Trading Goods for Lives: The Effect of NAFTA on Mortality

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Abstract

We leverage spatial variation in exposure to the 1994 North American Free Trade Agreement (NAFTA) to examine its impact on mortality and explore quantitative implications for the welfare effects of NAFTA. Areas more exposed to Mexican import competition by NAFTA experienced larger increases in mortality. In the 14 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). NAFTA-induced mortality increases are particularly pronounced among working-age men, a demographic that also experienced disproportionate NAFTA-induced employment declines. Welfare losses from NAFTA-induced mortality more than erase standard calculations of welfare gains from NAFTA based only on its economic impacts. Comparisons with the mortality effects of other economic contractions suggest that, unlike declines in the non-manufacturing employment-to-population (EPOP) ratio, declines in manufacturing EPOP consistently increase mortality.

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1 Introduction

The secular decline in U.S. manufacturing and the accompanying economic decline of particular local labor markets has been linked to a range of societal ills, including decreases in rates of marriage and civic engagement and increases in opioid addiction and deaths of despair (e.g. Winston (1996); Vance (2016); Case and Deaton (2020)). In this paper, we study the mortality consequences of a particular economic shock to the U.S. manufacturing sector: the 1994 North American Free Trade Agreement (NAFTA).

When it went into effect on January 1 1994, the North American Free Trade Agreement (NAFTA) was the most comprehensive free trade agreement that had been negotiated to date (Congressional Budget Office, 2003; Villareal and Fergusson, 2014). To examine its mortality impacts, we adapt the event study approach of Choi et al. (2024) who study the impact of NAFTA on U.S. manufacturing employment by exploiting differential exposure across industries to increased Mexican important competition from NAFTA combined with differential industry mixes across geographic areas in the U.S. Using this same spatial variation in exposure to NAFTA, we estimate that NAFTA also substantially increased over all-cause mortality. On average over the 1994 to 2008 period examined by Choi et al. (2024), a commuting zone with an average increase in exposure to Mexican import competition experienced an increase in annual, age adjusted mortality of 0.68 percent (standard error = 0.19). The mortality impacts of NAFTA grow over time, as tariffs were phased out and manufacturing employment gradually declined. Mortality increases appear across all broad age group by sex groups, but were disproportionately concentrated in working-age men, who also experienced disproportionate declines in employment from NAFTA.

[** TO COME: MECHANISMS **]

Of course, our design only captures the local labor market impacts of NAFTA and does not pick up any nationwide impacts of NAFTA that might operate, for example, through reduced prices and hence increased real disposable income. To gauge the quantitative importance of the mortality increases that we estimate relative to these general equilibrium welfare gains, we write down a simple model in which the welfare consequences of NAFTA with endogenous mortality can be approximated to first order as the sum of the welfare impacts of NAFTA with exogenous mortality and the welfare impacts of the mortality reductions. Under even conservative assumptions about the value of a statistical life year (VSLY), we find that the welfare losses from increases in mortality more than offset Caliendo and Parro (2015)'s estimates that, with exogenous mortality, NAFTA increased U.S. welfare by 0.08%-0.12%.

Finally, in the last section of the paper we compare the impacts of NAFTA on mortality with the mortality impacts of other U.S. economic contractions, specifically job losses due to plant closings (Sullivan and von Wachter, 2009), increased exposure to trade from China (Autor et al., 2013,

2019; Pierce and Schott, 2020), and recessions (Ruhm, 2000; Miller et al., 2009; Stevens et al., 2015; Finkelstein et al., 2025). Notably, the existing evidence indicates that, like NAFTA, job losses due to plant closings or the China Shock increase mortality while recessions decrease mortality.[1] These ostensibly contrasting results can be explained by differential mortality consequences of declines in manufacturing and non-manufacturing EPOP.

Specifically, we implement IV analyses of the relationship between age-adjusted mortality and EPOP, using different economic contractions as instruments for EPOP. We estimate that a 1 percentage point trade-induced decline in EPOP from either NAFTA or the China Shock increases age-adjusted mortality by about 1.5 percent; these estimates are of similar magnitude to the mortality effects of job loss from plant closings estimated by Sullivan and von Wachter (2009), but are of opposite sign and statistically distinguishable from prior estimates that a 1 percentage point recession-induced EPOP decline *reduces* mortality by about 0.5 percent (Ruhm, 2000; Finkelstein et al., 2025). But while recessions typically affect many sectors of the economy, NAFTA, the China Shock, and mass layoffs are concentrated in the manufacturing sector. Exploiting variation across areas in the share of the Great Recession-induced EPOP decline that comes from the manufacturing sector, we find that recession-induced declines in manufacturing EPOP also increase mortality. Indeed, we estimate that counterfactual recessions in which the share of the EPOP decline that comes from the manufacturing sector is similar to that from trade shocks produce quantitatively similar mortality increases. Naturally this finding raises the question of why manufacturing and non-manufacturing EPOP declines have such differently-signed impacts on mortality, and we offer some speculation for further work.

The rest of the paper proceeds as follows. Section 2 describes our data and empirical strategy. Section 3 presents our estimates of the impact of NAFTA on mortality. Section 4 [WILL SOON] present evidence of the mechanisms behind the NAFTA-induced mortality increases. Section 5 explores the implications our our estimates of the mortality impacts of NAFTA for its overall welfare impact. Section 6 shows that differing-signed mortality impacts from declines in manufacturing EPOP and non-manufacturing EPOP offer a parsimonious explanation for the ostensibly conflicting estimates of the impacts of trade-induced employment declines and recession-induced employment declines on mortality. The last section concludes.

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

2 Data and Empirical Strategy

2.1 Background: NAFTA

Signed into law in December 1993 and effective starting January 1 1994, NAFTA enacted 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). As shown in Figure 2, NAFTA created a gradual elimination of all tariffs and most non-tariff barriers over a 10 to 15 year period (Villareal and Fergusson, 2014).

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 with a literature suggesting that in large open economies like the United States where (mechanically) intra-national trade is going to be larger relative to inter-national trade than in small open economies, the welfare gains from international trade more broadly appear to small (Arkolakis et al., 2012; Costinot and Rodríguez-Clare, 2018).

2.2 Data

Following Choi et al. (2024), our baseline sample consists of individuals in the 50 states and the District of Columbia from 1986 to 2008. Our baseline geographic unit of analysis is across Commuting Zones (CZs), which are standard aggregations of counties that partition the United States into 741 areas designed to approximate local labor markets.[2] Following Choi et al. (2024) and Autor et al. (2013), we restrict our analysis to the 722 CZs in the continental US.

Mortality Rates. Following Ruhm (2016) and Finkelstein et al. (2025), we construct 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.

[2]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 is across counties, and we show below that results are similar for county-level analysis.

For each decedent in the CDC data, we observe their county of residence, date 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.

Employment. Our primary source of employment data is the Census Bureau's County Business Patterns (CBP). 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.

Trade exposure measures. We obtain geographic measures of vulnerability to NAFTA and exposure to Chinese import penetration directly from the replication packages of Choi et al. (2024) and Autor et al. (2019), respectively.

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.

2.3 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 depending on their industry composition. 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 g's vulnerabilty (i.e. exposure) to NAFTA is then defined as:

$$\tilde{V}_g = \sum_{j=1}^{J} \frac{L_{1980}^{gj}}{L_{1980}^{g}} \tilde{\text{RCA}}^j \tau_{1990}^j \tag{2}$$

where L_{1980}^{gj} is the number of workers employed in industry j in area g in 1980 expressed as a fraction of the total 1980 employment in area g L_{1980}^{g}, $\tilde{\text{RCA}}^j = \frac{\text{RCA}^j}{\bar{\text{RCA}}^j}$, where $\bar{\text{RCA}}^j$ is the (unweighted) average revealed comparative advantage over all industries j, and τ_{1990}^j is the tariff rate of industry j in 1990. Since the units of $\tilde{V}_g$ are not easily interpretable, we follow Choi et al. (2024) and instead work with a scaled vulnerability measure:

$$V_g = \frac{\tilde{V}_g}{\mathbb{E}\left[\tilde{V}_g | g \in \text{top quartile}\right] - \mathbb{E}\left[\tilde{V}_g | g \in \text{bottom quartile}\right]} \tag{3}$$

which scales $\tilde{V}_g$ 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_g 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,

$$y_{gt} = \beta_t \left[V_g \times \mathbf{1}\left(\text{Year}_t\right)\right] + \alpha_g + \tau_t + \gamma_t \left[\mathbf{1}\left(\text{Region}_{r(g)}\right) \times \mathbf{1}\left(\text{Year}_t\right)\right] + \lambda_t \left[\mathbf{1}\left(\text{Demo}_g\right) \times \mathbf{1}\left(\text{Year}_t\right)\right] + \epsilon_{gt} \tag{4}$$

where α_g and τ_t denote area and year fixed effects, respectively, and where we also also include controls for 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 g 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 g; all regressions are weighted by 1990 CZ population.[3]

[3] In addition to our use of CZ rather than county for g, our baseline specification in equation (4) differs in several other respects from the baseline in Choi et al. (2024). First, our definition of vulnerability $\tilde{V}_g$ in equation (2) involves the number of workers employed in industry j in area g in 1980 as a fraction of the *total* area employment in area g in 1980 rather than (as in Choi et al. (2024) a fraction of area employment in all industries for which the revealed comparative advantage measure RCA_j is defined; note that 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 show robustness below to the choice of controls.

The key coefficients of interest are the β_t's; they measure effects on outcome y_{gt} in year t across areas differentially exposed to NAFTA. Unless otherwise indicates, we omit the interaction with the NAFTA vulnerability measure $\tilde{V}_{g,1990}$ in 1993 (the year prior to NAFTA) so that all β_t coefficients are relative to 1993. The NAFTA vulnerability measure $\tilde{V}_{g,1990}$ 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 $\frac{L^{gj}_{1980}}{L^{g}_{1980}}$ 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. We detail the econometrics behind our empirical strategy in Appendix Section A.

2.4 Descriptive statistics.

Figure 1 panel (a) shows the spatial variation in vulnerability to NAFTA (V_g). Average vulnerability across (population weighted) CZs was 0.35. The figure shows significant variation within and across U.S. states in their exposure to NAFTA. 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, we allow for each census region to have its flexible census trend, so that 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.1a) 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 manufacturing share interacted with year fixed effects.[4] As a result, we identify the impact of manufacturing off of areas with *similar* manufacturing shares but differences in their industry mix within manufacturing that generates variation in their exposure to NAFTA.

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. Figure 1 panel (c) shows that CZs that were more vulnerable to NAFTA also had higher mortality rates in 1993; 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 930 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.

[4] Appendix Figure OA.1b 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 sets of clusters within manufacturing only as well as 3 clusets of the other controls.

3 Mortality Impacts of NAFTA

3.1 Overall Mortality

Figure 3 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). 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 absence of any differential trends in mortality (or employment) in these areas in the years prior to 1994 (i.e. the relatively flat pre-trend) is assuring for the identifying assumption. In addition, the timing of the mortality increase post-NAFTA closely aligns with the timing of the decline in EPOP (shown in light gray), suggesting a close link between the two. The gradual but steady decline in EPOP following NAFTA in turn likely reflects the gradual reduction in tariffs created by NAFTA (see Figure 1 panel (b)).[5]

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. Given that average (scaled) vulnerability across (population-weighted) CZs was 0.35, this implies that on average, NAFTA increased annual age adjusted mortality by 0.67% over the 1994 to 2008 period. Of course these 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 will return to this in the welfare analysis below.

Another way to gauge the magnitude of the mortality estimates is to compare the mortality increases associated with NAFTA to the decline in EPOP associated with NAFTA. Figure 3 indicates that CZs in the top quartile of NAFTA vulnerability experienced an average annual decrease in EPOP of 1.24 percentage points (standard error = 0.20), suggesting that a 1 percentage point decline in EPOP from NAFTA was associated with an approximately 1.5 percent average increase in annual mortality. Over three-quarters of this EPOP decline came from the manufacturing sector, even though manufacturing made up just 19% of employment in 1993 (see Appendix Figure OA.3 and Appendix Table OA.2). By way of comparison, Sullivan and von Wachter (2009) look at long-term, male workers in Pennsylvania who lose their jobs (primarily in manufacturing) between 1980 and 1986 due to mass layoffs and find that job loss increased the log-odds of mortality over the next several decades by 7 to 17%. Of course, 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; in Appendix B we show 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

[5] Choi et al. (2024) similarly find a gradual reduction in employment following the implementation of NAFTA.

point decline in EPOP to conclude that 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).

3.2 Heterogeneity by Sex and Birth Cohort

To better understand the results in Figure 3, we re-estimate equation (4) separately each sex by different birth cohorts, specifically those who, at the start of NAFTA, would have been 0-24, 25-44, 45-64 and 65 and over. Figure 4, panel (a) summarizes the estimated average impacts on mortality between 1994 and 2008; Appendix Figure OA.2 shows the underlying event studies behind each estimate. The results indicate that NAFTA was associated with an increase in mortality for all eight sex by birth cohort groups; effects were particularly pronounced for men born between 1950 and 1969, who would have been aged 25-44 at the time of NAFTA's implementation in 1994 (Figure OA.2c). The point estimates indicate 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 for men aged 25-44 of 8.9% (standard error = 2.2%), compared to the overall average increase in age adjusted mortality of 1.9% (standard error = 0.54%) between 1994 and 2008.

