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

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Abstract

We estimate the mortality impact of local labor market exposure to the 1994 North American Free Trade Agreement (NAFTA) as well as to other local area shocks, and provide a parsimonious empirical explanation for differently-signed mortality estimates across different sources of local labor market contractions. Leveraging spatial variation in exposure to Mexican important competition from NAFTA, we find that more exposed areas experienced larger increases in mortality. In the 15 years post-NAFTA, an area with average NAFTA exposure experienced an increase in annual, age-adjusted mortality of 0.68 percent (standard error = 0.19), an increase that more than erases prior estimates of the welfare gains from NAFTA's nationwide economic benefits. Mortality increases appear across all broad age by sex groups, but are particularly pronounced among working-age men, a demographic that also experienced disproportionate NAFTA-induced declines in (primarily manufacturing) employment. Additional evidence from other local labor market shocks reveals a systematic pattern: declines in local area manufacturing employment increase mortality, while declines in local area non-manufacturing employment decrease mortality. These findings suggest that the sign and magnitude of any mortality impacts of future economic shocks likely depends critically on the extent to which employment declines are concentrated in the manufacturing sector.

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"While expanding economies are all alike, every contracting economy is contracting in its own way."
– Ben Friedman, channelling 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 local labor market contractions to show that local labor market declines in manufacturing employment increase mortality while local labor market declines in non-manufacturing employment *decrease* mortality. Our findings suggest that the sign and magnitude of the mortality impact of future local labor market contractions may depend critically on the extent to which employment reductions are concentrated in the manufacturing sector. They also provide a parsimonious explanation for what has been something of an empirical puzzle: prior evidence that plant closings and increased exposure to trade from China (Sullivan and von Wachter, 2009; Autor et al., 2019; Pierce and Schott, 2020) increase mortality, while recessions reduce mortality (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 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 small or non-existent (Romalis, 2007; Caliendo and Parro, 2015). To estimate NAFTA's mortality impacts, we follow Choi et al. (2024) and exploit spatial variation across the US in local area exposure to increased Mexican import competition from NAFTA.[2]

Areas more exposed to NAFTA experienced an increase in all-cause mortality. Our estimates imply that in the 15 years post-NAFTA, a commuting zone with average exposure to Mexican import competition experienced an increase in annual, age-adjusted mortality of 0.68 percent (standard

[1] Such ostensibly conflicting results are not limited to the United States. Mortality appears to be pro-cyclical (i.e. falling during recessions) in Canada and in several European countries (Neumayer, 2004; Granados, 2005; Buchmueller et al., 2007; Ariizumi and Schirle, 2012). There is also evidence from a variety of other countries, including Denmark, the Netherlands, and Brazil, that men who lose their jobs due to plan closures or mass layoffs experience increases in mortality (Browning and Heinesen, 2012; Bloemen et al., 2018; Amorim et al., 2024).

[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.

error = 0.19). The mortality impacts of NAFTA grew over this 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. A simple calibration of a styled model suggests that the welfare losses from NAFTA-induced mortality can more than erase Caliendo and Parro (2015)'s estimates of the general equilibrium welfare gains from NAFTA operating through wages and prices.

We then show more broadly that local labor market declines in manufacturing EPOP have opposite-signed mortality impacts from local labor market declines in non-manufacturing EPOP. Specifically, we examine four sources of local labor market variation in EPOP over the 1986 to 2016 period: area-year variation in EPOP, exposure to the Great Recession, exposure to import competition from Mexico due to NAFTA, and exposure to import-competition from China. Unlike recession-induced declines in local labor market EPOP, the vast majority of trade-induced declines are in the manufacturing sector. We estimate that a 1 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 estimates are of similar magnitude to the mortality effects of job loss from plant closings (Sullivan and von Wachter, 2009), but are of opposite sign and statistically distinguishable from our estimates that a 1 percentage point recession-induced area EPOP decline *reduces* mortality by about 0.5 percent.

To more directly examine the mortality impacts of different types of local area EPOP declines, we leverage spatial variation in the share of the Great Recession-induced decline in local area EPOP that is in manufacturing. Qualitatively, 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 were similar to that from trade shocks would produce quantitatively similar mortality increases to what we estimate for NAFTA and the China Shock. These findings suggest that the sign and magnitude of any mortality impacts of future economic shocks likely depends critically on how much these shocks affect the manufacturing sector relative to non-manufacturing sectors. We offer some speculative thoughts on why local area declines in manufacturing and non-manufacturing EPOP have differently-signed impacts on mortality.

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, while Section 4 sheds light on potential mechanisms and implications. Section 5 expands our analysis to other economic shocks, showing differing-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 US.

Our analyses of both NAFTA and the Great Recession, as well as our panel data analysis of recessions more broadly, are all based on 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. For our panel data analysis of recessions (in the spirit of Ruhm (2000)), we take the union of these two data sets and analyze data from 1986 through 2016. Finally, for the China Shock analysis, we follow Autor et al. (2019) and analyze two (stacked) 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 provides yearly county-level population estimates by age, race, ethnicity, and sex.[4]

For most of our analyses, we examine age-adjusted mortality rates in the CZ-year, 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. 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] In some cases, we look separately at mortality in different age-group by sex bins. We also analyze mortality effects separately for the 11 top (mutually exclusive) causes of death and a residual category for all other causes.[6]

[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 data include education, unfortunately the SEER population counts do not.

[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 cause of death classification uses the International Classification of Diseases (ICD) codes and follows the categorization used in Finkelstein et al. (2025).

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]

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; this is inconsequential for the results but allows for greater comparability with the other analyses.

Additional area-level covariates. We obtain additional CZ-level covariates in 1980 from Autor et al. (2019), including share of employment in manufacturing, shares of employment in occupations susceptible to automation and offshoring, and each CZ's racial, education, and gender composition. We also compute 1990-CZ level cancer mortality rates – which we use in some robustness analyses – from the CDC and SEER data described above.

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 our analysis period (Appendix Table OA.9 provides the complete list).

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

[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.

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 US-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 tariffs, from about 2% in 1993 eventually down to zero by the early 2000s.

A priori, 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 US GDP when NAFTA went into effect, and trade between the US and Mexico - which is where most of the NAFTA provisions had an impact - accounted for only about 1.4% of GDP (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 (e.g. 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 intra-national trade is large relative to inter-national trade, the welfare gains from inter-national trade appear to small (Arkolakis et al., 2012; Costinot and Rodríguez-Clare, 2018).

3.2 Empirical Strategy

To assess the impact of NAFTA on mortality, we follow 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 US tariff rates on Mexico (τ^j_{1990}) and in industries that faced stiffer export competition from Mexico (RCA^j) were more vulnerable to NAFTA.

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 vulnerabilty (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}, $\tilde{\text{RCA}}^j = \frac{\text{RCA}^j}{\bar{\text{RCA}}^j}$, where $\bar{\text{RCA}}^j$ is the (unweighted) average revealed comparative advantage over all industries j, 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

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

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 demographic controls for 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 gender composition. 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.[9]

The key coefficients of interest are the β_t's; 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 $\tilde{V}_c$ in 1993 (the year prior to NAFTA) so that all β_t coefficients are relative to 1993. The NAFTA vulnerability measure $\tilde{V}_c$ interacted with year fixed effects have 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; the identifying assumption is therefore essentially a parallel trends assumption testable via the pattern of estimates of the pre-1994 β_t coefficients. In Appendix A.1 we discuss the empirical strategy and identifying assumptions in more detail.

Descriptive Statistics. Figure 1 panel (a) 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 like 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.[10] 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 1 panel (b) 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

[9] 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.

[10] Appendix Figure OA.2b shows how manufacturing share varies across our 3 k-means clusters, and we 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.

had higher mortality rates in 1993 (Figure 1 panel (c)); 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 mortality rates would bias against our finding that places that were more vulnerable to NAFTA experienced an increase in mortality rates.

3.3 Estimated Mortality Impacts

Figure 2 shows the results of estimating equation (4) for 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 goes 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 in the years prior to 1994 in mortality (or in employment) across areas facing different exposure to NAFTA (i.e. the relatively flat pre-trend) is assuring for 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 (shown in light gray), 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.6) even though manufacturing made up just 19% of employment in 1993.

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 1 panel a), this implies that on average, NAFTA increased annual age adjusted mortality by 0.68% over the 1994 to 2008 period. Quantitatively, these estimates 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.[11] Of course 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.

[11] Sullivan and von Wachter (2009) estimate that job loss for these men increased their log-odds of mortality over the next several decades by 7 to 17%. We show in Appendix A.2 how we can use von Wachter (2020)'s estimate that a 1 percentage point increase in the share of workers who are displaced translates into a 0.1 percentage point decline in EPOP to translate our estimates of the impact of EPOP decline to implications for the impact of job loss; our estimates imply that job loss leads to a 15% increase in mortality, squarely within the range of estimates of Sullivan and von Wachter (2009).

Sensitivity analysis. An important potential confound behind the estimates 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, raising the concern that endogenous, unobserved declines in population in more affected areas could lead to spurious estimated effects on mortality rates (Arthi et al., 2022).[12] However, 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.4); nor do we find evidence of compositional changes in population demographics when we look at impacts on population by birth cohrot by sex bins (Appendix Figure OA.5). 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 - or limiting the analysis to the Southern Census region where vulnerability to NAFTA was highest; Appendix A.3 describes these and other sensitivity analyses in more detail.

4 Mechanisms and Implications for NAFTA's Mortality Impact

4.1 Potential mechanisms

Mortality Impacts by Sex and Birth Cohort. To better understand the results in Figure 2, we re-estimate equation (4) separately by for different birth cohorts: those who, at the start of NAFTA, would have been 0-24, 25-44, 45-64 and 65 and over. NAFTA increases mortality for all eight sex by birth cohort groups, with the percentage increase in mortality smallest for men who were 65 and over when NAFTA was implemented in 1994, and largest for men who were 25-44 in 1994 (Figure 3, panel (a)). Relative to men aged 24-44 in CZs in the bottom quartile of NAFTA vulnerability, those 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). By contrast, for men 65 and over, the comparable estimate is a mortality increase of only 0.89% (standard error = 0.36).

EPOP declines from NAFTA were also disportionately concentrated among men aged 25-44 in 1994 (see Appendix A.4), suggesting that the larger mortality impacts for this demographic group could be related to their larger rate of EPOP decline. However, the evidence of NAFTA-induced mortality increases for individuals 65 and over points to the operation of additional mechanisms than a direct effect of job loss. Indeed, given the much higher baseline mortality rates for the elderly, men and women 65 and over account for about half of the increase in deaths due to NAFTA, while men aged 25-64 accounted for about one-third of the increase in deaths due to NAFTA (Figure

[12] 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/.

3b). One potential channel for increases in elderly mortality may be a loss in financial support from children or grandchildren who have lost their job. 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, may also reflect the indirect channel of reduced resources within the household for children. Some suggestive evidence that is consistent with reduced financial transfers as a mechanism for increased elderly mortality is the pattern of mortality increases among the elderly. Elderly women tend to outlive their spouses and experience a substantial decline in economic resources upon widowhood (e.g. Diamond and Orszag (2005)), which may make them more reliant on transfers from younger family members.[13] Moreover, three quarters of the NAFTA-induced deaths among elderly men and women are among elderly women (Figure 3b), with most of these increases coming from elderly widows (Appendix Figure OA.21).[14]

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.[15] Almost all causes of death show statistically significantly elevated effects, with particularly pronounced effects for infectious disease.

We also find that NAFTA increases so-called "deaths of despair" (Case and Deaton, 2020), a very small share of overall deaths but ones that also increased with exposure to the China Shock (Pierce and Schott, 2020). Figure 5 shows the impacts on deaths classified as "deaths of despair", as well as for the three sub-categories: drug-related deaths, suicides, and alcohol-related deaths.[16] For the full sample, there is a statistically significant increase in deaths of despair, with increases in all three sub-categories, and statistically significant increases in drug-related deaths and in suicides. For men who were 25-44 in 1994, there is a statistically significant increase in alcohol-related mortality, and large but imprecise increases in drug-related mortality.

[13]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.

[14]Another possible channel for effects on the elderly could be via impacts on pollution (Finkelstein et al., 2025), yet it is not clear why these would be disproportionately concentrated in elderly women. We do not find evidence of pollution effects of NAFTA, but our estimates are quite imprecise estimates due to data sparsity; only 234 counties accounting for 40% of the US 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.

[15]Appendix Figures OA.9 and OA.10 show results for the other demographic groups.

[16]We define alcohol-related deaths using ICD codes for liver disease, alcohol-induced psychosis, and alcohol dependence syndrome. We define suicide directly from the NCHS coding system. Finally, we define drug-related deaths using ICD codes for accidental drug poisonings, drug-induced psychosis, drug dependence, and non-dependent abuse of drugs.

Other health-related outcomes. We use the NHIS data to analyze impacts on self-reported health, health behaviors, health insurance coverage and health care utilization; Appendix Figures OA.11 through OA.14 show the results. Consistent with the NAFTA-induced increase in mortality, NAFTA also increased morbidity measures, specifically the probability someone reports themselves in fair or poor health (as oppposed 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 also increased smoking rates, overall and especially for men aged 45-64 when NAFTA was introduced, but has no statistically significant impact on rates of flu shots. 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; this presumably reflects an increase in the share of this demographic receiving Social Security Disability Insurance, 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 only capture the local labor market impacts of NAFTA and not any nationwide impacts that might operate, for example, through reduced prices and hence increased real disposable income. To gauge the quantitative importance of the local labor market mortality impacts of NAFTA relative to those general equilibrium welfare gains, 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 accept (as a percentage of lifetime consumption) to avoid facing NAFTA, and follow the approach in Finkelstein et al. (2025) to approximate the welfare effects of NAFTA with endogenous mortality (Δ^{dT}) by:

$$\Delta^{dT} \approx \Delta + dT * \left(\frac{VSLY}{c} + \frac{1}{\gamma - 1}\right) \tag{6}$$

where Δ denotes the welfare impact of NAFTA when mortality is exogenous, dT is the percentage change in life expectancy due to NAFTA, $VSLY$ is the value of a statistical life year, and γ is the CRRA parameter over annual consumption c. Appendix A.5 provides more details behind the model and this derivation.

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.

We calibrate equation (6) using our estimated impacts of NAFTA on mortality combined with 1993 SSA life tables for dT. Appendix Table OA.6 shows impacts on life expectancy (dT) using both our homogeneous mortality estimates (panel A), and 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. For the other parameters in equation 6 we take estimates from the literature. We calibrate $\Delta = 0.11\%$ (i.e.NAFTA increases real wages permanently by 0.11 percent) based on Caliendo and Parro (2015).[17] We assume a coefficient of relative risk aversion (γ) of 2, and we assume a value of a statistical life year that is either 2 or 5 times annual consumption (i.e. $VSLY/c = 2$ or 5).[18]

Strikingly, these calibrations suggest that accounting for our estimates of endogenous mortality changes the sign of the welfare effect of NAFTA from a 0.11 percent welfare *gain* (coming through the increase in real wages) to a net welfare *loss* (Appendix Table OA.7). For example, for a 45 year-old male, panel B suggests a net welfare loss from NAFTA of 0.17% to 0.45% of annual consumption, depending on whether we set VSLY/c to 2 or 5.

Naturally this calculation is highly stylized. We do not view it as a definitive welfare analysis of NAFTA per se, but rather as an illustration 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, 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.[19] Second, our mortality estimates (and our welfare analysis of them) have the standard "missing intercept" issue in empirical macroeconomics when extrapolating local labor market estimates nationally (Wolf, 2023). Specifically,

[17] This 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 (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.

[18] There are a wide range of risk aversion parameters in the literature, but we simply choose one in the range of reasonable alternatives for illustrative purposes. Likewise there are a range of plausible estimates for the VSLY. With annual consumption of roughly $50k in 2013 (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) and is used by, among others, Cutler (2005) and Cutler and Sportiche (2022) and is similar to the baseline VSLY in Hall and Jones (2007). A VSLY of 5 times average consumption (or about $250k) corresponds to about the middle of the range of VSLY estimates in Kniesner and Viscusi (2019).

[19] For example, additional potential benefits of tariff reductions could include welfare gains arising from changes in investment expenditures (Ding, 2025), 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.

we assume that we can aggregate our "local" NAFTA estimates to get an estimate of the overall national effect of NAFTA on mortality, ignoring any national general equilibrium effects that are not captured by our local labor market estimates. In particular, if NAFTA has an overall positive effect on income and consumption that is common across local labor markets (as in Caliendo and Parro (2015)) this might reduce mortality and would not be captured by our mortality estimates. However, in practice, as we discuss in Appendix A.5, any such national income effect on mortality is likely to be quantitatively important (and arguably wrong-signed).

Finally, it is worth noting that if NAFTA-induced mortality effects do not stem from externalities and agents are behaving privately optimally, the usual envelope theorem arguments would tell us that, to first order, they are not welfare-relevant.[20] However, even if these assumptions hold, NAFTA's mortality impacts may provide a way to characterize some of the distributional economic impacts of NAFTA given data limitations that preclude directly estimating heterogeneity in the consumption impacts of NAFTA, which 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), may serve as empirical proxies for some of the large drops in consumption experienced by a subset of the population.[21]

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)). Further muddying the waters is the lack of empirical clarity of the sign or magnitude of the impact of income on mortality.[22] Such findings raise questions about the likely sign of mortality impacts of other local

[20]By contrast, a failure of either of these assumptions would necessitate estimating the impact of NAFTA on all welfare-relevant arguments of the utility function, including presumably mortality (Finkelstein et al., 2019)

[21]Formally, our approach is valid whether or not individuals optimally adjust their behavior in response to NAFTA under the assumption that we have an accurate estimate of the willingness to pay for reductions in mortality.

[22]There is a well-documented negative relationship between income and mortality within countries, across countries, and over time (e.g. Cutler et al. (2006); Costa (2015); Chetty et al. (2016); Cutler et al. (2016)), but 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)), with some evidence that income receipt, by encouraging risky drug and alcohol use, may even be bad

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. Specifically, we consider whether the mortality impacts of local labor market declines in manufacturing EPOP and in non-manufacturing EPOP may differ. To do so, we examine four sources of local labor market economic 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)).

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

for health and mortality (e.g. Dobkin and Puller (2007); Evans and Moore (2012); Chorniy et al. (2025)).

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

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 EPOP overall ($EPOP^A_{ct}$) and mortality.

