Trading Goods for Lives:
NAFTA's Mortality Impacts and Implications

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Abstract

We estimate the mortality effects of local labor market exposure to NAFTA and compare them to the mortality effects of other U.S. local labor market contractions. Areas more exposed to NAFTA experienced sustained increases in mortality over the subsequent 15 years. Mortality increases occurred for all broad demographic groups, but were especially pronounced among working-age men. Extending the analysis to other economic contractions, we show that the health consequences depend critically on which sectors bear the losses: declines in manufacturing employment increase local area mortality, while declines in non-manufacturing employment reduce it.

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"While expanding economies are all alike, every contracting economy is contracting in its own way."
– Ben Friedman, channeling Leo Tolstoy (Friedman, 1993)

1 Introduction

The secular decline in U.S. manufacturing and the accompanying economic decline of particular local labor markets has been blamed for a range of societal ills, including decreases in rates of marriage and civic engagement and increases in rates of opioid addiction and deaths of despair (e.g., Wilson, 1996; Vance, 2016; Case and Deaton, 2020). In this paper, we document the adverse mortality consequences of a particular source of decline in U.S. manufacturing: the 1994 North American Free Trade Agreement (NAFTA). We then expand our analysis to other sources of local labor market contractions to show that declines in manufacturing employment increase local area mortality while declines in non-manufacturing employment reduce it. Our findings suggest that the sign and magnitude of any mortality impacts of local labor market contractions may depend critically on how much these shocks affect the manufacturing sector relative to non-manufacturing sectors. They also provide a parsimonious explanation for what has been something of an empirical puzzle: while plant closures and increased exposure to trade from China have been shown to raise mortality (e.g., Sullivan and von Wachter, 2009; Autor et al., 2019; Pierce and Schott, 2020), recessions have been found to reduce mortality (e.g., Ruhm, 2000; Miller et al., 2009; Stevens et al., 2015; Finkelstein et al., 2025).[1]

We first estimate the mortality impacts of local economic exposure to NAFTA. When it went into effect on January 1, 1994, NAFTA was the most comprehensive free trade agreement that had been negotiated to date (Congressional Budget Office, 2003; Villareal and Fergusson, 2014). Prior work has documented that areas in the U.S. that were more exposed to NAFTA experienced declines in wages and in the employment-to-population ratio (hereafter, EPOP) (Hakobyan and McLaren, 2016; Choi et al., 2024) and a shift in support away from the Democratic party (Choi et al., 2024), while aggregate welfare benefits of NAFTA were modest (Romalis, 2007; Caliendo and Parro, 2015). To estimate NAFTA's mortality impacts, we follow Hakobyan and McLaren (2016) and Choi et al. (2024) and exploit spatial variation across the U.S. in local area exposure to increased Mexican import competition from NAFTA.[2]

We find that areas more exposed to NAFTA experienced an increase in all-cause mortality. Our

[1] Such ostensibly conflicting results are not limited to the United States. Mortality appears to fall during recessions in Canada and in several European countries (Neumayer, 2004; Granados, 2005; Buchmueller et al., 2007; Ariizumi and Schirle, 2012), while men who lose their jobs due to plant closures or mass layoffs experience sharp increases in mortality in Denmark, the Netherlands, and Brazil (Browning and Heinesen, 2012; Bloemen et al., 2018; Amorim et al., 2024). Similar contrasts arise across different types of *positive* demand shocks: Auerbach et al. (2025) find that positive demand shocks to local area employment from defense contracting reduce mortality among those 45 and over, while more general positive demand shocks increase mortality.

[2] In concurrent, independent work, Noghanibehambari and Fletcher (2026) pursue a similar empirical strategy and also find increases in adult mortality from exposure to NAFTA.

estimates imply that in the 15 years post-NAFTA, a commuting zone (CZ) with average exposure to Mexican import competition experienced an average increase in annual, age-adjusted mortality of 0.68 percent (standard error = 0.19). To put that in perspective, a 0.68 percent increase in annual mortality offsets about one-half to two-thirds of the average, annual mortality declines in the U.S. from about 1965 through about 2013 (Cutler and Meara, 2004; Ma et al., 2015). The mortality impacts of NAFTA grew over the 15-year post-NAFTA period, as tariffs were phased out and manufacturing employment gradually declined. Mortality increases appear across all broad age-by-sex groups, but were disproportionately concentrated in working-age men, the group who also experienced disproportionately large declines in employment from NAFTA. Mortality increases appear across most major causes of death, as well as for deaths of despair. Exposure to NAFTA also worsened self-reported health and increased smoking rates. The pattern of results suggests an important role for both the direct impacts of job loss on mortality as well as intra-family spillover effects from job loss of one family member onto increased mortality of other members, with worsening health behaviors a potentially important mediating factor. A simple calibration of a stylized model suggests that the welfare losses from NAFTA-induced mortality increases can more than erase Caliendo and Parro (2015)'s estimates of the general equilibrium welfare gains from NAFTA.

We then expand our analysis to other sources of local labor market contractions, providing evidence that local area declines in manufacturing employment increase local area mortality, while local area declines in non-manufacturing employment decrease local area mortality. Specifically, in addition to exposure to import competition from Mexico due to NAFTA, we examine three other sources of local labor market variation in EPOP over the 1986 to 2016 period: local labor market fluctuations (i.e. CZ-year variation in EPOP), exposure to the Great Recession, and exposure to import competition from China (hereafter, the China Shock). Unlike recession-induced declines in local labor market EPOP, the vast majority of trade-induced employment declines are in the manufacturing sector. We estimate that a one percentage point trade-induced decline in area EPOP from either NAFTA or exposure to trade from China increases age-adjusted mortality by the same magnitude (about 1.5 percent). These mortality estimates are of the opposite sign and statistically distinguishable from our estimates that a one percentage point recession-induced decline in area EPOP *reduces* mortality by about 0.5 percent.

To more directly examine the mortality impacts of local area declines in manufacturing and non-manufacturing EPOP, we leverage spatial variation in the share of the Great-Recession-induced decline in local area EPOP that is in manufacturing. Qualitatively, we find that recession-induced declines in local area manufacturing EPOP also increase mortality, while recession-induced declines in local area non-manufacturing EPOP reduce mortality. Quantitatively, the results imply that a counterfactual recession in which the share of the local area EPOP decline that comes from the manufacturing sector was similar to that from trade shocks would produce similar mortality increases to what we estimate for NAFTA and the China Shock. We offer some speculative thoughts and initial empirical tests of why local area declines in manufacturing and non-manufacturing EPOP have opposite-signed impacts on mortality. These results suggest that both the type of displaced workers (primarily blue-collar men) and the type of displaced job (high-wage, high-rents) may contribute to the adverse local area mortality impacts of local area manufacturing job loss.

The rest of the paper proceeds as follows. Section 2 describes our data. Section 3 presents our empirical analysis of the impact of NAFTA on mortality, and Section 4 explores potential mechanisms and implications. Section 5 expands our analysis to other economic shocks, showing opposite-signed mortality impacts from declines in local area manufacturing and non-manufacturing EPOP. The last section concludes.

2 Sample and Data

Our baseline geographic unit of analysis is the commuting zone (CZ); CZs are standard aggregations of counties that partition the United States into 741 areas designed to approximate local labor markets.[3] Following Choi et al. (2024) and Autor et al. (2013), we restrict all of our analyses to the 722 CZs in the continental U.S.

We analyze four different sources of local labor market shocks. For three of them—NAFTA, the Great Recession, and area-level fluctuations in employment—we use annual, CZ-level data. For NAFTA, we follow Choi et al. (2024) and analyze data from 1986 to 2008. For the Great Recession, we follow Finkelstein et al. (2025) and analyze data from 2003 through 2016. Our panel data analysis of local area recessions follows the spirit of Ruhm (2000); we use data from 1986 through 2008. Finally, for our fourth source of local labor market shocks—the China Shock analysis—we follow Autor et al. (2019) and analyze two (stacked) CZ-level long differences from 1990 to 2000 and from 2000 to 2014.

Mortality rates. Following Ruhm (2016) and Finkelstein et al. (2025), we construct annual mortality rates by combining restricted-use microdata on the universe of U.S. mortality events from 1986 to 2016 from the Centers for Disease Control and Prevention (CDC) with population denominators from the National Cancer Institute's Surveillance Epidemiology and End Results (SEER) program. For each decedent in the CDC data, we observe their county of residence, date of death, cause of death, and demographic information including age, race, and sex. The SEER data provide yearly county-level population estimates by age, race, ethnicity, and sex.[4]

[3] Our analysis at the CZ level follows prior work exploiting spatial variation in the impact of the China Shock (Autor et al., 2019) and the Great Recession (Finkelstein et al., 2025) to examine mortality impacts. However, Choi et al. (2024)'s baseline unit of analysis of the impact of NAFTA on employment and support for the Democratic party is at the county level; we show below that our mortality estimates of NAFTA are similar at the county-level.

[4] Although the CDC mortality data include education, unfortunately the SEER population counts do not. We discuss below how we proxy for population by education in order to examine whether mortality impacts of NAFTA

The mortality rate is defined as the share of the population in area c at the beginning of year t who die during year t. In all of our analyses (except those that look separately at mortality by birth cohort), we follow the literature and examine age-adjusted mortality rates, so that, given differences in the age structure across CZs, our analysis is not affected by potentially different secular trends in mortality across age groups (e.g., Ruhm, 2000; Finkelstein et al., 2025). Specifically, we calculate the age-adjusted mortality rate in a CZ by averaging over the mortality rate in each of 19 age bins in the CZ, weighting each age bin by the national share of the population in that age bin in 2000.[5] We also analyze mortality effects separately for the 11 top (mutually exclusive) causes of death and a residual category for all other causes, as well as for what Case and Deaton (2020) term "deaths of despair," which consist of drug-related deaths, suicides, and alcohol-related deaths.[6]

EPOP ratios. The Census Bureau's County Business Patterns (CBP) provides annual, county-level employment data from 1986 through 2016. The CBP data contain employment counts by four-digit Standard Industrial Classification (SIC) industry codes and 6-digit North American Industry Classification System (NAICS) codes for each county and year. We construct employment-to-population (EPOP) ratios by combining these with annual county population counts for those aged 16 and older in the SEER. We construct both overall CZ-year EPOP as well as separate estimates of CZ-year manufacturing EPOP and CZ-year non-manufacturing EPOP, which together sum to the total CZ-year EPOP.[7] We multiply these ratios by 100 so that a one-unit change in each variable corresponds to one percentage point.

Measures of local labor market contractions. We leverage various sources of heterogeneity in exposure to local labor market contractions used in prior research. Specifically, we obtain geographic measures of exposure to NAFTA and of exposure to the China Shock directly from the replication packages of Choi et al. (2024), and Autor et al. (2019), respectively. For the Great Recession, we slightly adapt the exposure measure used in Yagan (2019)—which is the change in the unemployment rate in each CZ between 2007 and 2009—and use the change in the EPOP rate in each CZ between 2007 and 2009 instead; this is inconsequential for the results but allows for greater comparability with the other analyses.

vary by education.

[5]The age bin groups are 0, 1–4, 5–9, and then every five-year age bin up through 80–84, with a final bin for 85+.

[6]The mutually exclusive cause of death classification uses the International Classification of Diseases (ICD) codes and follows the categorization used in Finkelstein et al. (2025). To analyze deaths of despair, we define drug-related deaths using ICD codes for accidental drug poisonings, drug-induced psychosis, drug dependence, and non-dependent abuse of drugs, we define suicide directly from the NCHS coding system, and we define alcohol-related deaths using ICD codes for liver disease, alcohol-induced psychosis, and alcohol dependence syndrome.

[7]We define manufacturing employment using two-digit SIC codes between 20 and 39 and NAICS codes between 31 and 33.

Additional area-level covariates. We obtain additional CZ-level covariates in 1980 from Autor et al. (2019), including the share of employment in manufacturing, shares of employment in occupations susceptible to automation and offshoring, and each CZ's racial, education, and sex composition. We also compute the 1990 CZ-level cancer mortality rates—which we use in some robustness analyses—from the CDC and SEER data described above. To conduct heterogeneity analysis by baseline unionization rates, we draw on data compiled by Hirsch et al. (2026). These contain yearly state-level union membership and coverage computed using the Current Population Survey (CPS).

Other health-related outcomes. Our primary health outcome is mortality, which is well-measured for the entire population. However, we also make use of restricted-access data from the National Health Interview Surveys (NHIS) from 1986–2008 to examine the impact of NAFTA on (self-reported) health outcomes, health behaviors, health care utilization, and insurance coverage; the restricted-access version of the data allows us to identify counties and hence perform this analysis at the CZ level. The NHIS is a repeated annual, cross-sectional, household-level, in-person survey of about 40,000 people (30,000 households) per year; it is designed to be representative of the civilian, non-institutionalized population.[8] We selected the set of outcomes related to health insurance, health behaviors, health care use, and health outcomes that were consistently measured and available over most of our analysis period (Appendix Table OA.1 provides the complete list).

3 Mortality Impacts of NAFTA

3.1 Background

Signed into law in December 1993 and effective starting January 1, 1994, NAFTA involved both tariff and non-tariff trade liberalization between the United States, Mexico, and Canada, effectively creating a single market of approximately 400 million people who accounted for one-third of the world's output. Since trade between the United States and Canada had been mostly tariff-free since the 1987 U.S.-Canada Free Trade Agreement, the main impact of NAFTA on the United States was via the liberalization of trade with Mexico (Congressional Budget Office, 2003; Choi et al., 2024; Villareal and Fergusson, 2014). NAFTA gradually eliminated all tariff and most non-tariff barriers over a 10 to 15 year period (Villareal and Fergusson, 2014). Appendix Figure OA.1 shows the gradual elimination of all import tariffs on Mexico post NAFTA, from an average tariff rate of about 2% in 1993 eventually down to zero by the early 2000s.

The general expectation was that NAFTA would have a positive—but small—impact on the U.S. economy, since trade with Canada and Mexico accounted for less than 5% of U.S. GDP

[8]For more information, visit IPUMS NHIS User Notes. NHIS has a complex multistage survey design (with several redesigns over the study period), which are documented in great detail in the User Notes and in the original documentation from the National Center for Health Statistics.

when NAFTA went into effect and trade between the U.S. and Mexico—which is where most of the NAFTA provisions had an impact—accounted for only about 1.4% of GDP (e.g., Krugman, 1993; Burfisher et al., 2001; Villareal and Fergusson, 2014). Ex post, analyses of the aggregate welfare effects of NAFTA for the United States have tended to find small effects (Congressional Budget Office, 2003; Romalis, 2007; Caliendo and Parro, 2015). This is consistent more broadly with evidence that in large open economies like the United States—where intranational trade is large relative to international trade—the welfare gains from international trade appear to be small (Arkolakis et al., 2012; Costinot and Rodríguez-Clare, 2018).

3.2 Empirical Strategy

To assess the impact of NAFTA on mortality, we follow the empirical strategy of Hakobyan and McLaren (2016) and Choi et al. (2024) and leverage the fact that local labor markets were differentially exposed by NAFTA to import competition from Mexico. Differences in area-level exposure to NAFTA in turn reflect differences across industries in exposure to increased Mexican import competition from NAFTA and differences across areas in their mix of industries. Specifically, areas which in 1990 (i.e., prior to NAFTA) had a higher share of individuals employed in industries with higher U.S. tariff rates on Mexico (τ^j_{1990}) and in industries that faced stiffer export competition from Mexico (RCA^j) were more vulnerable to NAFTA.[9]

The amount of export competition industry j in the U.S. faced from Mexico in 1990 is known as Mexico's "revealed comparative advantage" (RCA^j) and defined by Choi et al. (2024) as:

$$\text{RCA}^j = \frac{x^{\text{MEX}}_{j,1990}/x^{\text{ROW}}_{j,1990}}{\left(\sum_i x^{\text{MEX}}_{i,1990}\right)/\left(\sum_i x^{\text{ROW}}_{i,1990}\right)} \tag{1}$$

where $x^{\text{MEX}}_{j,1990}$ is the value of Mexican exports to all countries except the U.S. in 1990 in industry j, and $x^{\text{ROW}}_{j,1990}$ is the value of the rest of the world's exports to all countries except Mexico and the U.S. in industry j. In other words, the numerator is roughly Mexico's share of exports in industry j, and the denominator is roughly Mexico's overall share of total exports.

Area c's vulnerability (i.e., exposure) to NAFTA is then defined as:

$$\tilde{V}_c = \sum_{j=1}^{J} \frac{L^{cj}_{1980}}{L^{c}_{1980}} \tilde{\text{RCA}}^j \tau^j_{1990} \tag{2}$$

where L^{cj}_{1980} is the number of workers employed in industry j in area c in 1980 expressed as a fraction of the total 1980 employment in area c L^c_{1980}. We let $\tilde{\text{RCA}}^j = \frac{\text{RCA}^j}{\frac{1}{J}\sum_j \text{RCA}^j}$ denote industry

[9] The import-weighted mean (standard deviation) tariff rate across industries in 1990 was 2.6% (5.4%). Some examples of highly tariffed industries include knitted outerwear (28.2%), house slippers (32.6%), and kitchen supplies (34.5%). Some examples of lower tariffed industries include leather, paper/cardboard, and candy, all of which were essentially zero.

j's normalized revealed comparative advantage, and τ^j_{1990} is the tariff rate of industry j in 1990. Since the units of $\tilde{V}_c$ are not easily interpretable, we follow Choi et al. (2024) and instead work with a scaled vulnerability measure:

$$V_c = \frac{\tilde{V}_c}{\mathbb{E}\left[\tilde{V}_c | c \in \text{top quartile}\right] - \mathbb{E}\left[\tilde{V}_c | c \in \text{bottom quartile}\right]} \tag{3}$$

which scales $\tilde{V}_c$ by the difference of the average unscaled vulnerability in the top and bottom quartiles. Thus, in our baseline specification a one-unit increase in vulnerability V_c corresponds to an increase from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile.

This vulnerability index forms the basis of our main event study specification:

$$y_{ct} = \beta_t \left[V_c \times \mathbf{1}\left(\text{Year}_t\right)\right] + \alpha_c + \tau_t + X_{ct}\phi + \epsilon_{ct} \tag{4}$$

where α_c and τ_t denote area and year fixed effects, respectively, and where the vector of controls

$$X_{ct} = \left[\begin{array}{cc} \mathbf{1}\left(\text{Region}_{r(c)}\right) \times \mathbf{1}\left(\text{Year}_t\right) & \mathbf{1}\left(\text{Demo}_c\right) \times \mathbf{1}\left(\text{Year}_t\right) \end{array}\right] \tag{5}$$

contains Census region indicators (there are 4 Census regions) interacted with year indicators, and indicators for demographic characteristics of the area interacted with year indicators. For the baseline demographic characteristics of area c we follow Autor et al. (2019) and consider the 1980 share of employment in manufacturing, share of employment in occupations susceptible to automation and offshoring, and each CZ's racial, education, and sex composition.[10]. We use k-means clustering to reduce dimensionality of these covariates; this algorithm clusters CZs into groups based on similarity of these covariates. We find 3 clusters to be the optimum following the Caliński–Harabasz stopping rule (Caliński and Harabasz, 1974); below we show robustness to alternative controls. We estimate equation (4) by OLS and cluster our standard errors on the local area c; all regressions are weighted by 1990 CZ population.[11]

Following the prior literature (e.g., Ruhm, 2000; Finkelstein et al., 2025) we define our main outcome variable y_{ct} to be the log age-adjusted mortality rate in area c and year t. For sufficiently low

[10]Specifically, following Autor et al. (2019), our full list of Demo_c controls includes: 1980 manufacturing share of employment, 1990 share of employment in occupations susceptible to automation and offshoring, and 1990 shares of the population share that are college-educated, foreign-born, Black, Asian, or other non-White, Hispanic share, and, finally, the 1990 female share of the employed population

[11]In addition to our use of CZ rather than county for c, our baseline specification in equation (4) differs in several other respects from the baseline in Choi et al. (2024). First, our definition of vulnerability $\tilde{V}_c$ in equation (2) involves the number of workers employed in industry j in area c in 1980 as a fraction of the *total* area employment in area c in 1980 rather than (as in Choi et al., 2024) as a fraction of area employment in all industries for which the revealed comparative advantage measure RCA_j is defined. Note that revealed comparative advantage (RCA_j) is not defined for all industries; specifically, it is not defined for industries that have no exports (see equation 1) which includes, for example, most service industries. Second, our set of baseline controls (beyond area and year fixed effects) differ from theirs; we will show robustness below to the choice of controls.

annual individual mortality rates, this specification is an approximation to a parametric individual-level survival model in which the individual's log odds of dying are given by the right-hand side of equation (4).

The key coefficients of interest are the β_ts; they measure effects on outcome y_{ct} in year t across areas differentially exposed to NAFTA. Unless otherwise indicated, we omit the interaction with the NAFTA vulnerability measure V_c in 1993 (the year prior to NAFTA) so that all β_t coefficients are relative to 1993. The NAFTA vulnerability measure V_c interacted with year fixed effects has a shift-share (or "Bartik") structure. We take the approach of Goldsmith-Pinkham et al. (2020) and assume that the lagged employment shares $\frac{L^{cj}_{1980}}{L^{c}_{1980}}$ are exogenous conditional on the covariates; the identifying assumption is therefore essentially a parallel trends assumption that can be assessed using the pattern of estimates of the pre-1994 β_t coefficients. In Appendix A.1 we discuss the identifying assumptions in more detail.

Descriptive Statistics. Figure 1a shows significant spatial variation within and across U.S. states in their vulnerability to NAFTA (V_c). The Southeast was particularly vulnerable, as were parts of the Midwest such as Michigan. By contrast, most of the mountain states were relatively unscathed, although parts of Utah and Idaho were fairly exposed. Because our baseline specification in equation (4) controls for Census region-by-year fixed effects, our estimated impact of NAFTA is not contaminated by differential exposure to NAFTA across Census regions that might otherwise be experiencing different secular changes. Relatedly, because exposure to NAFTA is correlated with an area's manufacturing share of employment (see Appendix Figure OA.2a) and because employment in the manufacturing sector was likely on a different secular trend—as well as exposed to different shocks—than other industrial sectors over our analysis period, our baseline specification includes flexible controls for 1980 manufacturing share interacted with year fixed effects.[12] As a result, we identify the impact of NAFTA off of areas with *similar* manufacturing shares but differences in their industry mix within manufacturing that generates variation in their exposure to NAFTA; Appendix Figure OA.2a shows that there is indeed substantial variation in exposure to NAFTA across CZs with similar baseline manufacturing shares.

Figure 1b documents substantial variation in age-adjusted mortality rates across CZs in 1993, as has been documented in prior work (e.g., Chetty et al., 2016; Currie and Schwandt, 2016; Finkelstein et al., 2021, 2025). Mortality rates were particularly high in the Southeastern United States and low in the Western United States. CZs that were more vulnerable to NAFTA had higher mortality rates in 1993 (Figure 1c); relative to CZs in the bottom quartile of vulnerability, CZs in the top quartile of vulnerability had an age-adjusted annual mortality rate per 100,000 that was 41.8 deaths larger (off a base of about 880 annual deaths per 100,000). Any mean-reverting tendencies of these

[12] Appendix Figure OA.2b shows how manufacturing share varies across our 3 k-means clusters; we also show in robustness analysis below that results look similar if we control for 3 k-means clusters within manufacturing only as well as 3 k-means clusters of the other controls.

mortality rates would bias against our finding that places that were more vulnerable to NAFTA experienced an increase in mortality rates relative to places that were less vulnerable.

3.3 Estimated Mortality Impacts

Figure 2 shows the results of estimating equation (4) with log age-adjusted mortality as the outcome, with β_{1993} normalized to zero. For context, it also shows (in light gray) the results with EPOP as the outcome (as in Choi et al., 2024). The figure shows that after NAFTA went into effect in 1994, places that were more vulnerable to NAFTA experienced a gradual but steady increase in mortality relative to places that were less exposed to NAFTA. The time pattern of mortality and employment effects mirror each other.

The absence of any differential trends from 1986 through 1994 in mortality (or in employment) across areas facing different exposure to NAFTA (i.e., the relatively flat pre-trend) is re-assuring for the validity of the identifying assumption. In addition, the time pattern of the estimated mortality effects post-NAFTA closely aligns with the time pattern of the estimated EPOP effects, suggesting a close link between the two (see also Appendix Figure OA.3). The gradual but steady decline in EPOP following NAFTA, which Choi et al. (2024) also found, in turn likely reflects the gradual reduction in tariffs created by NAFTA (recall Appendix Figure OA.1). About 80 percent of the NAFTA-induced EPOP declines came from manufacturing EPOP (see Appendix Figure OA.4) even though manufacturing made up just 19% of employment in 1993 (authors' calculations).

The point estimates imply that, relative to CZs in the bottom quartile of NAFTA vulnerability, CZs in the top quartile of NAFTA vulnerability experienced an average increase in annual age-adjusted mortality of 1.9% (standard error = 0.54) between 1994 and 2008. Since the average (scaled) vulnerability across (population-weighted) CZs was 0.35 (see Figure 1a), this implies that on average, NAFTA increased annual age-adjusted mortality by 0.68% over the 1994 to 2008 period. Quantitatively, this represents about one-half to two-thirds of the estimated average, annual secular mortality improvements in the U.S. from about 1965 through about 2013.[13] Naturally, our estimates reflect the average effect of the local labor market impacts of NAFTA and ignore any general equilibrium impacts of NAFTA on mortality or consumption operating through reduced prices; we return to this point in Section 4.2.

Sensitivity analysis. An important potential confound behind the estimates of NAFTA's mortality impact in Figure 2 is that, as is often the case in the literature examining the impact of economic shocks on mortality, deaths and population are measured in different data sets. This raises the concern that endogenous, unobserved declines in population in more affected areas could

[13] Cutler and Meara (2004) estimate that on average, age-adjusted, all-cause mortality declined by 1 to 1.5% per year from 1965 to 2000. Ma et al. (2015) estimate that on average, age-adjusted, all-cause mortality declines by 1.3% per year from 1969 to 2013.

lead to spurious estimated effects on mortality rates (Arthi et al., 2022).[14] In our setting, if areas more exposed to NAFTA experienced a decline in unobserved population, this would bias us against finding mortality increases from NAFTA. Moreover, consistent with the findings in Choi et al. (2024), we find no evidence that areas more exposed to NAFTA experience net population declines (Appendix Figure OA.5); nor do we find much evidence of compositional changes in population demographics when we look at impacts on population by birth cohort and sex bins (Appendix Figure OA.6). Indeed, if we use mortality and demographic data from the 1986–2008 National Health Interview Survey (NHIS) to construct predicted mortality rates based on age, race and sex, we find no impact of NAFTA on predicted mortality (see Appendix Figure OA.7).[15] These findings are consistent with the broader body of evidence indicating limited mobility responses within the U.S. to local labor demand shocks in recent decades, including other negative local labor demand shocks like the Great Recession (Yagan, 2019) and the China Shock (Autor et al., 2013, 2021), as well as positive local area demand shocks from Department of Defense contracts (Auerbach et al., 2025). Dao et al. (2017) find that the migration responses to local labor demand shocks have been weakening since the early 1990s, which likely explains the limited changes in population in the areas most exposed to NAFTA.

Our estimated impact of NAFTA on mortality is also robust to a number of other alternative specifications, including adding controls for other contemporaneous, spatially-varied shocks—such as import penetration from China or the opioid epidemic—limiting the analysis to the Southern Census region where vulnerability to NAFTA was highest, and alternative functional forms; Appendix A.2 describes these and other sensitivity analyses in more detail.

4 Mechanisms and Implications for NAFTA's Mortality Impact

4.1 Potential Mechanisms

To try to shed some suggestive light on the mechanisms behind the evidence of NAFTA's mortality impacts in Figure 2, we examine the impacts of NAFTA separately for different demographic groups and by cause of death. The results are broadly consistent with a large role for both the direct impacts of job loss on mortality as well as intra-family spillover effects from job loss of one family member onto increased mortality of other members, with some evidence that worsening health behaviors may be an important mediating factor.

[14]These concerns are heightened by the fact that intercensal area-level annual population counts are not directly observed, but instead imputed in the SEER based on area-level records of births, deaths and school attendance, as well as interpolation. More information about these data can be found here: https://seer.cancer.gov/popdata/.

[15]Specifically, we pool data from these years and estimate a logistic regression of one-year mortality on age, indicators for sex, indicators for race, and all pairwise interactions. We then use these coefficients to project predicted mortality rates for each age-by-sex-by-race bin in the SEER population data. Taking the population-weighted average of these predicted rates across bins in each CZ-year, we obtain the outcome used in this figure.

Mortality impacts by sex and birth cohort. We re-estimate equation (4) separately by sex and by birth cohort, looking at four different birth cohorts: those who, at the start of NAFTA, would have been 0–24, 25–44, 45–64, and 65 and over.[16] NAFTA increases mortality for all eight sex by birth cohort groups (Figure 3a). The percentage increase in mortality is largest for men who were 25–44 in 1994; relative to those in the bottom quartile of CZs in terms of NAFTA vulnerability, men aged 25–44 in 1994 in the top quartile experienced an increase in mortality between 1994 and 2008 of 8.9% (standard error = 2.2%), more than 4.5 times the average annual percent increase in age-adjusted mortality of 1.9% (standard error = 0.54). More broadly, working-age men (those aged 25–64 in 1994) accounted for almost one-third of the increase in deaths due to NAFTA, (Figure 3b), even though they accounted for only 15% of the deaths in 1993. This is suggestive of an important direct role for job loss in increasing mortality, as EPOP declines from NAFTA were concentrated among men, and particularly men aged 25–44 in 1994 (see Appendix A.3). Consistent with much of the male mortality increase reflecting direct impacts of job loss, the estimated mortality impacts for working-age men are broadly similar to Sullivan and von Wachter (2009)'s estimates of the mortality impacts from long-term, male workers in Pennsylvania losing their (primarily manufacturing) jobs between 1980 and 1986 due to mass layoffs (see Appendix A.4).

However, the evidence of NAFTA-induced mortality increases for individuals who were not working age underscores the existence of additional mechanisms beyond the direct effect of job loss. Indeed, even though the impact of NAFTA on elderly mortality is proportionally much smaller than on working-age men (Figure 3a), men and women aged 65 and over in 1994 still account for about half of the increase in deaths due to NAFTA (Figure 3b); this reflects the much higher baseline mortality rates for the elderly, who accounted for about three-quarters of deaths in 1993. One potential channel for increases in elderly mortality may be a loss in financial support from children or grandchildren who have lost their job. Consistent with this hypothesis, a strikingly disproportionate 60% share of the increase in mortality among the elderly comes from increased mortality among elderly female widows (Appendix Figure OA.9), a group who relies disproportionately on resources from younger family members, as they tend to outlive their spouses and experience a substantial decline in economic resources upon widowhood (e.g., Diamond and Orszag, 2005).[17] In a similar spirit, we suspect that the statistically significant increases in mortality rates for men and women under 25, which together account for a little under 10% of the NAFTA-induced increase in mortality,

[16] Here we add one to the mortality rate per 100,000 prior to taking logs to avoid taking logs of zeroes. In practice, however, most demographic groups have no CZ-years with zero deaths. The exceptions are when we analyze women in the 1970–1994 or 1950–1969 birth cohorts or men in the 1970–1994 birth cohorts, where the share of (population-weighted) CZ-years with zero deaths ranges from 0.1% to 0.3%. Appendix Figure OA.8 shows that our results are very similar if we instead estimate a Poisson specification for age-adjusted mortality rates, as recommended by Chen and Roth (2024).

[17] Indeed in the 1994–2008 Health and Retirement Surveys, we estimate that the average transfers to women 65+ from their children or grandchildren are twice as high for widowed women as for married women; they are also slightly higher for widowed men relative to married men, but a much lower share of men 65+ are widowed.

may also reflect the indirect channel of reduced resources within the household for children.[18]

Mortality impacts by cause of death. Figure 4 shows estimated mortality impacts of NAFTA for the top 11 causes of death (arranged in descending order of prevalence in 1993), and a final residual category for all other causes. The top panel shows results for the full sample, and the bottom panel shows results for the demographic group who had the largest mortality impacts: men who were 25–44 in 1994; Appendix Figures OA.12 and OA.13 show results for the other demographic groups. Almost all causes of death show statistically significantly elevated effects—with particularly pronounced effects for infectious disease—with the striking exception of little evidence of an increase in cardiovascular mortality, the single largest cause of death. Figure 5 shows that NAFTA also increased so-called "deaths of despair" (Case and Deaton, 2020), a small (6%) share of overall deaths but ones that also increased with exposure to the China Shock (Pierce and Schott, 2020); the mortality increases show up for all three sub-categories of "deaths of despair": drug-related deaths, suicides, and alcohol-related deaths.[19]

The evidence of NAFTA-induced increases in deaths of despair as well as increases in mortality from cancer, external causes, and infectious diseases (which together comprise over half of all the NAFTA-induced deaths) is suggestive of a potential role for deleterious health behaviors—including smoking, alcohol consumption, and illegal drug use—in contributing to the mortality increase.[20] Consistent with this, estimates from the NHIS data on self-reported health behaviors show that NAFTA also increased smoking rates, overall and especially for men aged 45–64 when NAFTA was introduced, but had no impact on rates of flu shots, a measure of a positive health behavior (see Appendix Figure OA.15).

Other health-related outcomes. We use the NHIS data to also analyze NAFTA's impacts on self-reported health, health insurance coverage, and health care utilization; Appendix Figures OA.16 through OA.18 show the results. Consistent with the NAFTA-induced increase in mortality,

[18] We also examined mortality effects by race and sex-by-educational attainment. Appendix Figure OA.10 shows that NAFTA increased mortality both for Whites (who are about 85% of the 1993 population) and non-Whites. Appendix A.5 describes how we construct mortality rates by sex and education (for individuals 25 and older in each year) in the absence of SEER population data by education, and Appendix Figure OA.11 shows results separately by sex and educational attainment (high school or less compared to some college or more, which roughly divides the sample in half); all groups but women with some college or more experienced increases in mortality.

[19] When we look by cause of death, in the full sample, the share of (population-weighted) CZ-years that have non-zero deaths is 0.1% for some of the 11 major causes of death and up to 2.3% for some of the deaths of despair sub-categories. For men who were 25–44 in 1994, these numbers are considerably higher, as high as almost 20% for some of the 11 major causes of death and as high as 7% for some sub-categories of deaths of despair. As a result, Appendix Figure OA.14 shows that all of the cause-of-death analyses are robust to estimating a Poisson specification for mortality rates, as recommended by Chen and Roth (2024), instead of examining the log of mortality rates per 100,000 plus 1 as in our baseline specification.

[20] For example, we estimate that over half of the increase in cancer mortality comes from respiratory system cancers, and that among infectious diseases, increases in HIV mortality account for over 20% of the increases in deaths. More broadly, alcohol abuse is understood to suppress the immune system and increase both the risk and severity of viral and bacterial infections (Molina et al., 2010).

NAFTA also increased morbidity measures, specifically the probability someone reports themselves in fair or poor health (as opposed to good, very good, or excellent health), and the probability they report limitations to their usual activities due to health. These results are statistically significant overall, and while precision declines for subgroups, prime-aged men (i.e., those 25–44 when NAFTA was introduced) experience statistically significant declines in both outcomes, as do prime-aged women. NAFTA did not impact rates of health insurance coverage, but did increase the probability of being covered by Medicare, primarily among men and women aged 45–64 in 1994. This presumably reflects an increase in the share of this demographic receiving Social Security Disability Insurance (as documented by Choi et al. 2024), which confers with it Medicare coverage. There is also some evidence of an increase in health care utilization (doctor visits and inpatient hospital stays), although these results are not always consistent across demographic groups.