As a point of comparison, we also estimate the impact of NAFTA on EPOP by sex and birth cohort. Since CZ-year EPOP by demographic group is not available during our study period, we instead gauged NAFTA's impact on EPOP for different demographic groups 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.[6] Appendix E provides more details.

Figure 5 panel (a) shows the results; Appendix Figure OA.11 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

[6]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.

by men in the 1950 to 1969 birth cohort (see Appendix Table OA.5). The NAFTA-induced EPOP decline for men in this cohort thus represented about a 1 percent decline in their average EPOP. In Figure 5 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 4).

However, the evidence of mortality increases for individuals 65 and over suggests that not all of the NAFTA-induced mortality increases can be the direct impact of a decline in EPOP. To better understand the magnitude of mortality effects for different demographic gruops which differ greatly in the baseline mortality rates, Figure 4, panel (b) combines the point estimates from panel (a) with baseline mortality rates by demographic group to show the contribution of the different demographic groups to the estimated, NAFTA-induced increase in total mortality. It shows that mortality effects are disproportionately large for prime age men, and disproportionately small for those 65 and over, particularly men 65 and over. Men aged 25-64 account for about 15 percent of deaths in 1993, but 35 percent of the increase in deaths due to NAFTA. Men and women 65 and over accounted for three-quarters of deaths in 1993, but only about half of the increase in deaths due to NAFTA. Since this is not a group that saw declines in EPOP, some other channel must be at stake than the direct impact of declines in EPOP. The fact that most (about three-quarters) of the increase in elderly deaths is for elderly women - who tend to outlive their spouse - raises the possibility that there may be an indirect channel of reduced transfers from adult children. Consistent with this hypothesis, Appendix Figure OA.9 shows that all of the NAFTA-induced increase in mortality for elderly women comes from widowed women, who tend to experience a substantial decline in economic resources upon widowhood (e.g. Diamond and Orszag (2005)). 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.

3.3 Sensitivity Analyses

Endogenous Population Changes. Since deaths and population are typically measured in two different data sets, a pervasive concern in the literature examining the impact of economic shocks on mortality is the possibility for such results to be confounded by endogenous population changes that are not captured by the analysis, a phenomenon termed 'migration bias' (Arthi et al., 2022). 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. In practice, we find no evidence of a population response to exposure to NAFTA; Appendix Figure OA.12 displays estimates of equation

(4) with log population for those aged 25 and older in 1994 in each CZ-year as the outcome.[7] This is consistent with the estimates in Choi et al. (2024) who find no evidence of population declines in counties more vulnerable to NAFTA. Looking within birth cohort by sex bins in Appendix Figure OA.13, we find little evidence of compositional changes as well.

Geography. As mentioned in Section 2.2, we follow our previous work (Finkelstein et al., 2025) and conduct our analysis primarily at the CZ level. However, Appendix Figure OA.10a, which displays estimates of equation (4) at the county level, shows that our finding that NAFTA increased mortality persists when using Choi et al. (2024)'s preferred unit of geography. Another concern is that these effects are driven by secular changes in manufacturing employment and mortality in the Southern Census region, where vulnerability is highest. However, when we limit the analysis to CZs within the Southern Census Region (Appendix Figures OA.4 and OA.5), the results are similar.

Contemporaneous Shocks. 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 their instrument (lagged U.S. employment shares interacted with the increase in imports to 8 other high-income countries). The results are given in Appendix Figure OA.10b; we see little difference from the baseline specification. Since there is a secular manufacturing decline in this period, we also try generating three separate k-means clusters for (1) the manufacturing share in 1980 and (2) our remaining controls. Figure OA.10c displays results controlling for each of these six clusters. Again, the results are quite similar.

4 Mechanisms

[** IN PROGRESS: RESULTS BY CAUSE OF DEATH, IMPACTS ON HEALTH CARE USE, HEALTH BEHAVIORS, HEALTH INSURANCE, SELF-REPORTED HEALTH, AND POLLUTION ***]

By Cause of Death. Since we observe large increases in mortality among prime-aged men (i.e. those born between 1950-1969) and suspect direct effects, we begin our analysis on mortality by cause of death with this subgroup. Following Finkelstein et al. (2025), we separate the International Classification of Diseases (ICD) codes used in the CDC into 11 mutually exclusive and exhaustive

[7] As for our analysis of EPOP, we exclude the youngest birth cohort - those born 1970 to 1994 who were 0-24 in 1994 - from the analysis. Not all of these individuals were yet alive in the 1986-1993 pre period.

groups and compute age-adjusted mortality rates for each cause. The average 1994-2008 estimates of β_t in equation (4) with these variables as the outcome are presented in Figure 6a. The event studies plotting all coefficients are given in Appendix Figures OA.6 and OA.7.

The causes with the largest increase in magnitude are respiratory diseases, infectious diseases, and metabolic disorders. In Figure 6b, we break out categories classified as "deaths of despair" following Finkelstein et al. (2025). We find significant increases in deaths from liver disease; we also find large but imprecise increases in drug overdoses. In the sample of all individuals, there is still a large but imprecise increase in drug overdoses and a marginally significant increase in suicides (Appendix Figure OA.8b). This is consistent with Pierce and Schott (2020)'s finding that job loss induced by trade competition from China led to deaths of despair.

External effects. In Finkelstein et al. (2025), we found relatively similar declines in mortality across age and gender groups. Here, however, we find the largest increases among prime-aged men but also significant impacts on women aged 65 and older when NAFTA was implemented. The fact that this group accounts for the majority of deaths in 1993 means that elderly women actually account for the largest share of the increase in mortality due to NAFTA (see Figure 4b). One potential explanation for this may be due to a loss in support due to mortality among younger family members. We find suggestive evidence of this by examining the impact of NAFTA on mortality for elderly separately by marital status. In Appendix Figure OA.9, we show that almost all of the increase in mortality among elderly women was among widows, the group most vulnerable to losing support from children.

We do not find evidence of pollution effects due to NAFTA. However, we obtain 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.

5 Welfare Implications of the Mortality Effects of NAFTA

To assess the quantitative importance of the estimated effects of NAFTA on mortality (overall and by age and demographic groups), we consider how incorporating our estimated mortality impacts affects estimates of the welfare consequences of NAFTA.

To do this, we develop a simplified model of the effects of NAFTA on wages and prices that we can calibrate based on the results in Caliendo and Parro (2015), and in addition we allow NAFTA to also affect mortality; this allows us to assess the quantitative importance of our estimates of "endogenous mortality" on an otherwise standard calibration that is typically done in quantitative trade papers. Our approach follows existing research that incorporates changes in life expectancy into welfare analysis of changes in economic well-being (e.g. Becker et al. (2005); Jones and Klenow (2016); Finkelstein et al. (2025)).

5.1 Model

Utility. There is a representative agent with exogenous labor supply L in each period t. 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 has a life expectancy T. 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 is given by $U(c) = T * u(c) = T * u(I/p) = T * u(wL/p)$.

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 b governs the willingness to pay for additional years of life.[8]

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:

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

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.[9]

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

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

[9] 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.

(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 2). 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 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:

$$\Delta^{dT}\approx\Delta+dT*\left(\frac{VSLY}{c}+\frac{1}{\gamma-1}\right) \tag{5}$$

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.

It is important to note that this welfare formula assumes that the mortality impacts of NAFTA are not the result of optimizing agents responding to the trade shock by changing their behavior in ways that increase their mortality risk. If it were, the usual envelope theorem arguments would indicate that mortality increases would not, to first order, be relevant for welfare analysis. In practice, however, there is likely to be involuntary unemployment so that individuals are off of their labor supply curve and therefore are not able to optimally allocate across leisure and other goods. Consistent with this, as Andres et al. (2024) observe, to generate the declines in EPOP that local area exposure to trade shocks such as the China Shock or NAFTA produce requires a labor market friction that prevents the market from clearing on wages, such as downward nominal wage rigidities (DNWR).

5.2 Calibration and Results

To calibrate the welfare approximation formula in equation 5 we use $\Delta = 0.11\%$ following Caliendo and Parro (2015) (i.e., NAFTA increases real wages permanently by 0.11 percent). To calculate dT we extrapolate our local labor market estimates nationally using the average exposure and estimate that NAFTA increased mortality by 0.68% for 15 years. To translate this percent change in mortality rate into a predicted change in life expectancy, we use SSA life tables from 1993 and calculate a change in life expectancy of -0.0316% for someone at age 40 in 1993. This is a small percentage reduction that comes partly from the very low baseline mortality rate for this age group. By comparison, for someone at age 60 in 1993 the same 0.68 percent mortality rate increase translates into a reduction in life expectancy of -0.143 percent (roughly 4.5 times larger than the age 40 percent change).

Following Finkelstein et al. (2025), we assume a value of a statistical life year that is five times annual consumption (i.e. $VSLY/c = 5$) and $\gamma = 2$ in our baseline scenario, which then gives $\Delta^{dT} \approx 0.11 + (5-1) * (-0.0316) = -0.0164$. Strikingly, this stylized caculation shows that the welfare effect of NAFTA changes sign accounting for the mortality effects, going from a 0.11 percent welfare *gain* (coming through the increase in real wages) to a 0.016 percent welfare *loss* (coming from the increased mortality rate).

6 Understanding mortality impacts of different economic contractions

To what extent do the mortality effects from NAFTA generalize to other economic contractions? The existing evidence indicates that recession-induced declines in local labor market *reduce* mortality (Ruhm, 2000; Miller et al., 2009; Stevens et al., 2015; Finkelstein et al., 2025) but 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). In this section we investigate these different results and suggest that a parsimonious explanation may lie in opposite-signed mortality impacts of declines in manufacturing and non-manufacturing EPOP.

6.1 Relationship between EPOP and death varies across economic contractions

We begin by revisiting and comparing the employment and mortality effects of NAFTA to those associated with increased exposure to trade from China (the so-called China Shock) and with recessions. To put these analyses in comparable units, we compare estimates of the impact of EPOP on log age-adjusted mortality across different sources of local economic contractions. Relative to the analyses in the preceding sections, for purposes of this comparison we are imposing the exclusion

restriction that local economic contractions affect mortality only via their impact on EPOP.

Table 1 reports the results from estimating CZ-level analyses of of the following form:

$$y_{ct} = \alpha_c + \tau_t - \beta \text{EPOP}_{ct} + X_{ct}\psi + \epsilon_{ct} \tag{6}$$

where y_{ct} denotes the log age-adjusted mortality in each CZ-year, 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 coefficient of interest β reflects the relationship between a decline in CZ-year EPOP (note the minus sign in front of β) and log age-adjusted mortality.

Column (1) shows the results from estimating equation (6) by OLS (with no additional covariates (X_{ct}); it represents a Ruhm (2000)-style two-way fixed effects regression of mortality on CZ and year fixed effects during the sample period for our NAFTA analysis (1986-2008). The OLS estimates of β indicate that a 1 percentage point decline in CZ-year EPOP is associated with a 0.35% (standard error = 0.12%) decline in mortality.

Column (2) of Table 1 shows the results of IV estimation of equation (6) using data from 2003 to 2016 and instrumenting for EPOP_{ct} using variation induced by the Great Recession, as in Finkelstein et al. (2025). Specifically, we instrument for EPOP_{ct} in equation (6) with a series of year fixed effects interacted with the Great Recession Shock (GR_SHOCK_c) where GR_SHOCK_c is the 2007-2009 change in the EPOP ratio in CZ c; prior work has shown that this area-level measure of exposure to the Great Recession is associated with a prolonged decline in EPOP through the end of our study period (Yagan, 2019; Finkelstein et al., 2025). In other words we estimate the first stage equation:

$$\text{EPOP}_{ct} = \alpha_c + \tau_t + Z_{ct}\phi + X_{ct}\psi + \eta_{ct} \tag{7}$$

where the instrument Z_{ct} is defined as:

$$Z_{ct} = \left[\begin{array}{cccc} \text{GR_SHOCK}_c \times \mathbf{1}(t = 2007) & \text{GR_SHOCK}_c \times \mathbf{1}(t = 2008) & \ldots & \text{GR_SHOCK}_c \times \mathbf{1}(t = 2016) \end{array} \right] \tag{8}$$

and where as in column (1) there are no additional covariates X_{ct} in either the first or second stage. The estimates indicate that a one percentage point Great Recession-induced decline in EPOP results in a 0.67% (standard error = 0.23%) decline in mortality. We are unable to reject that the OLS estimate of β in column (1) is the same as the IV estimate in column (2).

