and then taking a first-order approximation around the left-hand side of equation (15), which leads to the following expression:

$$1 + (1-\gamma) * \Delta^{dT} \approx \frac{-dT * b + \tilde{u}(c)}{(1+dT) * (p^L * (1-d^L)^{(1-\gamma)}\tilde{u}(c) + (1-p^L)\tilde{u}(c))} \tag{17}$$

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

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. Recall that the welfare cost of recessions denotes the willingness to pay to avoid recessions as a percent of average annual consumption. The second term shows that the an endogenous increase in life expectancy reduces this willingness to pay by the percentage change in life expectancy dT times the value of this saving ($VSLY$) as a share of annual consumption in the normal state, since the welfare cost of a recession is defined as a share of average annual consumption.[48]

This expression shows that no matter how costly the recession is in terms of labor earnings, there always exists a value of the VSLY (given a change dT) where $\Delta^{dT} < 0$, meaning that the agent is not willing to pay to avoid the recession, but would instead be willing to pay for nature to draw the recession state.[49]

Initial calibration. To get a rough sense of the potential quantitative importance of endogenous mortality for the welfare cost of a recession, we calibrate the basic model using the following parameters following Krebs (2007): $p^L = 0.05$, $p^H = 0.03$, $c = \$50$ (representing an annual income and consumption of \$50,000 per year), $T = 40$ (meaning 40 years of life remaining), $d^H = 0.09$, and $d^L = 0.21$. The p^S values correspond to the approximate job separation rates during a recession and normal times, respectively, and the d^S values likewise correspond to the average earnings loss from job displacement, which is assumed to be greater during recessions.

Using these parameters, we calculate values of Δ^{dT} in two scenarios: exogenous mortality ($dT = 0$) and endogenous mortality ($dT = 0.0021$). The first scenario corresponds to exogenous mortality risk (that does not depend on the state of the economy), and the second scenario corresponds to the

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

[48] Another way to interpret the second term is to multiply and divide by T, so that $dT * T$ is the actual recession-induced change in life expectancy in years, and $VSLY$ is the money-metric value of this increase in life expectancy. Then this is divided by $T * c$ to scale by lifetime consumption.

[49] Mathematically, this comes from the fact that the value of b is unbounded from above, so unless we assume an upper bound on the VSLY we cannot say in this model whether or not recessions have a positive welfare cost.

0.21 percent increase in life expectancy that would arise from a Great Recession-induced mortality decline of 2.3 percent per year (corresponding to our estimates from Section 2), applied to the 2007 SSA life tables and assuming that the effects of the Great Recession last exactly 10 years.[50] We report sensitivity to different values of the VSLY by choosing different values of b (given an assumed value for γ) to correspond to values of the VSLY of \$100k, \$250k, or \$400k.[51]

Table 4 reports the calibration results. The first column shows the welfare cost of a recession with exogenous mortality. The welfare cost is increasing in γ, as in Lucas (1987) and Krebs (2007). The agent is willing to pay between 1.7 and 1.9 percent of annual consumption to avoid the recession state. The remaining columns show how the welfare cost varies with the VSLY. A larger value of the VSLY leads to a smaller value of Δ^{dT} at all values of γ. At the intermediate value of the VSLY (\$250k), the welfare cost of the recession is reduced by between 54 and 62 percent relative to the exogenous mortality benchmark.

The first-order approximation formula in equation (18) above shows that the welfare cost of a recession with endogenous mortality is equal to the sum of the welfare cost with exogenous mortality and the welfare benefit from the percentage increase in life expectancy from the recession. Consistent with this result, Table 4 shows that the differences in values of Δ^{dT} across columns vary little with γ, and the differences in Δ^{dT} across rows (as γ increases) also vary little with the VSLY. These comparisons both imply that the basic model's calibration results indicate a quantitatively small *interaction* between the welfare cost of a recession coming through the earnings consequences of job displacement and the welfare benefit of a recession through lower mortality risk, which is consistent with the additive separability in the approximation formula above.

An initial look at heterogeneity by age. The basic model abstracts from heterogeneity in the welfare cost of a recession by age. Our full dynamic model will explicitly allow for this, but the approximation formula in equation (18) for the basic model allows us to anticipate heterogeneity in the effect of a recession by age. To see this, note that the formula for Δ^{dT} in equation (18) depends on the percent change in life expectancy dT caused by the recession, and recall that we estimated that the Great Recession caused a constant proportional decline in mortality rates across ages. The percent increase in life expectancy dT is increasing in the baseline mortality rate, which is higher for older people.[52]. Thus a given percentage decline in mortality rates produces larger percentage

[50]Specifically, it is the average percent life expectancy increase by age from age 0 to age 99, weighted by the age of the population.

[51]We choose this range based on several sources. Kniesner and Viscusi (2019) report a \$369,000 VSLY used by the US Department of Health and Human Services and the Food and Drug Administration in 2016. The paper also calculates the VSLY from the value of a statistical life (VSL) using the identity VSLY $= r * \text{VSL}/(1-(1+r)^{-L})$, where L is life expectancy and r is the interest rate. When we use a range of the VSL from \$3 million to \$10 million based on Hall and Jones (2007) and Viscusi (2018) and values of r from 0.01 to 0.03 (using the same range in Kniesner and Viscusi (2019)), then we calculate a range of VSLY from roughly \$122k to \$433 given $L = 50$.

[52] To see this, assume that the effect of a recession on life expectancy in our basic model comes entirely from an instantaneous change in mortality at $t = 0$, reducing the mortality rate from $m(0)$ to $m(0) * (1 + dm)$ (with $dm < 0$), and after that all of the other mortality rates in future periods revert back to normal (so that $m(t)$ stays the same

gains in life expectancy at older ages, as can be seen in Appendix Table A.9. For example, for men at age 35, remaining life expectancy is 42 years, and a 10-year 0.5 percent decline in the mortality rate translates into a 0.05 percent increase in life expectancy while for men at age 65, life expectancy is 16.7 years and a 10-year, 0.5 percent decline in the mortality rate translates into a 0.43 percent increase in life expectancy, which is almost ten times higher.

4.2 Full Dynamic Model

We now turn to the full dynamic model to incorporate several more realistic features of the economic environment: age-specific mortality rates, state-dependent and state-independent persistent income shocks, stochastic beginning and ending of recessions, and retirement. This will also allow us to calibrate welfare costs of recessions across the age distribution.

Utility. The representative agent's lifetime utility and per-period utility functions are the same as the basic model (see equations (7) and (8)).

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

Income process. The full dynamic model follows Krebs (2007) in allowing for two types of persistent income shocks. Income in period $t = 0$ is normalized to 1, and evolves according to the following stochastic process:

$$y_{t+1} = (1+g)(1+\theta_{t+1})(1+\eta_{t+1})y_t \tag{19}$$

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

$$\eta_{t+1} = \begin{cases} -d^S & \text{with probability } p^S \\ \frac{p^S d^S}{1-p^S} & \text{with probability } 1-p^S \end{cases} \tag{20}$$

for all $t > 0$). Using the definitions above, we can calculate dT as follows:

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

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

Retirement. When the representative agent turns 65, they enter retirement, and they receive a fixed income payment for the remainder of their life when alive which is assumed (in the spirit of Guvenen and Smith (2014)) to be equal to their income in the last period before retirement. Thus, in our baseline model, we assume that recessions have no effect on consumption for individuals aged 65+; we relax this assumption in our sensitivity analysis.

While the baseline assumption that recessions have no impact on the consumption of the elderly is unlikely to hold literally, we suspect it is a reasonable approximation. Most of the 65 and over are retired and living on a fixed income; indeed, time series evidence suggests that the elderly experienced little change in consumption during the Great Recession (see Malmendier and Shen (2018) figure 1). Our own empirical analysis of the Great Recession in the Health and Retirement Survey indicates that it had no impact on household income for the elderly. And under the hand-to-mouth assumptions of the model, this implies that the Great Recession would have no effect on elderly consumption.

Of course, in practice, recessions can also affect both financial and housing assets—the latter was particularly true of the Great Recession—and in richer models this will affect consumption. However, most elderly households have no financial wealth and the available evidence suggests that the consumption response to changes in house prices declines with age (Berger et al. 2018).

Welfare cost of recessions. Following Krebs (2007), we define the welfare cost of recessions Δ^{dT} as the fraction of income the agent would be needed to be paid to accept the stochastic aggregate state relative to an otherwise similar economy that stays in state $S = H$ for all time periods:

$$\underbrace{\mathbb{E}_0 \left[\sum_{t=0}^{\infty} \beta^t S(m^S(t)) u((1 + \Delta^{dT}) y(t)) \right]}_{\text{Expected Lifetime Utility with Stochastic Aggregate State}} = \underbrace{\mathbb{E}_0^{S=H} \left[\sum_{t=0}^{\infty} \beta^t S(m^{S=H}(t)) u(y(t)) \right]}_{\text{Expected Lifetime Utility without Recessions}}, \tag{21}$$

where $m^S(t)$ is age-specific mortality risk in state S (potentially endogenous to the aggregate state). If mortality is exogenous, then $m^{S=H}(t) = m^{S=L}(t) = m(t)$, and the expression above simplifies to the same expression in Krebs (2007) with the only modification being age-specific rather than constant mortality rates. If instead mortality risk is endogenous, then we assume that a recession lowers the mortality rate by a constant percentage across all age groups, so that $m^L(t) = (1 + dm) * m^H(t)$ for all t (recall $dm < 0$).

Note that this expression corresponds to the welfare cost of eliminating *all* future recessions, not a single recession. To calculate the welfare cost of eliminating a single recession (that lasts several years), we can compare the expected lifetime utility from experiencing a recession in the first several periods (followed by state $S = H$ after that forever) to the right-hand side above where the state is always $S = H$.

To calibrate equation (21) above, we numerically simulate the economy for a large number of individuals (N) and time periods ($\overline{T}$) to approximate expectations, allowing us to solve for the value of Δ^{dT} that equalizes the following expression:

$$\sum_{i=0}^{N}\left[\sum_{t=0}^{\overline{T}}\beta^t S(m^S(t))u((1+\Delta^{dT})y_i(t))\right] = \sum_{i=0}^{N}\left[\sum_{t=0}^{\overline{T}}\beta^t S(m^{S=H}(t))u(y_i^{S=H}(t))\right] \tag{22}$$

Parameterization. We report results across the same range of γ and VSLY parameters as in the basic model. We simulate workers starting at different ages (35, 45, 55, and 65), we normalize $y(0) = c(0) = 1$, and we use the same 2007 SSA life tables to calculate age-specific mortality rates which we use for the $m^H(t)$ vector. Following Krebs (2007), we use the same values of p^S and d^S as in the basic model, and we choose $g = 0.02$, $\sigma = 0.01$. 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 in the baseline scenario of exogenous mortality that is fairly similar to Krebs (2007).

Lastly, based on our empirical estimates we choose $dm = -0.015$; this means that mortality rates fall by 1.5 percent across the age distribution during the recession state.[53] We (conservatively) assume that the mortality rate reductions only last during the recession state and do not persist after the recession has ended.

Calibration results. Table 5 shows our calibration results of the welfare costs of recessions for the fully dynamic model with exogenous and endogenous mortality for different values of γ and VSLY. This table focuses on workers starting at age 35. The welfare cost of recessions is therefore the lifetime cost of recessions as a percent of average annual consumption starting from age 35.

The first column shows results ignoring mortality. Workers would be willing to pay between 4.2 and 6.8 percent of average annual consumption to avoid recessions. As expected, these estimates are substantially higher than those in Krebs (2007) due to our higher assumed discount factor $\beta = 0.99$. Relatedly, the welfare cost of recessions is reduced substantially when adding exogenous mortality; as Krebs (2007) shows, this is mathematically equivalent to decreasing the discount factor, which reduces the welfare cost of recessions. Column 2 shows that with an (unrealistic) constant annual mortality rate of 2.4 percent—corresponding to a 40-year life expectancy—workers are now willing to pay substantially less - between 2.1 and 3.6 percent of consumption - to avoid recessions. Column 3 shows that using realistic age-specific mortality rates and adding retirement

[53]This is based on our estimates that a 1 percentage point increase in unemployment causes a 0.5 percent decline in the mortality rate, together with the assumption that a typical recession leads to an increase in the unemployment rate of 3 percentage points.

reduces the welfare cost of recessions a bit more, to between 1.5 and 2.7 percent of consumption. This is still much larger than Lucas (1987) estimates but broadly similar to the baseline results in Krebs (2007) which assume infinitely lived agents but a higher discount rate.[54]

The remaining columns of Table 5 show how incorporating our estimates of endogenous mortality affects the welfare costs of recessions. For the lowest value of VSLY (\$100k, column 4), we find very similar costs of recessions —1.2 to 2.4 percent of average annual consumption - to the estimates in column (3) with exogenous mortality. However, increasing the VSLY to the higher-end estimates of the literature substantially reduces the welfare cost of business cycles. For example, for $\gamma = 2$ and VSLY of \$250k (column 5) and \$400k (column 6), the welfare costs of recessions are reduced by 35 and 56 percent, respectively, relative to when the exogenous mortality case in column (3).

Table 6 shows that accounting for mortality effects magnifies the heterogeneity in welfare effects of recessions by age. Here, each panel reports results from a different starting age, first reproducing the above results for a 35-year-old worker in Panel A, and then examining welfare costs for starting ages 45, 55, and 65 in Panels B through D. Column (1) shows that with exogenous mortality, for any given value of γ, the welfare cost of a recession is declining with age; this arises because workers have shorter working lives—and hence periods in which they experience consumption declines due to recessions—before retirement. Indeed, under our baseline assumption that income is fixed in retirement, the welfare cost of recessions with exogenous mortality is 0 at age 65 (Panel D).

Columns (2) through (4) show that accounting for endogenous mortality lowers the welfare cost of recession at all ages, and that this impact is increasing in the worker's age. Consider for example the case of endogenous mortality at the "intermediate" VSLY in column (3) compared to the exogenous mortality in column (1). The difference between these two cases is fairly similar for the 35 and 45-year-old workers. This is intuitive since these workers have similar changes in life expectancy caused by recessions, and the result from the basic model (see equation (18)) suggests that given a similar change in life expectancy, the effect of endogenous mortality should be similar. For the even older workers (Panels C, D and E), however, they have much larger changes in the welfare cost of recessions when accounting for endogenous mortality. For example, for $\gamma = 2$ and $\text{VSLY} = 250K$, the welfare cost of recessions for a 45-year old declines from 1.5 percent of average annual consumption with exogenous mortality to 0.68 percent of consumption when accounting for endogenous mortality, a decline of 0.84 percentage points of average annual consumption. However under the same parameters the welfare cost of recessions for a 65-year old declines from 0 to -1.12 percent of average annual consumption, a decline of 1.12 percentage points.