4.2 Implications of Endogenous Mortality for Welfare Consequences of NAFTA

Our empirical estimates capture mortality impacts of NAFTA by comparing how outcomes evolve in more and less exposed regions; they do not incorporate any nationwide, general equilibrium *economic* benefits of NAFTA that might operate, for example, through reduced prices and hence increased real disposable income. This limitation relates to the well-known "missing intercept" problem in macroeconomic counterfactuals and the question of whether or when analyses of regional shocks and outcomes can inform estimates of aggregate national shocks (e.g. Chodorow-Reich 2020; Guren et al. 2021; Wolf 2023; Auerbach et al. 2024). We therefore benchmark our estimates of the mortality impact of the average local labor market exposure to NAFTA against estimates of the national, general equilibrium economic impacts of NAFTA. Specifically, we consider Caliendo and Parro (2015)'s finding that nationally, NAFTA increased U.S. welfare by 0.08%, operating through increased real wages, decreased tariff revenue, and changes in the volume and terms of trade.[21]

To translate our estimated mortality impacts into implied welfare impacts, we consider a representative individual who, as in Hall and Jones (2007), gets per-period utility both from being alive and from consumption. We define the welfare effects of NAFTA as the hypothetical amount the representative agent would be willing to pay (as a percentage of annual consumption) to experience NAFTA, and we follow the approach in Finkelstein et al. (2025) to approximate the welfare effects of NAFTA with endogenous mortality (Δ^{dT}) by:

$$\Delta^{dT} \approx \Delta + dT * \left(\frac{\text{VSLY}}{c}\right) \tag{6}$$

[21] The finding of a fairly small overall welfare gain from NAFTA is consistent with a broader literature suggesting that in large open economies the welfare gains from international trade will be small (see, e.g., Arkolakis et al., 2012; Costinot and Rodríguez-Clare, 2018). Another intuition for the small welfare impacts comes from the fact that NAFTA reduced tariff rates from about 2–3 percent to zero (see Appendix Figure OA.1). Even with a very large elasticity of imports with respect to trade costs (see, e.g., Anderson and van Wincoop, 2004), very low tariffs likely lead to small welfare costs of tariffs following the standard Harberger-style logic that the welfare cost of tariffs is proportional to the square of the tariff rate.

where Δ denotes the welfare impact of NAFTA when mortality is exogenous (estimated at 0.08% in Caliendo and Parro, 2015), dT is the percentage change in life expectancy due to NAFTA, and VSLY is the value of a statistical life year. Equation (6) indicates that the welfare effects of NAFTA are approximately separable in the effects of NAFTA on consumption (which determines Δ) and the effects of NAFTA on mortality (which affects life expectancy via dT). The effect of NAFTA on life expectancy is scaled by the value of a statistical life-year (VSLY) divided by annual consumption in order to be comparable to the effects of NAFTA on consumption. Appendix A.6 provides more details behind the model and this derivation.

To translate our mortality estimates into changes in life expectancy dT, we conservatively assume the mortality increases stop after the 15 years we observe them and use the 1993 Social Security Administration (SSA) life tables for the baseline age- and sex-specific mortality rates. Appendix Table OA.2 shows impacts of NAFTA life expectancy (dT) using our homogeneous estimates of NAFTA's mortality impacts (Panel A), and using birth-cohort-by-sex-specific estimates (Panel B). For a 45-year-old male, for example, the results in Panel B imply that about 3% of 45-year-old men lost a year of remaining life expectancy due to NAFTA.[22] Appendix Table OA.3 translates these estimated declines in life expectancy into their implications for the welfare impact of NAFTA with endogenous mortality based on an assumed value of a statistical life year that is either 2, 5, or 8 times annual consumption (i.e., $\text{VSLY}/c = 2, 5, \text{ or } 8$).[23]

Strikingly, the calibrations suggest that accounting for our estimates of endogenous mortality changes the sign of the welfare effect of NAFTA from a 0.08 percent welfare *gain* (coming through the increase in real wages) to a net welfare *loss*. Overall, across all demographic groups, the results in Appendix Table OA.3 Panel B suggest a net welfare loss from NAFTA of 0.11% to 0.69% of annual consumption, depending on whether we set VSLY/c to 2 or 8. Indeed, net welfare effects of NAFTA are negative for virtually all ages and both sexes.[24] Moreover, this calculation may understate the welfare losses from the health impacts of NAFTA, as we assume they stop after 15 years, and we do not attempt to incorporate our estimates of the negative morbidity impacts of NAFTA (recall Appendix Figure OA.16).

That said, the calibration exercise is highly stylized and we caution against placing too much weight on the particular numbers. Rather, we view it as indicative of how, relative to the canonical welfare analysis of NAFTA to date, accounting for the endogenous mortality effects of NAFTA can have quantitatively important implications for its overall welfare consequences. In that spirit,

[22] Specifically, their remaining life expectancy declines on average from 30.38 to 30.35 years.

[23] There are a range of plausible estimates for the VSLY. With average annual consumption of roughly \$50k (Foster, 2015) a VSLY of twice average consumption corresponds to a VSLY of \$100k, which is at the low end of the range of VSLY estimates described in Kniesner and Viscusi (2019). This is used by, among others, Cutler (2005) and Cutler and Sportiche (2022) and is similar to the baseline VSLY in Hall and Jones (2007). VSLY values of 5 and 8 times average consumption (or about \$250k and \$400k) correspond to about the middle of the range and high end of the VSLY estimates reported in Kniesner and Viscusi (2019).

[24] For example, for a 45-year-old male we compute a net welfare loss from NAFTA of 0.11% to 0.66% of annual consumption. Welfare losses are increasing with age (birth cohort) and larger for men than women.

we note several potentially important caveats. First, there may be important welfare impacts of NAFTA—of either sign—not captured by the Caliendo and Parro (2015) analysis.[25] Second, NAFTA's positive national impact on real income (estimated in Caliendo and Parro, 2015 to be 0.11%) might in turn reduce mortality, but would not be captured by our mortality estimates; in practice, however, as we discuss in Appendix A.6, any such national income effect on mortality is likely to be quantitatively unimportant. Finally, in the absence of externalities or internalities, the usual envelope theorem arguments imply that, to first order, NAFTA's mortality effects are not welfare-relevant; of course, a failure of either of these assumptions necessitates estimating the impact of NAFTA on all welfare-relevant arguments of the utility function, including presumably mortality (Finkelstein et al., 2019).[26]

5 Differential Mortality Impacts Across Economic Contractions

The finding that increased local area exposure to import competition from Mexico due to NAFTA increases mortality is consistent with other evidence that greater local area exposure to import competition from China increases mortality of young men relative to young women (Autor et al., 2019) and increases fatal drug overdoses among the working-age population (Pierce and Schott, 2020), as well as evidence that job displacement from mass layoffs increases mortality (Sullivan and von Wachter, 2009). However, sitting somewhat awkwardly with this body of evidence is another set of findings that recession-induced local labor market contractions *reduce* mortality (e.g., Ruhm, 2000; Miller et al., 2009; Stevens et al., 2015; Finkelstein et al., 2025). This tension was directly highlighted by Auerbach et al. (2025), who document that local area demand stimulus via defense contracts decreases mortality among those 45 and older while more general positive local area demand shocks increase mortality. Further muddying the waters is the lack of empirical clarity on the impact of income on mortality.[27] Such findings raise questions about the likely sign of mortality

[25]For example, additional potential benefits of tariff reductions could include welfare gains arising from changes in investment expenditures (Ding, forthcoming), technology adoption (Bustos, 2011), and firm productivity (Amiti and Konings, 2007). On the other hand, relaxing the assumption of a perfectly competitive labor market to allow for search frictions and downward nominal wage rigidities could reduce the welfare gains from NAFTA; indeed, Rodríguez-Clare et al. (forthcoming) estimate that the welfare gains from the China Shock are reduced by about two-thirds after accounting for its effects on unemployment and labor force participation.

[26]Moreover, NAFTA's mortality impacts may provide a way to characterize some of the distributional economic impacts of NAFTA given the data limitations that preclude directly estimating heterogeneity in the consumption impacts of NAFTA. For example, Hakobyan and McLaren (2016) find evidence of substantial heterogeneity in the wage effects of NAFTA by geography and industry, which likely translate into substantial heterogeneity in consumption effects, as well; in other words, NAFTA may entail small increases in consumption for a large share of the population alongside substantial decreases in consumption for a small share of the population (such as the working-age adults experiencing involuntary job displacements in the areas hardest hit by NAFTA). If the estimated mortality increases from NAFTA are driven by the small share of the population experiencing large decreases in consumption, then the mortality effects (combined with external estimates of the willingness to pay for reductions in mortality) can serve as empirical proxies for some of the large drops in consumption experienced by a subset of the population.

[27]There is, of course, a well-documented negative relationship between income and mortality within countries, across countries, and over time (e.g., Cutler et al., 2006; Costa, 2015; Chetty et al., 2016; Cutler et al., 2016).

impacts of other local labor market contractions, past or future.

In this section, therefore, we develop and test a unified framework to explain these seemingly disparate results and to offer suggestive guidance for the likely mortality impacts of other local economic shocks. To do so, we examine four different sources of local labor market shocks: panel variation in EPOP across CZ-years (a la Ruhm, 2000), variation across areas in exposure to the Great Recession (a la Yagan, 2019; Finkelstein et al., 2025), variation across areas in exposure to NAFTA (a la Choi et al., 2024 and our analysis in Section 3) and variation across areas in exposure to the China Shock (a la Autor et al., 2013, 2019). The resulting evidence suggests that the mortality impacts of local labor market declines in manufacturing EPOP and in non-manufacturing EPOP have opposite signs.

We start with two pieces of suggestive evidence. First, in contrast to recession-induced declines in local area EPOP, the vast majority of trade-induced EPOP declines are in the manufacturing sector. Second, trade-induced declines in local area EPOP increase mortality while recession-induced declines in local area EPOP decrease mortality; this pattern was already implied by the existing reduced form evidence of the impact of different local economic shocks on EPOP and on mortality, but we re-estimate these relationships via IV so that we can compare magnitudes. We find that the relationship between trade-induced declines in local area EPOP and mortality is very similar across trade shocks (specifically NAFTA and the China Shock) and statistically distinguishable from the (opposite-signed) relationship for recessions.

We then directly estimate the relationship between each type of local area EPOP decline and mortality by exploiting variation across local labor markets in the share of recession-induced EPOP declines that are in manufacturing. Qualitatively, we find that recession-induced declines in manufacturing EPOP increase mortality, but recession-induced declines in non-manufacturing EPOP decrease mortality. Quantitatively, our estimates imply that a counterfactual recession in which the share of the EPOP decline that comes from manufacturing were set to that of trade shocks would produce similar mortality increases to what we estimate for trade shocks.

5.1 Estimated Impacts of Different Contractions

5.1.1 Empirical Framework

We are interested in the relationship between various local economic contractions (Z_{ct}) on the one hand and the employment to population ratio (EPOP^s_{ct}) or mortality y_{ct} on the other hand. Here, $s \in A, M, N$ denotes either all EPOP (EPOP^A), manufacturing EPOP (EPOP^M) or non-manufacturing EPOP (EPOP^N) in CZ c and year t (and $\text{EPOP}^A_{ct} = \text{EPOP}^M_{ct} + \text{EPOP}^N_{ct}$), and y_{ct}

However, estimates of the causal effect of income on mortality tend to find small or no benefits (see, e.g., Cesarini et al., 2016 and Miller et al., 2024), and there is even some evidence that income receipt, by encouraging risky drug and alcohol use, may actually be bad for health and mortality (e.g., Dobkin and Puller, 2007; Evans and Moore, 2012; Chorniy et al., 2025).

denotes the log age-adjusted mortality rate in CZ c and year t. We therefore consider the following relationships:

$$\text{EPOP}^s_{ct} = \alpha_c + \tau_t + Z'_{ct}\kappa + X'_{ct}\gamma + \epsilon_{ct} \tag{7}$$

and

$$y_{ct} = \alpha_c + \tau_t - \beta\text{EPOP}^A_{ct} + X'_{ct}\psi + \epsilon_{ct} \tag{8}$$

where α_c denotes CZ-level fixed effects, τ_t denotes calendar year fixed effects and X_{ct} is a (possibly empty) set of control variables. The key coefficients of interest are the coefficients κ in equation (7) on the relationship between various local economic shocks (Z_{ct}) and various types of EPOP ($EPOP^s_{ct}$), and the coefficient β in equation (8) on the relationship between local area overall EPOP ($EPOP^A_{ct}$) and mortality.

We consider four different vectors of economic shocks Z_{ct}. First, we simply set $Z_{ct} = \text{EPOP}^A_{ct}$ for the period (1986-2008) and include no time varying controls X_{ct}; here, κ from equation (7) measures the extent to which a one percentage point increase in the overall EPOP ratio is distributed across the manufacturing and non-manufacturing sectors, and β from equation (8) measures the OLS relationship between local labor market variations in total EPOP (EPOP^A_{ct}) and mortality (as in Ruhm, 2000).

For the three other sources of economic shocks Z_{ct}, we perform an analogous estimation of equation (7) but estimate equation (8) by IV, instrumenting for the endogenous right-hand side variable EPOP^A_{ct} in equation (8) with the first stage equation (7). The three economic shocks we consider are local area variation in exposure to the Great Recession, to NAFTA, and to the China Shock. Note that unlike prior, reduced-form estimates of the impact of each of these shock on EPOP or on mortality, the IV analysis of equation (8) requires additional assumptions.[28] It imposes the exclusion restriction that each of these local economic contractions affects mortality only via its impact on EPOP^A_{ct}, and it assumes that that any relationship between EPOP and mortality is contemporaneous.[29]

[28] For prior estimates of the reduced form impact of each shock on EPOP and log age-adjusted mortality see Yagan (2019) and Finkelstein et al. (2025) for the Great Recession, and see Choi et al. (2024) and Section 3 for NAFTA. Although the first stage EPOP effect of the China Shock has been amply documented (e.g., Autor et al., 2013, 2021, 2025), to the best of our knowledge, the impact of the China Shock on all-age, all-cause mortality has not been previously reported.

[29] This is a common assumption in the literature (eg., Ruhm, 2000; Stevens et al., 2015). It is consistent with the observed relationship between annual mortality increases and annual EPOP declines from NAFTA (recall Figure 2 and Appendix Figure OA.3) as well as evidence that the Great Recession shock was associated with immediate and persistent declines in both employment (Yagan, 2019) and mortality (Finkelstein et al., 2025). That said, while it may be a reasonable approximation for the current analysis given these empirical results, it is unlikely to be strictly true; health is a stock and factors that impact health may well accumulate over time (Grossman, 1972; Lleras-Muney and Moreau, 2022; Goodman-Bacon et al., 2025).

For the Great Recession:

$$Z_{ct} = \left[\begin{array}{cc} \text{GR\_SHOCK}_c \times \tilde{t} \times \text{POST}_t & \text{GR\_SHOCK}_c \times \tilde{t}^2 \times \text{POST}_t \end{array} \right] \tag{9}$$

where (GR_SHOCK_c) denotes the percentage point change in CZ c's EPOP^A between 2007 and 2009; in other words, $\text{GR\_SHOCK}_c = \text{EPOP}^A_{c,2007} - \text{EPOP}^A_{c,2009}$. In addition, POST_t is an indicator variable for years 2007 and later, and $\tilde{t} = t - 2007$; thus area-level variation in the exposure to the Great Recession is allowed to impact the outcome through a quadratic spline.[30] There are no additional covariates X_{ct}, and we follow Finkelstein et al. (2025) in analyzing the impact of the Great Recession over the 2003 to 2016 period.

For NAFTA:

$$Z_{ct} = \left[\begin{array}{cc} V_c \times \tilde{\tilde{t}} \times \text{POST}_t & V_c \times \tilde{\tilde{t}}^2 \times \text{POST}_t \end{array} \right] \tag{10}$$

where V_c is the previously defined NAFTA vulnerability measure (see equation 3), POST_t is now an indicator variable for years 1994 and later, and $\tilde{\tilde{t}} = t - 1994$; thus, area-level variation in the exposure to NAFTA is also allowed to impact the outcome through a quadratic spline. Here, X_{ct} are the same set of baseline controls used in our reduced form analysis of NAFTA in equation (4), and we use the same set of analysis years (1986–2008).

For the China Shock, the structure of the analysis is a slightly different because we follow Autor et al. (2019)'s implementation which estimates the model in stacked long differences (one from the 1990 to 2000 period, and one from the 2000 to 2014 period) rather than in annual data.[31] Therefore in equation (7):

$$Z_{ct} = \left[\, \Delta \text{IP}_{ct} \, \right] \tag{11}$$

where ΔIP_{ct} is the measure of Chinese import penetration into CZ c and period t used by Autor et al. (2019). Because ΔIP_{ct} is constructed using 1990 employment shares and contemporaneous changes in imports into the United States, it is potentially endogenous. As a result, we follow Autor et al. (2019) and when estimating equation (7) we instrument for Z_{ct} as defined in equation (11) using

$$\tilde{Z}_{ct} = \left[\, \Delta \tilde{\text{IP}}_{ct} \, \right] \tag{12}$$

[30]We parametrize the post-period this way instead of using individual event study dummies to avoid having too many instruments, since adding instruments with little additional explanatory power mechanically reduces the first stage F-statistic and increases bias (Bound et al., 1995).

[31]This necessitates a number of changes to equations (7) and (8). The dependent variables are now the long-difference change in EPOP (in equation 7) and log age-adjusted *cumulative* mortality over each period (in equation 8). In addition, we now omit the CZ fixed effects α_c (since the model is in first-differences) and replace calendar year fixed effects τ_t with period fixed effects. Appendix B describes and presents the China Shock analysis in additional detail.

where $\Delta \tilde{\mathrm{IP}}_{ct}$ is Autor et al. (2019)'s instrument for changes in Chinese import penetration in each period, and depends on the 1980 industry-mix of employment in each CZ as well as the aggregate growth (in eight other wealthy countries) in imports from China in each industry in the relevant time period. Here our baseline set of controls X_{ct} includes the same vector of controls used in Autor et al. (2019). When estimating equation (8), we estimate β by instrumenting for EPOP^{A}_{ct} directly with $\tilde{Z}_{ct}$.

5.1.2 Results

Relative to recession-induced declines in EPOP, a substantially larger share of trade-induced EPOP reductions are in manufacturing. Table 1 shows the results. Over 80 percent of NAFTA-induced and over 90 percent of China-Shock-induced EPOP declines are in the manufacturing sector, compared to only 15 percent of the Great-Recession-induced EPOP declines and only 33 percent of CZ-year fluctuations in EPOP.[32]

Table 2 shows that a one percentage point decline in local area overall EPOP (EPOP^{A}_{ct})—whether in the OLS or instrumenting for EPOP^{A}_{ct} based on exposure to the Great Recession—is associated with about a 0.5 percent *decrease* in mortality, while a trade-induced percentage point decline in local area overall EPOP—whether from NAFTA or the China Shock—is associated with about a 1.5 percent *increase* in mortality.[33] Specifically, the OLS estimates in column (1) indicate that a one percentage point decline in CZ-year overall EPOP is associated with a 0.35% (standard error = 0.12%) decline in mortality, while IV estimates using variation in exposure to the Great Recession as instruments for overall EPOP in column (2) indicate that a one percentage point Great-Recession-induced decline in overall EPOP results in a 0.75% (standard error = 0.27%) decline in mortality; we are unable to reject that the OLS estimate of β in column (1) is the same as the IV estimate in column (2).

However, the results look very different when we use variation in exposure to trade shocks to instrument for overall EPOP. Column (3) shows that a one percentage point NAFTA-induced decline in overall EPOP results in a 1.44% (standard error = 0.56%) *increase* in mortality, a finding that is not only of the opposite sign from but also statistically significantly different from the estimates of the relationship between mortality and recession-induced declines in overall EPOP in columns (1) and (2). Moreover, our estimate of the relationship between NAFTA-induced declines in overall EPOP and mortality is very close to the relationship we estimate in column (4) when we use variation in exposure to the China Shock as instruments for overall EPOP; a one percentage point China-Shock-induced decline in EPOP results in a 1.54% (standard error = 0.65) increase

[32]The share of the Great-Recession-induced EPOP decline that is in manufacturing is roughly proportional to the manufacturing share of EPOP at the start of the Great Recession (12% in 2006). The average manufacturing share was higher over the 1986–2008 period analyzed in row 1 of Table 1.

[33]In Appendix Table OA.4, we show that the IV results in columns (2) and (3) are robust when controlling for a linear pre-period time trend in the instruments (either the Great Recession Shock $\mathrm{GR\_SHOCK}_c$ or the NAFTA vulnerability measure V_c).

in mortality.[34] As with NAFTA-induced overall EPOP declines, we can reject the null hypothesis that the mortality impact of China-Shock-induced overall EPOP declines is the same as the impact of recession-induced overall EPOP declines in columns (1) and (2). Furthermore, we are unable to reject the hypothesis that the mortality impact of NAFTA-induced and China-Shock-induced overall EPOP declines are the same.

5.2 Mortality Impacts of Manufacturing vs Non-Manufacturing EPOP Declines

Finally, we directly examine whether declines in local area manufacturing and non-manufacturing EPOP have differential effects on mortality. To do so, we re-analyze the impact of the Great Recession on mortality, exploiting the same spatial variation in its severity across the U.S. that has been used in prior work (Yagan, 2019; Finkelstein et al., 2025) but now extending that analysis to allow the mortality impact of area employment declines to vary by sector.

5.2.1 Empirical Framework

Using CZ-level annual data from 2003 through 2016 we estimate:

$$y_{ct} = \sum_{s \in \mathcal{S}} \theta_{s,t} \left[\text{GR\_SHOCK}_{s,c} \times \mathbf{1}\left(\text{Year}_t\right) \right] + \alpha_c + \tau_t + \epsilon_{ct} \tag{13}$$

where y_{ct} is log age-adjusted mortality in CZ c and year t and $\text{GR\_SHOCK}_{s,c}$ is the 2007–2009 change in the EPOP ratio in CZ c and sector $s \in S$. In our baseline analysis, $\mathcal{S}$ consists of the manufacturing ($s = m$) and non-manufacturing ($s = n$) sectors, with the overall Great Recession shock defined as the sum of the sector-specific Great Recession shocks.[35] This analysis leverages geographic variation not only in the *size* of the overall EPOP decline in c from 2007–2009, but also in the *share* of that EPOP decline that comes from the manufacturing sector. The size of these two shocks are largely uncorrelated within a CZ (see Appendix Figure OA.19).

To quantify the relationship between different EPOP shocks and mortality, we estimate via IV an augmented version of equation (8) on 2003–2016 CZ-level data:

$$y_{ct} = \alpha_c + \tau_t - \beta_m \text{EPOP}^M_{ct} - \beta_n \text{EPOP}^N_{ct} + \epsilon_{ct} \tag{14}$$

where y_{ct} is the log age-adjusted mortality rate, α_c and τ_t denote CZ and year fixed effects, and the endogenous variables are now annual, CZ-level manufacturing and non-manufacturing EPOP (i.e.,

[34] Our first stage in column (4) is not as strong as those in columns (2) and (3), but weak instruments bias toward the OLS relationship between mortality and EPOP in column (1), and would therefore attenuate our estimate toward zero; in other words, it would bias against our finding that EPOP declines lead to mortality increases in this context.

[35] The Great Recession shock defined in equation (9) as the 2007–2009 change in the overall EPOP ratio ($\text{GR\_SHOCK}_c = \text{EPOP}^A_{c,2007} - \text{EPOP}^A_{c,2009}$) thus gets partitioned into two separate 2007–2009 sector-specific changes in EPOP: $\text{GR\_SHOCK}_{s,c} = \text{EPOP}^S_{c,2007} - \text{EPOP}^S_{c,2009}$ (for $s = m, n$).

EPOP_{ct}^M and EPOP_{ct}^N). We analogously augment the Great Recession instruments from equation (9) to include 2007–2009 CZ changes in both manufacturing and non-manufacturing EPOP:

$$Z_{ct} = \begin{bmatrix} \text{GR\_SHOCK}_{m,c} \times \tilde{t} \times \text{POST}_t \\ \text{GR\_SHOCK}_{m,c} \times \tilde{t}^2 \times \text{POST}_t \\ \text{GR\_SHOCK}_{n,c} \times \tilde{t} \times \text{POST}_t \\ \text{GR\_SHOCK}_{n,c} \times \tilde{t}^2 \times \text{POST}_t \end{bmatrix} \tag{15}$$

which includes a quadratic spline fitted to the post-period (recall from equation (9) that $\tilde{t} = t - 2007$). The IV estimates of β_m and β_n from equation (14) give the percent change in mortality caused by a one percentage point recession-induced decrease in manufacturing and non-manufacturing EPOP, respectively.

We use the IV estimates of β_m and β_n from equation (14) to predict the percentage change in mortality induced by a given economic shock r that produces a decline in manufacturing EPOP of ΔEPOP_r^M and a decline in non-manufacturing EPOP of ΔEPOP_r^N. Assuming additive separability, the predicted percent change in mortality per unit change in EPOP induced by economic shock r is therefore given by:

$$\Delta y^r = \frac{\hat{\beta}_m \Delta\text{EPOP}_r^M + \hat{\beta}_n \Delta\text{EPOP}_r^N}{\Delta\text{EPOP}_r^M + \Delta\text{EPOP}_r^N} \tag{16}$$

We use the estimates of ΔEPOP_r^M and ΔEPOP_r^N for each of the shocks from Table 1 to predict the counterfactual mortality impacts of a recession that experienced those EPOP shocks.

5.2.2 Results

Qualitatively, Great-Recession-induced declines in manufacturing EPOP *increase* mortality, while Great-Recession-induced declines in non-manufacturing EPOP *decrease* mortality. Figure 6 displays the results. For reference, panel (a) displays the estimates of the event study coefficients (θ_t) from estimating equation (13) on a single Great Recession shock variable (GR_SHOCK_c) measuring the CZ-level change in overall EPOP between 2007 and 2009; as seen in Finkelstein et al. (2025), a one percentage point drop in EPOP during the Great Recession decreases average annual age-adjusted mortality from 2007 through 2016 by 0.7% (standard error = 0.2%). However, this estimate masks important underlying heterogeneity in the relationship between mortality and sector-specific employment declines. This can be seen in panel (b) which displays estimates of $\theta_{s,t}$ from estimating equation (13) with two Great Recession shocks on the right hand side ($\text{GR\_SHOCK}_{s,c}$) measuring the CZ-level change in manufacturing EPOP and in non-manufacturing EPOP between 2007 and 2009. A one-point decrease in EPOP in the manufacturing sector leads to a (statistically significant) *increase* in average, annual age-adjusted mortality from 2007 through 2016 of 1.4% (standard error = 0.4%), while a one-point decrease in EPOP in the non-manufacturing sector leads to an average annual (statistically significant) *decrease* of 1.1% (standard error = 0.2%).[36]

Quantitatively, we show in Table 3 that these estimates imply that a counterfactual Great Recession that had a similar share of its EPOP declines in manufacturing as NAFTA or the China Shock would have produced average mortality increases similar to what we estimate for each of these trade shocks. For NAFTA (column 1), we predict that every percentage point decline in overall EPOP would increase mortality by 1.1 percent, which is quite close to our estimated effect of a 1.4 percent increase. For the China Shock (column 2), we predict that each percentage point increase in overall EPOP would increase mortality by 1.4 percent, which is again similar to our estimated effect of a 1.5 percent increase. Finally, column (3) shows that we predict a 0.30 percent decline in mortality from a one percentage point decline in yearly, CZ-level overall EPOP, which is very similar to the estimated impact of a 0.35 percent mortality decline. In all three cases, we cannot reject the hypothesis that the effects predicted using variation from the Great Recession are the same as the actual estimates in the data, which use no variation from the Great Recession at all.

5.2.3 Potential Mechanisms

An important question for further work is *why* manufacturing and non-manufacturing local area EPOP declines have opposite-signed impacts on mortality. A complete answer is beyond the scope of this paper, but we offer some initial, suggestive indications.

A first clue comes from the fact that not only the sign but also the nature of the mortality impacts appears to differ across these two types of local area EPOP declines. Existing evidence from recessions indicates that about three-quarters of the averted deaths are among those 65 and older; this pattern suggests that the health benefits of recessions are not driven by direct effects of (primarily non-manufacturing) EPOP declines, such as increased time for improved health behaviors like better diet and exercise. Indeed, the evidence indicates that the primary drivers of recession-induced mortality declines are from externalities from EPOP declines, including increases in the quality of elder care available (Stevens et al., 2015) and reductions in air pollution (Chay and Greenstone, 2003; Heutel and Ruhm, 2016; Finkelstein et al., 2025).[37] By contrast, for both NAFTA and the China Shock, increased mortality from (primarily manufacturing) local area EPOP declines was disproportionately concentrated among working-age men whose employment was most directly

[36] Appendix Figure OA.20 shows that, as expected, areas with larger shocks to manufacturing EPOP see larger subsequent declines in manufacturing EPOP and little change in non-manufacturing EPOP, and vice versa.

[37] Likewise, Auerbach et al. (2025) find that general, positive local demand shocks (which, consistent with Ruhm (2000), they find increase mortality) are associated with increases in pollution and in traffic congestion. However, positive local demand shocks from winning defense contracts (which they find reduce mortality) do not increase pollution or traffic congestion; they note that compared to general demand shocks, defense contracting primarily increases mining and manufacturing employment and is disproportionately concentrated in smaller cities. We are unable to detect any impact of NAFTA on air pollution (not reported), but our estimates are quite imprecise due to data sparsity; only 234 counties accounting for 40% of the U.S. population had data on PM10 (particulate matter less than 10 micrometers in diameter) for all years between 1990 and 2008 in the EPA's Air Quality System database.

affected.[38] Moreover, as discussed in Section 4.1, the evidence from NAFTA suggests that the direct and intra-family spillover effects of (primarily manufacturing) job loss are likely important drivers of NAFTA-induced mortality increases.

To make some progress in understanding the differentially -signed mortality impacts of different types of local labor market EPOP declines, we first confirmed that the mortality-increasing effect of a local area EPOP decline is indeed specific to manufacturing. To do so, we re-estimated equation (13) including seven sector-specific (mutually exclusive and exhaustive) Great Recession shocks instead of two. Strikingly, Appendix Figure OA.21 shows that manufacturing is the only sector where local area EPOP declines are associated with increases in mortality; all other sector-specific Great Recession shocks are associated with declines in mortality.[39]

We then considered two broad classes of explanations for why manufacturing job loss is bad for local area mortality while non-manufacturing job loss is not: differences in the nature of the jobs, and differences in the types of people who work in the jobs. There is suggestive evidence consistent with both of these hypotheses. Specifically, both existing evidence and our own additional analyses indicate that *male* manufacturing job loss in particular is bad for mortality, and that rents from manufacturing jobs may be part of the channel behind the mortality-increasing effect of declines in manufacturing employment.

Relative to those in non-manufacturing jobs, manufacturing workers tend to be disproportionately male, and also more likely not to have a college degree (e.g., Autor et al., 2025).[40] Several pieces of existing evidence are consistent with male job loss having more adverse impacts on health and well-being than female job loss. In particular there is evidence that men are much more likely than women to report poor levels of emotional well-being when unemployed (Krueger, 2017), that China-Shock-induced male job loss is bad for mortality but China-Shock-induced female job loss is not (Autor et al., 2019 Table A4), and that early retirement increases mortality among blue-collar men, but not among white collar men or among women (Kuhn et al., 2010). Indeed, our additional analysis of different types of local labor market EPOP shocks in the Great Recession (see Appendix Figure OA.22) suggests that only declines in *male manufacturing* EPOP increase mortality; declines in female manufacturing EPOP have no discernible effect on mortality, while declines in either male or female non-manufacturing EPOP are associated with similarly sized declines in mortality.[41]

There is also reason to think that the nature of manufacturing jobs, not just who works in

[38] Figure 3b showed mortality effects by birth cohort and sex for NAFTA, while Appendix Table OA.8 shows this analysis for the China Shock.

[39] As shown in Appendix Figure OA.21, the Health, Education, Government and other Services sector did not experience a sector-specific Great Recession shock.

[40] In the 1990 Census, we estimate that men make up about 66% of manufacturing employees compared to 52% of non-manufacturing employees. Among men employed in manufacturing, about 54% have a high school degree or less, compared to about 44% of men in non-manufacturing employment.

[41] To proxy for sex-specific employment declines within manufacturing and within non-manufacturing, we follow the approach of Autor et al. (2019) and exploit sex dissimilarities in industry specialization. Appendix C provides details.

them, may play an important role. Following job displacement, manufacturing workers experience larger and more persistent earnings declines compared to non-manufacturing workers (Carrington and Zaman, 1994).[42] Relatedly, Autor et al. (2025) note that manufacturing jobs are heavily over-represented among the set of industries that pay high, industry-specific wage premiums. A natural hypothesis, therefore, is that manufacturing jobs offer workers high rents in wages or in non-wage amenities relative to their outside option, and that the loss of these rents is detrimental to well-being. To investigate this possibility, we examined one possible source of these rents, namely the historical presence of strong unions among manufacturing workers (Alder et al., 2023). Appendix Figure OA.23 shows that the impacts of NAFTA on mortality are over twice as large in states with above-median union coverage prior to NAFTA, although these states did not experience different employment declines from NAFTA. We interpret this as suggestive evidence that the loss of jobs with high union coverage were particularly bad for health—consistent with the idea that the loss of jobs with high rents may be an important mechanism. Interestingly, however, a similar analysis of the Great Recession in Appendix Figure OA.24 shows little difference in the impact of manufacturing or non-manufacturing local area EPOP declines by baseline union coverage; this is consistent with evidence that union strength has declined over time (Farber et al., 2021), and suggests that union rents—along with effects concentrated among working-age men—are only part of the story.

6 Conclusion

We examined the impact of local-area exposure to import competition via NAFTA on mortality and explored implications both for NAFTA and for our broader understanding of the relationship between local area economic shocks and mortality. NAFTA increased mortality overall and across all age-by-sex groups. These mortality increases were particularly pronounced among working-age men, who were also the group who experienced disproportionate NAFTA-induced employment declines. The pattern of results suggests an important role for both the direct impacts of job loss on mortality as well as intra-family spillover effects from job loss, with worsening health behaviors a potentially important channel.

The welfare consequences of these NAFTA-induced mortality increases are large enough to more than erase prior estimates of the general equilibrium welfare gains from NAFTA operating through increased real wages. This finding is consistent with two hitherto fairly distinct themes that have emerged in the recent literature: first, that the welfare consequences from health changes can be enormous (e.g., Murphy and Topel, 2006; Jones, 2016; Finkelstein et al., 2025) and second that the

[42] In related work, Couch and Placzek (2010) write that "manufacturing workers, in particular, are thought to develop more specific skills than others and would be expected to have larger than average earnings losses when they separate from employment." On the other hand, Yagan (2019) finds persistent, 10-year employment and earnings declines in areas harder hit by the Great Recession, even though most of the job loss is not in manufacturing; he does not directly examine differential persistence for manufacturing and non-manufacturing sectors.

welfare gains from trade in a large open economy like the United States are likely small (e.g., Arkolakis et al., 2012; Costinot and Rodríguez-Clare, 2018). More broadly, our findings underscore the potential importance of incorporating health impacts into welfare analyses of economic phenomena (Jones and Klenow, 2016; Finkelstein et al., 2025).