However the results look very different if we instead examine the impact of NAFTA-induced declines in EPOP - rather than recession-induced declines in EPOP - on mortality. Specifically, we estimate equation (6) over the 1986-2008 period by IV, but now we replace the instruments Z_{ct} in equation (7) with a series of year fixed effects interacted with our CZ-level measure of NAFTA vulnerability V_c:

$$Z_{ct} = \left[\begin{array}{cccc} V_c \times \mathbf{1}\left(t = 1994\right) & V_c \times \mathbf{1}\left(t = 1995\right) & ... & V_c \times \mathbf{1}\left(t = 2008\right) \end{array} \right] \tag{9}$$

and where X_{ct} in both the first and second stage is the same set of baseline controls used in our reduced form analysis of NAFTA in equation (4). Column (3) of of Table 1 shows the results which indicate that a 1 percentage point NAFTA-induced decline in EPOP results in a 1.37% (standard error = 0.53%) *increase* in mortality. The sign of this estimate of β is unsurprising given the reduced-form estimates presented in Section 3. Strikingly, however, the NAFTA-induced decline in EPOP produces an estimate of the relationship between EPOP and mortality β 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 EPOP and mortality in columns (1) and (2).

Moreover, our estimate of the relationship between NAFTA-induced declines in EPOP and mortality is very close to what we find when we estimate the relationship between China Shock-induced declines in EPOP and mortality. To the best of our knowledge, the impact of the China shock on all-age, all-cause mortality has not previously been examined. To do so, we follow the empirical strategy of Autor et al. (2013) who used variation in local area exposure to the China Shock to study the impact of the China Shock on the gender gap in cumulative mortality for adults ages 20 to 39 using a stacked long-differences specification that relates changes in CZ-level outcomes to changes in important penetration from China which varies across CZs based on their baseline industry mix. We extend their analysis to look at impacts of exposure to the China Shock on all-age, all-cause mortality. Appendix C describes our analysis and results in more detail.

We estimate that a 1 percentage point increase in CZ exposure to Chinese import penetration is associated with an increase in the 10-year cumulative mortality rate of 215 per 100,000 (standard error = 99.7), or about a 2.4 percent increase in mortality relative to average 10-year mortality of 8,922 per 100,000. Using the same empirical approach, we also estimate 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). Combining these two estimates in a manual "IV", in column 4 of Table 1 we estimate that a 1 percentage point China-Shock induced decline in EPOP results in a 1.66% (standard error = 0.95) increase in age-adjusted mortality. Unlike the 'reduced form' impact on mortality, the IV estimate of the relationship between EPOP and mortality is only statistically significant at the 10 percent level, but we are able to reject the null hypothesis that it is the same as the recession-induced relationship between EPOP and mortality in column 1 (p-value = 0.04).

Taken as a whole, the results in Table 1 display a striking pattern. A recession-induced percentage point decline in EPOP - whether using area x year variation or instrumenting for EPOP 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 decine in EPOP - whether from NAFTA or the China Shock - is associated with about a 1.5 percentage point *increase* in mortality. The mortality

effects of recession-induced EPOP declines vs. trade-induced EPOP declines are statistically distinguishable from each other, while difference sources of recession-induced EPOP declines yield similar point estimates and statistically indistinguishable (compare columns (1) and (2)) and likewise for difference sources of trade-induced EPOP declines (compare columns (3) and (4)).

6.2 Mortality impacts of manufacturing and non-manufacturing EPOP declines

A natural candidate explanation for these findings is that trade-induced EPOP declines are much more concentrated in the manufacturing sector than recession-induced EPOP declines.[10] Consistent with this, Table 2 repeats the above analyses of the EPOP impacts of different economic shocks separately for manufacturing and non-manufacturing EPOP. It shows that over 90-percent of NAFTA-induced EPOP declines or China-Shock induced EPOP declines are in the manufacturing sector, but only 14% of the Great-Recession induced EPOP declines and only 33 percent of CZ-year fluctuations in EPOP is in manufacturing.

To examine this hypothesis more directly, 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 employment declines to vary by sector. Specifically, we now leverage geographic variation not only in the *size* of the Great Recession EPOP shock but also in the *share* of the Great Recession-induced employment decline that comes from the manufacturing sector an examine how the relationship with the log age adjusted mortality rate y_{ct} varies across these sectors. We find that Great Recession-induced declines in manufacturing EPOP *increase* mortality while Great Recession-induced declines in non-manufacturing EPOP *decrease* mortality.

Specifically, we estimate:

$$y_{ct} = \sum_{s \in \mathcal{S}} \theta_{s,t} \left[\text{GR_SHOCK}_{s,c} \times \mathbf{1} \left(\text{Year}_t \right) \right] + \alpha_c + \tau_t + \epsilon_{ct} \tag{10}$$

where $\text{GR_SHOCK}_{s,c}$ is the 2007-2009 change in the EPOP ratio in sector s, and $\mathcal{S}$ consists of the manufacturing and non-manufacturing sectors. The Great Recession shock —defined as the 2007-2009 change in the EPOP ratio— that we used as an instrument for EPOP in equation (9) is the sum of the 2007-2009 changes in the EPOP ratio in the manufacturing and non manufacturing sector.

Figure 7a displays the event study coefficients from estimating (10) on a single Great Recession shock variable, while Figures 7b and 7c display estimates of $\theta_{s,t}$ from estimating (10) on both manufacturing and non-manufacturing EPOP. Figure 7a replicates the finding in Finkelstein et al. (2025) that, on average between 2007 and 2016, a 1-point drop in the EPOP ratio during

[10] Recall also that the estimates of the mortality effects of job loss in Sullivan and von Wachter (2009) were focused primarily on job loss in manufacturing and implied a relationship between EPOP declines and mortality that was similar in magnitude to our NAFTA estimates.

the Great Recession decreases annual ave-adjusted mortality by 0.5% (standard error = 0.1%). However, it turns out this result masks important underlying heterogeneity in the relationship between mortality and industry-specific employment. Figure 7b shows that a one-point decrease in EPOP in the manufacturing sector led to a (statistically significant) *increase* in mortality by 1.4% (standard error = 0.4%) while Figure (7c) shows that a one percentage point decrease in EPOP in the non-manufacturing sectorled to a (statistically signficiant) *decrease* in mortality by 1.1% (standard error = 0.2%). In other words, when treating the Great Recession as a shock purely to employment in manufacturing—as Figure 7b does by controlling for shocks to non-manufacturing industries—we find that reductions in employment increase mortality. This is consistent with the fact that NAFTA and Chinese import penetration, two economic shocks that primarily affect employment in manufacturing, led to increases in mortality.

Moreover, projecting the Great Recession's sector-specific EPOP effects on mortality onto the sector-specific shares of EPOP declines from NAFTA or from the China Shock, we estimate that a counterfactual Great Recession that had a similar share of its EPOP declines in manufacturing as these trade shocks would have produced average mortality increases very similar to what we estimate for each of these trade shocks. Specifically, the estimates of $\theta_{s,t}$ from equation (10) allow us to "predict" the effect of NAFTA on mortality based on its effects on industry-specific employment. We sketch the basic framework here; the full details are in Appendix D.

Suppose that the structural relationship between changes in mortality in each CZ in a period τ ($\Delta m_{c\tau}$) and changes in employment differs by industry, so that

$$\Delta m_{c\tau} = \tilde{\beta}_m \Delta \text{MFG_EPOP}_{c\tau} + \tilde{\beta}_n \Delta \text{NONMFG_EPOP}_{c\tau} + \epsilon_{c\tau} \tag{11}$$

where $\Delta \text{MFG_EPOP}_{c\tau}$ and $\Delta \text{NONMFG_EPOP}_{c\tau}$ denote the change in the EPOP ratio in manufacturing and non-manufacturing industries in CZ c and period τ, respectively. Using variation from the Great Recession, we can obtain unbiased estimates of $\tilde{\beta}_s$ from a "Wald"-type IV estimator in which we combine "reduced form" estimates of the relationship between mortality and the Great Recession shock to manufacturing EPOP and between mortality and the Great Recession shock to non-manufacturing EPOP (eg. $\theta_{s,t}$ from equation (10)) with "first-stage" estimates of $\theta_{s,t}$ with sector-specific EPOP ratios as the outcome. We then multiply the estimates $\tilde{\beta}$s, by the estimated changes in sector-specific EPOP induced by NAFTA or the China Shock.

The result using estimates of $\tilde{\beta}_m$ and $\tilde{\beta}_n$ obtained using various time periods after the Great Recession are given in Table 3. For NAFTA, we consistently predict increases in mortality of between 1.3 and 1.5 percent, compared to the 1.9 percent estimate in Figure 3. For the China Shock, we predict mortality to have increased by 2.0 to 2.8 percent, compared to our estimated mortality increase of 2.4%.

An important question for further work is *why* these two types of EPOP declines appear to have opposite signed impacts on mortality. One factor that may be at play is that job loss in

manufacturing tends to produce greater percentage declines in long-run earnings than job losses in other sectors, which may in turn reflect the higher rates of unionization and of wages and job tenure in manufacturing (Rose and Shem-Tov, 2023). Consistent with this hypothesis, we found that for both NAFTA and the China Shock , increased mortality is disproportionately concentrated among working age men - 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 economically affected, but who may benefit from reduced pollution or improved quality of nursing home staffing (Stevens et al., 2015; Finkelstein et al., 2025).

7 Conclusion

We examined the impact of local-area exposure to import competition via NAFTA on mortality and explored implications for the overall welfare consequences of NAFTA. NAFTA substantially increased mortality, particularly among working-age men, who were also the group who experienced disproportionate NAFTA-induced employment declines. [MECHANISMS IN PROGRESS]

On average we estimate that NAFTA increased the age-adjusted annual mortality rate by 1.9 percent (standard error = 0.54) between 1994 and 2008. This estimate, however, only reflects the local labor market impacts of NAFTA and does not pick up any nationwide impacts of NAFTA that might operate, for example, through reduced prices and hence increased real disposable income. However, our welfare analysis suggests that, even conservative assumptions about the value of a statistical life year (VSLY), welfare losses from NAFTA-induced mortality increases more than erase standard calculations of welfare gains from NAFTA based only on its economic impacts. 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 small (e.g. Arkolakis et al. (2012); Costinot and Rodríguez-Clare (2018)).

Finally, we demonstrate that the ostensible conflict between our findings that trade-induced employment declines increase mortality and existing evidence that recession-induced employment declines decrease mortality can be explained by differences in the role of manufacturing and non-manufacturing EPOP declines induced by trade shocks compared to recessions. Recessions typically affect many sectors of the economy, while the existing evidence of the mortality increases from declines in employment—whether due to mass layoffs or trade-induced economic declines—pertains primarily to the manufacturing sector. We estimate that counterfactual recessions in which the share of the EPOP decline that comes from the manufacturing sector is similar to that from trade shocks produce quantitatively similar mortality increases. An important question for further work is why declines in manufacturing EPOP increase mortality while declines in non-manufacturing

EPOP do not. Possible explanations include heterogeneity in the types of workers affected as well as the nature of rents in manufacturing jobs.

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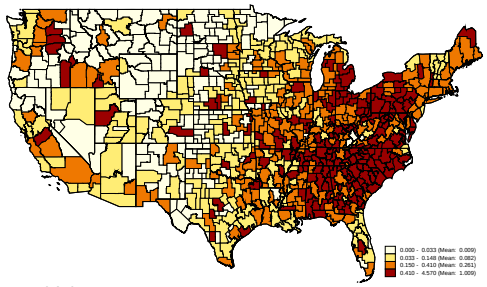
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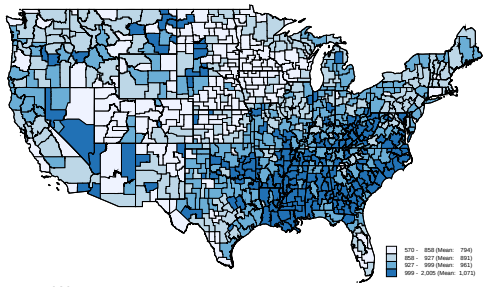
Figures