We consider four different vectors of economics 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-point increase in the 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 analagous estimation of equation (7) but estimate equation (8) by IV, instrumenting for the endogenous variable EPOP^A_{ct} with the first stage equation (7). The three economics 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 an additional assumption, namely the exclusion restriction that each of these local economic contractions affects mortality only via their impact on EPOP.[23]

For the Great Recession:

$$Z_{ct} = \begin{bmatrix} \text{GR\_SHOCK}_c \times \tilde{t} \times \text{POST}_t & \text{GR\_SHOCK}_c \times \tilde{t}^2 \times \text{POST}_t \end{bmatrix} \tag{9}$$

where (GR_SHOCK_c) denotes the percentage point change in CZ c's EPOP^A between 2007 and 2009, 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. There are no additional covariates X_{ct} and we follow Finkelstein et al. (2025) and analyze the impact of the Great Recession over the 2003 to 2016 period.

For NAFTA:

[23] For prior estimates of the 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, 2019, 2025)), to the best of our knowledge, the impact of the China Shock on all-age, all-cause mortality has not been previously reported.

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

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 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 little 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.[24] Therefore in equation (7):

$$Z_{ct} = \left[\begin{array}{c} \Delta\text{IP}_{c,t} \end{array}\right] \tag{11}$$

where $\Delta\text{IP}_{c,t}$ is the measure of Chinese import penetration into CZ c and period t used by Autor et al. (2019). Because this is constructed using contemporary employment shares and imports into the United States, it is potentially endogenous. As a result, we follow Autor et al. (2019) and instrument for Z_{ct} in equation (7) using

$$\tilde{Z}_{ct} = \left[\begin{array}{c} \Delta\tilde{\text{IP}}_{c,t} \end{array}\right] \tag{12}$$

where $\Delta\tilde{\text{IP}}_{c,t}$ is Autor et al. (2019)'s instrument for changes in Chinese import penetration in each period, and depends on the lagged 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). In equation (8), we estimate β 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 and 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.[25]

[24] 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 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.

[25] 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

Table 2 shows that a recession-induced percentage point decline in local area overall EPOP ($EPOP_{ct}^{A}$) - whether in the OLS or instrumenting for $EPOP_{ct}^{A}$ based on exposure to the Great Recession - is associated with about a 0.5 percentage point *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 percentage point *increase* in mortality.[26] Specifically, the OLS estimates in column (1) indicate that a 1 percentage point decline in CZ-year overall EPOP is associated with a 0.35% (standard error = 0.12%) decline in mortality. 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 = 0.26%) decline in mortality and 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 column (3) shows that the results look very different if we instead use variation in exposure to NAFTA as instruments for overall EPOP; a 1 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 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 1 percentage point China-Shock induced decline in EPOP results in a 1.54% (standard error = 0.76) increase in mortality.[27] 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 and non-manufacturing EPOP declines

Finally, to directly examine whether declines in local area manufacturing and non-manufacturing EPOP have differential effects on mortality, 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.

was higher over the 1986-2008 period analyzed in row 1.

[26] In Appendix Table OA.5, 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 GR_SHOCK_c or the NAFTA vulnerability measure V_c).

[27] Our first stage is not as strong as those in columns (2) and (3), but weak instruments bias toward the OLS relationship between mortality and EPOP 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.

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, $\text{GR\_SHOCK}_{s,c}$ is the 2007-2009 change in the EPOP ratio in CZ c and sector $s \in S$, and $\mathcal{S}$ consists of the manufacturing ($s = m$) and non-manufacturing $s = n$) sectors.[28] 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.

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:

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

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. EPOP^M_{ct} and EPOP^N_{ct}). 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^M_r and a decline in non-manufacturing EPOP of ΔEPOP^N_r. Assuming additive separability, the predicted percent change in mortality per unit change in EPOP induced by economic shock r is given by

[28] The Great Recession shock GR_SHOCK_c defined in equation (9) as the 2007-2009 change in the overall EPOP ratio is the sum of the 2007-2009 changes in the EPOP ratio in the manufacturing section ($\text{GR\_SHOCK}_{m,c}$) and non-manufacturing sector ($\text{GR\_SHOCK}_{n,c}$).

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

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); as seen in Finkelstein et al. (2025), a 1-point drop in the EPOP ratio during the Great Recession decreases annual age-adjusted mortality by 0.5% (standard error = 0.1%). However, this estimate masks important underlying heterogeneity in the relationship between mortality and industry-specific employment. This can be seen in panel (b) which displays estimates of $\theta_{s,t}$ from equation (13). A one-point decrease in EPOP in the manufacturing sector leads to a (statistically significant) *increase* in mortality by 1.4% (standard error = 0.4%) while a one percentage point decrease in EPOP in the non-manufacturing sector leads to a (statistically significant) *decrease* in mortality by 1.1% (standard error = 0.2%).

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 of 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 0.32 percent decline in mortality from a 1 percentage point decline in yearly, CZ-level overall EPOP, which is very similar to the estimated impact of ofa 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.

An important question for further work is *why* these two types of EPOP declines appear to have opposite signed impacts on mortality. Broadly speaking, there are two classes of potential explanations. The first is that it is not declines in manufacturing EPOP *per se* that increase mortality, but rather declines in EPOP among the demographic that is disproportionately employed in manufacturing, namely prime aged men. Consistent with this hypothesis, we found that for both NAFTA and the China Shock, increased mortality is disproportionately concentrated among working age men (see Appendix Table OA.2) - whose employment is most affected - while prior evidence from recession-induced mortality declines suggest that mortality declines by a similar percent across age groups, meaning that the vast majority of the mortality declines are among the elderly who are not directly affected. However, we find that declines in local area manufacturing EPOP for either prime age men or for other demographics are associated with rises in mortality, whereas declines in local area non-manufacturing EPOP for either prime age men or for other demographics are associated with declines in mortality. Specifically, we re-estimate the impact of the Great Recession EPOP declines on mortality in equation (13), now allowing for separate effects of local area declines in manufacturing EPOP among prime age men (ages 25-44 in 2006) and other demographics, as well as separate effects of local area declines in non-manufacturing EPOP among prime age men, and other demographics (see Appendix Figure OA.24). The other class of potential explanations is that there is something about declines in manufacturing EPOP per se that increase mortality. For example, manufacturing jobs may be high rent jobs – they have higher rates of unionization, wages and job tenure (Rose and Shem-Tov, 2023) – and therefore the outside option for workers who lose a manufacturing job may be considerably worse relative to their manufacturing job than for workers in other sectors. Naturally, this warrants further investigation.

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 welfare consequences of these NAFTA-induced mortality declines are large enough to more than erase prior estimates of the general equilibrium welfare gains from NAFTA operating through increased real wages. These results are 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 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.

We also developed a unified empirical framework to explain disparate findings across economic settings in the sign of the mortality impacts of local economic contractions. 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 for trade shocks. These 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.

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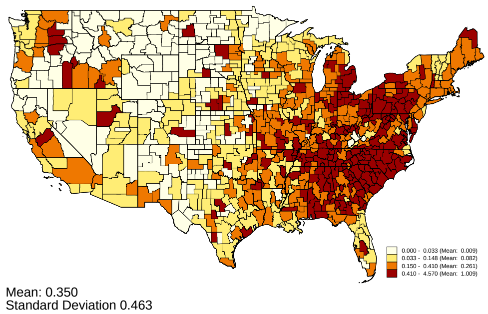
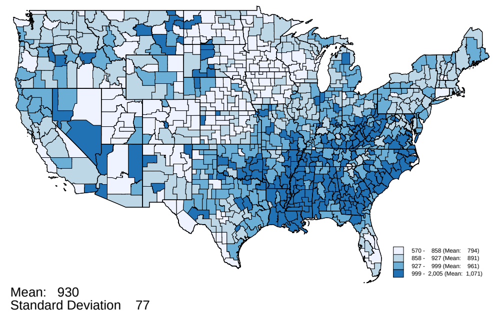
Figures

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

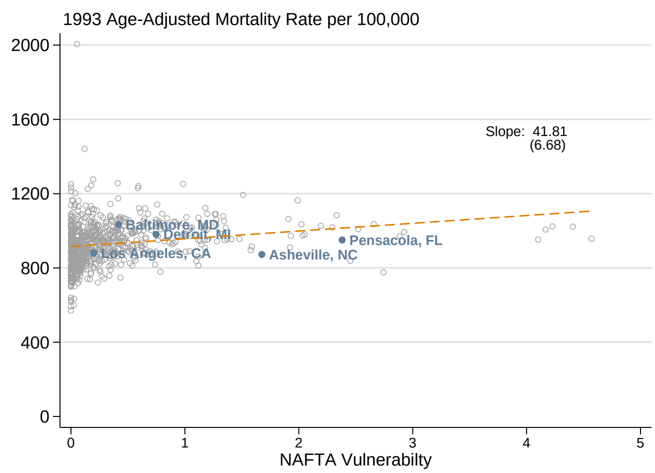
(a) NAFTA Vulnerability



(b) 1993 Age-Adjusted Mortality

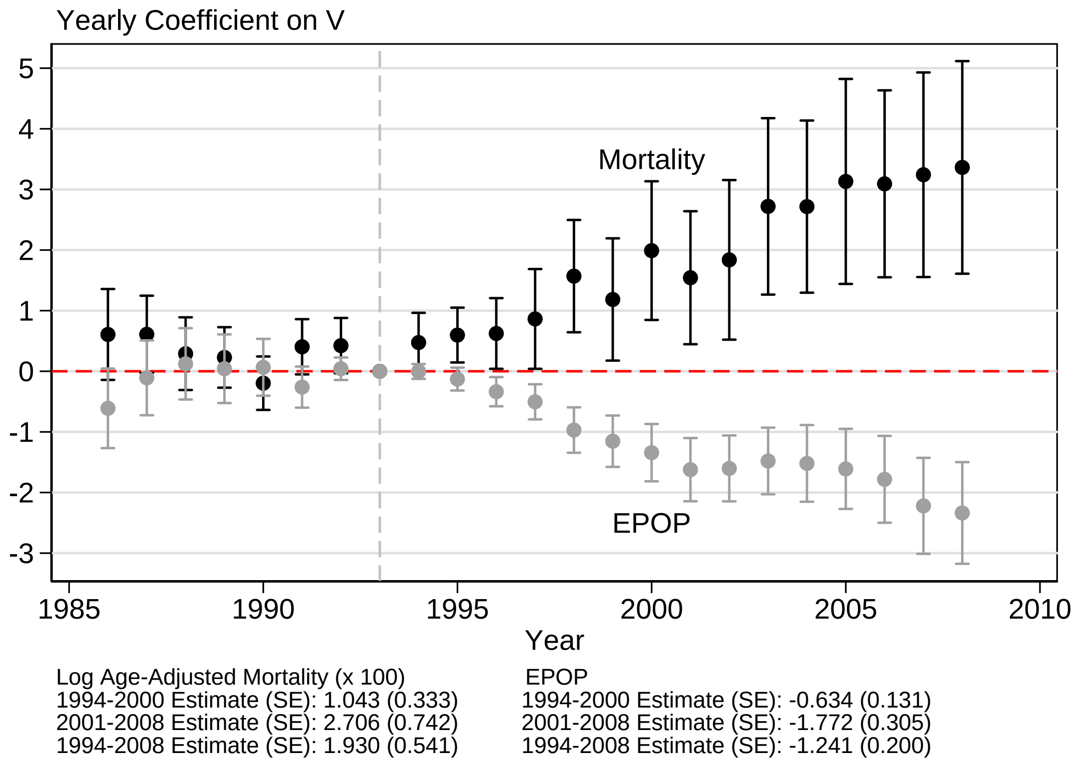


(c) Correlation of Baseline Mortality and Vulnerability



Notes: Panel a displays a heatmap of the NAFTA vulnerability measure 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.

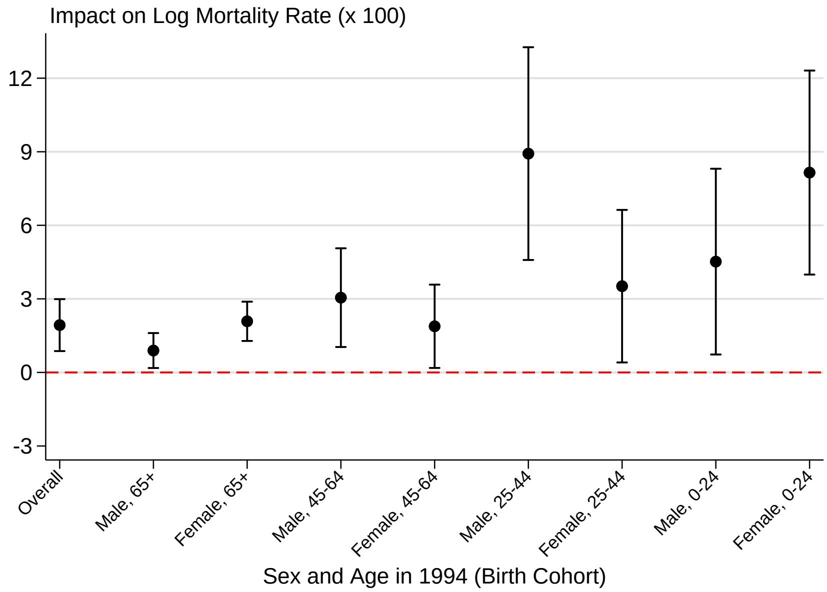
Figure 2: Impact of NAFTA Vulnerability on Log Mortality



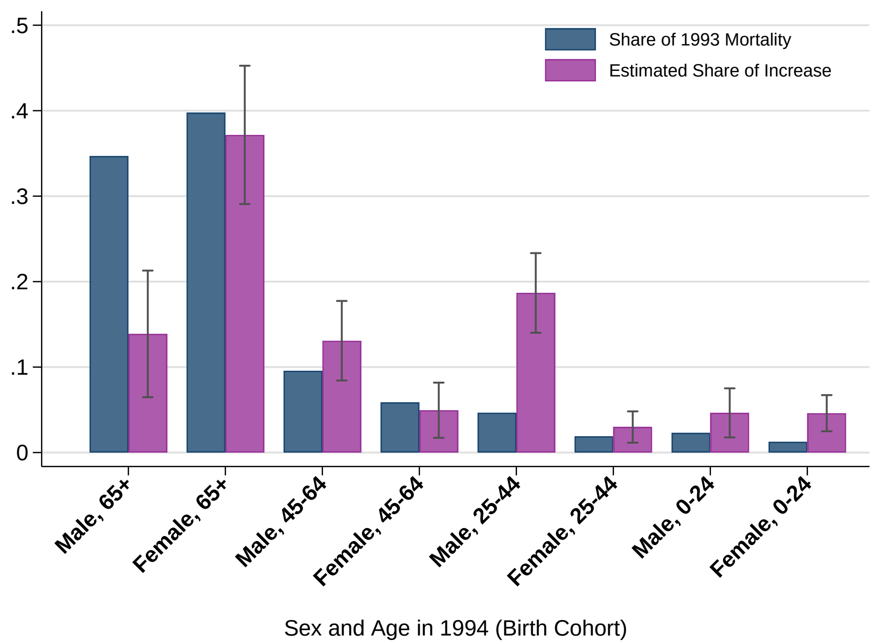
Notes: This figure displays (in black) 100 times estimates of β_t from equation (4), where the outcome y_{gt} is the log age-adjusted CZ mortality rate per 100,000. It also shows (in gray) estimates of β_t with EPOP as the outcome. The units can be interpreted in terms of percent changes for mortality and percentage *point* changes in EPOP. A one-point increase in NAFTA vulnerability V_g 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: Mortality Decomposition By Birth Cohort and Gender

(a) 1994-2008 Pooled Estimates



(b) 1994-2008 Decomposition

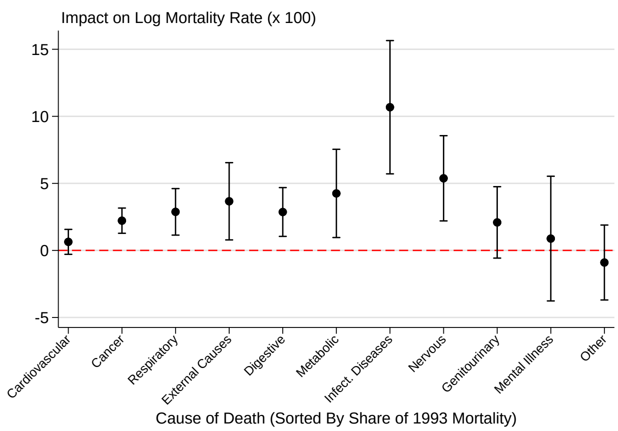


Notes: Panel (a) gives the average 1994-2008 estimate of β_t in equation (4) with the log mortality rate for each demographic group given on the x-axis as the outcome; Appendix Figure OA.7 shows the underlying event studies behind each estimate. In panel (b), the blue bars denote the share of deaths 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.

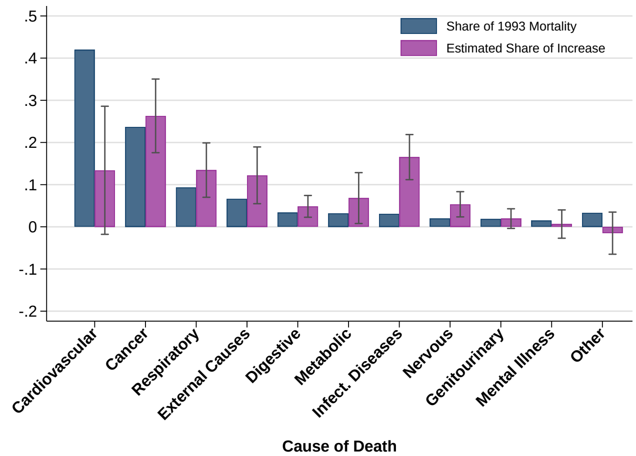
Figure 4: NAFTA Mortality Impacts By Cause of Death

Full Sample

(a) Point Estimates

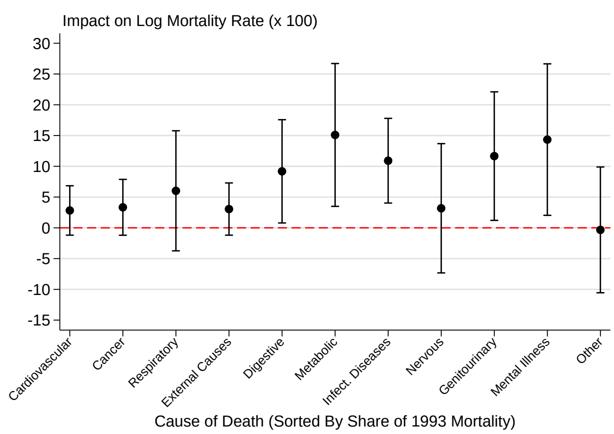


(b) Decomposition

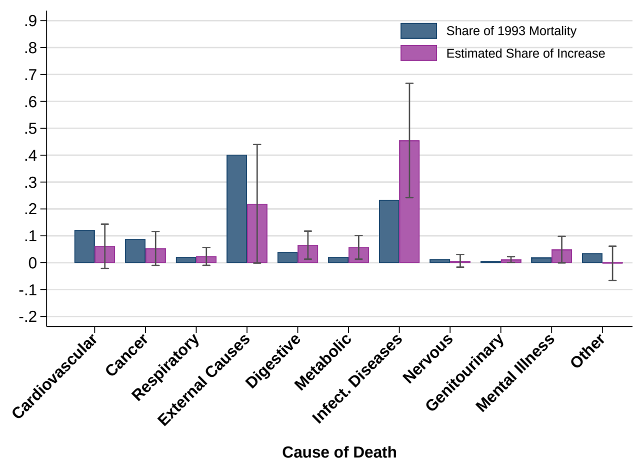


(Men Born 1950-1969)

(c) Point Estimates



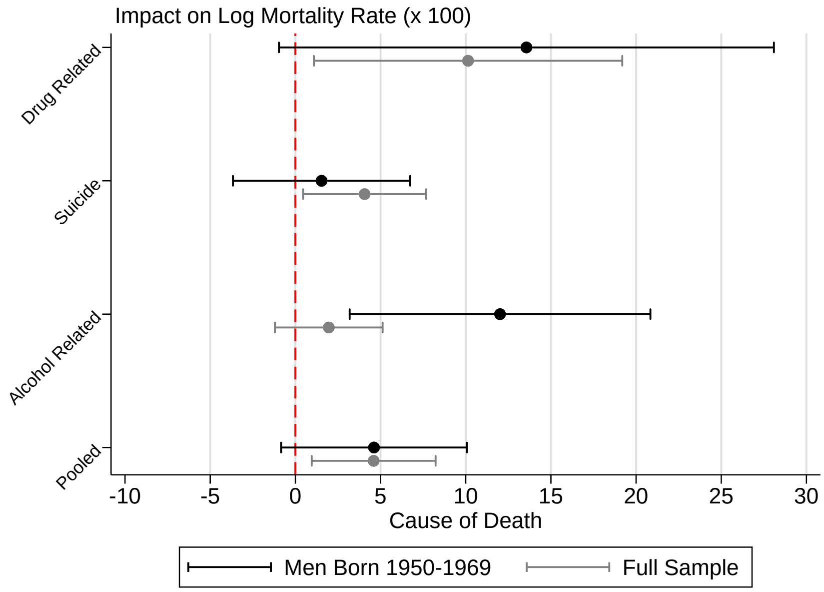
(d) Decomposition



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.15, OA.16, OA.17 and OA.18.

