The Impact of the Great Recession on Health and Welfare

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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 average, annual age-adjusted mortality rate by 2.3 percent, 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 cost of recession-induced consumption changes substantially reduces the implied welfare cost of the Great Recession, particularly at older ages where it may even have been welfare-improving.

****PRELIMINARY AND INCOMPLETE!****
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1 Introduction

People hate recessions. Macro-economists have calibrated their welfare costs, focusing on their impact on the level and volatility of consumption (e.g. Lucas 1987, 2003; Krebs 2007). At the same time, health economists have found that, in the 1970s and 1980s, mortality was pro-cylical (e.g. Ruhm 2000, 2003, 2005; Stevens et al. 2015), although perhaps not in the subsequent two decades (Ruhm 2015). Any such mortality impacts of recessions could potentially have substantial impacts on their welfare consequences, both overall and across groups.

We consider this possibility in the context of the 2007-2009 Great Recession in the United States. At the time, the Great Recession produced the largest decline in employment since the Great Depression. 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 the annual mortality rate by 2.3 percent, with effects persisting for at least 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 explore potential mechanisms behind the evidence for a recession-induced mortality decline. We first confirm that our results are not spuriously driven by unmeasured changes in the local

[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).

population by confirming that our findings still hold when we analyze individual-panel level data for the elderly, which allows us to use their pre-recession location as an instrument for their current location. We then explore potential causes of mortality declines, 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 assess the quantitative importance of our estimated mortality effects by considering how incorporating them alters a standard welfare analysis of the Great Recession based solely on its impacts on consumption. To do so, we extend the Krebs (2007) model of the welfare cost of recessions from consumption changes to allow for mortality to also vary with recessions and for these mortality changes to affect welfare. Our results suggest that accounting for endogenous mortality effects substantially reduces standard estimates of the welfare cost of the Great Recession. 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 cost of the Great Recession for someone who was 45 years old at its onset was 1.8 percent of average annual consumption if mortality is assumed to be exogenous to aggregate economic conditions, but is 25 percent lower—only 1.4 percent of consumption, once we account for the mortality benefits from the Great Recession. We also find that the reduction in the welfare cost of the Great Recession 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.

Our paper relates to several literatures. Most narrowly, our paper contributes to the literature on the impacts of the Great Recession. Researchers have studied its impacts on a variety of economic outcomes including employment (Yagan 2019), consumption (Mian et al. 2013), time use (Aguiar et al. 2013), and educational attainment (Charles et al. 2015). They have also studied its impact on health, with mixed results. Seeman et al. (2018) find time-series evidence that blood pressure and blood glucose levels worsened for adults during the Great Recession. Currie et al. (2015) examine the relationship between mothers' health and changes in the state unemployment rate and find that the Great Recession worsened physical and mental health of disadvantaged women, but may have improved the health of more advantaged women. Cutler and Sportiche (2022) find no impact of the Great Recession on the mental health of pre-retirement adults (ages 51-61) in the Health and Retirement Survey, exploiting geographic variation in the extent of house price declines during the Great Recession.

More broadly, our paper relates to literature on the relationship between the economy and health. A large body of evidence suggests that improvements in the economy are likely good for health. There is a well-documented negative relationship between income and mortality within country, across countries, and over time (e.g. Chetty et al. 2016; Cutler et al. 2006; Costa 2015; Cutler et al. 2016).[2] There is also evidence that job loss increases mortality (Sullivan and Von Wachter 2009), that reduced economic prospects contribute to "deaths of despair" (Case and Deaton 2021), and that counties exposed to greater 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 (Autor et al. 2019). All of this suggests that the Great Recession would reduce mortality.

However, the existing empirical work on the relationship between recessions and mortality raises questions about what to expect for the Great Recession. On the one hand, for the decades before the Great Recession, a series of papers starting with the influential paper of Ruhm (2000) have found a negative association between cross-area unemployment rates and mortality.[3] This relationship appears both in the United States (Ruhm 2000; Stevens et al. 2015; Miller et al. 2009), as well as 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).[4] On the other hand, the relationship between local unemployment and mortality in the US appears to have weakened over time and to have disappeared by 2010 (Ruhm 2015).[5] Moreover, Cutler et al. (2016) look at the relationship between business cycles and mortality across almost three dozen countries and two hundred years, and find that while small recessions are associated with reduced mortality, large recessions are associated with increased mortality.

We therefore look directly at the impact of the Great Recession of mortality. Our empirical approach follows in the spirit of Bartik (1991), Blanchard et al. (1992), and Yagan (2019) in exploiting the fact that different areas of the country had very different exposure to this large, aggregate economic shock. This empirical approach complements the existing literature on the mortality impacts of recessions which uses panel data at the local area-by-year level to analyze the relationship between an area's mortality rate and its contemporary unemployment rate, controlling for area and year fixed effects. Relative to this literature, our approach may help isolate the causal

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

[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] 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).

[5] 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.

impacts of recessions from potential confounding factors that could simultaneously increase local unemployment and also directly affect health.[6] Our use of a single (spatially-differentiated) shock also helps us more easily identify the temporal pattern of effects.

Finally, our paper also 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.[7]

Naturally, our analysis comes with important caveats. First, our design will not pick up any impacts of the Great Recession that do not run solely through local labor market impacts. Our estimates thus excluded, for example, any mortality impacts from the nationwide collapse of the stock market, or any nationwide increase in malaise.[8] They also exclude impacts of the Great Recession that are spatially differentiated but not perfectly correlated with the local labor market declines, such as declines in pollution that may originate from declines in local labor markets but impact other areas due to wind patterns, or declines in housing wealth. 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.[9] Third, our analysis so far has focused only on mortality impacts; we hope to expand to morbidity impacts going forward.

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

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

[7]Two important exceptions are Edwards (2009) who extends Lucas (1987) to allow for cyclical mortality, and Egan et al. (2017) who contrast fluctuations in GDP to fluctuations in mortality-adjusted GDP. They reach different conclusions, with Edwards (2009) finding little effects on the analysis of business cycles from including cyclical mortality, and Egan et al. (2017) finding substantial effects.

[8]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.

[9]Although, looking across many countries and several centuries, Cutler et al. (2016) find that while small recessions are associated with reduced mortality, large ones are associated with increases in mortality.

2 Data and Empirical Strategy

2.1 Data

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

Mortality data. We use two major sources of data to study the mortality impacts of the Great Recession. Appendix A.1 provides more detail on both underlying data sources. First, following Ruhm (2016), we use death counts from the restricted-use mortality microdata from the Centers for Disease Control and Prevention, combined with population data—the denominator in constructing mortality rates—from the National Cancer Institutes Surveillance Epidemiology and End Results (SEER) program. 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 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. The SEER population data provide annual, county-level population estimates by single year of age, race, ethnicity, and sex.

Our second major source of mortality data comes from the universe of Medicare enrollees aged 65+ in the United States from 2003 to 2016. The enrollee-level panel data contain information on zip code of residence 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. 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.[11] 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.[12]

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

[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] 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.

[12] 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.

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 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. Another disadvantage of the Medicare data is that we have not been able to obtain the cause of death data for this population. 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.[13]

Data on other outcomes. We draw on several other data sources to probe possible mechanisms behind our mortality findings. First, we use data from the Behavioral Risk Factor Surveillance Survey (BRFSS) to examine impacts on self-reported health and on health behaviors. The BRFSS is an annual, telephone survey administered to approximately 400,000 individuals across the United States. Over our sample period, we observe annual measures of self-reported health behaviors (specifically, exercise, smoking, and drinking beahviors) as well as self-reported health and self-reported diagnoses for diabetes and asthma. The BRFSS contain information on individuals' state of residence, which allows us to exploit state-level variation in the impact of the Great Recession to estimate its effect on these outcomes.

Second, to measure the impact of the Great Recession on nursing home staffing, we use facility-level administrative data from annual certification inspections of nursing facilities across the United States.[14] Data are available annually at the facility level, covering a range of nursing home staffing measures as well as other characteristics such as patient volume and composition. We aggregate the data to the CZ-level and analyze data from 2003 through 2016.

Third, we obtain air pollution data from the EPA's Air Quality System (AQS) database, which provides annual data at the pollutant-monitor level for pollutants that are regulated by the Clean

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

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

Air Act.[15] We aggregate the annual pollutant monitor level data to the county-level and analyze data from 2003 through 2016. Specifically, we average the mean monitor reading for the year across monitors in the county.As in other recent papers (e.g. Deryugina et al. 2019) we focus on exposure to fine particulate matter (PM 2.5), which is measured in micrograms per cubic meter (μg/m^3).

2.2 Empirical Strategy

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

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

where $SHOCK_c$ is a measure of the impact of the Great Recession on area c, $\mathbb{1}(Year_t)$ is an indicator for calendar year, 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.

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.[16]

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.[17,18] Our analysis of the log mortality rate follows the prior literature on the impacts of recessions

[15] A pollutant monitor is defined as the unique combination of the collection site, the specific pollutant measured, and the instrument used to collect the data at the site.

[16] 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).

[17] 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.

[18] 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

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:

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

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.

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 1a shows the spatial variation in this shock across CZs. The Great Recession was a nationwide shock: virtually every CZ in the country experienced an increase in the unemployment rate. The average (population-weighted) CZ experienced a 4.7 percentage point increase in the unemployment rate between 2007 and 2009. 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

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.

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).[19] 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. Mortality rates also vary widely across the United States (e.g. Chetty et al. (2016); Finkelstein et al. (2021). Figure 1b documents the variation in age-adjusted mortality rates across CZs in 2006, immediately prior to the Great Recession.[20] Mortality rates were particularly high in the South-Eastern United States and low in the Western United States.[21] 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 2 shows that a 1 percentage point higher Great Recession shock is associated with a statistically insignificant 3.8 per 100,000 (standard error 4.9) higher 2006 mortality rate.

To provide a preliminary look at how changes in mortality correlate with areas more or less hard hit by the Great Recession, Figure 3 plots age-adjusted mortality rates from 1999 through 2016 for the CZs in the lowest quartile of the 2007-2009 unemployment shock (mean unemployment shock of 2.9 percentage points) and the CZs in the highest quartile (mean unemployment shock of 6.7 percentage points). Both exhibit decreasing mortality over this study period. Their mortality rates are indistinguishable in 2003; by 2006, the CZs that will be harder hit by the Great Recession have, if anything, experienced a relative increase in mortality.[22] After 2006, however, there is an immediate and pronounced decline in age-adjusted mortality in the harder-hit CZs relative to the less harder-hit ones, creating a gap in age-adjusted mortality rates that persist through the end of the series in 2016.

[19]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.

[20]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.

[21]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.

[22]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 in employment in the preceding years).

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 (2007-2009), a one-percentage point greater decline in the unemployment rate from the Great Recession is associated with a 0.50 percent (standard error = 0.15) decline in the annual, age-adjusted mortality rate.[23] The mortality decline is essentially constant over our 10-year study period; over the next seven years (2010-2016), the estimates imply that a one-percentage point greater decline in the unemployment rate from the Great Recession is associated with a 0.58 percent (standard error = 0.34) decline in the annual, age-adjusted mortality rate; this estimate is statistically indistinguishable (p-value = 0.78) from the 0.50 percent decline estimated in the first three years of the Great Recession. Places that were harder hit by the recession thus 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, with effects persisting for at least ten years. To put these numbers in perspective, for a 55-year old male facing the standard, population life table, this corresponds to an increase in life expectancy from the Great Recession of about 0.05 years, or about 18 days (see Appendix Table A.9, panel B); put differently, it suggests that 1 in 20 55-year olds gets an extra year of life from the Great Recession.

We can also compare these estimates to other estimates of mortality declines. For example, over the half-century preceding the Great Recession, average annual age-adjusted mortality declined by 1.1 percent per year.[24] The mortality benefits from the Great Recession are thus equivalent to the mortality declines typically achieved over a two-year period. As another benchmark, we can compare the mortality impacts of the Great Recession to estimates of the mortality impact of the health insurance expansions under the Affordable Care Act (ACA). There, Goldin et al. (2021) estimate that each additional month of insurance coverage provided under the Affordable Care Act to previously uninsured 45-64 year olds reduced 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

[23] 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.

[24] 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).

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 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 rates vary substantially across demographic groups (Appendix Table A.1). For example in 2006, the elderly (65 and older) accounted for almost three-quarters of deaths, although they are only 12 percent of the population. Relative to non-Hispanic Whites, age-adjusted mortality rates were higher for Non-Hispanic Blacks and lower for Hispanics. The two most common causes of (age-adjusted) deaths were cardiovascular disease (34 percent of deaths) and malignant neoplasms - i.e. cancer - (23 percent). To examine heterogeneity in mortality impacts, we focus on estimates from the 2007-2009 period where we have greater precision. [25]

Figure 5 indicates that mortality declines from the Great Recession appear for essentially all major causes of death, with the important exception of cancer where there is no impact. Panel (a) reports the pooled estimate for each of the top 11 causes of death (arranged in descending order of prevalence) as well as a final residual category for all other columns. Several of these causes of death show a statistically significant mortality decline; we estimate that a 1 percentage point increase in local area unemployment reduces the mortality rate from cardiovascular disease by 0.65% (standard

[25] Appendix Tables A.2, A.3 and A.4 report the results separately for this period, the 2010-2016 period, and the pooled 2007-2016 period; the patterns are largely the same although precision often worsens. The underlying event studies behind each of the cause- or group-specific estimates are displayed in Appendix Figures A.11, A.12, A.7, A.8, A.9, and A.10.

error =0.21), the mortality rate from motor vehicle accidents by 1.7% (standard error = 0.56), and from liver disease by 1.1% (standard error =0.43). In addition, several other causes of death - including respiratory disease, influenza/pneumonia, and kidney disease - experience a percentage decline in their mortality rate similar to that of cardiovascular disease but these declines are not statistically significant. We also estimate statistically insignificant declines in suicides.[26] No cause of death experiences a statistically significant increase in mortality.

Panel (b) of Figure 5 combines these point estimates with prevalence rates to report the share of the mortality reduction accounted for by each cause of death. Cardiovascular disease is the largest cause of death (one-third of total mortality in 2006) and accounts for the largest share (44 percent) of the estimated total reduction in deaths. By contrast, motor vehicle accidents account for only 1.9% of 2006 mortality, and liver disease accounts for only 1.1%, so their contribution to the total mortality decline is only 6.4% and 2.4% respectively. Not surprisingly, we estimate a precise null effect on cancer deaths (0.02 percent, standard error = (0.11)), which is the second largest cause of death.

The impacts on log mortality rates are broadly similar across age groups (Figure 6). Panel (a) indicates estimated declines for all age groups, with many statistically significant. The point estimates are also broadly similar; while the decline in log mortality rates appears to be larger for younger population groups, these estimates are quite imprecise. Panel (b) combines the point estimates with mortality rates by age to show the contribution of different age groups to the estimated reduction in deaths. It shows that the elderly (individuals 65 and older) account for the majority - 74.3 percent - of the deaths averted by the Great Recession, which is roughly proportional to their 72.5 percent share of total mortality in 2006. This finding is similar to that of Stevens et al. (2015) who found that in state-year panel data, estimates of reduced deaths associated with increases in the local unemployment rate were also concentrated in the elderly.[27]

Finally, Figure 7 summarizes the mortality impacts of the Great Recession by gender and by race/Hispanic background. 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.

[26] 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)

[27] One source of mortality and mortality declines where the elderly are under-represented, however, is motor vehicle accidents. The elderly 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.

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.

To get a sense of the potential for confounding effects of unmeasured population changes, we examined the impact of the recession on (measured) population magnitude and composition. Appendix Table A.5 summarizes the results, and Appendix Figure A.6 summarizes the event studies. 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.[28] 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.[29] 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.

The individual-level panel nature of the Medicare data allow us to more directly explore the sensitivity of our findings to unmeasured population changes. For the elderly (who account for the vast majority of the mortality declines), we are able to define a cohort of Medicare enrollees and their location in 2003, and directly examine how subsequent location changes affect our estimates of the mortality impact of the Great Recession. The Medicare data also have another added attraction: the measures of deaths in the numerator and of the population in the denominator are reported together, rather than coming from different sources (death certificate data and SEER population data, with the latter based partly on interpolations).

To do so, we follow the standard approach in the literature (e.g. Olshansky and Carnes (1997); Chetty et al. (2016); Finkelstein et al. (2021)), and adopt a Gompertz specification in which the

[28] 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.

[29] 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).

log of the mortality rate for individual i in year t ($\log(m_{it})$) is linear in age a_{it}. Without access to an individual-level panel, we would run the following type of OLS analysis:

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

Once again, 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, and cluster the standard errors at the Commuting Zone level. Once again, $\alpha_{c(i,t)}$ and γ_t are location and year fixed effects, respectively.

However, with individual panel data we can also estimate a 'reduced form' based on individual's location in 2003:

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

Here, we 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.

To more directly compare how accounting for potential non-random re-sorting of the population across Commuting Zones that is correlated with the Great Recession shock the CZ experiences affects our estimates, we compare the OLS estimates in equation 3 to estimates from a control function model in which the shock the person would have experienced based on their CZ in 2003 is 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 current location to the shock that she would have experienced based on her 2003 location:[30]

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

and then use the the $\hat{v_{it}}$ residuals from equation (5) as a regressor in the following equation:

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

The identifying assumption 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

[30] As in equation (1), in equations (5) and (6) we omit the interaction with yearly location and 2003 location shock variables in 2006, so that all coefficients are relative to 2006.

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.

The results are summarized in Panel B of Table 1, and the underlying event studies are shown in Appendix Figure A.13. 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 estimates of the Great Recession impact are larger, with a point estimate of -0.48 (standard error = 0.16).