We also developed a unified empirical framework to explain disparate findings across four different sources of local labor market declines in the sign of their mortality impacts. We show qualitatively that declines in local area manufacturing EPOP *increase* area mortality while declines in local area non-manufacturing EPOP *decrease* area mortality. Quantitatively, we find that although observed recessions have been found to reduce mortality (e.g., Ruhm, 2000; Finkelstein et al., 2025), counterfactual recessions that, like trade shocks, have most of their EPOP declines concentrated in manufacturing, would increase mortality by a similar amount to what we estimate from trade shocks.

Our findings suggest that the sign and magnitude of the mortality impact of other local area economic shocks—including past and future increases in exposure to trade—likely depend critically on how much these shocks affect the manufacturing sector relative to non-manufacturing sectors. We explored why these two sources of local area employment declines have opposite-signed local area mortality impacts, and provided evidence consistent with declines in male manufacturing employment being particularly bad for mortality, and with rents from manufacturing job being a potentially important part of the explanation. Further analysis of these and other potential explanations is an important area for further work.

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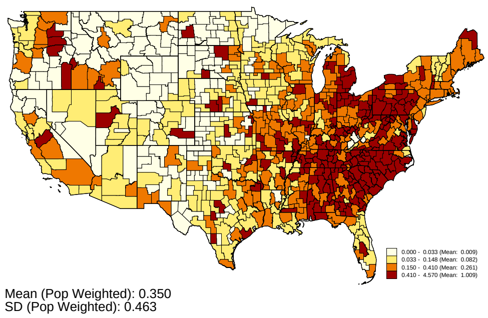
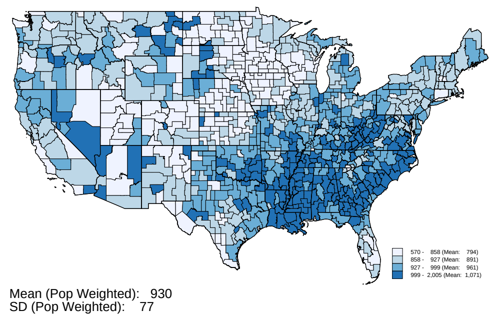
Figures

Figure 1: Geographic Distributions and Correlations of NAFTA Vulnerability and Mortality

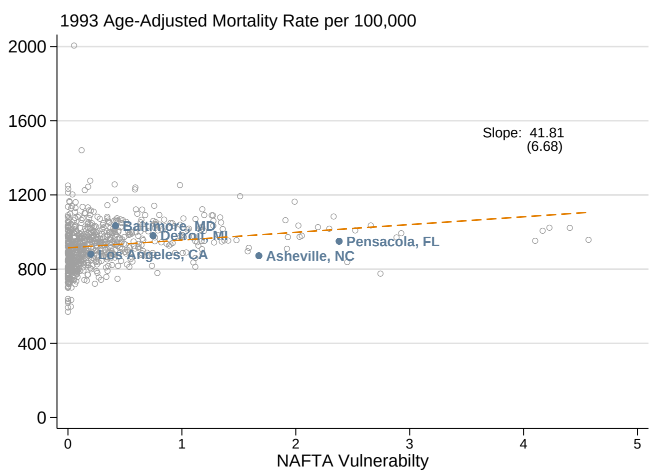
(a) NAFTA Vulnerability



(b) 1993 Age-Adjusted Mortality

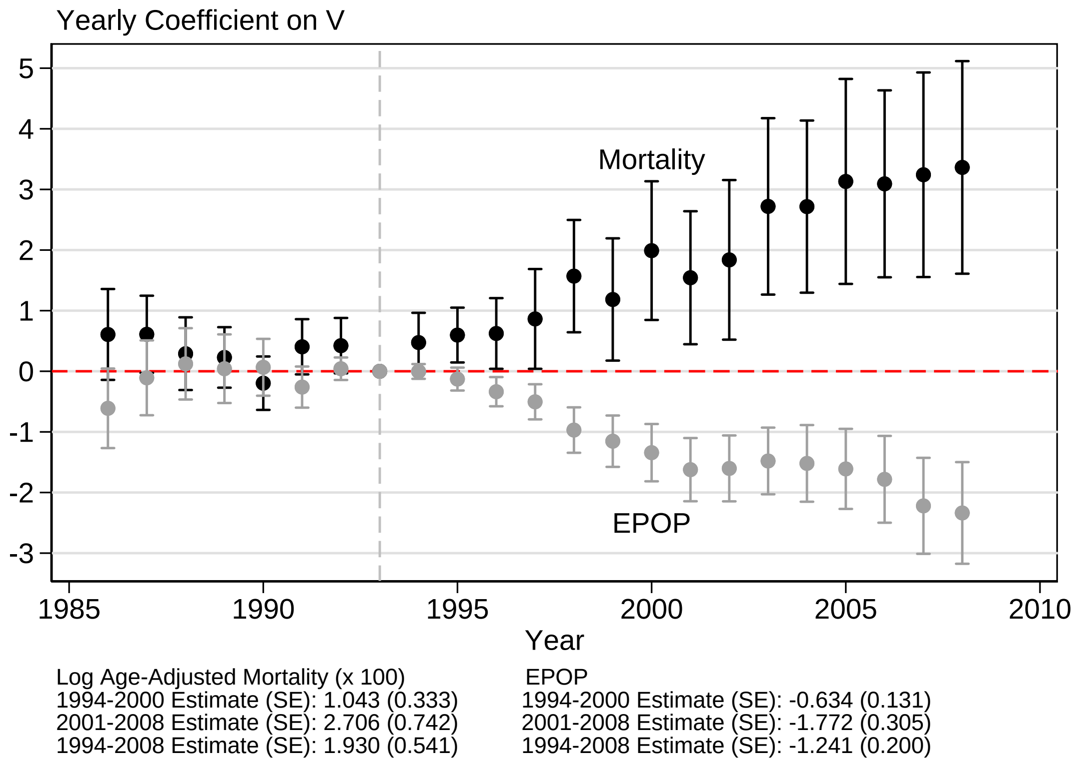


(c) Correlation of Baseline Mortality and Vulnerability



Notes: Panel (a) displays a heatmap of the NAFTA vulnerability measure (V_c) across CZs, while Panel (b) displays a heatmap of 1993 age-adjusted mortality rates per 100,000. Panel (c) displays a scatterplot of these measures against each other, along with the regression slope coefficient and heteroskedasticity-robust standard error. The regression is weighted by 1990 CZ population, and the sample size is 722 CZs.

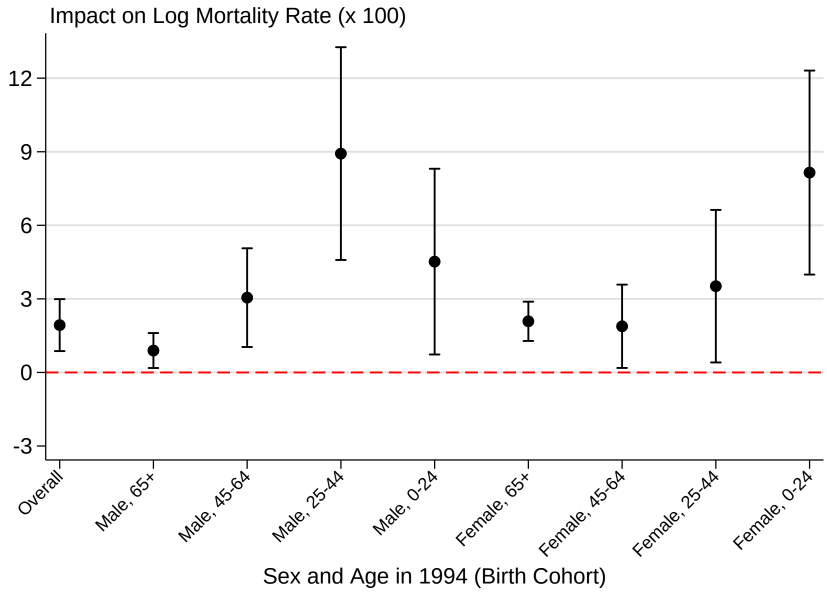
Figure 2: Impact of NAFTA Vulnerability on Log Age-Adjusted Mortality



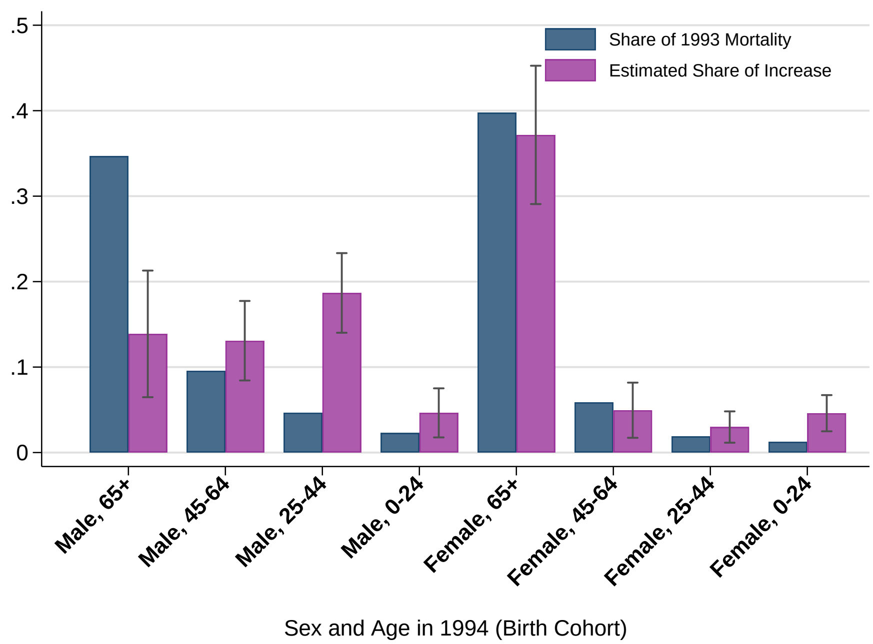
Notes: This figure displays (in black) 100 times estimates of β_t from equation (4), where the outcome y_{ct} is the log age-adjusted CZ mortality rate per 100,000. It also shows (in gray) estimates of β_t with EPOP as the outcome (i.e. percentage point changes in EPOP). A one-point increase in NAFTA vulnerability V_c corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The average estimate across several periods and their corresponding standard errors are given in the lower left corner. The sample size is 722 CZs.

Figure 3: NAFTA Mortality Decomposition By Birth Cohort and Sex

(a) 1994–2008 Pooled Estimates



(b) 1994–2008 Decomposition

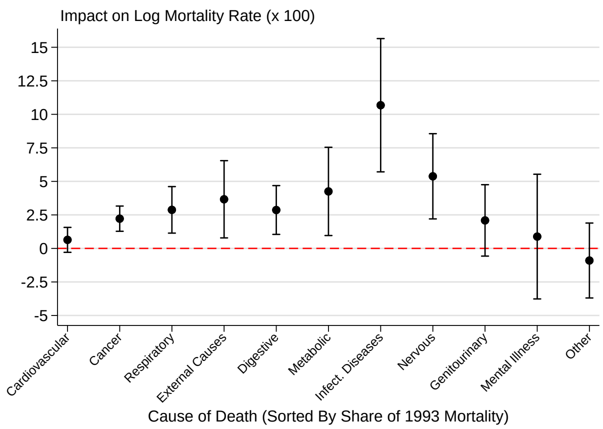


Notes: Panel (a) gives the average 1994–2008 estimate of β_t in equation (4) with the log mortality rate for each demographic group given on the x-axis as the outcome; Appendix Figure OA.25 shows the underlying event studies behind each estimate. In panel (b), the blue bars denote the share of deaths each demographic group accounted for in 1993, while the purple bars denote the share of the increase in mortality each group accounted for (averaged over the 1994–2008 post-period) as a result of NAFTA. These shares are computed by multiplying the number of deaths in each demographic group in 1993 by the percent change in mortality in the post-period according to equation (4), then dividing by this quantity summed over all 8 demographic groups (which gives the total implied change in mortality). Vertical lines give 95% confidence intervals computed using standard errors clustered at the CZ level; they are computed by estimating equation (4) for all 8 demographic groups simultaneously in a stacked regression. The regression is weighted by each CZ's population in 1990. The sample size for each individual group is 722 CZs.

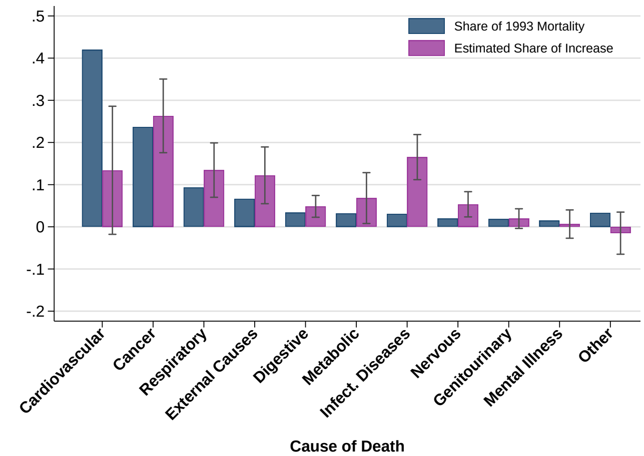
Figure 4: NAFTA Mortality Impacts By Cause of Death

Full Sample

(a) Point Estimates

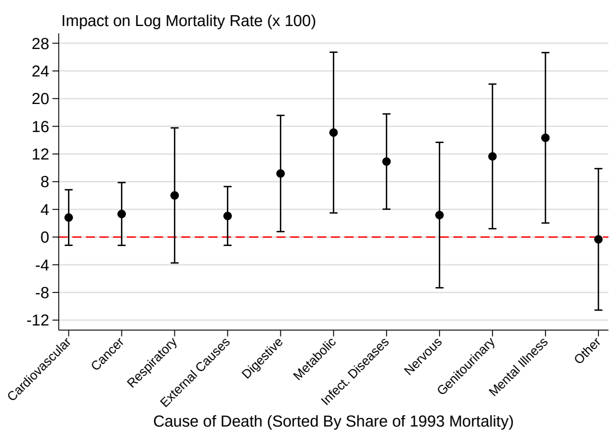


(b) Decomposition

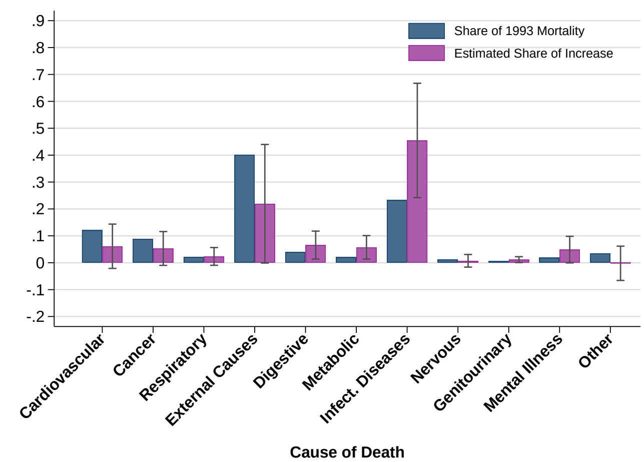


(Men Born 1950–1969)

(c) Point Estimates

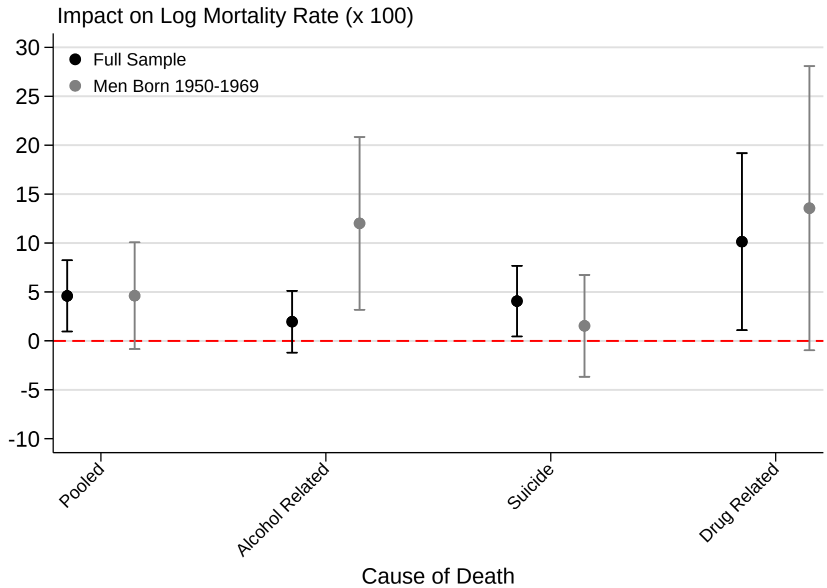


(d) Decomposition



Notes: Panels (a) and (c) display 100 times the average estimate of β_t in equation (4) over the 1994–2008 period, where the outcomes are the log age-adjusted mortality rate per 100,000 by cause of death for all individuals (panel a) and for men born between 1950 and 1969 (panel c); the underlying event studies are shown in Appendix Figures OA.26, OA.27, OA.28 and OA.29. In panels (b) and (d), the blue bars denote the share of deaths each cause accounted for in 1993, while the purple bars denote the share of the increase in mortality each cause accounted for (averaged over the 1994–2008 post-period) as a result of NAFTA. Vertical lines denote 95% confidence intervals constructed using standard errors clustered at the CZ level. Observations are weighted by CZ population in 1990. The sample size is 722 CZs.

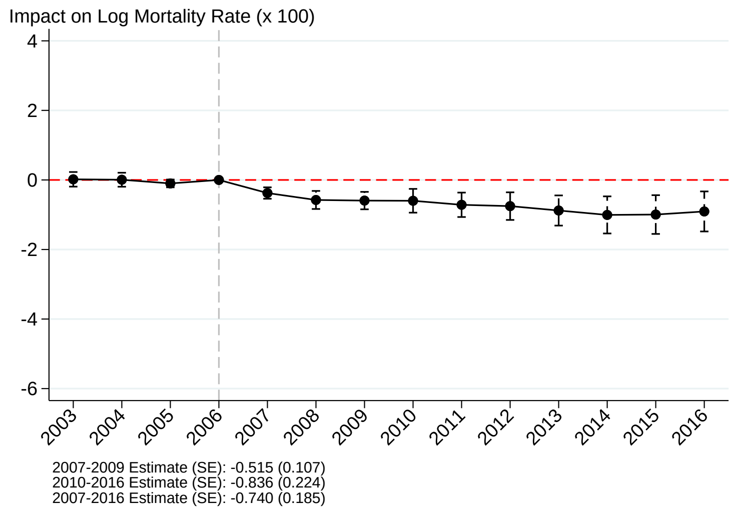
Figure 5: NAFTA Mortality Impacts on Deaths of Despair



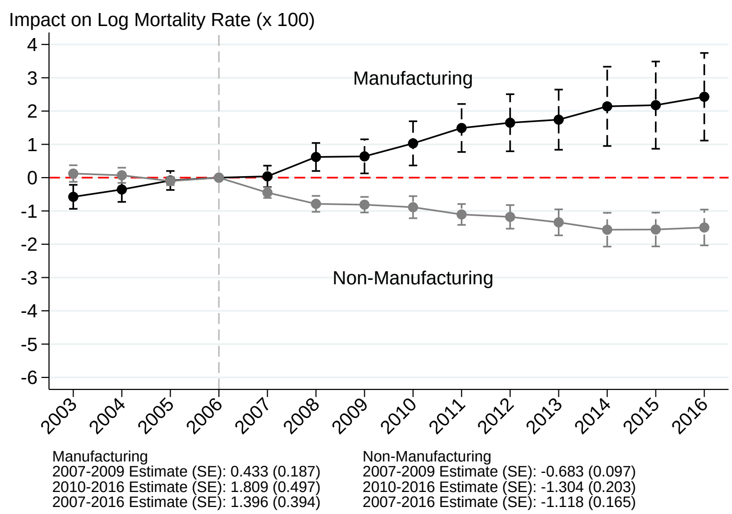
Notes: This figure displays 100 times the average estimate of β_t in equation (4) over the 1994–2008 period, where the outcomes are the log age-adjusted mortality rate per 100,000 for each listed cause (in black) and the log mortality rate per 100,000 among men born between 1950 and 1969 (in gray). Appendix Figures OA.30 and OA.31 show the underlying event studies. In 1993, these causes accounted for 6.1% of overall mortality and 9.4% of mortality among men born between 1950 and 1969. A one-point increase in NAFTA vulnerability V_c corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile. Vertical lines denote 95% confidence intervals constructed using standard errors clustered at the CZ level. Observations are weighted by CZ population in 1990. The sample size is 722 CZs.

Figure 6: Effects of Sector-Specific Great Recession Shocks on Mortality

(a) Total Great Recession Shock



(b) Separate Great Recession Shocks to Manufacturing and Non-Manufacturing Sectors



Notes: This figure displays 100 times event study coefficients $\theta_{s,t}$ from estimating equation (13). Panel (a) shows estimates of the coefficients θ_t from estimating equation equation (13) on a single Great Recession shock variable (GR_SHOCK_c) that measures the total CZ-level change in EPOP between 2007 and 2009 (i.e. $\text{GR\_SHOCK}_c = \text{EPOP}^A_{c,2007} - \text{EPOP}^A_{c,2009}$). Panel (b) shows estimates of the coefficients $\theta_{s,t}$ from estimating equation (13) with two Great Recession shocks on the right hand side ($\text{GR\_SHOCK}_{s,c}$) for $s \in m, n$; these measure the CZ-level change in manufacturing EPOP and in non-manufacturing EPOP between 2007 and 2009 (i.e. $\text{GR\_SHOCK}_{s,c} = \text{EPOP}^S_{c,2007} - \text{EPOP}^S_{c,2009}$, for $s = m, n$). The outcome y_{ct} is the log age-adjusted mortality rate per 100,000 in each CZ-year. We estimate equation (13) using annual data from 2003 through 2016, omitting the interaction with the shock variables in 2006, so that all of the $\theta_{s,t}$ coefficients are relative to 2006. Estimates of the average of coefficients from 2007–2009, 2010–2016, and 2007–2016 are reported in the lower left-hand corner. Observations are weighted by CZ population in 2006. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. Coefficients, standard errors, and confidence intervals are multiplied by 100 for ease of interpretability. The sample size is 722 CZs.

Tables

Table 1: Effects of Shocks on EPOP By Sector

	EPOP			
	Total	Manufacturing	Non-Manufacturing	Share Manufacturing
	(1)	(2)	(3)	(4)
EPOP	-1.000	-0.327	-0.673	0.327
		(0.020)	(0.020)	
Great Recession	-0.957	-0.139	-0.818	0.146
	(0.074)	(0.043)	(0.078)	
NAFTA	-1.278	-1.054	-0.225	0.824
	(0.328)	(0.250)	(0.230)	
China Shock	-1.448	-1.319	-0.129	0.911
	(0.572)	(0.229)	(0.471)	

Notes: Table displays estimates from equation (7) of the effect of different economic shocks (Z_{ct}) shown in each row on different measures of EPOP shown in the first three columns. The fourth column shows the ratio of the EPOP declines in manufacturing (column 2) to total (column 1). Each row displays estimates for a different measure of economic shock Z_{ct}. Row 1 shows estimates of κ for $Z_{ct} = \text{EPOP}^A_{ct}$. Row 2 displays estimates of $4.5\kappa_1 + 4.5^2\kappa_2$ for Z_{ct} defined in equation (9); this gives the predicted impact of the Great Recession at the middle of the 2007–2016 post-period ($\tilde{t} = 4.5$). Row 3 displays estimates of $7\kappa_1 + 7^2\kappa_2$ for Z_{ct} defined in equation (10); this gives the predicted impact of NAFTA at the middle of the 1994–2008 post-period ($\tilde{\tilde{t}} = 7$). Row 4 displays IV estimates of κ in equation (7), instrumenting for Z_{ct} as defined in equation (11) with $\tilde{Z}_{ct}$ as defined in equation (12). Sample is 722 CZs and years 1986–2008 in rows (1) and (3), years 2003–2016 in row (2), and stacked periods 1999–2000 and 2000–2014 in row (4). Regressions are weighted in rows (1) and (3) by each CZ's population in 1990, in row (2) by each CZ's population in 2006, and in row (4) by the product of period length and start of period population. Standard errors clustered at the CZ level are displayed in parentheses.

Table 2: IV Estimates of the Impact of EPOP on Mortality

	OLS (1)	IV (Great Recession) (2)	IV (NAFTA) (3)	IV (China Shock) (4)
EPOP Decline (×100)	-0.353	-0.746	1.435	1.543
	(0.122)	(0.267)	(0.561)	(0.649)
First Stage F-Statistic		83.25	10.01	6.65
p-value		0.000	0.000	0.010
N	16,606	10,108	16,606	1,444
Hansen J Statistic		1.684	0.482	
p-value		0.194	0.488	
Testing equality with:				
OLS (p-value)		0.228	0.003	0.000
China Shock (p-value)		0.000	0.848	
NAFTA (p-value)		0.000		

Notes: Table shows estimates of β from equation (8) with log age-adjusted mortality as the outcome. Column (1) presents OLS estimates with no additional controls X_{ct}. Columns (2) through (4) present IV estimates in which we instrument for the endogenous variable EPOP^{A}_{ct} with the first stage equation (7), and the instruments Z_{ct} defined in, respectively, equation (9), equation (10) and equation (12); the additional controls X_{ct} in each analysis are defined in the text. Standard errors clustered at the CZ level are displayed in parentheses. All estimates and standard errors are multiplied by 100 for ease of interpretability. Columns (2) through (4) display Kleibergen-Paap first stage F-statistics. Sample is 722 CZs and years 1986–2008 in columns (1) and (3), years 2003–2016 in column (2), and stacked periods 1990–2000 and 2000–2014 in column (4). Regressions are weighted in rows (1) and (3) by each CZ's population in 1990, in row (2) by each CZ's population in 2006, and in row (4) by the product of period length and start of period population.

Table 3: Predicted vs Estimated Mortality Effects of Different Local Labor Market Shocks

	Percent Change in Mortality		
	NAFTA	China Shock	OLS
	(1)	(2)	(3)
Predicted Effect	1.144	1.396	-0.303
	(0.674)	(0.405)	(0.270)
Estimated Effect	1.435	1.543	-0.353
	(0.561)	(0.649)	(0.122)
Test of Equality (p-value)	0.656	0.718	0.877

Notes: The first row of this table displays the predicted effect of each economic shock (indicated by the column heading) on the percent change in age-adjusted mortality using the formula in equation (16). Specifically, $\Delta\text{EPOP}_{ct}^{M}$ and $\Delta\text{EPOP}_{ct}^{N}$ are defined as the corresponding estimates in columns (2) and (3) of Table 1 for each economic shock, while $\hat{\beta}_m$ and $\hat{\beta}_n$ are estimated in equation (14) via IV, with the instruments given by the sector-specific Great Recession instruments in equation (15). The second row of this table replicates the estimated impacts of total EPOP (EPOP_{ct}^{A}) on log age-adjusted mortality from Table 2; specifically, it displays IV (columns 1 and 2) and OLS (column 3) estimates of β for equation (8). In column (1), we instrument for EPOP_{ct}^{A} using the set of NAFTA instruments as defined in equation (10), and in column (2) we use the set of China Shock instruments defined in equation (12). The regressions are weighted by each CZ's population in 1990 in columns (1) and (3) and the product of period length and start of period population share in column (2). Controls for each specification are given in the text. To construct standard errors for the predicted effects in the first row (shown in parentheses), we estimate a seemingly unrelated regression stacking three regressions: equation (14) to estimate $\hat{\beta}_m$ and $\hat{\beta}_n$ along with two copies of equation (7), one with manufacturing EPOP as the outcome and the other with non-manufacturing EPOP as the outcome, to estimate $\Delta\text{EPOP}_{ct}^{M}$ and $\Delta\text{EPOP}_{ct}^{N}$. For NAFTA (column 1), we define Z_{ct} according to equation (10); for the China Shock (column 2) we estimate the equation in long differences and instrument for Z_{ct} as defined in equation (11) with $\tilde{Z}_{ct}$ as defined in equation (12); for yearly fluctuations (OLS) in column (3), we simply take $Z_{ct} = \text{EPOP}_{ct}^{A}$. To test the equality of coefficients between the first and second rows, we stack the regression corresponding to each economic shock an additional time with log mortality as the outcome, recovering the estimated effects in the second row. Standard errors clustered at the CZ level are given in parentheses. The sample size is 722 CZs.

Appendices

A NAFTA

A.1 Empirical Strategy: Additional Discussion

Our NAFTA vulnerability measure ($\tilde{V}_c$ in equation 2) has a shift-share (or "Bartik") structure. Therefore, identification of the event study coefficients β_t in equation (4) can come from assuming exogeneity of the "shares" $\frac{L^{cj}_{1980}}{L^{c}_{1980}}$ (Goldsmith-Pinkham et al., 2020) or the "shifts" $\tilde{\text{RCA}}^j \tau^j_{1990}$ (Borusyak et al., 2022). We take the exogenous shares approach, which Goldsmith-Pinkham et al. (2020) show is equivalent to a parallel trends assumption in our event study framework.

Goldsmith-Pinkham et al. (2020) formalize their argument as follows. Consider the structural equation

$$y_{ct} = x_{ct}\beta_0 + D_{ct}\rho + \epsilon_{ct} \tag{17}$$

where y_{ct} denotes the wage *growth* (or, in our case, the mortality growth) in CZ c and period t, x_{ct} denotes employment growth, D_{ct} is a vector of controls, and ϵ_{ct} is the structural error term. To instrument for the endogeneous variable x_{ct}, we use the instrument

$$B_{ct} = \sum_k z_{ck0} g_{kt} \tag{18}$$

where z_{ck0} denotes the share of employment in each industry k in some base year and g_{kt} denotes the growth in employment in industry k. They show that with multiple industries k, the estimate of β_0 under a two-stage least squares setup is numerically equivalent to estimating β_0 using GMM with the industry shares z_{ck0} as instruments, with a particular weighting matrix that they characterize.

Thus, the identifying assumption in this case is that the industry shares z_{ck0} are orthogonal to y_{ct}. Recall that in their setup, y_{ct} denotes the *growth* in wages, which means that we require orthogonality in changes rather than levels. With the inclusion of controls D_{ct}, we require exogeneity conditional on these observables. As noted by Goldsmith-Pinkham et al. (2020), this assumption is more credible if z_{ck0} is orthogonal to changes in the outcome prior to period t; this is simply a difference-in-differences assumption.

Our specification has two key differences from the canonical setup in Goldsmith-Pinkham et al. (2020). First, there is no endogenous variable x_{ct}; instead, we regress the outcome directly on the instrument. The identifying assumption for this "reduced-form" regression is unaffected by this change.

Second, we use an event study framework rather than estimating the equation in changes. However, each β_t in equation (4) is equivalent to regressing changes in the outcome on V_c without area and year fixed effects; in other words, estimates of β_t prior to 1993 are the pre-trend tests described in Goldsmith-Pinkham et al. (2020), while estimates of β_t in the post-period are the reduced-form effects of V_c conditional on controls. Thus, we can use the pre-trends in our event study estimates to examine the validity of the empirical design.

A.2 Sensitivity Analysis of Mortality Estimates

We explored the sensitivity of our baseline estimates of the impact of NAFTA on mortality (summarized in the top row of Appendix Table OA.5) to a number of alternative specifications.

Contemporaneous shocks. A source of potential confounds to the estimated impact of NAFTA on mortality is the existence of other spatially-varied shocks that occurred over the same period, may be correlated with exposure to NAFTA, and may have their own, direct effects on mortality. Appendix Table OA.5 panel A therefore shows that the estimated mortality effects of NAFTA are robust to controlling flexibly for these other shocks.

First, as documented in Autor et al. (2019), import penetration from China is also increasing during our sample period. Since this also has positive effects on mortality, we probe robustness to controlling for Chinese import penetration. To do this, we follow Choi et al. (2024) and include yearly fixed effects interacted with each CZ's 1990–2000 China Shock import penetration rate as defined in Autor et al. (2013). To avoid endogeneity, we use Autor et al. (2013)'s instrument (lagged U.S. employment shares interacted with the increase in imports to 8 other high-income countries). Results look very similar to our baseline findings.

In addition, the opioid epidemic began shortly after the introduction of Oxycontin in 1996 (Alpert et al., 2022) and also had positive effects on mortality. We therefore probe robustness to controlling for the extent of the opioid epidemic. Specifically, we add yearly fixed effects interacted with cancer mortality rates in 1990; this approach follows Arteaga and Barone (forthcoming) who show that baseline cancer incidence rates are a predictor of where Oxycontin was initially marketed most heavily and hence a plausible instrument for exposure to the opioid epidemic. Once again the baseline results are largely unaffected.

Finally, since there is a secular manufacturing decline during our study period more generally, we also try generating three separate k-means clusters for (1) the manufacturing share in 1980 and (2) our remaining controls. Again, the results are quite similar.

Geography. We also explored the sensitivity of our findings to the geographic scope of the analysis as well as the geographic unit of analysis. Appendix Table OA.5 panel B summarizes the results.

One concern is that estimates of the effect of NAFTA might be confounded by secular changes in manufacturing employment and mortality in the Southern Census region, where vulnerability was highest. However, when we limit the analysis to CZs within the Southern Census Region, the results are similar.

If we use Choi et al. (2024)'s preferred unit of geography and estimate (4) at the county level, results are somewhat attenuated but we still find statistically significant impacts of NAFTA on mortality that grow over time.

Functional form. Finally, we explored sensitivity across functional form choices. Appendix Table OA.5 panel C summarizes the results. If we replace the dependent variable with the age-adjusted mortality rate in levels in year t, we obtain very similar results. For example, over the 1994–2008 period, we estimate that, relative to CZs in the bottom quartile of NAFTA vulnerability, CZs in the top quartile of vulnerability experienced an average increase in annual age-adjusted mortality of 14.7 deaths per 100,000 (standard error = 4.4), or about 1.6 percent relative to the 1993 baseline age-adjusted mortality of 880 per 100,000 (an increase in V_c of 1).

The next row shows what happens if we estimate our specification with a Poisson regression using the age-adjusted mortality rate in levels as the outcome. Specifically, we estimate:

$$y_{ct} = \exp(\beta_t \left[V_c \times \mathbf{1}\left(\text{Year}_t\right)\right] + \alpha_c + \tau_t + X_{ct}\phi), \tag{19}$$

where all variables are defined as in equation (4) except that y_{ct} is now the age-adjusted mortality rate per 100,000. The estimates are very similar to our baseline.