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

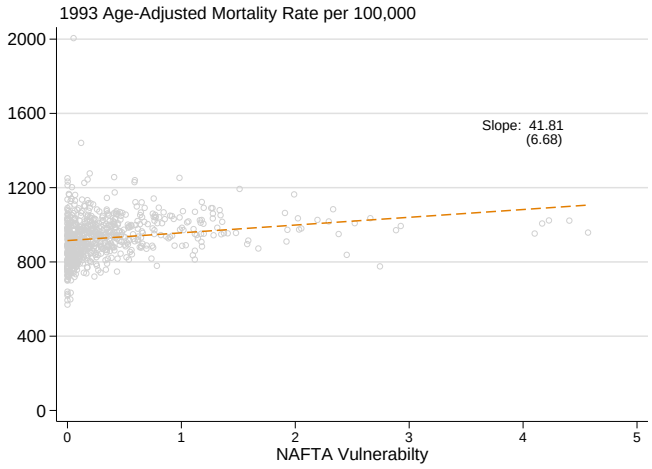
(a) NAFTA Vulnerability



(b) 1993 Age-Adjusted Mortality

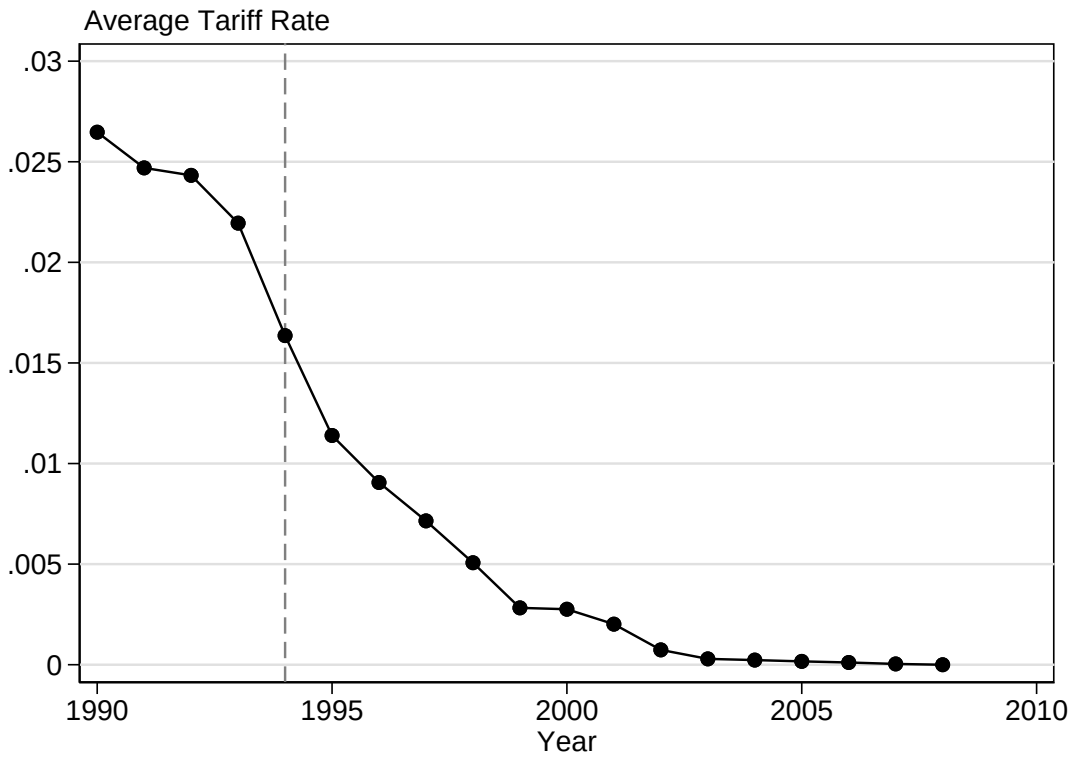


(c) Correlation of Baseline Mortality and Vulnerability



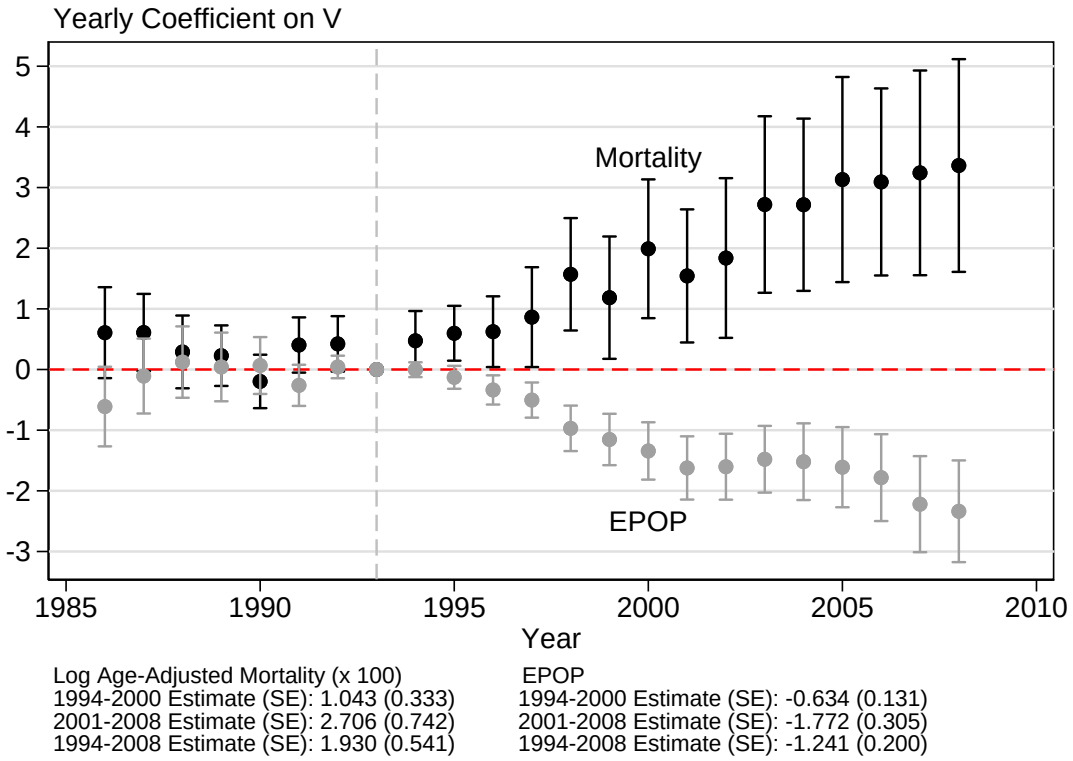
Notes: Panel A displays a heatmap of the NAFTA vulnerability measure across CZs, while Panel B displays a heatmap of 1993 age-adjusted mortality rates. Panel C displays a scatterplot of these measures against each other, along with the regression slope coefficient and heteroskedasticity robust standard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

Figure 2: 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).

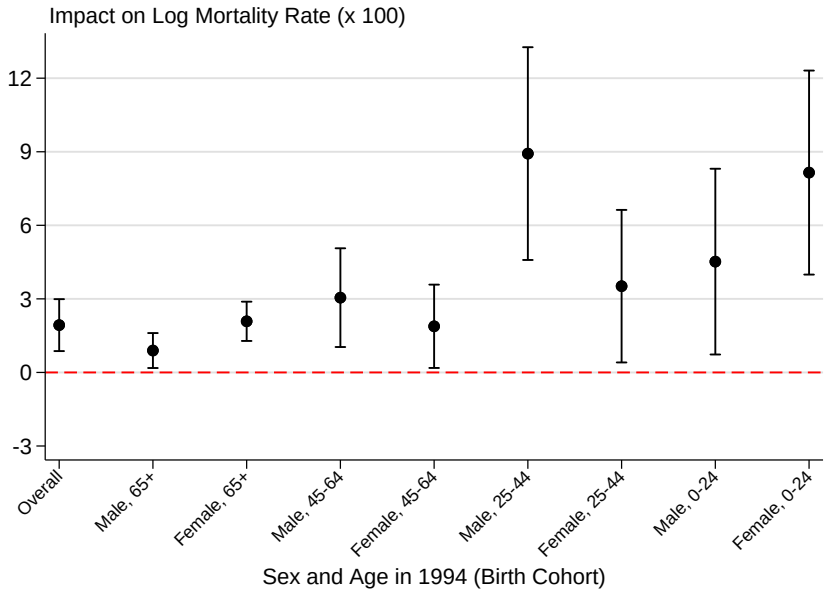
Figure 3: Impact of NAFTA Vulnerability on Log Mortality



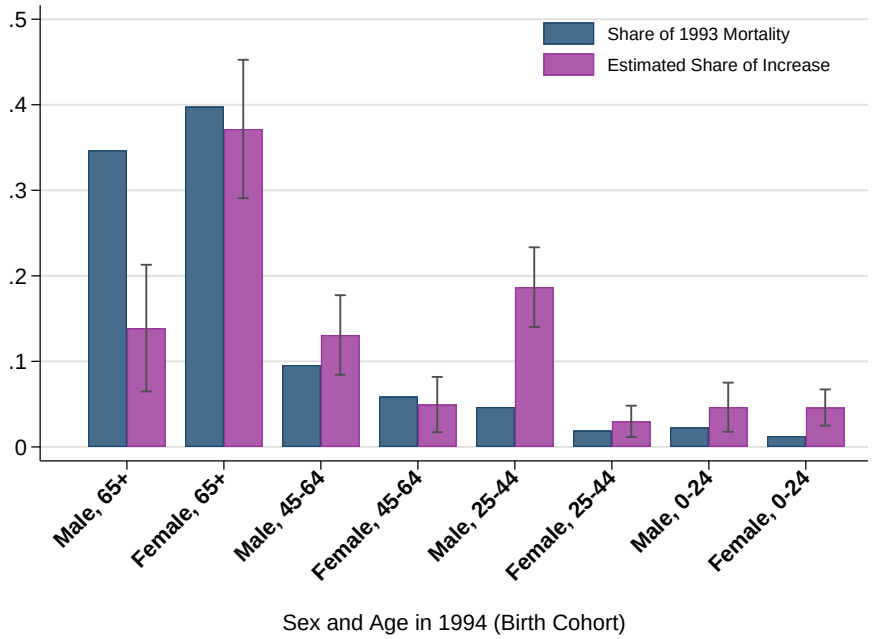
Notes: This figure displays (in black) 100 times estimates of β_t from equation (4), where the outcome y_{gt} is the log age-adjusted CZ mortality rate per 100,000. It also shows (in gray) estimates of β_t with EPOP as the outcome. The units can be interpreted in terms of percent changes for mortality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

(a) 1994-2008 Pooled Estimates



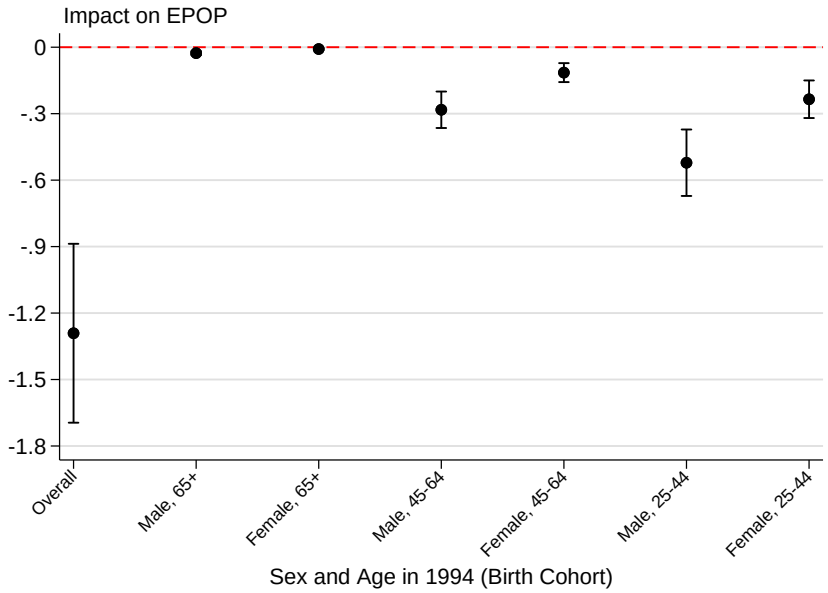
(b) 1994-2008 Decomposition



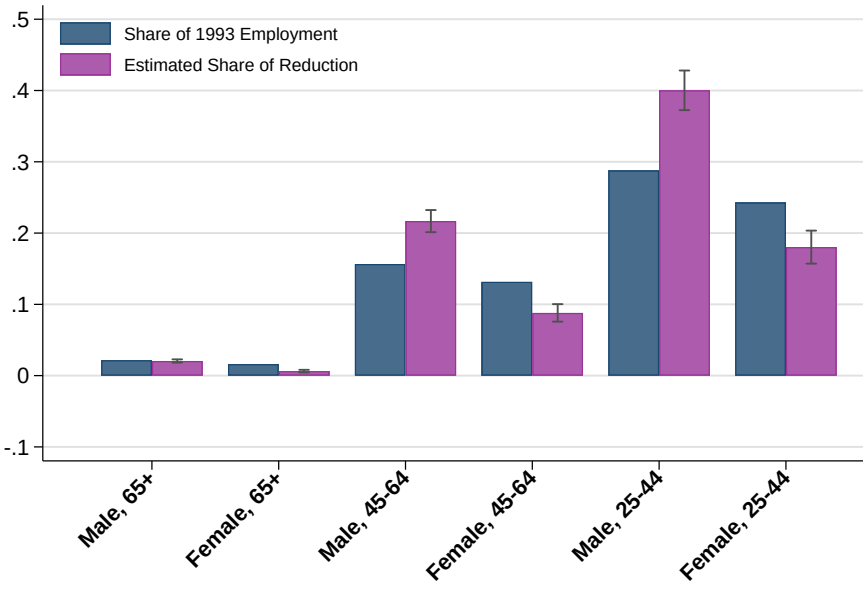
Notes: Panel (a) gives the average 1994-2008 estimate of β_t in equation (4) with the log mortality rate for each demographic group given on the x-axis as the outcome. In panel (b), the blue bars denote the share of deaths each demographic group accounted for in 1993, while the purple bars denote the 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 5: EPOP Decomposition By Birth Cohort and Gender