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. The evidence discussed in the Introduction is consistent with this, as it finds that job loss and reduced economic prospects increase mortality in general as well as mortality from so-called "deaths of despair" (e.g. Sullivan and Von Wachter 2009; Case and Deaton 2021; Autor et al. 2019; Pierce and Schott 2020). 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; if health investments are privately optimal before and after an exogenous reduction in consumption, then the welfare effect of this consumption reduction is, to first order, the same as the reduction in consumption, and there are no additional welfare consequences from any health effects. Of course, if individuals are engaged in privately suboptimal health behaviors such as smoking or medication non-adherence (e.g. Gruber and Köszegi (2001)), recession-induced changes in behavior could be welfare improving.

4.1 Internal Effects

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 pro-cyclical 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.[31] 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).

We find no evidence that recessions are associated with improved health behaviors. Specifically, we re-estimate equation 1 at the state-level with the outcome variables the log share of individuals who report that they currently smoke, that they have exercised within the past 30 days, or that they having consumed more than than 5 drinks in one sitting in the past five days. . We find statistically insignificant impacts on all these outcomes. Specifically, we estimate that on average over the 2007-2010 period, a 1 percentage point increase in state unemployment from 2007-2009 decreases the share smoking by 1.2 percent (standard error 0.8 percent), increases the share excessively drinking by 0.2 percent (standard error 0.7), and increases the share exercising by 0.2 percent (standard error = 0.3 percent).[32]

Several pieces of indirect evidence also 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 with a lag, and to grow over time as health capital improves.[33] By contrast, an immediate mortality decline is consistent with a role for pollution—which has been found to decline immediately during

[31] Indeed, Coile et al. (2014) using the standard state-year panel analysis of the relationship between unemployment and mortality but following birth cohorts, find that the short-term mortality reductions for workers who experience local increases in unemployment in their late 50s up to the SSA early retirement age of 62 are offset by subsequent mortality increases, a finding that they attribute to the impacts of reduced income and health insurance.

[32] By way of comparison, Ruhm (2000) estimates that a 1 percentage point increase in the state unemployment rate reduces the share who smoke by 0.3 percentage points (standard error 0.07), or about 1 percent relative to the mean and increases the share who exercised within the past 30 days by 0.64 percentage points (standard error 0.02), again about a 1 percent increase relative to the sample mean.

[33] 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))

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).[34] 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.[35] 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.

4.2 Externalities

We explore three main potential sources of positive health externalities from recessions suggested by prior literature: reductions in the spread of infectious disease during recessions, increases in the quality of health care and reductions in pollution. Our preliminary results below show little support for the first two potential sources of externalities, but evidence consistent with a quantitatively important role for pollution.

Reduction in spread of infectious disease. Adda (2016) finds that epidemics of infectious disease (specifically influenza, gastroenteritis, and chickenpox) spread faster during booms. Infectious disease accounted for a relatively small share of mortality in 2006, and there is little evidence of a statistically significant decline in mortality from infectious disease during the Great Recession. As shown in Figure 5b, influenza and pneumonia accounted for only 2% of deaths in 2006, and experienced a statistically insignificant 0.73% (standard error = 0.50%) decline for every 1 percentage point increase in unemployment from 2007-2009.

Improved 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. Quality of care for the elderly in particular might increase as much of it does not require formal training and may therefore be relatively elastically supplied. For example, informal care provided by adult children might increase with tighter labor markets. In addition, there could be an increase in the relatively low-skilled, direct care workers who provide formal home care and nursing care and where there are widespread

[34] 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.

[35] 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).

concerns about shortages (e.g. Geng et al. 2019; Grabowski et al. 2023). Stevens et al. (2015) emphasize this latter channel, with evidence from state-year panel data from 1978-2006 that cyclical fluctuations in the quality of nursing home staff are correlated with reductions in elderly mortality during recessions.

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. We analyze data from 2003 through 2016, covering a range of nursing home staffing measures and other characteristics.

Figure 9 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.[36] 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.[37] We also find no evidence of an impact of the Great Recession on nursing home occupancy rates or resident characteristics (Appendix Figure A.14). 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.15b but not among the elderly with recent or current nursing home use.

Reduction in Pollution A body of evidence 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 pro-cyclical mortality. Indeed, Chay and Greenstone (2003) and Heutel and Ruhm (2016) provide direct evidence that recession-induced changes in pollution affect infant mortality

[36] 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.

[37] 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.

and total mortality, respectively.[38]

We find evidence consistent with a quantitatively important role for this pollution channel. For our baseline analysis, we limit our analysis to the approximately two-thirds of (population weighted) counties for which we have a pollution monitor in any year from 2003- 2016, and for which we also have a pollution monitor in 2006 and 2010; Appendix Figure A.17 shows a map of these counties. We also conduct the baseline analysis at the county level, since we expect any impacts of pollution to have the biggest impact on people in closer proximity, however we continue to measure the Great Recession shock at the commuting zone level since the local labor market s likely the right area for the impact of that shock. We show robustness to other samples and specifications below.

We begin by estimating the following county-level analysis:

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

where c now denotes county, cz denotes commuting zone, and GR_SHOCK is our SHOCK measure from equation (1); we continue to cluster our standard errors at the commuting zone level. Figure 10 shows the results from estimating equation (7) for the dependent variable log age adjusted mortality (panel a) and PM 2.5 (panel b). Panel (a) shows that the impact of the Great Recession is quite similar when we conduct the analysis at the county level in this restricted set of counties; we estimate that a 1 percentage point increase in the CZ level unemployment rate from 2007-2009 is associated with an average reduction in log age adjusted mortality from 2007-2009 of 0.52 percent (standard error 0.23), which is very similar to our baseline estimate in Figure 4 of 0.50 percent (standard error 0.15 percent). Panel (b) shows that that 1 percentage point increase in the CZ level unemployment rate from 2007-2009 is associated with an average reduction in PM 2.5 from 2007-2009 of 0.18 micrograms per cubic meter (μg/m^3), standard error 0.04, or about 1.5 percent relative to the national average level of PM 2.5 in 2006 of about 12 μg/m^3.

The time pattern in subsequent years is also worth noting. In areas harder hit by the Great Recession, mortality remains at a constant, lower level through 2016 (much as Yagan (2019) documents that employment does as well); however pollution starts rising in harder hit areas starting in about 2010, and by about 2014 has returned to pre-recession levels. This is consistent with output also returning to pre-recession levels much more quickly than employment as part of the so-called "jobless recovery". It also raises questions about the role of pollution in contributing to the continued lower levels of mortality in 2010-2016, a question which depends in part on the lag structure by which changes in pollution feed through to changes in mortality, which is an open

[38] 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)

empirical question.[39]

We perform a back-of-the-envelope calculation to gauge the potential quantitative importance of the pollution channel for our mortality estimates. To do this, we take advantage of the fact that while the Great Recession shock reduced pollution on average, these impacts were heterogeneous across counties, so that there is variation in the magnitude of the pollution change experienced by counties with the same Great Recession shock. This is illustrated in panel (c) of Figure 10 by plotting the county-level change in PM 2.5 between 2006 and 2010 against our measure of the Great Recession shock. It shows that while counties that were harder hit by the Great Recession on average experienced a larger decline in pollution, there is substantial heterogeneity in this relationship. We can therefore examine how much the estimated impact of the Great Recession on mortality changes when we control for changes in pollution. Specifically we estimate:

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

where PM2.5_SHOCK measures the decline in PM 2.5 in county c between 2006 and 2010 (with positive numbers reflecting a decline). Naturally this analysis is merely suggestive, as counties that experienced greater declines in PM 2.5 may have also experienced changes in other factors that directly affect mortality, and declines in PM 2.5 may in turn be driven by factors other than the local labor market shock of the Great Recession. The ideal way to gauge the role of pollution in contributing to the Great Recession reduced mortality declines would be to cross-randomize labor market declines and pollution declines across different areas of the United States. Nonetheless, our informal 'mediation' analysis is suggestive.

Table 2 shows the results from estimating equation (8); the underlying event study coefficients are shown in the Appendix Figure A.18. Column (1) shows the results from estimating equation 7 with only the Great Recession Shock on the right hand side, column (2) from re-estimating it with the PM 2.5 shock on the right hand side instead, and column (3) shows the results of the 'horse race' comparison from estimating equation 8. Comparing columns (1) and (3), we find that controlling for the pollution shock attenuates the estimated impact of the Great Recession on mortality by about 40 percent, from a 1 percentage point increase in unemployment reducing mortality by 0.51 percent to 0.35 percent. This is suggestive of a quantitatively important role for pollution reductions in driving the recession-induced declines in mortality. In the Appendix Tables A.16 (see also Appendix Figure A.20) and A.15, we show that the results in Table 2 are robust to measuring the Great Recession shock at the county level rather than the CZ level, and to restricting the analysis to a balanced set of counties for which we can measure pollution in every year from 2003 through 2010.

[39]The quasi-experimental literature on the mortality impacts of air pollution tend to focus on relatively short-run variation in pollution exposure, and study impacts over relatively short time horizons (typically less than one year, and sometimes over a matter of days). Ebenstein et al. (2017) and Barreca et al. (2021) are important exceptions.

5 Welfare Consequences of Recessions

We extend the Krebs (2007) model which analyzes the welfare cost of recessions based on their estimated impact on consumption to incorporate our estimates of the impact of recessions on mortality as well. In doing so, we follow the approach of much of the existing literature incorporating changes in life expectancy into welfare analyses (e.g. Becker et al. (2005); Jones and Klenow (2016)) in assuming that gains in life expectancy represent improvements in well-being. In our setting, this assumption is consistent with recession-induced mortality improvements arising from positive health externalities—such as reduced infectious disease or reduced pollution—that are exogenous to the individual's choices. Of course, if the recession-induced mortality reductions are the result of optimizing agents choosing to use some of their increased leisure time to produce more health or to reduce their consumption of mortality-increasing goods (such as alcohol or sky-diving), then the consumption impacts of recessions are all that would be relevant for welfare analysis.

5.1 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:

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

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

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

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

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

which implies that the VSLY is increasing in c if $\gamma > 1$ (Hall and Jones 2007). The agent receives income $y(t)$ when alive, and, 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:

$$\mathbb{E}[U(c, m)]^{\text{normal}} = p^H * T * u((1 - d^H)c) + (1 - p^H) * T * u(c) \tag{12}$$

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

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

Following Krebs (2007), we calculate the welfare cost of a recession as the representative agent's willingness to pay each period to avoid the recession state, calculated as a percentage of their average annual consumption. This involves solving for Δ such that[40]

$$\mathbb{E}[U((1 + \Delta)c, m)]^{recession} = \mathbb{E}[U(c, m)]^{normal} \tag{14}$$

[40]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:

$$\Delta = \left(\frac{p^H(1-d^H)^{(1-\gamma)} + (1-p^H)}{p^L(1-d^L)^{(1-\gamma)} + (1-p^L)} \right)^{1/(1-\gamma)} - 1 \tag{15}$$

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.[41]

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 $T(1+dT)$.[42] This leads to the following expressions for expected lifetime utility in the two states:

$$\mathbb{E}[U]^{\text{normal}} = p^H * T * u((1-d^H)c) + (1-p^H) * T * u(c) \tag{16}$$

$$\begin{aligned} \mathbb{E}[U]^{\text{recession}} &= p^L * T(1+dT) * u((1-d^L)c) \\ &\quad + (1-p^L) * T(1+dT)u(c) \end{aligned} \tag{17}$$

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

$$\Delta^{dT} = \left(\frac{-dT * b/\tilde{u}(c) + p^H(1-d^H)^{(1-\gamma)} + (1-p^H)}{(1+dT)(p^L(1-d^L)^{(1-\gamma)} + (1-p^L))} \right)^{1/(1-\gamma)} - 1 \tag{18}$$

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 (18) is valid for any value of dT and it simplifies to the expression for Δ in equation (15) if $dT = 0$.[43]

[41] 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).

[42] 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.

[43] 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 $\Delta^{dT} < \Delta$,

We can build further intuition by setting $p^H = 0$ and then taking a first-order approximation around the left-hand side of equation (18), which leads to the following expression:

$$1 + (1-\gamma) * \Delta^{dT} \approx \frac{-dT * b + \tilde{u}(c)}{(1+dT) * (p^L * (1-d^L)^{(1-\gamma)}\tilde{u}(c) + (1-p^L)\tilde{u}(c))} \quad (19)$$

$$\Delta^{dT} \approx \Delta - dT\frac{\text{VSLY}}{c} \quad (20)$$

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 every period to avoid recessions as a percent of average annual consumption. The second term shows that 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.

One way to gain some intuition for this approximation for the welfare cost of recessions with endogenous mortality is to multiply both sides by lifetime consumption ($T * c$) to achieve an expression for the total amount an individual is willing to pay to avoid a recession:

$$\Delta^{dT} * (T * c) \approx \Delta * (T * c) - (dT * T) * \text{VSLY} \quad (21)$$

Compared to the total amount an individual is willing to pay to avoid a recession with exogenous mortality ($\Delta * (T * c)$), willingness to pay to avoid a recession with endogenous mortality is increased by the increase in life years ($dT * T$), scaled by the willingness to pay for those life years (VSLY).

Both expressions indicate 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.[44]

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 from Krebs (2007): $p^H = 0.03$, $p^L = 0.05$, $d^H = 0.09$, and $d^L = 0.21$. The p^S values correspond to the approximate job separation rates during normal times and a recession, respectively, and the d^S values likewise correspond to the average earnings loss from job displacement, which is assumed to be greater during recessions. Like Krebs (2007), we also report results for a

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.

[44] 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.

range of risk aversion parameters (γ), in our case allowing values of $\gamma = 1.5, 2, 2.5$.

We must also make assumptions regarding life expectancy in each state $S \in \{L, H\}$ as well as the VSLY. We assume that in 'normal times' (S=H), individuals have 40 years of life expectancy remaining, i.e. $T = 40$. We are interested in calculating 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 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 male life tables and assuming that the effects of the Great Recession last exactly 10 years.[45]

There is a range of existing empirical estimates of the VSLY. We therefore report results under different assumptions regarding the VSLY. Specifically, based on the range of estimates in the literature, we consider a VSLY of $\$100k$, $\$250k$, or $\$400k$.[46] Given an assumption for the VSLY, we compute the implied b in equation (11) for each assumed value of γ and an assumed value of average annual consumption $c = \$50,000$.[47]

Table 3 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 and 1.1 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 95 and 109 percent relative to the exogenous mortality benchmark.

The first-order approximation formula in equation (20) 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 3 shows that the differences in values of Δ^{dT} across columns vary

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

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

[47] As seen in equation (20), it is actually the VSLY scaled by average annual consumption that affects the value of Δ^{dT}. Our assumptions thus correspond to assuming that the value of a statistical life year is two, five or eight times larger than average annual consumption.

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 (20) for the basic model allows us to anticipate that the welfare costs of recessions will fall more with age when we allow for endogenous mortality. To see this, note that equation (20) indicates that the impact of endogenous mortality on the welfare cost of a recession is increasing in the percent change in life expectancy dT caused by the recession. And recall that we estimated that the Great Recession caused a constant proportional decline in mortality rates across ages. Appendix Table A.9 shows, using the 2007 SSA male life tables, that a given percentage decline in mortality rates produces larger percentage gains in life expectancy at older ages.[48] For example, for men at age 35, the 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.

5.2 Full Dynamic Model

We now turn to the full dynamic model to incorporate several more realistic features of the economic environment: state-dependent and state-independent persistent income shocks, retirement, and different types of recessions. We will also replace the assumed life expectancy T with the actual, US age-specific mortality rates; this will also allow us to calibrate welfare costs of recessions across the age distribution.

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

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

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

Utility. The representative agent's lifetime utility and per-period utility functions are the same as the basic model (see equations (9) and (10)).

Recessions. The aggregate state $S \in \{L, H\}$ affects the agent's stochastic income process. Following the empirical pattern of the Great Recession (e.g. Yagan (2019)) we assume the Great Recession corresponds to an aggregate state of $S = L$ for 10 years. After that, the aggregate state is $S = H$ forever. As a result, we recover the willingness to pay to avoid the Great Recession. We also will consider the willingness to pay to avoid the risk of future recessions. For this, we will assume that the aggregate state S is drawn each period, with the probability of a normal state $(S = H)$ given by π_H.

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:

$$y_{t+1} = (1 + g)(1 + \theta_{t+1})(1 + \eta_{t+1})y_t \tag{22}$$

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:

$$\eta_{t+1} = \begin{cases} -d^S & \text{with probability } p^S \\ \frac{p^S d^S}{1-p^S} & \text{with probability } 1 - p^S \end{cases} \tag{23}$$

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 consequences of recessions. We analyze both the welfare consequences of the Great Recession and the welfare consequences of facing the stochastic aggregate state. The former allows us to calculate the welfare consequences of recession-induced mortality reductions in the context in which we estimated these reductions, while the latter allows us to more directly consider how accounting for endogenous mortality affects prior consumption-based analyses of the welfare consequences of recessions. We refer to this latter analysis by the shorthand of 'regular recessions'.

Following Krebs (2007), we therefore define the welfare cost of regular 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:

$$\underbrace{\mathbb{E}_0\left[\sum_{t=0}^{\infty}\beta^t S(m^S(t))u((1+\Delta^{dT})y(t))\right]}_{\text{Expected Lifetime Utility with Stochastic Aggregate State}} = \underbrace{\mathbb{E}_0^{S=H}\left[\sum_{t=0}^{\infty}\beta^t S(m^{S=H}(t))u(y(t))\right]}_{\text{Expected Lifetime Utility without Recessions}}, \tag{24}$$

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 $dm < 0$). In either case, equation (24) corresponds to the welfare cost of eliminating *all* future recessions, not a single recession.