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.

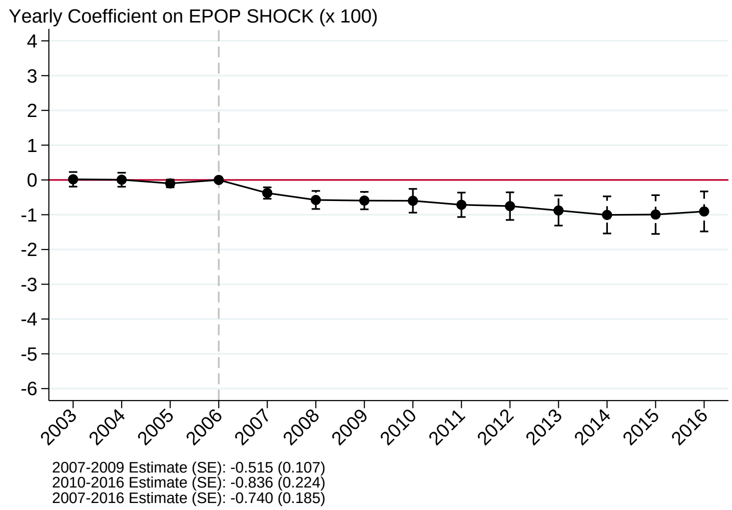
Figure 5: NAFTA Mortality Impacts on Deaths of Despair



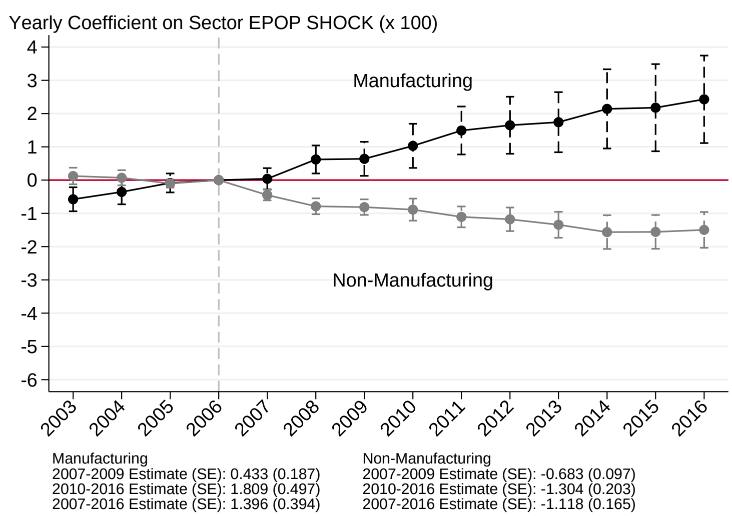
Notes: This figure displays 100 times the average estimate of β_t in equation (4) over the 1994-2008 period, where the outcomes are the log mortality rate per 100,000 among men born between 1950 and 1969 (black bars) and age-adjusting the entire sample (gray bars) by selected causes of death. Appendix Figures OA.19 and OA.20 show the underlying event studies. A one-point increase in NAFTA vulnerability V_g 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 Great Recession EPOP Shocks on Mortality by Industry

(a) Total EPOP



(b) Manufacturing vs. Nonmanufacturing



Notes: This figure displays 100 times event study coefficients from estimating equation (13) on a single Great Recession shock variable (GR_SHOCK$_c$) in panel a, and estimates of $\theta_{s,t}$ from estimating equation (13) on two Great Recession Shocks (GR_SHOCK$_{s,c}$) for $s \in m, n$ in panel b. 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}. The first row 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 (3), 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 ($\times$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 (3), 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 estimates of the effect of each economic shock on 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 Great Recession instruments in equation (15). To construct standard errors (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 $Z_{ct} = \text{EPOP}_{ct}^{A}$. Controls for each specification are given in the text. 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). 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 exogeneous 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 the 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 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. We found that a 1 percentage point decrease in EPOP as a result of NAFTA increases average annual age adjusted mortality rates by 1.5%. To compare these numbers, we note that a one percentage point decline in EPOP (whose effects we estimate) does not necessarily map directly into a one-percentage point increase in the rate of job loss; some individuals who lose their job may find new employment within the year (making the job loss rate higher than the EPOP decline), and some individuals may voluntarily leave their jobs (making the job loss rate lower than the EPOP decline).

To benchmark these against each other, we therefore follow the framework in von Wachter (2020) and write the EPOP ratio as

$$\mathrm{EPOP}_t = \mathrm{EPOP}_t^{\mathrm{ND}} + \delta^D \times \pi_t^D \tag{19}$$

where $\mathrm{EPOP}_t^{\mathrm{ND}}$ denotes the number of individuals who were not displaced between years $t-1$ and t divided by the working-age population, δ^D denotes the reduction in EPOP due to displacement, and π_t^D is the share of workers displaced between years $t-1$ and t. Taking first differences, we have

$$\mathrm{EPOP}_{t+1} - \mathrm{EPOP}_t = \underbrace{\mathrm{EPOP}_{t+1}^{\mathrm{ND}} - \mathrm{EPOP}_t^{\mathrm{ND}}}_{=0} + \delta^D \left(\pi_{t+1}^D - \pi_t^D\right) \tag{20}$$

von Wachter (2020) estimates $\delta^D = -0.1$, meaning that a 1 percentage point decrease in EPOP implies a 10 percentage point increase in share of workers displaced. Thus, we scale 1.5% by 10 (since losing one's job corresponds to a 100% chance displaced) to conclude that our estimates imply that job loss leads to a 15% increase in mortality, which is precisely in Sullivan and von Wachter (2009)'s range of estimates.

A.3 Sensitivity analysis of mortality estimates.

Contemporaneous shocks. Another 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.4 panel B therefore shows that the estimated mortality effects of NAFTA are robust to controlling flexibly for these other shocks; Appendix Figure OA.22 presents the underlying event study estimates.

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.4 panel a summarizes the results, and Appendix Figure OA.22 presents the underlying event studies.

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.

A.4 Imputed Employment Effects By Cohort and Gender

As a point of comparison, 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 birth cohort and gender 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.[29] Specifically, we compute the employment-to-population ratio in each industry i by year by commuting zone using the CBP and SEER data, and estimate equation (4) using each industry-specific EPOP ratios as an outcome to obtain estimates β_t^i of the impact of NAFTA on EPOP in different industries. 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 demographic d working in industry i in 1993. Specifically, we use the 1993 CPS to compute $s_{i,1993}^d$, 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_t^i and treat the shares $s_{i,1993}^d$ as fixed.

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

Results. Appendix Figure OA.8 panel (a) summarizes the results; Appendix Figure OA.23 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.3). The NAFTA-induced EPOP decline for men in this cohort thus represented about a 1 percent decline in their average EPOP.

In Appendix Figure OA.8 panel (b), 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 are responsible for a much larger share of the decrease in employment than women in the same age group, mirroring the fact that they make up a much larger share of the increase in mortality as well (Figure 3).

A.5 Welfare Analysis of NAFTA with Endogenous Mortality

To gauge how allowing for NAFTA to affect mortality impacts welfare analysis of NAFTA, we write and calibrate down 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.[30] 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 stochaster 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:

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

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

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

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

[30] 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.

additional years of life.[31] 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

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

The welfare effects of NAFTA when mortality is exogenous. In this simplified model, if we ignore any potential effects of NAFTA on mortality, the effects of NAFTA on welfare come entirely from its effects 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 effects of NAFTA as the hypothetical amount the representative agent would be willing to accept (as a percentage of lifetime consumption) to avoid facing the wage and price effects of NAFTA. We denote this by Δ, and it is defined implicitly as:

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

In other words, Δ represents the percentage of annual consumption that you would have to give an individual to leave her with the same expected utility as she has 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 NAFTA increased real wages by 0.11% (i.e., this is 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.[32]

The overall welfare gains from NAFTA are fairly small in Caliendo and Parro (2015) which 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 tarrif 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.

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 by assuming 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

[31] Since consumption is constant over time, the value of a statistical life-year (VSLY) is given by $\text{VSLY} = \frac{U/u'(c)}{T} = bc^{\gamma} - \frac{c}{\gamma-1}$.

[32] Caliendo and Parro (2015) report an overall welfare gain of 0.08% which is somewhat lower than the effect of NAFTA on real wages; the difference comes from the additional effects of NAFTA on the trade deficit and changes tariff revenue, which we ignore here.

as:

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

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:

$$\Delta^{dT} \approx \Delta + dT * \left(\frac{VSLY}{c} + \frac{1}{\gamma - 1}\right) \tag{22}$$

In other words, 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 $T * (1 + dT)$). 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.6 and OA.7 are based on local labor market impacts of NAFTA on mortality, and 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 this unlikely to be quantitatively important. For one thing, we conduct a simple calibration of the possible mortality benefits by assuming that the overall national change in income and consumption as estimated in Caliendo and Parro (2015) is the same across all local labor markets, and using the cross-sectional relationship between income and life expectancy reported in Chetty et al. (2016) together with our baseline parameterization results (i.e. $\gamma = 2$ and VSLY/c = 5). This produces a fairly small change in our estimate of Δ^{dT} for a 45 year old male, from -0.0926 (see Appendix Table OA.7 Panel B) to -0.0902.[33] 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)).

An alternative way to think about the missing intercept problem is that the overall effect of NAFTA on EPOP may be different than what we get from aggregating our local labor market estimates; specifically, there may be places that produce goods and services that are not directly affected by tariffs but are indirectly (positively) affected through changes in the terms of trade.[34]

[33] 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), 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.

[34] Intuitively, places with "zero vulnerability" to tariffs may have still experienced EPOP increases, but our aggre-

If these areas actually did experience NAFTA-induced increases in EPOP, and thes EPOP changes in turn affected mortality, then these mortality effects are missing from our welfare analysis. We note that to the extent that this occurred, the "missing" increased EPOP likely occurred in *non-manufacturing* sectors, and we present evidence in Section 5 that changes in non-manufacturing EPOP have the opposite-signed impact on mortality from changes in manufacturing EPOP. As a result, the fact that we ignore potential increases in non-manufacturing EPOP in "zero vulnerability" places suggests that if anything we are *understating* the magnitude of the adverse effect of NAFTA on mortality nationally.

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):

$$Y_{c,\tau} = \alpha_\tau + \beta_1 \Delta \text{IP}_{c,\tau} + \mathbf{X}'_{c,\tau}\beta_2 + \epsilon_{c,\tau} \tag{23}$$

where $Y_{c\tau}$ is the age-adjusted cumulative mortality rate in period τ (we stack the 1990-2000 and 2000-2014 periods), normalized to ten-year equivalents (that is, $Y_{c,\tau}$ is multiplied by $\frac{10}{14}$ for the second period) to make units comparable across periods.[35] Period fixed effects are denoted by α_τ, and $\mathbf{X}_{c,\tau}$ denotes the vector of controls used in Autor et al. (2019)[36]. $\Delta \text{IP}_{c,\tau}$ is Autor et al. (2019)'s measure of the change in Chinese import penetration in each period, and 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:

$$\Delta \text{IP}_{c,\tau} = \sum_i \frac{L_{c,i,90}}{L_{c,90}} \Delta \bar{\text{IP}}_{i,\tau} \tag{24}$$

where $L_{c,90}$ is the total employment in CZ c in 1990, $L_{c,i,90}$ is the industry-i specific employment in CZ c in 1990, and

$$\Delta \bar{\text{IP}}_{i,\tau} = \frac{\Delta M_{i,\tau}}{Y_{i,91} + M_{i,91} - X_{i,91}} \tag{25}$$

where $\Delta M_{i,\tau}$ represents the growth in imports from China in industry i and period τ divided by initial absorption (industry shipments in 1991 $Y_{i,91}$, plus net imports $M_{i,91} - X_{i,91}$).

To avoid simultaneity bias, we follow Autor et al. (2019) and instrument for $\Delta \text{IP}_{c,\tau}$ using 1980 industry employment shares in the CZ interacted with growth in Chinese import penetration in each industry to eight other wealthy nations[37]:

gation implicitly assumes that they were unaffected by NAFTA. This argument is similar to the oft-repeated claims that workers in Silicon Valley benefited from the China Shock even though Silicon Valley was not directly affected according to standard measures of import competition.

[35] 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.

[36] These include time trends for Census division, 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)

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

$$\Delta \tilde{\text{IP}}_{c,\tau} = \sum_i \frac{L_{c,i,80}}{L_{c,80}} \Delta \tilde{\text{IP}}_{i,\tau} = \sum_i \frac{L_{c,i,80}}{L_{c,80}} \frac{\Delta \tilde{M}_{i,\tau}}{\tilde{Y}_{i,88} + \tilde{M}_{i,88} - \tilde{X}_{i,88}} \tag{26}$$

where $\Delta \tilde{M}_{i,\tau}$ represents the growth in imports for industry i from China in period τ for the other countries divided by initial absorption (industry shipments for these other countries in 1988 $\tilde{Y}_{i,88}$, plus net imports $\tilde{M}_{i,88} - \tilde{X}_{i,88}$).

Appendix Table OA.1 column (1) reports the results: a 1 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 222 per 100,000 (standard error = 74.1), or about a 2.5 percent increase in mortality relative to an average 10-year mortality of 8,856 per 100,000. In columns (2), (3), and (4) we estimate equation (23) with the long-differenced EPOP and sector-specific EPOP in each period on the left-hand side. Like NAFTA (and as documented in previous work), manufacturing accounts for the vast majority (91%) of the overall decline in the EPOP ratio. This is even starker than the 78% due to NAFTA as noted earlier in Figure OA.6.Column (2) shows that a 1 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 = 0.5).

To align this with our IV analysis of NAFTA and the Great Recession in Table 2, we estimate the analogue of equations (7) and (8) in first differences. Specifically, we estimate

$$y_{c,\tau} = \alpha_\tau - \beta \Delta \text{EPOP}_{c,\tau} + \mathbf{X}'_{c,\tau}\psi + \epsilon_{c,\tau} \tag{27}$$

where $y_{c,\tau}$ denotes the log age-adjusted cumulative mortality rate in CZ c and period τ, α_τ denotes period fixed effects, $\mathbf{X}_{c,\tau}$ is the same set of control variables as in equation (23), and $\Delta \text{EPOP}_{c,\tau}$ is the change in EPOP over the period. We instrument for this using the first stage equation

$$\Delta \text{EPOP}_{c,\tau} = \alpha_\tau + \phi \Delta \tilde{\text{IP}}_{c,\tau} + \mathbf{X}'_{c,\tau}\psi + \eta_{ct} \tag{28}$$

where $\Delta \tilde{\text{IP}}_{c,\tau}$ is defined as in equation (26). 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 $\Delta \text{EPOP}_{c,\tau}$. The estimate of β in column (4) of Table 2 indicates that a 1 percentage point China-Shock induced decline in EPOP results in a 1.54% (standard error = 0.76) increase in age-adjusted mortality.

In Table OA.2, we estimate equation (23) with the cumulative mortality rate for several demographic subgroups defined by age and gender. 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.

C Heterogeneous Great Recession Impacts By Sector

In Section 5, we explored the idea that the mortality impacts of economic contractions depend on how the contraction affects employment in the manufacturing vs. non-manufacturing sectors. Even during the Great Recession, for which harder-hit CZs experienced *decreases* in mortality, we found that areas with a larger shock to manufacturing employment—holding shocks to non-manufacturing employment constant—experienced subsequent *increases* in mortality. To do this, we estimated the augmented event study equation

$$y_{ct} = \sum_{s \in \mathcal{S}} \theta_{s,t} \left[\text{GR\_SHOCK}_{s,c} \times \mathbf{1}\left(\text{Year}_t\right) \right] + \alpha_c + \tau_t + \epsilon_{ct} \tag{29}$$

where $\text{GR\_SHOCK}_{s,c}$ is the 2007-2009 change in the EPOP ratio in sector $s \in S$, and $\mathcal{S}$ consists of the manufacturing ($s = m$) and non-manufacturing $s = n$) sectors. We found positive post-period estimates of $\theta_{m,t}$ (indicative of an increase in mortality due to manufacturing shocks) and negative post-period estimates of $\theta_{n,t}$ (indicative of a decrease in mortality due to non-manufacturing shocks).