(a) 1994-2008 Pooled Estimates



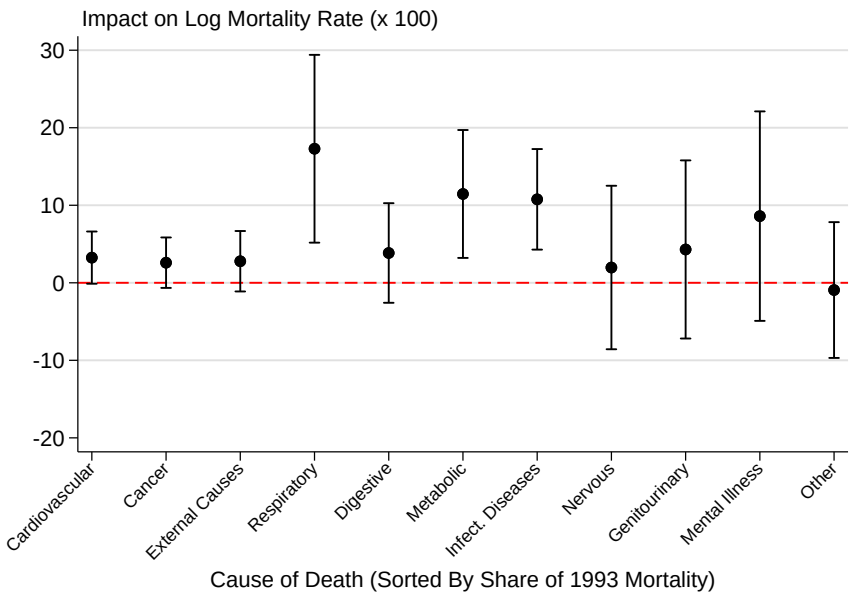
(b) 1994-2008 Decomposition



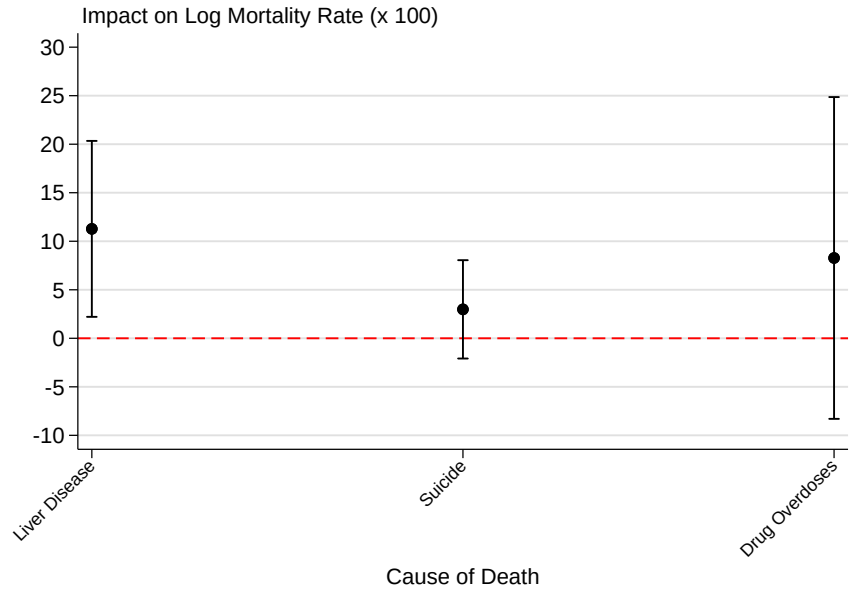
Notes: Panel (a) gives the imputed average 1994-2008 estimate of β_t in equation (4) for EPOP in each demographic group given on the x-axis. In panel (b), the blue bars denote the share of employment each demographic group accounted for in 1993, while the purple bars denote the share of the decline in 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 E. 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 6: NAFTA Mortality Impacts By Cause of Death (Men Born 1950-1969)

(a) Broad Categories



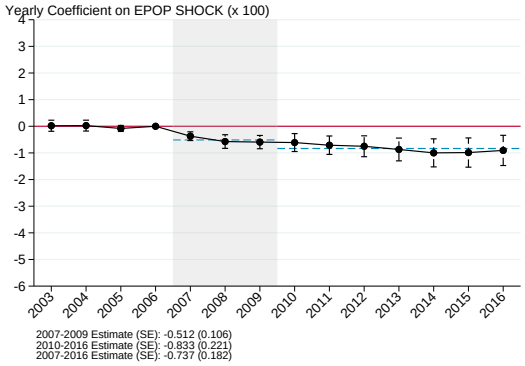
(b) Deaths of Despair



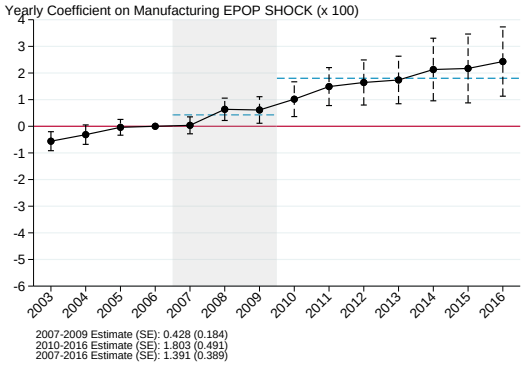
Notes: This figure displays 100 times the average estimate of β_t in equation (4) over the 1994-2008 period, where the outcomes are the log mortality rate per 100,000 among men born between 1950 and 1969 by cause of death. A one-point increase in NAFTA vulnerability V_g corresponds to moving from the 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 7: Effects of Great Recession EPOP Shocks on Mortality by Industry

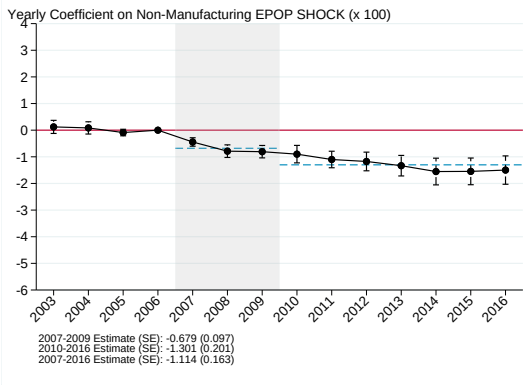
(a) Total EPOP



(b) Manufacturing



(c) Non-Manufacturing



Notes: This figure displays 100 times event study coefficients from estimating equation (10) on a single Great Recession shock variable (panel a) and estimates of $\theta_{s,t}$ from estimating equation (10) in panels b and c. The outcome y_{ct} is the log age-adjusted mortality rate per 100,000 in each CZ-year. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 2007-2009 and 2010-2016. These estimates (and corresponding standard errors) are reported in the lower left-hand corner, along with the corresponding estimate for the entire 2007-2016 period. 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.

Tables

Table 1: IV Estimates of the Impact of EPOP on Mortality

	OLS	IV (Great Recession)	IV (NAFTA)	IV (China Shock)
	(1)	(2)	(3)	(4)
EPOP Decline (×100)	-0.353	-0.667	1.371	1.664
	(0.122)	(0.233)	(0.525)	(0.954)
First Stage F Statistic		136.09	4.06	
p-value		0.00000	0.00000	
$\beta^{IV} = \beta^{OLS}$ (p-value)		0.285	0.003	0.040
N	16,606	10,332	16,606	1,444

Notes: column (1) presents OLS estimates of β in equation (6) with log age-adjusted mortality as the outcome. Columns (2) and (3) present IV estimates, instrumenting for EPOP_{ct} using yearly 2007-2016 post-period indicators for GR_SHOCK_c (column 2) or yearly 1994-2008 post-period indicators for V_c and (column 3). Standard errors clustered at the CZ level are displayed in parentheses. Column (4) gives the implied percent change in cumulative mortality due to a one-point increase in the EPOP ratio induced by Chinese import penetration. This is computed by dividing the estimate of β_1 in equation (16) with cumulative mortality as the outcome by the estimate of β_1 with the change in the EPOP ratio in each period as the outcome. All estimates and standard errors are multiplied by 100 for ease of interpretability. For the relevant columns, I display Kleibergen-Paap first stage F-statistics. Columns (1) and (3) are estimated on a sample of 722 CZs between 1986 and 2008, and each regression is weighted by the CZ's population in 1990. Column (2) is estimated on a sample of 738 CZs between 2003 and 2016, and the regression is weighted by the CZ's population in 2006. Column (4) is estimated on a sample of 722 CZs in the 1990-2000 and 2000-2014 periods, and the regression is weighted by the product of period length and the start of period population share.

Table 2: Effects of Shocks on EPOP By Sector

	Manufacturing EPOP	Non-Manufacturing EPOP	Share Manufacturing
	(1)	(2)	(3)
EPOP (OLS)	0.327	0.673	0.327
	(0.020)	(0.020)	
Great Recession	-0.092	-0.580	0.137
	(0.034)	(0.072)	
NAFTA	-1.072	-0.080	0.930
	(0.233)	(0.198)	
China Shock	-1.319	-0.129	0.911
	(0.210)	(0.437)	

Notes: the first row presents estimates of β in equation (6) with manufacturing and non-manufacturing EPOP as outcomes. The second row presents average estimates of ϕ in equation (7) for each type of EPOP, where Z_{ct} is the Great Recession shock interacted with 2007-2016 post-period indicators. The third row also presents average estimates of ϕ in equation (7), except Z_{ct} denotes NAFTA vulnerability interacted with 1994-2008 post-period indicators. The last row presents estimates of β_1 in equation 16 with the change in each EPOP ratio in period τ. Standard errors clustered at the CZ (rows 1-3) or state (row 4) level are displayed in parentheses. The first and third regressions are weighted by each CZ's population in 1990, the second is weighted by each CZ's population in 2006, and the fourth regression is weighted by the product of period length and start-of-period population shares. The sample size is 722 CZs in rows (1), (3), and (4) and 740 CZs in row (2).

Table 3: Predicted NAFTA Mortality Effects

	Percent Change in Mortality	
	NAFTA	China Shock
Predicted Using Great Recession Post-Period	(1)	(2)
2007-2009	1.547	2.825
2010-2016	1.313	1.996
2007-2016	1.415	2.203
Estimated Effect	1.930	2.409
	(0.538)	(1.117)

Notes: Column (1) of this table displays the predicted impact of a one-point increase in scaled NAFTA vulnerability on log mortality rates constructed from estimates of NAFTA's impact on manufacturing and non-manufacturing EPOP ratios and the effect of changes in EPOP on changes in mortality, as described in Appendix D. Likewise, column (2) displays the predicted percent change in cumulative mortality induced by a one-point increase in Chinese import penetration. Briefly, we estimate the propagation matrix for the impact of changes in manufacturing and non-manufacturing EPOP induced by the Great Recession on mortality and each type of EPOP in the post-period given in each row of the table. In column (1), we then multiply by the average 1994-2008 estimate of β_t in equation (4) with manufacturing and non-manufacturing EPOP ratios as outcomes. In column (2), we multiply by the estimate of β_1 in equation (16) with the change in manufacturing and non-manufacturing EPOP ratios as outcomes. The sample size is 722 CZs in both columns.

Appendices

A Econometric Details

As our NAFTA vulnerability measure $\tilde{V}_{g,1990}$ has a shift-share (or "Bartik") structure, identification of the event study coefficients β_t in equation (4) can come from assuming exogeneity of the "shares" $\frac{L^{gj}_{1980}}{L^{g}_{1980}}$ (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 we show is equivalent to a parallel trends assumption in our event study framework.

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

$$y_{ct} = D_{ct}\rho + x_{ct}\beta_0 + \epsilon_{ct} \tag{12}$$

where y_{ct} denotes the wage *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

$$B_{ct} = \sum_k z_{ck0} g_{kt} \tag{13}$$

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_{gt} 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_{gt} conditional on controls. Thus, we can indeed use the flat pre-trends in our event study estimates to test the validity of the empirical design.

B Benchmarking 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

$$\text{EPOP}_t = \text{EPOP}_t^{\text{ND}} + \delta^D \times \pi_t^D \tag{14}$$

where $\text{EPOP}_t^{\text{ND}}$ 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

$$\text{EPOP}_{t+1} - \text{EPOP}_t = \underbrace{\text{EPOP}_{t+1}^{\text{ND}} - \text{EPOP}_t^{\text{ND}}}_{=0} + \delta^D \left(\pi_{t+1}^D - \pi_t^D\right) \tag{15}$$

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.

C Revisiting the China Shock

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

$$Y_{c,\tau} = \alpha_\tau + \beta_1 \Delta \text{IP}_{c,\tau} + \mathbf{X}'_{c,\tau}\beta_2 + \epsilon_{c,\tau} \tag{16}$$

where $Y_{c\tau}$ is the 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.[11] Period fixed effects are denoted by α_τ, and $\mathbf{X}_{c,\tau}$ denotes the vector of controls used in Autor et al. (2019)[12]).