In the final set of rows, we relax the assumption that the log mortality rate is linear in NAFTA vulnerability. To do so, we replace V_c in equation (4) with indicators for which quartile of the (population-weighted) CZ distribution of V the CZ is in. Specifically, we estimate:

$$y_{ct} = \sum_{j=2}^{4} \beta_t^{(j)} \left[(VQ)_c^{(j)} * 1(\text{Year}_t)\right] + \alpha_c + \tau_t + X_{ct}\phi + \epsilon_{ct}, \tag{20}$$

where the outcome is once again log age-adjusted mortality and $(VQ)_c^{(j)}$ is an indicator for the j^{th} quartile of the distribution of V_c across (1990 population-weighted) CZs; we omit the 1st quartile and report estimates of $\beta_t^{(2)}$, $\beta_t^{(3)}$, and $\beta_t^{(4)}$. The average V_c is 0.08 in quartile 1 (the omitted quartile), 0.19 in quartile 2, 0.29 in quartile 3, and 0.97 in quartile 4. The impact of being in the fourth quartile of vulnerability relative to the first is roughly 2–3 times as large as the impact of being in the third quartile of vulnerability relative to the first, which is somewhat smaller than the ratio that would be expected if the relationship was exactly linear, since $(0.97 - 0.08)/(0.29 - 0.08) = 4.24$. When scaled by the difference in average V_c, the mortality estimates for both quartile 3 and quartile 4 (relative to quartile 1) are larger than the baseline results, which is consistent with the above-median exposure CZs driving the main results and below-median exposure CZs having minimal mortality impacts from NAFTA.

A.3 Employment Effects By Birth Cohort and Sex

As a point of comparison to NAFTA's mortality impacts by sex and birth cohort, we also estimate the impact of NAFTA on EPOP by sex and birth cohort. CZ-year EPOP by demographic group is not available during our study period. We therefore impute the effect of NAFTA on employment by sex and birth cohort by estimating NAFTA's impact on EPOP for each of the 20 two-digit NAICS industries in the CBP and then taking a linear combination of these estimates for each sex by birth cohort based on data from the CPS of each demographic group's share of 1993 national employment in each industry.[43] Specifically, we compute the EPOP ratio in each industry i by year and CZ using the CBP employment and SEER population data, and estimate equation (4) using each industry-specific EPOP ratio as an outcome to obtain estimates β_t^i of the impact of NAFTA on EPOP in each industry i. We then aggregate the industry-specific effects by computing

$$\tilde{\beta}_t^d = \sum_{i \in \mathcal{I}} s_{i,1993}^d \times \beta_t^i \tag{21}$$

where $\mathcal{I}$ denotes the set of 2-digit NAICS industries and $s_{i,1993}^d$ denotes the share of workers of

[43] Since EPOP is mechanically low for individuals in the 1970 to 1994 birth cohort in the 1986 to 1993 pre-period—as most of them are not 16+ and therefore not included in the risk set—we exclude this youngest cohort from the EPOP heterogeneity analysis.

demographic d working in industry i in 1993. Specifically, we use the 1993 CPS to compute $s^d_{i,1993}$, the share of employed workers in each 2-digit NAICS industry who belong in each demographic subgroup. To compute standard errors, we estimate equation (4) for each industry simultaneously in a stacked regression to obtain β^i_t and treat the shares $s^d_{i,1993}$ as fixed.

Results. Appendix Figure OA.32a summarizes the results; Appendix Figure OA.33 shows the underlying event studies. EPOP declines also appear to be concentrated in men in the 1950 to 1969 birth cohort (aged 25–44 in 1994), with the next largest declines for men in the 1930- 1949 birth cohort (aged 45–64 in 1994); NAFTA-induced EPOP declines are about one-half to one-third the size for women in the same birth cohorts and are, as would be expected, essentially zero for the birth cohorts that were 65 or older in 1994. Relative to CZs in the bottom quartile of NAFTA vulnerability, CZs in the top quartile experienced an average annual reduction in annual EPOP for the 1950 to 1969 male birth cohort of 0.5 percentage points (standard error = 0.08), compared to a decline of 0.24 (standard error = 0.04) for women in that birth cohort. Given average vulnerability across CZs of 0.35, this implies that NAFTA on average reduced EPOP for men in the 1950 to 1969 birth cohort by 0.18 percentage points. Baseline EPOP in 1993 (defined as the share of the population 16+ employed) was 47.6 percent, of which about 13.7 percentage points—or almost one third—was accounted for by men in the 1950 to 1969 birth cohort (see Appendix Table OA.6). The NAFTA-induced EPOP decline for men in this cohort thus represented about a one percent decline in their average EPOP.

In Appendix Figure OA.32b, we use these estimated demographic-specific EPOP declines to construct the share of the employment decline attributable to each sector. This shows that men aged 25–44 and 45–64 in 1994 are responsible for a much larger share of the decrease in employment than women in the same age group (men aged 25–64 in 1994 account for over 60% of the EPOP decline, compared to about 30% for women in that age group). This mirrors the fact that men in this age group make up a much larger share of the increase in mortality than women in this age group; men aged 25–64 in 1994 make up almost one-third of the increase in deaths due to NAFTA, while women aged 25–64 in 1994 make up less than 10 percent of the increase in deaths (Figure 3b).

A.4 Benchmarking Mortality Estimates Against Sullivan and von Wachter (2009)

Using administrative data on long-tenure workers in Pennsylvania and mass layoffs between 1980 and 1986, Sullivan and von Wachter (2009) find that job displacement increases the log-odds of mortality by 7–17% over the next several decades. In Table 2, we found that a one percentage point decrease in EPOP as a result of NAFTA increases average annual age-adjusted mortality rates by 1.44%. To compare these numbers, we make several adjustments detailed below.

First, rather than using the log age-adjusted mortality rate as the left hand side of our instrumental variables regression in equation (7), we use the log mortality rate among working-age men (that is, those aged 25–64 at NAFTA's implementation in 1994). Continuing to use the NAFTA vulnerability measures in equation (10) as instruments for EPOP, we estimate that a one-point NAFTA-induced decline in EPOP increased the mortality rate among working-age men by 4.16% (standard error = 1.74%). Ideally, however, we would want an estimate of the effect of a one percentage point decrease in the employment rate among working-age men instead of a one percentage point decrease in the total employment to total population ratio. To that end, we note (from Figure OA.32) that working-age men accounted for 61.7% of the total decline in EPOP and compute from the SEER that they accounted for 33.5% of the population aged 16+ in 1993. Thus, we estimate that a one-point NAFTA-induced decline in EPOP corresponds to a $\frac{61.7}{33.5} = 1.84$ percentage point decline in the employment of working-age men as a fraction of working-age men. This implies that among working-age men, the increase in mortality associated with a one percentage point decrease in employment is $\frac{4.16}{1.84} = 2.26\%$.

Second, we note that a one percentage point decline in the employment rate is not the same as a one percentage point increase in the rate of job loss (which is the object that Sullivan and von Wachter (2009) consider); many individuals who lose their job will eventually find new employment within the next several years (making the job loss rate higher than the decline in the employment rate, especially over longer time horizons), and some individuals may also voluntarily leave their jobs (which will reduce the employment rate beyond what would be predicted from the rate of job loss). To convert our estimated impacts on the employment rate into implied impacts on job loss, we therefore follow the framework in Song and von Wachter (2014) and write the change in EPOP between years t and $t + \tau$ as

$$\text{EPOP}_{t+\tau} - \text{EPOP}_t = \underbrace{\text{EPOP}^{\text{ND}}_{t+\tau} - \text{EPOP}^{\text{ND}}_t}_{E[.]=0} + \delta^D_\tau \left(\pi^D_{t+\tau} - \pi^D_t\right) \tag{22}$$

where $\text{EPOP}^{\text{ND}}_t$ denotes the number of individuals who remained employed and were not displaced ("ND") in year t divided by the working-age population in year t, δ^D_τ denotes the reduction in EPOP τ years later due to displacement in year t, and π^D_t is the share of the working-age population displaced in year t. We assume that $E[\text{EPOP}^{\text{ND}}_{t+\tau} - \text{EPOP}^{\text{ND}}_t] = 0$, so that the average change in EPOP between years is driven by job displacements.

To calibrate this formula, we use Song and von Wachter (2014)'s estimate of $\delta^D_\tau = -0.1$, which means that a one percentage point decrease in EPOP causes a 0.1 percentage point increase in the job displacement rate. Thus, we scale the implied 1.84 percentage point decrease in employment among working-age men by 0.1 to map to a 0.184 percentage point increase in the job displacement rate among working-age men. Combining all of this together, we estimate that the 4.16% increase in working-age male mortality as a result of a one-point decline in their EPOP rate maps to a 4.16% increase in working-age male mortality as a result of a 0.184 percentage point increase in the job displacement rate among working-age men. Thus, a working-age man being displaced (i.e. having a job displacement rate of 1) would correspond to a $\frac{4.16}{0.184} = 22.6\%$ (standard error = 9.4%, treating the scaling factors as constants) increase in the working-age male mortality rate. This is slightly above Sullivan and von Wachter (2009)'s range of estimates, with a 95% confidence interval that entirely covers it.

A.5 Mortality Effects By Education and Sex

To evaluate the mortality impacts of NAFTA by education and sex, we compute mortality rates by combining directly measured mortality counts in the NCHS data with imputed population denominators. Specifically, the NCHS data contain each decedent's level of education by years of schooling (as well as their sex and age). We can thus construct the number of decedents in each sex-by-education-by-age bin cell in each CZ and year. However, education levels are only reported starting in 1989; furthermore, some states (including Texas and Maryland) only reported education data for a small share of decedents in 1989. As a result, we begin our analysis by education and sex in 1990. Due to issues with reporting education data throughout the sample period, we also remove CZs in Georgia, Louisiana, New York, Oklahoma, South Dakota, and Washington.

Constructing population denominators is more difficult, because the CZ-year SEER population data do not contain population data by education. To circumvent this issue, we impute population denominators in each sex-by-education-by-age bin using the 1990 Census. Specifically, we use education data in the Census to construct the share of the population aged 25 or older in each CZ and each sex-by-age bin that had (1) a high school degree or less and (2) more than a high school degree. Multiplying these shares by the CZ-level population estimates in each sex-by-age bin according to the SEER, we obtain an estimate of the population by age, sex, and education.

Note that such shares cannot be calculated in intercensal years due to a lack of data. As a result, we make the assumption that these shares were constant over time; thus, the method described above is used to impute population by age, sex, and education in all CZ-years. Combining this with death counts in each bin from the NCHS data, we age-adjust and obtain the age-adjusted mortality among those aged 25 and older by education and sex. Note that here, the analysis is restricted to individuals aged 25 and older in each year rather than aged 25 and older in 1994. This is because the age restriction allows us to isolate individuals who had sufficient time to complete their education; in the pre-period, individuals aged 25 and older in 1994 may still have been in school.

A.6 Welfare Analysis of NAFTA with Endogenous Mortality

To gauge how allowing for NAFTA to affect mortality impacts welfare analysis of NAFTA, we write down and calibrate a simple model in which the welfare consequences of NAFTA with endogenous mortality can be approximated to first order as the sum of welfare impacts of NAFTA with exogenous mortality and the welfare impacts of the reductions in life expectancy.

Utility. There is a representative agent with exogenous labor supply L in each period t.[44] The agent faces wage $w(t)$ and receives total income $I(t) = w(t) * L$ in each period. The agent consumes a single composite good $c(t)$ that is available at price $p(t)$. The agent faces stochastic mortality and we let T denote their life expectancy. There is no discounting, and we assume there is no saving, borrowing, or insurance, and that wages and prices are constant over time; these assumptions imply that consumption is also constant over time. As a result, lifetime utility $U(c)$ is given by:

$$U(c) = \mathrm{T} \cdot u(c) = \mathrm{T} \cdot u(I/p) = T \cdot u(wL/p).$$

Following Hall and Jones (2007), we assume the per-period utility function $u(c)$ is given by

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

where γ denotes the coefficient of relative risk aversion, and b governs the willingness to pay for additional years of life.

Lifetime utility is therefore given by $U(c) = T * u(c)$. Since consumption (c) is constant over time, the value of a statistical life-year (VSLY) is given by

[44] The assumption of exogenous labor supply is made for simplicity, but the main approximation result still holds in a more general model with endogenous labor supply that responds to the wage.

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

The welfare effects of NAFTA when mortality is exogenous. In this simplified model, if we ignore any potential effects of NAFTA on mortality, the effect of NAFTA on welfare comes entirely from its effect on wages and prices. Denote the proportional effects of NAFTA on wages and prices as dw and dp, respectively. We can then quantify the welfare effect of NAFTA as the hypothetical amount the representative agent would be willing to pay (as a percentage of annual consumption) to experience the wage and price effects of NAFTA. We denote this by Δ, and it is defined implicitly as:

$$\mathrm{T} * u(c * (1 + \Delta)) = \mathrm{T} * u(w * (1 + dw) * \mathrm{L}/(p * (1 + dp))) \tag{23}$$

In other words, Δ represents the percentage change in annual consumption that would give the same change in expected utility that the individual experiences under NAFTA. It can therefore be thought of as a willingness to pay for NAFTA.

Solving for Δ gives:

$$\Delta = \frac{dw - dp}{1 + dp}$$

Intuitively, the welfare gains from NAFTA are increasing in the increase in the real wage, which is increasing in dw and decreasing in dp. Caliendo and Parro (2015) estimate that, for NAFTA, $\Delta = 0.08$; in other words, NAFTA increased the welfare of the representative U.S. agent by 0.08% of annual consumption.[45]

The relatively small overall U.S. welfare gain from NAFTA in Caliendo and Parro (2015) is consistent with a broader literature suggesting that in large open economies the welfare gains from international trade will be small (e.g., Arkolakis et al., 2012; Costinot and Rodríguez-Clare, 2018). Another intuition for the small welfare impacts comes from the fact that NAFTA reduced tariff rates from about 2–3 percent to zero (see Figure OA.1). Even with a very large elasticity of imports with respect to trade costs (see, e.g., Anderson and van Wincoop, 2004), very low tariffs likely lead to small welfare costs of tariffs following a standard Harberger-style logic that the welfare cost of tariffs is proportional to the square of the tariff rate. Of course, NAFTA also reduced non-tariff barriers which are not captured in this Harberger-style analysis but should be captured by the Caliendo and Parro (2015) estimates.

The welfare effects of NAFTA when mortality is endogenous. We now extend the simple model above to allow for mortality to be endogenous to NAFTA; specifically, we assume that the representative agent's life expectancy changes from T to $T * (1 + dT)$. We can then solve for the overall welfare effects of NAFTA (inclusive of the mortality) effects, denoted by Δ^{dT}, which is defined implicitly as:

[45] Specifically, they estimate an increase in U.S. welfare of 0.08% and an increase in U.S. real wages of 0.11% (i.e., the combined effects of dw and dp in the simplified model presented here) using a much more sophisticated quantitative trade model that allows for intermediate goods, sectoral linkages, and multilateral trade between many countries. We use their estimate of the overall welfare gain of 0.08%, since this is more directly comparable to our welfare estimates of NAFTA's mortality impacts; the difference between Caliendo and Parro (2015)'s estimates of the impact of NAFTA on welfare and real wages comes from the additional effects of NAFTA on reduced tariff revenue.

$$T * u(c * (1 + \Delta^{dT})) = (T * (1 + dT)) * u(w * (1 + dw) * L/(p * (1 + dp))) \tag{24}$$

Following Finkelstein et al. (2025), if we define $\tilde{u}(c) = u(c) - b$, then we can solve for Δ^{dT} as follows:

$$(1 + \Delta^{dT})^{1-\gamma} = (1 + dT) * \left(\frac{1 + dw}{1 + dp}\right)^{1-\gamma} + dT * b/\tilde{u}(c)$$

Since NAFTA is a small change in tariffs (that starts from a small tariff rate to begin with), we can follow the derivations in Finkelstein et al. (2025) by taking a first-order approximation around $\Delta^{dT} = 0$ and arrive at the following approximation result:

$$\Delta^{dT} \approx \Delta + dT * \left(\frac{\text{VSLY}}{c}\right) \tag{25}$$

In other words, equation (25) indicates that the welfare effects of NAFTA are approximately separable in the effects of NAFTA on wages and prices (which determines Δ) and the effects of NAFTA on mortality (which affects life expectancy by changing T to $T * (1 + dT)$).[46] The effect of NAFTA on life expectancy is scaled by the value of a statistical life-year (VSLY) divided by annual consumption to be comparable to the effects of NAFTA on real wages.

Extension for potential GE mortality effects. As noted in Section 4.2, our estimate of the average mortality impact of NAFTA and the calibration results based on them in Appendix Tables OA.2 and OA.3 are based on local labor market impacts of NAFTA on mortality. They thus abstract from any nation-wide impacts on mortality that might arise due to NAFTA-induced increases in national real income and consumption.

In practice, however, we consider any such general equilibrium mortality impacts unlikely to be quantitatively important. To arrive at this conclusion, we conducted a simple calibration of the possible mortality benefits from the NAFTA-induced national increase in consumption. We assumed that the overall national change in consumption (i.e. real wages) as estimated in Caliendo and Parro (2015) is the same across all local labor markets, and used the cross-sectional relationship between income and life expectancy reported in Chetty et al. (2016) together with our baseline parameterization results (i.e., VSLY/c = 5). This produces a fairly small change in our estimate of dT for a 45 year old male, from -0.0926 (see Appendix Table OA.2 Panel B) to -0.0902.[47]

[46] The full derivation comes from the following steps:

$$\begin{aligned}
1 + (1-\gamma) * \Delta^{dT} &\approx (1 + dT) * (1 + (1-\gamma) * \Delta) + dT * b/\tilde{u}(c) \\
1 + (1-\gamma) * \Delta^{dT} &\approx 1 + dT + (1-\gamma) * \Delta + (1-\gamma) * dT * \Delta + dT * b/\tilde{u}(c) \\
(1-\gamma) * \Delta^{dT} &\approx dT + (1-\gamma) * \Delta + dT * b/\tilde{u}(c) \\
\Delta^{dT} &\approx \Delta + dT(b/\tilde{u}(c)/(1-\gamma) + 1/(1-\gamma)) \\
\Delta^{dT} &\approx \Delta + dT * \left(\frac{VSLY}{c}\right)
\end{aligned}$$

where the third line uses the approximation $dT * \Delta \approx 0$ since both terms will typically be relatively small in magnitude, and the last line uses the definition $VSLY/c = b/\tilde{u}(c)/(1-\gamma) - 1/(\gamma - 1)$.

[47] Specifically, based on the difference in life expectancy and income levels at the 99th and 20th percentiles of income for men and women from Figure 2 in Chetty et al. (2016) we assume an income elasticity of life expectancy of 0.0214 percent. Multiplying this elasticity by the 0.11% increase in income obtained from Caliendo and Parro (2015),

Moreover, this calibration is likely extremely aggressive, as the cross-sectional relationship between income and life expectancy that we use is significantly larger than estimates of the causal effect of income on mortality, which tend to find small or null effects (see, e.g., Cesarini et al., 2016 and Miller et al., 2024). Indeed, there is even some evidence that income receipt may be bad for health and mortality (e.g., Dobkin and Puller, 2007; Evans and Moore, 2012; Chorniy et al., 2025).

B Mortality Impacts of the China Shock

To examine the impact of the China Shock on mortality, we use the baseline estimating equation from Autor et al. (2019):

$$Y_{ct} = \alpha_t + \beta_1 \Delta \mathrm{IP}_{ct} + \mathbf{X}'_{ct}\beta_2 + \epsilon_{ct} \tag{26}$$

where Y_{ct} is the age-adjusted cumulative mortality rate in period t (we stack the 1990–2000 and 2000–2014 periods), normalized to ten-year equivalents (that is, Y_{ct} is multiplied by $\frac{10}{14}$ for the second period) to make units comparable across periods.[48] Period fixed effects are denoted by α_t, and $\mathbf{X}_{ct}$ denotes the vector of controls used in Autor et al. (2019).[49] $\Delta \mathrm{IP}_{ct}$ is Autor et al. (2019)'s measure of the change in Chinese import penetration in each period; it depends on the industry-mix of employment in each CZ in 1990 as well as the growth in imports from China in each industry in the relevant time period. Specifically:

$$\Delta \mathrm{IP}_{ct} = \sum_j \frac{L^{cj}_{1990}}{L^{c}_{1990}} \Delta \bar{\mathrm{IP}}_{jt} \tag{27}$$

where L^{c}_{1990} is the total employment in CZ c in 1990, L^{cj}_{1990} is the industry-j specific employment in CZ c in 1990, and

$$\Delta \bar{\mathrm{IP}}_{jt} = \frac{\Delta M_{jt}}{Y_{j,1991} + M_{j,1991} - X_{j,1991}} \tag{28}$$

where ΔM_{jt} represents the growth in imports from China in industry j and period t, which is normalized by initial absorption (industry shipments in 1991 $Y_{j,1991}$, plus net imports $M_{j,1991} - X_{j,1991}$).

To avoid simultaneity bias, we follow Autor et al. (2019) and instrument for $\Delta \mathrm{IP}_{ct}$ using 1980 industry employment shares in the CZ interacted with growth in Chinese import penetration in each industry to eight other wealthy nations:[50]

we estimate a "national general equilibrium"-adjusted effect of NAFTA on life expectancy for a 45 year-old male of $-0.0926 + 0.0214 \times 0.11 = -0.0902$ percent, instead of our baseline estimate of -0.0926.

[48] Again this follows Autor et al. (2019), who define $Y_{c\tau}$ as the cumulative mortality for young men relative to the cumulative mortality for young women. In contrast to Autor et al. (2019), we focus on effects of import penetration on mortality among the entire population. This allows us to benchmark the effects of the "China Shock" against our findings regarding the mortality impacts of NAFTA.

[49] These include time trends for census divisions, along with the lagged share of employment in manufacturing, employment in occupations susceptible to automation and offshoring, as well as start-of-period demographics (education, race, and the fraction of working-age women employed).

[50] These are Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland.

$$\Delta \tilde{\mathrm{IP}}_{ct} = \sum_j \frac{L^{cj}_{1980}}{L^{c}_{1980}} \Delta \tilde{\mathrm{IP}}_{it} = \sum_j \frac{L^{cj}_{1980}}{L^{c}_{1980}} \frac{\Delta \tilde{M}_{jt}}{\tilde{Y}_{j,1988} + \tilde{M}_{j,1988} - \tilde{X}_{j,1988}} \tag{29}$$

where $\Delta \tilde{M}_{jt}$ represents the growth in imports for industry j from China in period t for the other countries, which is normalized by initial absorption (industry shipments for these other countries in 1988 $\tilde{Y}_{j,1988}$, plus net imports $\tilde{M}_{j,1988} - \tilde{X}_{j,1988}$).

Appendix Table OA.7 reports IV estimates of β_1 in equation (26), using $\Delta \tilde{\mathrm{IP}}_{ct}$ from equation (29) as the instrument. Column (1) shows that a one percentage point increase in CZ exposure to Chinese import penetration is associated with an increase in the 10-year age-adjusted cumulative mortality rate of 229 per 100,000 (standard error = 76.6), or about a 2.5 percent increase in mortality relative to an average 10-year mortality of 9,218 per 100,000. In columns (2), (3), and (4) we use the long-differenced change in EPOP or in sector-specific EPOP in each period as the left hand side variable. Like NAFTA (and as documented in previous work), manufacturing accounts for the vast majority (91%) of the China-Shock-induced overall EPOP decline. This is even starker than the 78% due to NAFTA as noted earlier in Figure OA.4. Column (2) shows that a one percentage point increase in CZ exposure to Chinese import penetration is associated with an average 10-year decline in EPOP of 1.4 percentage points (standard error = 0.6).

In Table OA.8, we estimate equation (26) again by IV but now with the outcomes as the cumulative mortality rate for several demographic subgroups defined by age and sex. Note that in contrast to our analysis of NAFTA and the Great Recession, our analysis here uses age groups rather than birth cohorts. This is because the empirical strategy studies increases in Chinese import penetration over two periods—1990-2000 and 2000-2014—rather than considering a discrete "event" against which to define birth cohorts. As with Autor et al. (2019), we find the (proportionally) largest effects among working-age men.

The analysis in Tables OA.7 and OA.8 follow exactly the approach in Autor et al. (2019), just expanded to look at additional outcomes. Relatedly, for our IV analysis of the impact of China-Shock-induced EPOP declines on mortality in Table 2, we have to modify our IV analysis of NAFTA and the Great Recession and instead estimate the analogue of equations (7) and (8) in first differences. Specifically, we estimate

$$y_{ct} = \alpha_t - \beta \Delta \mathrm{EPOP}_{ct} + \mathbf{X}'_{ct}\psi + \epsilon_{ct} \tag{30}$$

where y_{ct} denotes the log age-adjusted cumulative mortality rate in CZ c and period t, α_t denotes period fixed effects, $\mathbf{X}_{ct}$ is the same set of control variables as in equation (26), and $\Delta\mathrm{EPOP}_{ct}$ is the change in EPOP over the period. We instrument for this using the first stage equation

$$\Delta \mathrm{EPOP}_{ct} = \alpha_t + \phi \Delta \tilde{\mathrm{IP}}_{ct} + \mathbf{X}'_{ct}\psi + \eta_{ct} \tag{31}$$

where $\Delta \tilde{\mathrm{IP}}_{ct}$ is defined as in equation (29). Note that this is Autor et al. (2019)'s instrument for Chinese import penetration purged of simultaneity bias, so that it is a valid instrument for $\Delta\mathrm{EPOP}_{ct}$. The estimate of β in column (4) of Table 2 indicates that a one percentage point China-Shock-induced decline in EPOP results in a 1.54% (standard error = 0.65) increase in age-adjusted mortality.

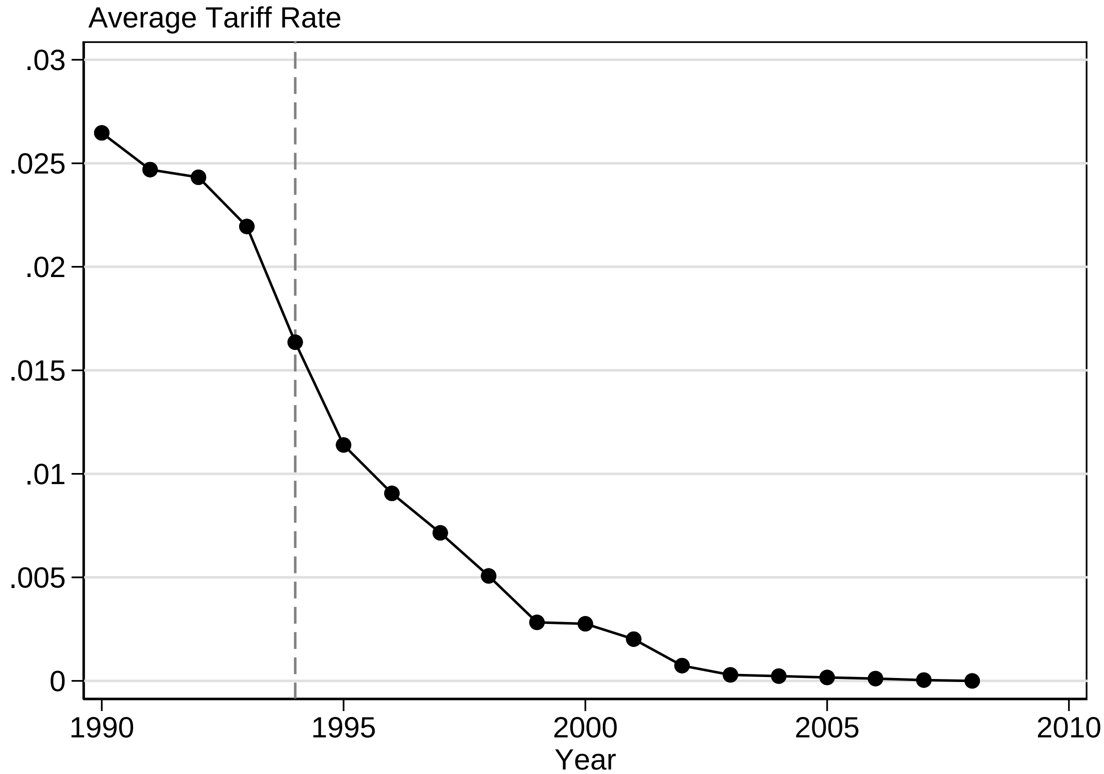
C Heterogeneous Great Recession Impacts By Sector and Sex

We augment our analysis in equation (13) which allows for heterogeneous mortality impacts of Great-Recession-induced local area employment declines in manufacturing vs non-manufacturing sectors to now consider heterogeneous impacts across four possible sub-groups $s \in \mathcal{S}$ instead of only two: manufacturing among men, manufacturing among women, non-manufacturing among men, and non-manufacturing among women. To estimate this equation, we construct the corresponding EPOP shocks $\text{GR\_SHOCK}_{s,c}$, denoting the 2007-2009 decline in EPOP in subgroup s in CZ c. To construct these $\text{GR\_SHOCK}_{s,c}$ measures, we use data from the 2007 and 2009 American Community Survey (ACS) to impute employment by industry and sex. Specifically, we crosswalk each respondent's Public Use Micro Area (PUMA) to CZs, then take sex and industry NAICS codes directly from the ACS. This allows us to construct the share of employed individuals in each CZ who are employed in each sex-by-industry sector (manufacturing or non-manufacturing) bin in 2007 and 2009. Multiplying these shares by the manufacturing and non-manufacturing employment counts in each CZ-year in the CBP data (our main source of employment data) and dividing by the population aged 16 or older in the SEER, we impute the EPOP ratio for each $s \in \mathcal{S}$ and thus construct $\text{GR\_SHOCK}_{s,c}$. This approach follows the spirit of Autor et al. (2019) who leverage differences between the sexes in their industry specialization to identify sex-specific labor demand shocks from the China Shock.

This allows us to obtain four sets of event study coefficients $\hat{\theta}_{s,t}$—one for each sex-by-sector bin—and display them in Appendix Figure OA.22. We see clearly that shocks to male manufacturing EPOP increase mortality (panel a), but that shocks to female manufacturing EPOP do not (panel b). Moreover, shocks to either male or female non-manufacturing EPOP reduce mortality.

D Appendix Figures

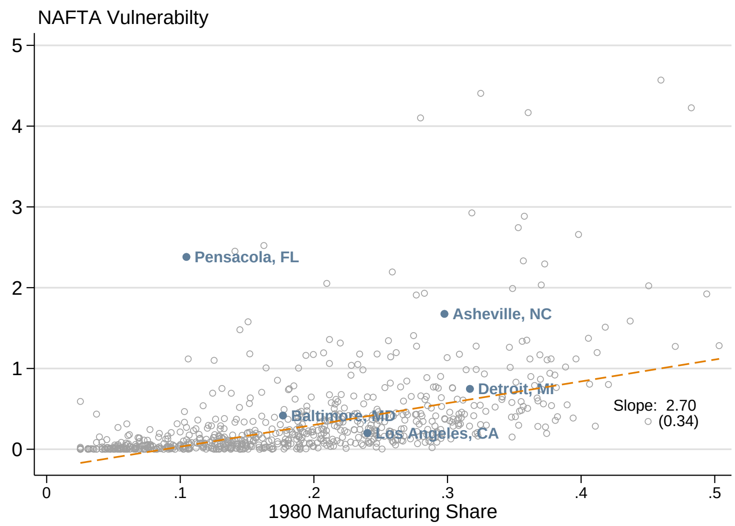
Figure OA.1: U.S. Tariff Rates on Mexico



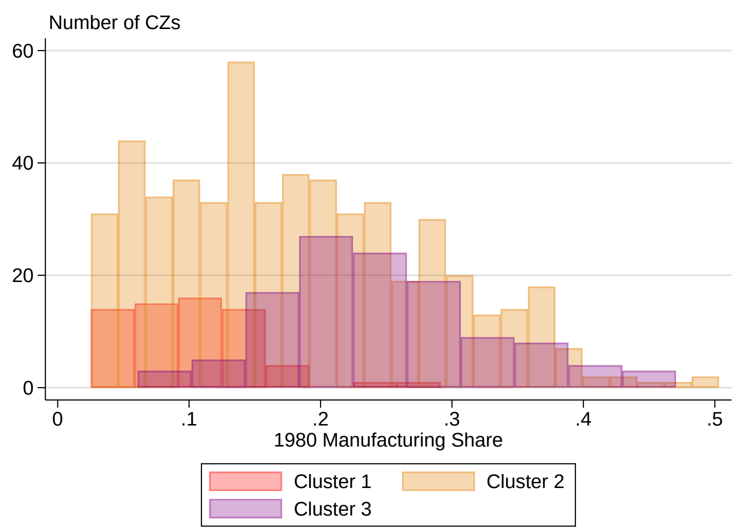
Notes: Figure displays the import-weighted average tariff rate against Mexico across industries over time. Source: Choi et al. (2024).

Figure OA.2: Relationship Between NAFTA Vulnerability and Baseline Manufacturing

(a) Correlation of Baseline Manufacturing and Vulnerability

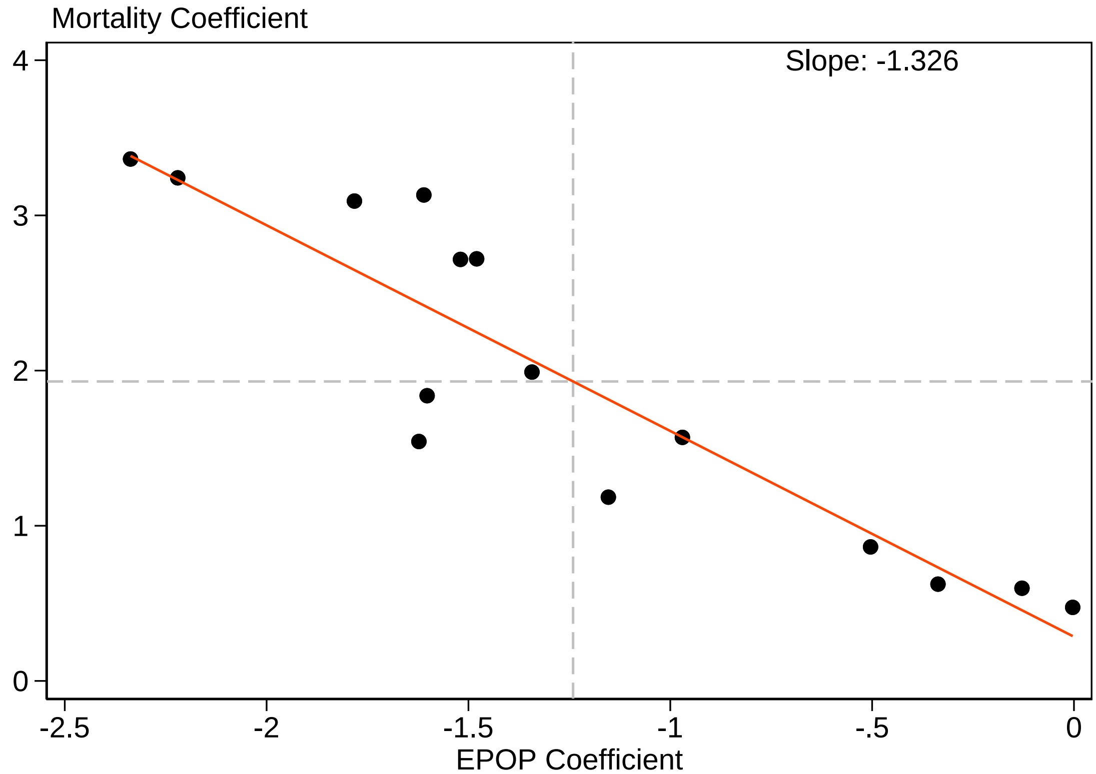


(b) Distribution of Manufacturing Within k-means Clusters



Notes: Panel (a) displays a scatterplot of the 1980 share of manufacturing employment in each CZ and its NAFTA vulnerability, along with the regression slope coefficient and heteroskedasticity robust standard error. The regression is weighted by 1990 CZ population, and the sample size is 722 CZs. Panel (b) displays the distribution of manufacturing shares within each of our k-means clusters.