These results also show that for older workers, accounting for endogenous mortality can turn the welfare costs of recessions negative at higher values of the VSLY and γ. Indeed, for 65-year-old workers recessions are welfare-enhancing for any values of VSLY and γ. This follows from the fact

[54] If we apply his higher discount rate to the model with no mortality in column (1) we recover his results.

that (by assumption) there is no welfare cost of recessions for them under exogenous mortality, and so accounting for endogenous mortality leads to a welfare benefit for them. As discussed, the assumption of zero consumption declines for the elderly may be a reasonable approximation but is unlikely to hold exactly. As a conservative alternative, Appendix Tables A.11 shows the welfare costs of recessions under the (aggressive) assumption that consumption declines from recessions are the same for all ages. Compared to our baseline, this naturally raises the welfare cost of recessions at all ages and makes it strictly positive for the elderly with exogenous mortality. Nonetheless, we still find allowing for endogenous mortality can turn the welfare costs of recessions negative for 55-year olds and 65-year olds at higher values of the VSLY and γ.

The calibration results in Table 6 report our estimates for workers' willingness to pay to avoid all future recessions in their lifetime. We can also use the same model to calibrate the willingness to pay to avoid the Great Recession. To do this, we assume that the Great Recession corresponds to an aggregate state of $S = L$ for 10 years, and there is a decrease in mortality rate during each of those years of 2.3 percent. All other model parameters stay the same. After that, the aggregate state is $S = H$ forever (so that compared to $S = H$ for all time periods recovers willingness to pay to avoid the Great Recession only).

Table 7 reports results from these calibrations across the same age groups as in Table 6. A comparison of these findings with those in Table 6 highlights two interesting findings: on the cost side, the consumption declines from the Great Recession are worse for older workers than younger workers relative to regular recessions, while on the benefits side the mortality declines from the Great Recession are better for older workers than younger workers relative to regular recessions. To see this, first consider the exogenous mortality results in column (1). Here, the model, as in Krebs (2007) focuses solely on the consumption consequences of recessions. For $\gamma = 2$ for example, Table 6 shows that the welfare cost of regular recessions declines from 2.04 percent of annual average consumption for a 35-year old to 0.93 percent of average annual consumption for a 55-year old. By contrast, Table 7 shows that for the Great Recession, these numbers are substantially more similar: 1.84 percent and 1.76 percent respectively. Intuitively, the labor market consequences of the Great Recession are higher for older workers than younger workers compared to regular recessions because the Great Recession lasts longer and therefore affects retirement income substantially. However, accounting for endogenous mortality provides more benefits for older workers than younger workers from the Great Recession than it does for regular recessions. This is because the percent reductions in mortality from the Great Recession are concentrated at higher mortality rates. This is because the longer length of the Great Recession leads to great change in life expectancy for older workers, while for younger workers, the Great Recession has a very small effect on life expectancy. Thus for example, focusing on VSLY $= 250k$ and $\gamma = 2$, endogenous mortality reduces the welfare cost of the Great Recession by only about 11 percent compared to its welfare cost with exogenous mortality (from 1.84 percent of consumption to 1.63 percent), while for 55-year old workers accounting for endogenous mortality reduces the welfare cost of the Great Recession by 45 percent (from 1.76 percent of consumption to 0.97 percent). For 65-year-old workers, the Great Recession is welfare improving once we account for endogenous mortality.[55]

Overall, these results show that accounting for the mortality effects of recessions changes the welfare cost of recessions substantially, both overall and across age groups. The fact that a given change in mortality rates has very different effects on life expectancy across age groups means that accounting for endogenous mortality affects some age groups much more than others, and it leads to greater differences in welfare cost across age groups. In other words, the distributional consequences are more important under endogenous mortality, since it magnitudes the welfare differences under exogenous mortality.

While we aimed to capture many realistic features of the labor market in our calibrations, we recognize that our results are likely at best only a rough approximation of the true welfare cost of recessions across age groups. Nevertheless, we find it striking that the welfare costs are negligible (or even negative) for older workers, suggesting that many older workers may benefit from recessions when accounting for the endogenous mortality effects. By contrast, for younger workers, the welfare costs are very similar whether or not endogenous mortality is taken into account since the percentage change in mortality rates translates into only a very small change in life expectancy.

5 Conclusions

We provided new evidence on the impact of the Great Recession on mortality and explored the consequences of incorporating this pro-cyclical mortality into analyses of the welfare consequences of recessions. Our findings indicate recessions are good for health, and that accounting for recession-induced mortality declines substantially reduces estimates of the welfare costs of recessions. They also indicate important distributional implications of incorporating pro-cyclical mortality. Since we estimate that the Great Recession reduces mortality equi-proportionally across the age distribution—and mortality rates increase substantially with age—the mortality consequences of recessions reduce their welfare cost less for younger workers than for older workers. Indeed, for some reasonable parameter values, we find that recessions in general—and the Great Recession in particular—may be welfare-improving for the elderly. In ongoing work, we are exploring the mechanisms behind the recession-induced mortality reductions.

[55] Again we find (see Appendix Table A.12) that even under the aggressive alternative assumption that consumption declines from recessions are the same for all ages, the Great Recession is welfare improving for 65-year olds at higher values of the VSLY and *gamma*.

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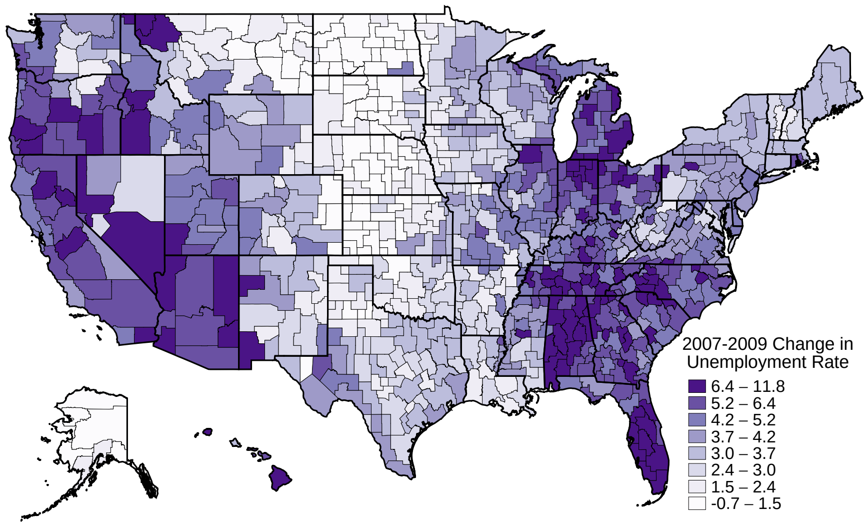
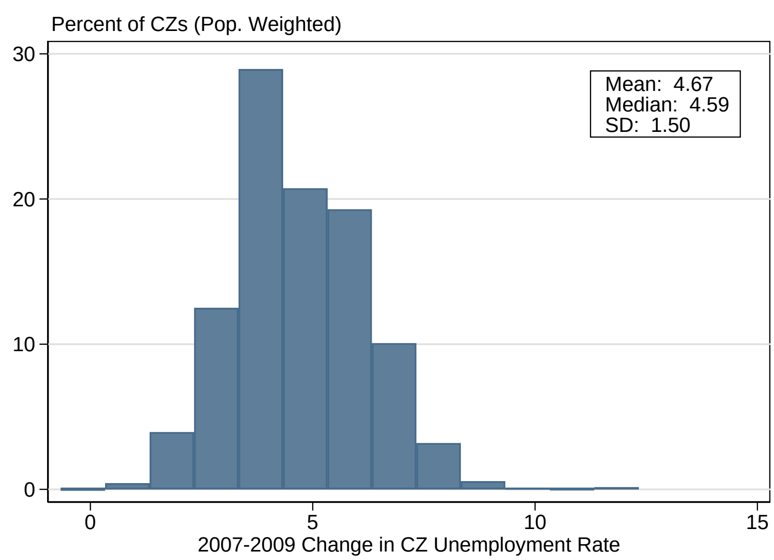
6 Figures

Figure 1: Changes in Unemployment Rates Across CZs During the Great Recession

(a) Heatmap



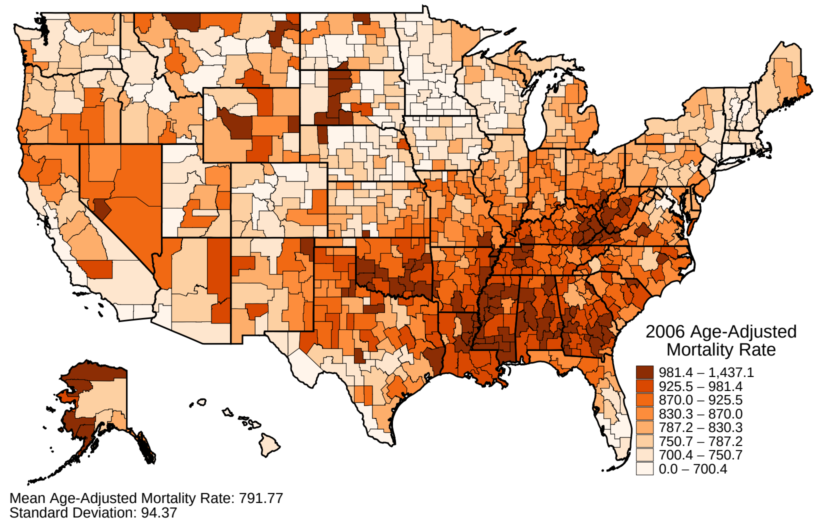
(b) Histogram



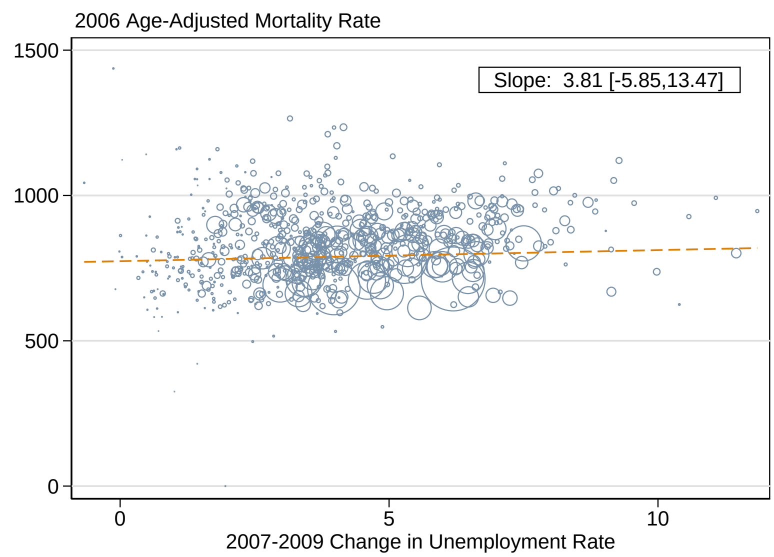
Notes: Figures display the change in Commuting Zone unemployment rates from 2007-2009, drawn from Yagan (2019). Figure 1a displays a heat map of the change in unemployment, binned into octiles. Figure 1b displays a histogram of the same shocks to unemployment, weighted by 2006 CZ population as measured in the SEER data. Mean, median, and standard deviations of the CZ unemployment shock (also weighted by 2006 CZ population) are listed in the top right-hand corner. $N = 741$ CZs.

Figure 2: 2006 Age-Adjusted Mortality Rates: Geographic Patterns

(a) Mortality Rates by CZ

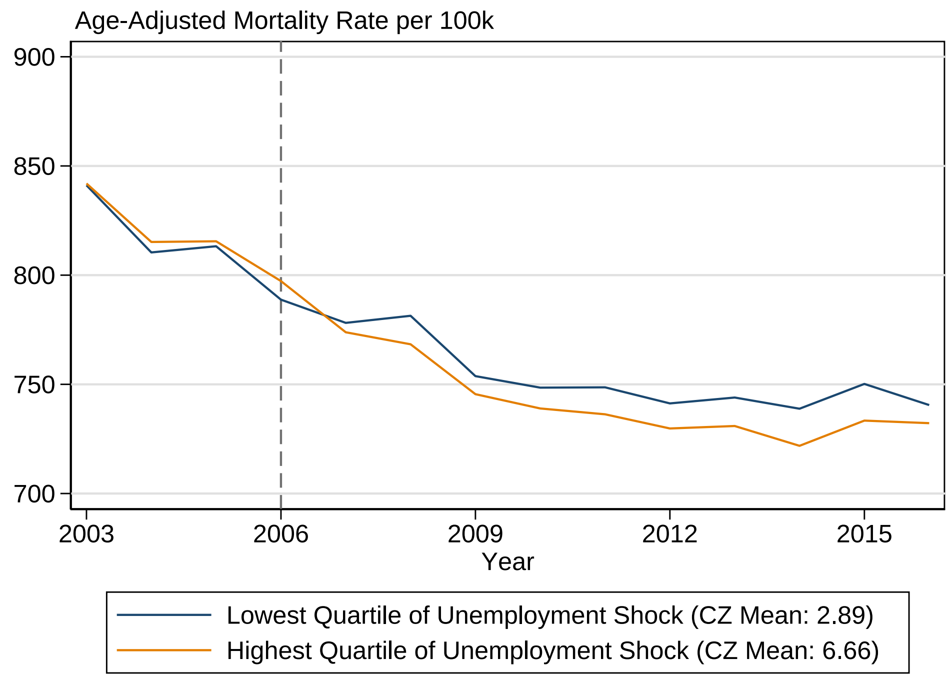


(b) Correlation between Pre-Recession Mortality Rates and Great Recession Shock



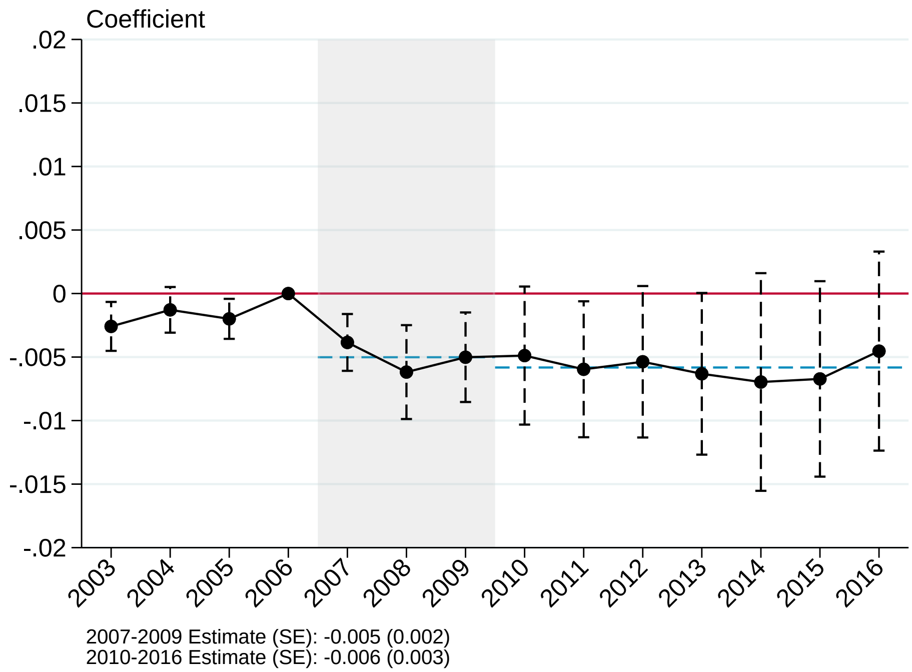
Notes: Figure 2a displays a heatmap of 2006 Commuting Zone age-adjusted mortality rates per 100,000. Colors are assigned according to octiles, with darker orange indicating higher mortality rates. The 2006 CZ population-weighted mean and standard deviation of the mortality rates are reported in the lower left-hand corner. Figure 2b displays a scatterplot of the 2006 CZ age-adjusted mortality rate against the 2007-2009 change in CZ unemployment rates. Each circle represents one of 741 CZs, scaled in size according to its 2006 population. A linear fit is plotted as a dashed orange line in each figure, and the slope and 95% confidence intervals from a linear fit (with heteroskedasticity robust standard errors) are reported in the top right hand corner the figure.