[11] 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.

[12] 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 demographics (education, race, and

$\Delta \text{IP}_{c,\tau}$ 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:

$$\Delta \text{IP}_{c,\tau} = \sum_i \frac{L_{c,i,90}}{L_{c,90}} \Delta \bar{\text{IP}}_{i,\tau} \tag{17}$$

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

$$\Delta \bar{\text{IP}}_{i,\tau} = \frac{\Delta M_{i,\tau}}{Y_{i,91} + M_{i,91} - X_{i,91}} \tag{18}$$

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[13]:

$$\Delta \tilde{\text{IP}}_{c,\tau} = \sum_i \frac{L_{c,i,80}}{L_{c,80}} \Delta \tilde{\text{IP}}_{i,\tau} = \sum_i \frac{L_{c,i,80}}{L_{c,80}} \frac{\Delta \tilde{M}_{i,\tau}}{\tilde{Y}_{i,88} + \tilde{M}_{i,88} - \tilde{X}_{i,88}} \tag{19}$$

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.3 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 cumulative mortality rate of 215 per 100,000 (standard error = 99.7), or about a 2.4 percent increase in mortality relative to average 10-year mortality of 8,922 per 100,000. Using the same empirical approach, column (2) of Appendix Table OA.3 reports the 'first stage' estimate 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). Combining these two estimates in a manual "IV", column 4 of Table 1 we estimate that a 1 percentage point China-Shock induced decline in EPOP results in a 1.66% (standard error = 0.95) increase in age-adjusted mortality. Unlike the 'reduced form' impact on mortality, the IV estimate of the relationship between EPOP and mortality is only statistically significant at the 10 percent level, but we are able to reject the null hypothesis that it is the same as the recession-induced relationship between EPOP and mortality in column 1 (p-value = 0.04).

In columns (3), (4), and (5) of Appendix Table OA.3, we estimate equation (16) 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.3. In column (1) of Table OA.3, we find that a one-unit increase in import penetration led to an increase of 215.4 in the cumulative mortality rate. This represents a 2.4% increase from the baseline rate of 8,954 deaths per 100,000.

the fraction of working-age women employed

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

D Accounting for NAFTA's Mortality Impacts: Empirical Details

D.1 Setup

Let $\Delta m_{c\tau}$ denote the change in mortality in CZ c during period τ. Furthermore, let $\Delta\text{MFG_EPOP}_{c\tau}$ and $\Delta\text{OTHER_EPOP}_{c\tau}$ denote the changes in manufacturing and non-manufacturing EPOP, respectively. The structural relationship is characterized via

$$\Delta m_{c\tau} = \tilde{\beta}_m \Delta\text{MFG_EPOP}_{c\tau} + \tilde{\beta}_n \Delta\text{OTHER_EPOP}_{c\tau} + \epsilon_{c\tau} \tag{20}$$

where $\epsilon_{c\tau}$ is mean zero. The goal is to estimate the vector

$$\begin{bmatrix} \tilde{\beta}_m & \tilde{\beta}_n \end{bmatrix}$$

However, we are unwilling to assume that $\Delta m_{c\tau}$ is independent of $\epsilon_{c\tau}$ conditional on EPOP changes in the different sectors, so we cannot estimate equation (20) directly via OLS.

Instead, suppose we have unbiased estimates of β_m and β_n in the "reduced form" equation

$$\Delta m_{c\tau} = \beta_m \text{GR_SHOCK}_{m,c} + \beta_n \text{GR_SHOCK}_{n,c} + \epsilon_{c\tau} \tag{21}$$

where e.g. β_m is the effect of the 2007-2009 change in manufacturing EPOP ($\text{GR_SHOCK}_{m,c}$) on the period τ change mortality, controlling for 2007-2009 changes in EPOP in the non-manufacturing sector.

We can also estimate this specification with sector-specific EPOP on the left-hand side to obtain estimates of the θ parameters in the equations

$$\Delta\text{MFG_EPOP}_{c\tau} = \theta_m^m \text{GR_SHOCK}_{m,c} + \theta_n^m \text{GR_SHOCK}_{n,c} + \epsilon_{c\tau}^m \tag{22}$$

$$\text{OTHER_EPOP}_{c\tau} = \theta_m^n \text{GR_SHOCK}_{m,c} + \theta_n^n \text{GR_SHOCK}_{n,c} + \epsilon_{c\tau}^n \tag{23}$$

Writing equations (22) and (23) in matrix form, we have

$$\begin{bmatrix} \Delta\text{MFG_EPOP}_{c\tau} \\ \Delta\text{OTHER_EPOP}_{c\tau} \end{bmatrix} = \begin{bmatrix} \theta_m^m & \theta_n^m \\ \theta_m^n & \theta_n^n \end{bmatrix} \begin{bmatrix} \text{GR_SHOCK}_{m,c} \\ \text{GR_SHOCK}_{n,c} \end{bmatrix} + \begin{bmatrix} \epsilon_{c\tau}^m \\ \epsilon_{c\tau}^n \end{bmatrix} \tag{24}$$

Denote the matrix of θ values by M. In matrix form, equations (20) and (21) become

$$\Delta m_{c\tau} = \begin{bmatrix} \tilde{\beta}_m & \tilde{\beta}_n \end{bmatrix} \begin{bmatrix} \Delta\text{MFG_EPOP}_{c\tau} \\ \Delta\text{OTHER_EPOP}_{c\tau} \end{bmatrix} + \tilde{\epsilon}_{c\tau} \tag{25}$$

and

$$\Delta m_{c\tau} = \begin{bmatrix} \beta_m & \beta_n \end{bmatrix} \begin{bmatrix} \text{GR_SHOCK}_{m,c} \\ \text{GR_SHOCK}_{n,c} \end{bmatrix} + \epsilon_{c\tau} \tag{26}$$

respectively. Equating equations (25) and (26), we have

$$\begin{bmatrix} \tilde{\beta}_m & \tilde{\beta}_n \end{bmatrix} \begin{bmatrix} \Delta\text{MFG_EPOP}_{c\tau} \\ \Delta\text{OTHER_EPOP}_{c\tau} \end{bmatrix} + \tilde{\epsilon}_{c\tau} = \begin{bmatrix} \beta_m & \beta_n \end{bmatrix} \begin{bmatrix} \text{GR_SHOCK}_{m,c} \\ \text{GR_SHOCK}_{n,c} \end{bmatrix} + \epsilon_{c\tau} \tag{27}$$

Substituting equation (24), we have

$$\left[\begin{array}{cc}\tilde{\beta}_m & \tilde{\beta}_n\end{array}\right]\left(M\left[\begin{array}{c}\text{GR_SHOCK}_{m,c}\\ \text{GR_SHOCK}_{n,c}\end{array}\right]+\left[\begin{array}{c}\epsilon^m_{c\tau}\\ \epsilon^n_{c\tau}\end{array}\right]\right)+\tilde{\epsilon}_{c\tau}=\left[\begin{array}{cc}\beta_m & \beta_n\end{array}\right]\left[\begin{array}{c}\text{GR_SHOCK}_{m,c}\\ \text{GR_SHOCK}_{n,c}\end{array}\right]+\epsilon_{c\tau} \tag{28}$$

Assume that

$$\left[\begin{array}{cc}\tilde{\beta}_m & \tilde{\beta}_n\end{array}\right]\left[\begin{array}{c}\epsilon^m_{c\tau}\\ \epsilon^n_{c\tau}\end{array}\right]=\epsilon_{c\tau}=\tilde{\epsilon}_{c\tau}=0 \tag{29}$$

which are true in expectation for $\epsilon_{c\tau}$ and $\tilde{\epsilon}_{c\tau}$ by definition (see equations 20 and 21). Since each of the $\tilde{\epsilon}^s_{c\tau}$ is also mean 0 and the β_s parameters are constants, the first term will equal 0 in expectation as well. Then we have

$$\left[\begin{array}{cc}\tilde{\beta}_m & \tilde{\beta}_n\end{array}\right]M\left[\begin{array}{c}\text{GR_SHOCK}_{m,c}\\ \text{GR_SHOCK}_{n,c}\end{array}\right]=\left[\begin{array}{cc}\beta_m & \beta_n\end{array}\right]\left[\begin{array}{c}\text{GR_SHOCK}_{m,c}\\ \text{GR_SHOCK}_{n,c}\end{array}\right] \tag{30}$$

Thus, we see that defining

$$\left[\begin{array}{cc}\tilde{\beta}_m & \tilde{\beta}_n\end{array}\right]=\left[\begin{array}{cc}\beta_m & \beta_n\end{array}\right]M^{-1} \tag{31}$$

we can recover estimates of $\tilde{\beta}_s$ for each sector.

D.2 Estimation

We estimate the parameters on the right-hand side of equation (31) using estimates of $\theta_{s,t}$ from equation (10). Specifically, define $\hat{\beta}_s$ to be the average of the post-period (e.g. 2007-2016) estimates of $\theta_{s,t}$ with mortality as the outcome, and define $\hat{\theta}^{s_2}_{s_1}$ as the average of the post-period estimates of $\theta_{s_1,t}$ with the EPOP ratio in sector s_2 as the outcome. This gives unbiased estimates of $\left[\begin{array}{cc}\beta_m & \beta_n\end{array}\right]$ and M, which we can use to construct an unbiased estimate of $\left[\begin{array}{cc}\tilde{\beta}_m & \tilde{\beta}_n\end{array}\right]$.

In Table 3, we estimate $\left[\begin{array}{cc}\beta_m & \beta_n\end{array}\right]$ using various post-Great Recession period definitions for robustness. We then multiply by the average 1994-2008 change in manufacturing and non-manufacturing EPOP induced by NAFTA (i.e. the average of the β_t estimates in equation 4) by the resulting estimates of $\left[\begin{array}{cc}\tilde{\beta}_m & \tilde{\beta}_n\end{array}\right]$. This gives a "predicted" impact of NAFTA on mortality using changes in mortality and employment induced by the Great Recession only.

E Imputed Employment Effects By Cohort and Gender

Due to limited data availability on employment within demographics in our study period, we impute the effect of NAFTA on employment by birth cohort and gender as follows. First, we compute the share of employed works in each 2-digit NAICS industry who belong in each demographic subgroup according to the Current Population Survey (CPS). Then, we compute the employment-to-population ratio in each industry using the CBP and SEER data, as with the by-industry analysis in the main text. We then estimate equation (4) using these industry-specific EPOP ratios as the outcome to obtain estimates β^i_t. We then aggregate industry-specific effects by computing

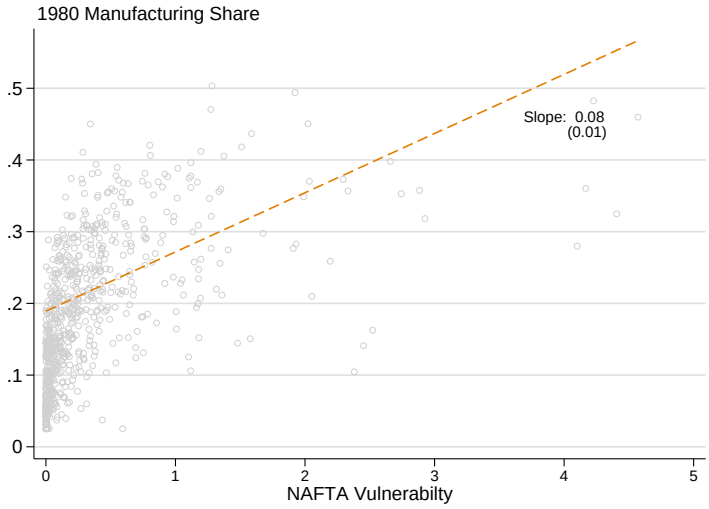
$$\tilde{\beta}_t^d = \sum_{i \in \mathcal{I}} s_{i,1993}^d \times \beta_t^i \tag{32}$$

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. 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.