We also calculate the welfare consequences of the ten-year-long Great Recession as a special case of Equation (24) in which on the left-hand side the aggregate state is non-stochastic, with $S = L$ for $t \in [0, 9]$, and $S = H$ afterward. We consider this a conservative approach in that we assume that the impacts of the Great Recession last only as far as we track them in our data (i.e. 10 years).

To calibrate equation (24) 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:

$$\sum_{i=0}^{N}\left[\sum_{t=0}^{\overline{T}}\beta^t S(m^S(t))u((1+\Delta^{dT})y_i(t))\right]=\sum_{i=0}^{N}\left[\sum_{t=0}^{\overline{T}}\beta^t S(m^{S=H}(t))u(y_i^{S=H}(t))\right] \tag{25}$$

Parameterization. Following Krebs (2007), we use the same values of p^S and d^S as in the basic model, and we choose $g = 0.02$, $\sigma = 0.01$, and $\pi_H = 0.5$. We choose a higher discount factor ($\beta = 0.99$) compared to $\beta = 0.96$ in Krebs (2007), so that when we use realistic mortality rates we end up with a welfare cost of recessions with exogenous mortality that is fairly similar to Krebs (2007). We report results across the same range of γ and VSLY parameters as in the basic model. We normalize $y(0) = c(0) = 1$.[49]

A key departure from the basic model is that we use realistic mortality rates rather than the crude assumption of $T = 40$ in non-recession times. Specifically, we use the 2007 SSA male life tables to calculate age-specific mortality rates for the $m^H(t)$ vector. We simulate workers starting at different ages (35, 45, 55, and 65).

Finally, based on our empirical estimates we choose $dm = -0.023$ for each of the ten years of the Great Recession. This comes from our empirical estimates that a 1 percentage point increase in unemployment causes a 0.5 percent decline in the mortality rate together with the average increase in unemployment during the Great Recession of 4.6 percentage points. When we model the welfare cost of facing the stochastic aggregate state relative to an economy that stays in the state $S = H$ for all time periods, we choose $dm = -0.015$. 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 a 3-percentage-point increase in the unemployment rate.

Calibration results. Table 4 shows our calibration results for the welfare cost of the Great Recession for the fully dynamic model. Looking across the columns allows us to compare results for exogenous mortality with results for endogenous mortality at different values of the VSLY. Looking down the rows shows results for different values of γ and for different ages. Panel A shows results for people who were 35 at the start of the Great Recession. With exogenous mortality, column 1 finds that a 35 year old would be willing to pay between 1.4 and 2.4 percent of average annual consumption for the rest of their lives to avoid the Great Recession, with this willingness to pay naturally rising with γ. The remaining columns show how incorporating our estimates of endogenous mortality affects these estimates of the welfare cost of the Great Recession. For the

[49] As a result, the range for $VSLY$ from the basic model (i.e. \$100k, \$250k, and \$400k) where we set $c = \$50k$, correspond to $VSLY$'s in the calibration exercise of \$2, \$5 and \$8 respectively. Recall from equation 20 that the impact of endogenous mortality on the welfare cost of recessions is proportional to the ratio of the $VSLY$ to average annual consumption in the normal state c).

lowest value of the VSLY (100k$, column 2), we find very similar costs of recessions—1.3 to 2.3 percent of average annual consumption—to the estimates in column (1) with exogenous mortality. However, increasing the VSLY to the higher-end estimates of the literature more noticeably reduces the welfare cost of business cycles. For example, for γ=2 and VSLY of 250k$ (column 3), accounting for endogenous mortality reduces the welfare cost of the Great Recession by about 11 percent, from 1.84 percent of average annual consumption with exogenous mortality to 1.63 percent. At a VSLY of 400k$ (column 4) the welfare cost of the Great Recession is reduced further, to 1.50 percent of consumption, or by about 18 percent relative to the welfare cost with exogenous mortality.

At older ages, the impact of accounting for endogenous mortality is much more pronounced. For example, focusing once again on $\gamma = 2$ and the 'intermediate" VSLY of 250k$ in column (3), we saw in panel A that endogenous mortality reduces the welfare cost of the Great Recession at age 35 by only 11 percent. However at age 45 (panel B), endogenous mortality reduces the welfare cost of the Great Recession by 24 percent (from 1.82 percent of average annual consumption with exogenous mortality to 1.39), and at age 55 (panel C) it reduces the welfare cost of the Great Recession by 45 percent (from 1.76 with exogenous mortality to 0.97). The intuition for the larger effects of endogenous mortality at older ages was previewed above in the context of the basic model: the percentage increase in life expectancy from the Great Recession rises with age at onset (see Appendix Table A.9 panel B).

Finally, for individuals who are 65 at the start of the recession, accounting for endogenous mortality makes the Great Recession welfare-enhancing for any value of the VSLY and of γ (panel D). This follows from the fact that (by assumption) there is no welfare cost of the Great Recession for the elderly under exogenous mortality (column 1), and therefore accounting for endogenous mortality leads to a welfare benefit for them from the Great Recession. For example, for γ=2 and VSLY of 250k$, the results indicate that the welfare *gains* from the Great Recession for a 65 year old are equivalent to a 1.44 percent average annual increase in consumption. Of course, 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 Table A.13 therefore explores the welfare consequences of the Great Recession under the (aggressive) alternative 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 that when we account for endogenous mortality, the Great Recession is welfare improving for 65-year olds at higher values of the VSLY and γ.

These results speak to the welfare consequences of a particular—and particularly large—recession. In Table 5 we explore the welfare consequences of facing a stochastic aggregate state relative to the economy always being in the normal state. This is more directly analogous to the analysis of the welfare costs of recessions in Krebs (2007). With exogenous mortality, for a given value of γ, the welfare cost of recessions is declining with age (column 1). This arises because people have shorter working lives—and hence fewer periods in which they experience consumption declines due to recessions—before retirement. Accounting for endogenous mortality lowers the welfare cost of recession at all ages, and that once again 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 percentage increases in life expectancy caused by the risk of recession (see Appendix Table A.9 panel A). For the 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 γ=2 and 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 (or 55 percent) 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.[50]

A comparison of the welfare costs of recession risk in Table 5 with the welfare cost of the Great Recession in Table 4 highlights two interesting findings. First, on the cost side, the consumption declines from the Great Recession are worse for older workers than younger workers relative to regular recessions. Intuitively, the labor market consequences of the Great Recession are higher for older workers than younger workers compared to the risk of regular recessions because the Great Recession lasts longer and therefore affects retirement income substantially. This can be seen by focusing on the results with exogenous mortality (column 1). Here, the model, as in Krebs (2007), focuses solely on the consumption consequences of recessions. For γ=2, for example, the welfare of regular recessions declines from 2.04 percent of average annual consumption for a 35-year-old to 0.93 percent for a 55-year old (Table 5). By contrast, for the Great Recession, these numbers are substantially more similar: 1.84 percent and 1.76 percent, respectively (Table 4).

Second, on the benefits side, mortality declines from the Great Recession provide more gains for older people than younger people relative to regular recessions. For younger people, the mortality reductions from having a recession for 10 years are smaller than from having recessions stochastically for the rest of their life, because their mortality rates will be so much higher later in life.

Overall, these results show that accounting for the mortality effects of recessions changes their welfare costs and also their distributional consequences across generations. In particular, while accounting for the mortality effects of recessions always reduces estimates of their welfare costs, these effects are much more pronounced at older ages. Of course, we recognize that our calibra-

[50]Once again, as a conservative alternative, Appendix Tables A.14 shows the welfare costs of recessions under the (aggressive) assumption that consumption declines from recessions are the same for all ages. 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.

tion results are likely at best only a rough approximation of the true welfare cost of recessions. 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.

6 Conclusions

We provide 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, as 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.

Our findings also raise a number of important questions. First, the Great Recession may have also had impacts on non-mortality health measures, particularly at younger ages where our focus on mortality may cause us to underestimate the health benefits at younger ages. Second, further work is needed to uncover the mechanism behind our findings, which is crucial for welfare analysis and which we are continuing to explore in ongoing work. A third question, which we are also examining, is whether other substantial adverse economic shocks—such as rising Chinese import competition (e.g. Autor et al. (2013, 2014, 2021)—also reduce mortality in groups not directly affected such as the elderly.

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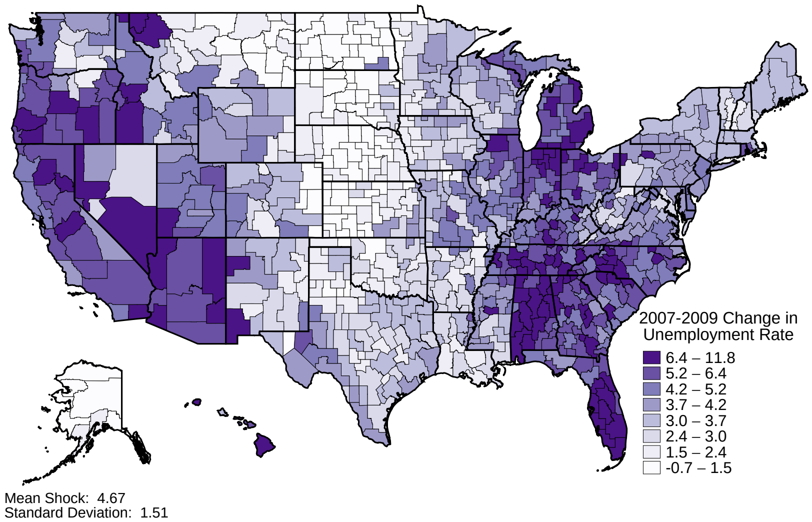
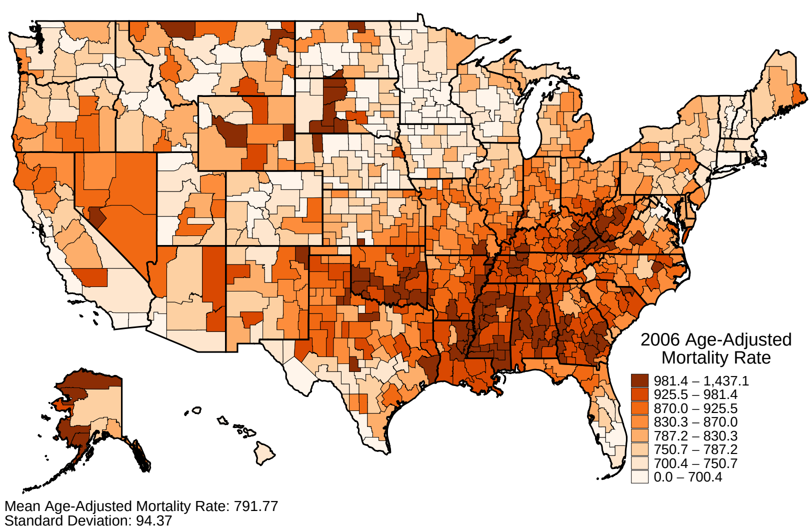
Figures

Figure 1: Geographic Patterns of Unemployment and Mortality

(a) 2007-2009 Change in Unemployment Rate

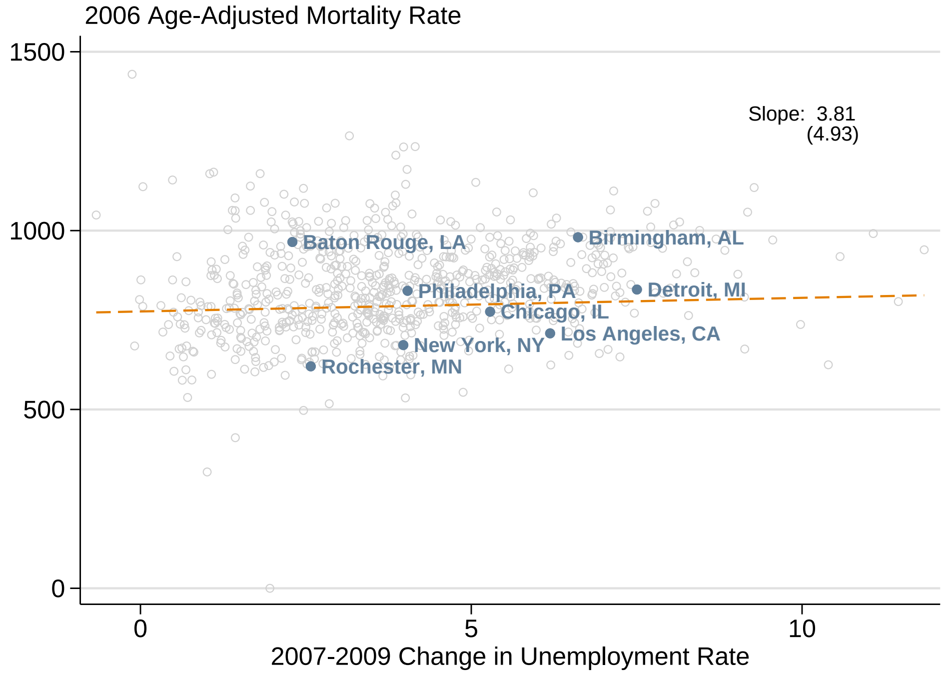


(b) 2006 Age-Adjusted Mortality Rate



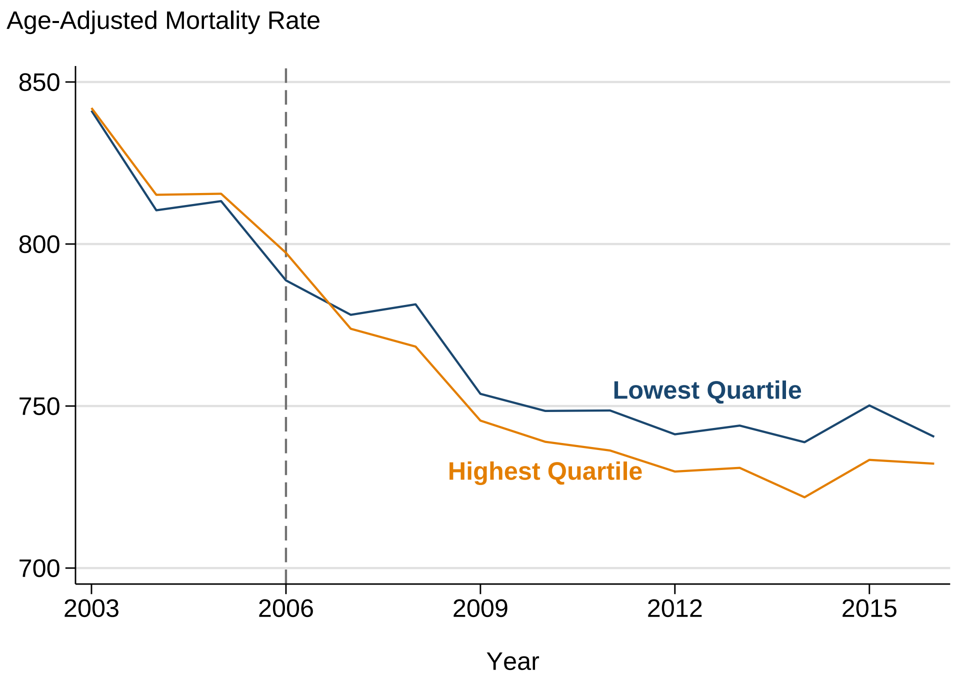
Notes: Figures display the change in Commuting Zone unemployment rates from 2007-2009, drawn from Yagan (2019). Figure 1a displays a heat map of the change in unemployment, binned into octiles. Figure 1b displays a heatmap of 2006 Commuting Zone age-adjusted mortality rates per 100,000. Colors are assigned 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. The mean and standard deviations of the CZ unemployment shock (also weighted by 2006 CZ population) in the top right-hand corner. $N = 741$ CZs.

Figure 2: Correlation between Pre-Recession Mortality Rates and Great Recession Shock



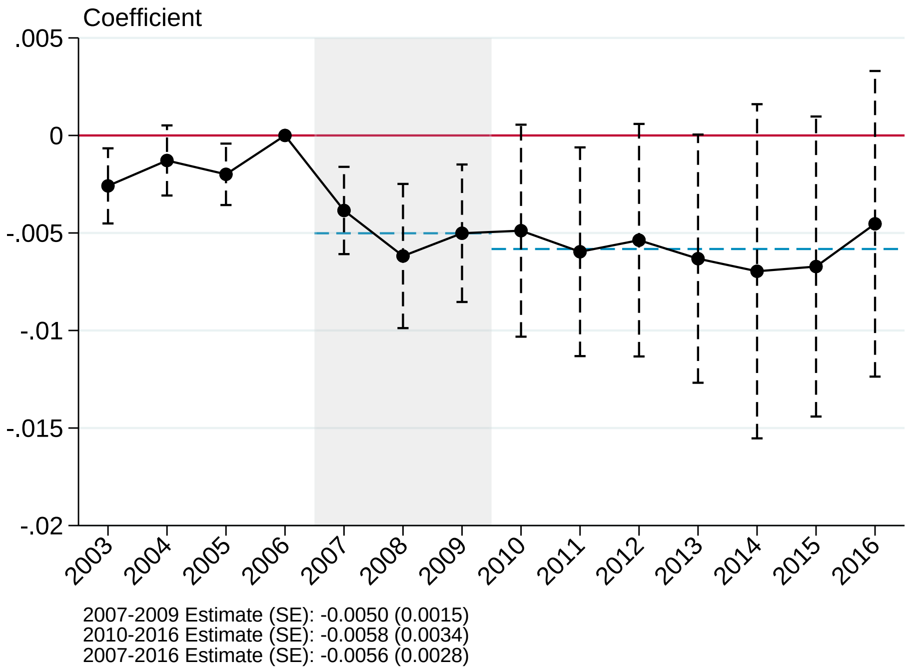
Notes: Figure 2 displays a scatterplot of the 2006 CZ age-adjusted mortality rate against the 2007-2009 change in CZ unemployment rates. Each circle represents one of 741 CZs, scaled in size according to its 2006 population. A linear fit is plotted as a dashed orange line in each figure, and the slope 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.