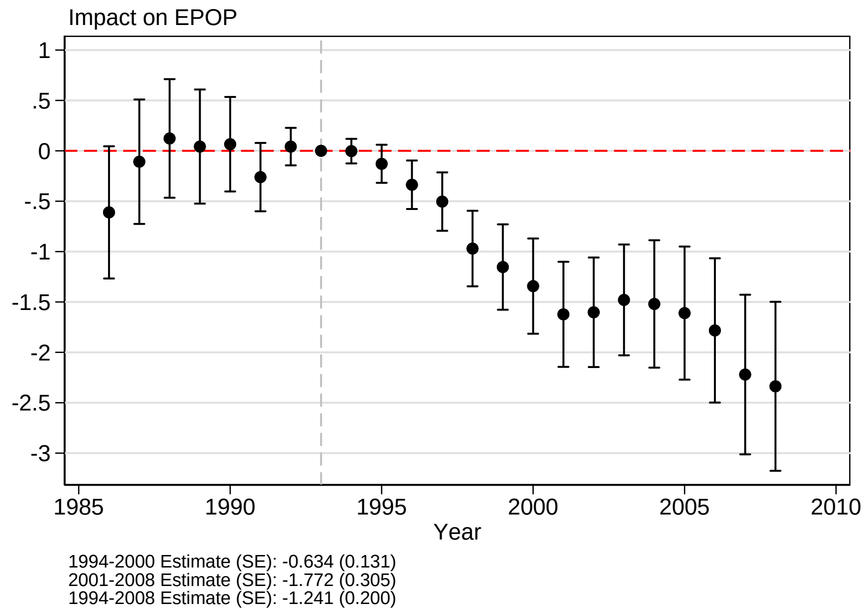
Figure OA.3: Visual IV: NAFTA Annual Impacts on Mortality vs EPOP



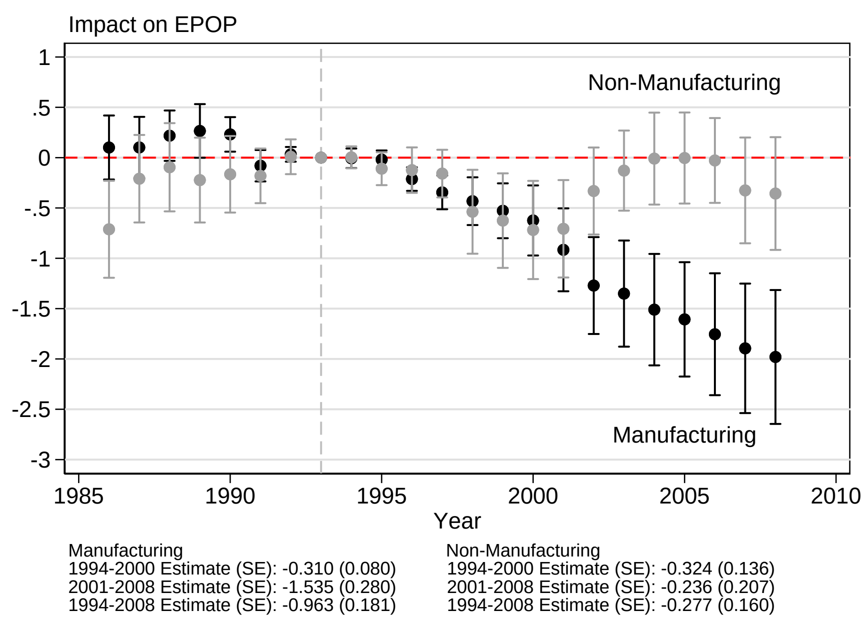
Notes: This figure compares post-period (1994–2008) event study estimates of β_t in equation (4) with the log age-adjusted mortality as the outcome (y-axis) and the employment-to-population ration as the outcome (x-axis). The underlying regressions are weighted by 1990 CZ population, and the sample size is 722 CZs. The red line denotes an unweighted OLS regression fitted to these coefficients.

Figure OA.4: NAFTA EPOP Effects by Industry

(a) Total EPOP

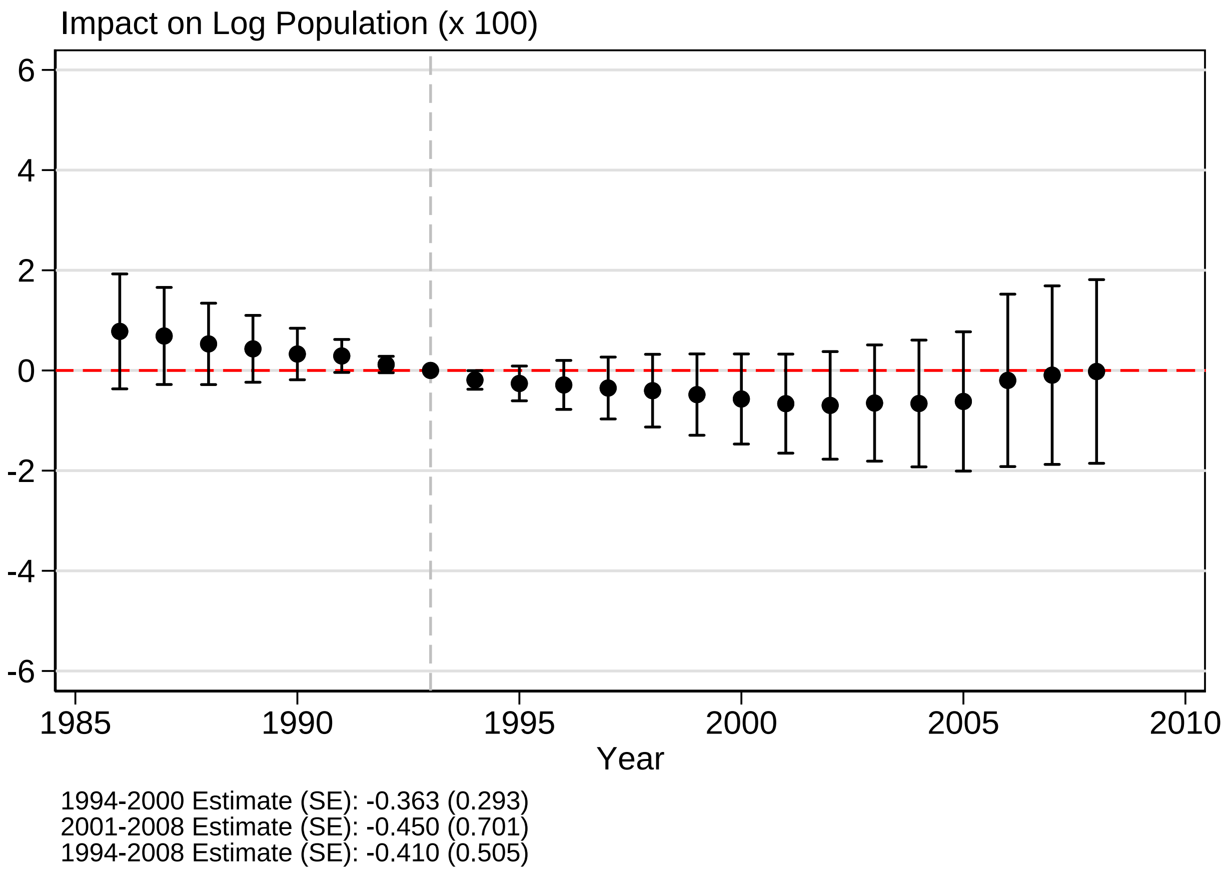


(b) By Sector



Notes: This figure displays estimates of β_t from equation (4), where the outcome y_{ct} is the employment-to-population ratio across all industries (panel a), and manufacturing industries versus non-manufacturing industries (panel b). A one-point increase in NAFTA vulnerability V_c corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.5: Impact of NAFTA Vulnerability on Population Aged 25+ Upon Implementation

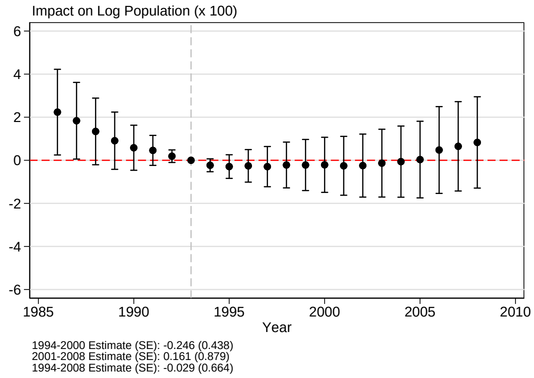


Notes: This figure displays 100 times estimates of β_t from equation (4) where the outcome is the log population of those born in 1969 or earlier (i.e., aged 25 and older in 1994). We exclude the youngest birth cohort, those born 1970 to 1994 (who were 0–24 in 1994), from the analysis as not all of these individuals were yet alive in the 1986–1993 pre-period. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

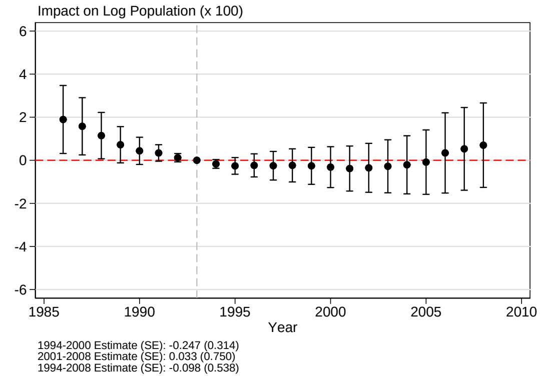
Figure OA.6: NAFTA Population Impacts by Birth Cohort and Sex

Born 1950–1969 (Ages 25–44)

(a) Male

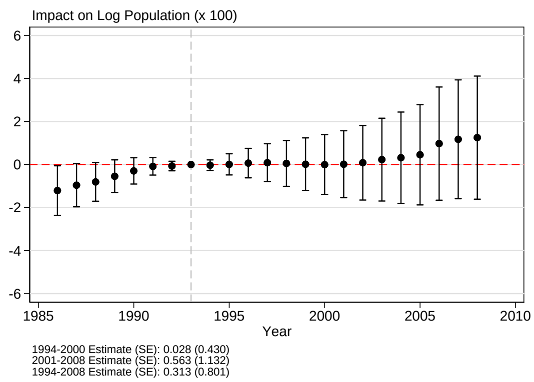


(b) Female

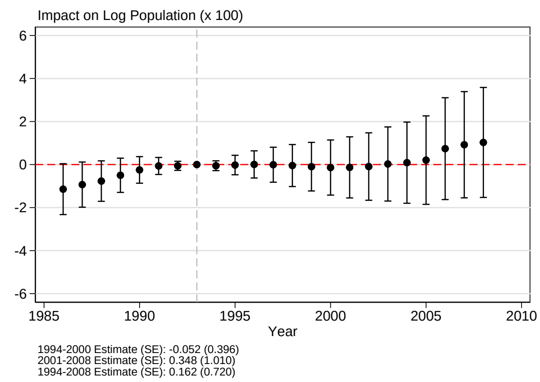


Born 1930–1949 (Ages 45–64)

(c) Male

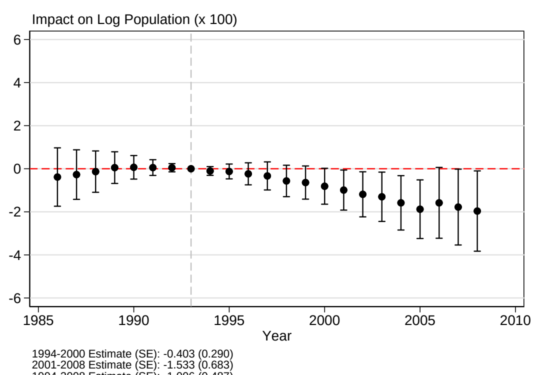


(d) Female

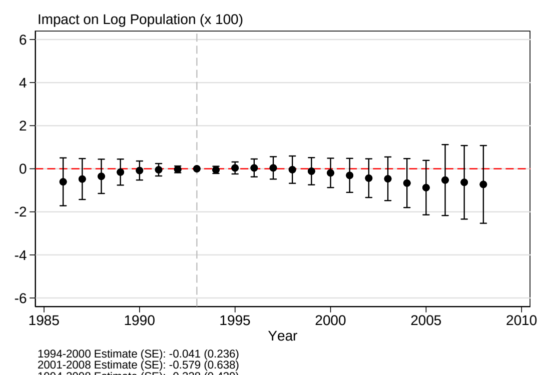


Born Before 1929 (Ages 65+)

(e) Male

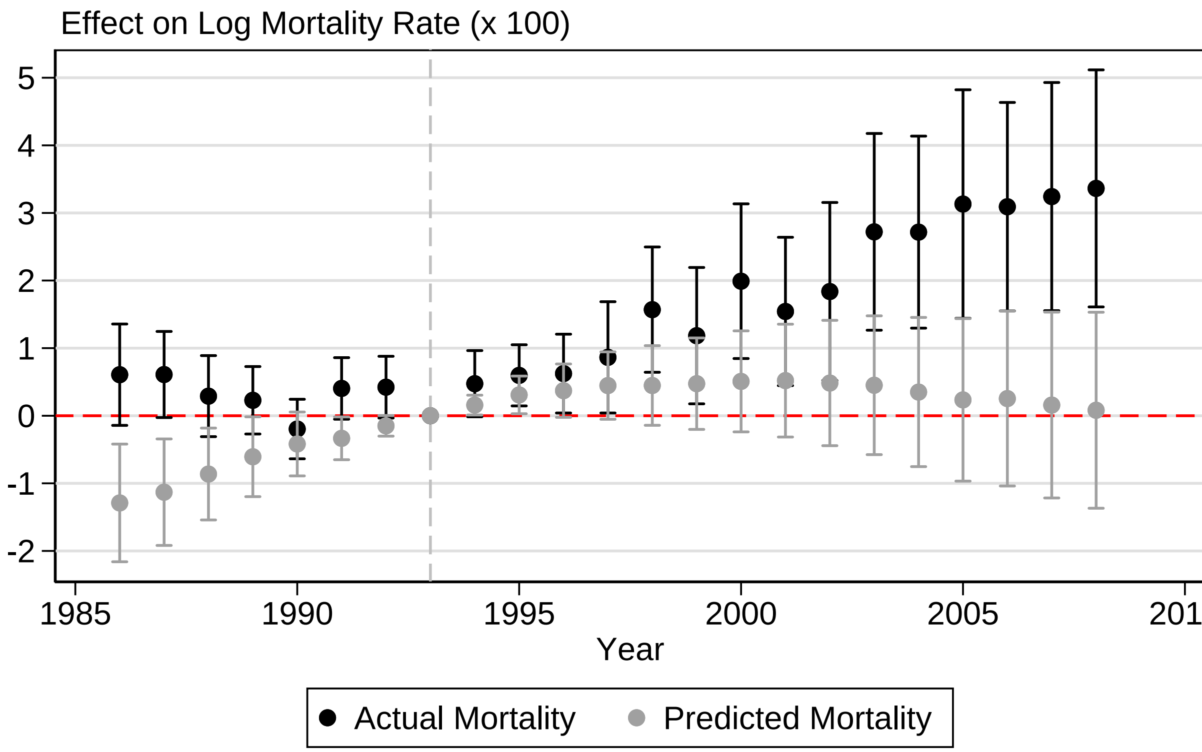


(f) Female



Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{ct} is the log population of individuals in each demographic group within each CZ. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.7: Impact of NAFTA Vulnerability on Predicted Mortality

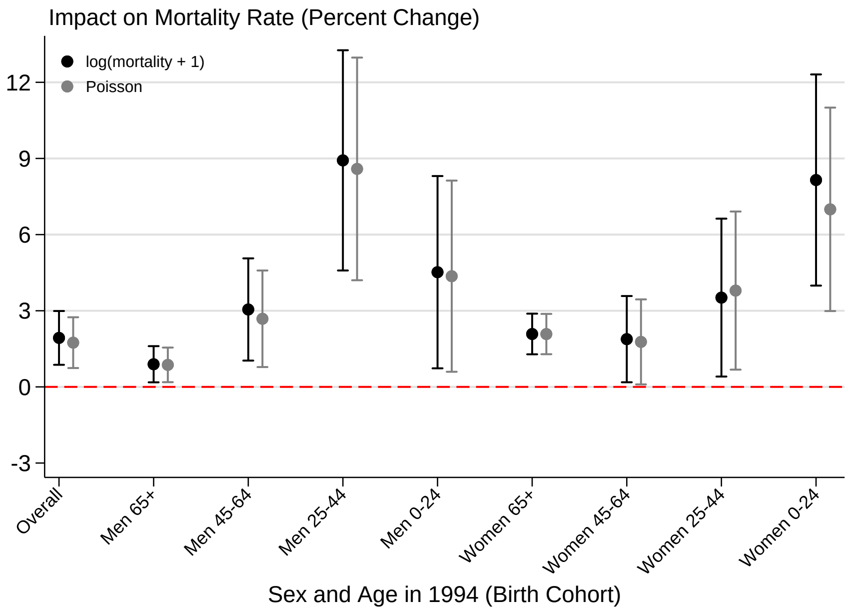


Actual Mortality
1994-2000 Estimate (SE): 1.043 (0.333)
2001-2008 Estimate (SE): 2.706 (0.742)
1994-2008 Estimate (SE): 1.930 (0.541)

Predicted Mortality
1994-2000 Estimate (SE): 0.388 (0.239)
2001-2008 Estimate (SE): 0.317 (0.581)
1994-2008 Estimate (SE): 0.350 (0.413)

Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{ct} is the log age-adjusted mortality rate (in black) and the log predicted mortality rate (in gray). The predicted mortality is constructed by estimating a logit model of one-year mortality on age, sex, and race indicators as well as all pairwise interactions estimated on NHIS data pooled from 1986-2008, then projecting onto population counts in each age-by-sex-by-race bin in the SEER. These predicted rates are then averaged across bins (weighting by population) to construct a predicted mortality rate for each CZ-year. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

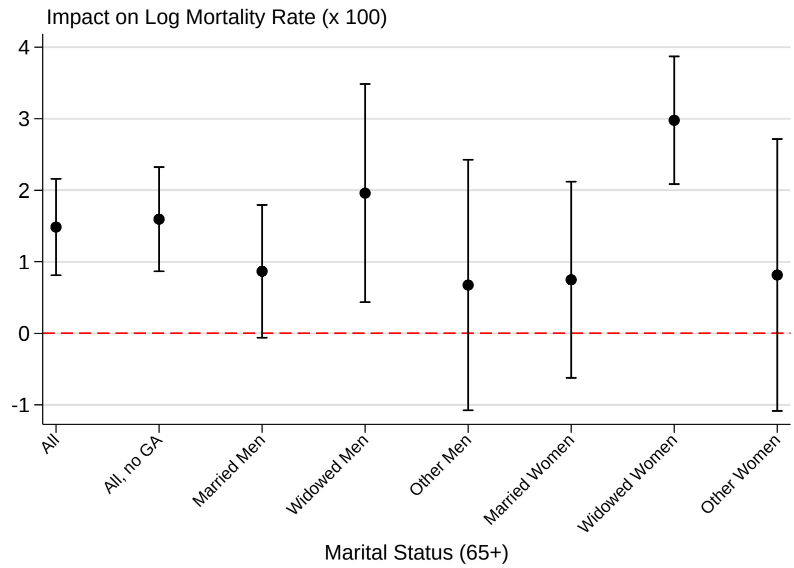
Figure OA.8: NAFTA Mortality Impacts By Birth Cohort by Sex: Poisson Robustness



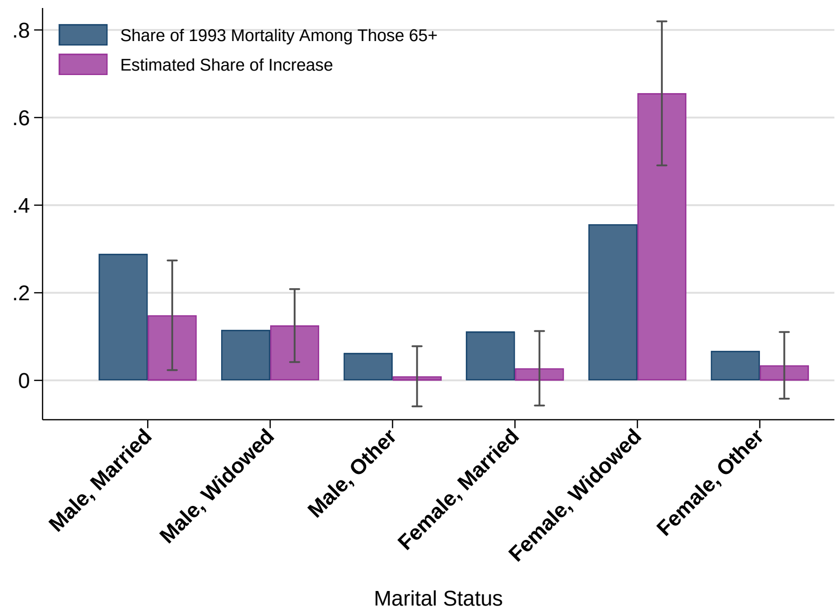
Notes: This figure displays 100 times the 1994–2008 average estimates of β_t from equation (4) estimated using OLS (in black) and Poisson regression (in gray). The outcomes in the OLS model are the log mortality rates per 100,000 separately by birth cohort and by sex. The outcome in the Poisson model are the CZ mortality rates in levels; the Poisson regression coefficients can be interpreted as percent changes. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.9: Impact of NAFTA on Mortality: Men and Women Aged 65+ By Marital Status

(a) 1994–2008 Pooled Estimates



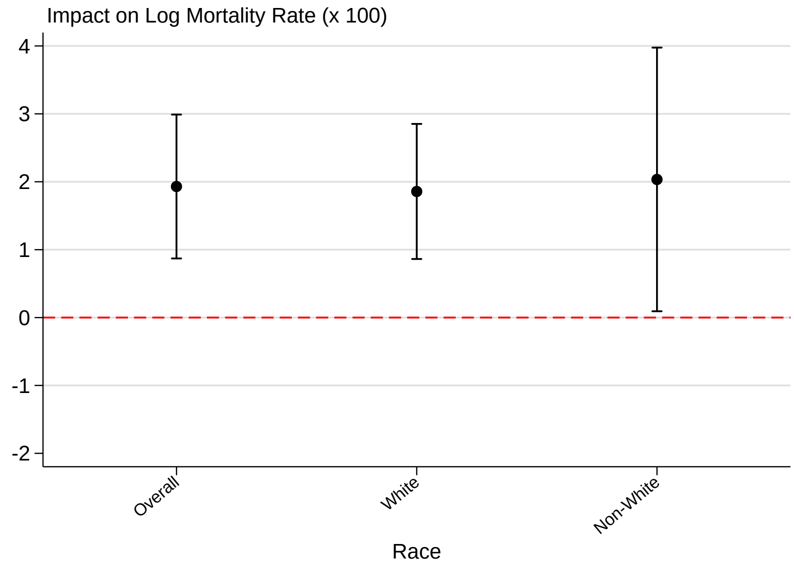
(b) 1994–2008 Decomposition



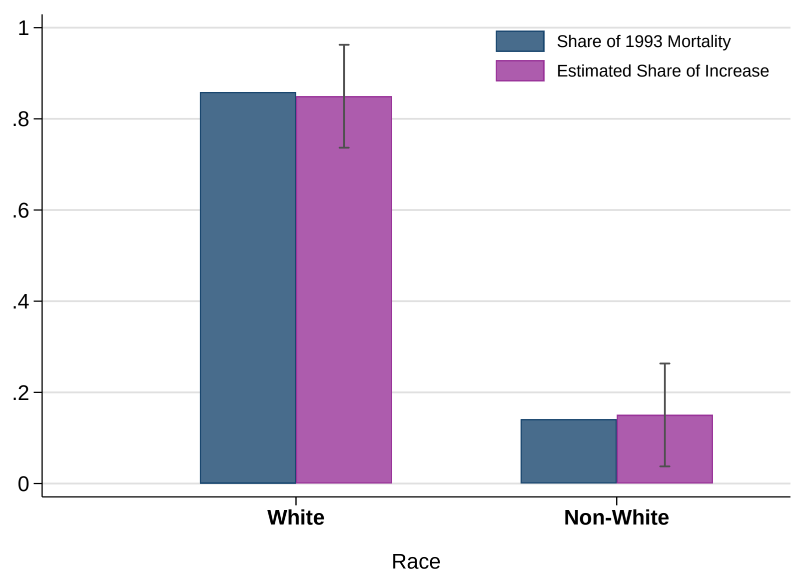
Notes: Panel (a) gives the average 1994–2008 estimate of β_t in equation (4) with the log mortality rate for individuals aged 65+ in 1994 by sex and marital status. For each marital-status specific result, the sample is restricted to CZs outside of Georgia due to a lack of marital status codes in the data. We present full event study plots in Figure OA.36. In panel (b), the blue bars denote the share of deaths each sex-by-marital status group accounted for in 1993, while the purple bars denote the share of the increase in mortality each group accounted for (averaged over the 1994–2008 post-period) as a result of NAFTA. These shares are computed by multiplying the number of deaths in each group in 1993 by the percent change in mortality in the post-period according to equation (4), then dividing by this quantity summed over all 6 groups (which gives the total implied change in mortality). Vertical lines give 95% confidence intervals computed using standard errors clustered at the CZ level; they are computed by estimating equation (4) for all 6 groups simultaneously in a stacked regression. The regression is weighted by each CZ's population in 1990. The sample size for each individual group is 690 CZs.

Figure OA.10: NAFTA Mortality Decompositions by Race

(a) 1994–2008 Pooled Estimates



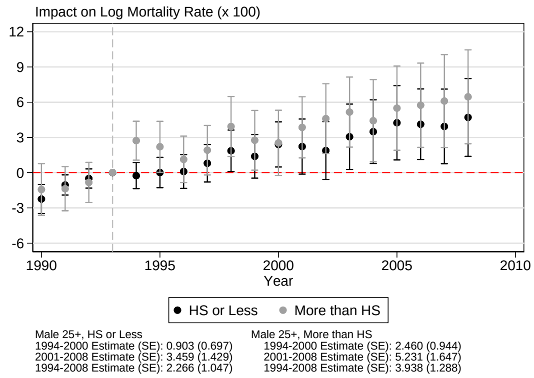
(b) 1994–2008 Decomposition



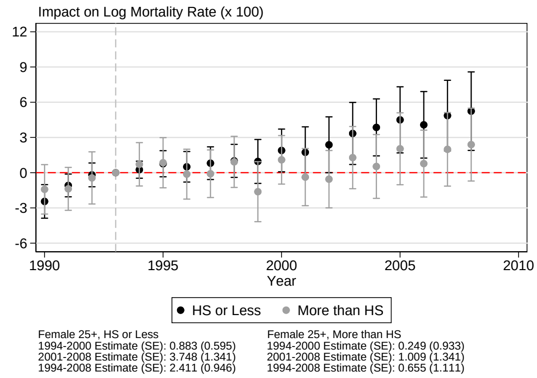
Notes: Panel (a) gives the average 1994–2008 estimate of β_t in equation (4) with the log mortality rate for Whites and non-Whites separately. In panel (b), the blue bars denote the share of deaths each demographic group accounted for in 1993, while the purple bars denote the share of the increase in mortality each group accounted for (averaged over the 1994–2008 post-period) as a result of NAFTA. These shares are computed by multiplying the number of deaths in each demographic group in 1993 by the percent change in mortality in the post-period according to equation (4), then dividing by this quantity summed over both groups (which gives the total implied change in mortality). Vertical lines give 95% confidence intervals computed using standard errors clustered at the CZ level; they are computed by estimating equation (4) for both groups simultaneously in a stacked regression. The regression is weighted by each CZ's population in 1990. The sample is limited to the 533 CZs (accounting for almost 98% of the 1990 population) that have at least one person of each racial group in all 19 age bins in all years in our sample period.

Figure OA.11: NAFTA Mortality Decompositions by Education and Sex

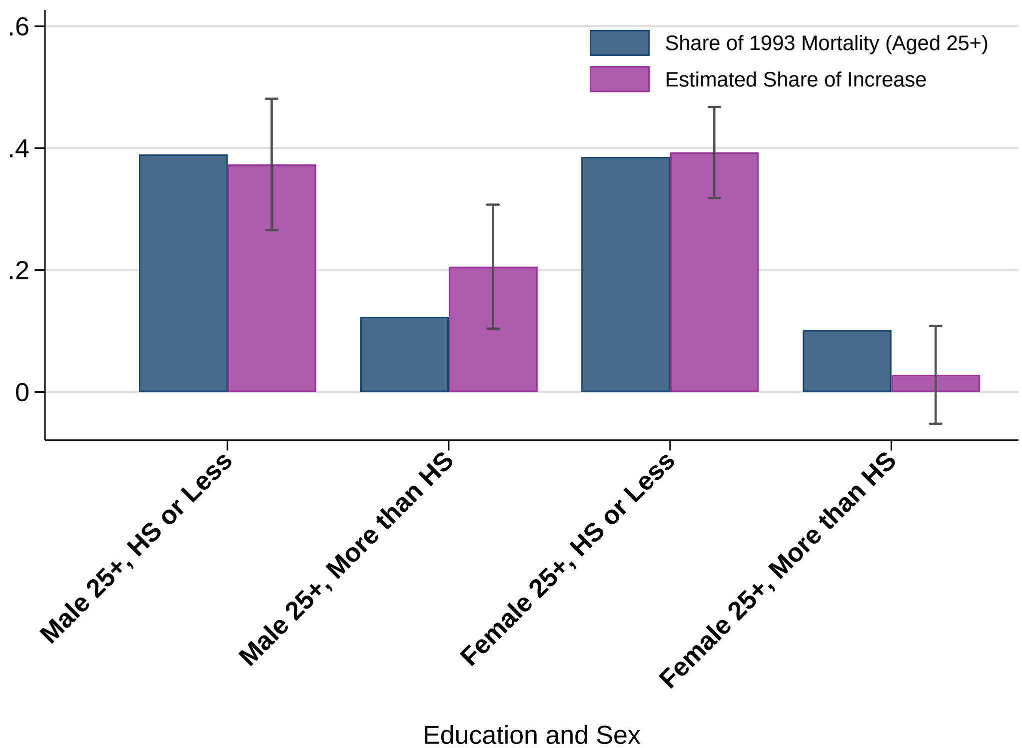
(a) Men



(b) Women



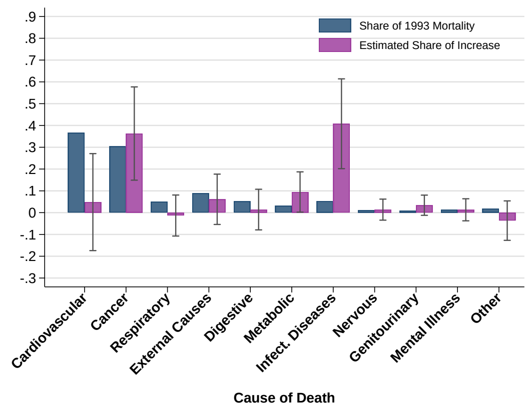
(c) Decomposition of Effects



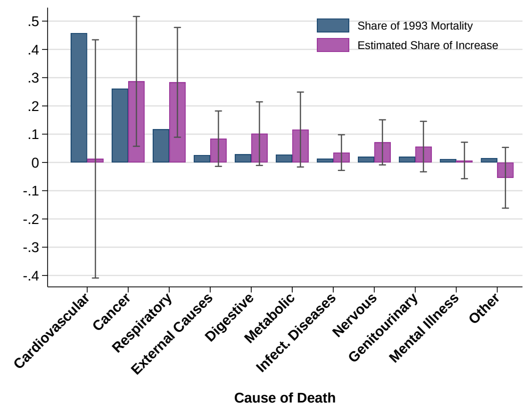
Notes: Panels (a) and (b) display 100 times estimates of β_t from equation (4), where the outcome y_{ct} is the log age-adjusted mortality rate among men and women aged 25 and older in each year, respectively. The estimates in black give effects for those with a high school degree or less, while the estimates in gray give effects for those with more than a high school degree. In panel (c), the blue bars denote the share of deaths each group accounted for in 1993, while the purple bars denote the share of the increase in mortality among those aged 25+ that each group accounted for (averaged over the 1994–2008 post-period) as a result of NAFTA. These shares are computed by multiplying the number of deaths in each group in 1993 by the percent change in mortality in the post-period according to equation (4), then dividing by this quantity summed over both groups (which gives the total implied change in mortality). Vertical lines give 95% confidence intervals computed using standard errors clustered at the CZ level; they are computed by estimating equation (4) for both groups simultaneously in a stacked regression. The regression is weighted by each CZ's population in 1990. The sample is limited to the 598 CZs that report education data in 1990 and later. See Appendix A.5 for more details on sample and data construction.

Figure OA.12: NAFTA Mortality Decomposition by Cause of Death: Male Birth Cohorts

(a) Born 1930–1949 (Ages 45–64)



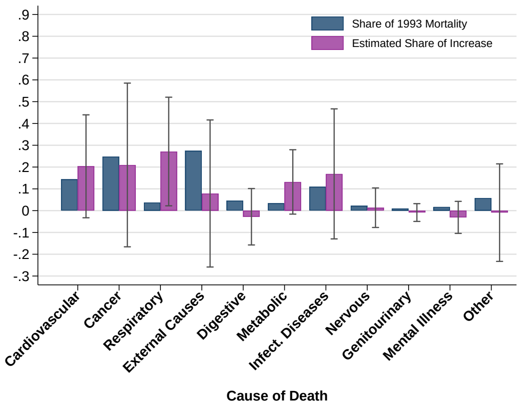
(b) Born Before 1930 (Ages 65+)



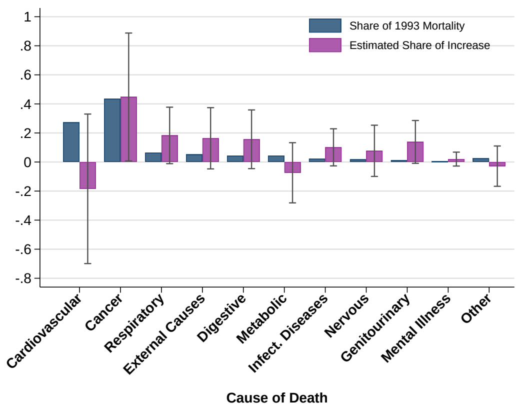
Notes: In each panel, the blue bars denote the share of deaths each cause accounted for in 1993 among men in each birth cohort. The purple bars denote the share of the increase in mortality each cause accounted for (averaged over the 1994–2008 post-period) as a result of NAFTA. Men born between 1950–1969 are excluded as they are displayed in the main text (Figure 4) and men born between 1970–1994 are excluded because the cause of death is so low (and about 80% of the deaths are either external causes of "other"). Vertical lines denote 95% confidence intervals constructed using standard errors clustered at the CZ level. Observations are weighted by CZ population in 1990. The sample size is 722 CZs.