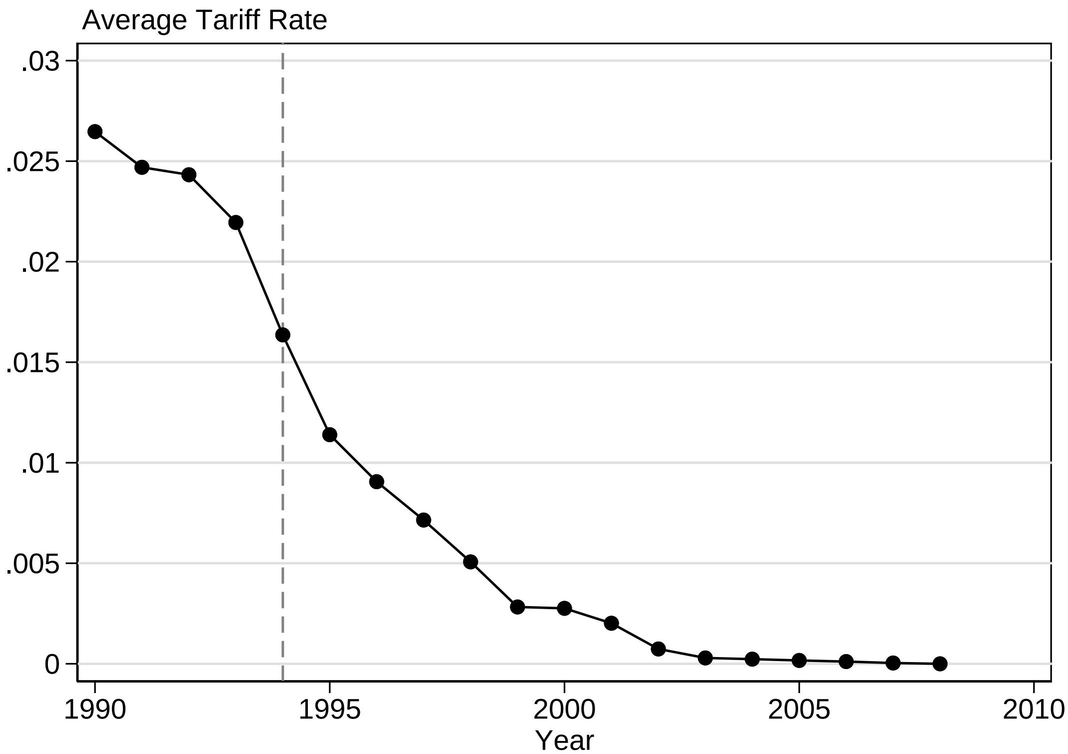
A natural question, then, is whether this heterogeneity is really driven by shocks to manufacturing, per se. In our analysis of NAFTA, we found that the largest EPOP decreases and mortality increases were concentrated among prime-aged (25-44 year-old) men. Previous studies of the relationship between job loss and mortality (e.g. Sullivan and von Wachter, 2009) also tend to focus on this demographic group. Furthermore, prime-age men composed 30% of manufacturing employment in 2006. In this section, we explore the extent to which shocks to employment among prime-aged men may be driving these results rather than shocks to manufacturing.

To do this, we augment equation (29) so that $\mathcal{S}$ consists of four subgroups instead of two: manufacturing among prime-aged men (i.e. those born 1963-1982 and were thus aged 25-44 in 2007), which we denote m_p, manufacturing among all other age/gender bins (m_o), non-manufacturing among prime-aged men (n_p), and non-manufacturing among all other age/gender bins (n_o). To estimate this equation, we construct the corresponding EPOP shocks $\text{GR\_SHOCK}_{s,c}$, we use data from the American Community Survey (ACS) to impute employment by birth cohort, industry, and gender. Specifically, we crosswalk each respondent's Public Use Micro Area (PUMA) to CZs, use their age and survey year to impute birth cohorts, and take genders and industry NAICS codes directly. This allows us to construct the share of employed individuals in each CZ who are employed in each birth cohort-by-gender-by-industry sector bin. Multiplying these shares by the total employment in each CZ 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 $\text{GR\_SHOCK}_{s,c}$.

With this data in hand, we estimate the augmented version of equation (29) and obtain four sets of event study coefficients $\hat{\theta}_{s,t}$—one for each demographic group-by-sector bin—and display them in Figure OA.25. We see clearly in panels (a) and (c) that shocks to manufacturing result in mortality increases during the Great Recession, rather than shocks to employment among prime-aged men. Panel (b) shows that like shocks to non-manufacturing employment among other demographics (panel d), shocks to non-manufacturing employment among prime-age men also result in decreased mortality.

D Appendix Figures

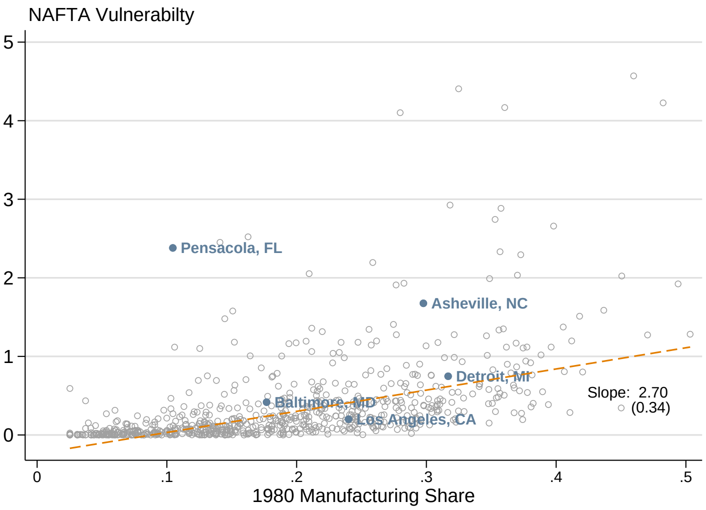
Figure OA.1: US Tariff Rates on Mexico



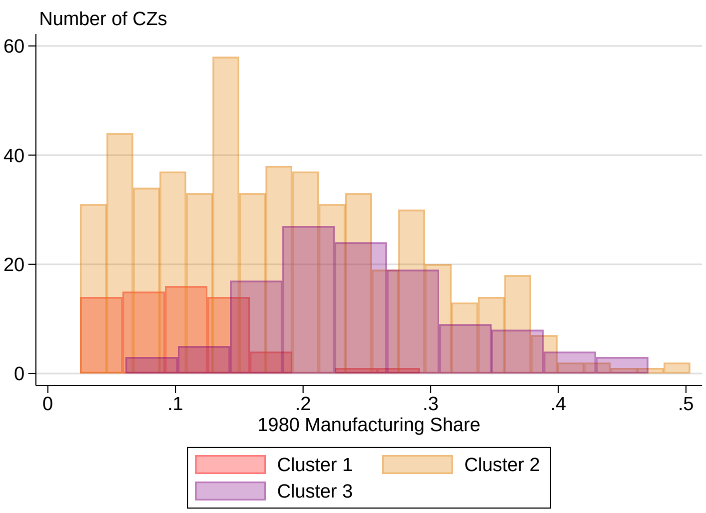
Notes: Figure displays the import-weighted average tariff rate against Mexico across industries over time. Source: Choi et al. (2024).

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

(a) Correlation of Baseline Manufacturing and Vulnerability

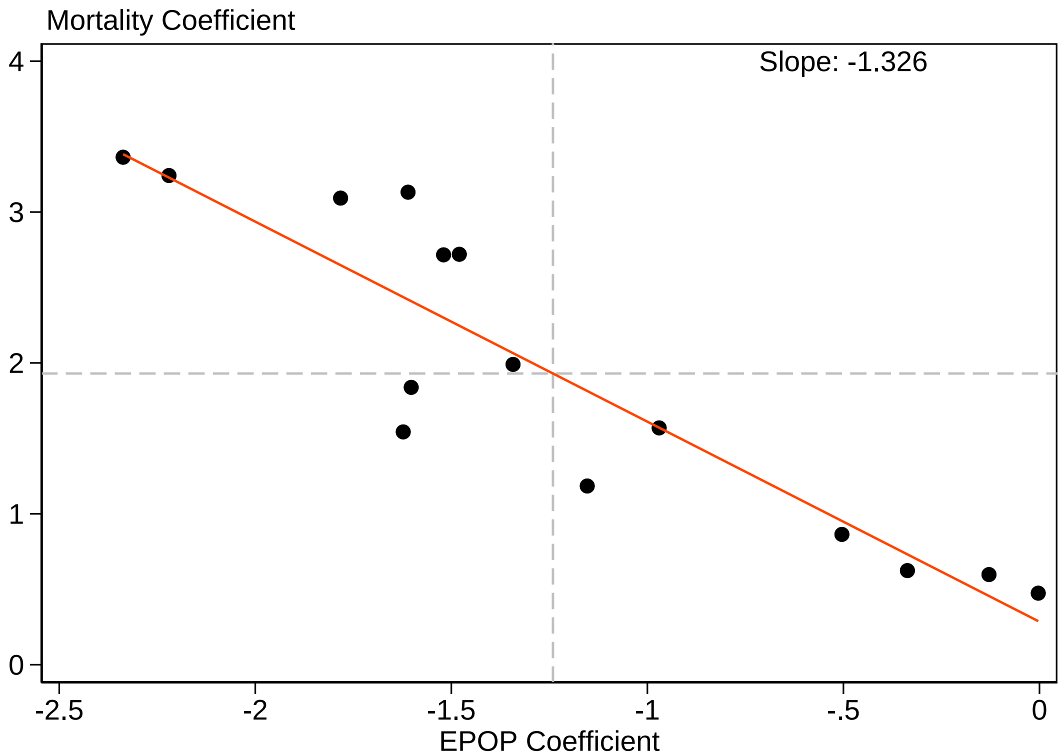


(b) Distribution of Manufacturing Within k-means Clusters



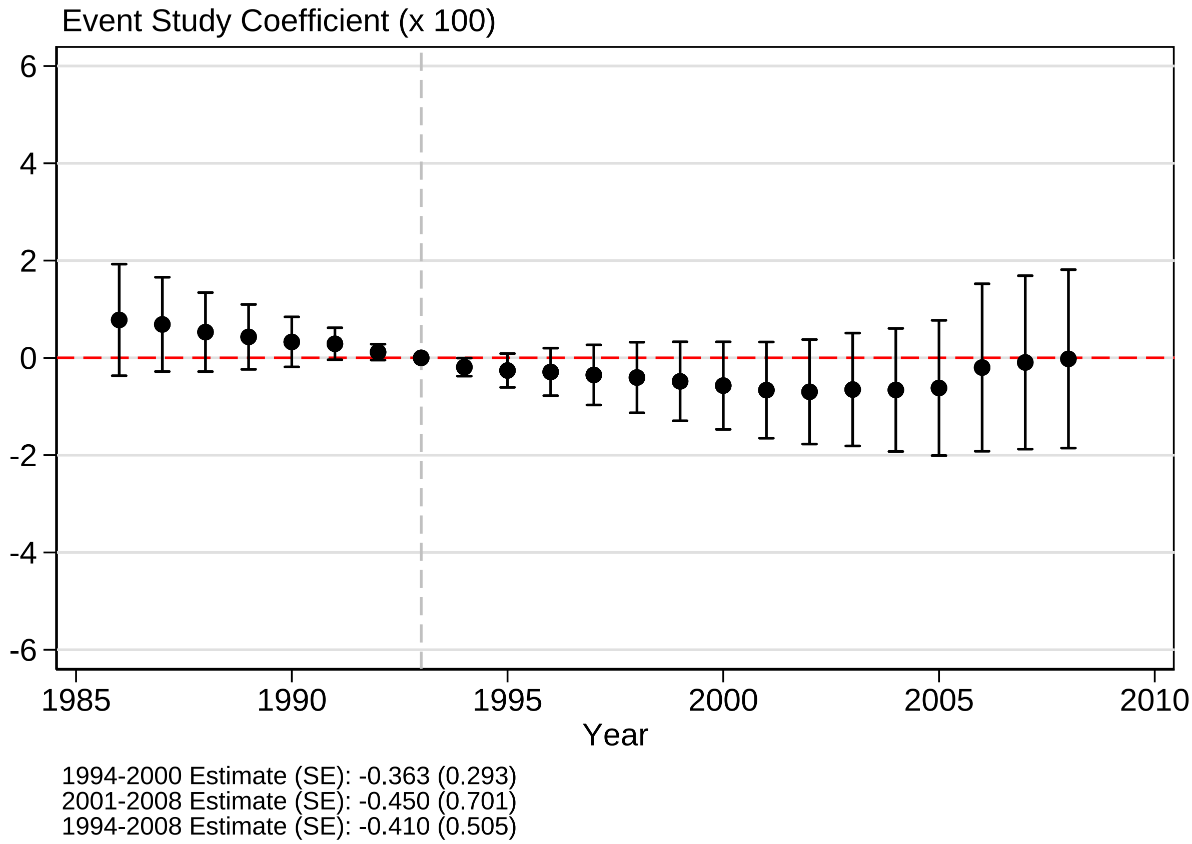
Notes: Panel A displays a scatterplot of the 1980 share of manufacturing employment in each CZ and its NAFTA vulnerability, along with the regression slope coefficient and heteroskedasticity robust standard error. The regression is weighted by 1990 CZ population, and the sample size is 722 CZs. Panel 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: Impact of NAFTA Vulnerability on Population Aged 25+ Upon Implementation

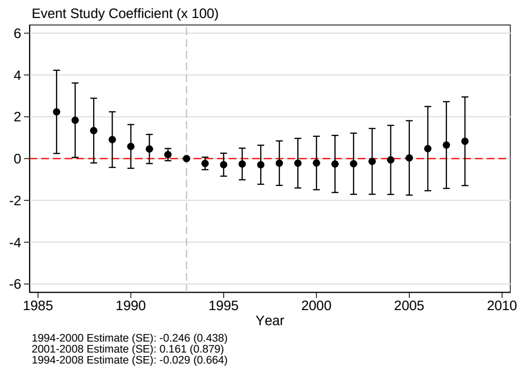


Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{gt} is the log population aged 25 or older in 1994 in each CZ-year. shows estimated impacts of NAFTA on population based on estimating equation (4) for the dependent variable log population of those born in 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.

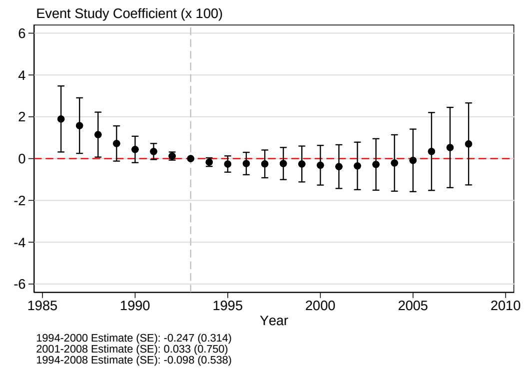
Figure OA.5: NAFTA Population Impacts by Birth Cohort and Sex

Born 1950-1969 (Ages 25-44)

(a) Male

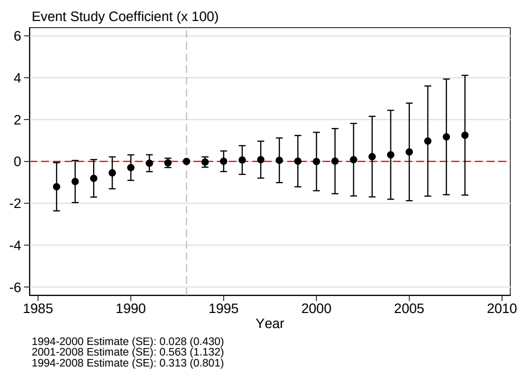


(b) Female

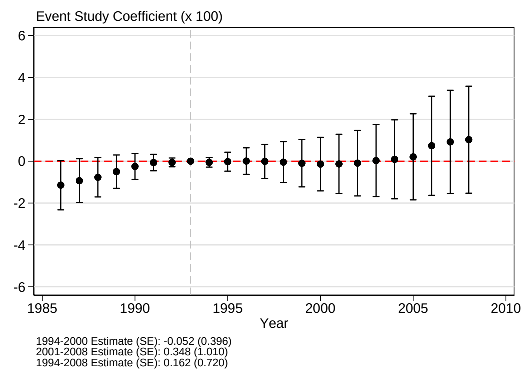


Born 1930-1949 (Ages 45-64)

(c) Male

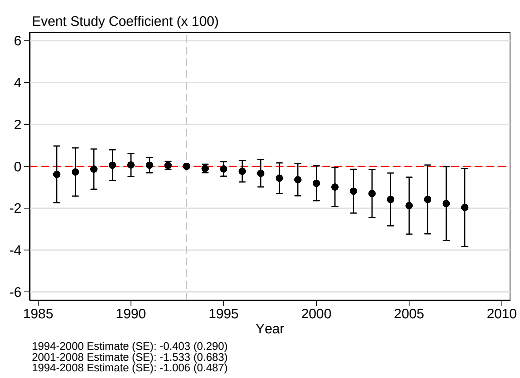


(d) Female

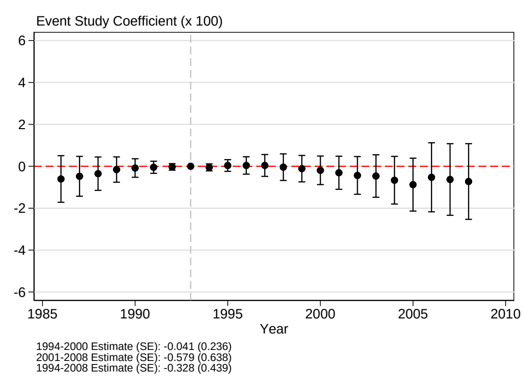


Born Before 1929 (Ages 65+)

(e) Male



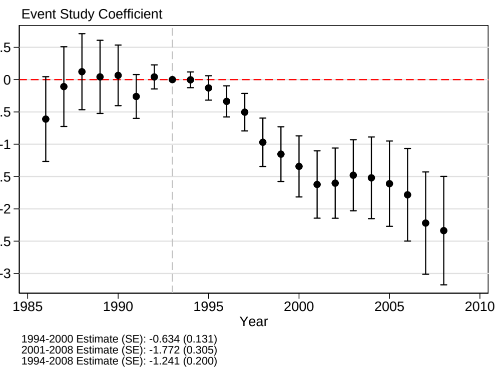
(f) Female



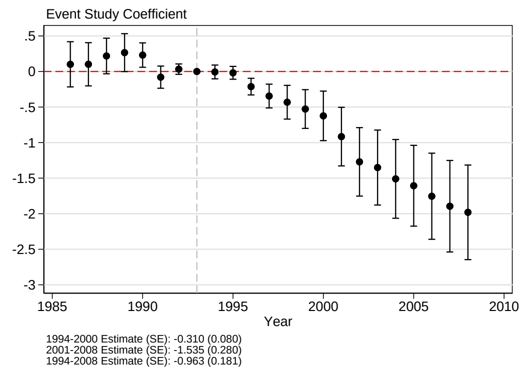
Notes: This figure displays estimates of β_t from equation (4), where the outcome y_{gt} is the log population of individuals in each demographic group within each CZ. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered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

Figure OA.6: NAFTA EPOP Effects by Industry

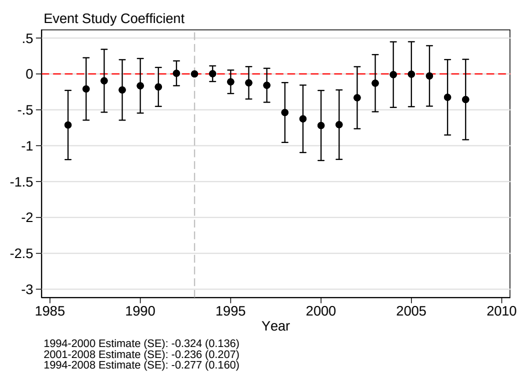
(a) Total EPOP



(b) Manufacturing



(c) Non-Manufacturing

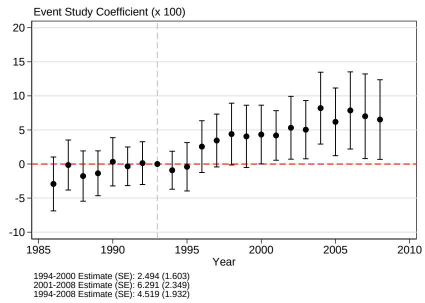


Notes: This figure displays estimates of β_t from equation (4), where the outcome y_{gt} is the employment-to-population ratio across all industries (Panel a), manufacturing industries (Panel b), and non-manufacturing industries (Panel c). A one-point increase in NAFTA vulnerability V_g corresponds to 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.