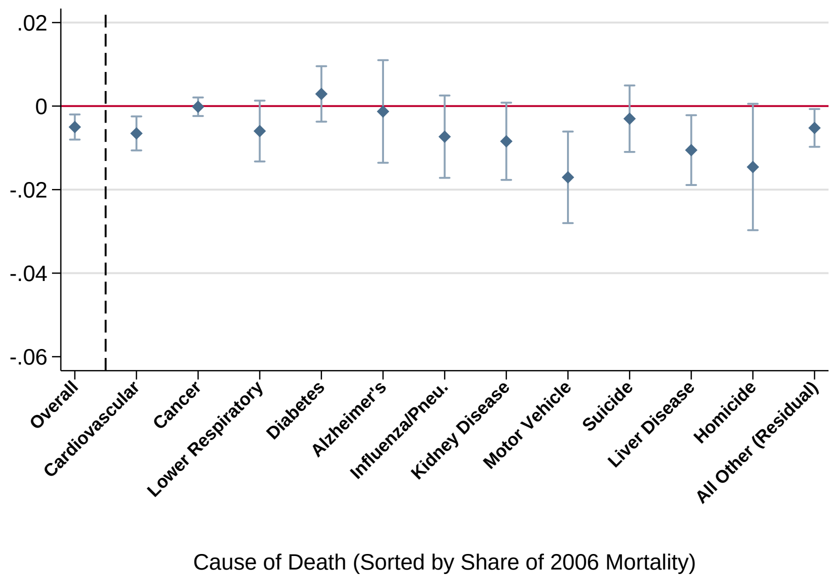
Figure 4: Impact of Great Recession Shock on Log Age-Adjusted Mortality Rate



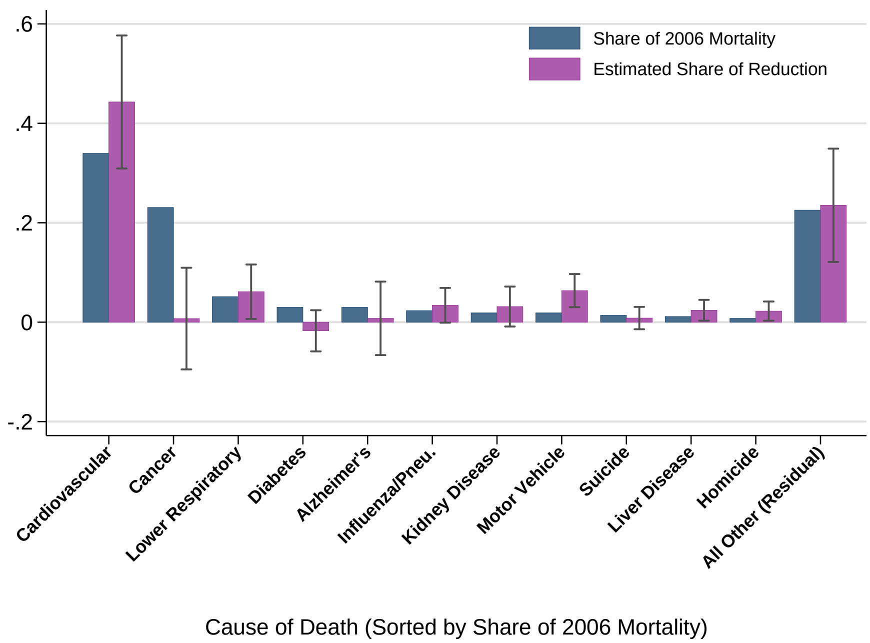
Notes: Figure displays the yearly coefficients β_t from equation (1), where the outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000 population (plus one) and observations are weighted by CZ population in 2006. Annual mortality is constructed according to the county of residence observed 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 average annual point estimate for the periods 2007-2009 and 2010-2016. These estimates (and corresponding standard errors) are reported in the lower left hand corner along with the corresponding estimate for the entire 2007-2016 period. Standard errors are clustered at the CZ level (741 CZs).

Figure 5: Impact on Mortality, by Cause of Death

(a) 2007-2009 Pooled Estimates



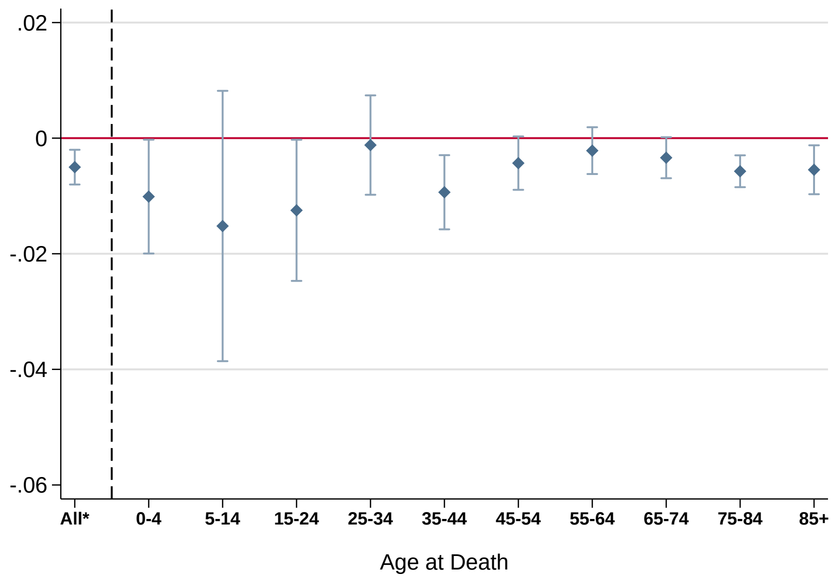
(b) 2007-2009 Decomposition



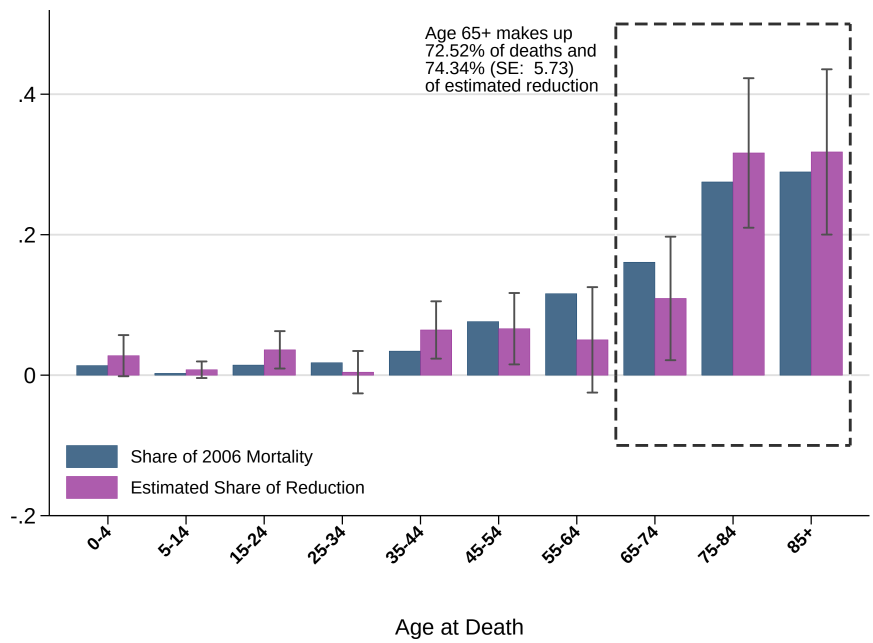
Notes: Figure 5a displays the group-specific 2007-2009 average of coefficients β_{tg} from equation (2), where groups g are defined as the 11 most common causes of death in the ICD10 39-group classification (presented in order of decreasing prevalence), and the final category is a residual category which captures all other mortality. All estimates are of age-adjusted mortality, and weighted by 2006 CZ population from the SEER. Point estimates are displayed as diamonds; vertical bars indicate 95% confidence intervals, clustered at the CZ level. Figure 5b decomposes the contribution of each of these 12 mutually-exclusive and exhaustive cause of death categories to the overall estimated 2007-2009 pooled reduction in mortality (i.e. estimate from Figure 5a). The blue bars indicate each cause of death's share of 2006 mortality. The purple bars present the implied share of the mortality decline accounted for by a given cause of death; to construct these, we 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. 95% confidence intervals for these estimates, clustered by CZ, are shown as vertical lines.

Figure 6: Impact on Mortality, by Age

(a) 2007-2009 Pooled Estimates



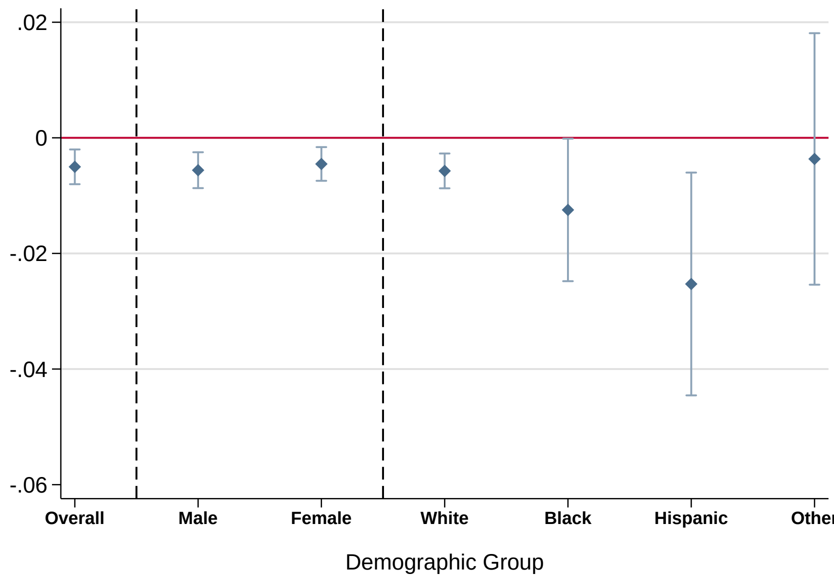
(b) 2007-2009 Decomposition



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

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

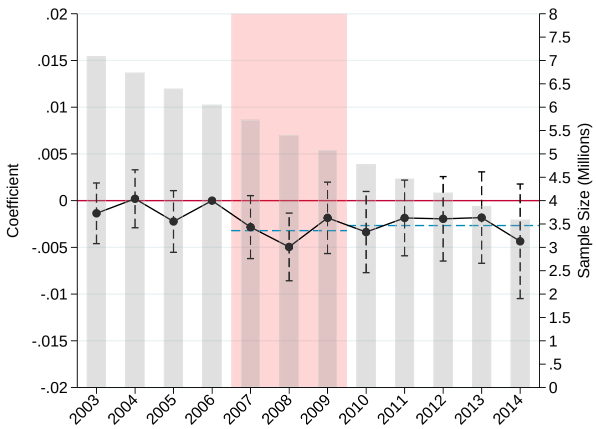
Figure 7: Impact on Mortality, by Sex and Race: 2007-2009 Pooled Estimates



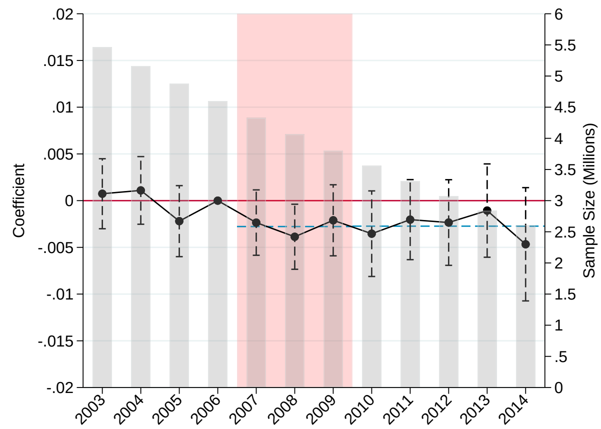
Notes: Figure 7 displays the group-specific 2007-2009 average of coefficients β_{tg} from equation (2), where groups g are defined by sex and race categories. Overall estimates (i.e. the average of the 2007-2009 coefficient from Figure 4) is displayed on the far left; 2007-2009 estimates of β_{tg}. All estimates are of age-adjusted mortality, and weighted by 2006 CZ population from the SEER. Period point estimates are displayed as diamonds; vertical bars indicate 95% confidence intervals, clustered at the CZ level.

Figure 8: Impact of Great Recession Shock on Log Mortality Hazard Rate

(a) All 2003 Medicare Beneficiaries

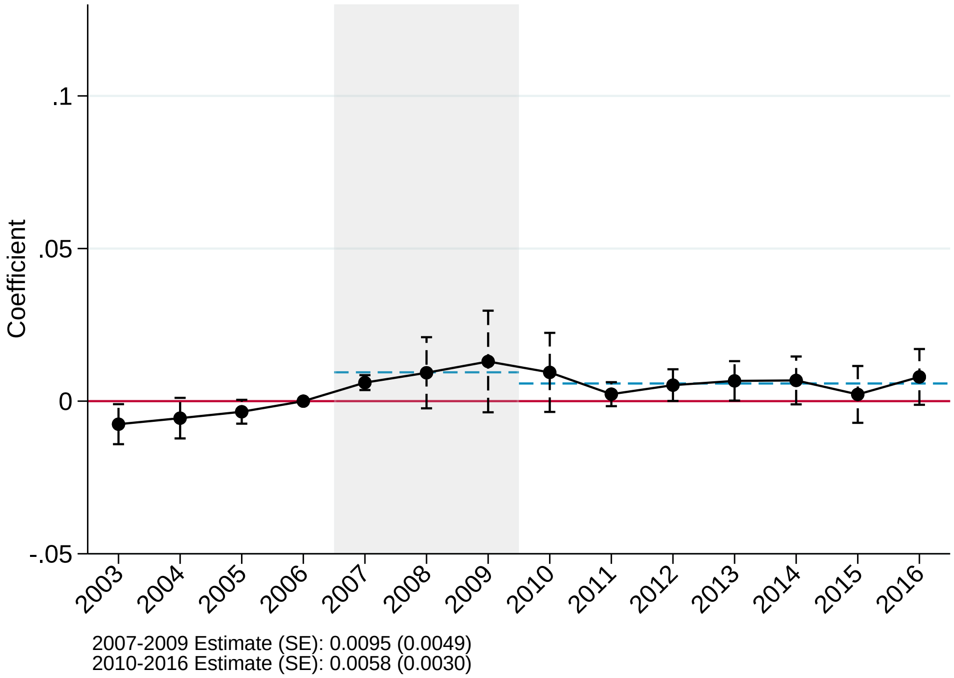


(b) 2003 Traditional Medicare Sample



Notes: This figure displays coefficients β_t from equation (4), 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.

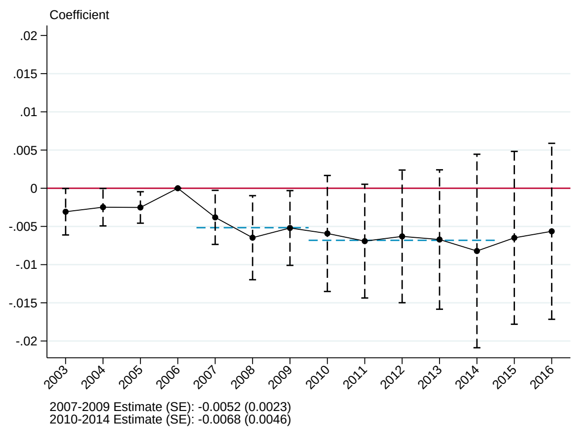
Figure 9: Impact of Great Recession Shock on Log Direct-Care Staff Hours



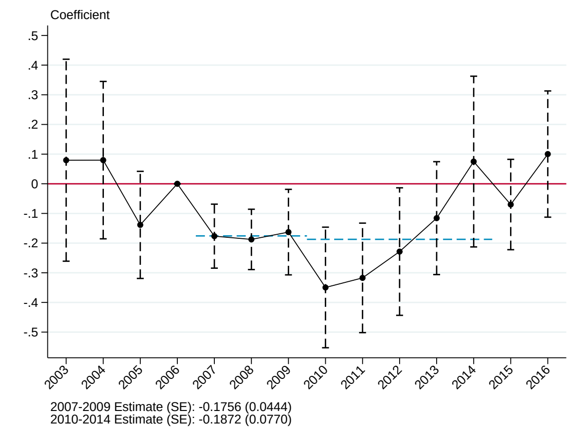
Notes: Figure displays coefficients β_t from equation $y_{it} = \beta_t[SHOCK_{c(i)} * \mathbb{1}(Year_t)] + \alpha_{c(i)} + \gamma_t + \varepsilon_{it}$ from 2003-2016, where i indexes skilled nursing facilities and $c(i)$ the Commuting Zone of facility i. The outcome y_{it} is the log of the sum of 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.