Figure OA.13: NAFTA Mortality Decomposition By Cause of Death: Female Birth Cohorts

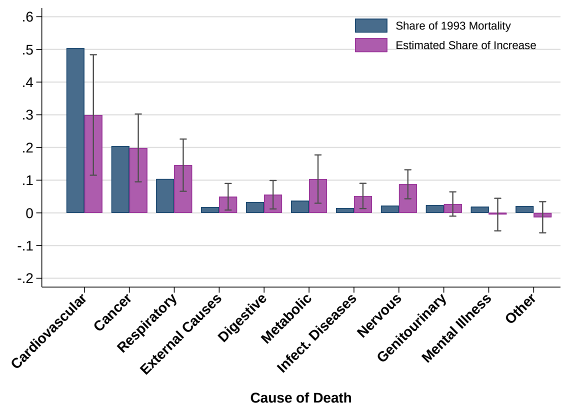
(a) Born 1950–1969 (Ages 25–44)



(b) Born 1930–1949 (Ages 45–64)



(c) Born Before 1930 (Ages 65+)

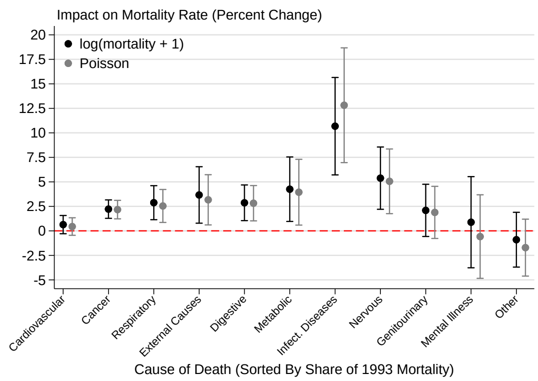


Notes: In each panel, the blue bars denote the share of deaths each cause accounted for in 1993 among women in each birth cohort. The purple bars denote the share of the increase in mortality each cause accounted for (averaged over the 1994–2008 post-period) as a result of NAFTA. Women born between 1970–1994 are excluded because the cause of death is so low (and about 80% of the deaths are either external causes of "other".) Vertical lines denote 95% confidence intervals constructed using standard errors clustered at the CZ level. Observations are weighted by CZ population in 1990. The sample size is 722 CZs.

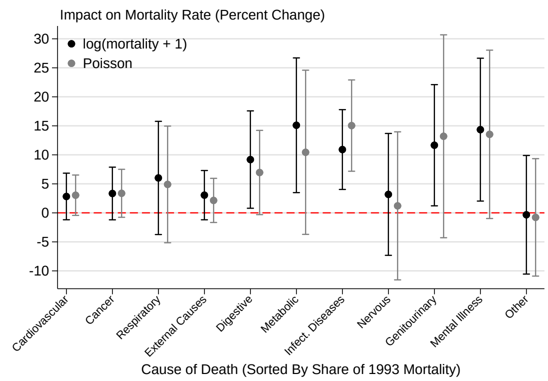
Figure OA.14: NAFTA Mortality Impacts by Cause of Death: Poisson Robustness

Main Categories

(a) Full Sample

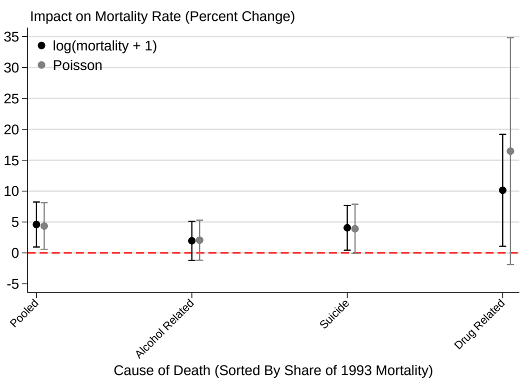


(b) Prime-Aged Men

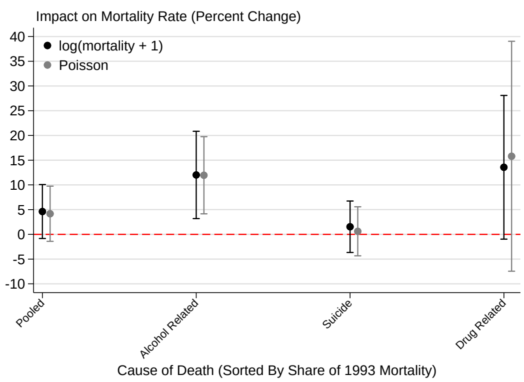


Deaths of Despair

(c) Full Sample



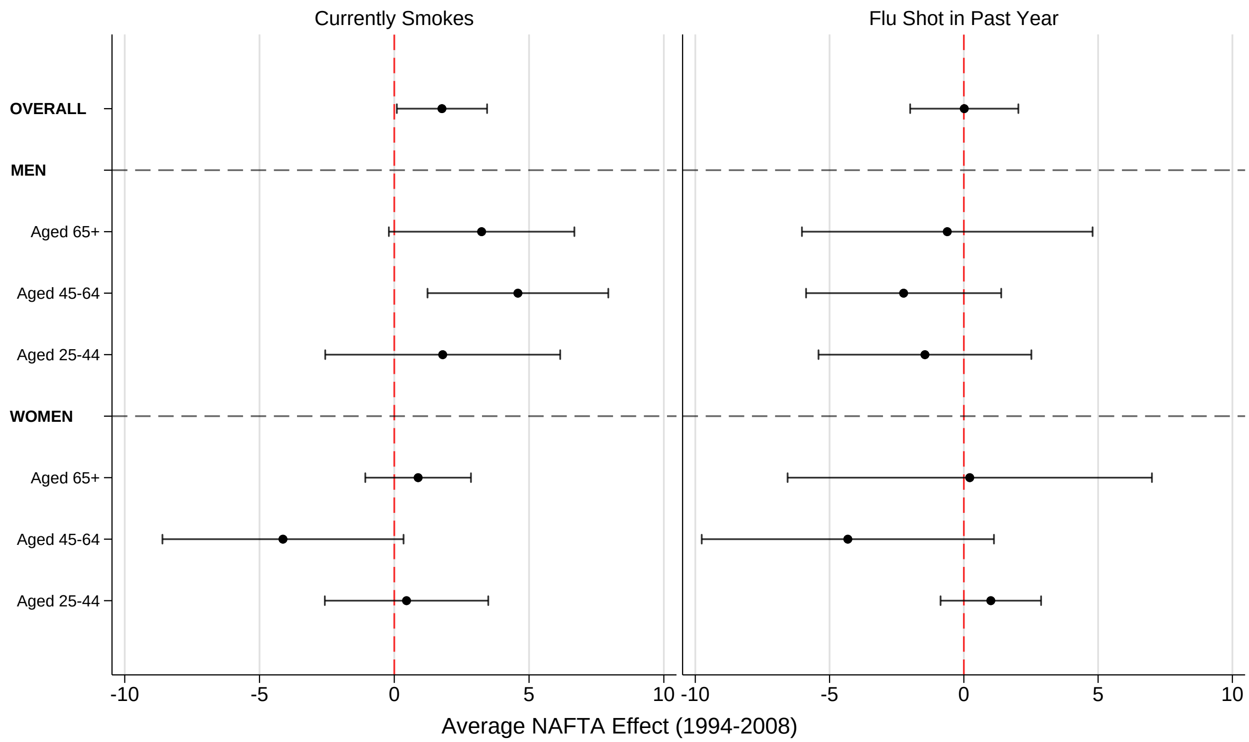
(d) Prime-Aged Men



Notes: This figure displays 100 times the 1994–2008 average estimates of β_t from equation (4) estimated using OLS (in black) and Poisson regression (in gray). The outcomes in the OLS model are the log age-adjusted CZ mortality rates per 100,000 separately by cause of death and deaths of despair. The outcomes in the Poisson model are the age-adjusted CZ mortality rates in levels; however, the Poisson regression coefficients can be interpreted as percent changes. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.15: NAFTA Impact on Health Behaviors (Smoking and Flu Vaccination)

(a) Average Estimates (1994–2008)



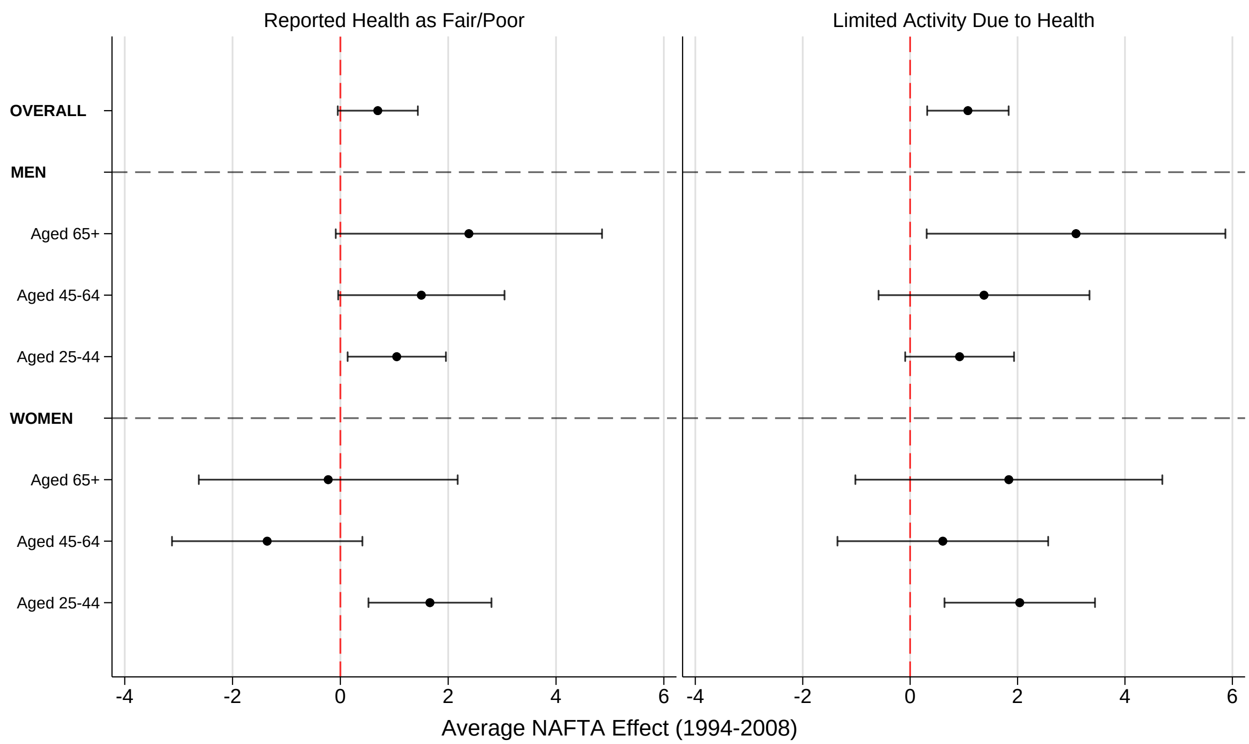
(b) 1993 Mean Outcomes

	Currently Smokes	Flu Shot in Past Year
Overall	0.25	0.19
Men		
65+	0.13	0.53
45–64	0.29	0.17
25–44	0.31	0.10
Women		
65+	0.10	0.50
45–64	0.23	0.22
25–44	0.27	0.10

Notes: Panel (a) displays average 1994–2008 estimates of β_t from equation (4) estimated at the individual level, where the outcomes y_{it} are whether the respondent reported currently smoking and whether they reported getting a flu shot in the past year. Panel (b) shows the baseline (1993) mean outcomes, both overall and by sex and birth cohort. The units can be interpreted in terms of percentage point changes in the probability of each y_{it}. A one-point increase in NAFTA vulnerability V_c corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile. Observations are weighted by NHIS survey weights for each individual. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size consists of adults (aged 18+) only.

Figure OA.16: NAFTA Impact on General Health

(a) Average Estimates (1994–2008)



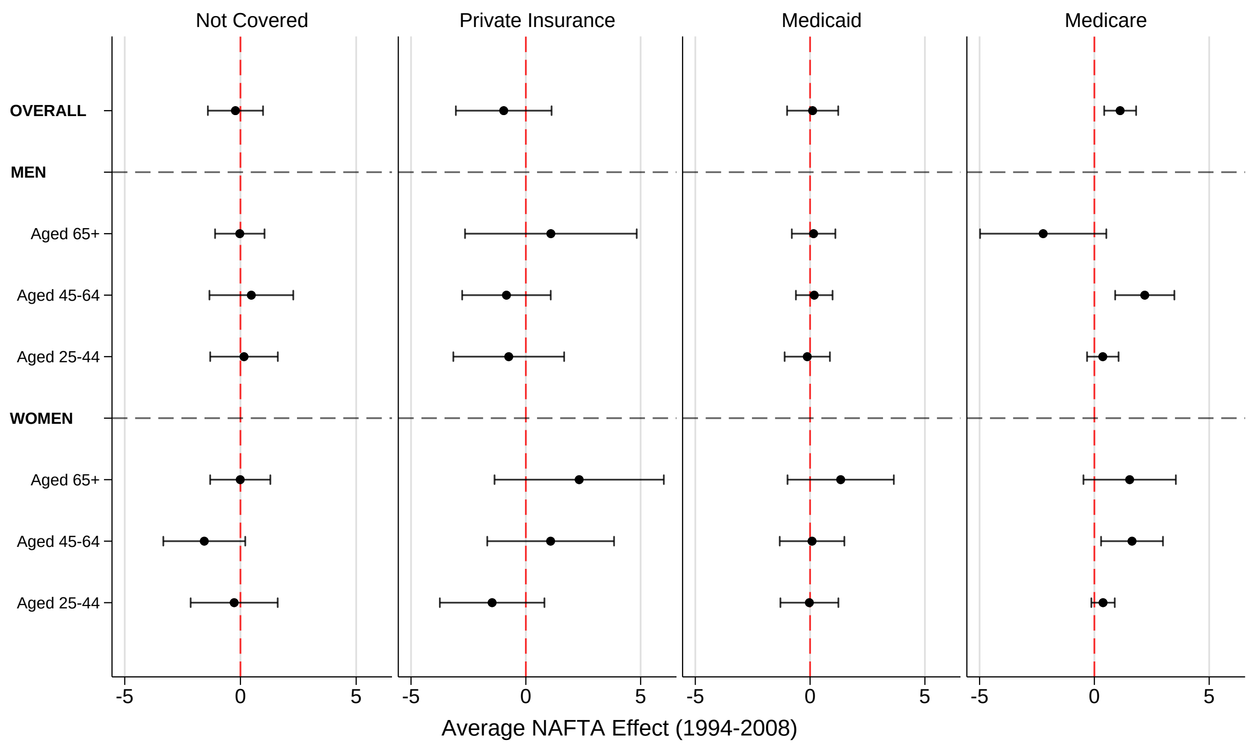
(b) 1993 Mean Outcomes

	Reported Health as Fair/Poor	Limited Activity Due to Health
Overall	0.10	0.15
Men		
65+	0.28	0.38
45–64	0.16	0.22
25–44	0.07	0.12
Women		
65+	0.28	0.39
45–64	0.18	0.24
25–44	0.08	0.11

Notes: Panel (a) displays average 1994–2008 estimate of β_t from equation (4) estimated at the individual level, where the outcomes y_{it} are whether individuals reported their health as Fair or Poor (given the options Poor, Fair, Good, Very Good, and Excellent) and whether individuals reported any limitation to their typical activity due to their health. Panel (b) shows the baseline (1993) mean outcomes, both overall and by sex and birth cohort. The units can be interpreted in terms of percentage point changes in the probability of each y_{it}. A one-point increase in NAFTA vulnerability V_c corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile. Observations are weighted by NHIS survey weights for each individual. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level.

Figure OA.17: NAFTA Impact on Health Insurance Coverage

(a) Average Estimates (1994–2008)



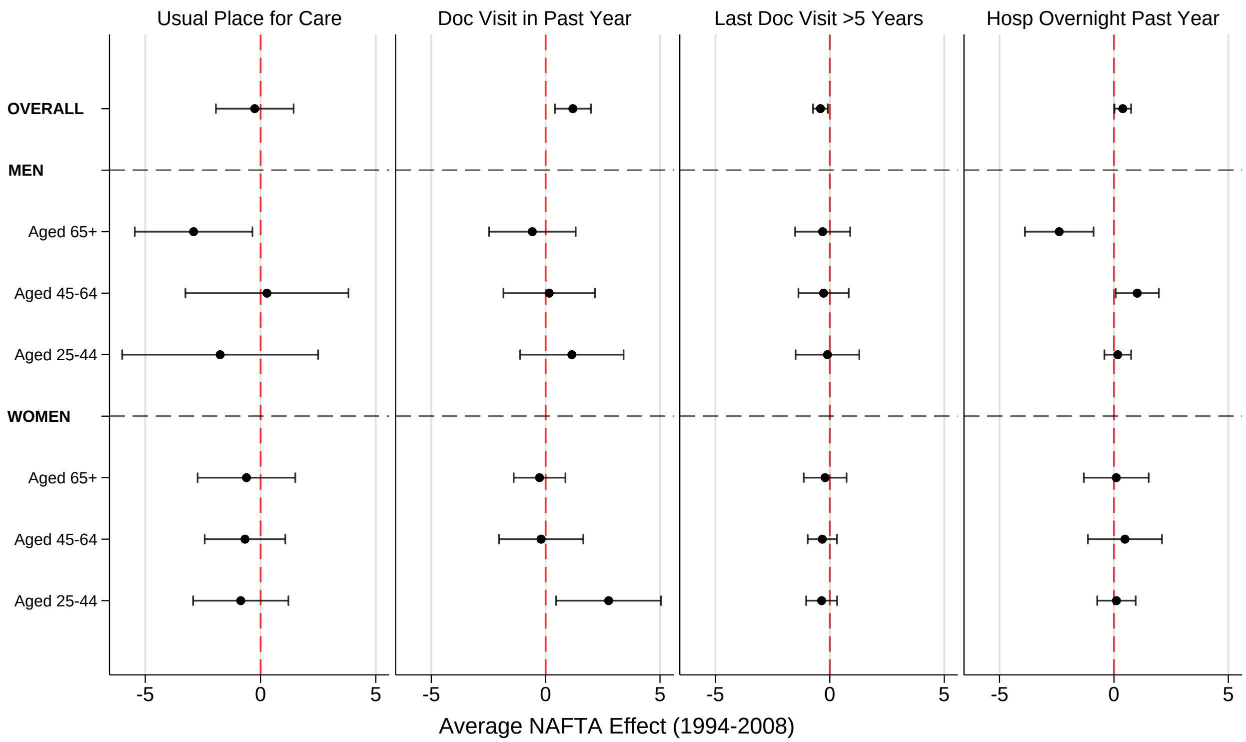
(b) 1993 Mean Outcomes

	Not Covered	Private	Medicaid	Medicare
Overall	0.15	0.66	0.08	0.12
Men				
65+	0.02	0.73	0.03	0.89
45–64	0.11	0.74	0.02	0.04
25–44	0.20	0.67	0.03	0.01
Women				
65+	0.02	0.70	0.08	0.90
45–64	0.13	0.73	0.04	0.03
25–44	0.15	0.68	0.07	0.01

Notes: Panel (a) displays average 1994–2008 estimate of β_t from equation (4) estimated at the individual level, where the outcomes y_{it} are whether the individual reported not being covered by any health insurance, covered by private insurance, covered by Medicaid, or covered by Medicare. Panel (b) shows the baseline (1993) mean outcomes, both overall and by sex and birth cohort. The units can be interpreted in terms of percentage point changes in the probability of each y_{it}. A one-point increase in NAFTA vulnerability V_c corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile. Observations are weighted by NHIS survey weights for each individual. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level.

Figure OA.18: NAFTA Impact on Health Care Use

(a) Average Estimates (1994–2008)



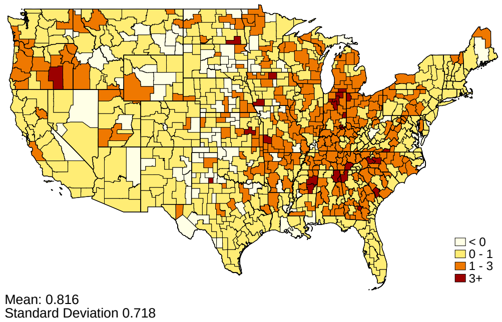
(b) 1993 Mean Outcomes

	Usual Place for Care	Doc Visit in Past Year	Last Doc Visit >5 Years	Hosp Overnight in Past Year
Overall	0.80	0.77	0.03	0.08
Men				
65+	0.87	0.86	0.03	0.17
45–64	0.79	0.71	0.07	0.08
25–44	0.69	0.62	0.07	0.04
Women				
65+	0.88	0.88	0.03	0.15
45–64	0.83	0.82	0.03	0.08
25–44	0.80	0.82	0.02	0.10

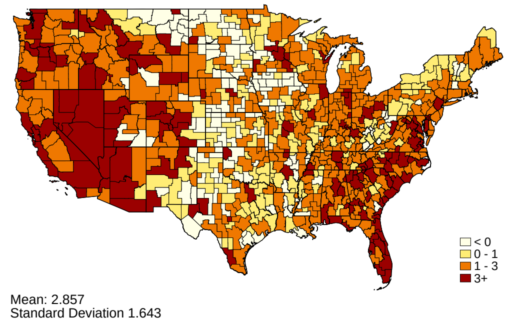
Notes: Panel (a) displays average 1994–2008 estimate of β_t from equation (4) estimated at the individual level, where the outcomes y_{it} are whether the individual reported having a usual place for care, visiting a health professional in the past year, having last visited a health professional more than 5 years ago, and having spent a night in the hospital (as a patient) in the past year. Panel (b) shows the baseline (1993) mean outcomes, both overall and by sex and birth cohort. The units can be interpreted in terms of percentage point changes in the probability of each y_{it}. A one-point increase in NAFTA vulnerability V_c corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile. Observations are weighted by NHIS survey weights for each individual. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level.

Figure OA.19: Distribution of Manufacturing and Non-Manufacturing Great Recession Shocks

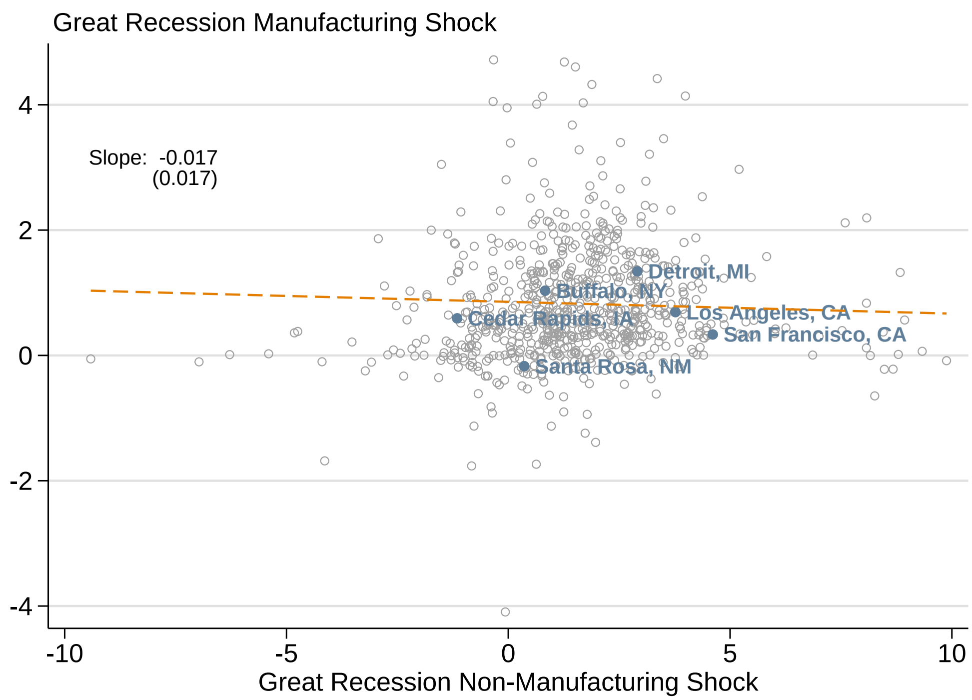
(a) Great Recession Manufacturing Shock



(b) Great Recession Non-Manufacturing Shock



(c) Spatial Correlation of Great Recession Manufacturing and Non-Manufacturing Shocks

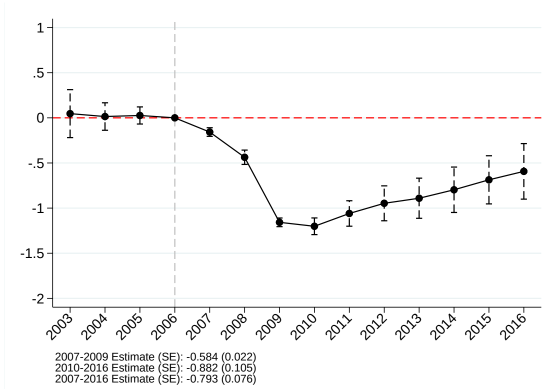


Notes: Panels (a) and (b) display the spatial distribution of the great Recession manufacturing and non-manufacturing shocks, respectively, where $\text{GR\_SHOCK}_{s,c} = \text{EPOP}^s_{c,2009} - \text{EPOP}^s_{c,2007}$ (for $s = m, n$). Panel (c) displays a scatterplot of the Great Recession manufacturing shock against the Great Recession non-manufacturing shock. For ease of interpretability, we omit 5 outlier CZs accounting for 0.14% of the population in 2006 from the scatter plot, but include them when estimating the regression line which is fit on the full sample of 722 CZs, weighted by 2006 population, with the heteroskedasticity-robust standard error in parentheses.

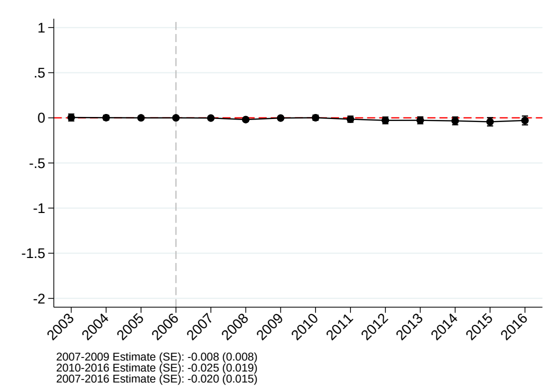
Figure OA.20: Effects of Sector-Specific Great Recession Shocks on Sector-Specific EPOP

Effect of Great Recession Shocks on Manufacturing EPOP

(a) Great Recession Manufacturing Shock

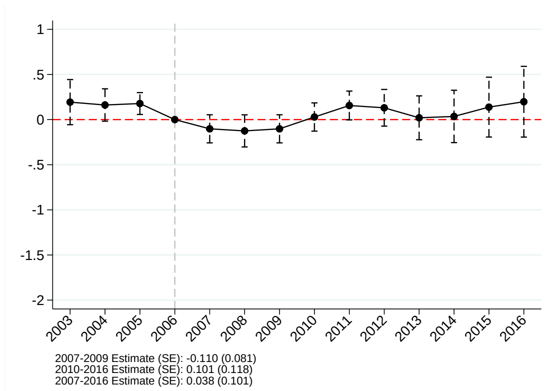


(b) Great Recession Non-Manufacturing Shock

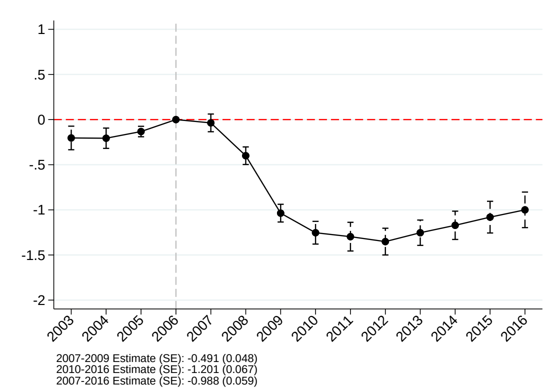


Effect of Great Recession Shocks on Non-Manufacturing EPOP

(c) Great Recession Manufacturing Shock

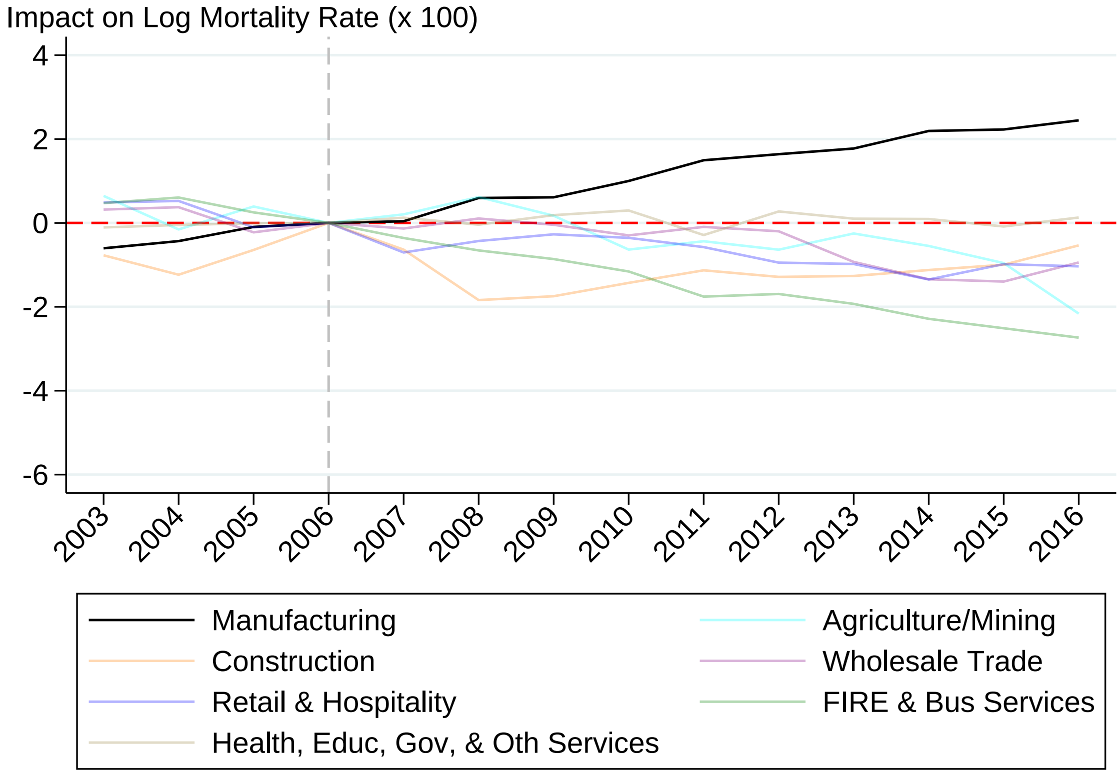


(d) Great Recession Non-Manufacturing Shock



Notes: Panels (a) and (b) display event study estimates of $\theta_{s,t}$ from estimating equation (13) for the outcome manufacturing EPOP; the right hand side includes two Great Recession Shocks (GR_SHOCK˙s,c) for $s \in \{m, n\}$. Panels (c) and (d) display event study coefficients from estimating the same equation but now with non-manufacturing EPOP on the left hand side. In both cases, we estimate equation (13) using annual data from 2003 through 2016, omitting the interaction with the shock variables in 2006, so that all of the $\theta_{s,t}$ coefficients are relative to 2006. Estimates of the average of coefficients from 2007–2009, 2010–2016, and 2007–2016 are reported in the lower left-hand corner. Observations are weighted by CZ population in 2006. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.21: Effects of Sector-Specific Great Recession Shocks on Mortality: Seven Sector Split

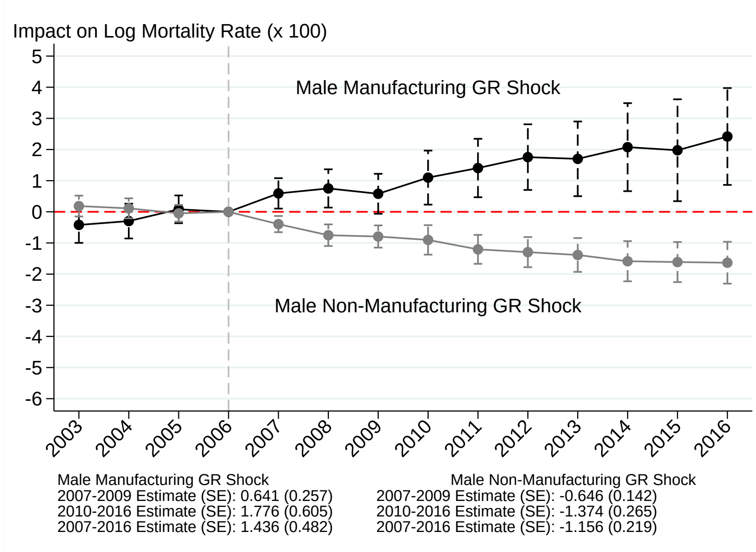


	Share of:		2007-2016 Average Effect on
	2006 EPOP	Great Recession Shock	Log Age-Adjusted Mortality
Sector	(1)	(2)	(3)
Manufacturing	0.151	0.221	1.403
			(0.431)
Agriculture and Mining	0.020	0.016	-0.463
			(0.669)
Construction	0.059	0.167	-1.198
			(0.762)
Wholesale Trade	0.087	0.069	-0.527
			(0.705)
Retail and Hospitality	0.261	0.192	-0.763
			(0.590)
Finance, Information, Real Estate, Business Services	0.186	0.341	-1.594
			(0.322)
Health, Education, Government, and Other Services	0.237	-0.005	0.079
			(0.505)

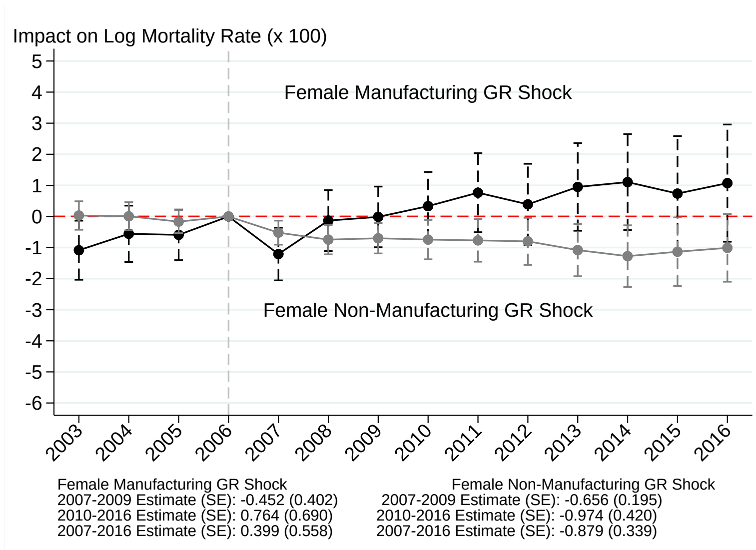
Notes: The figure displays 100 times estimates of $\theta_{s,t}$ from estimating equation (13) with the log age-adjusted mortality rate as the outcome and with seven (mutually exclusive and exhaustive) sector-specific Great Recession shocks ($\text{GR\_SHOCK}_{s,c}$) on the right hand side; these measure the CZ-level change in sector-specific EPOP between 2007 and 2009 (i.e. $\text{GR\_SHOCK}_{s,c} = \text{EPOP}^s_{c,2007} - \text{EPOP}^s_{c,2009}$). The regressions are weighted by each CZ's population in 2006. In the table, column (1) displays each sector's national share of 2006 EPOP. Column (2) displays the average across 2006 population-weighted CZs of the fraction of the total Great Recession shock that comes from that sector (i.e. $\frac{\text{GR\_SHOCK}_{s,c}}{\text{GR\_SHOCK}_c} = \frac{\text{EPOP}^s_{c,2007} - \text{EPOP}^s_{c,2009}}{\text{EPOP}_{c,2007} - \text{EPOP}_{c,2009}}$). Column (3) displays 100 times the average 2007–2016 estimates of $\theta_{s,t}$ in equation (13) in the figure above; standard errors clustered at the CZ level are given in parentheses. The sample size is 722 CZs.