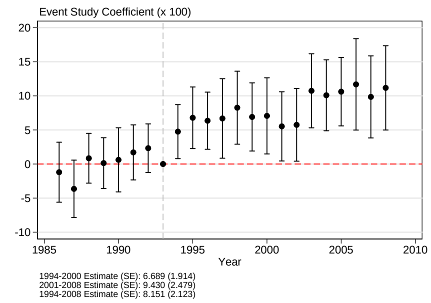
Figure OA.7: NAFTA Mortality Impacts by Sex and Birth Cohort

Born 1970-1994 (Ages 0-24)

(a) Male

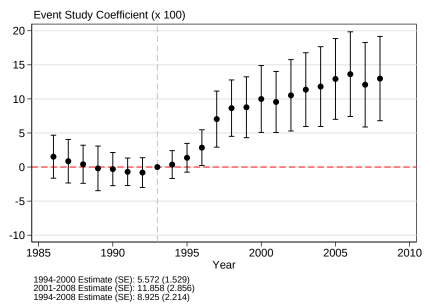


(b) Female

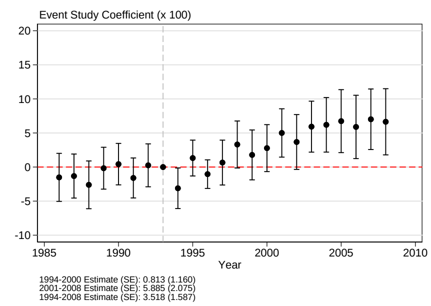


Born 1950-1969 (Ages 25-44)

(c) Male

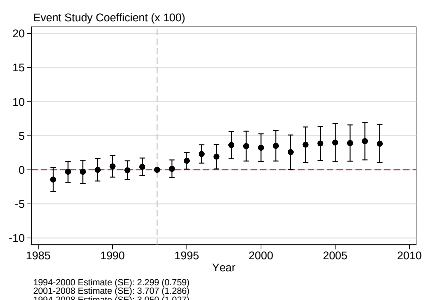


(d) Female

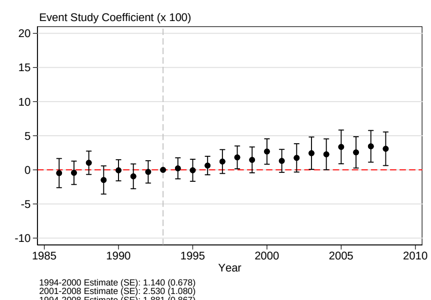


Born 1930-1949 (Ages 45-64)

(e) Male

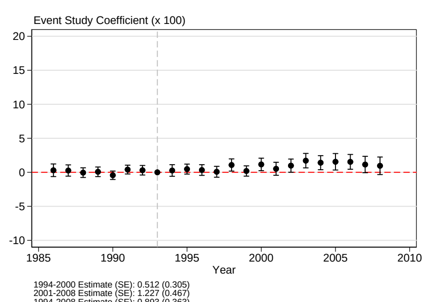


(f) Female

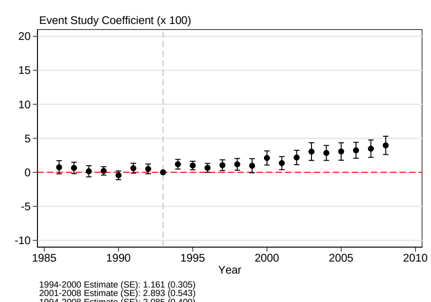


Born Before 1929 (Ages 65+)

(g) Male



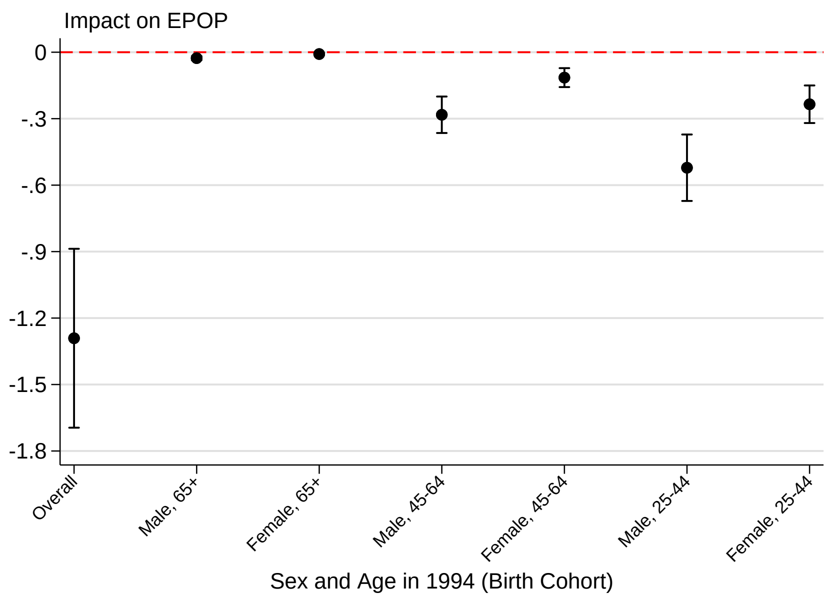
(h) Female



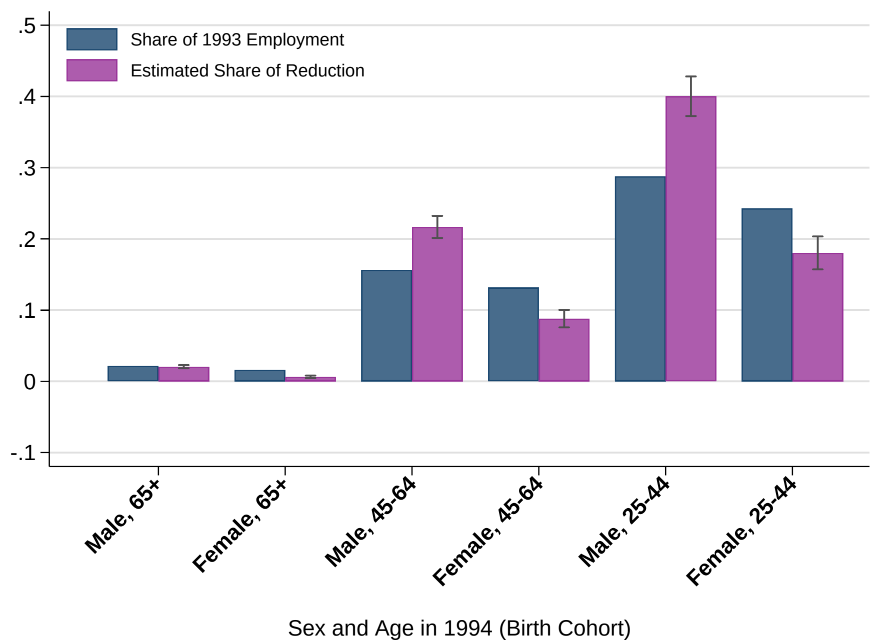
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{gt} is the log CZ mortality rate per 100,000 for individuals in the birth cohort and sex denoted by each panel title. A one-point increase in NAFTA vulnerability V_g corresponds to moving from the average CZ 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.8: EPOP Decomposition By Birth Cohort and Gender

(a) 1994-2008 Pooled Estimates



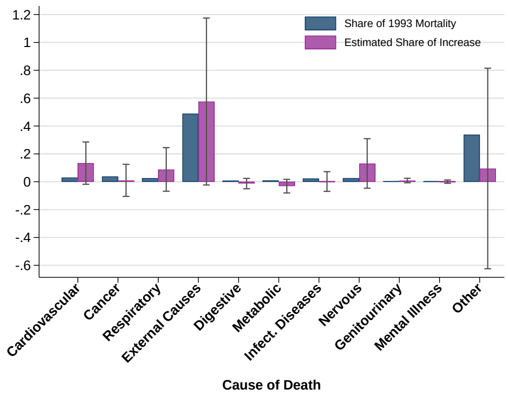
(b) 1994-2008 Decomposition



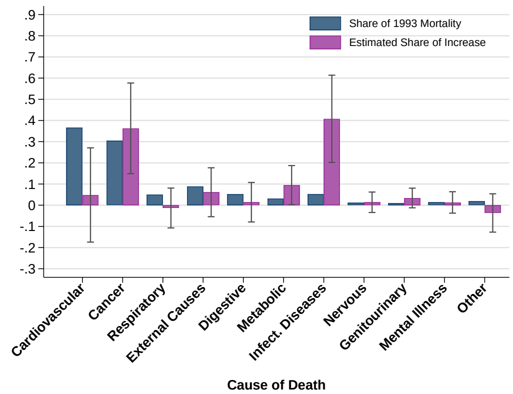
Notes: Panel (a) gives the imputed average 1994-2008 estimate of β_t in equation (4) for EPOP in each demographic group given on the x-axis. In panel (b), the blue bars denote the share of employment each demographic group accounted for in 1993, while the purple bars denote the share of the decline in 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.4. 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.9: NAFTA Mortality Decomposition By Cause of Death: Male Birth Cohorts

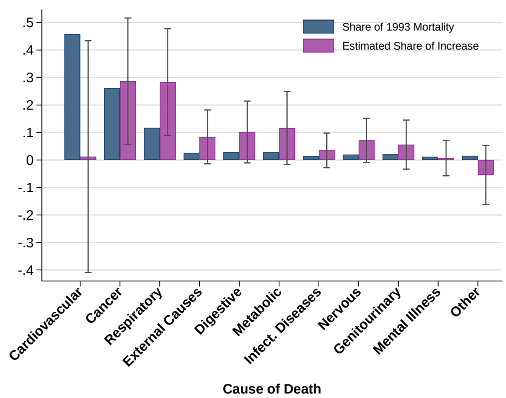
(a) Born 1970-1994 (Ages 0-24)



(b) Born 1930-1949 (Ages 45-64)

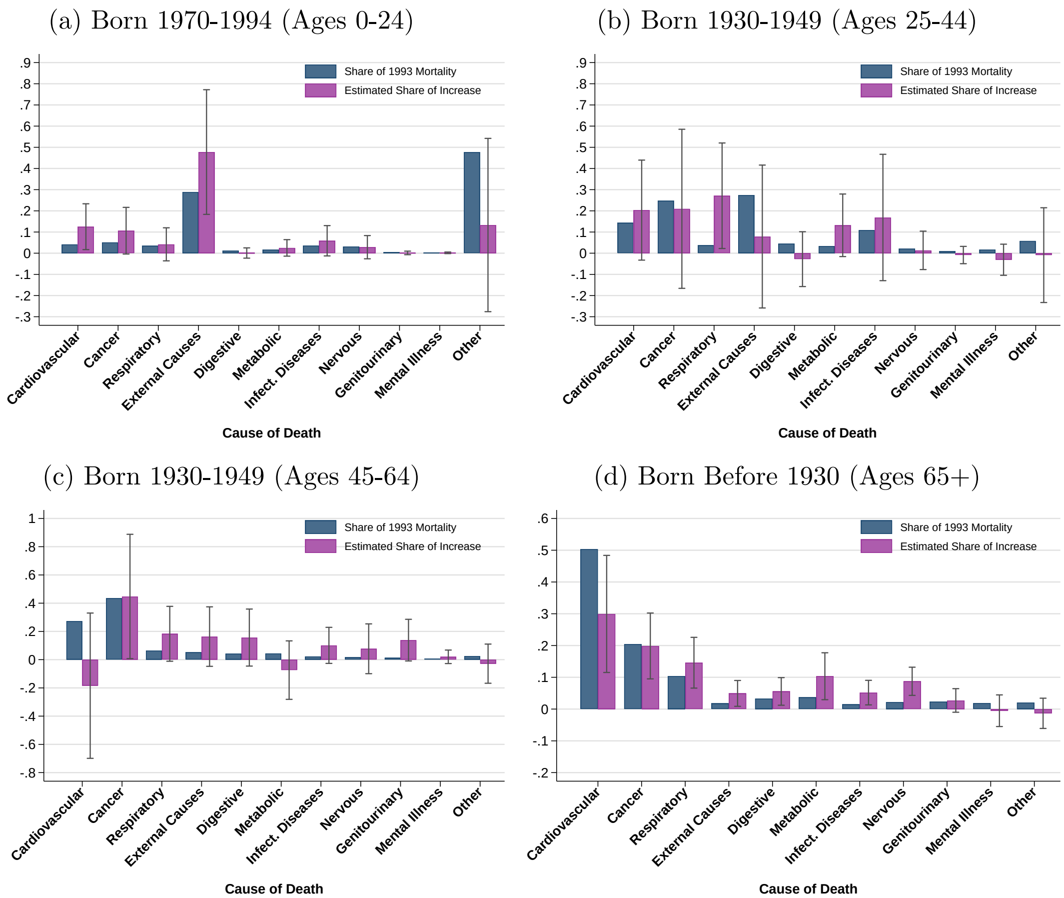


(c) Born Before 1930 (Ages 65+)



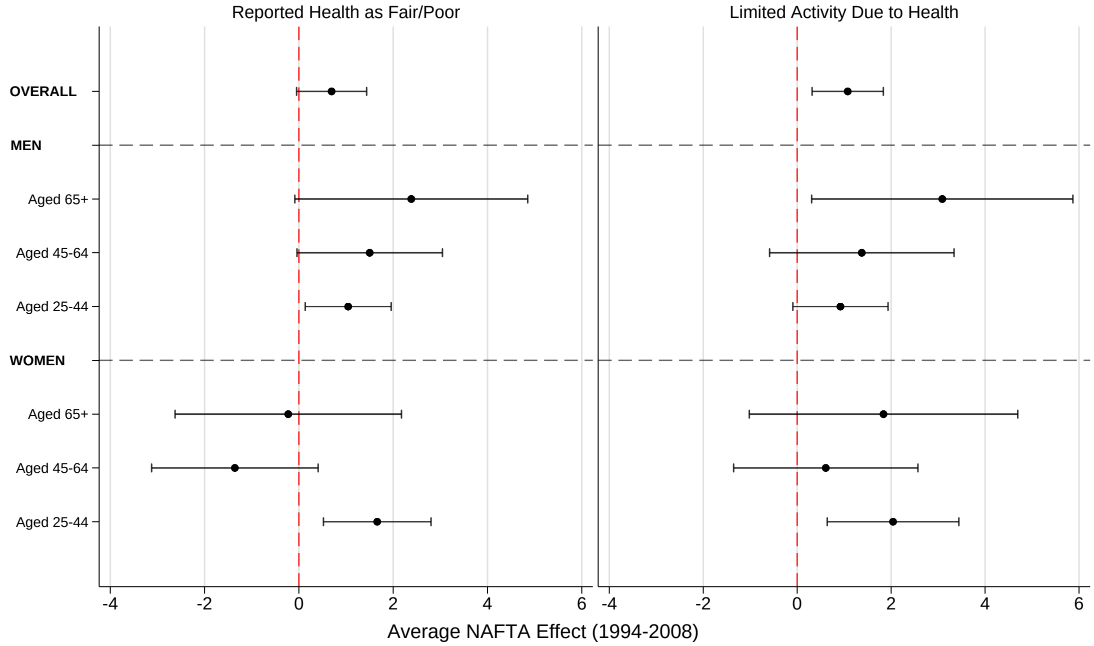
Notes: In each panel, the blue bars denote the share of deaths each cause accounted for in 1993 among men in each birth cohort. The purple bars denote the share of the increase in mortality each cause accounted for (averaged over the 1994-2008 post-period) as a result of NAFTA. Men born between 1950-1969 are excluded as they are displayed in the main text (Figure 4). 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.10: NAFTA Mortality Decomposition By Cause of Death: Female Birth Cohorts



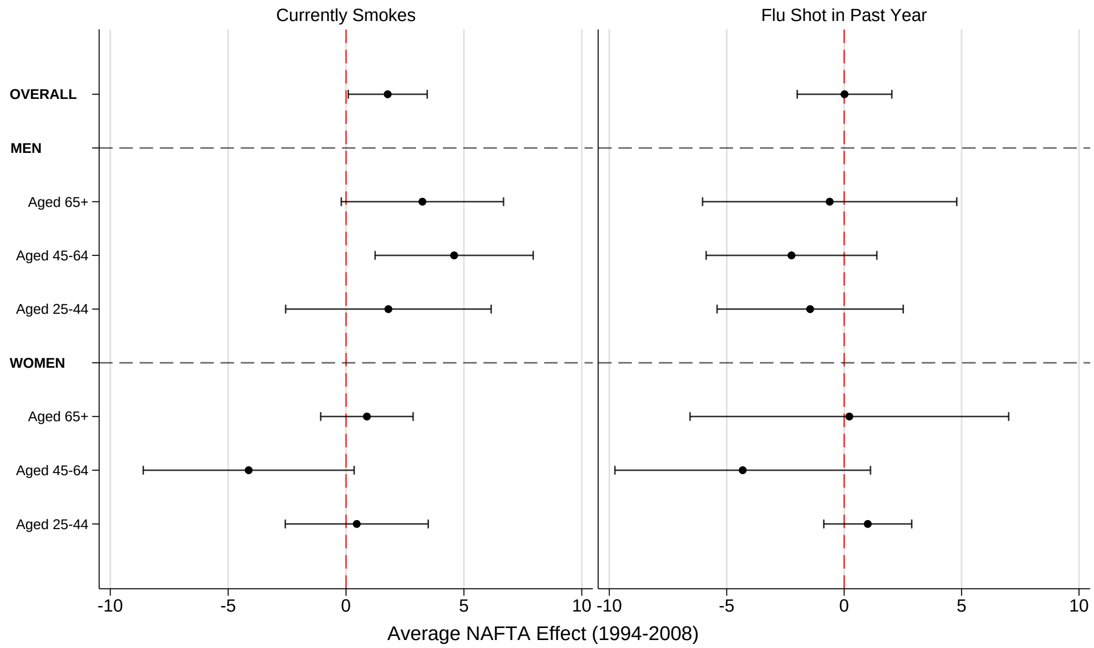
Notes: In each panel, the blue bars denote the share of deaths each cause accounted for in 1993 among women in each birth cohort. The purple bars denote the share of the increase in mortality each cause accounted for (averaged over the 1994-2008 post-period) as a result of NAFTA. Vertical lines denote 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.11: NAFTA Impact on General Health