Figure 10: Impact of Great Recession Shock on Log Age-Adjusted Mortality Rate and PM2.5 Levels

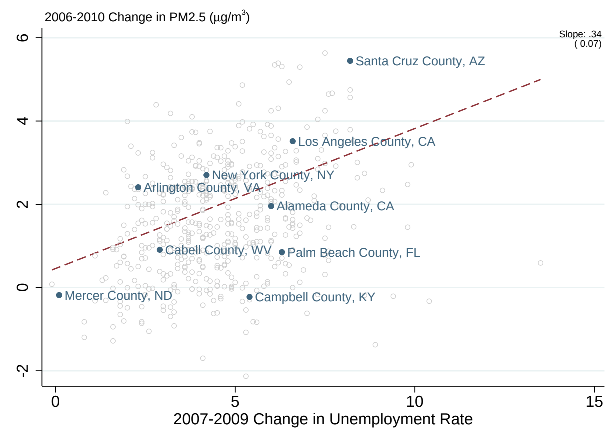
(a) Log Age-Adjusted Mortality Rate



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



(c) Correlation of Great Recession and PM2.5 Shock



Notes: Panel (a) and (b) display coefficients β_t from equation (7), where the outcome y_{ct} is the log age-adjusted county mortality rate per 100,000 population in Panel (a) and is PM2.5 levels in $\mu g/m^3$ in Panel (b), and in both cases β_t is the coefficient on the CZ-level Great Recession shock interacted with calendar year. Observations are weighted by county population in 2006. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the average annual point estimate for the periods 2007-2009 and 2010-2014. These estimates (and corresponding standard errors) are reported in the lower left hand corner. Standard errors are clustered at the CZ level. Panel (c) displays a scatterplot of the (negative of the) 2006-2010 change in PM2.5 levels against the 2007-2009 change in county unemployment rates. Each circle represents one county. For clarity of visualization counties with a change in PM2.5 levels below the 1st percentile and above the 99th are excluded. A linear fit weighted by county population in 2006 is plotted as a dashed red line and the slope and heteroskedasticity robust standard error is reported in the top right hand corner of the figure. For all results shown here, analysis is restricted to the 521 counties (accounting for 64.32% of the 2006 US population) for which we ever observe a PM2.5 monitor between 2003 and 2016 and also observe a PM2.5 monitor both in 2006 and 2010.

Tables

Table 1: Impact of Great Recession on Mortality for the cohort of 2003 Medicare beneficiaries

Regression Specification	2007-2009 Period Estimate & Standard Error
2003 Residence (Reduced Form) (β_t, eq. 4)	-0.00321
	(0.00157)
First Stage (π_t^{FS}, eq. 5)	0.945
	(0.003)
Control Function (β_t, eq. 6)	-0.00337
	(0.00169)
Yearly Residence (OLS) (β_t, eq. 3)	-0.00483
	(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 (4) (for 2003 residence specifications), coefficients β_t from equation (3) (for the yearly residence specification), and coefficients β_t from equation (6) (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 (5) (for the first stage regression), with outcome defined as the sum of the interactions of GR shock based on yearly CZ of residence and yearly dummies. Shock is defined as the difference in unemployment between 2009 and 2007 within a given CZ. Standard errors are clustered at the CZ 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. N = 7,088,974.

Table 2: Mortality Impact of Great Recession and of Pollution Change

	(1) 2007-2009 Period Estimate	(2) 2007-2009 Period Estimate	(3) 2007-2009 Period Estimates
Great Recession Shock	-0.0052 (0.0023)		-0.0035 (0.0020)
PM2.5 Shock		-0.0060 (0.0019)	-0.0048 (0.0016)

Notes: Table displays the average annual impact of the Great Recession and/or PM2.5 pollution shock on log age-adjusted mortality over 2007-2009. PM2.5 shock is defined as the negative of the county-level change in PM2.5 level between 2006 and 2010. Great Recession shock is defined, per usual, as the CZ-level change in the unemployment rate from 2007-2009. Specifically, columns (1) and (2) report the 2007-2009 average of the β_t's from equation (7), and column (3) reports the 2007-2009 average of the β_t's or ϕ_t's from equation (8). Standard errors, clustered at the CZ level, are reported in parentheses below each period estimate. Analysis is restricted to the 521 counties (accounting for 64.32% of the 2006 US population according to the SEER population estimates) for which we ever observe a PM2.5 monitor between 2003 and 2016 and also observe a PM2.5 monitor both in 2006 and 2010.

Table 3: Welfare Cost of a Recession: Basic Model

	$dT = 0$	$dT = 0.0021$		
VSLY	-	\$100k	\$250k	\$400k
$\gamma = 1.5$	0.96	0.54	-0.09	-0.71
$\gamma = 2$	1.03	0.61	-0.01	-0.63
$\gamma = 2.5$	1.10	0.68	0.06	-0.55

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 ($dT = 0$) and endogenous mortality ($dT = 0.0021$).

Table 4: Welfare Costs of the Great Recession 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	-	\$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 10-year duration of the Great Recession is considered, followed by a period without recessions until the end of life.

Table 5: 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	-	$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 Mortality Data

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

These microdata offer several key advantages over the publicly-available CDC mortality data, which can be found at `https://wonder.cdc.gov/wonder/help/ucd.html`). In particular, the public data report only coarse age bins, do not allow an analysis of mortality for combinations of sub-groups (e.g. certain causes of death within a certain age group), 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.

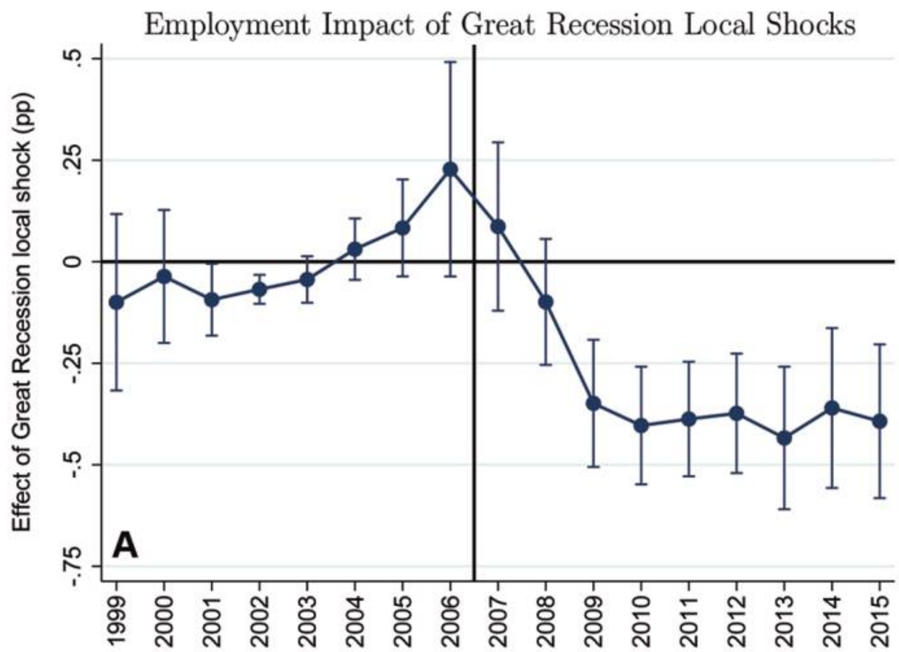
To turn the death counts in the CDC microdata into mortality rates, we use population data from the National Cancer Institutes Surveillance Epidemiology and End Results (SEER) program. More information about these data can be found here: `https://seer.cancer.gov/popdata/`. The SEER population estimates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

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

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

A.2 Figures

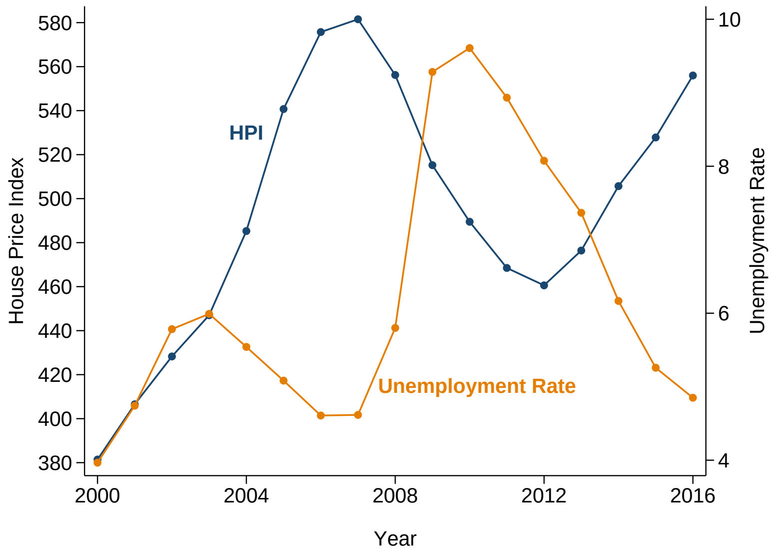
Figure A.1: Figure 4 from Yagan (2019)



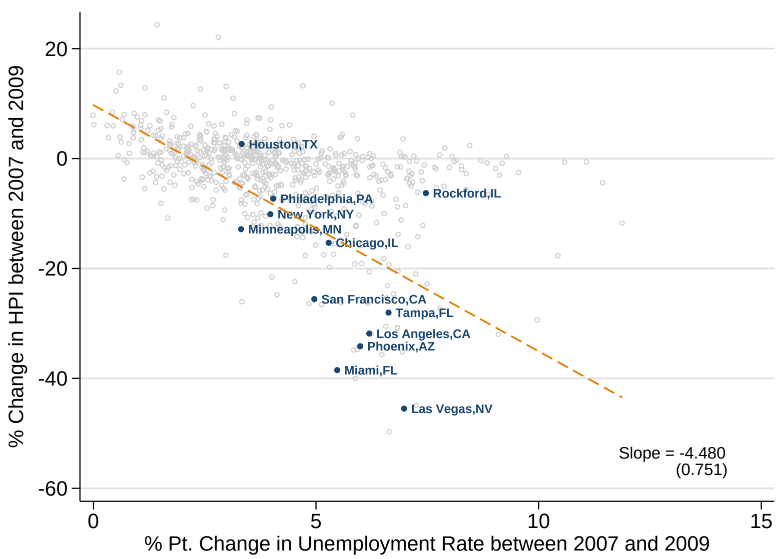
Notes: Figure 4a from Yagan (2019). Original notes: "Regression estimates of the effect of Great Recession local shocks on relative employment, controlling for 2007 age-earnings-industry fixed effects in the main sample. Each year t's outcome is year t relative employment: the individual's year t employment (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

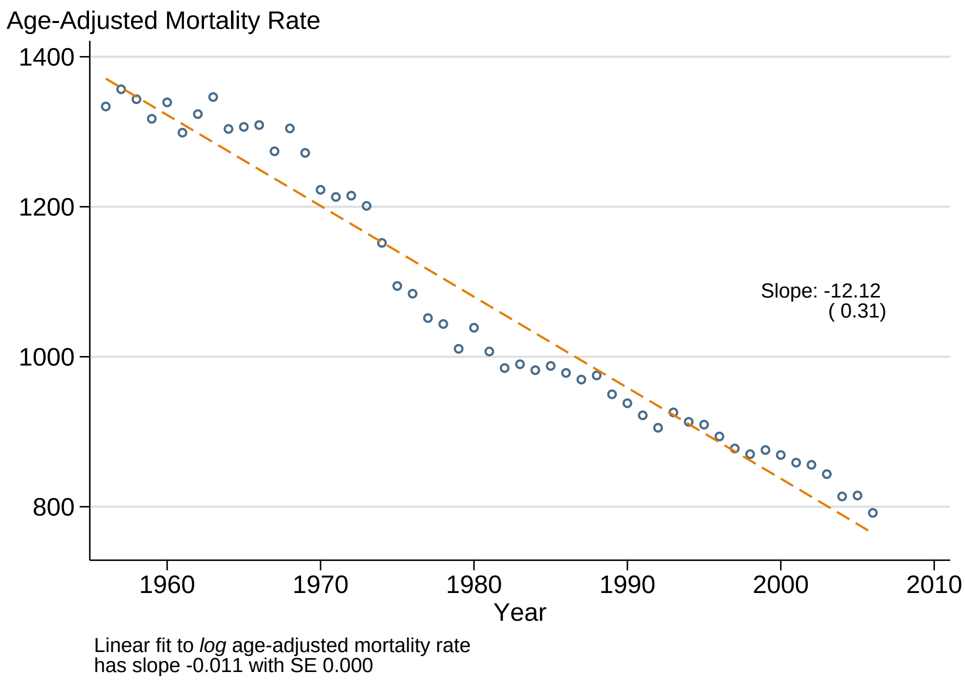


(b) CZ House Prices and Unemployment Rate



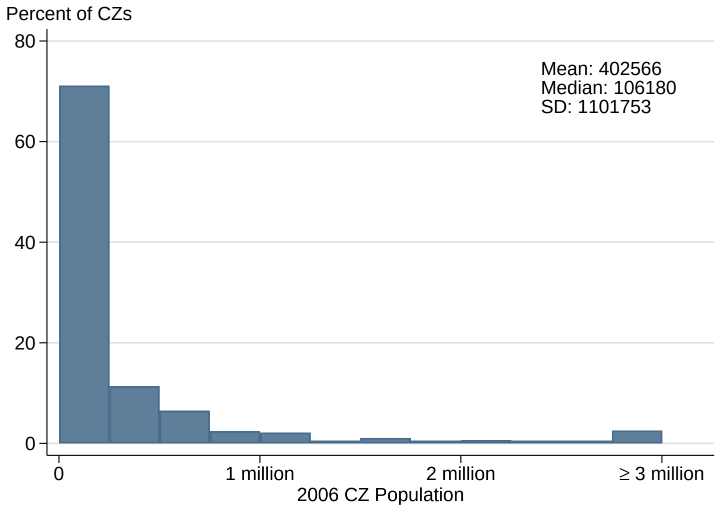
Notes: Figure A.2a plots a national time series of the Federal Housing Finance Agency's yearly House Price Index (HPI) and the annual (average) unemployment rate from the Bureau of Labor Statistics between 2000 and 2016. The raw HPI scale is on the left-hand vertical axis, and the unemployment rate is 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



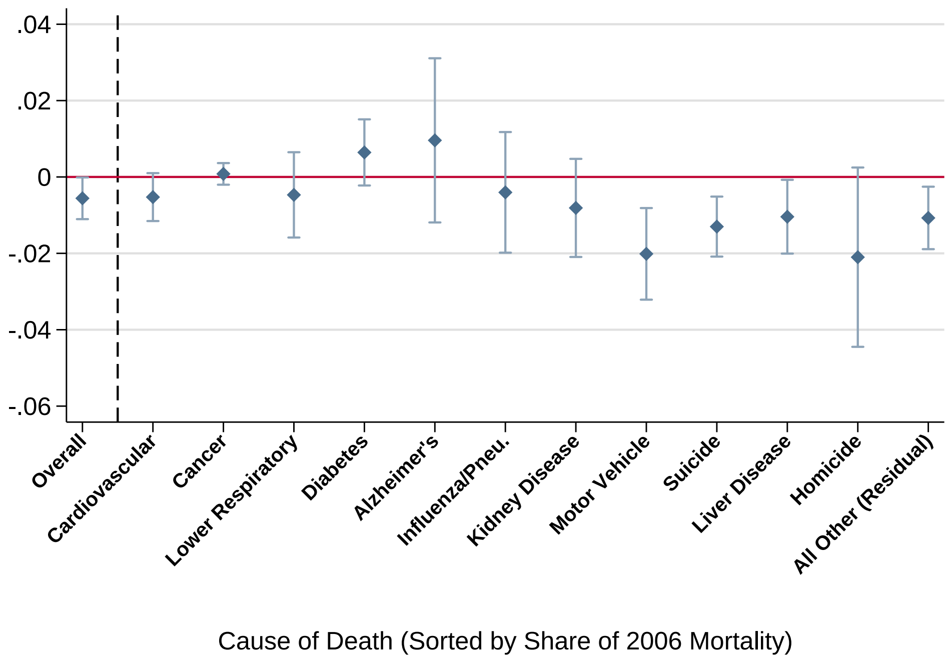
Notes: Figure reports age-adjusted mortality rates per 100,000 in the United States from 1956-2006. Data are drawn from the National Center for Health Statistics, "Mortality Trends in the United States, 1900-2018." Slope reported in text box is a linear fit of the age-adjusted mortality rate to a linear 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.