Figure 3: Age-Adjusted Mortality Rate by Severity of Shock



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

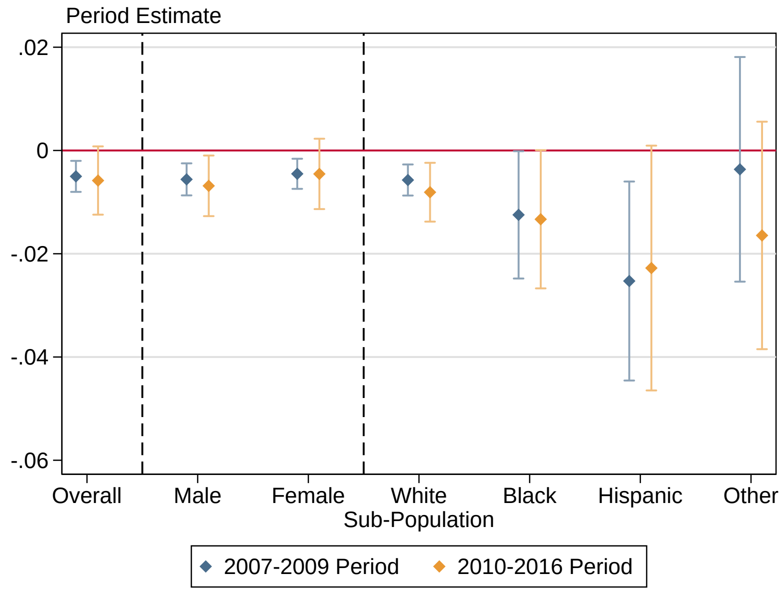
Figure 4: Impact of Great Recession Shock on Log Age-Adjusted Mortality Rate



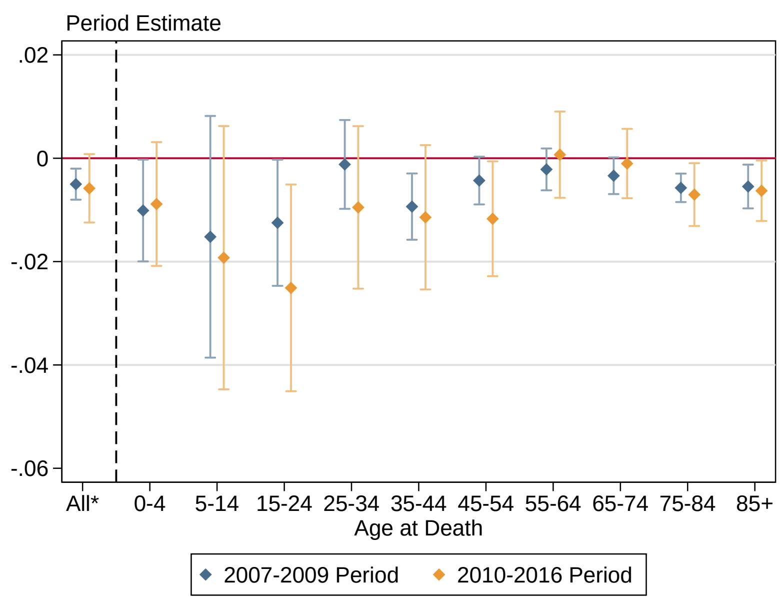
Notes: Figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000 population (plus one) and observations are weighted by CZ population in 2006. Annual mortality is constructed according to the county of residence observed in the NCHS detailed mortality microdata, and population estimates are drawn from the SEER. The age-adjustment procedure weights age-bin specific mortality rates according to their population share in the US 2000 Standard Population. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the point estimate for the linear combination of coefficients from 2007-2009 and 2010-2016. These period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner. Standard errors are clustered at the CZ level (741 CZs).

Figure 5: Impact on Mortality, by Demographics

(a) Log Age-Adjusted Mortality Rate, by Sex and Race



(b) Log Mortality Rate, by Age Group

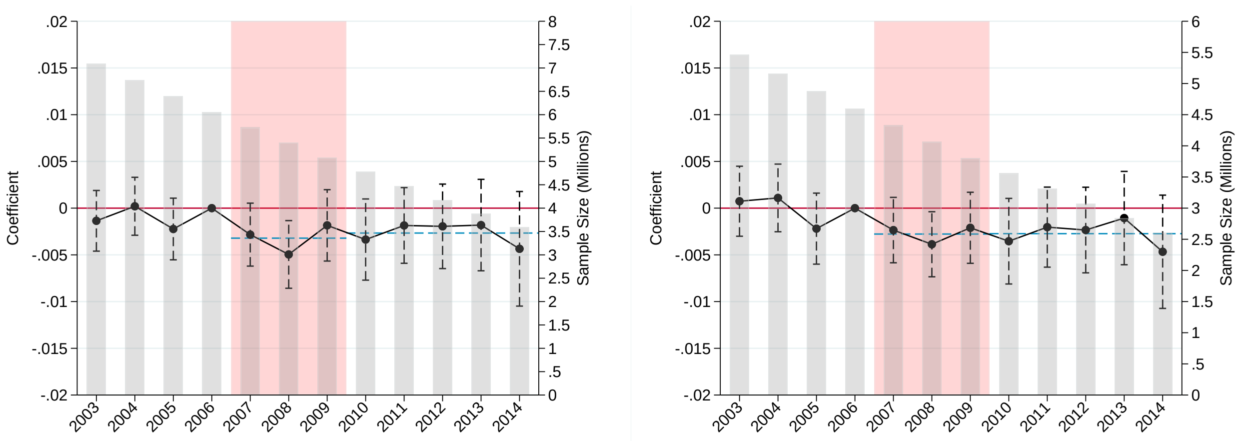


*"All" Age Group estimate is of log age-adjusted mortality

Notes: Figure displays period estimates and 95% confidence intervals for the average of the coefficients on the interacted Great Recession Shock across 2007-2009 and 2010-2016 from equation (2). As in Figure 4, estimates are weighted by the 2006 CZ population from the SEER, and standard errors are clustered at the CZ level. In Panel 5a, period estimates are displayed for the overall sample and by sex and race. The dependent variable is the log age-adjusted CZ mortality rate (per 100,000 plus one). Panel 5b shows period estimates for the overall sample ("All") and ten age bins. The dependent variable for the full sample is log age-adjusted mortality rate; for age group estimates, the dependent variable is the log age-group mortality rate.

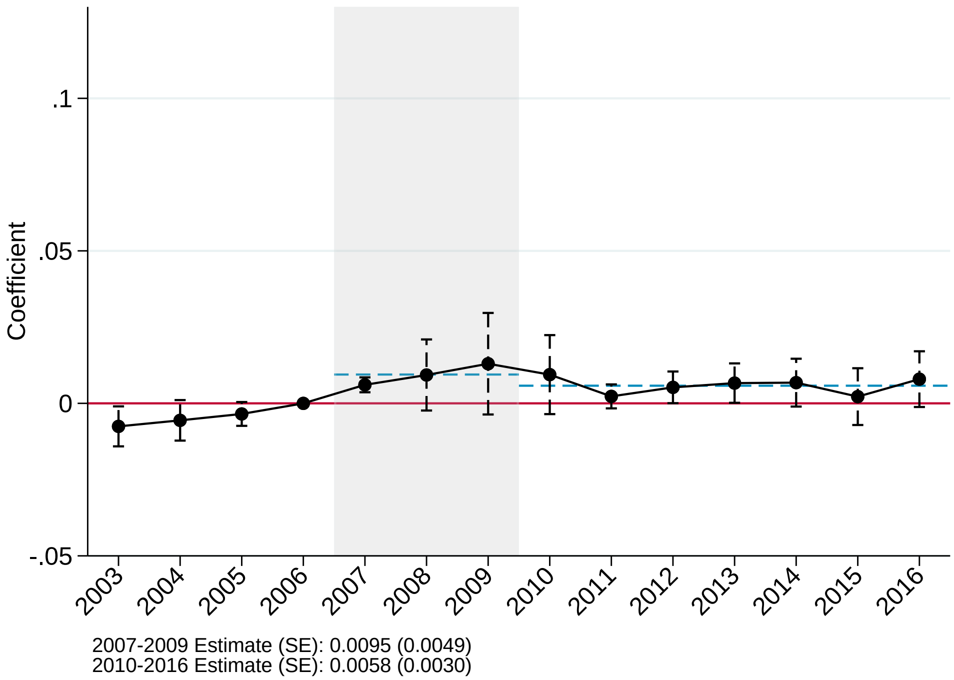
Figure 6: Impact of Great Recession Shock on Log Mortality Hazard Rate

(a) All 2003 Medicare Beneficiaries (b) 2003 Traditional Medicare Sample



Notes: This figure displays coefficients β_t from equation (3), with outcome $log(h_{it}(a))$ defined as the log of the individual-level hazard rate at age a. Each individual is assigned their 2003 CZ of residence, and shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the point estimate for the linear combination of coefficients from 2007-2009 and 2010-2014. Standard errors are clustered by CZ. In Panel A, the sample is 2003 Medicare beneficiaries, subject to the restrictions in Table A.7. In Panel B, the sample is further restricted to beneficiaries enrolled in Medicare Part B in every 2003 month in which they are alive, which excludes Medicare Advantage recipients in any 2003 month and 2003 Medicare entrants in any month other than January. Gray bars indicate the sample size by year (which is reduced each year due to mortality), with the scale displayed by the secondary y-axis. N(2003, Panel A) = 7,088,974; N(2003, Panel B) = 5,459,866.

Figure 7: Impact of Great Recession Shock on Log Direct-Care Staff Hours



Notes: Figure displays coefficients β_t from equation $y_{it} = \beta_t[SHOCK_{c(i)} * \mathbb{1}(Year_t)] + \alpha_{c(i)} + \gamma_t + \varepsilon_{it}$ from 2003-2016, where i indexes skilled nursing facilities and $c(i)$ the Commuting Zone of facility i. The outcome y_{it} is the log of the sum of the hours worked by RN, LPN, and CNA staff per resident day at facility i during the two weeks prior to the annual OSCAR survey. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the mean estimates β_t over the 2007-2009 and 2010-2016 periods (presented with standard errors in the lower left hand corner). Facility observations are weighted by 2006 CZ population from the SEER, and standard errors are clustered at the CZ level.

7 Tables

Table 1: Descriptive Statistics – 2006 Mortality

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

* Age-adjusted mortality rates reported for these categories.
Notes: This table presents descriptive statistics of mortality events in the United States in 2006 in the National Center for Health Statistics microdata. The sample is all mortality events among the resident US population with observed age at death (99.99% of resident mortality events). Population estimates are drawn from the annual SEER data.

Table 2: Decomposition Estimates — Cause of Death

Cause of Death	(1) *Share of Total Mortality (2006)*	(2) *Estimated 2007-2009 Percent Reduction in Mortality Rate*	(3) *Share of Estimated 2007-2009 Reduction*
All Causes	*1.0000*	*-0.0050*	*1.0000*
		(0.0015)	
Mutually-Exclusive ICD10 Categories:			
Cardiovascular Disease	0.3395	-0.0065	0.4430
		(0.0021)	(0.0683)
Malignant Neoplasms (Cancer)	0.2308	-0.0002	0.0072
		(0.0011)	(0.0521)
Chronic Lower Respiratory Disease	0.0513	-0.0060	0.0612
		(0.0037)	(0.0280)
Diabetes	0.0299	0.0029	-0.0173
		(0.0034)	(0.0211)
Alzheimer's	0.0299	-0.0013	0.0077
		(0.0063)	(0.0377)
Influenza/Pneumonia	0.0232	-0.0073	0.0339
		(0.0050)	(0.0179)
Nephritis, etc. (Kidney Disease)	0.0187	-0.0084	0.0314
		(0.0047)	(0.0205)
Motor Vehicle Accidents	0.0187	-0.0171	0.0635
		(0.0056)	(0.0170)
Suicide	0.0137	-0.0030	0.0083
		(0.0041)	(0.0114)
Liver Disease/Cirrhosis	0.0114	-0.0105	0.0239
		(0.0043)	(0.0107)
Homicide	0.0077	-0.0146	0.0223
		(0.0077)	(0.0099)
Residual	*0.2253*	*-0.0052*	*0.2351*
		(0.0023)	*(0.0581)*

Notes: Table presents a decomposition of the overall estimated mortality reduction by cause of death. The first column indicates the share of 2006 mortality contributed by each ICD10 grouping. The second column presents the point estimates for the 2007-2009 period for the decline in log (age-adjusted) mortality rates from the Great Recession, estimated from equation (2), where $Group_g$ is an indicator for the cause of death. The third column presents our "decomposition," analogous to the exercise conducted in Ruhm (2000): we divide each semi-elasticity by the semi-elasticity of the all-cause mortality rate with respect to the Great Recession shock, and multiply the resulting fraction by the cause of death's share of 2006 mortality. Standard errors for the estimates in columns (2) and (3) are included in parentheses, clustered by CZ.

Table 3: Event Study Period Estimates

Regression Specification	2007-2009 Period Estimate & Standard Error	N (2003)
	(1)	(2)
A. 2003 Traditional Medicare Sample		
2003 Residence (β_t, eq. 3)	-0.00277	5,459,866
	(0.00154)	
B. All 2003 Medicare Beneficiaries		
2003 Residence (Reduced Form) (β_t, eq. 3)	-0.00321	7,088,974
	(0.00157)	
First Stage (π_t^{FS}, eq. 4)	0.945	7,088,974
	(0.003)	
Control Function (β_t, eq. 5)	-0.00337	7,088,974
	(0.00169)	
Yearly Residence (OLS) (β_t, eq. 6)	-0.00483	7,088,974
	(0.00163)	

Notes: This table displays the point estimate and standard errors (in parentheses) for the linear combination of yearly coefficients from 2007-2009; estimates are based on coefficients β_t from equation (3) (for 2003 residence specifications), coefficients β_t from equation (6) (for the yearly residence specification), and coefficients β_t from equation (5) (for the control function specification), with outcome $log(h_{it}(a))$ defined as the log of the individual-level hazard rate at age a. Estimates are also based on coefficients π_t^{FS} from equation (4) (for the first stage regression), with outcome defined as the sum of the interactions of GR shock based on yearly CZ of residence and yearly dummies. Shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. Standard errors are clustered at the CZ except for the Control function standard errors which are calculated via a Bayesian bootstrap procedure with 450 repetitions. In Panel B, the sample is all 2003 Medicare beneficiaries, subject to the restrictions in Table A.7. In Panel A, the sample is further restricted to beneficiaries enrolled in Medicare Part B in every 2003 month in which they are alive, which excludes Medicare Advantage recipients in any 2003 month and 2003 Medicare entrants in any month other than January.