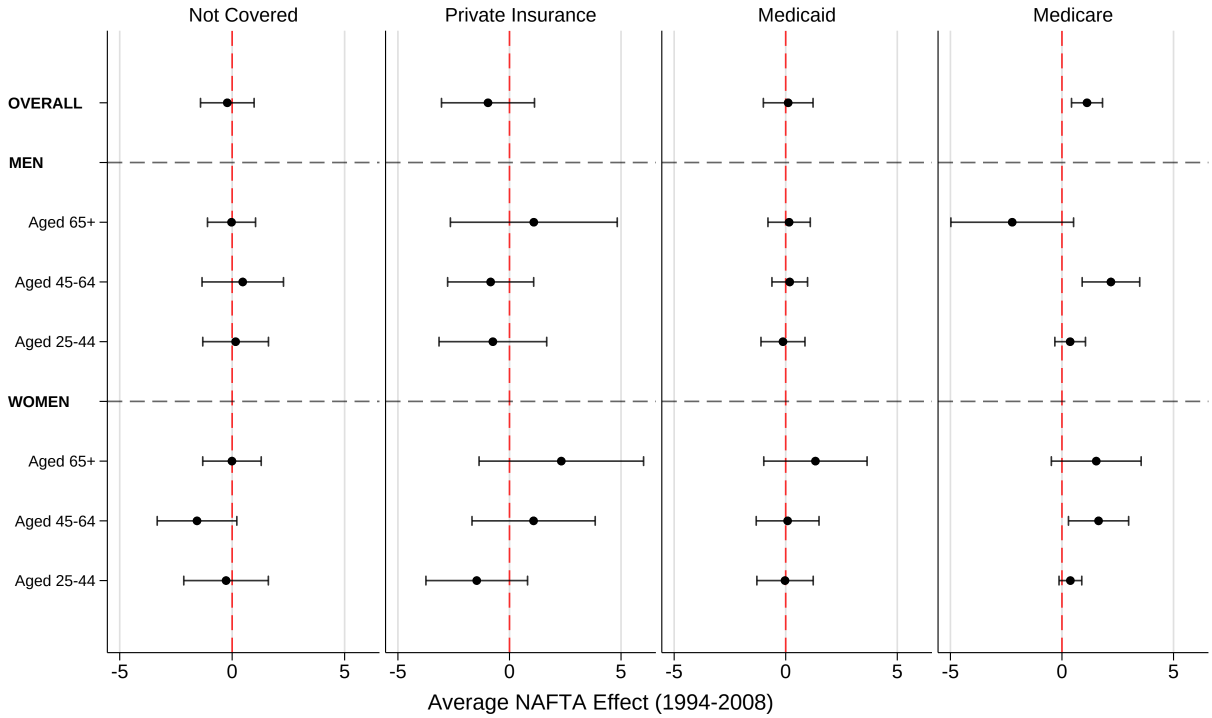
Notes: This figure displays average 1994-2008 estimate of β_t from equation (4) estimated at the individual level, where the outcomes y_{it} are whether individuals reported their health as Fair or Poor (given the options Poor, Fair, Good, Very Good, and Excellent) and whether individuals reported any limitation to their typical activity due to their health. Appendix Table OA.8 shows the baseline (1993) mean outcomes. 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.12: NAFTA Impact on Health Behaviors (Smoking and Flu Vaccination)



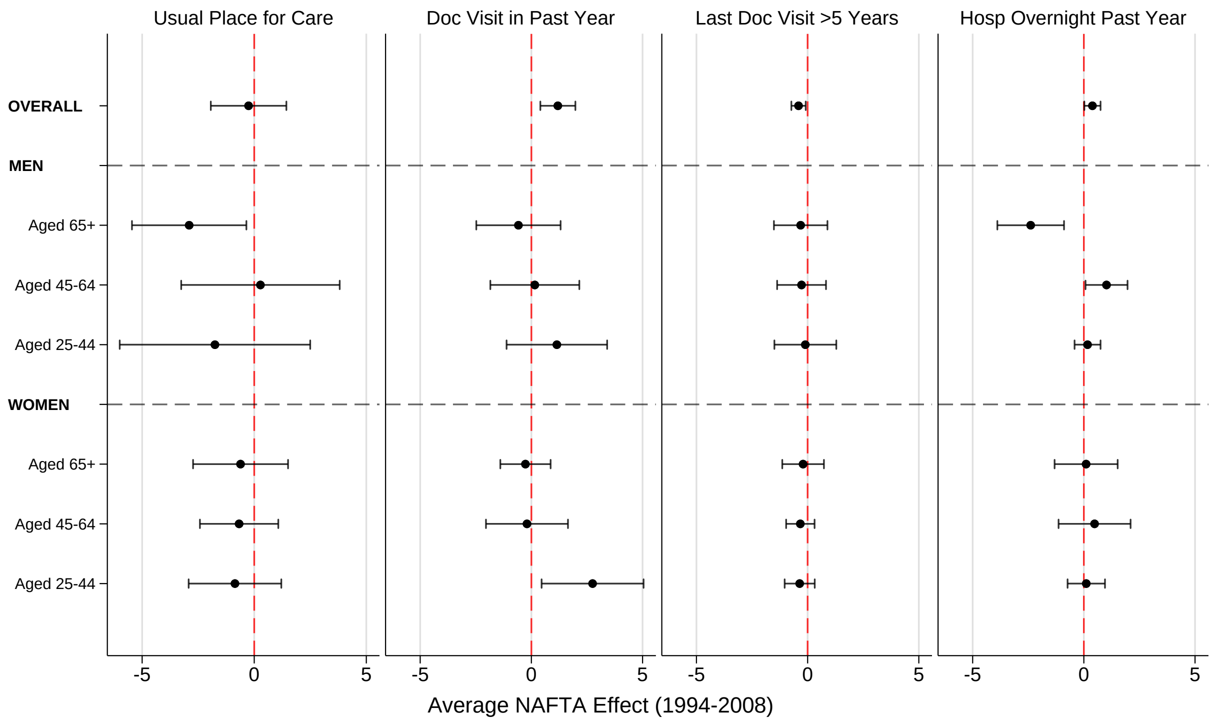
Notes: This figure displays average 1994-2008 estimate of β_t from equation (4) estimated at the individual level, where the outcomes y_{it} are whether the respondent reported currently smoking and whether they reported getting a flu shot in the past year. Appendix Table OA.8 shows the baseline (1993) mean outcomes. 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.13: NAFTA Impact on Health Insurance Coverage



Notes: This figure 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. Appendix Table OA.8 shows the baseline (1993) mean outcomes. 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.

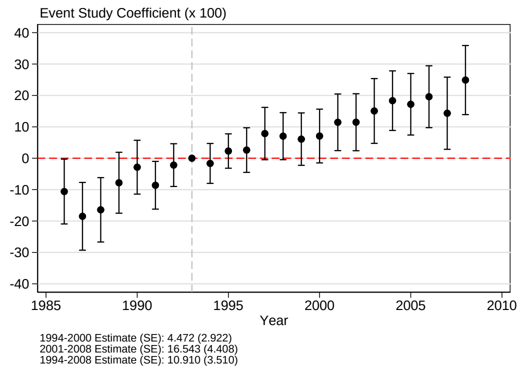
Figure OA.14: NAFTA Impact on Health Care Use



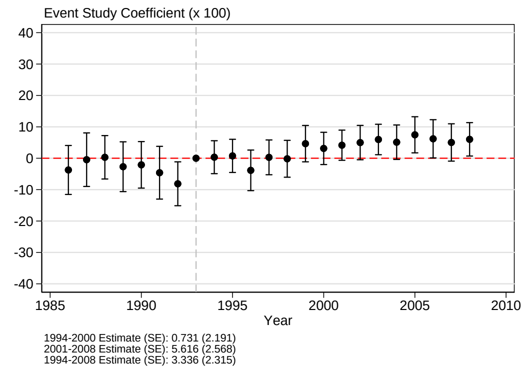
Notes: This figure displays average 1994-2008 estimate of β_t from equation (4) estimated at the individual level, where the outcomes y_{it} are whether the individual reported having a usual place for care, visiting a health professional in the past year, having last visited a health professional more than 5 years ago, and having spent a night in the hospital (as a patient) in the past year. Appendix Table OA.8 shows the baseline (1993) mean outcomes. 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.15: NAFTA Mortality Impacts by Cause of Death (Men Born 1950-1969), Part 1

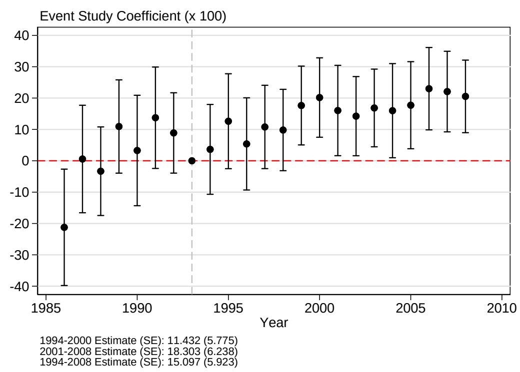
(a) Infectious Diseases



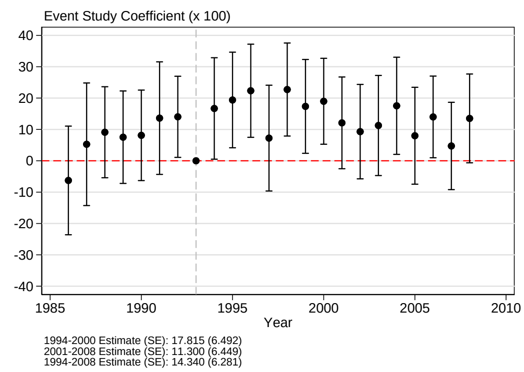
(b) Cancer



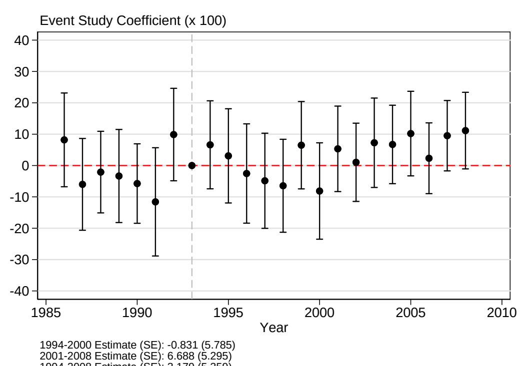
(c) Metabolic Diseases



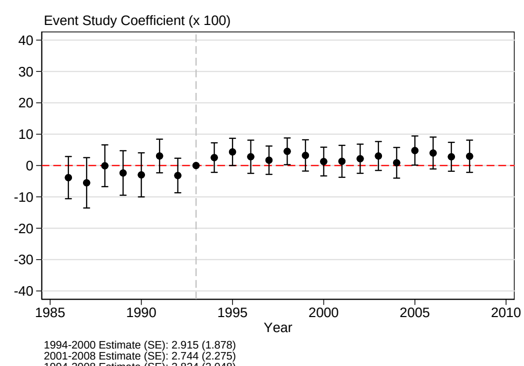
(d) Mental Illness



(e) Nervous System Disorders



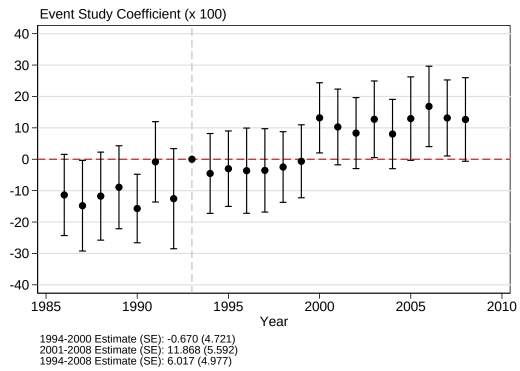
(f) Circulatory System Disorders



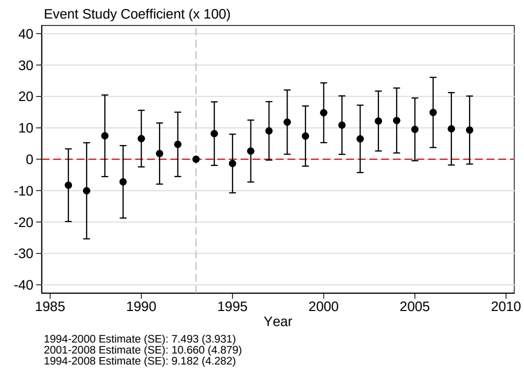
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log CZ mortality rates per 100,000 for men born between 1950 and 1969 separately by cause of death. Along with Figure OA.16, these groups partition all causes of death in the CDC data. Observations are 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.16: NAFTA Mortality Impacts by Cause of Death (Men Born 1950-1969), Part 2

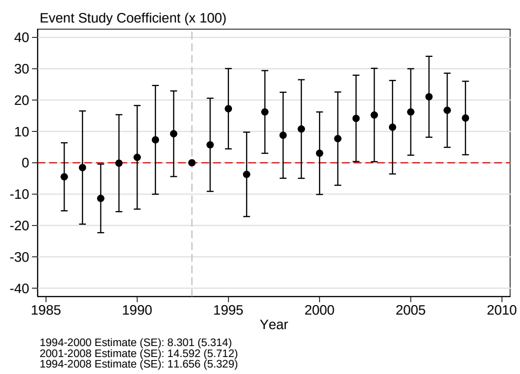
(a) Respiratory System Disorders



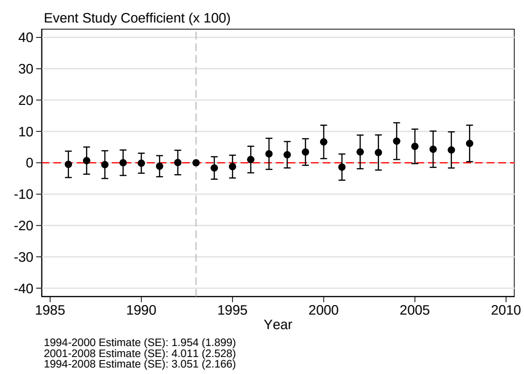
(b) Digestive System Disorders



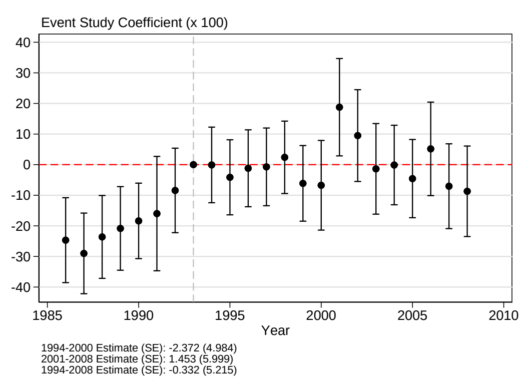
(c) Genitourinary Disorders



(d) External Causes



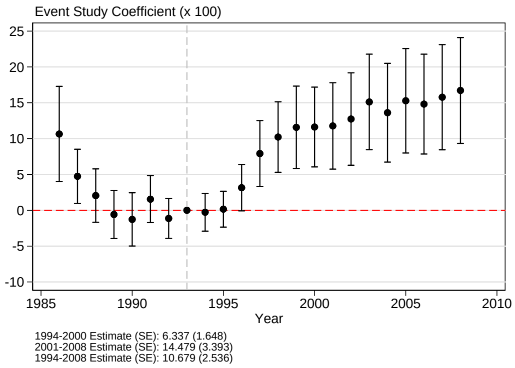
(e) Other Causes



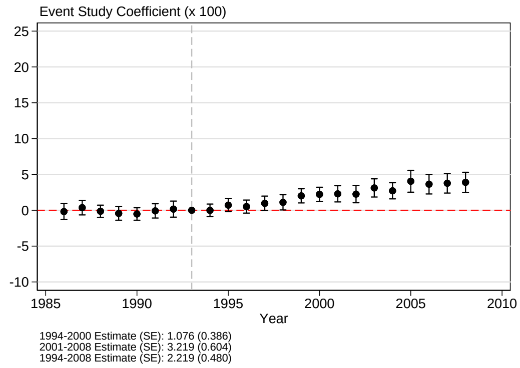
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log CZ mortality rates per 100,000 for men born between 1950 and 1969 separately by cause of death. Along with Figure OA.15, these groups partition all causes of death in the CDC data. Observations are 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.17: NAFTA Mortality Impacts by Cause of Death (Full Sample), Part 1