Figure OA.22: Effects of Great Recession on Mortality by Sector-by-Sex-Specific EPOP Shocks

(a) Male Great Recession Shocks to Manufacturing and Non-Manufacturing



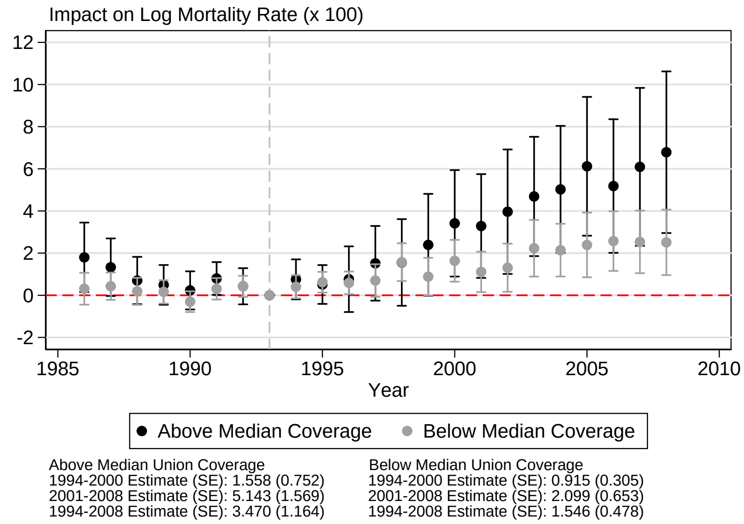
(b) Female Great Recession Shocks to Manufacturing and Non-Manufacturing



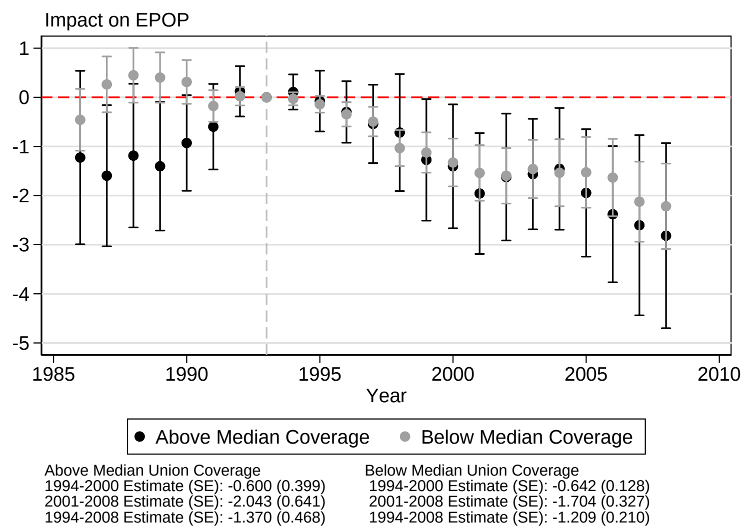
Notes: This figure displays 100 times estimates of $\theta_{s,t}$ from estimating equation (13) with four (mutually exclusive and exhaustive) Great Recession Shocks ($\text{GR\_SHOCK}_{s,c}$) on the right hand side; these measure the CZ-level change in sector-specific EPOP between 2007 and 2009 (i.e. $\text{GR\_SHOCK}_{s,c} = \text{EPOP}^s_{c,2009} - \text{EPOP}^s_{c,2007}$). Specifically, we allow for separate effects for the 2007–2009 EPOP decline in each CZ c for four mutually exclusive and exhaustive sub-groups $s \in \mathcal{S}$: manufacturing among men, manufacturing among women, non-manufacturing among men, and non-manufacturing among women; see Appendix C for more details. The outcome y_{ct} for this single regression is the log age-adjusted mortality rate per 100,000 in each CZ-year. Panel (a) displays the resultant $\theta_{s,t}$ estimates for the Great Recession shocks to male manufacturing EPOP (in black) and to male non-manufacturing EPOP (in gray); panel (b) displays the resultant $\theta_{s,t}$ estimates for the Great Recession shocks to female manufacturing EPOP (in black) and to female non-manufacturing EPOP (in gray). Manufacturing accounted for 15% of EPOP in 2006. Men accounted for 71% of employment in manufacturing, relative to 51% of employment in non-manufacturing. We estimate equation (13) using annual data from 2003 through 2016, omitting the interaction with the shock variables in 2006, so that all of the $\theta_{s,t}$ coefficients are relative to 2006. Estimates of the average of coefficients from 2007–2009, 2010–2016, and 2007–2016 are reported in the lower left-hand corner. Observations are weighted by CZ population in 2006. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. Coefficients, standard errors, and confidence intervals are multiplied by 100 for ease of interpretability. The sample size is 722 CZs.

Figure OA.23: Effects of NAFTA on Mortality and EPOP By Area-Level Baseline Union Coverage

(a) Log Age-Adjusted Mortality



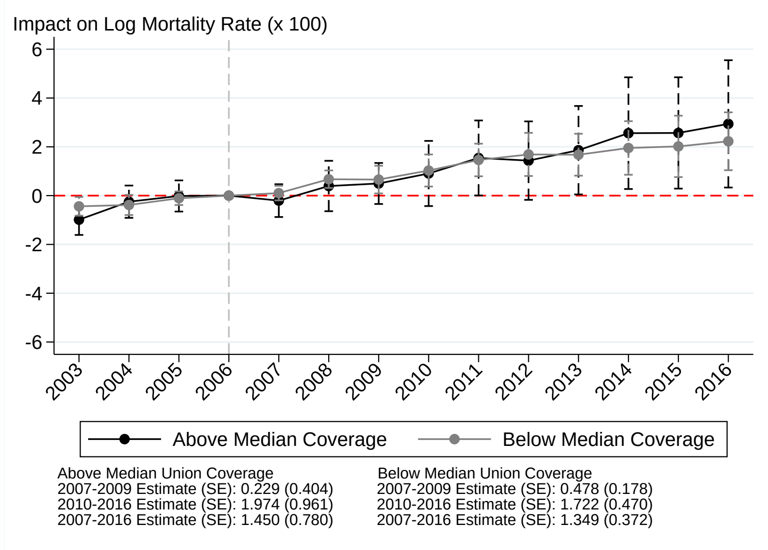
(b) EPOP



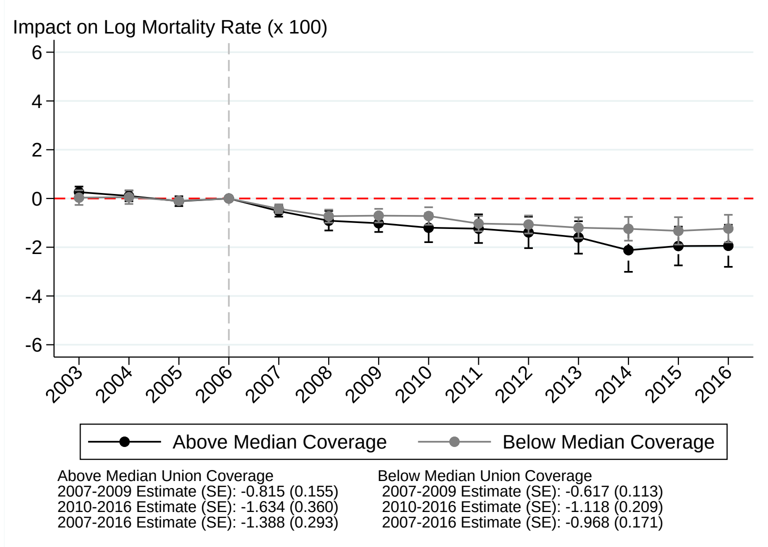
Notes: This figure displays results from estimating equation (4), allowing for separate coefficients on the yearly event study dummies interacted with V_c (i.e., the β_t's) for CZs that are in states with above median union coverage (black line) and below median union coverage (gray line). Data on unionization rates comes from pooled 1990-1992 CPS data on unionization rates by states; for CZs that span states we use the information from the state with the higher share of that CZ's 1990 population. Median unionization rate across states is constructed by weighting unionization rates by each state's 1990 population. The outcome y_{ct} is the log age-adjusted mortality rate in panel (a) and the EPOP ratio in panel (b); the estimates in panel (a) are multiplied by 100 for ease of interpretation. The units can be interpreted in terms of percent changes for mortality and percentage *point* changes in EPOP. A one-point increase in NAFTA vulnerability V_c corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The average estimate across several periods and their corresponding standard errors are given in the lower left corner. The sample size is 722 CZs.

Figure OA.24: Effects of Great Recession on Overall Mortality by Sector-Specific shocks by Area-Level Baseline Union Coverage

(a) Great Recession Shocks to Manufacturing



(b) Great Recession Shocks to Non-Manufacturing

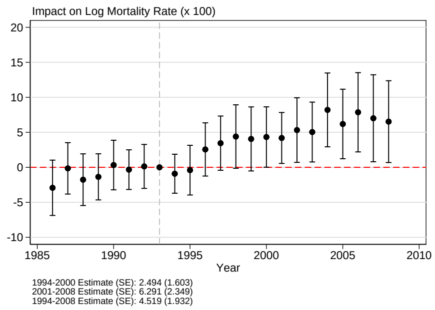


Notes: This figure displays estimates of $\theta_{s,t}$ from estimating equation (13), interacting each of the GR_SHOCK$_{s,c}$ variables for the manufacturing and non-manufacturing sectors with an indicator for CZ c being located in a state with above median union coverage (constructed pooling 2003–2005 data) and an indicator for CZ c being located in a state with below median union coverage. The single regression therefore yields four sets of event study coefficients, delineated by whether or not the shock variable is measuring the Great Recession shock to the manufacturing or the non-manufacturing sector and whether the CZ is in a state with above or below median union coverage. For CZs that span states we use the information from the state with the higher share of that CZ's 1990 population. Median unionization rate across states is constructed by weighting unionization rates by each state's 2006 population. The outcome y_{ct} is the log age-adjusted mortality rate per 100,000. We estimate equation (13) using annual data from 2003 through 2016, omitting the interaction with the shock variables in 2006, so that all of the $\theta_{s,t}$ coefficients are relative to 2006. Estimates of the average of coefficients from 2007–2009, 2010–2016, and 2007–2016 are reported in the lower left-hand corner. Observations are weighted by CZ population in 2006. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. Coefficients, standard errors, and confidence intervals are multiplied by 100 for ease of interpretability. The sample size is 722 CZs.

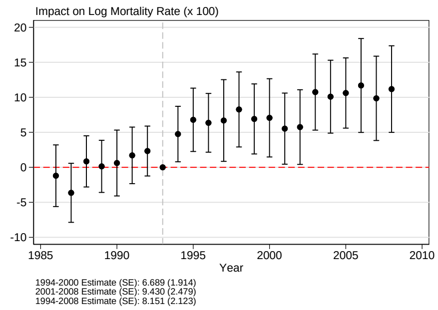
Figure OA.25: NAFTA Mortality Impacts by Sex and Birth Cohort

Born 1970–1994 (Ages 0–24)

(a) Male

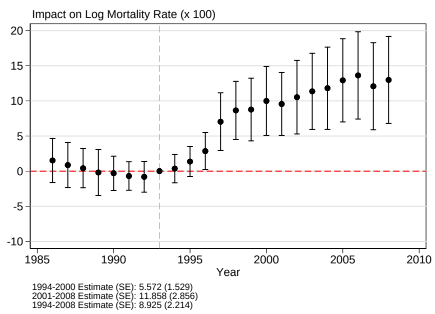


(b) Female

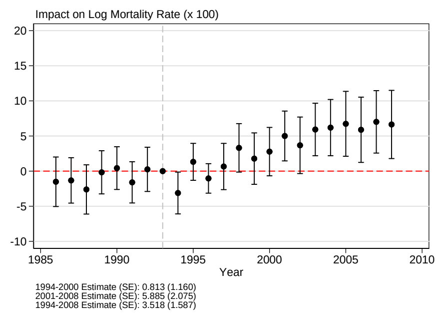


Born 1950–1969 (Ages 25–44)

(c) Male

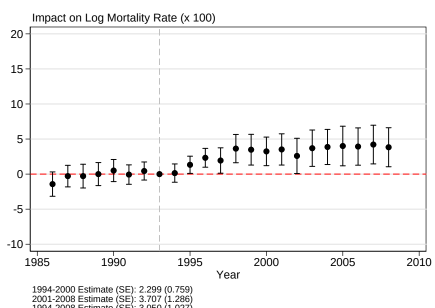


(d) Female

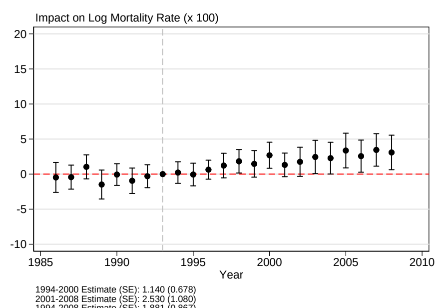


Born 1930–1949 (Ages 45–64)

(e) Male

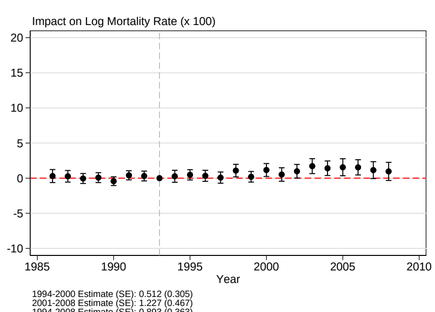


(f) Female

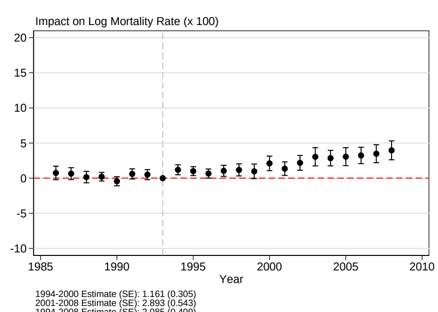


Born Before 1929 (Ages 65+)

(g) Male



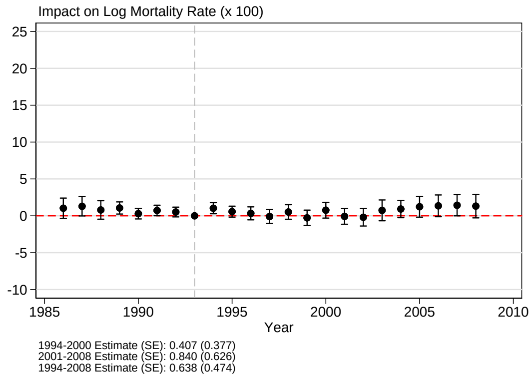
(h) Female



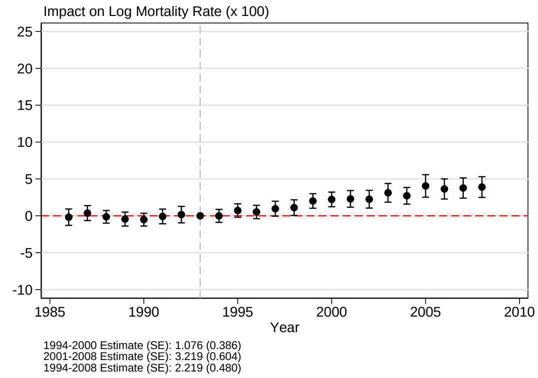
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{ct} is the log mortality rate per 100,000 for individuals in the birth cohort and sex denoted by each panel title. A one-point increase in NAFTA vulnerability V_c corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile. The age range in each panel title corresponds to the age of the cohort at the time of NAFTA's implementation. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.26: NAFTA Mortality Impacts by Cause of Death (Full Sample), Part 1

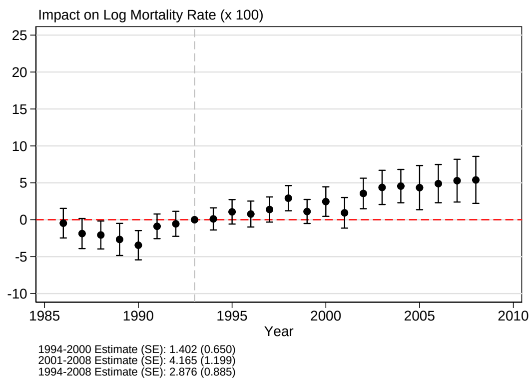
(a) Cardiovascular Disease



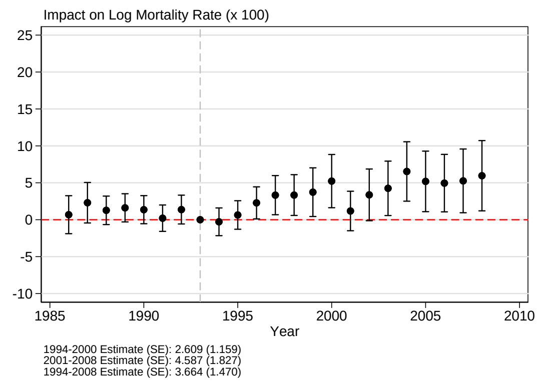
(b) Cancer



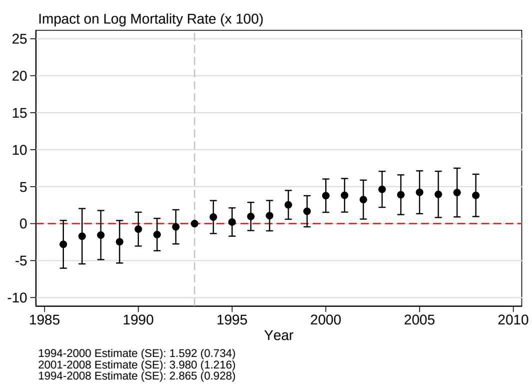
(c) Respiratory System Disorders



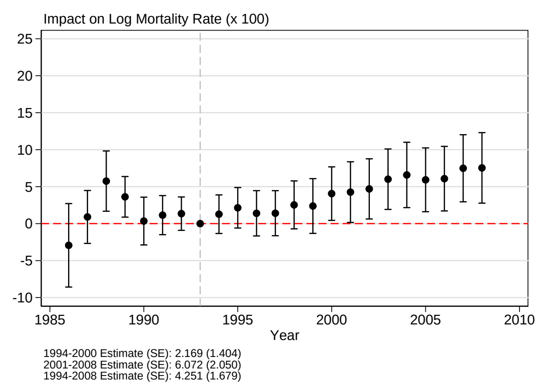
(d) External Causes



(e) Digestive System Disorders



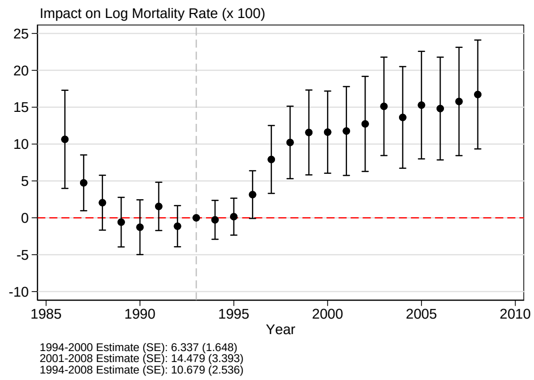
(f) Metabolic Diseases



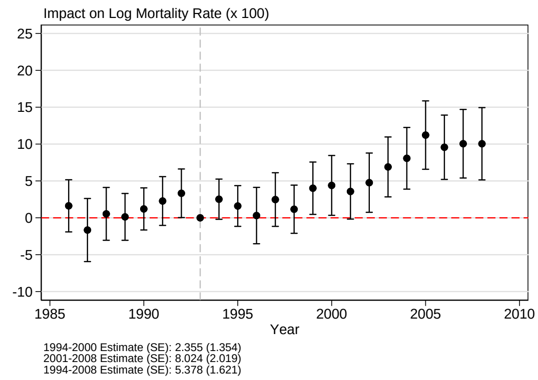
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log age-adjusted mortality rates per 100,000 separately by cause of death. Along with Figure OA.27, these groups partition all causes of death in the CDC data. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.27: NAFTA Mortality Impacts by Cause of Death (Full Sample), Part 2

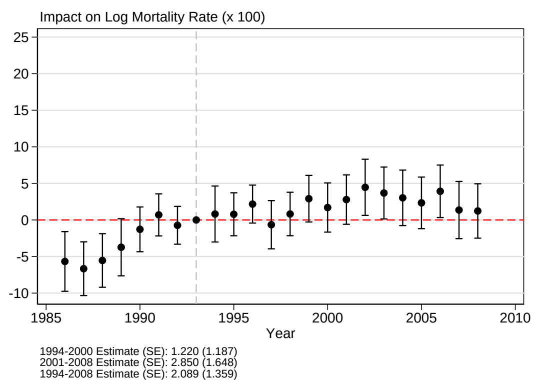
(a) Infectious Diseases



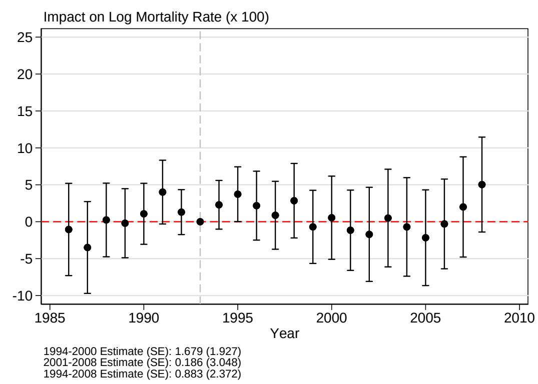
(b) Nervous System Disorders



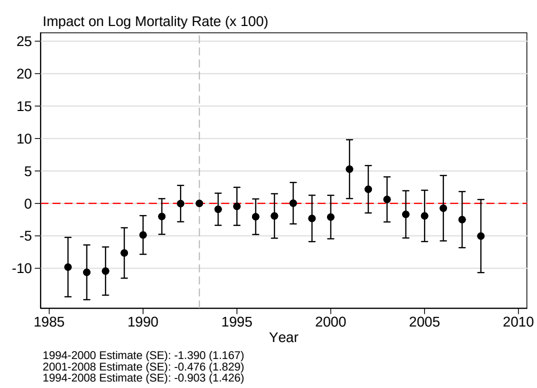
(c) Genitourinary Disorders



(d) Mental Illness



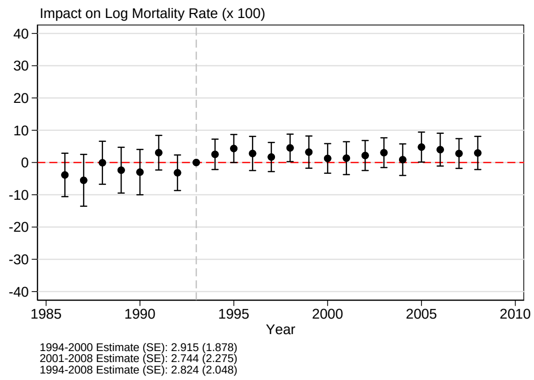
(e) Other Causes



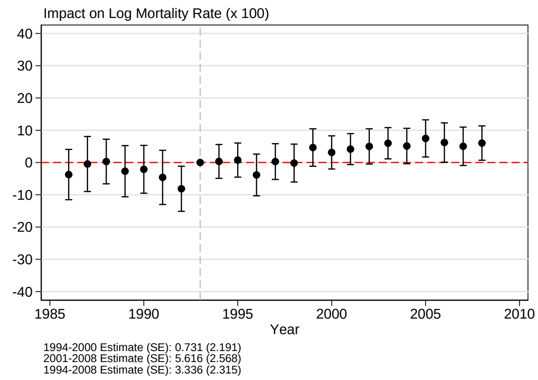
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log age-adjusted mortality rates per 100,000 separately by cause of death. Along with Figure OA.26, these groups partition all causes of death in the CDC data. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.28: NAFTA Mortality Impacts by Cause of Death (Men Born 1950–1969), Part 1

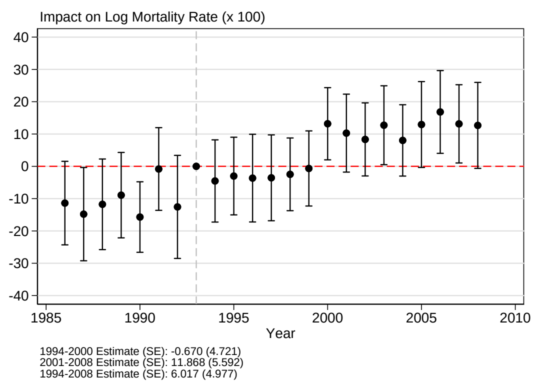
(a) Cardiovascular Disease



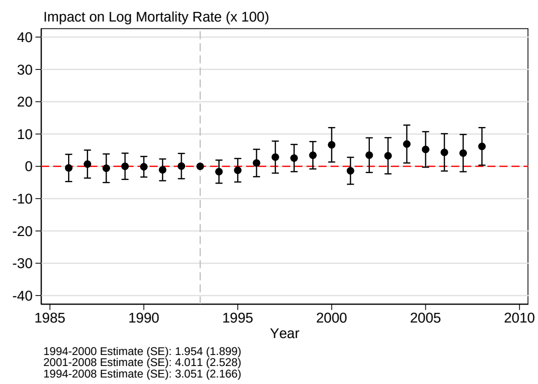
(b) Cancer



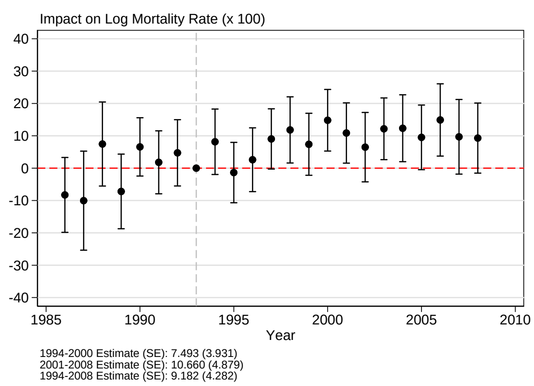
(c) Respiratory System Disorders



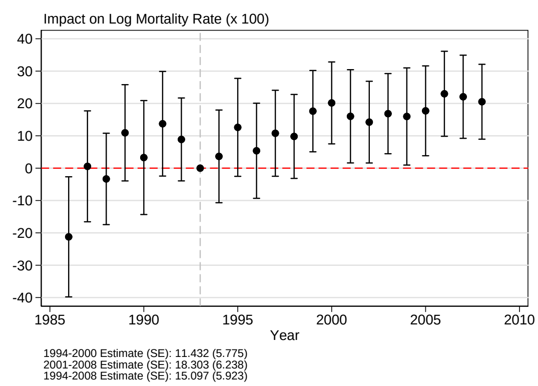
(d) External Causes



(e) Digestive System Disorders



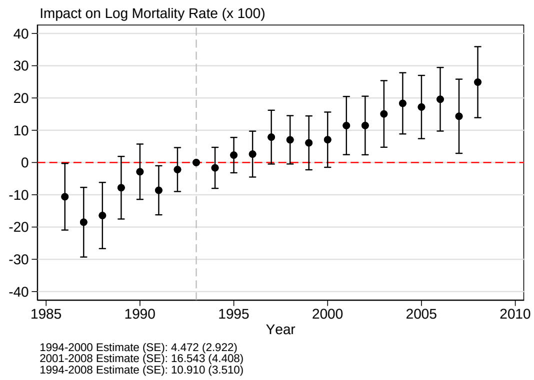
(f) Metabolic Diseases



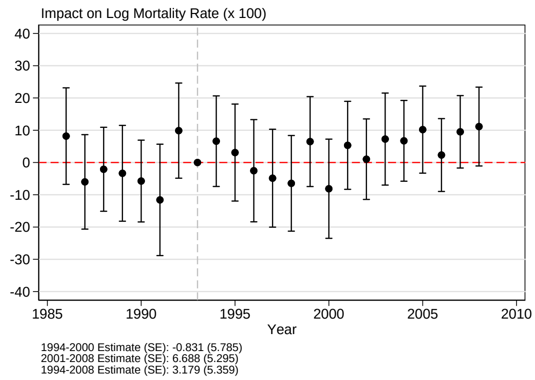
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log mortality rates per 100,000 for men born between 1950 and 1969 separately by cause of death. Along with Figure OA.29, these groups partition all causes of death in the CDC data. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.29: NAFTA Mortality Impacts by Cause of Death (Men Born 1950–1969), Part 2

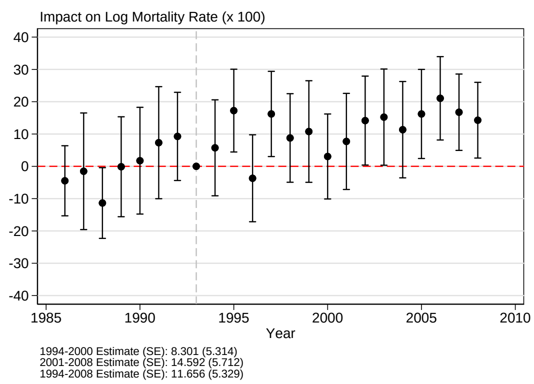
(a) Infectious Diseases



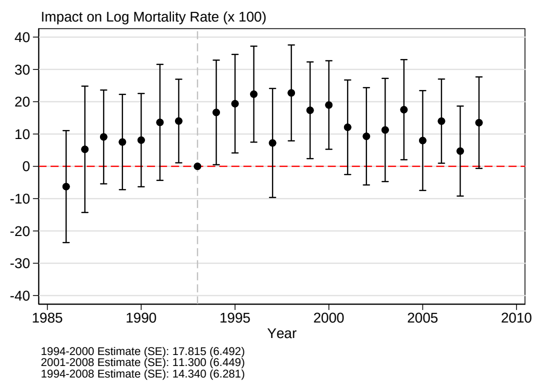
(b) Nervous System Disorders



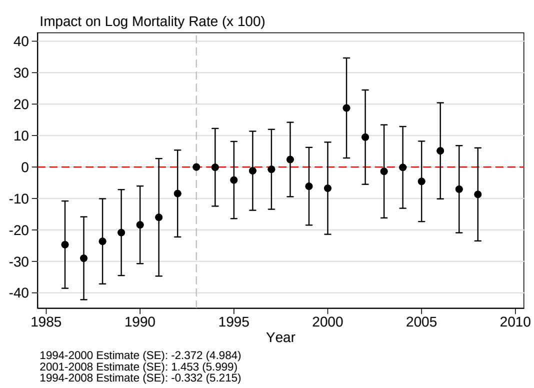
(c) Genitourinary Disorders



(d) Mental Illness



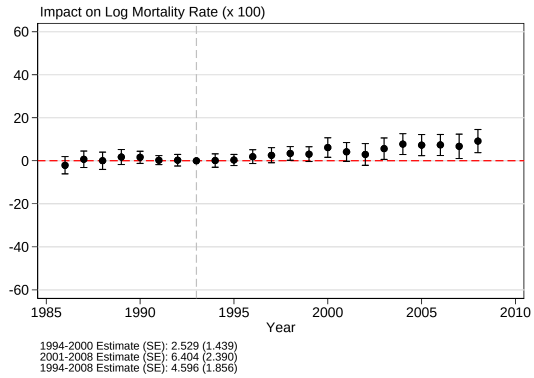
(e) Other Causes



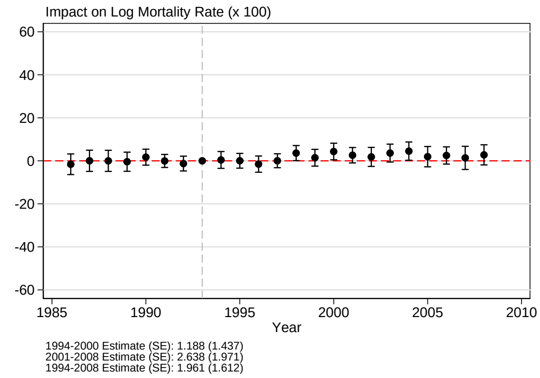
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log mortality rates per 100,000 for men born between 1950 and 1969 separately by cause of death. Along with Figure OA.28, these groups partition all causes of death in the CDC data. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.30: NAFTA Mortality Impacts on Deaths of Despair (Full Sample)

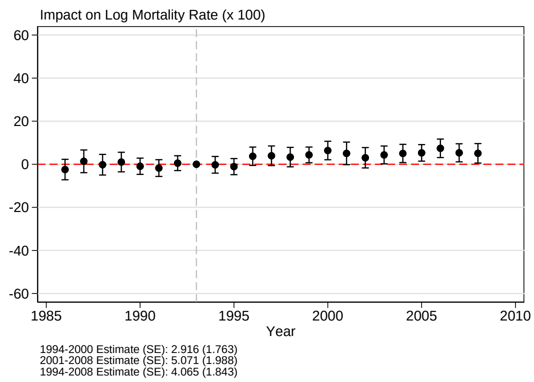
(a) Pooled



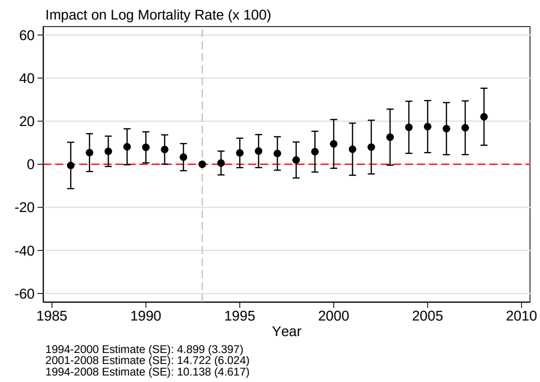
(b) Alcohol-Related



(c) Suicide



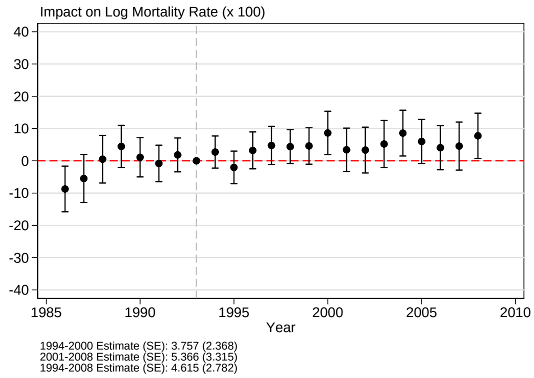
(d) Drug-Related



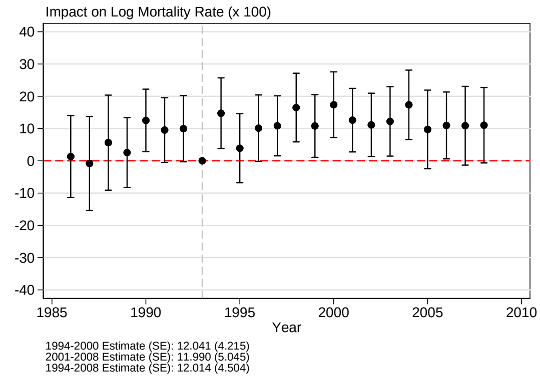
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log age-adjusted CZ mortality rates per 100,000 separately by deaths of despair. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.31: NAFTA Mortality Impacts on Deaths of Despair (Men Born 1950–1969)