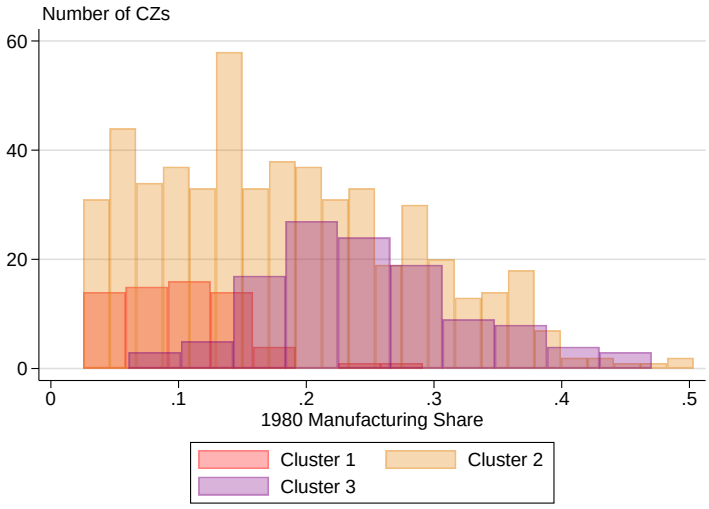
F Appendix Figures

Figure OA.1: Relationship Between NAFTA Vulnerability and Baseline Manufacturing

(a) Correlation of Baseline Manufacturing and Vulnerability



(b) Distribution of Manufacturing Within k-means Clusters

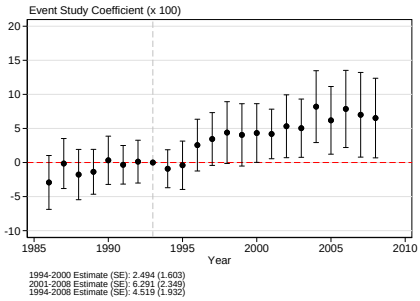


Notes: Panel A displays a scatterplot of the 1980 share of manufacturing employment in each CZ and its NAFTA vulnerability, along with the regression slope coefficient and heteroskedasticity robust standard error. The regression is weighted by 1990 CZ population, and the sample size is 722 CZs. Panel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

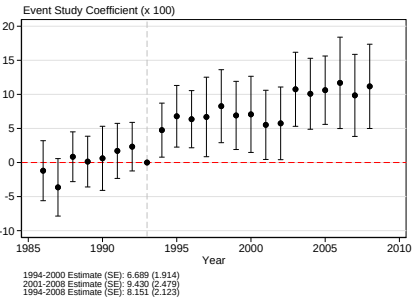
Figure OA.2: NAFTA Mortality Impacts by Sex and Birth Cohort

Born 1970-1994 (Ages 0-24)

(a) Male

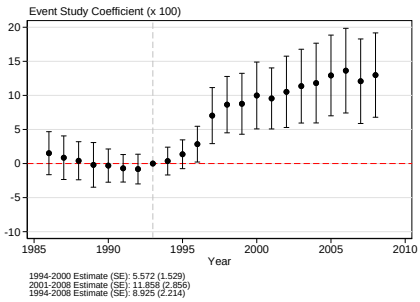


(b) Female

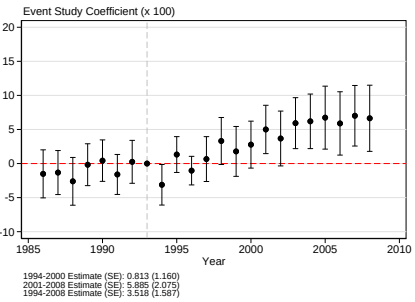


Born 1950-1969 (Ages 25-44)

(c) Male

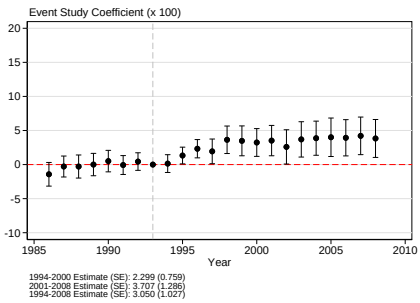


(d) Female

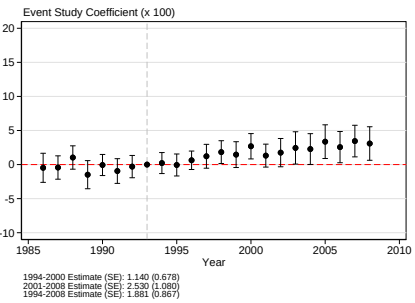


Born 1930-1949 (Ages 45-64)

(e) Male

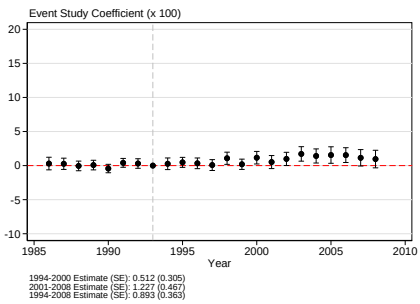


(f) Female

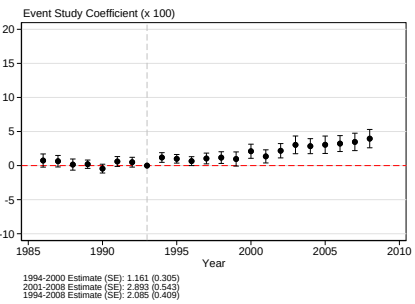


Born 1929 (Ages 65+)

(g) Male



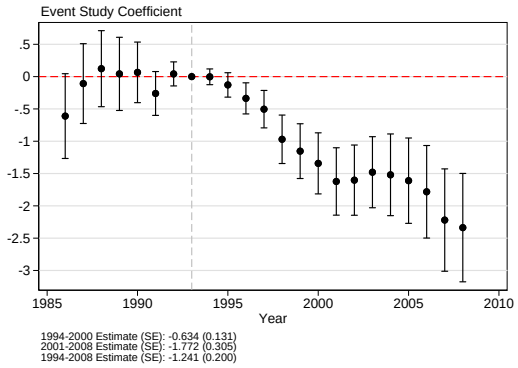
(h) Female



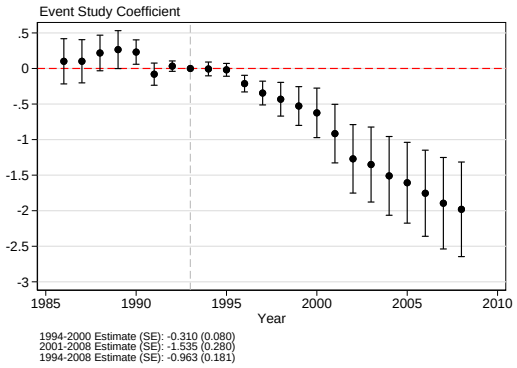
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{gt} is the log CZ mortality rate per 100,000 for individuals in the birth cohort and sex denoted by each panel title. A one-point increase in NAFTA vulnerability V_g corresponds to moving from the average CZ 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.3: NAFTA EPOP Effects by Industry

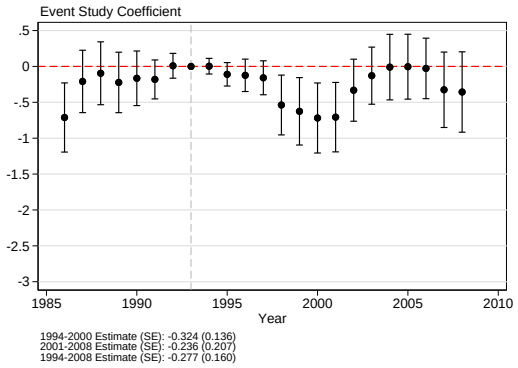
(a) Total EPOP



(b) Manufacturing

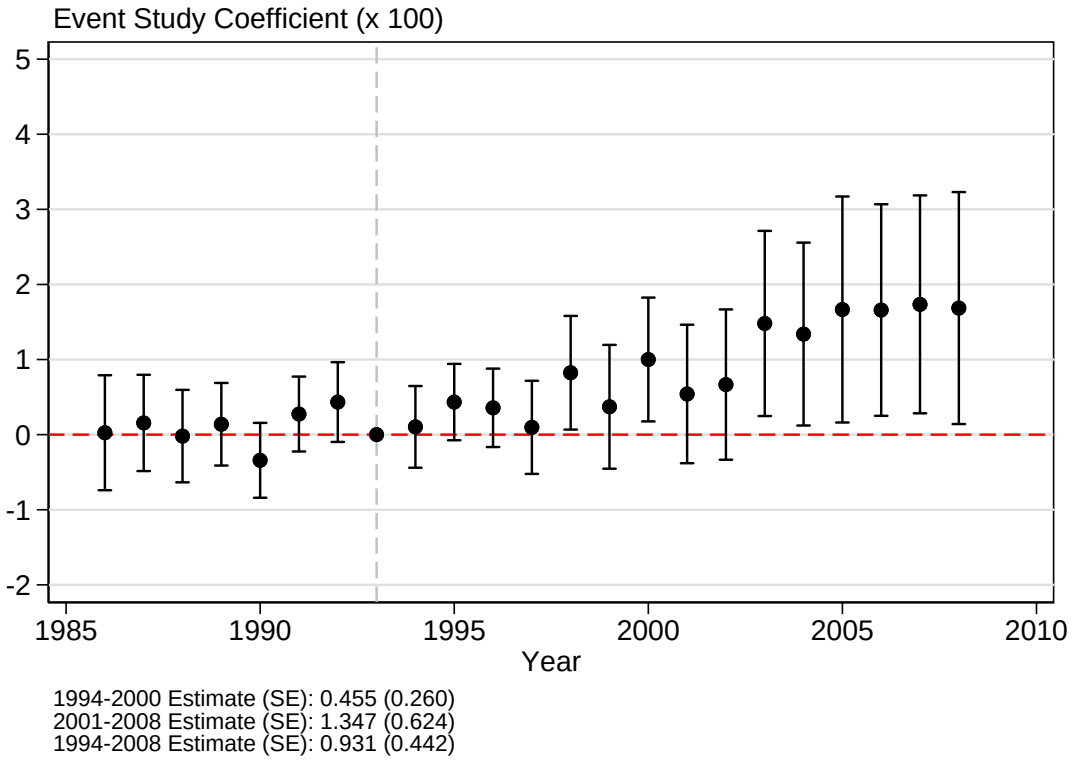


(c) Non-Manufacturing



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.4: Impact of NAFTA Vulnerability on Log Mortality (Southern Census Region Only)

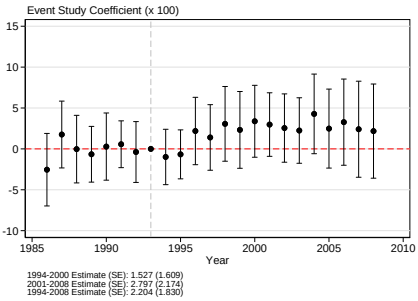


Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{gt} is the log age-adjusted CZ mortality rate per 100,000. A one-point increase in NAFTA vulnerability V_g corresponds to moving from the average CZ in the least vulnerable quartile to the average CZ in the 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 consists of CZs in the Southern Census region only (288 CZs).

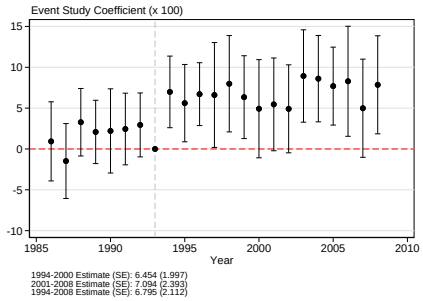
Figure OA.5: NAFTA Mortality Impacts by Sex and Birth Cohort (Southern Census Region Only)

Born 1970-1994 (Ages 0-24)

(a) Male

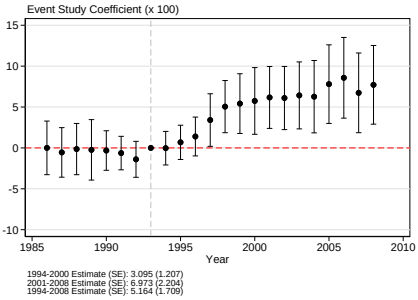


(b) Female

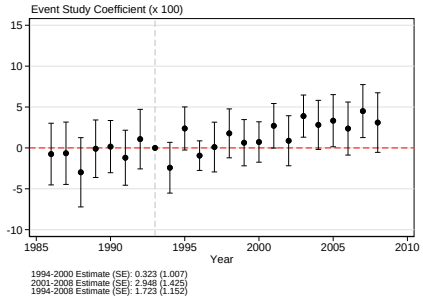


Born 1950-1969 (Ages 25-44)

(c) Male

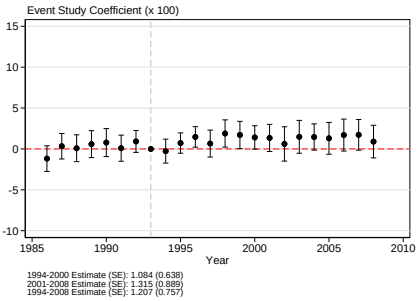


(d) Female

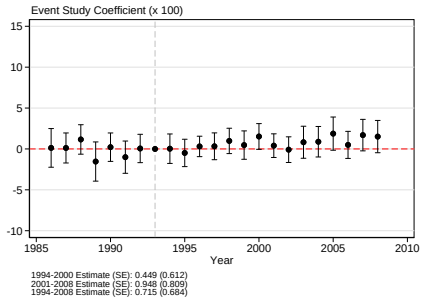


Born 1930-1949 (Ages 45-64)

(e) Male

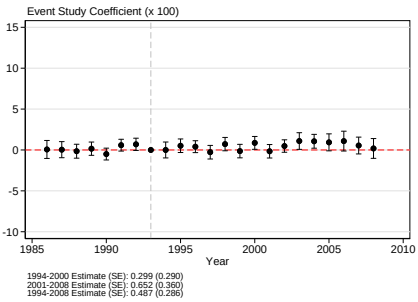


(f) Female

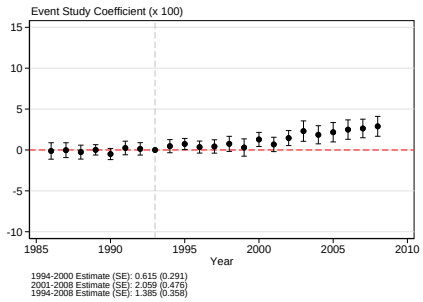


Born Before 1930 (Ages 65+)