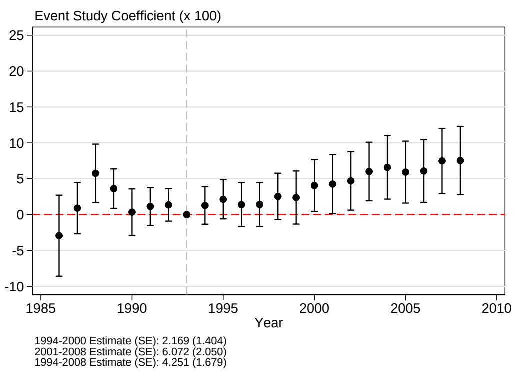
(a) Infectious Diseases



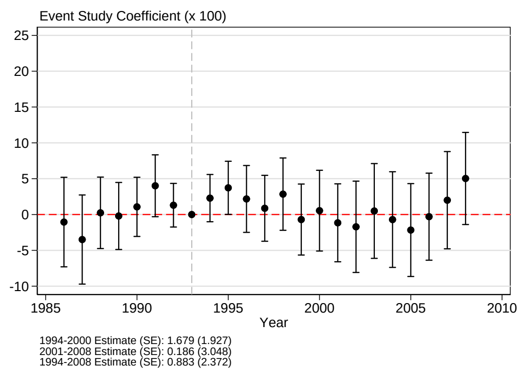
(b) Cancer



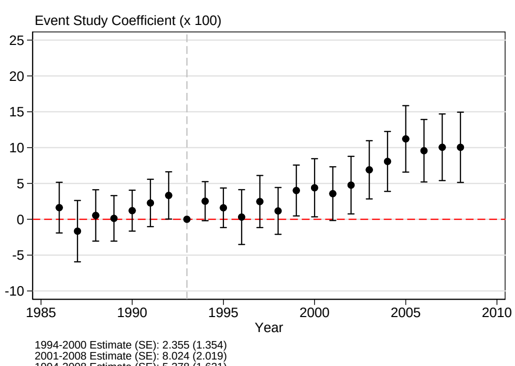
(c) Metabolic Diseases



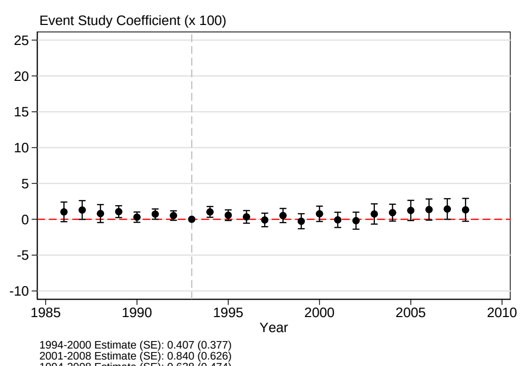
(d) Mental Illness



(e) Nervous System Disorders



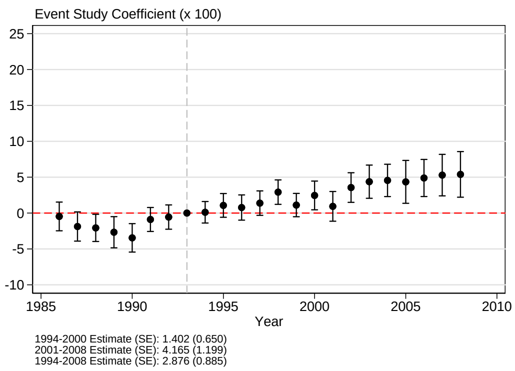
(f) Circulatory System Disorders



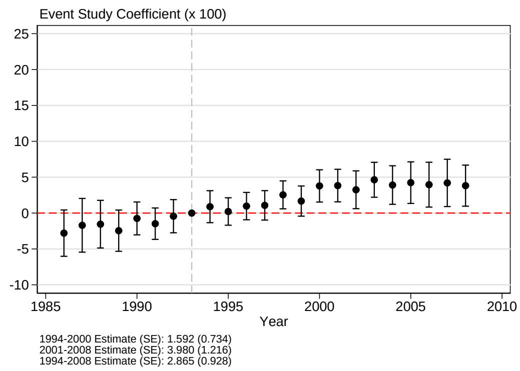
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log age-adjusted CZ mortality rates per 100,000 separately by cause of death. Along with Figure OA.18, these groups partition all causes of death in the CDC data. Observations are weighted by CZ population 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.18: NAFTA Mortality Impacts by Cause of Death (Full Sample), Part 2

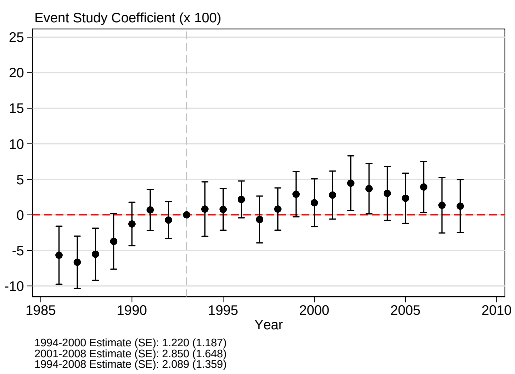
(a) Respiratory System Disorders



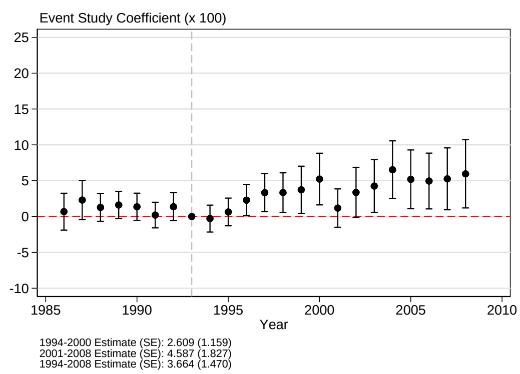
(b) Digestive System Disorders



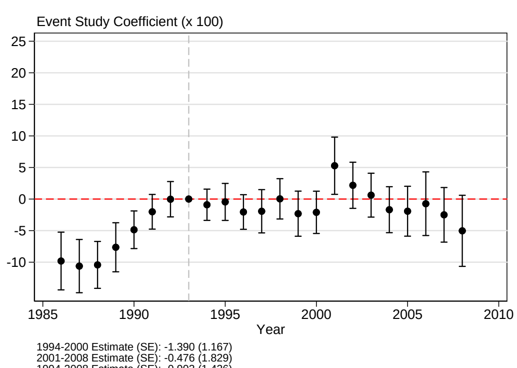
(c) Genitourinary Disorders



(d) External Causes



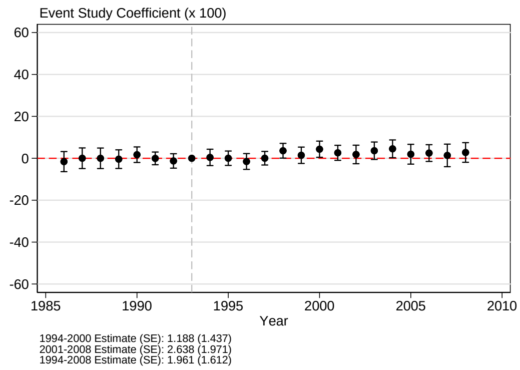
(e) Other Causes



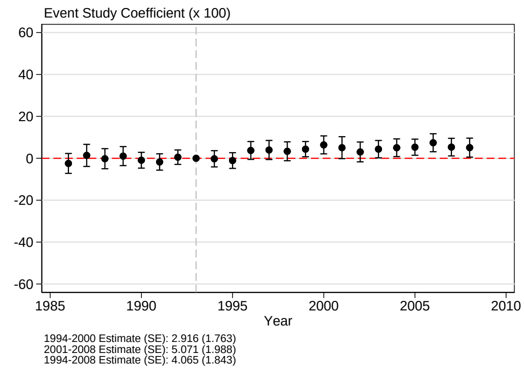
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log age-adjusted CZ mortality rates per 100,000 separately by cause of death. Along with Figure OA.17, these groups partition all causes of death in the CDC data. Observations are weighted by CZ population 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.19: NAFTA Mortality Impacts on Deaths of Despair (Full Sample)

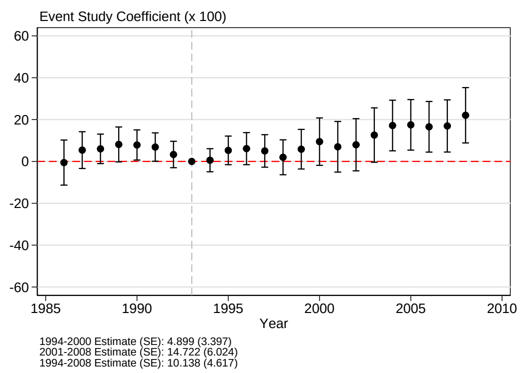
(a) Alcohol Related



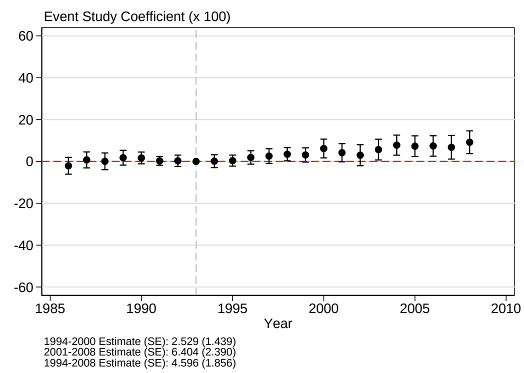
(b) Suicide



(c) Drug-Related



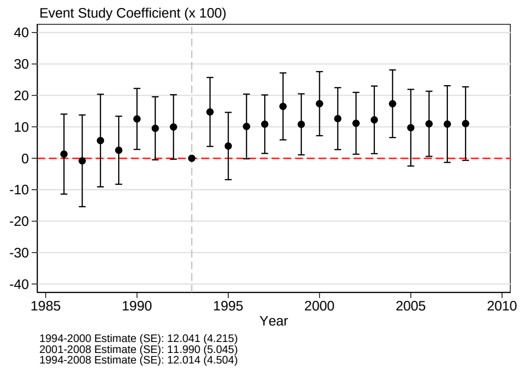
(d) Total



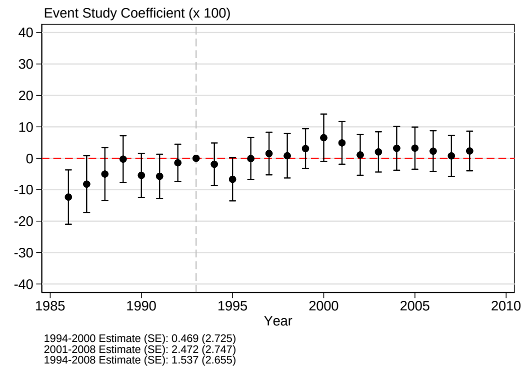
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log age-adjusted CZ mortality rates per 100,000 separately by deaths of despair. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard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

Figure OA.20: NAFTA Mortality Impacts on Deaths of Despair (Men Born 1950-1969)

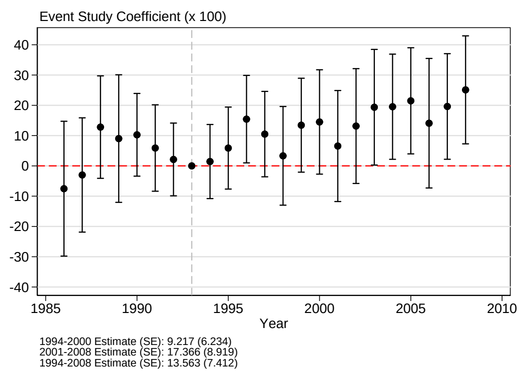
(a) Alcohol Related



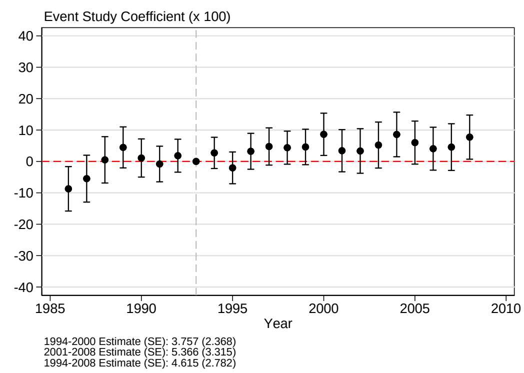
(b) Suicide



(c) Drug-Related



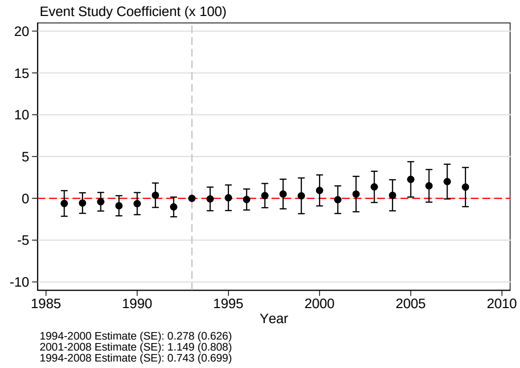
(d) Total



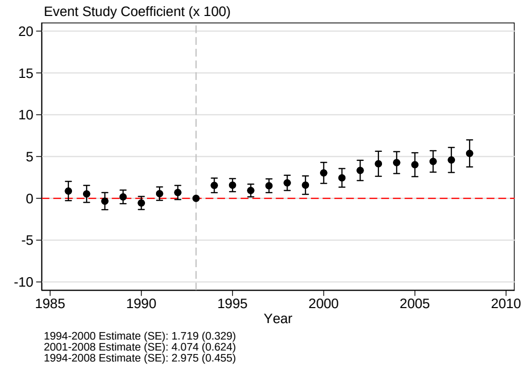
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log CZ mortality rates per 100,000 for men born between 1950 and 1969 separately by deaths of despair. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals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

Figure OA.21: Impact of NAFTA on Mortality: Women Aged 65+ By Marital Status

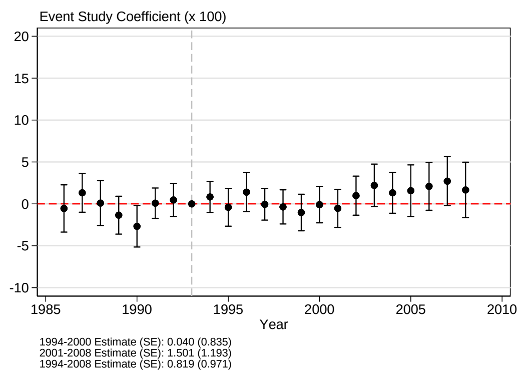
(a) Married



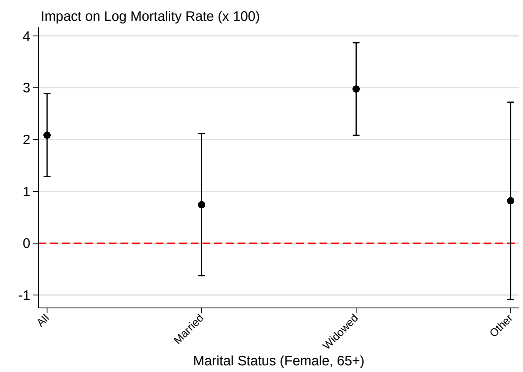
(b) Widowed



(c) Other



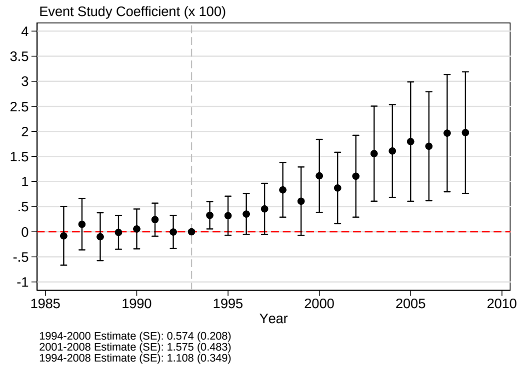
(d) 1994-2008 Estimates



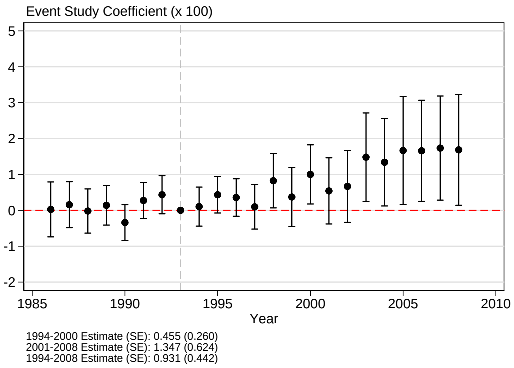
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{gt} is the mortality rate per 100,000 for women aged 65+ in 1994 by marital status. A one-point increase in NAFTA vulnerability V_g corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the most vulnerable quartile. Observations are weighted by each CZ's population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 689 CZs; CZs from Georgia are excluded because it stopped reporting marital status from most death certificates starting in 2008. The 1994 share of women aged 65+ who were married was 34%, widowed was 34%, and other was 32%.

Figure OA.22: Impact of NAFTA on Mortality: Robustness Checks

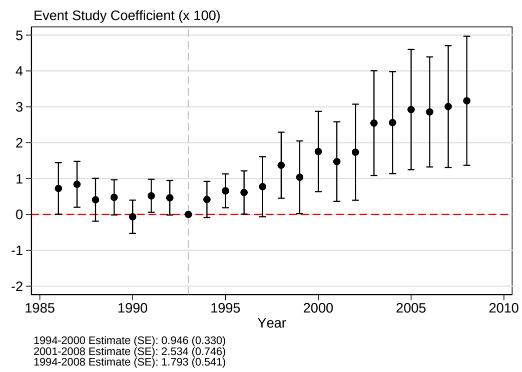
(a) County Level



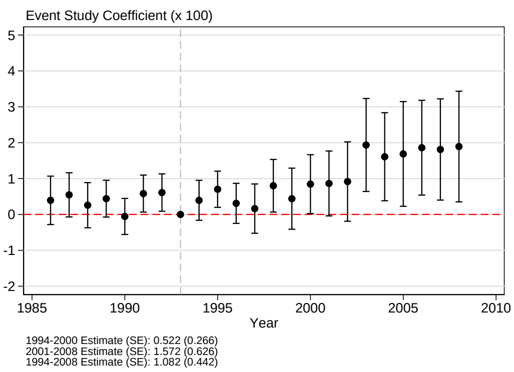
(b) Southern Census Region Only



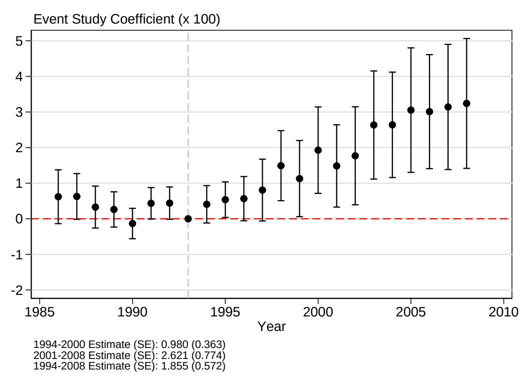
(c) With Import Penetration-By-Year FE



(d) Separate Manufacturing Clusters



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

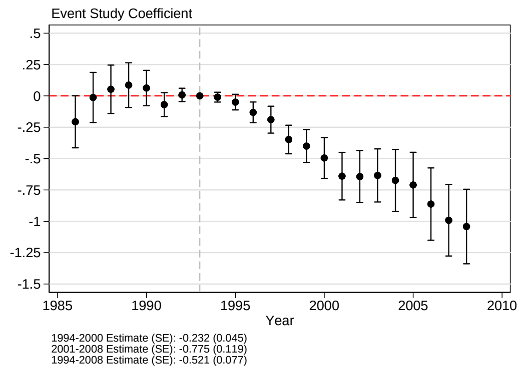


Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{gt} is the log age-adjusted mortality rate per 100,000. A one-point increase in NAFTA vulnerability V_g corresponds to moving from the average county or CZ in the least vulnerable quartile to the average county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