Table 4: Welfare Cost of a Recession: Basic Model

	$dT = 0$	$dT = 0.0021$		
VSLY =	-	\$100k	\$250k	\$400k
$\gamma = 1.5$	1.72	1.29	0.66	0.04
$\gamma = 2$	1.82	1.40	0.77	0.15
$\gamma = 2.5$	1.94	1.52	0.89	0.27

Notes: The welfare cost is measured as a percentage of average annual consumption. This table shows the welfare cost of a recession using the basic model for different values of γ and VSLY, and for recessions with exogenous mortality ($\Delta^{dT} = 0$) and endogenous mortality ($\Delta^{dT} = 0.0021$) .

Table 5: Welfare Costs of Recessions: Full Dynamic Model

	Exogenous mortalities			Endogenous mortality		
	None (1)	Constant (2)	Realistic (3)	Realistic (4)	Realistic (5)	Realistic (6)
$\gamma = 1.5$	4.23	2.12	1.48	1.16	0.70	0.24
$\gamma = 2$	5.34	2.74	2.04	1.75	1.31	0.88
$\gamma = 2.5$	6.84	3.56	2.68	2.42	2.02	1.63
Retirement	No	No	Yes	Yes	Yes	Yes
VSLY (US\$)	-	-	-	100K	250K	400K

Notes: The welfare cost is measured as a percentage of average annual consumption. All columns use estimates from simulations with starting age 35. For simulations with none or constant mortality, agents die when they are 180 years old; for realistic mortality, when they are 100.

Table 6: Welfare Costs of Recessions by Age

	Mortality			
	Exogenous	Endogenous		
	(1)	(2)	(3)	(4)
Panel A. Starting age 35				
$\gamma = 1.5$	1.48	1.16	0.70	0.24
$\gamma = 2$	2.04	1.75	1.31	0.88
$\gamma = 2.5$	2.68	2.42	2.02	1.63
Panel B. Starting age 45				
$\gamma = 1.5$	1.09	0.72	0.17	-0.37
$\gamma = 2$	1.52	1.19	0.68	0.17
$\gamma = 2.5$	2.01	1.71	1.25	0.79
Panel C. Starting age 55				
$\gamma = 1.5$	0.67	0.26	-0.40	-1.05
$\gamma = 2$	0.93	0.55	-0.05	-0.64
$\gamma = 2.5$	1.21	0.88	0.34	-0.19
Panel D. Starting age 65				
$\gamma = 1.5$	0.00	-0.47	-1.26	-2.04
$\gamma = 2$	0.00	-0.41	-1.12	-1.81
$\gamma = 2.5$	0.00	-0.36	-0.99	-1.60
VSLY (US$)	-	100K	250K	400K

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

Table 7: Welfare Costs of Great Recession (10 Years) by Age

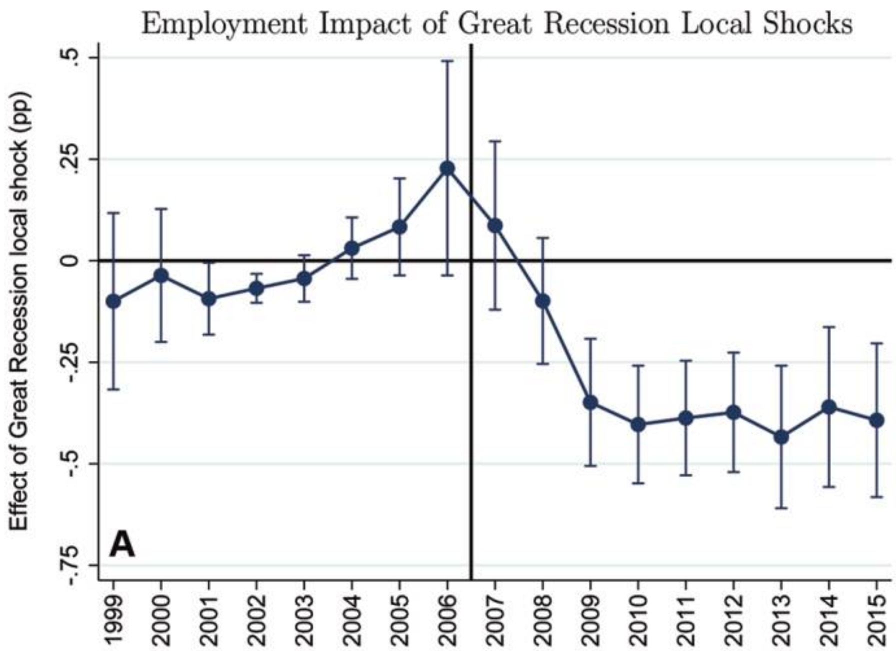
	Mortality			
	Exogenous	Endogenous		
	(1)	(2)	(3)	(4)
Panel A. Starting age 35				
$\gamma = 1.5$	1.35	1.26	1.12	0.99
$\gamma = 2$	1.84	1.76	1.63	1.50
$\gamma = 2.5$	2.38	2.31	2.19	2.08
Panel B. Starting age 45				
$\gamma = 1.5$	1.32	1.14	0.85	0.57
$\gamma = 2$	1.82	1.66	1.39	1.12
$\gamma = 2.5$	2.38	2.23	1.99	1.75
Panel C. Starting age 55				
$\gamma = 1.5$	1.28	0.94	0.40	-0.13
$\gamma = 2$	1.76	1.46	0.97	0.48
$\gamma = 2.5$	2.29	2.02	1.58	1.14
Panel D. Starting age 65				
$\gamma = 1.5$	0.00	-0.61	-1.63	-2.64
$\gamma = 2$	0.00	-0.54	-1.44	-2.34
$\gamma = 2.5$	0.00	-0.47	-1.28	-2.07
VSLY (US$)	-	100K	250K	400K

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

A Appendix

A.1 Figures

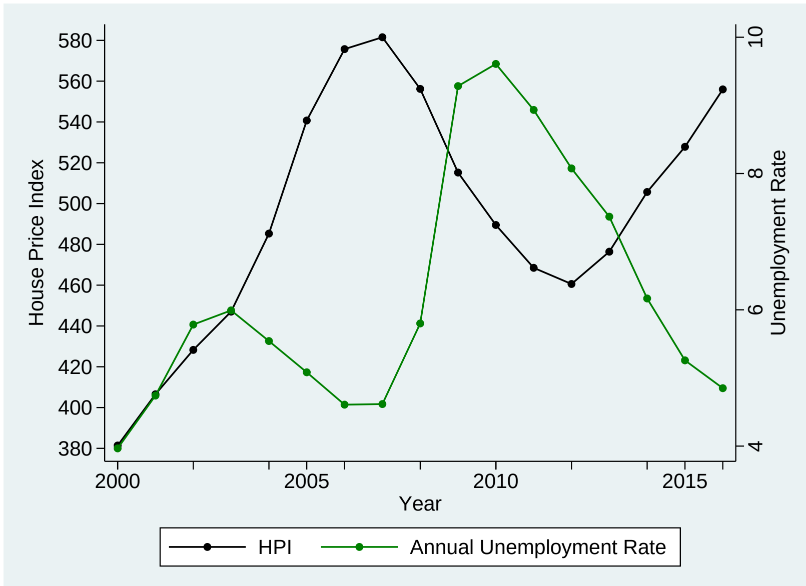
Figure A.1: Figure 4 from Yagan (2019)



Notes: Figure 4a from Yagan (2019). Original notes: "Regression estimates of the effect of Great Recession local shocks on relative employment, controlling for 2007 age-earnings-industry fixed effects in the main sample. Each year t's outcome is year t relative employment: the individual's year t employment (indicator for any employment in t) minus the individual's mean 1999-2006 employment. The 95 confidence intervals are plotted around estimates, clustering on 2007 state. For reference, the 2015 data point) the paper's main estimate implies that a 1 percentage point higher Great Recession local shock causes individuals to be 0.383 percentage points less likely to be employed in 2015."

Figure A.2: House Price Changes and Unemployment

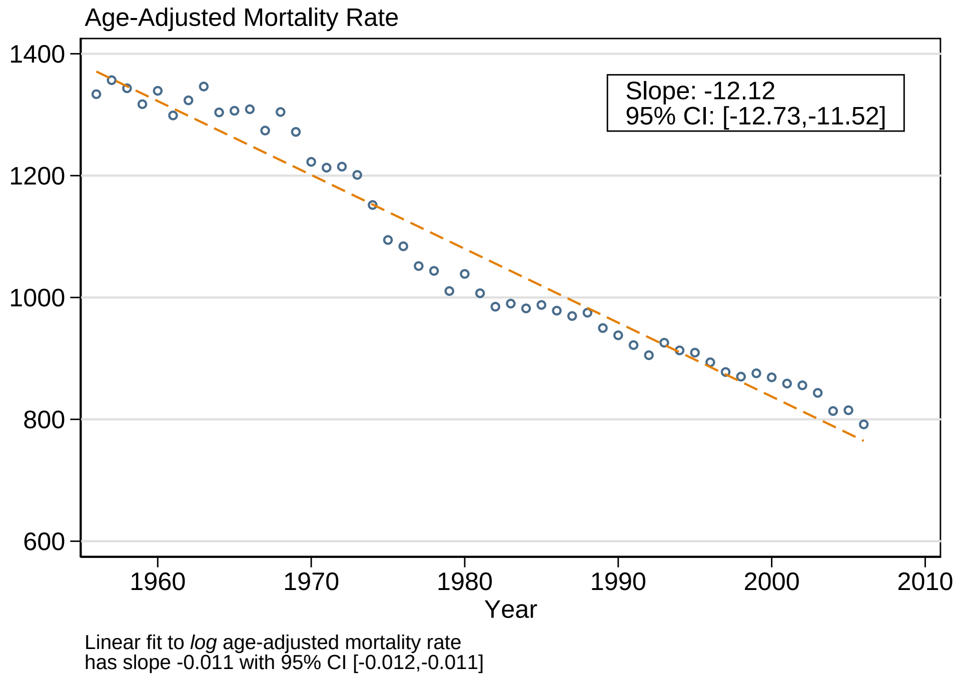
(a) National Time Series



(b) CZ House Prices and Unemployment Rate

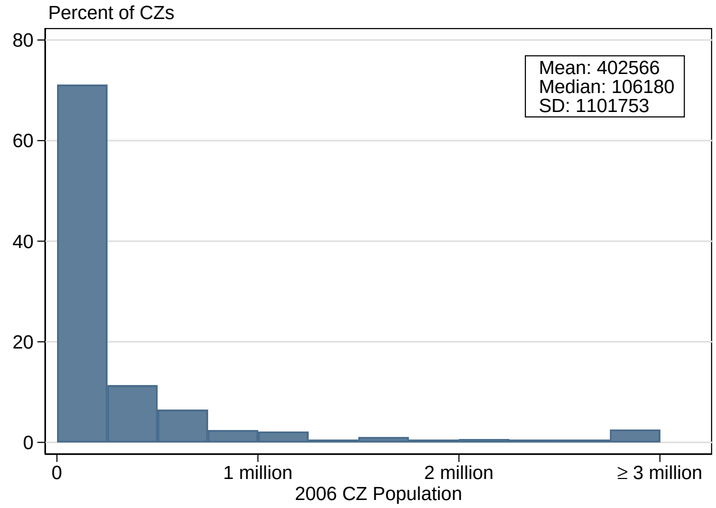
Notes: Figure A.2a plots a national time series of the Federal Housing Finance Agency's yearly House Price Index (HPI) and the annual (average) unemployment rate from the Bureau of Labor Statistics between 2000 and 2016. The raw HPI scale is on the left-hand vertical axis, and the unemployment rate is on the right. Figure A.2b plots the percent change in the CZ-level HPI against the percentage point change in the CZ unemployment rate between 2007 and 2009 by Commuting Zone. Raw county-level data from the House Price Index are collapsed to CZs using 2006 SEER county populations as weights. Note that 405 counties (approximately 1% of the 2006 US population) have no HPI information available for at least one of 2007 and 2009 and are thus excluded from the data. The resulting data displays 690 CZs. A linear fit weighted by 2006 SEER CZ population is displayed in red, with the slope and robust standard error in the lower right-hand corner.

Figure A.3: Age-Adjusted Mortality Rates in the United States, 1956-2006



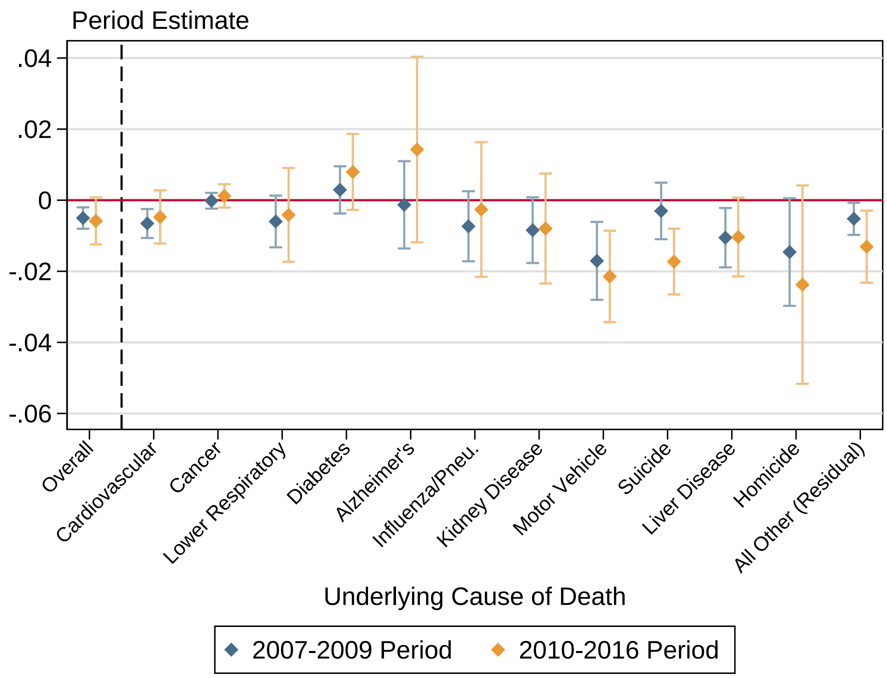
Notes: Figure reports age-adjusted mortality rates per 100,000 in the United States from 1956-2006. Data are drawn from the National Center for Health Statistics, "Mortality Trends in the United States, 1900-2018." Slope reported in text box is a linear fit of the age-adjusted mortality rate to a linear time trend, reported with 95% confidence intervals from robust standard errors. The slope reported in the note below the figure is from a regression of the log age-adjusted mortality rates to the same time trend, similarly with robust standard errors.

Figure A.4: 2006 Commuting Zone Population



Notes: Figure displays a histogram of 2006 Commuting Zone populations as reported in the SEER in bins of 250,000. For visualization purposes, Commuting Zones with populations larger than three million are reported as having populations of three million. Descriptive statistics in the upper right hand corner are reported for the full (not truncated) distribution.