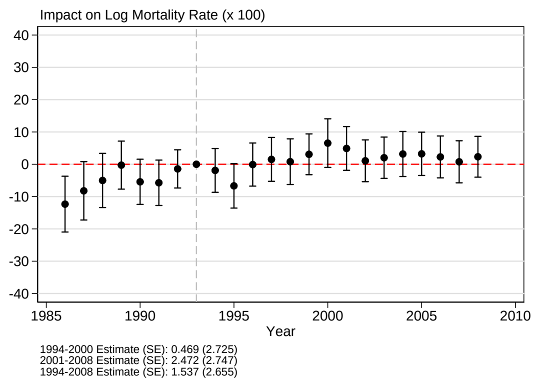
(a) Pooled



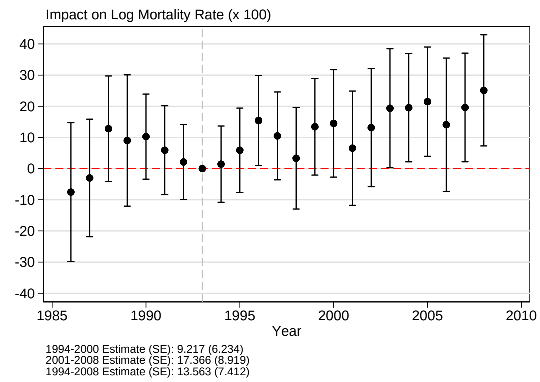
(b) Alcohol-Related



(c) Suicide



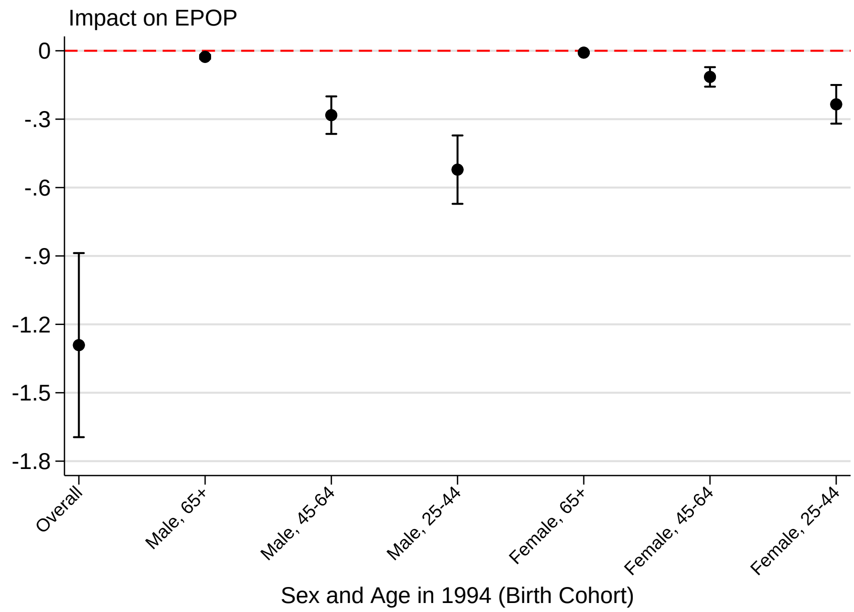
(d) Drug-Related



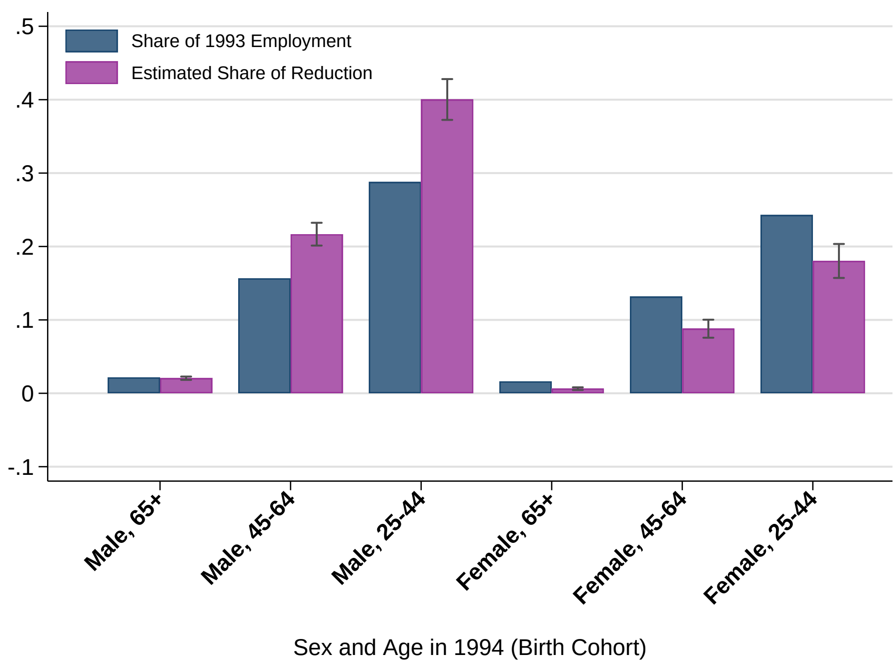
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log mortality rates per 100,000 for men born between 1950 and 1969 separately by deaths of despair. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.32: NAFTA EPOP Impacts By Birth Cohort and Sex

(a) 1994–2008 Pooled Estimates



(b) 1994–2008 Decomposition

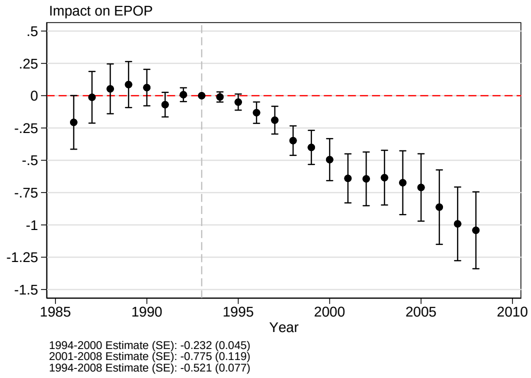


Notes: Panel (a) gives the imputed average 1994–2008 estimate of β_t in equation (4) for EPOP in each demographic group given on the x-axis; Appendix Figure OA.33 shows the underlying event studies. In panel (b), the blue bars denote the share of employment each demographic group accounted for in 1993, while the purple bars denote the share of the decline in the EPOP ratio each demographic group accounted for (averaged over the 1994–2008 post-period) as a result of NAFTA. The imputation is described in Appendix A.3. Note that the youngest birth cohort—those who are 0–24 in 1994—are excluded from the analysis; as a result, the groups shown here only account for 91.3% of the total estimated EPOP decline. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. They are computed by estimating equation (4) for all industries simultaneously in a stacked regression and treating 1993 employment shares as fixed. The regression is weighted by each CZ's population in 1990. The sample size for each group is 722 CZs.

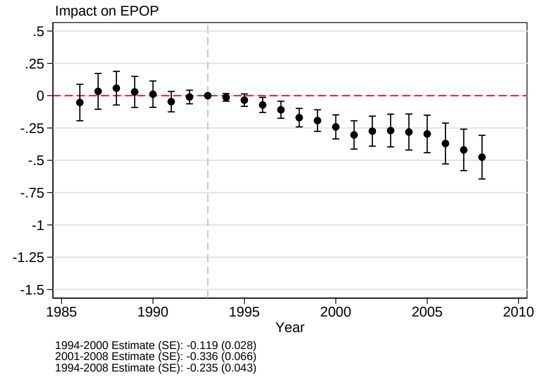
Figure OA.33: NAFTA Employment Impacts by Birth Cohort and Sex

Born 1950–1969 (Ages 25–44)

(a) Male

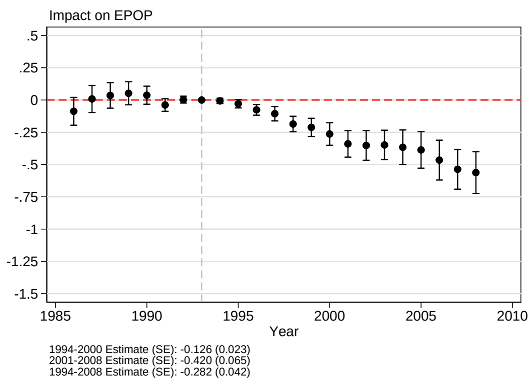


(b) Female

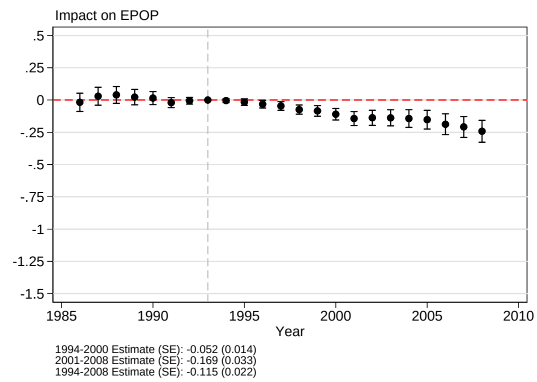


Born 1930–1949 (Ages 45–64)

(c) Male

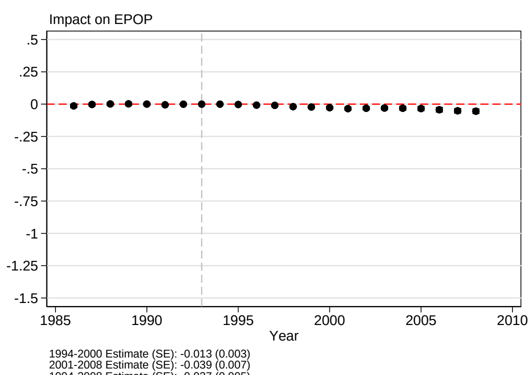


(d) Female

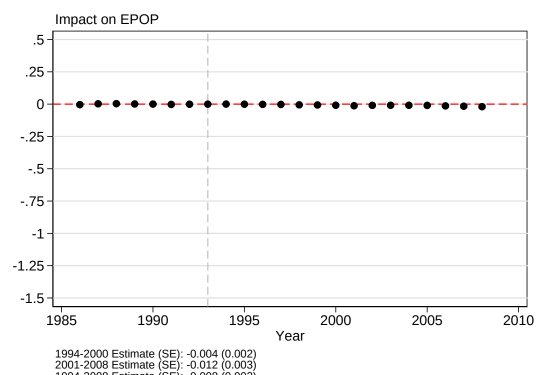


Born Before 1929 (Ages 65+)

(e) Male



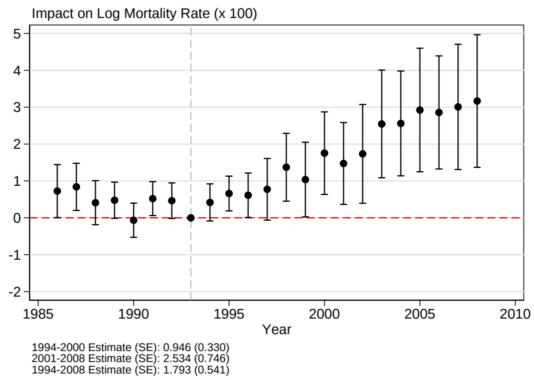
(f) Female



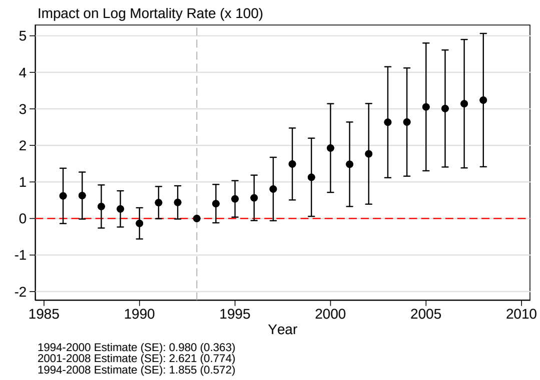
Notes: This figure displays imputed estimates of β_t from equation (4), where the outcome y_{ct} is the number of individuals employed in each birth cohort-by-sex bin given by the panel title divided by the population aged 16 or older. These estimates are imputed by estimating equation (4) for employment in all 20 two-digit NAICS codes in a stacked regression, multiplying the resulting estimates by each demographic's share of employment in that industry, and finally summing across industries. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

Figure OA.34: Impact of NAFTA on Mortality: Robustness Checks

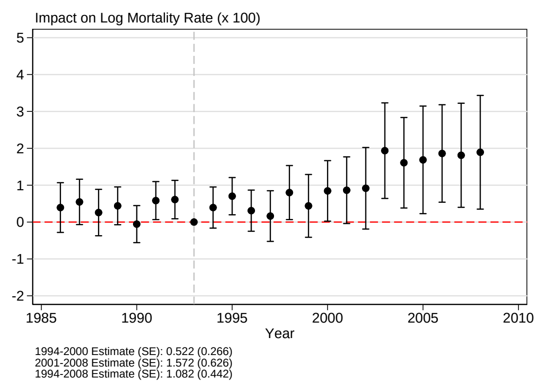
(a) Chinese Import Penetration-By-Year FE



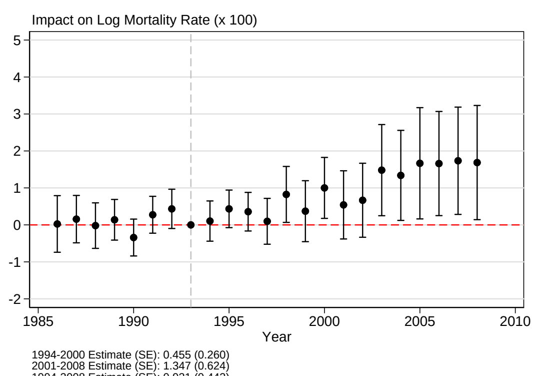
(b) 1990 Cancer Mortality Rate-By-Year FE



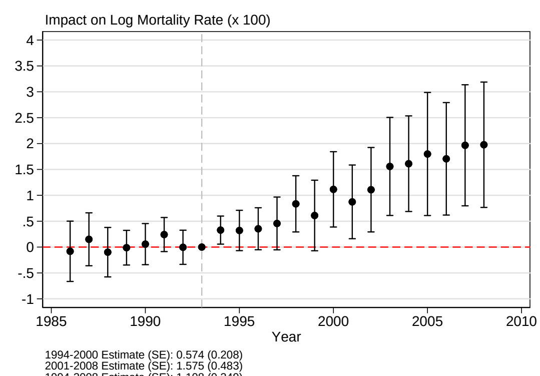
(c) Additional Manufacturing Clusters



(d) Southern Census Region Only



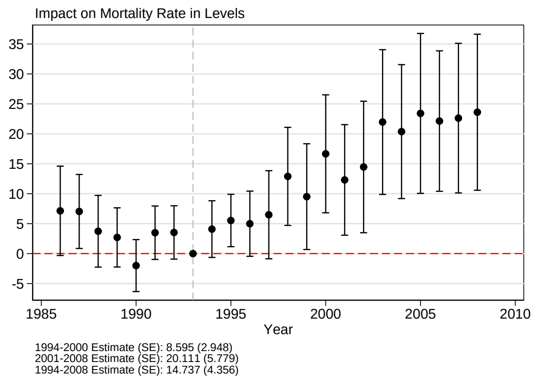
(e) County Level



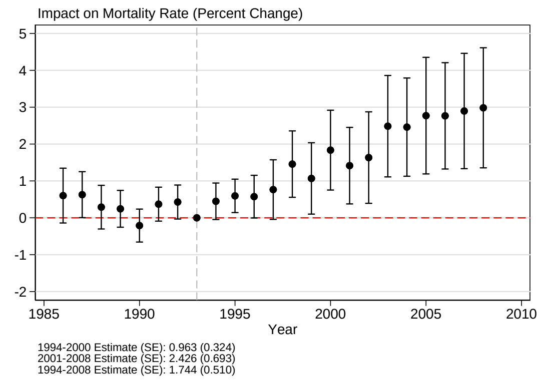
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{ct} is the log age-adjusted mortality rate per 100,000. A one-point increase in NAFTA vulnerability V_c corresponds to moving from the average county or CZ in the least vulnerable quartile to the average county or CZ in the most vulnerable quartile. Panel (a) includes all CZs, controlling for 1990–2000 Autor et al. (2013) Chinese import penetration. Panel (b) controls for the 1990 cancer mortality rate as a proxy for the opioid crisis (Arteaga and Barone, forthcoming). Panel (c) controls for three separate k-means clusters of the 1980 manufacturing share in addition to 3-kmeans clusters of our other control variables. Panel (d) restricts the sample to CZs in the Southern Census Region only. Panel (e) estimates the specification at the county level. Observations are weighted by each area's population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level in panels (a) through (d) and state level in panel (e). The sample size is 722 CZs in panels (a) through (c), 288 CZs in panel (d), and 3,096 counties in panel (e).

Figure OA.35: Impact of NAFTA on Mortality: Robustness Checks (Functional Form)

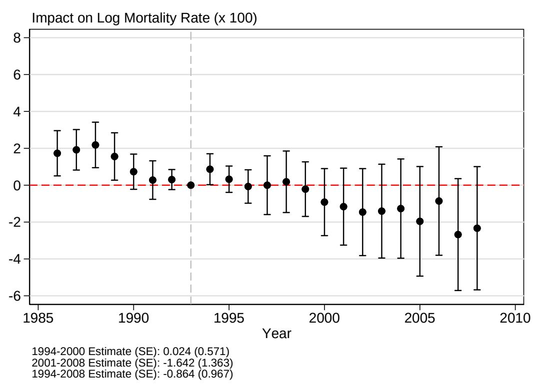
(a) Mortality in Levels



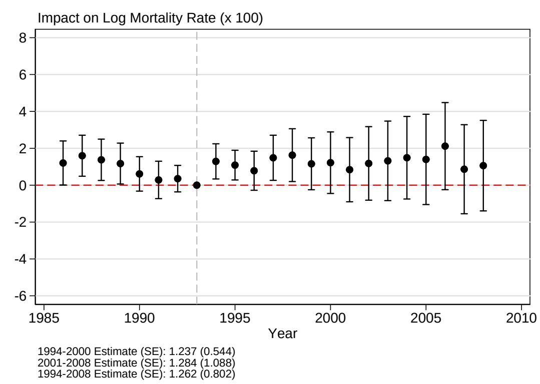
(b) Poisson



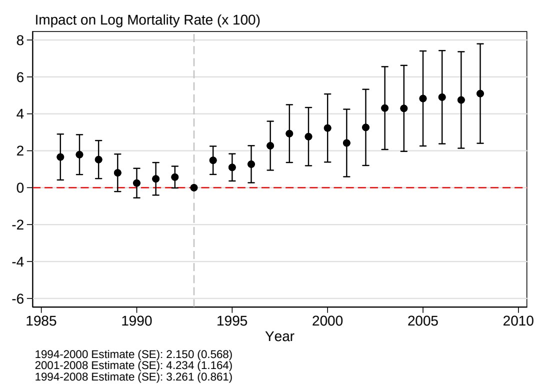
(c) Quartile 2



(d) Quartile 3



(e) Quartile 4

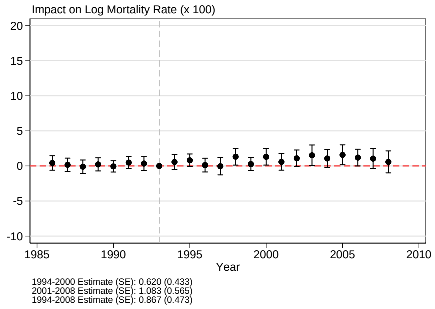


Notes: Panel (a) displays estimates of β_t from equation (4), where the outcome y_{ct} is the age-adjusted mortality rate in levels. Panel (b) displays estimates of β_t, multiplied by 100, from equation (19), where the outcome is also the age-adjusted mortality rate in levels. Given a one-point increase in NAFTA vulnerability V_c, which corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile, coefficients in panel (a) report the change in deaths per 100,000 and coefficients in panel (b) report the percent change in the mortality rate. Panels (c)–(e) display estimates of $\beta_t^{(j)}$ from equation (20), where the outcome is once again log age-adjusted mortality per 100,000, and we can interpret coefficients as the percent change in mortality when moving from a first quartile CZ in terms of vulnerability (V_c) to a j^{th} quartile CZ for $j \in (2, 3, 4)$. Quartiles are calculated based on the distribution of V_c across (1990 population-weighted) CZs. Average V_c is 0.08 in quartile 1, 0.19 in quartile 2, 0.29 in quartile 3, and 0.97 in quartile 4. Across all panels, observations are weighted by each area's population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

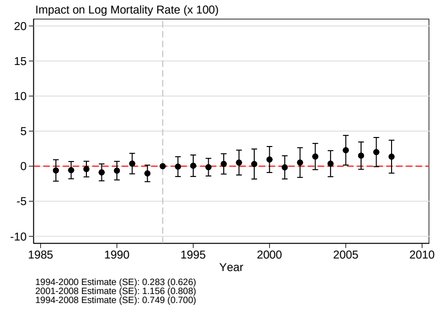
Figure OA.36: NAFTA Mortality Impacts by Marital Status (Elderly Only)

Married

(a) Male

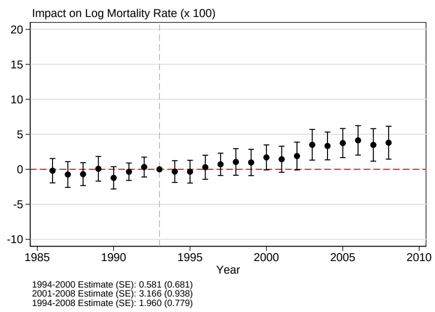


(b) Female

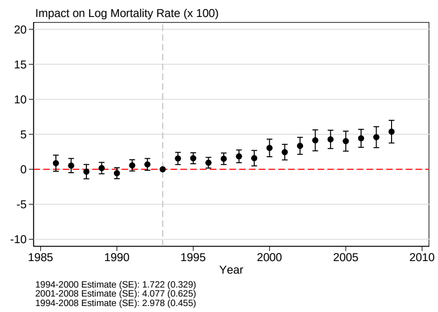


Widowed

(c) Male

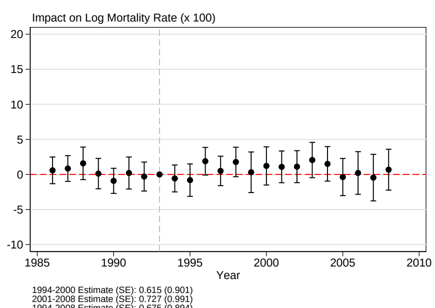


(d) Female

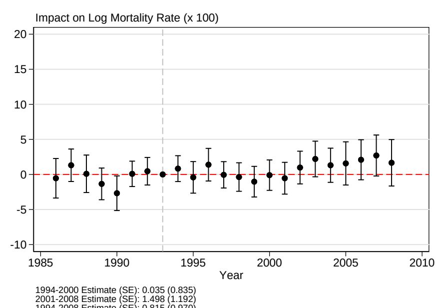


Other

(e) Male



(f) Female



Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{ct} is the log mortality rate per 100,000 for individuals in the pre-1930 birth cohort split by marital status. "Other" includes Divorced and Never Married. For each marital-status specific result, the sample is restricted to CZs outside of Georgia due to a lack of marital status codes in the data. A one-point increase in NAFTA vulnerability V_c corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 690 CZs.

E Appendix Tables

Table OA.1: Summary of NHIS Outcomes Analyzed and Years Available

Variable	Years available
Health Behaviors	
Current smoker	1991-1995, 1997-2018
Flu shot in past year	1989, 1991, 1993-1995, 1997-2018
General Health	
Fair or poor self-reported health	1986-2018
Any limitation in usual activities	1986-2018
Healthcare Access	
Has a usual place for medical care	1987-1988, 1990-2018
Doctor visit in past year	1986-2018
Last doctor visit 5+ years ago	1986-1996, 1999-2018
Hospital overnight stay in past year	1986-2018
Health Insurance	
No health insurance coverage	1986, 1989-2018
Covered by private health insurance	1986, 1989-2018
Covered by Medicaid	1990-2018
Covered by Medicare	1986, 1989-2018

Notes: This table gives the years each outcome analyzed was available in the NHIS. In Figures OA.15 through OA.18, the 1994–2008 post-period average estimates naturally only include the years available above (e.g., for flu shots the average does not include a coefficient for 1996).

Table OA.2: Changes in Life Expectancy Due to NAFTA

	Remaining Life Expectancy (Unisex)			Remaining Life Expectancy (Male)			Remaining Life Expectancy (Female)		
Age in 1994	Normal	NAFTA	Percent Change	Normal	NAFTA	Percent Change	Normal	NAFTA	Percent Change
Panel A: Homogeneous Mortality Effects									
25	51.45	51.44	-0.013%	48.34	48.33	-0.020%	54.56	54.55	-0.008%
45	32.95	32.93	-0.046%	30.38	30.36	-0.059%	35.51	35.50	-0.035%
65	16.57	16.54	-0.199%	14.67	14.63	-0.246%	18.48	18.45	-0.162%
Panel B: Heterogeneous Mortality Effects									
25	51.45	51.42	-0.050%	48.34	48.29	-0.091%	54.56	54.55	-0.014%
45	32.95	32.93	-0.061%	30.38	30.35	-0.093%	35.51	35.50	-0.034%
65	16.57	16.55	-0.147%	14.67	14.65	-0.113%	18.48	18.45	-0.173%

Notes: This table displays the life expectancy for individuals overall and by sex in 1993 for several age cuts. The "normal" life expectancies are computed using the mortality rates implied by the SSA's life tables. "NAFTA" life expectancy is computed by applying our estimates of the percent increase in the mortality rate due to NAFTA to the "normal" life expectancy tables. In Panel A, we assume that NAFTA increases annual mortality by 0.68% for 15 years for all individuals; this is obtained by multiplying the average annual 1.93% mortality increase from 1994–2008 in Figure 2 by the average NAFTA vulnerability (0.35). In Panel B, we replace the 1.93% average annual percent increase in the mortality rate from 1994–2008 with estimates of the birth cohort by sex-specific average annual percent increases in mortality rates from 1994–2008 in Figure OA.25.

Table OA.3: Welfare Effects of NAFTA

	$\frac{\text{VSLY}}{c} = 2$			$\frac{\text{VSLY}}{c} = 5$			$\frac{\text{VSLY}}{c} = 8$		
Age in 1994	All Individuals	Men	Women	All Individuals	Men	Women	All Individuals	Men	Women
Panel A: Homogeneous Mortality Effects									
Overall	-0.066%	-0.076%	-0.055%	-0.284%	-0.311%	-0.258%	-0.502%	-0.546%	-0.461%
25	0.053%	0.040%	0.064%	0.013%	-0.019%	0.041%	-0.027%	-0.078%	0.018%
45	-0.012%	-0.038%	0.010%	-0.150%	-0.215%	-0.095%	-0.288%	-0.392%	-0.200%
65	-0.317%	-0.411%	-0.243%	-0.913%	-1.148%	-0.728%	-1.510%	-1.884%	-1.213%
Panel B: Heterogeneous Mortality Effects									
Overall	-0.112%	-0.147%	-0.079%	-0.401%	-0.487%	-0.318%	-0.689%	-0.828%	-0.557%
25	-0.020%	-0.102%	0.052%	-0.171%	-0.375%	0.009%	-0.322%	-0.648%	-0.033%
45	-0.042%	-0.105%	0.012%	-0.225%	-0.383%	-0.089%	-0.408%	-0.661%	-0.191%
65	-0.213%	-0.146%	-0.267%	-0.654%	-0.485%	-0.787%	-1.094%	-0.824%	-1.308%

Notes: This table displays estimates of the welfare effects of NAFTA with endogenous mortality as defined in equation (6). We calibrate $\Delta = 0.08\%$ from Caliendo and Parro (2015). In the first three columns, we set the ratio between the value of a statistical life year and consumption to be 2; in the next three columns, we set it to 5; in the final three columns, we set it to 8. In Panel A, we obtain dT from the changes in life expectancy using a homogeneous mortality impact of NAFTA across all demographics, as in Panel A of Table OA.2. In Panel B, we compute dT using birth cohort and sex specific effects, as in Panel B of Table OA.2. The "overall" welfare change is computed by averaging age (0–85+) and sex-specific welfare changes weighted by each demographic's share of the population in 1993.

Table OA.4: IV Estimates of the Impact of EPOP on Mortality: Sensitivity to Instruments

	OLS	IV (Great Recession)	IV (NAFTA)	IV (China Shock)
	(1)	(2)	(3)	(4)
EPOP Decline ($\times$100)	-0.353	-0.558	1.434	1.543
	(0.122)	(0.201)	(0.412)	(0.649)
First Stage F-Statistic		198.25	19.06	6.65
p-value		0.000	0.000	0.010
N	16,606	10,108	16,606	1,444
Hansen J Statistic		2.109	0.650	
p-value		0.146	0.420	
Testing equality with:				
OLS (p-value)		0.439	0.000	0.000
China Shock (p-value)		0.000	0.792	
NAFTA (p-value)		0.000		

Notes: Table shows sensitivity of the IV estimates of the impact of EPOP declines on mortality in Table 2 to additional controls. Specifically, in columns (2) and (3) we add a control to the second stage equation (8) and the first stage equation (7) for a linear trend in either GR_SHOCK$_c$ (column 2) or V_c (column 3) fitted to the pre-period (i.e., before 2007 in column 2 or before 1994 in column 3). Everything else is as described in Table 2.

Table OA.5: NAFTA Mortality Impacts: Sensitivity Analysis

	Period		
	1994-2000	2001-2008	1994-2008
Baseline	1.043	2.706	1.930
	(0.333)	(0.742)	(0.541)
A: Additional Covariates			
Chinese Import Penetration	0.946	2.534	1.793
	(0.330)	(0.746)	(0.541)
1990 Cancer Mortality Rate	0.980	2.621	1.855
	(0.363)	(0.774)	(0.572)
Separate Manufacturing Clusters	0.522	1.572	1.082
	(0.266)	(0.626)	(0.442)
B: Geography			
Limit to Southern Census Region	0.455	1.347	0.931
	(0.260)	(0.624)	(0.442)
County Level	0.574	1.575	1.108
	(0.208)	(0.483)	(0.349)
C: Functional Form			
Mortality Rate in Levels	8.595	20.111	14.737
	(2.948)	(5.779)	(4.356)
Implied Percent Change	0.925	2.163	1.585
Poisson	0.963	2.426	1.744
	(0.324)	(0.693)	(0.510)
By Vulnerability Quartile			
Quartile 2	0.024	-1.642	-0.864
	(0.571)	(1.363)	(0.967)
Quartile 3	1.237	1.284	1.262
	(0.544)	(1.088)	(0.802)
Quartile 4	2.150	4.234	3.261
	(0.568)	(1.164)	(0.861)

Notes: This table displays post-period average estimates of β_t in equation (4) with the log age-adjusted mortality rate as the outcome under various specifications. Appendix Figures OA.34 and OA.35 present the underlying event studies. The first row displays the baseline estimates (summarizing the estimates in Figure 2). In Panel A, we add year fixed effects interacted with cross sectional variables: first for the Chinese import penetration measure from Autor et al. (2013), next for the 1990 cancer mortality rate (predictive of the opioid crisis), and finally for 3 additional k-means clusters of the 1980 manufacturing share as well as 3 k-means clusters for our remaining controls. In Panel B, we probe sensitivity to geography by limiting the sample to CZs in the Southern Census Region only and by estimating the specification at the county level. Finally, in Panel C, we probe sensitivity to functional form. First, we estimate the effects of mortality in levels using the same specification (equation 4) and then computing the implied percent change off of the population-weighted average age-adjusted mortality rate across CZs in 1993. Next, we run a Poisson regression (specified by equation 19) whose coefficients can be interpreted as percent changes in mortality. Finally, we estimate $\beta_t^{(j)}$ from equation (20), where the outcome is once again log age-adjusted mortality, and we can interpret coefficients as the percent change in mortality when moving from a first quartile CZ in terms of vulnerability (V_c) to a j^{th} quartile CZ for $j \in (2, 3, 4)$. Quartiles are calculated based on the distribution of V_c across (1990 population-weighted) CZs. Average V_c is 0.08 in quartile 1, 0.19 in quartile 2, 0.29 in quartile 3, and 0.97 in quartile 4. Across all panels, standard errors (displayed in parentheses) are clustered at the CZ level, except for the county-level regression which is clustered at the state level. Each regression is weighted by each area's population in 1990. The sample sizes are 722 total CZs, 288 Southern CZs, and 3,096 counties.

Table OA.6: Baseline Employment By Sex and Birth Cohort

Demographic	EPOP	Share of Employment
Men Born Before 1929 (65+)	1.028	0.022
Men Born 1930-1949 (45-64)	7.452	0.157
Men Born 1950-1969 (25-44)	13.699	0.288
Men Born 1970-1994 (0-24)	3.594	0.076
Women Born Before 1929 (65+)	0.771	0.016
Women Born 1930-1949 (45-64)	6.268	0.132
Women Born 1950-1969 (25-44)	11.558	0.243
Women Born 1970-1994 (0-24)	3.220	0.068

Notes: This table displays the imputed share of employment each demographic group accounted for in 1993 as well as the demographic's employment-to-population ratio, where the total population aged 16 and older is the denominator. The imputation is described in Appendix A.3.

Table OA.7: China Shock Impacts on Mortality and EPOP

	Cumulative Mortality Rate	EPOP		
		Total	Manufacturing	Non-Manufacturing
	(1)	(2)	(3)	(4)
Import Penetration	229.0	-1.448	-1.319	-0.129
	(76.6)	(0.572)	(0.229)	(0.471)
Mean	9,218.2	47.7	5.7	41.9
First Stage F-Statistic	98.5	98.5	98.5	98.5
N	1,444	1,444	1,444	1,444

Notes: This table displays IV estimates of β_1 in equation (26), using $\Delta\tilde{\text{IP}}_{c,\tau}$ from equation (29) as the instrument. The outcomes are the decadal, age-adjusted cumulative mortality rate (column 1) and long-differenced total EPOP, manufacturing EPOP, and non-manufacturing EPOP (columns 2 through 4). The regressions are weighted by the product of period length and start-of-period CZ populations shares. Standard errors clustered at the CZ level are given in parentheses. The sample size is 722 CZs.

Table OA.8: China Shock Impacts on Mortality By Age and Sex

	Men				Women			
	65+	45-64	25-44	0-24	65+	45-64	25-44	0-24
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import Penetration	454.3	401.0	93.3	17.1	239.3	90.2	23.4	11.3
	(456.8)	(122.8)	(46.4)	(13.3)	(398.7)	(61.7)	(21.1)	(7.8)
Implied % Change	0.77	4.09	4.34	1.77	0.49	1.54	2.21	2.03
Mean	58,686	9,814	2,151	971	48,517	5,854	1,060	558
First Stage F-Statistic	98.5	98.5	98.5	98.5	98.5	98.5	98.5	98.5
N	1,444	1,444	1,444	1,444	1,444	1,444	1,444	1,444

Notes: This table displays IV estimates of β_1 in equation (26), using $\Delta\tilde{\text{IP}}_{c,\tau}$ from equation (29) as the instrument. The outcomes are the decadal, cumulative mortality rate in each age and sex bin given in the column titles as outcomes. Note that, as discussed further in Appendix B, we analyze results by age rather than birth cohort. The regressions are weighted by the product of period length and start-of-period CZ populations shares. Standard errors clustered at the CZ level are given in parentheses. The sample size is 722 CZs.