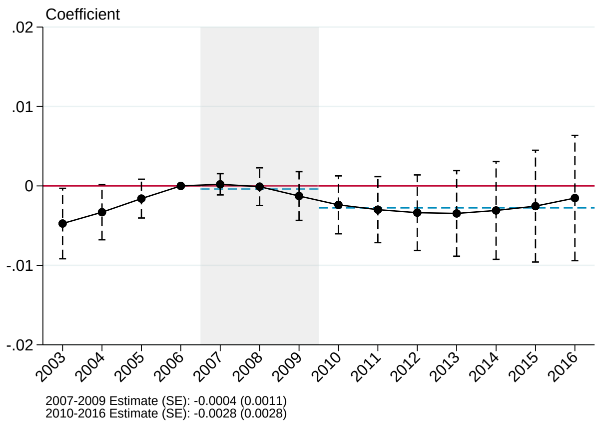
Figure A.5: Impact on Mortality, by Cause of Death



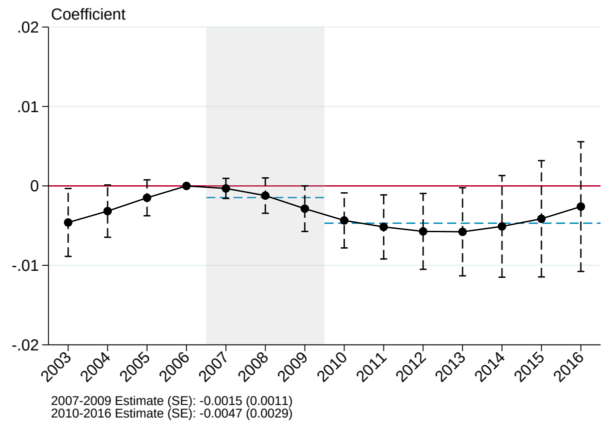
Notes: Figure displays period estimates and 95% confidence intervals for the linear combination of coefficients on $SHOCK_{ct}$ from 2007-2016 from equation (2). As in Figure 4, estimates are weighted by the 2006 CZ population from the SEER, and standard errors are clustered at the CZ level. Estimates 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

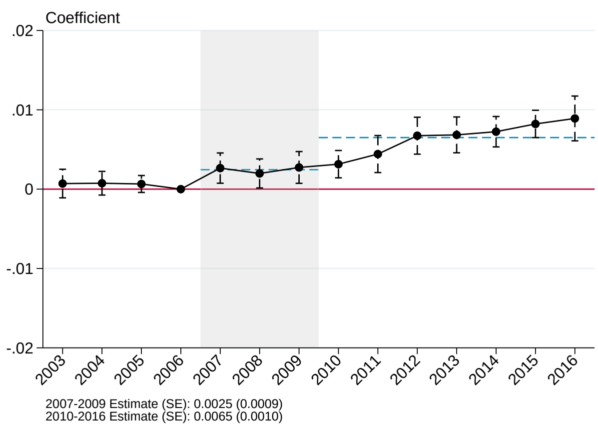
(a) Total Population



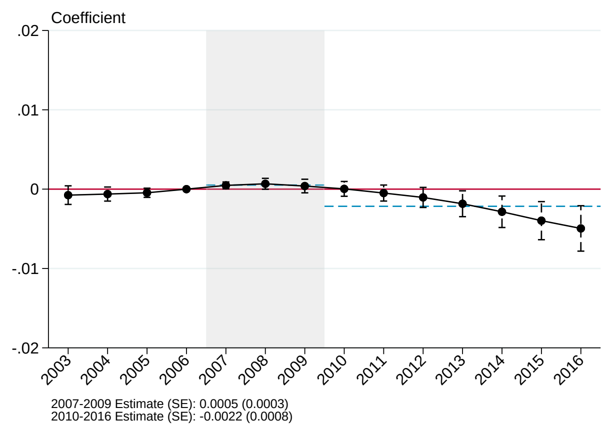
(b) Population Age 25-64



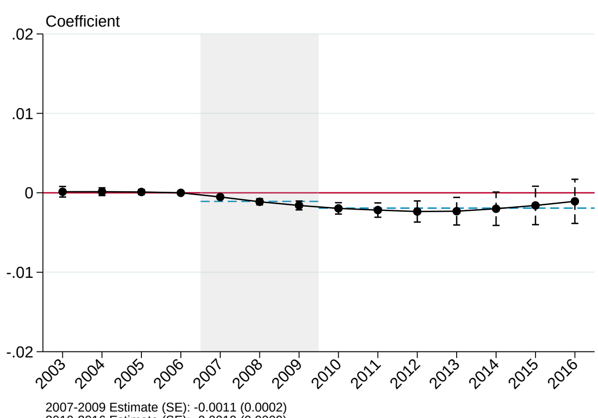
(c) Log Median Age



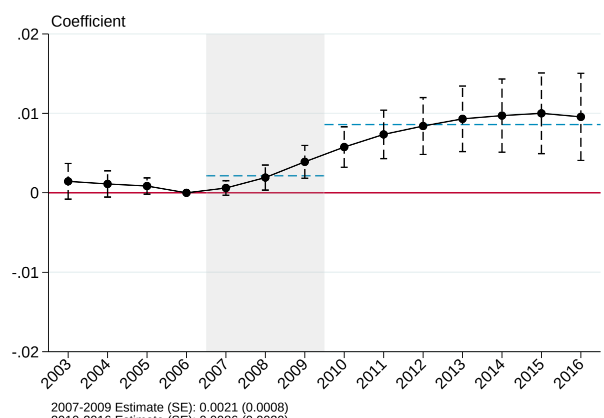
(d) Log Share < 25 Years Old



(e) Log Share 25-64 Years Old



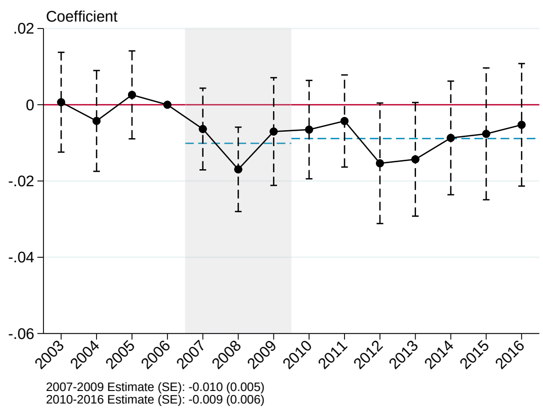
(f) Log Share $\geq$ 65 Years Old



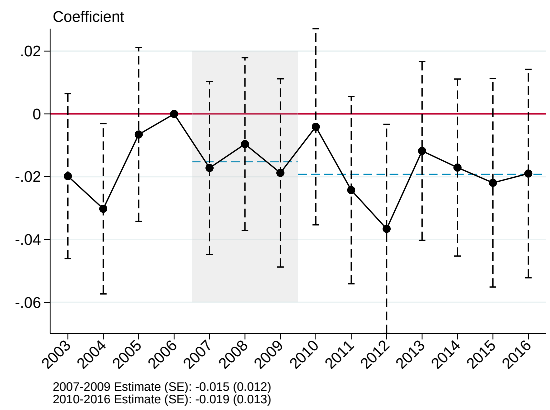
Notes: Figures plot yearly coefficients β_t estimated from equations (1) and (2), where the outcome y_{ct} is the log annual total CZ population from the SEER (Panels A.6a); the age 25-64 CZ population (A.6b); the log median age in the CZ (Panel A.6c); the log share of the population under age 25 (Panel A.6d); the log share age 25-64 (Panel A.6e); and the log share 65+ years old (Panel A.6f). 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, by Age Group: Age 0-54

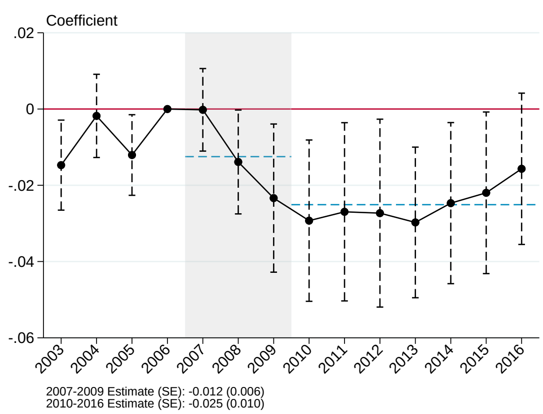
(a) Age 0-4



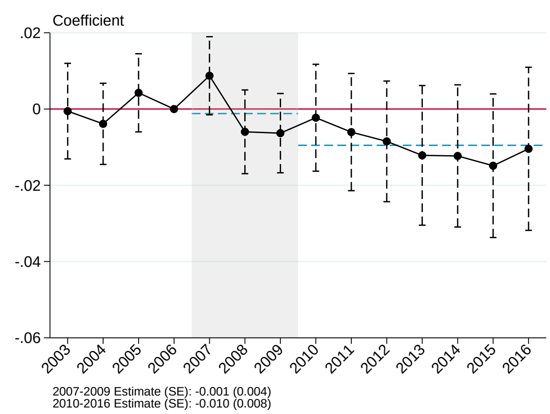
(b) Age 5-14



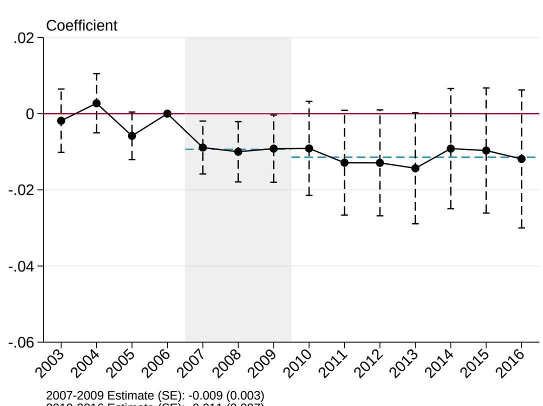
(c) Age 15-24



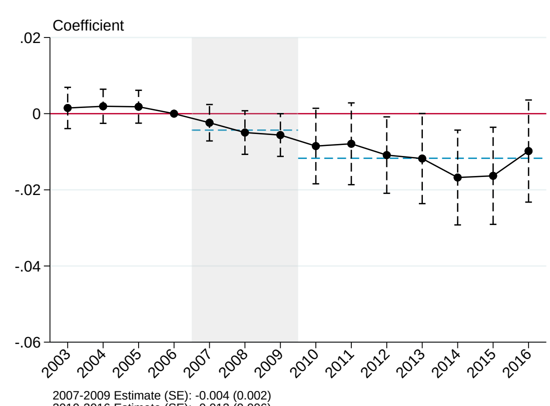
(d) Age 25-34



(e) Age 35-44



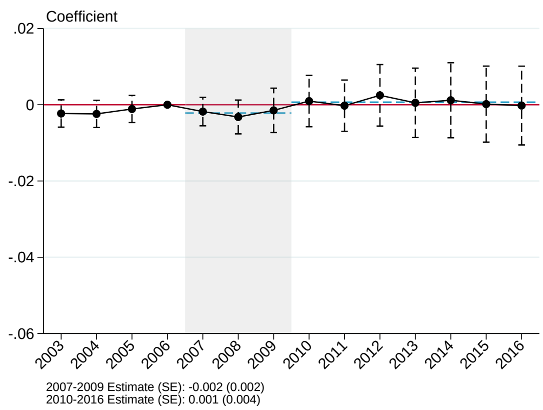
(f) Age 45-54



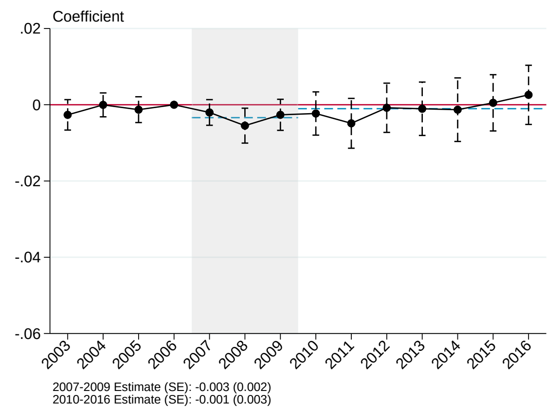
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ct} is the log mortality rate of the CZ population in one of six age bins (all estimated from the SEER). Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are 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.8: Impact of Great Recession, by Age Group: Age 55+

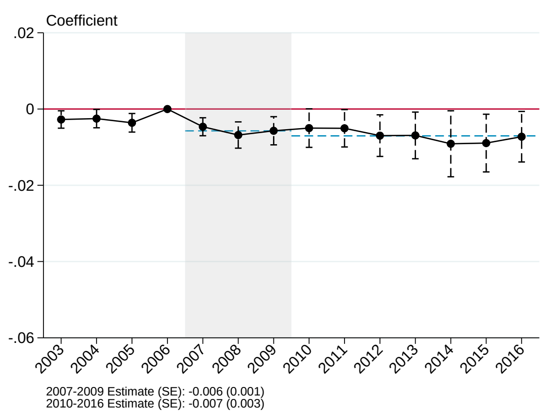
(a) Age 55-64



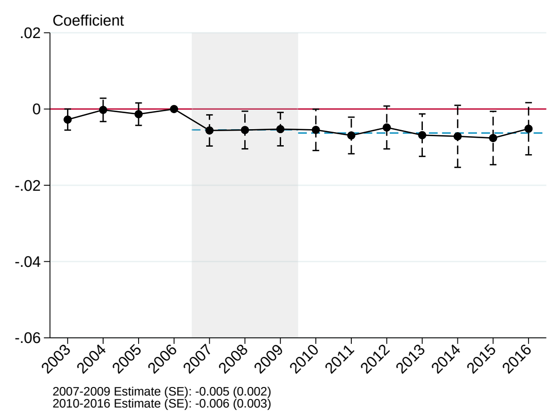
(b) Age 65-74



(c) Age 75-84



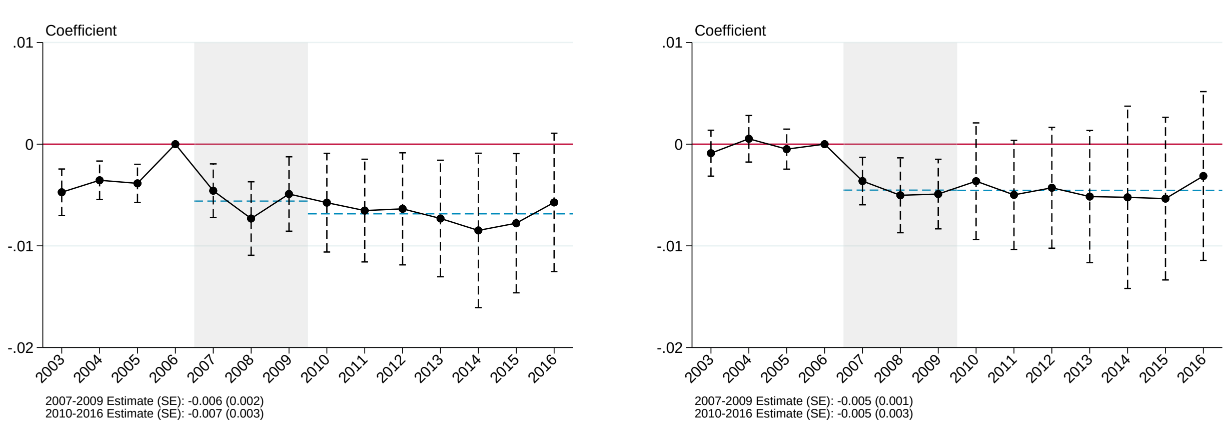
(d) Age 85+



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.9: Impact of Great Recession, by Sex

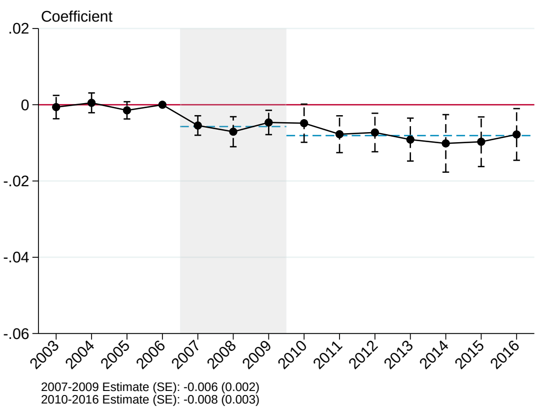
(a) Male (b) Female



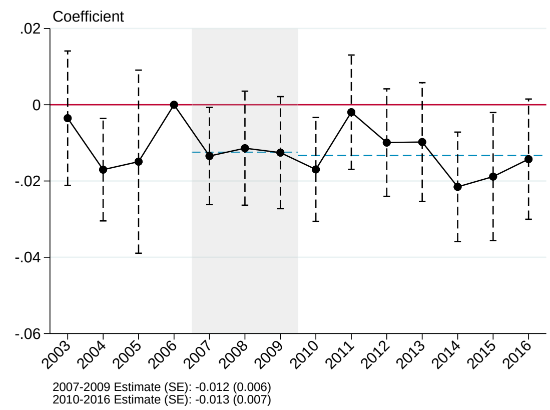
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log CZ mortality rate among either males (Panel A.9a) or females (Panel A.9b). Event study estimates are weighted by 2006 CZ population as measured in the SEER. Standard errors are clustered at 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 Race

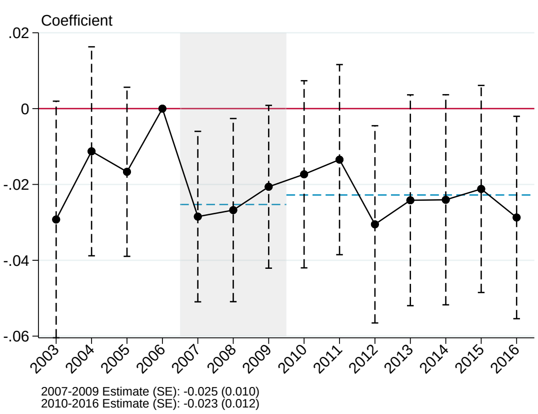
(a) Non-Hispanic White



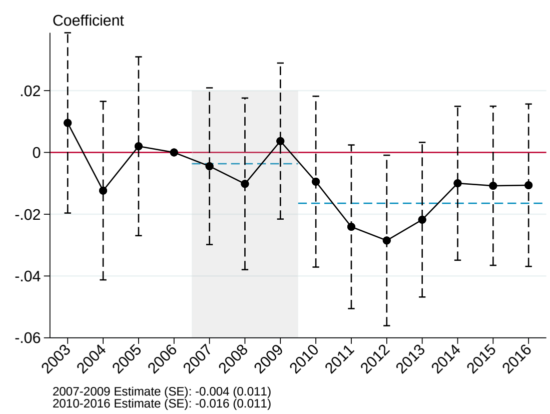
(b) Non-Hispanic Black



(c) Hispanic



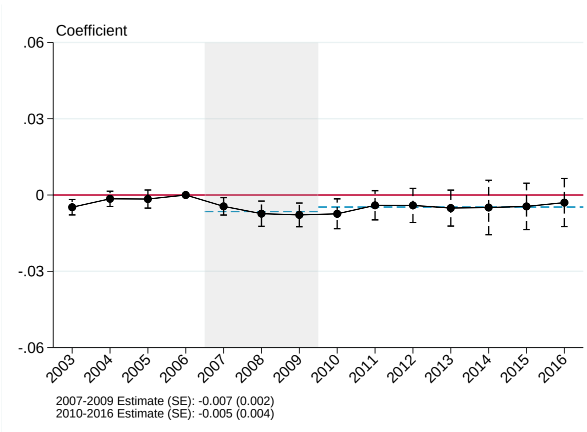
(d) Other



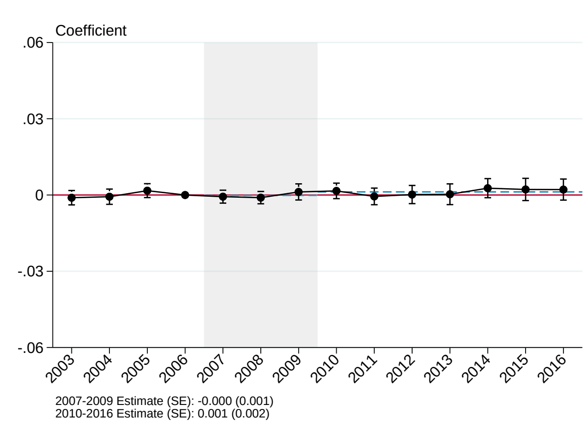
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log mortality rate among the CZ population that is Non-Hispanic White (Panel A.10a), Non-Hispanic Black (Panel A.10b), Hispanic (Panel A.10c) or Other (Panel A.10d). Event study estimates are 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 Cause of Death I