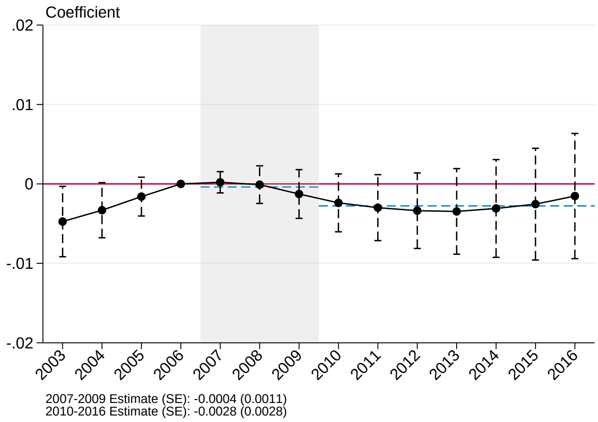
Figure A.5: Impact on Mortality, by Cause of Death



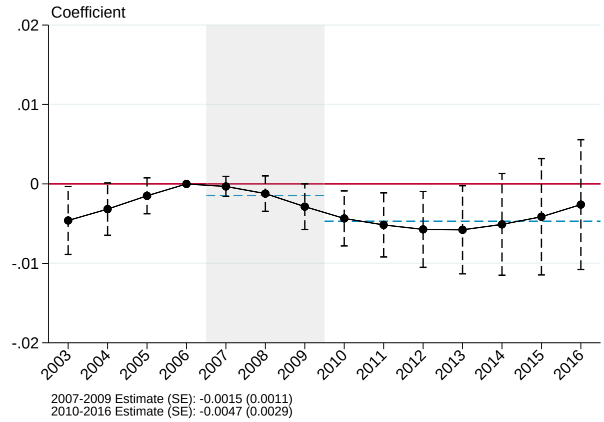
Notes: Figure displays period estimates and 95% confidence intervals for the linear combination of coefficients on $SHOCK_{ct}$ across 2007-2009 and 2010-2016 from equation (2). As in Figure 4, estimates are weighted by the 2006 CZ population from the SEER, and standard errors are clustered at the CZ level. Estimates are displayed for log age-adjusted mortality rates from the 11 most common underlying causes of death as determined by ICD-10 39-Cause mortality classifications: Cardiovascular disease, malignant neoplasms, chronic lower respiratory disease, diabetes, Alzheimer's disease, influenza/pneumonia, kidney disease, motor vehicle accidents, suicide, liver disease, and homicide. A residual category captures mortality from all other causes of death. Causes of death are ordered by frequency, except for "all others," which is reported last.

Figure A.6: Population Impact of the Great Recession

(a) Total Population



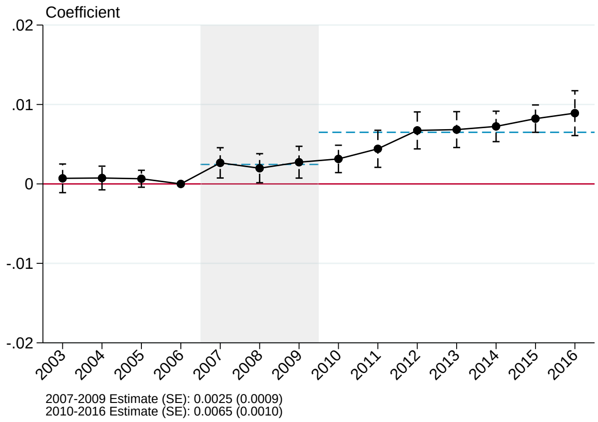
(b) Population Age 25-64



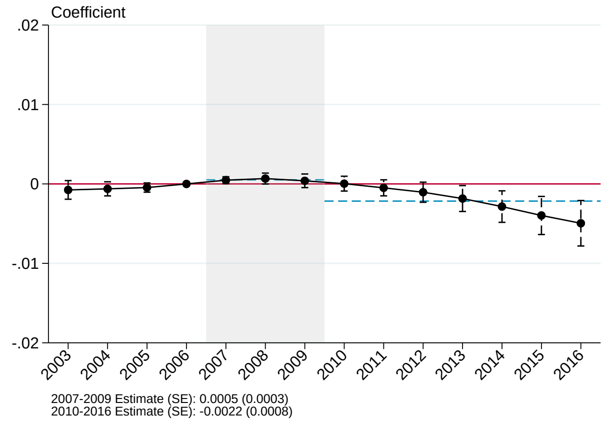
Notes: Figure plots yearly coefficients β_t estimated from equation (1), where the outcome y_{ct} is the log annual total and age 25-64 CZ population from the SEER (Panels A.6a and A.6b, respectively). Event study estimates are weighted by 2006 CZ population. Standard errors are clustered at the CZ level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner.

Figure A.7: Impact of Great Recession on Age Distribution

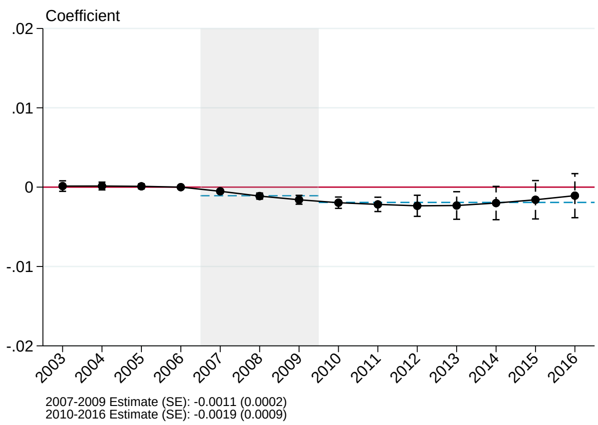
(a) Log Median Age



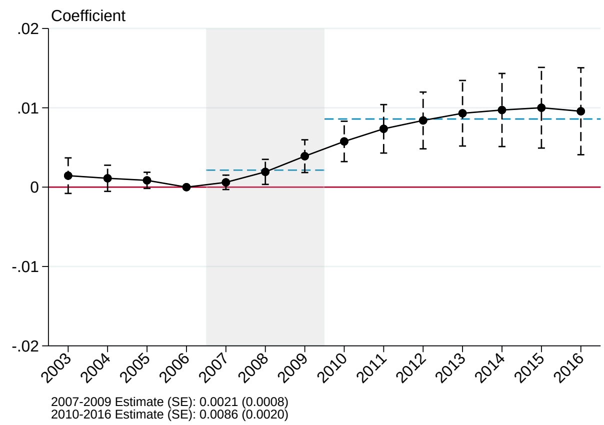
(b) Log Share < 25 Years Old



(c) Log Share 25-64 Years Old



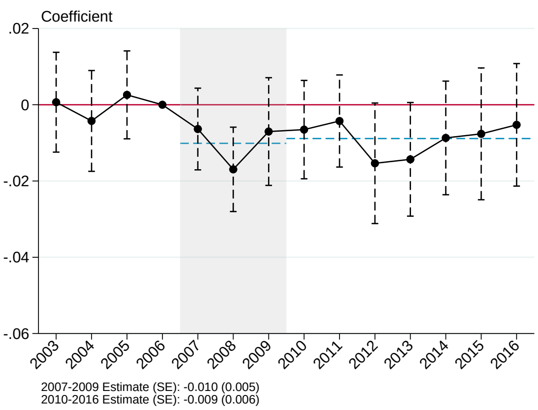
(d) Log Share $\geq$ 65 Years Old



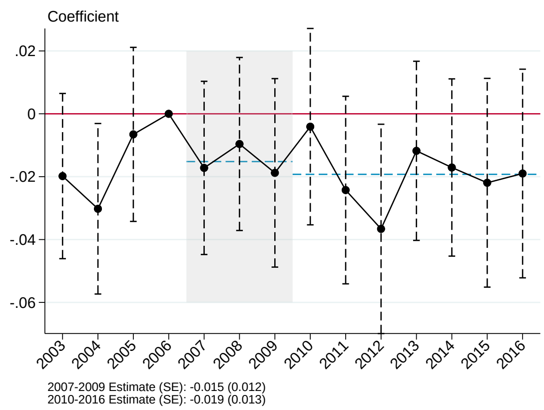
Notes: Figure plots yearly coefficients β_t estimated from equations (1) and (2), where the outcome y_{ct} is the log median age (equation (1)) or the log share of the CZ population in one of three age bins (equation (2), all estimated from the SEER). Panel A.7a displays event studies of the log median age; Panel A.7b the log share under age 25; Panel A.7c the log share age 25-64; and A.7d the log share 65+ years old. Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at the CZ level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel.

Figure A.8: Impact of Great Recession, by Age Group: Age 0-54

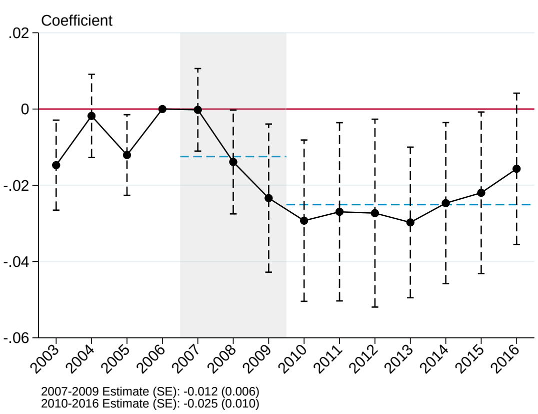
(a) Age 0-4



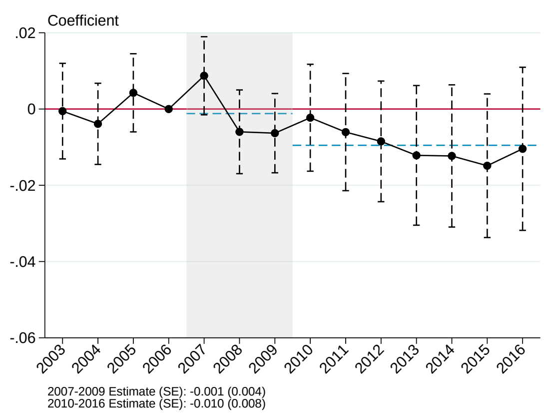
(b) Age 5-14



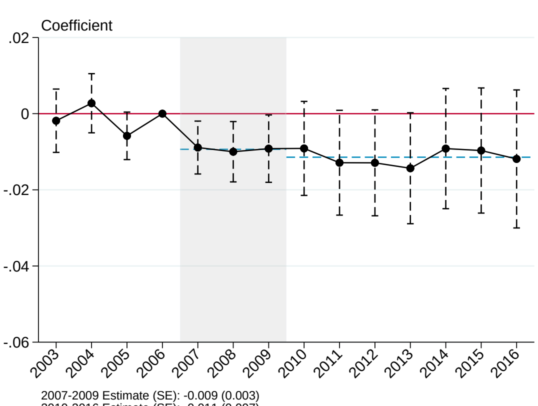
(c) Age 15-24



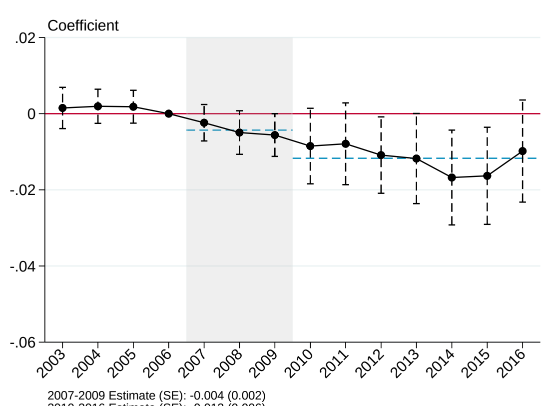
(d) Age 25-34



(e) Age 35-44



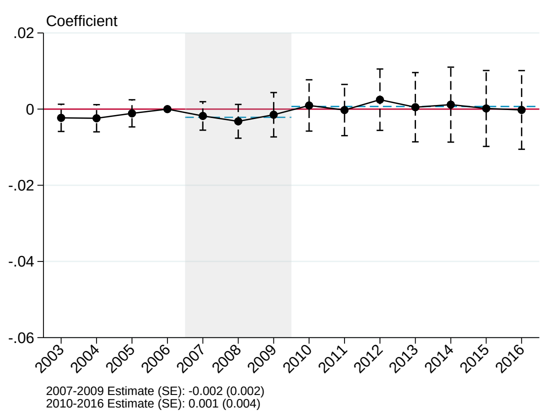
(f) Age 45-54



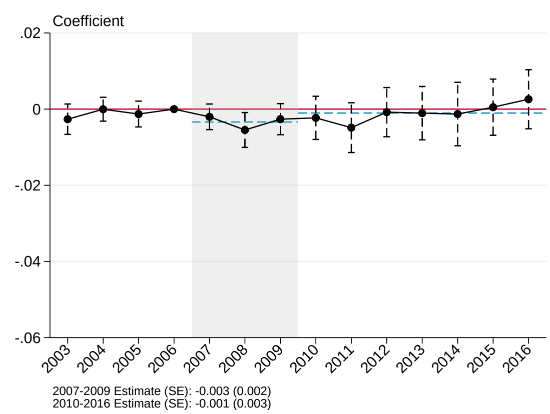
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ct} is the log mortality rate of the CZ population in one of six age bins (all estimated from the SEER). Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are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

Figure A.9: Impact of Great Recession, by Age Group: Age 55+

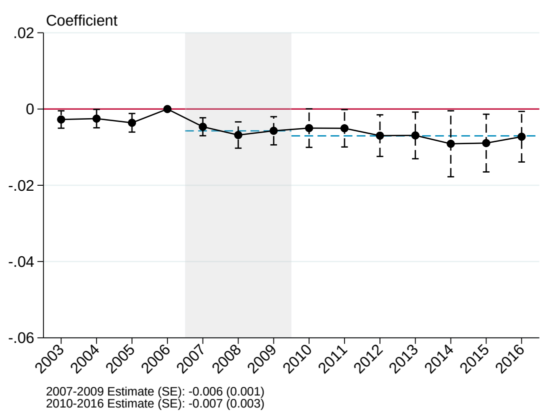
(a) Age 55-64



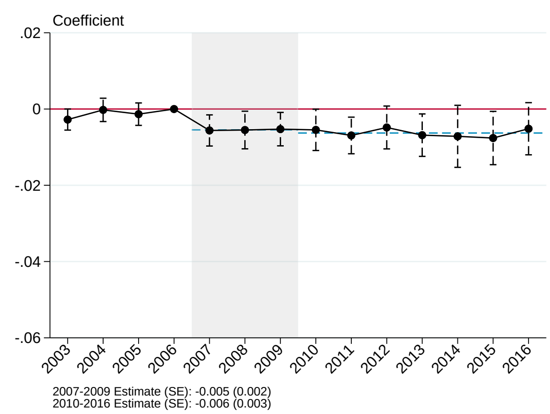
(b) Age 65-74



(c) Age 75-84



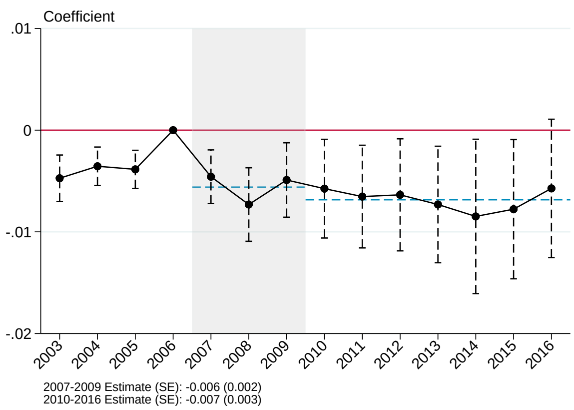
(d) Age 85+



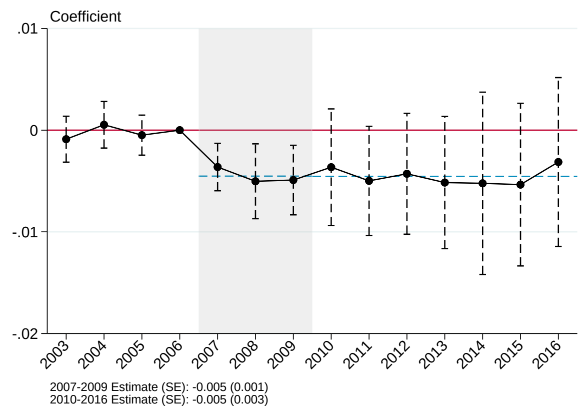
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ct} is the log mortality rate of the CZ population in one of six age bins (all estimated from the SEER). Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are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