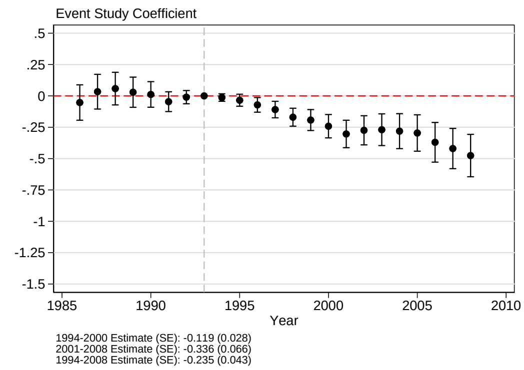
Figure OA.23: NAFTA Employment Impacts by Birth Cohort and Sex

Born 1950-1969 (Ages 25-44)

(a) Male

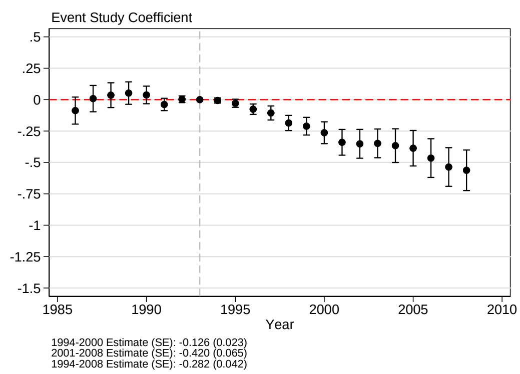


(b) Female

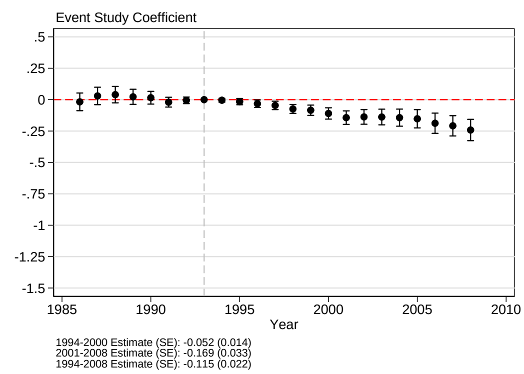


Born 1930-1949 (Ages 45-64)

(c) Male

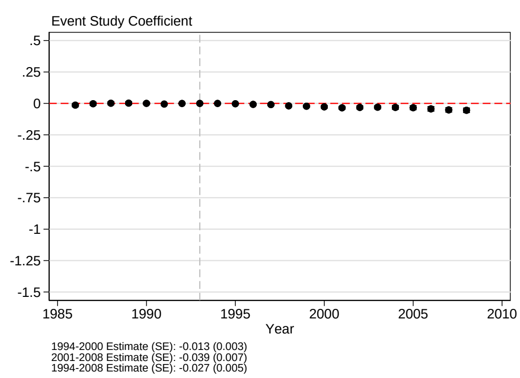


(d) Female

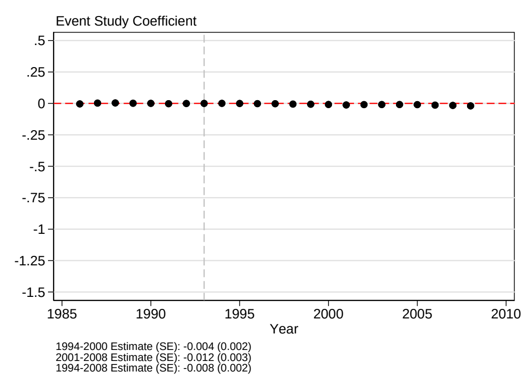


Born Before 1929 (Ages 65+)

(e) Male



(f) Female

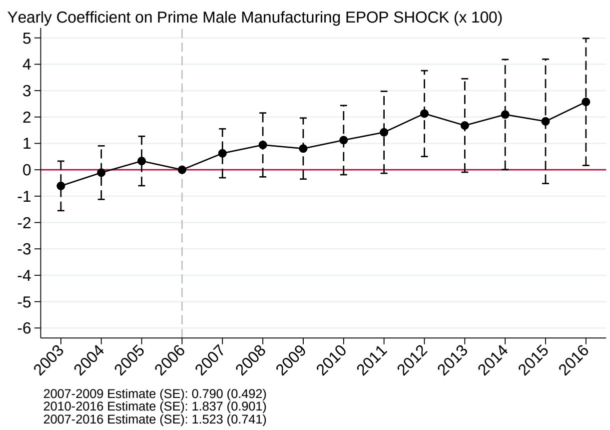


Notes: This figure displays imputed estimates of β_t from equation (4), where the outcome y_{gt} is the number of individuals employed in each birth cohort-by-sex bin given by the panel title divided by the population aged 16 or older. These estimates are imputed by estimating equation (4) for employment 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.

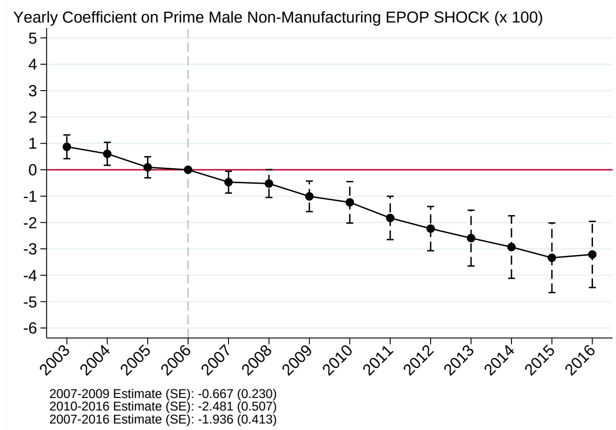
Figure OA.24: Effects of Great Recession EPOP Shocks on Mortality by Industry and Demographic

Shocks to EPOP Among Men Born 1963-1982 in:

(a) Manufacturing

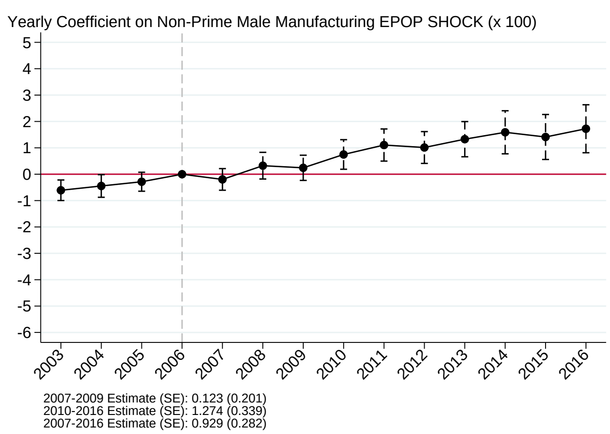


(b) Non-Manufacturing

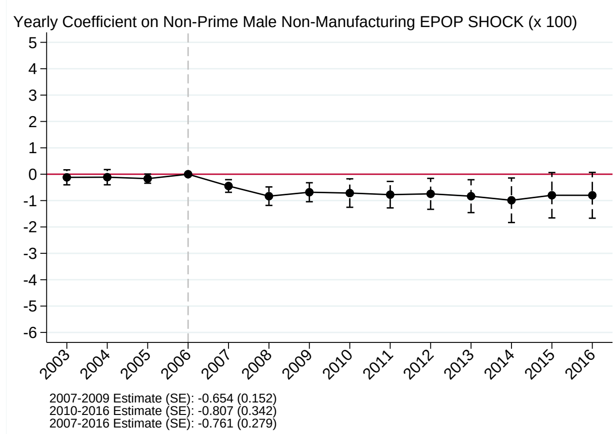


Shocks to EPOP Among All Other Demographics in:

(c) Manufacturing

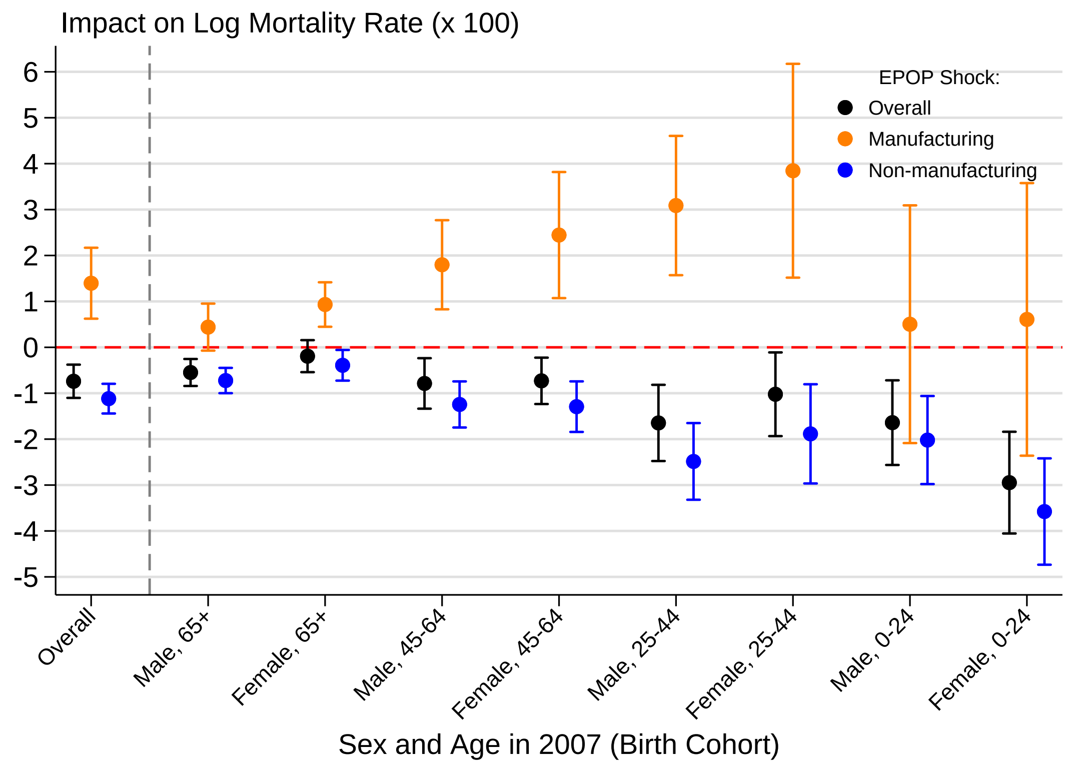


(d) Non-Manufacturing



Notes: This figure displays 100 times estimates of $\theta_{s,t}$ from estimating equation (13), where the employment categories $\mathcal{S}$ consist of manufacturing EPOP among prime-aged men (panel a), non-manufacturing EPOP among prime-aged men (panel b), manufacturing EPOP among all other demographics (panel c), and non-manufacturing EPOP among all other demographics (panel d). Prime age men are those born 1963-1982, who were therefore 25-44 at the start of the Great Recession in 2007. 80% of the Great Recession EPOP Shock was in non-manufacturing; prime-age men consistent about two-fifths of the EPOP decline in both manufacturing and non-manufacturing sectors. 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 738 CZs.

Figure OA.25: Effects of Great Recession Sectoral EPOP Shocks on Mortality by Sex and Birth Cohort



Notes: This figure displays 100 times event study coefficients from estimating equation (13) on a single Great Recession shock variable (in black) and estimates of $\theta_{s,t}$ from estimating equation (13) (in orange and blue) with the log mortality rate overall and for each birth cohort and gender as outcomes. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The regressions are weighted by each CZ's population in 2006. The sample size is 738 CZs.

E Appendix Tables

Table OA.1: 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 estimates of β_1 in equation (23) with the decadal age-adjusted cumulative mortality rate and long-differenced total EPOP, manufacturing EPOP, and non-manufacturing EPOP as outcomes. 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.2: China Shock Impacts on Mortality By Age and Gender

	65+		45-64		25-44		0-24	
	Male	Female	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import Penetration	454.3	239.3	401.0	90.2	93.3	23.4	17.1	11.3
	(456.8)	(398.7)	(122.8)	(61.7)	(46.4)	(21.1)	(13.3)	(7.8)
Implied % Change	0.77	0.49	4.09	1.54	4.34	2.21	1.77	2.03
Mean	58,685.8	48,517.0	9,814.1	5,854.1	2,151.1	1,059.7	971.2	557.8
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 estimates of β_1 in equation (23) with the cumulative mortality rate in each age and gender bin given in the column titles as outcomes. We emphasize that we use age cuts instead of birth cohort cuts as explained further in Appendix B. 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.3: Baseline Employment By Sex and Birth Cohort

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

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.4

Table OA.4: 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)
Geography			
County Level	0.574	1.575	1.108
	(0.208)	(0.483)	(0.349)
Southern CZs	0.455	1.347	0.931
	(0.260)	(0.624)	(0.442)
Additional Covariates			
Chinese Import Penetration	0.946	2.534	1.793
	(0.330)	(0.746)	(0.541)
Separate Manufacturing Clusters	0.522	1.572	1.082
	(0.266)	(0.626)	(0.442)
1990 Cancer Mortality Rate	0.980	2.621	1.855
	(0.363)	(0.774)	(0.572)

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. The first row displays the baseline estimate. The next two rows probe sensitivity to geography by (1) estimating the specification at the county level and (2) limiting the sample to CZs in the Southern Census Region only. The following rows add year fixed effects interacted with cross sectional variables first for the Chinese import penetration measure from Autor et al. (2013), next for 3 additional k-means clusters of the 1980 manufacturing share as well as 3 k-means clusters for our remaining controls, and finally for the 1990 cancer mortality rate (predictive of the opioid crisis). The last row displays estimates under the original Choi et al. (2024) specification at the CZ level, which uses a different vulnerability measure and controls for state-by-year fixed effects instead of region-by-year fixed effects. 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 Souhern CZs, and 3,096 counties

Table OA.5: IV Estimates of the Impact of EPOP on Mortality: Sensitivity to Instruments

	OLS (1)	IV (Great Recession) (2)	IV (NAFTA) (3)	IV (China Shock) (4)
EPOP Decline (×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.6: Changes in Life Expectancy Due to NAFTA

	Remaining Life Expectancy (Unisex)			Remaining Life Expectancy (Male)			Remaining Life Expectancy (Female)		
Age	Normal	NAFTA	Percent Change	Normal	NAFTA	Percent Change	Normal	NAFTA	Percent Change
Panel A: Homogeneous Mortality Effects									
15	60.92	60.92	-0.009%	57.57	57.57	-0.014%	64.27	64.27	-0.005%
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									
15	60.92	60.91	-0.026%	57.57	57.56	-0.032%	64.27	64.26	-0.020%
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. The "NAFTA" columns increase these by the effect of NAFTA on mortality rates for 15 years. In Panel A, this is simply 0.68%, obtained by multiplying the 1.93% increase in Figure 2 by the average NAFTA vulnerability (0.35). In Panel B, we replace the 1.93% increase with the birth cohort and gender-specific changes in mortality rates due to NAFTA given in Figure OA.7.

Table OA.7: Welfare Effects of NAFTA

Age	$\frac{\text{VSLY}}{c} = 5$			$\frac{\text{VSLY}}{c} = 2$		
	All Individuals	Men	Women	All Individuals	Men	Women
Panel A: Homogeneous Mortality Effects						
Overall	-0.327%	-0.359%	-0.296%	-0.108%	-0.125%	-0.093%
15	0.056%	0.028%	0.081%	0.083%	0.069%	0.096%
25	0.029%	-0.009%	0.063%	0.070%	0.051%	0.087%
45	-0.166%	-0.244%	-0.100%	-0.028%	-0.067%	0.005%
65	-1.082%	-1.363%	-0.859%	-0.486%	-0.627%	-0.375%
Panel B: Heterogeneous Mortality Effects						
Overall	-0.467%	-0.571%	-0.367%	-0.178%	-0.230%	-0.129%
15	-0.044%	-0.081%	-0.010%	0.033%	0.015%	0.050%
25	-0.191%	-0.436%	0.025%	-0.041%	-0.163%	0.068%
45	-0.256%	-0.446%	-0.093%	-0.073%	-0.168%	0.008%
65	-0.770%	-0.568%	-0.931%	-0.330%	-0.229%	-0.410%

Notes: This table displays estimates of the welfare effects of NAFTA with endogenous mortality as defined in equation (6). We calibrate $\Delta = 0.11\%$ from Caliendo and Parro (2015) and $\gamma = 2$. In the first three columns, we set the ratio between the value of a statistical life year and consumption to be 5; in the next three columns, we set it to 3. 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.6. In Panel B, we compute dT using birth cohort and gender specific effects, as in Panel B of Table OA.6. The "overall" welfare change is computed by averaging age (0-85+) and gender-specific welfare changes weighted by each demographic's share of the population in 1993.

Table OA.8: Baseline Shares of NHIS Outcomes (1993)

	All	Men				Women			
		Pre-1930	1930–49	1950–69	1970–94	Pre-1930	1930–49	1950–69	1970–94
Health Behaviors									
Current Smoker	0.10	0.28	0.16	0.07	0.03	0.28	0.18	0.08	0.04
Flu Shot in Past Year	0.15	0.38	0.22	0.12	0.08	0.39	0.24	0.11	0.06
General Health									
Poor/Fair Health	0.25	0.13	0.29	0.31	0.29	0.10	0.23	0.27	0.23
Limited Activity	0.19	0.53	0.17	0.10	0.10	0.50	0.22	0.10	0.09
Health Access									
Usual Place for Care	0.80	0.87	0.79	0.69	0.80	0.88	0.83	0.80	0.83
Doc Visit Past Year	0.77	0.86	0.71	0.62	0.76	0.88	0.82	0.82	0.83
Last Doc Visit >5 Years	0.03	0.03	0.07	0.07	0.02	0.03	0.03	0.02	0.01
Hosp Overnight Past Year	0.08	0.17	0.08	0.04	0.03	0.15	0.08	0.10	0.06
Health Insurance									
Not Covered	0.15	0.02	0.11	0.20	0.19	0.02	0.13	0.15	0.16
Private Plan	0.66	0.73	0.74	0.67	0.60	0.70	0.73	0.68	0.59
Medicaid	0.08	0.03	0.02	0.03	0.13	0.08	0.04	0.07	0.15
Medicare	0.12	0.89	0.04	0.01	0.00	0.90	0.03	0.01	0.00

Table OA.9: Summary of NHIS Outcomes

Variable	Description	Years available
Health Behaviors		
smokes	Current smoker	1991-1995, 1997-2018
vacflush12m	Flu shot in past year	1989, 1991, 1993-1995, 1997-2018
General Health		
health_bad	Fair or poor self-reported health	1986-2018
limactivity	Any limitation in usual activities	1986-2018
Healthcare Access		
usualpl	Has a usual place for medical care	1987-1988, 1990-2018
docvis1yr	Doctor visit in past year	1986-2018
docvis5upyr	Last doctor visit 5+ years ago	1986-1996, 1999-2018
hospnght	Hospital overnight stay in past year	1986-2018
Health Insurance		
hinotcov	No health insurance coverage	1986, 1989-2018
hiprivate	Covered by private health insurance	1986, 1989-2018
himcaid	Covered by Medicaid	1990-2018
himcare	Covered by Medicare	1986, 1989-2018