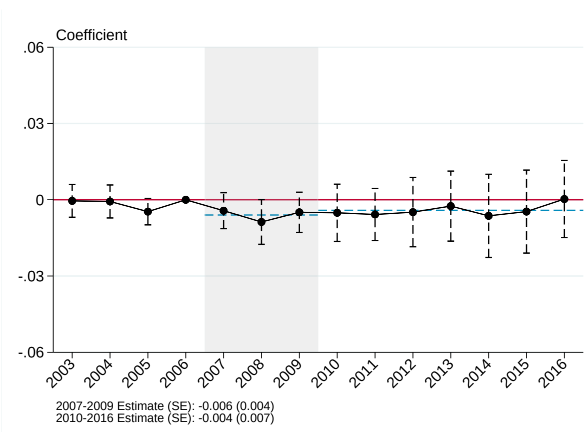
(a) Cardiovascular Disease



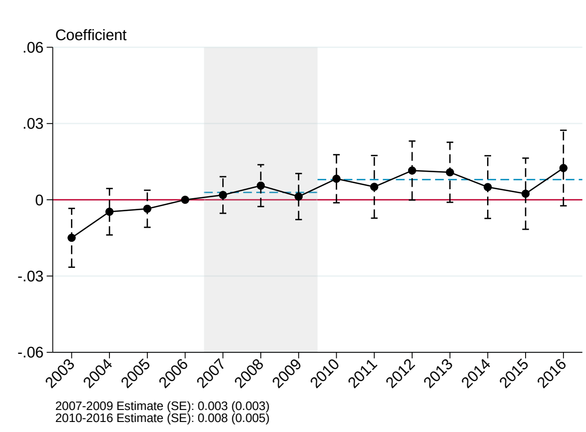
(b) Malignant Neoplasms



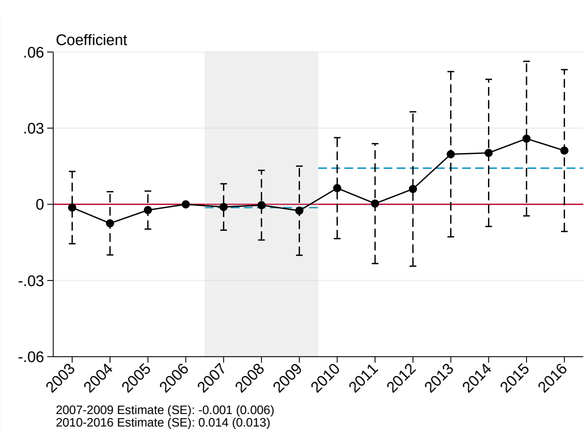
(c) Chronic Lower Respiratory Disease



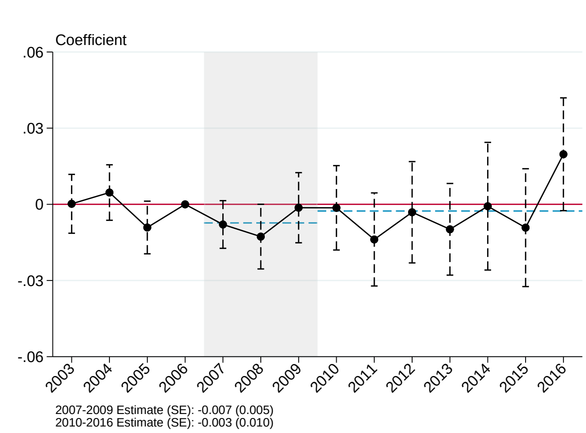
(d) Diabetes



(e) Alzheimer's Disease



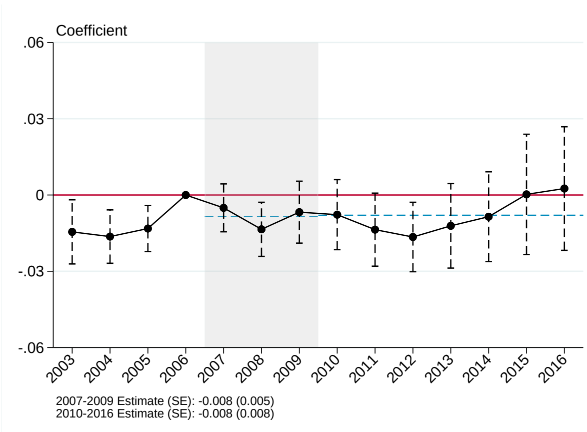
(f) Influenza/Pneumonia



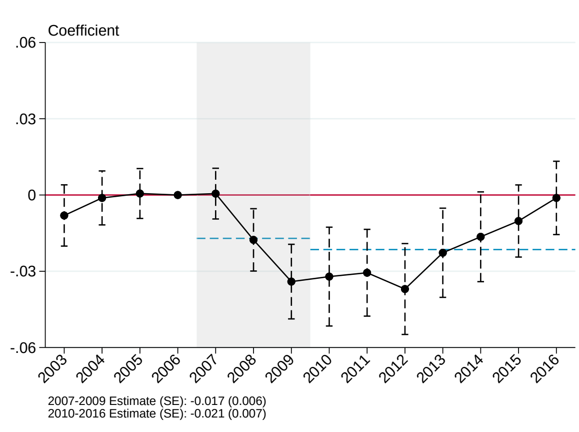
Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log CZ mortality rate from one of six causes of death. Panel A.11a displays event studies of the log mortality rate from cardiovascular disease; Panel A.11b from cancer; Panel A.11c from chronic lower respiratory disease; Panel A.11d from diabetes; Panel A.11e from Alzheimer's disease; and Panel A.11f 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.12: Impact of Great Recession, by Cause of Death II

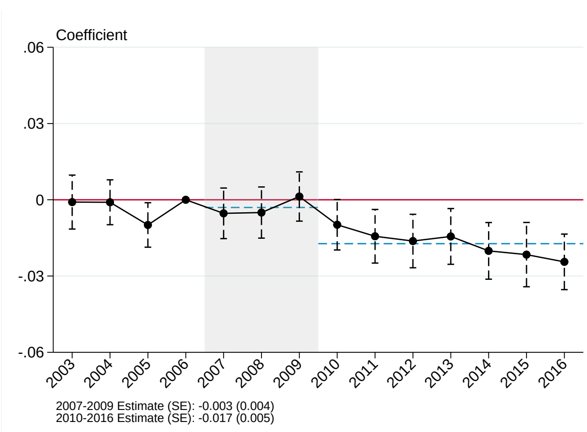
(a) Kidney Disease



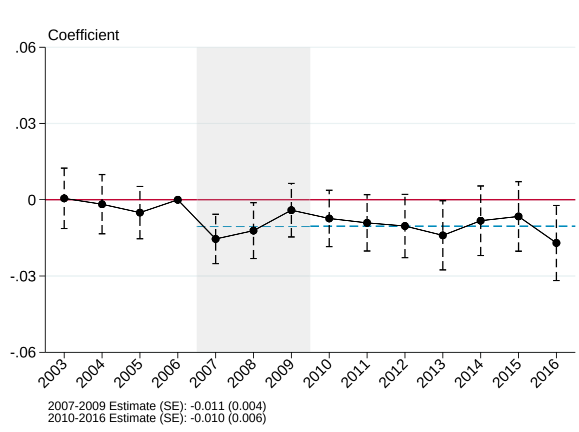
(b) Motor Vehicle Accidents



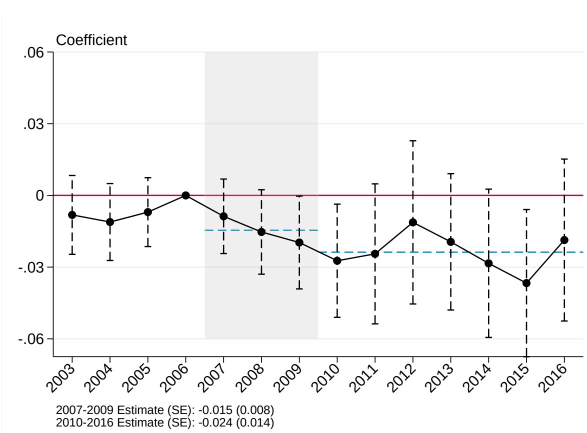
(c) Suicide



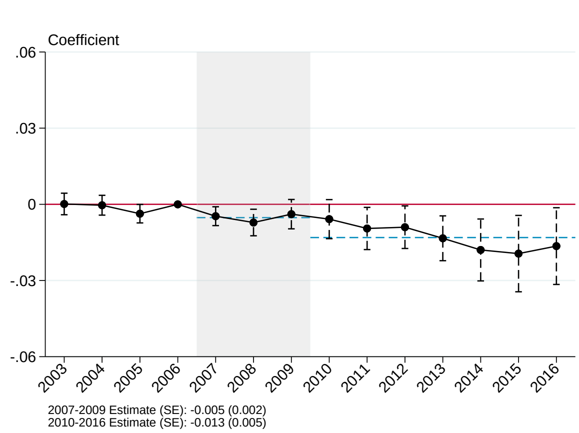
(d) Liver Disease/Cirrhosis



(e) Homicide



(f) All Other Causes (Residual)

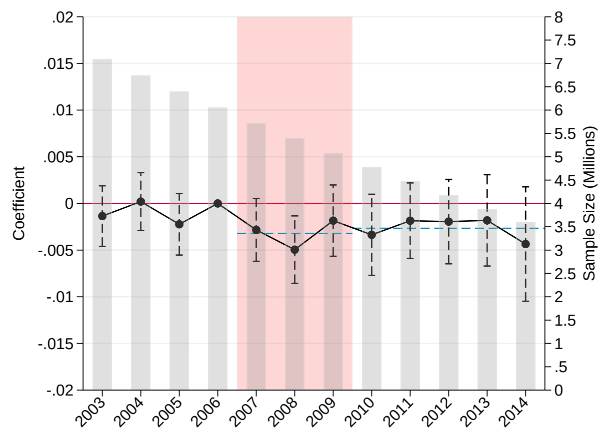


Notes: Figure plots yearly coefficients β_{tg} estimated from equation (2), where the outcome y_{ctg} is the log CZ mortality rate from one of six causes of death. Panel A.12a displays event studies of the log mortality rate from kidney disease; Panel A.12b from motor vehicle accidents; Panel A.12c from suicide; Panel A.12d from liver disease; Panel A.12e from homicide; and Panel A.12f from all other causes of death not described in Figure A.11 or A.12. 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.

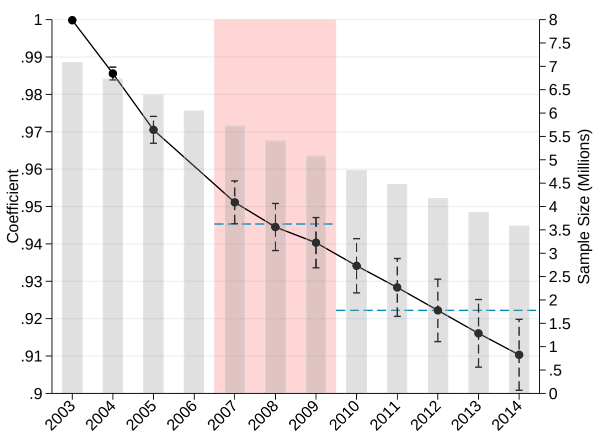
Figure A.13: Sensitivity to yearly vs. baseline residence

(a) Yearly Residence (OLS) (β_t, equation (3))

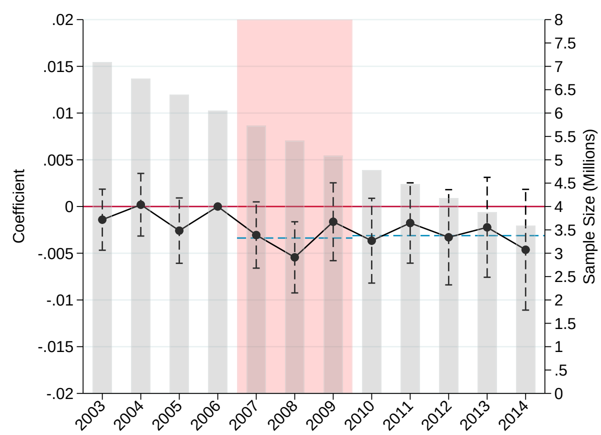
(b) 2003 Residence (Reduced Form) (π_t^{RF}, equation (4))



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



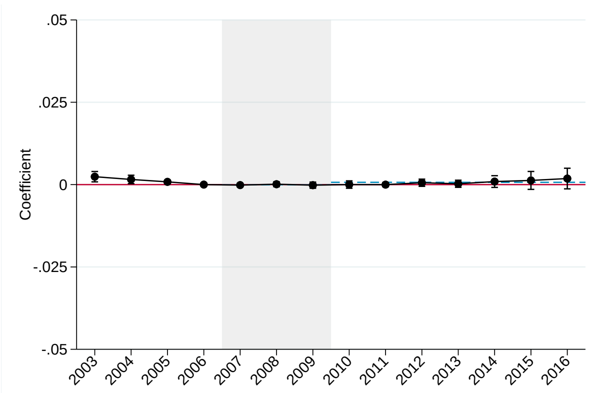
(d) Control Function (β_t, equation (6))



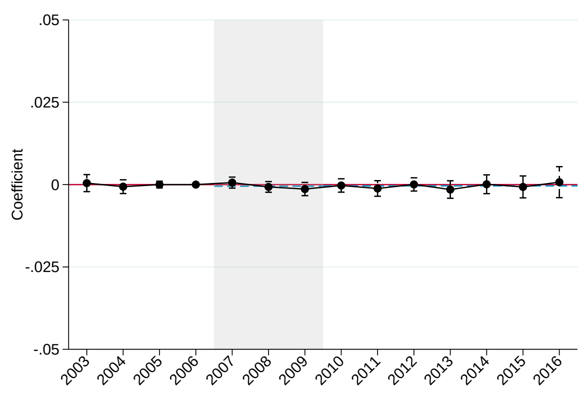
Notes: This figure displays coefficients coefficients β_t from equation (3) (for Panel A), coefficients π_t^{RF} from equation (4) (for Panel B), and coefficients β_t from equation (6) (for Panel D), with outcome $log(h_{it}(a))$ defined as the log of the individual-level hazard rate at age a. The figure also displays coefficients π_t^{FS} from equation (5) (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.14: Impact of Great Recession on Nursing Home Volume and Resident Characteristics

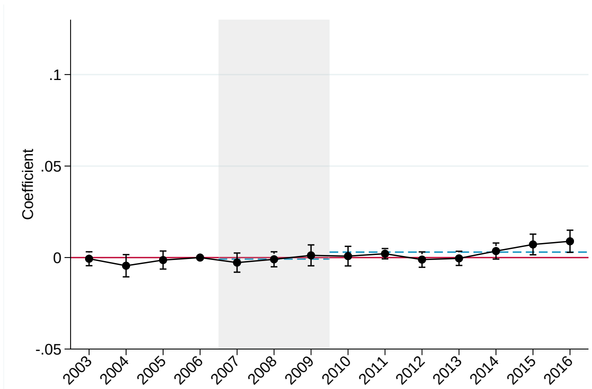
(a) Log Average Age



(b) Log Female Resident Share

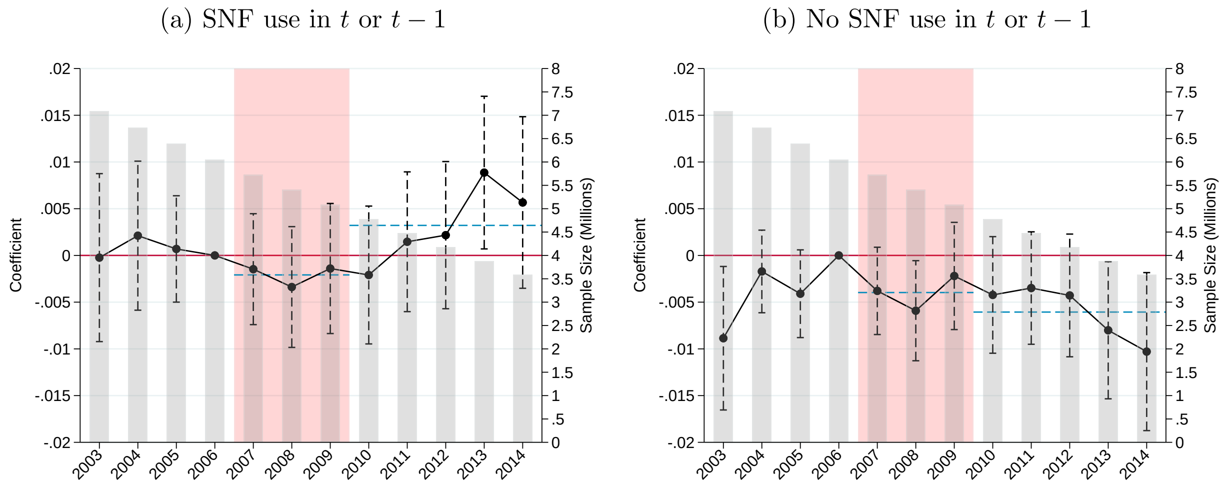


(c) Log Occupants per Bed



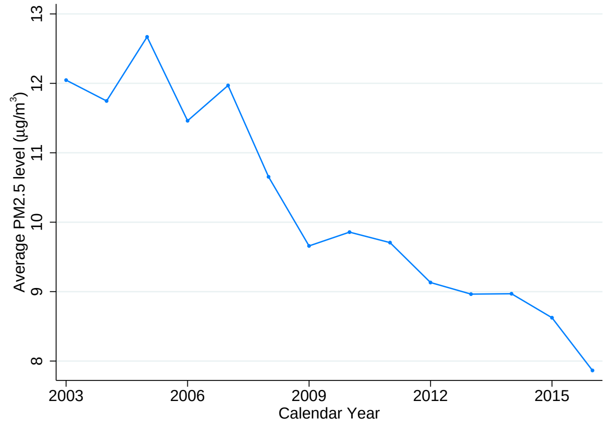
Notes: Figure displays coefficients β_t from equation $y_{it} = \beta_t[SHOCK_{c(i)} * \mathbb{1}(Year_t)] + \alpha_{c(i)} + \gamma_t + \varepsilon_{it}$ from 2003-2016, where i indexes skilled nursing facilities and $c(i)$ the Commuting Zone of facility i. The outcome y_{it} in Panel A.14a is the log average age of residents in facility i as of the first Thursday in April of the survey year (from the MDS); in Panel A.14b, the log share of facility residents who are female on the same day (from the MDS); and in Panel A.14c, 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.15: Impact of the Great Recession on Log Mortality Hazard Rate, by SNF Use



Figures display yearly coefficients β_t from equation (4), 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.