Figure A.10: Impact of Great Recession, by Sex

(a) Male



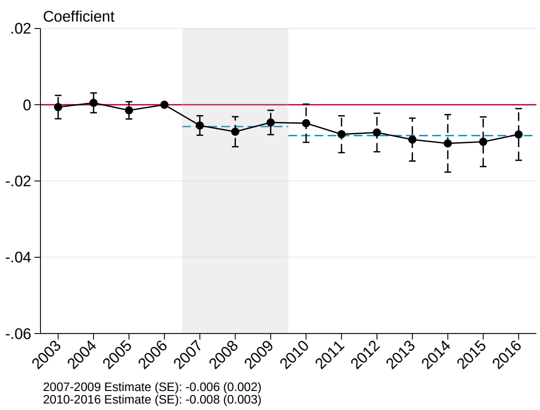
(b) Female



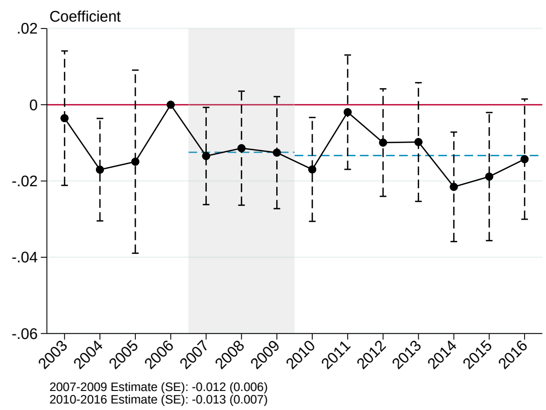
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log CZ mortality rate among either males (Panel A.10a) or females (Panel A.10b). Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at the CZ level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel.

Figure A.11: Impact of Great Recession, by Race

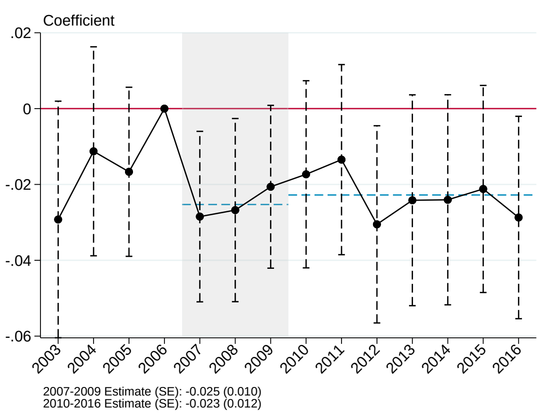
(a) Non-Hispanic White



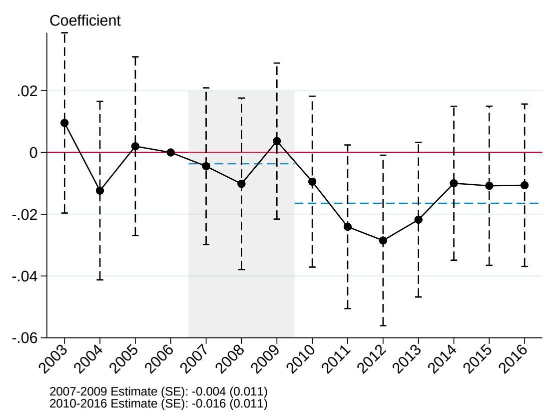
(b) Non-Hispanic Black



(c) Hispanic



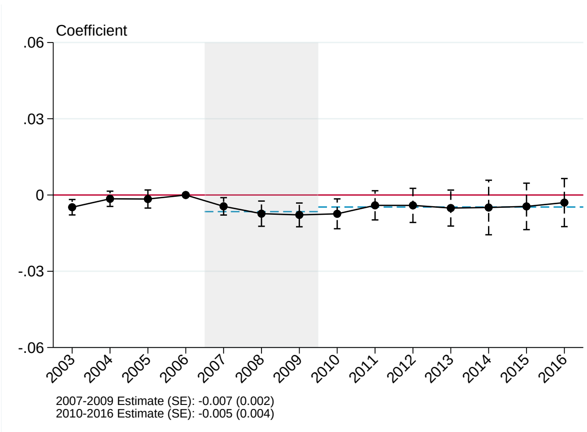
(d) Other



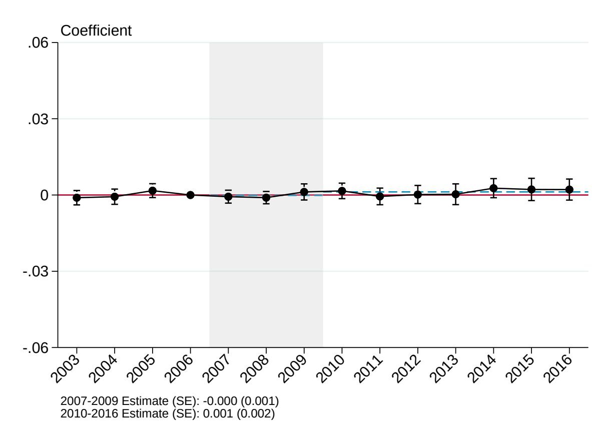
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log mortality rate among the CZ population that is Non-Hispanic White (Panel A.11a), Non-Hispanic Black (Panel A.11b), Hispanic (Panel A.11c) or Other (Panel A.11d). Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at the CZ level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel.

Figure A.12: Impact of Great Recession, by Cause of Death I

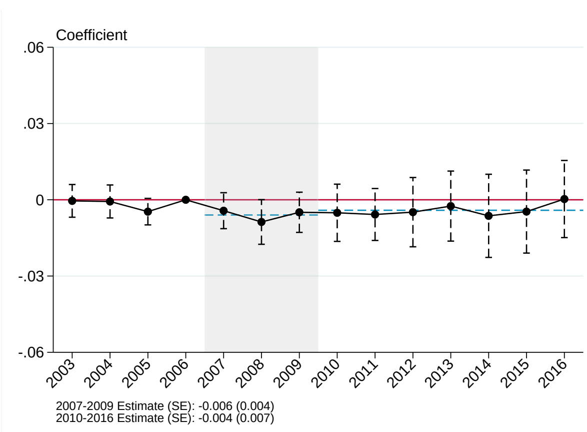
(a) Cardiovascular Disease



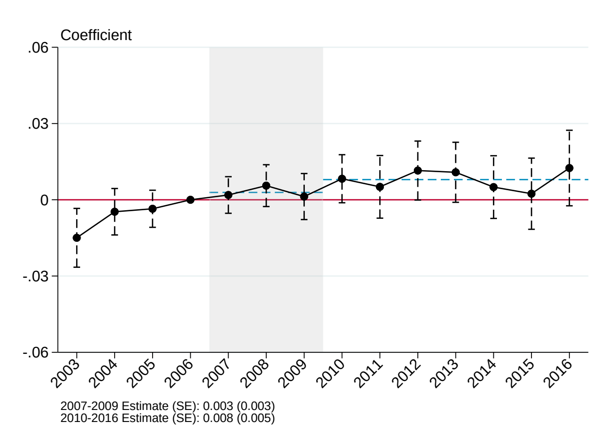
(b) Malignant Neoplasms



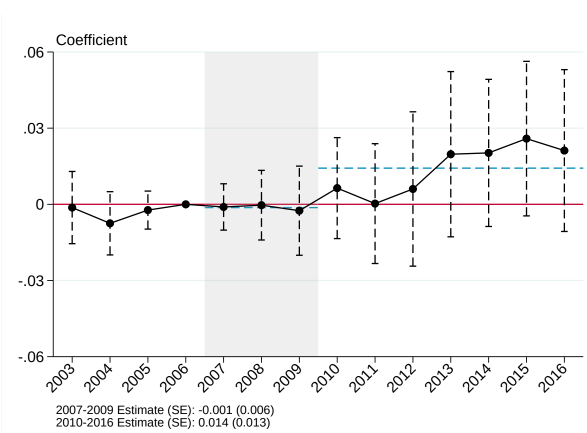
(c) Chronic Lower Respiratory Disease



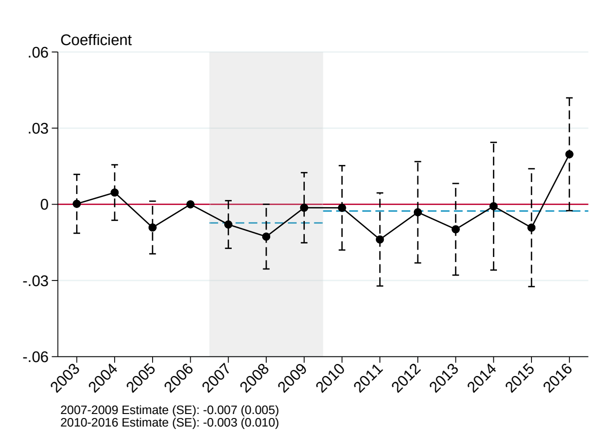
(d) Diabetes



(e) Alzheimer's Disease



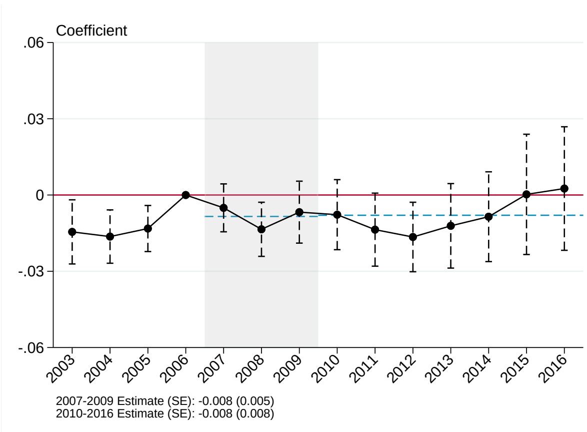
(f) Influenza/Pneumonia



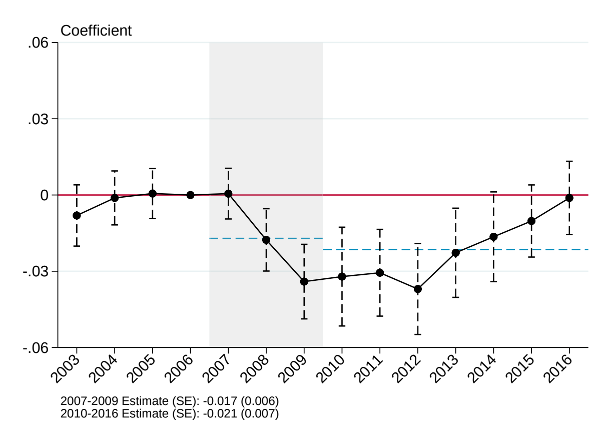
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log CZ mortality rate from one of six causes of death. Panel A.12a displays event studies of the log mortality rate from cardiovascular disease; Panel A.12b from cancer; Panel A.12c from chronic lower respiratory disease; Panel A.12d from diabetes; Panel A.12e from Alzheimer's disease; and Panel A.12f from influenza or pneumonia. Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at the CZ level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel.

Figure A.13: Impact of Great Recession, by Cause of Death II

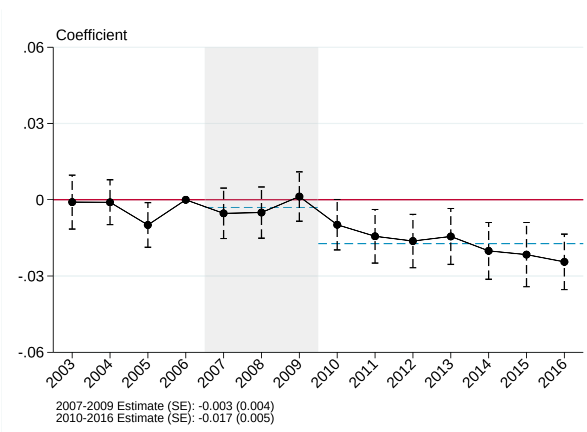
(a) Kidney Disease



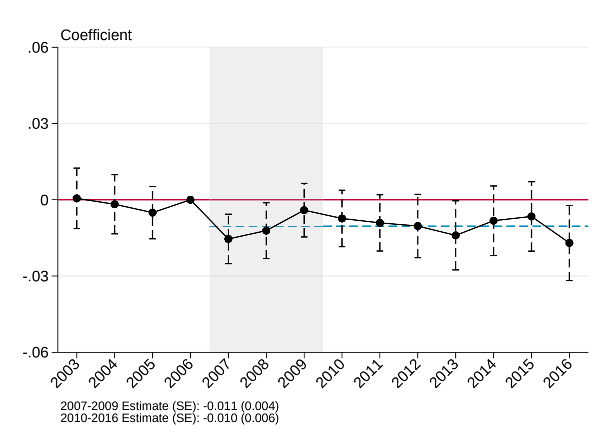
(b) Motor Vehicle Accidents



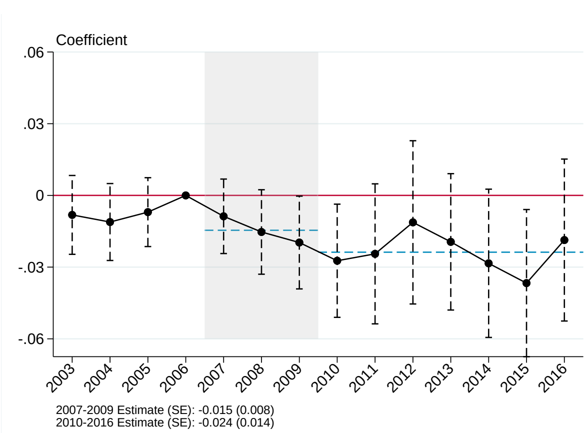
(c) Suicide



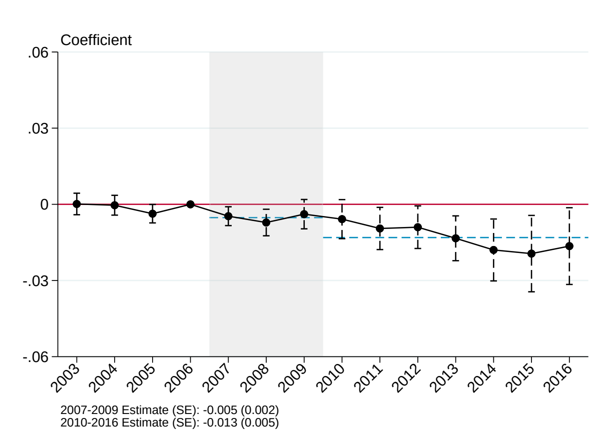
(d) Liver Disease/Cirrhosis



(e) Homicide

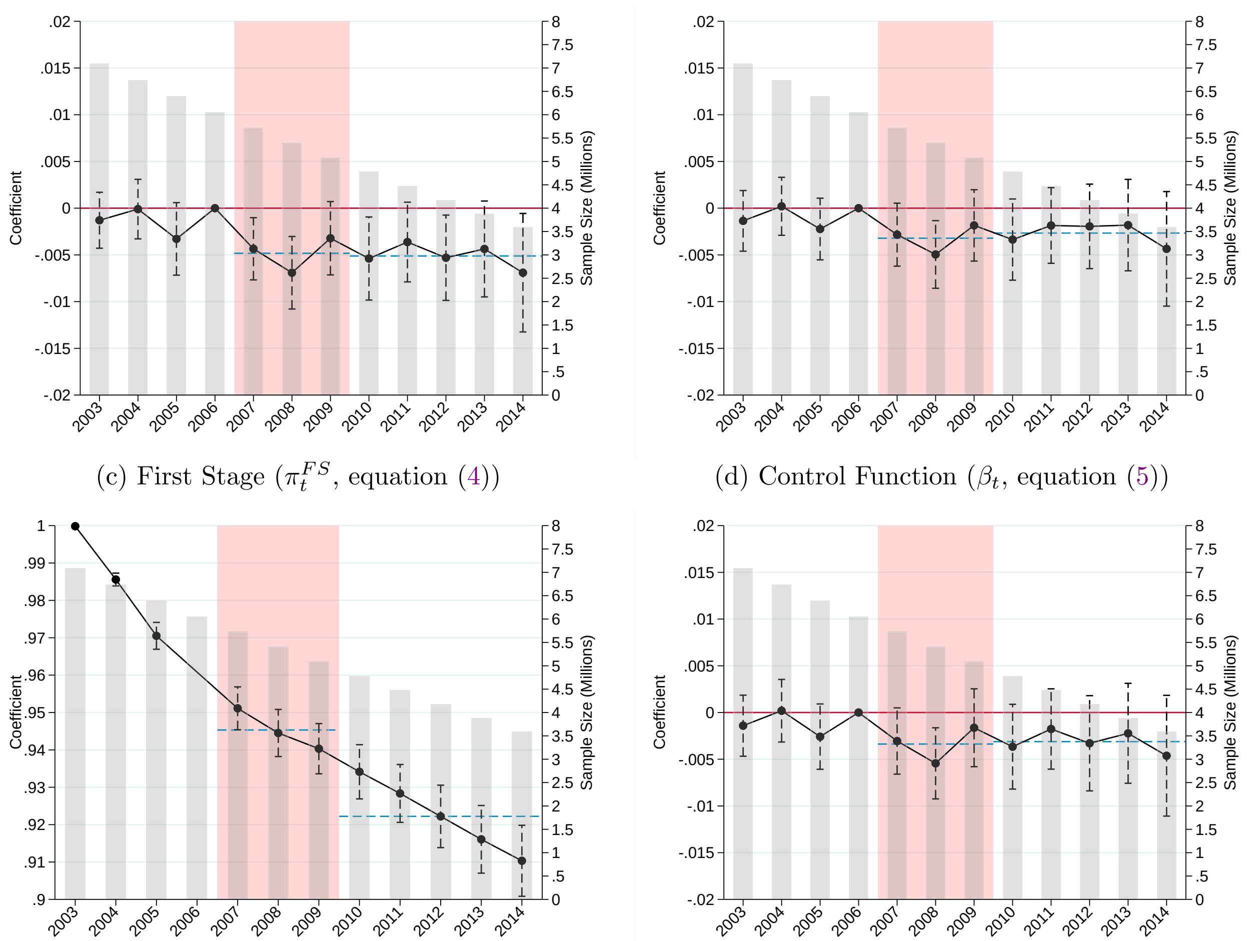


(f) All Other Causes (Residual)



Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log CZ mortality rate from one of six causes of death. Panel A.13a displays event studies of the log mortality rate from kidney disease; Panel A.13b from motor vehicle accidents; Panel A.13c from suicide; Panel A.13d from liver disease; Panel A.13e from homicide; and Panel A.13f from all other causes of death not described in Figure A.12 or A.13. Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at the CZ level. Period estimates for 2007-2009 and 2010-2016 (the average of annual coefficients) are presented with the corresponding standard errors in the lower left hand corner of each panel.

Figure A.14: Sensitvity to yearly vs. baseline residence



(a) Yearly Residence (OLS) (β_t, equation (6))

(b) 2003 Residence (Reduced Form) (π_t^{RF}, equation (3))

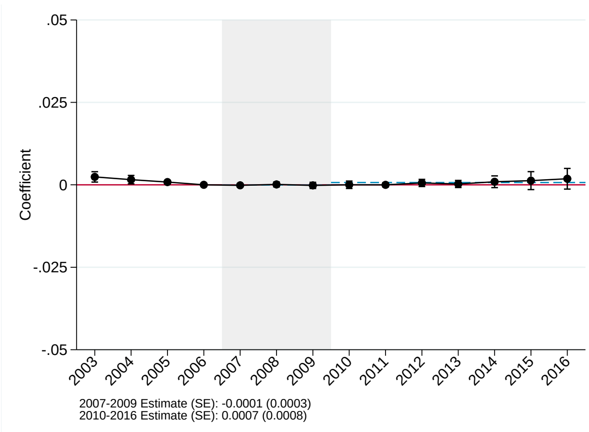
(c) First Stage (π_t^{FS}, equation (4))

(d) Control Function (β_t, equation (5))

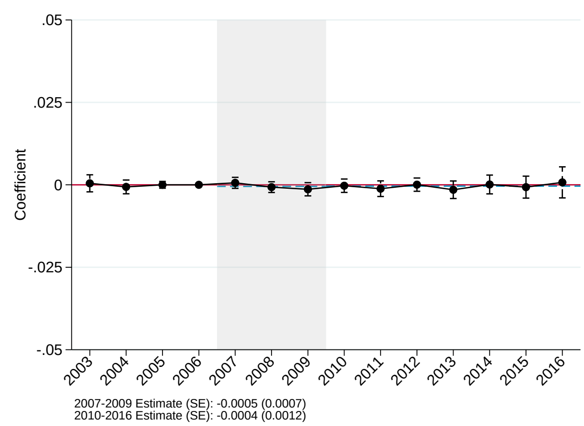
Notes: This figure displays coefficients coefficients β_t from equation (6) (for Panel A), coefficients π_t^{RF} from equation (3) (for Panel B), and coefficients β_t from equation (5) (for Panel D), with outcome $log(h_{it}(a))$ defined as the log of the individual-level hazard rate at age a. The figure also displays coefficients π_t^{FS} from equation (4) (for Panel C), with outcome defined as the sum of the interactions of GR shock based on yearly CZ of residence and yearly dummies. In Panels A and D, each individual is assigned their yearly CZ of residence, while in Panel B each individual is assigned their 2003 CZ of residence. Shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the point estimate for the linear combination of coefficients from 2007-2009 and 2010-2014. Standard errors are clustered by CZ. Control function standard errors are calculated via a Bayesian bootstrap procedure with 450 repetitions. The sample reflects 2003 Medicare beneficiaries, subject to the restrictions in Table A.7. Gray bars indicate the sample size by year (which is reduced each year due to mortality), with the scale determined by the secondary y-axis. N(2003) = 7,088,974.

Figure A.15: Impact of Great Recession on Nursing Home Volume and Resident Characteristics

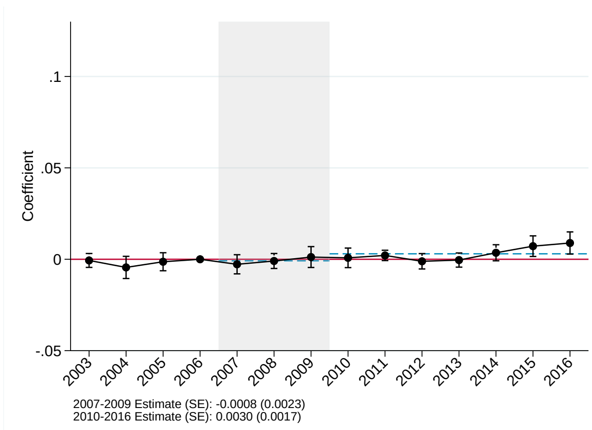
(a) Log Average Age



(b) Log Female Resident Share

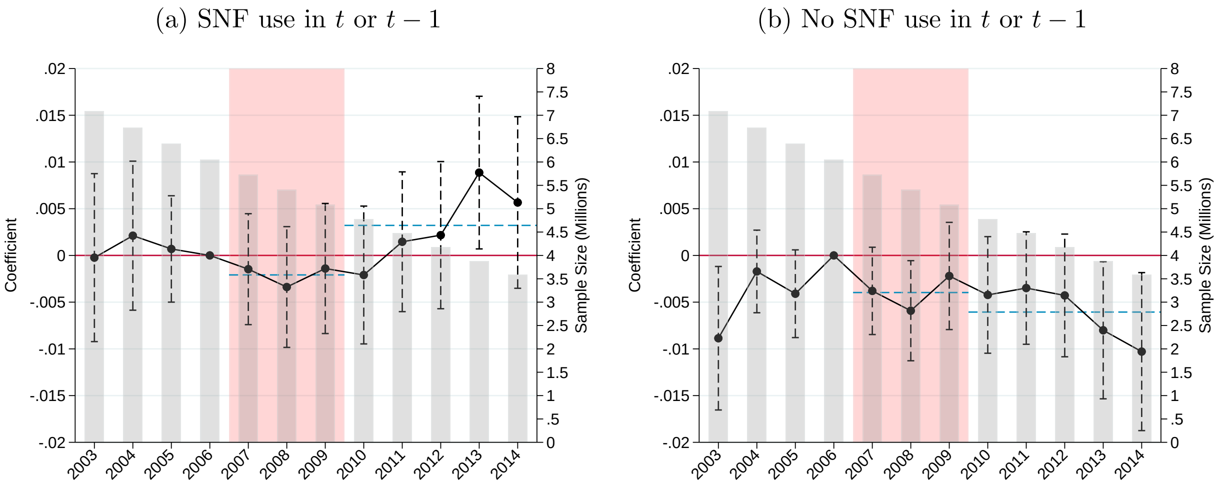


(c) Log Occupants per Bed



Notes: Figure displays coefficients β_t from equation $y_{it} = \beta_t[SHOCK_{c(i)} * \mathbb{1}(Year_t)] + \alpha_{c(i)} + \gamma_t + \varepsilon_{it}$ from 2003-2016, where i indexes skilled nursing facilities and $c(i)$ the Commuting Zone of facility i. The outcome y_{it} in Panel A.15a is the log average age of residents in facility i as of the first Thursday in April of the survey year (from the MDS); in Panel A.15b, the log share of facility residents who are female on the same day (from the MDS); and in Panel A.15c, the log number of occupants per facility bed (the numerator calculated directly from the OSCAR, and the denominator from LTCFocus). Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the mean estimates β_t over the 2007-2009 and 2010-2016 periods (presented with standard errors in the lower left hand corner). Facility observations are weighted by 2006 CZ population from the SEER, and standard errors are clustered at the CZ level.

Figure A.16: Impact of the Great Recession on Log Mortality Hazard Rate, by SNF Use



Figures display yearly coefficients β_t from equation (3), where the outcome used to define a mortality event in year t is either mortality for individuals who are recorded in a SNF in year t or $t-1$ (Panel A) or mortality for individuals not in a SNF in those years (Panel B). Dashed blue lines show the average coefficient over the periods 2007-2009 and 2010-2014; vertical dashed lines indicate 95% confidence intervals. Standard errors are clustered by CZ.

A.2 Tables

Table A.1: Impacts of the Great Recession on Mortality, by Sex and Race

	(1) 2007-2009 Period Estimate	(2) 2010-2016 Period Estimate	(3) 2007-2016 Period Estimate
Overall	-0.0050	-0.0058	-0.0080
	(0.0015)	(0.0034)	(0.0040)
Sex			
Male	-0.0056	-0.0068	-0.0065
	(0.0016)	(0.0030)	(0.0025)
Female	-0.0045	-0.0045	-0.0045
	(0.0015)	(0.0035)	(0.0028)
Race			
Non-Hispanic White	-0.0057	-0.0081	-0.0074
	(0.0015)	(0.0029)	(0.0024)
Non-Hispanic Black	-0.0125	-0.0133	-0.0131
	(0.0063)	(0.0068)	(0.0065)
Hispanic	-0.0253	-0.0228	-0.0235
	(0.0098)	(0.0121)	(0.0109)
Non-Hispanic Other	-0.0037	-0.0165	-0.0126
	(0.0111)	(0.0112)	(0.0106)

Notes: Table displays the average annual impact of the Great Recession on age-adjusted mortality over three periods: 2007-2009, 2010-2016, and 2007-2016. Estimates are displayed for the overall population (averages of β_t from equation (1)), as well as separately by sex and race (within-group averages of β_{tg} from equation (2)). Standard errors, clustered at the CZ level, are reported in parentheses below each period estimate.

Table A.2: Impacts of the Great Recession on Mortality, by Age Group

	(1) 2007-2009 Period Estimate	(2) 2010-2016 Period Estimate	(3) 2007-2016 Period Estimate
Overall	-0.0050	-0.0058	-0.0080
	(0.0015)	(0.0034)	(0.0040)
Age Bin			
0-4 years	-0.0101	-0.0089	-0.0092
	(0.0050)	(0.0061)	(0.0054)
5-14 years	-0.0152	-0.0193	-0.0180
	(0.0119)	(0.0130)	(0.0121)
15-24 years	-0.0125	-0.0251	-0.0213
	(0.0062)	(0.0102)	(0.0088)
25-34 years	-0.0012	-0.0095	-0.0070
	(0.0044)	(0.0080)	(0.0065)
35-44 years	-0.0094	-0.0114	-0.0108
	(0.0033)	(0.0071)	(0.0057)
45-54 years	-0.0043	-0.0117	-0.0095
	(0.0024)	(0.0057)	(0.0045)
55-64 years	-0.0022	0.0007	-0.0002
	(0.0021)	(0.0043)	(0.0035)
65-74 years	-0.0034	-0.0010	-0.0017
	(0.0018)	(0.0034)	(0.0029)
75-84 years	-0.0057	-0.0070	-0.0066
	(0.0014)	(0.0031)	(0.0025)
85+ years	-0.0055	-0.0063	-0.0060
	(0.0022)	(0.0030)	(0.0027)

Notes: Table displays the average annual impact of the Great Recession on mortality over three periods: 2007-2009, 2010-2016, and 2007-2016. Estimates are displayed for the overall population (averages of β_t from equation (1)), as well as separately by 10 age groups (within-group averages of β_{tg} from equation (2)). Note that age group mortality is the raw mortality rate; overall mortality is the age-adjusted mortality rate. Standard errors, clustered at the CZ level, are reported in parentheses below each period estimate.