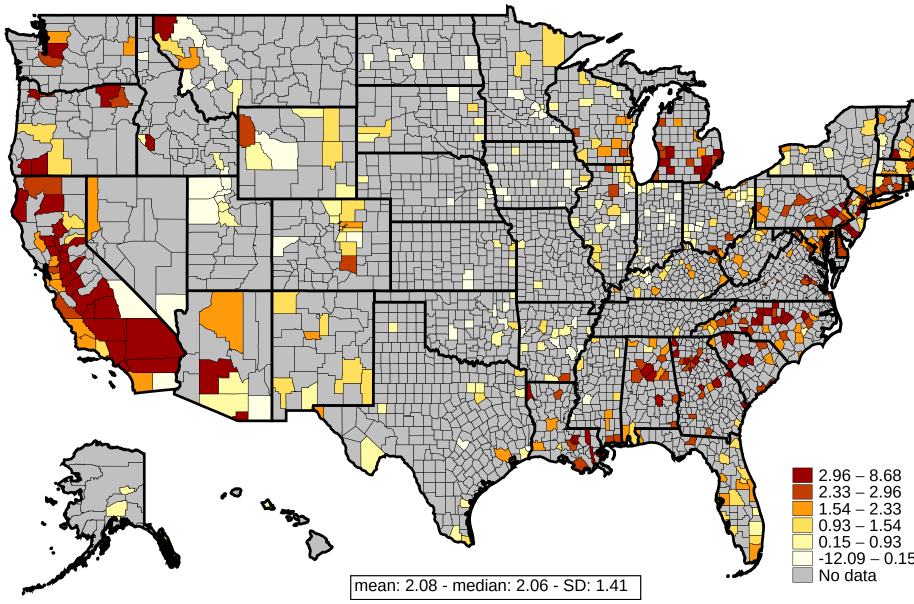
Figure A.16: Average PM2.5 Levels: 2003-2016



[]

Notes: Figure displays a time-series of average annual PM2.5 levels from 2003-2016 across all PM2.5 monitors located in counties included in our baseline sample of 521 counties (accounting for 64.32% of the 2006 US population according to the SEER population estimates) for which we ever observe, a PM2.5 monitor between 2003 and 2016 and also observe a PM2.5 monitor both in 2006 and 2010.

Figure A.17: PM2.5 Shock, Baseline Sample of Counties



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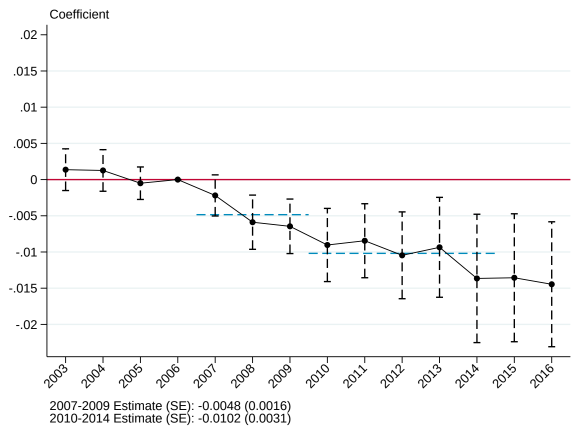
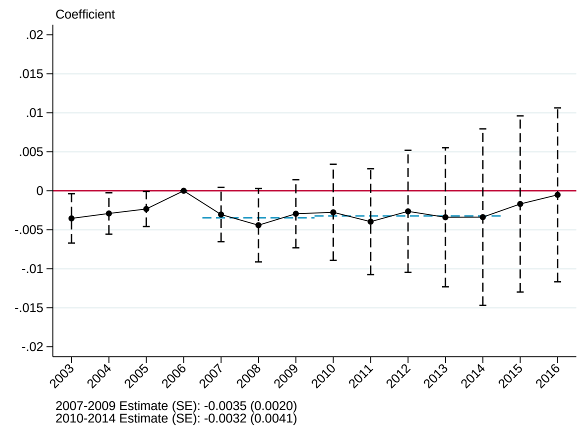
Notes: Figure displays a heat map of the (negative of) the PM 2.5 shock (panel a) for the counties in our baseline sample of 521 counties (accounting for 64.32% of the 2006 US population) for which we ever observe a PM2.5 monitor between 2003 and 2016 and also observe a PM2.5 monitor both in 2006 and 2010. Counties in gray are ones that are excluded from our baseline sample.

Figure A.18: Impact of Great Recession and PM2.5 Shocks on Log Age-Adjusted Mortality Rate

(a) PM2.5 Shock Coefficients

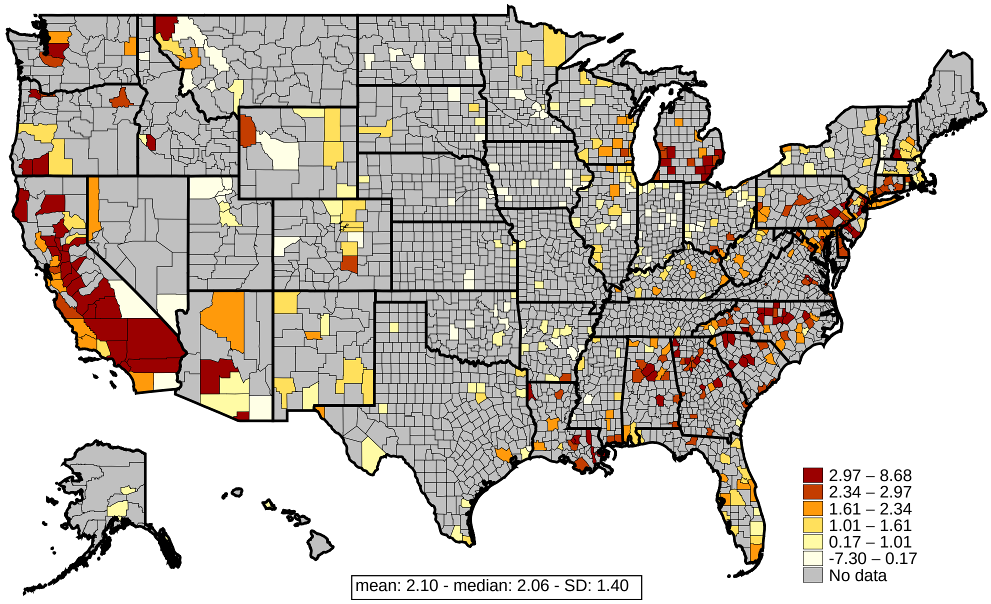


(b) Great Recession Shock Coefficients



Notes: Panel (a) and (b) display coefficients β_t and ϕ_t, respectively, from equation (8), where the outcome y_{ct} is the log age-adjusted county mortality rate per 100,000 population. β_t is the coefficient on the county-level PM2.5 shock interacted with calendar year and ϕ_t is the coefficient on the CZ-level Great Recession shock interacted with calendar year. Observations are weighted by county population in 2006. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the average annual point estimate for the periods 2007-2009 and 2010-2014. These estimates (and corresponding standard errors) are reported in the lower left hand corner. Standard errors are clustered at the CZ level. For all results shown here, analysis is restricted to the 521 counties (accounting for 64.32% of the 2006 US population) for which we ever observe a PM2.5 monitor between 2003 and 2016 and also observe a PM2.5 monitor both in 2006 and 2010.

Figure A.19: PM2.5 Shock, Balanced Sample of Counties



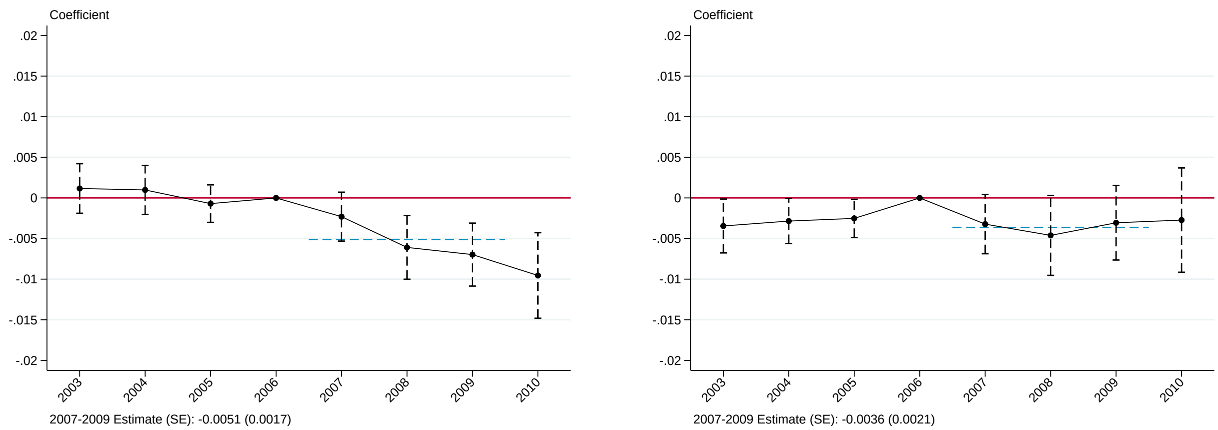
[]

Notes: Figure displays a heat map of the (negative of) the PM 2.5 shock for the counties in our balanced sample of 495 counties (accounting for 62.88% of the 2006 US population according to the SEER population estimates) for which we observe a PM2.5 monitor in every year between 2003 and 2010. Counties in gray are ones that are excluded from our balanced sample.

Figure A.20: Impact of Great Recession and PM2.5 Shocks on Log Age-Adjusted Mortality Rate: 2003 - 2010 Balanced Sample

(a) PM2.5 Shock Coefficients

(b) Great Recession Shock Coefficients



Notes: Panel (a) and (b) display coefficients β_t and ϕ_t, respectively, from equation (8), where the outcome y_{ct} is the log age-adjusted county mortality rate per 100,000 population. β_t is the coefficient on the county-level PM2.5 shock interacted with calendar year and ϕ_t is the coefficient on the CZ-level Great Recession shock interacted with calendar year. Observations are weighted by county population in 2006. Dashed vertical lines indicate 95% confidence intervals on each coefficient. Horizontal blue dashed lines indicate the average annual point estimate for the periods 2007-2009 and 2010-2014. These estimates (and corresponding standard errors) are reported in the lower left hand corner. Standard errors are clustered at the CZ level. For all results shown here, analysis is restricted to the 495 counties (accounting for 62.88% of the 2006 US population according to the SEER population estimates) for which we observe a PM2.5 monitor in every year between 2003 and 2010.

A.3 Tables

Table A.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 A.2: 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	-0.0056
	(0.0015)	(0.0034)	(0.0028)
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.3: 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	-0.0056
	(0.0015)	(0.0034)	(0.0028)
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.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	-0.0056
	(0.0015)	(0.0034)	(0.0028)
Underlying Cause of Death			
Cardiovascular Disease	-0.0065	-0.0047	-0.0053
	(0.0021)	(0.0038)	(0.0032)
Malignant Neoplasms (Cancer)	-0.0002	0.0012	0.0008
	(0.0011)	(0.0017)	(0.0014)
Chronic Lower Respiratory Disease	-0.0060	-0.0041	-0.0047
	(0.0037)	(0.0067)	(0.0057)
Diabetes	0.0029	0.0079	0.0064
	(0.0034)	(0.0054)	(0.0044)
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	-0.0030	-0.0173	-0.0130
	(0.0041)	(0.0047)	(0.0040)
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 $\geq$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: From Krebs (2007) to our extension

	Costs of Great Recession			Costs of Recessions		
	(1)	(2)	(3)	(4)	(5)	(6)
$\gamma = 1.5$	1.22	1.33	1.35	1.83	1.68	1.48
$\gamma = 2$	1.70	1.81	1.84	2.39	2.28	2.04
$\gamma = 2.5$	2.23	2.35	2.38	3.10	2.98	2.68
β	0.96	0.99	0.99	0.96	0.99	0.99
Mortality	None	Realistic	Realistic	None	Realistic	Realistic
Retirement	No	No	Yes	No	No	Yes
Periods	151	66	66	151	66	66

Notes: The welfare cost is measured as a percentage of average annual consumption. In the specifications without mortality, agents live more periods to replicate infinitely-lived agents from the original model. Realistic (age-specific) mortalities are exogenous. A 10-year duration of the Great Recession is considered, followed by a period without recessions until the end of life.

Table A.11: 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	-	$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 5-year duration of the Great Recession is considered, followed by a period without recessions until the end of life.

Table A.12: Welfare Costs of Business Cycles by Age

	Mortality			
	Exogenous	Endogenous		
	(1)	(2)	(3)	(4)
Panel A. Starting age 35				
$\gamma = 1.5$	0.54	0.23	-0.23	-0.68
$\gamma = 2$	0.77	0.48	0.06	-0.36
$\gamma = 2.5$	1.03	0.78	0.40	0.03
Panel B. Starting age 45				
$\gamma = 1.5$	0.40	0.04	-0.51	-1.05
$\gamma = 2$	0.58	0.25	-0.25	-0.75
$\gamma = 2.5$	0.78	0.50	0.05	-0.39
Panel C. Starting age 55				
$\gamma = 1.5$	0.27	-0.14	-0.79	-1.44
$\gamma = 2$	0.38	0.01	-0.59	-1.17
$\gamma = 2.5$	0.49	0.17	-0.36	-0.88
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	-	\$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.13: Welfare Costs of Great Recession 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	-	$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). A 10-year duration of the Great Recession is considered, followed by a period without recessions until the end of life.

Table A.14: 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	-	$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.15: Mortality Impact of Great Recession and of Pollution Change: County Level Great Recession Shock

	(1) 2007-2009 Period Estimate	(2) 2007-2009 Period Estimate	(3) 2007-2009 Period Estimates
Great Recession Shock	-0.0062		-0.0048
	(0.0018)		(0.0015)
PM2.5 Shock		-0.0060	-0.0042
		(0.0019)	(0.0014)

Notes: Table displays the average annual impact of the Great Recession and/or PM2.5 pollution shock on log age-adjusted mortality over 2007-2009. PM2.5 shock is defined as the negative of the county-level change in PM2.5 level between 2006 and 2010. Great Recession shock is defined here, alternatively, as the county-level change in the unemployment rate from 2007-2009. Specifically, columns (1) and (2) report the 2007-2009 average of the β_t's from equation (7), and column (3) reports the 2007-2009 average of the β_t's or ϕ_t's from equation (8). Standard errors, clustered at the CZ level, are reported in parentheses below each period estimate. Analysis is restricted to the 521 counties (accounting for 64.32% of the 2006 US population according to the SEER population estimates) for which we ever observe a PM2.5 monitor between 2003 and 2016 and also observe a PM2.5 monitor both in 2006 and 2010.

Table A.16: Mortality Impact of Great Recession and of Pollution Change: 2003-2010 Balanced Sample

	(1) 2007-2009 Period Estimate	(2) 2007-2009 Period Estimate	(3) 2007-2009 Period Estimates
Great Recession Shock	-0.0054		-0.0036
	(0.0024)		(0.0021)
PM2.5 Shock		-0.0064	-0.0051
		(0.0020)	(0.0017)

Notes: Table displays the average annual impact of the Great Recession and/or PM2.5 pollution shock on log age-adjusted mortality over 2007-2009. PM2.5 shock is defined as the negative of the county-level change in PM2.5 level between 2006 and 2010. Great Recession shock is defined, per usual, as the CZ-level change in the unemployment rate from 2007-2009. Specifically, columns (1) and (2) report the 2007-2009 average of the β_t's from equation (7), and column (3) reports the 2007-2009 average of the β_t's or ϕ_t's from equation (8). Standard errors, clustered at the CZ level, are reported in parentheses below each period estimate. Analysis is restricted to the 495 counties (accounting for 62.88% of the 2006 US population according to the SEER population estimates) for which we observe a PM2.5 monitor in every year between 2003 and 2010.