Table A.3: Decomposition Estimates — Age Bins

Age at Death	(1) *Age Group Share of Total Mortality (2006)*	(2) *Age Group Mortality Rate (2006)* r_i	(3) *Share of Total Population (2006)* w_i	(4) *Estimated 2007-2009 Percent Reduction in Mortality Rate* δ_i	(5) *Share of Overall Estimated 2007-2009 Reduction* $\frac{r_i w_i \delta_i}{\sum_i r_i w_i \delta_i}$
All Ages	*1.0000*	*0.0079*[a]	*1.0000*	*-0.0050*	*1.0000*
				(0.0015)	
Age Bins (i):					
0-4 years	0.0137	0.0017	0.0668	-0.0101	0.0278
				(0.0050)	(0.0149)
5-14 years	0.0025	0.0002	0.1360	-0.0152	0.0077
				(0.0119)	(0.0060)
15-24 years	0.0144	0.0008	0.1436	-0.0125	0.0361
				(0.0062)	(0.0136)
25-34 years	0.0177	0.0011	0.1320	-0.0012	0.0043
				(0.0044)	(0.0154)
35-44 years	0.0342	0.0019	0.1449	-0.0094	0.0643
				(0.0033)	(0.0208)
45-54 years	0.0763	0.0043	0.1451	-0.0043	0.0661
				(0.0024)	(0.0259)
55-64 years	0.1160	0.0088	0.1070	-0.0022	0.0503
				(0.0021)	(0.0383)
65-74 years	0.1608	0.0203	0.0644	-0.0034	0.1092
				(0.0018)	(0.0449)
74-84 years	0.2751	0.0510	0.0439	-0.0057	0.3164
				(0.0014)	(0.0543)
85+ years	0.2894	0.1443	0.0163	-0.0055	0.3178
	.	.	.	(0.0022)	(0.0600)

[a] Age-adjusted mortality rate.

Notes: Table presents a decomposition of the overall estimated mortality reduction by age group. Decompositions are estimated algebraically: For groups i with base period mortality rate r_i, population share w_i, and percent mortality reduction δ_i, the share of the overall mortality reduction contributed by group i is $\frac{r_i w_i \delta_i}{\sum_i r_i w_i \delta_i}$. Age group mortality reductions δ_i are estimated as the period average of the β_{tg} from equation (2), where $Group_g$is one of ten age bins. Standard errors for the estimates in columns (4) and (5) are included in parentheses, clustered at the CZ level.

Table A.4: Impacts of the Great Recession on Mortality, by Cause of Death

	(1) 2007-2009 Period Estimate	(2) 2010-2016 Period Estimate	(3) 2007-2016 Period Estimate
Overall	-0.0050	-0.0058	-0.0080
	(0.0015)	(0.0034)	(0.0040)
Underlying Cause of Death			
Cardiovascular Disease	-0.0065	-0.0047	-0.0053
	(0.0021)	(0.0038)	(0.0032)
Malignant Neoplasms (Cancer)	0.0011	0.0017	0.0014
	(-0.0002)	(0.0012)	(0.0008)
Chronic Lower Respiratory Disease	-0.0060	-0.0041	-0.0047
	(0.0037)	(0.0067)	(0.0057)
Diabetes	0.0034	0.0054	0.0044
	(0.0029)	(0.0079)	(0.0064)
Alzheimer's Disease	-0.0013	0.0143	0.0096
	(0.0063)	(0.0133)	(0.0110)
Influenza/Pneumonia	-0.0073	-0.0026	-0.0040
	(0.0050)	(0.0097)	(0.0081)
Kidney Disease	-0.0084	-0.0080	-0.0081
	(0.0047)	(0.0079)	(0.0066)
Motor Vehicle Accidents	-0.0171	-0.0215	-0.0201
	(0.0056)	(0.0066)	(0.0061)
Suicide	0.0041	0.0047	0.0040
	(-0.0030)	(-0.0173)	(-0.0130)
Liver Disease/Cirrhosis	-0.0105	-0.0104	-0.0104
	(0.0043)	(0.0057)	(0.0049)
Homicide	-0.0146	-0.0237	-0.0210
	(0.0077)	(0.0142)	(0.0120)
All Other Causes (Residual)	-0.0052	-0.0131	-0.0107
	(0.0023)	(0.0052)	(0.0042)

Notes: Table displays the average annual impact of the Great Recession on age-adjusted mortality over three periods: 2007-2009, 2010-2016, and 2007-2016. Estimates are displayed for the overall population (averages of β_t from equation (1)), as well as separately by the 11 most common causes of death in 2006 and a residual mortality category (within-group averages of β_{tg} from equation (2)). Standard errors, clustered at the CZ level, are reported in parentheses below each period estimate.

Table A.5: Impacts of the Great Recession on CZ Population

	(1) 2007-2009 Period Estimate	(2) 2010-2016 Period Estimate	(3) 2007-2016 Period Estimate
Log Total Population	-0.0004	-0.0028	-0.0021
	(0.0011)	(0.0028)	(0.0023)
Log 25-64 Population	-0.0015	-0.0047	-0.0037
	(0.0011)	(0.0029)	(0.0023)
Log Median Age	0.0893	0.2494	0.2013
	(0.0299)	(0.0329)	(0.0308)
Log Share ¡ 25 Years Old	0.0005	-0.0022	-0.0014
	(0.0003)	(0.0008)	(0.0007)
Log Share 25-64 Years Old	-0.0011	-0.0019	-0.0017
	(0.0002)	(0.0009)	(0.0006)
Log Share ≥65 Years Old	0.0021	0.0086	0.0067
	(0.0008)	(0.0020)	(0.0016)
Log Share Female	-0.0003	-0.0012	-0.0009
	(0.0001)	(0.0002)	(0.0001)
Log Share White	-0.0013	-0.0026	-0.0022
	(0.0008)	(0.0024)	(0.0019)

Notes: Table displays the average of coefficients β_t estimated from equation (1), where the outcome Y_{ct} is one of several CZ-level population statistics: log total population, log median age, and the log shares under age 25, age 25-64, age 65+, female, and White. Period estimates are calculated over 2007-2009, 2010-2016, and 2007-2016. Coefficients are weighted by 2006 CZ population as measured in the SEER. Standard errors, clustered at the CZ level, are reported in parentheses below each period estimate.

Table A.6: Decomposition Estimates — Motor Vehicle Accidents, by Age Bins

Age at Death	(1) *Age Group Share of Motor Vehicle Mortality (2006)*	(2) *Age Group Mortality Rate (2006)* r_{ij}	(3) *Age Group Share of Total Population (2006)* w_i	(4) *Estimated 2007-2009 Percent Reduction in Motor Vehicle Mortality Rate* δ_{ij}	(5) *Share of Overall Estimated 2007-2009 Reduction* $\frac{r_{ij}w_i\delta_{ij}}{\sum_i r_{ij}w_i\delta_{ij}}$
All Ages	*1.0000*	*0.0001*[a]	*1.0000*	*-0.0171*	*1.0000*
				(0.0056)	
Age Bins (i):					
0-4 years	0.0161	0.0000	0.0668	-0.0124	0.0110
				(0.0277)	(0.0246)
5-14 years	0.0296	0.0000	0.1360	-0.0260	0.0425
				(0.0196)	(0.0312)
15-24 years	0.2431	0.0003	0.1436	-0.0254	0.3415
				(0.0113)	(0.0984)
25-34 years	0.1622	0.0002	0.1320	-0.0063	0.0568
				(0.0106)	(0.0923)
35-44 years	0.1474	0.0002	0.1449	-0.0345	0.2817
				(0.0120)	(0.0943)
45-54 years	0.1460	0.0002	0.1451	-0.0325	0.2627
				(0.0107)	(0.0826)
55-64 years	0.0997	0.0001	0.1070	-0.0040	0.0223
				(0.0114)	(0.0605)
65-74 years	0.0644	0.0002	0.0644	-0.0026	0.0091
				(0.0140)	(0.0491)
74-84 years	0.0641	0.0002	0.0439	0.0057	-0.0201
				(0.0165)	(0.0617)
85+ years	0.0274	0.0003	0.0163	0.0049	-0.0074
				(0.0316)	(0.0490)

[a] Age-adjusted mortality rate.

Notes: Table presents a decomposition of the overall estimated reduction in motor vehicle mortality by age group. Decompositions are estimated algebraically: For age groups groups i and cause of death j, with base period cause-of-death mortality rate r_{ij}, age group population share w_i, and estimated cause-of-death percent mortality reduction δ_{ij}, the share of the overall mortality reduction contributed by group i is $\frac{r_{ij}w_i\delta_{ij}}{\sum_i r_{ij}w_i\delta_{ij}}$. Age group mortality reductions δ_i are estimated as the period average of the β_{tg} from equation (2), where $Group_g$is one of ten age bins. Standard errors for the estimates in columns (4) and (5) are included in parentheses, clustered at the CZ level.

Table A.7: Medicare Beneficiary Sample Restrictions

	Number of Beneficiaries (2003)
Unique beneficiaries in the 2003 Medicare beneficiary 20% sample	8,624,883
Exclude beneficiaries that are:	
Younger than 65 or older than 99 in 2003	7,319,817
Living overseas or in US territories in at least one year	7,168,886
Not observed until the end of the period, but no death date	7,097,655
Not matched with a commuting zone in at least one year	7,095,616
Associated with missing records in a pre-death year	7,088,974
Number of beneficiaries	**7,088,974**

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

Table A.8: Medicare Beneficiary Sample Demographic Summary Statistics

	All Beneficiaries	Traditional Medicare (TM) in 2003
	(1)	(2)
Share female	0.58	0.59
Share white	0.87	0.88
Mean age (2003)	75.56	76.33
Share in age group (2003)		
65-74	0.50	0.46
75-84	0.36	0.39
85+	0.14	0.15
Share movers	0.11	0.11
Share enrolled in Medicaid (2003)	0.12	0.14
Share enrolled in Medicare Advantage (2003)	0.15	0.00
Mortality Rate (2003, per 100,000)	4,980	5,470
Number of patients	7,088,974	5,459,866

Notes: The table displays summary statistics on two Medicare beneficiary samples: all beneficiaries and 2003 Traditional Medicare beneficiaries. The "All Beneficiaries" sample represents 2003 Medicare beneficiaries, subject to the restrictions in Table A.7. In the "Traditional Medicare in 2003" sample, beneficiaries must be enrolled in Medicare Part B in every 2003 month. This excludes Medicare Advantage recipients in any month and 2003 Medicare entrants in any month other than January. Medicaid and Medicare Advantage enrollment in 2003 is determined as enrollment in any 2003 month.

Table A.9: Recession Effect in Life Expectancy by Age and Recession Type

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

Age	Mortality Rate (per 100,000)	Life Expectancy (without recession)	Life Expectancy (with recession)	Percent Difference	Increase in Life Expectancy
35	167	41.970	41.972	0.005%	0.002
45	355	32.843	32.846	0.011%	0.004
55	790	24.369	24.374	0.024%	0.006
65	1685	16.659	16.667	0.052%	0.009
75	4003	10.104	10.116	0.125%	0.013

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

Age	Mortality Rate (per 100,000)	Life Expectancy (without recession)	Life Expectancy (with recession)	Percent Difference	Increase in Life Expectancy
35	167	41.970	41.990	0.047%	0.020
45	355	32.843	32.877	0.105%	0.034
55	790	24.369	24.419	0.207%	0.050
65	1685	16.659	16.730	0.430%	0.072
75	4003	10.104	10.195	0.899%	0.091

Notes: Age-specific mortality rates taken from the Social Security Administration 2007 life tables for males, available at `https://www.ssa.gov/oact/HistEst/PerLifeTables/2022/PerLifeTables2022.html`. Life expectancy is calculated from age-specific mortality rates. To calculate mortality rates with recessions, we assume that a one percentage point increase in unemployment generates a 0.5% decrease in mortality rates for the duration of the recession, as per the empirical sections of this paper.

Table A.10: Welfare Costs of Great Recession (5 Years) by Age

	Mortality			
	Exogenous	Endogenous		
	(1)	(2)	(3)	(4)
Panel A. Starting age 35				
$\gamma = 1.5$	0.58	0.54	0.48	0.42
$\gamma = 2$	0.79	0.75	0.70	0.64
$\gamma = 2.5$	1.02	0.99	0.94	0.88
Panel B. Starting age 45				
$\gamma = 1.5$	0.63	0.54	0.42	0.29
$\gamma = 2$	0.86	0.78	0.67	0.55
$\gamma = 2.5$	1.12	1.05	0.94	0.84
Panel C. Starting age 55				
$\gamma = 1.5$	0.62	0.46	0.21	-0.05
$\gamma = 2$	0.85	0.71	0.48	0.24
$\gamma = 2.5$	1.10	0.98	0.77	0.56
Panel D. Starting age 65				
$\gamma = 1.5$	0.00	-0.30	-0.80	-1.31
$\gamma = 2$	0.00	-0.26	-0.71	-1.16
$\gamma = 2.5$	0.00	-0.23	-0.63	-1.03
VSLY (US$)	-	100K	250K	400K

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

Table A.11: Welfare Costs of Recessions by Age: Without Retirement

	Mortality			
	Exogenous	Endogenous		
	(1)	(2)	(3)	(4)
Panel A. Starting age 35				
$\gamma = 1.5$	1.68	1.33	0.86	0.40
$\gamma = 2$	2.28	1.96	1.52	1.07
$\gamma = 2.5$	2.98	2.71	2.30	1.90
Panel B. Starting age 45				
$\gamma = 1.5$	1.39	0.99	0.43	-0.13
$\gamma = 2$	1.91	1.54	1.01	0.49
$\gamma = 2.5$	2.51	2.19	1.71	1.23
Panel C. Starting age 55				
$\gamma = 1.5$	1.14	0.67	-0.01	-0.69
$\gamma = 2$	1.55	1.12	0.49	-0.14
$\gamma = 2.5$	2.02	1.65	1.07	0.51
Panel D. Starting age 65				
$\gamma = 1.5$	0.86	0.30	-0.54	-1.38
$\gamma = 2$	1.18	0.68	-0.10	-0.87
$\gamma = 2.5$	1.54	1.10	0.40	-0.28
VSLY (US$)	-	100K	250K	400K

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

Table A.12: Welfare Costs of Great Recession (10 Years) by Age: Without Retirement

	Mortality			
	Exogenous	Endogenous		
	(1)	(2)	(3)	(4)
Panel A. Starting age 35				
$\gamma = 1.5$	1.33	1.24	1.10	0.96
$\gamma = 2$	1.81	1.73	1.60	1.47
$\gamma = 2.5$	2.35	2.27	2.15	2.03
Panel B. Starting age 45				
$\gamma = 1.5$	1.29	1.09	0.80	0.51
$\gamma = 2$	1.77	1.59	1.32	1.05
$\gamma = 2.5$	2.32	2.16	1.91	1.66
Panel C. Starting age 55				
$\gamma = 1.5$	1.22	0.85	0.30	-0.25
$\gamma = 2$	1.68	1.34	0.82	0.31
$\gamma = 2.5$	2.18	1.89	1.42	0.96
Panel D. Starting age 65				
$\gamma = 1.5$	1.11	0.40	-0.70	-1.77
$\gamma = 2$	1.54	0.90	-0.11	-1.09
$\gamma = 2.5$	2.02	1.46	0.55	-0.34
VSLY (US$)	-	100K	250K	400K

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