(g) Male



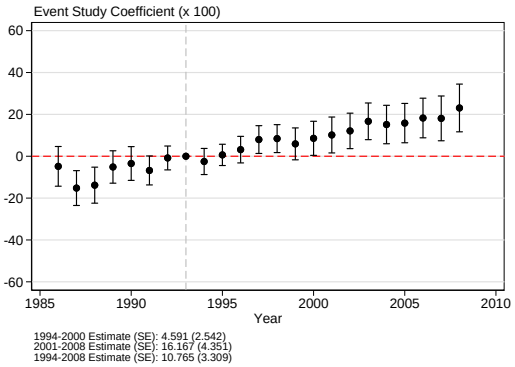
(h) Female



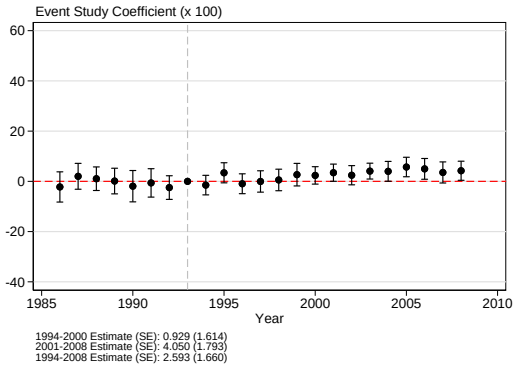
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log age-adjusted CZ mortality rates per 100,000 for individuals in the birth cohort and sex denoted by each panel title. A one-point increase in NAFTA vulnerability V_g corresponds to moving from the 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 consists of CZs in the Southern Census region only (288 CZs).

Figure OA.6: NAFTA Mortality Impacts by Cause of Death (Men Born 1950-1969), Part 1

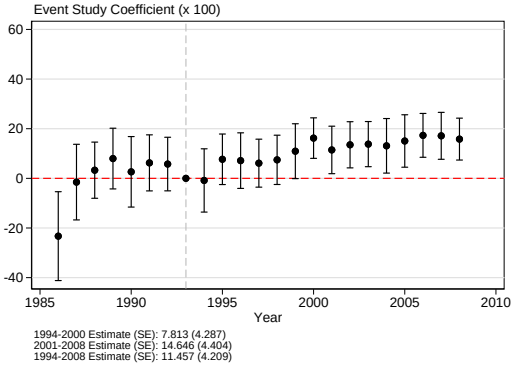
(a) Infectious Diseases



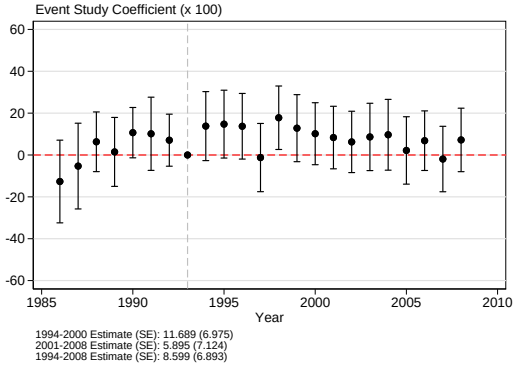
(b) Cancer



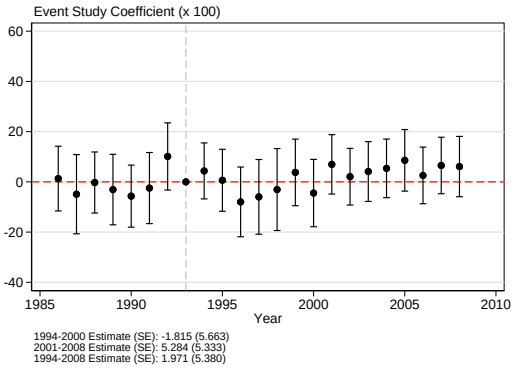
(c) Metabolic Diseases



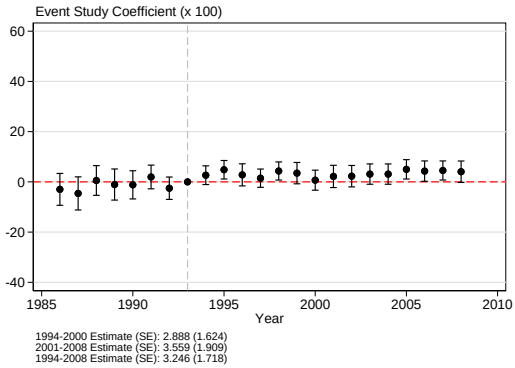
(d) Mental Illness



(e) Nervous System Disorders



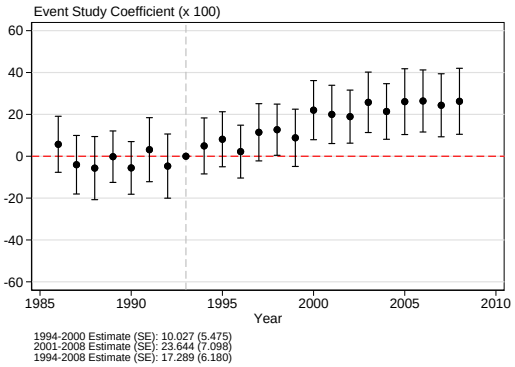
(f) Circulatory System Disorders



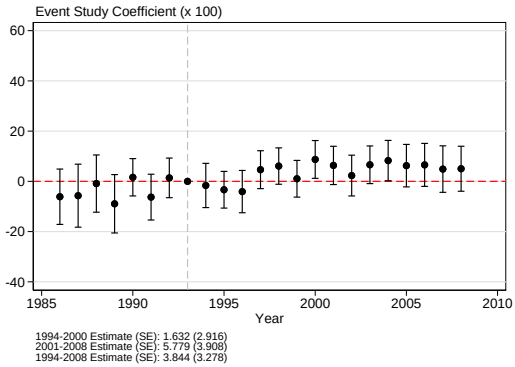
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log age-adjusted CZ mortality rates per 100,000 for men born between 1950 and 1969 separately by cause of death. Along with Figure OA.7, these groups partition all causes of death in the CDC data. Observations 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.7: NAFTA Mortality Impacts by Cause of Death (Men Born 1950-1969), Part 2

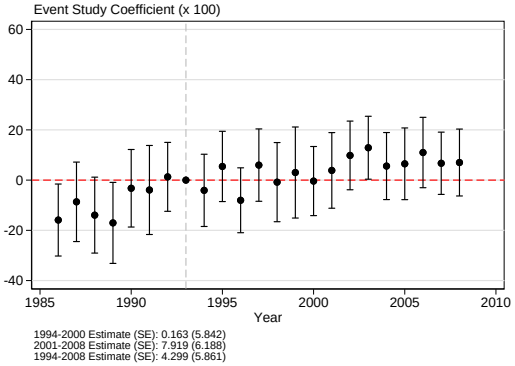
(a) Respiratory System Disorders



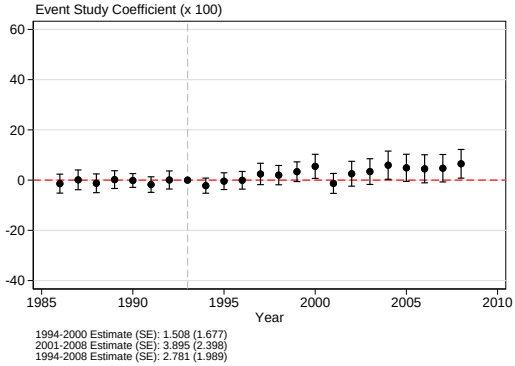
(b) Digestive System Disorders



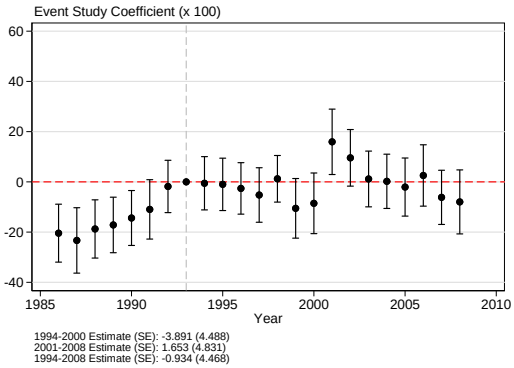
(c) Genitourinary Disorders



(d) External Causes



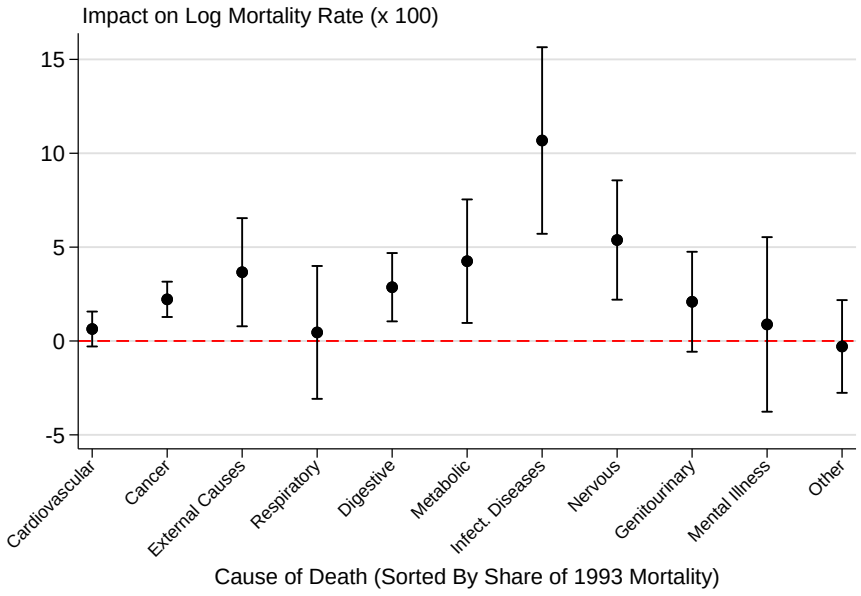
(e) Other Causes



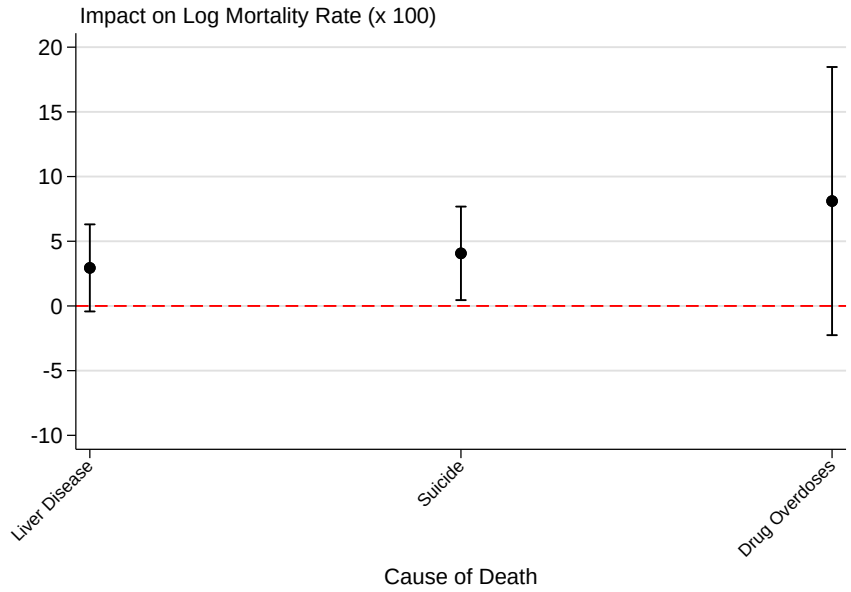
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcomes are the log age-adjusted CZ mortality rates per 100,000 for men born between 1950 and 1969 separately by cause of death. Along with Figure OA.6, these groups partition all causes of death in the CDC data. Observations 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.8: NAFTA Mortality Impacts By Cause of Death: Overall Mortality

(a) Broad Categories



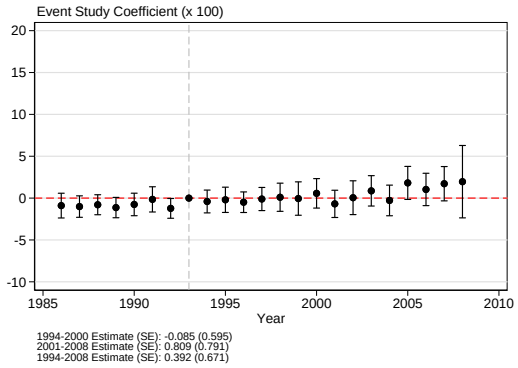
(b) Deaths of Despair



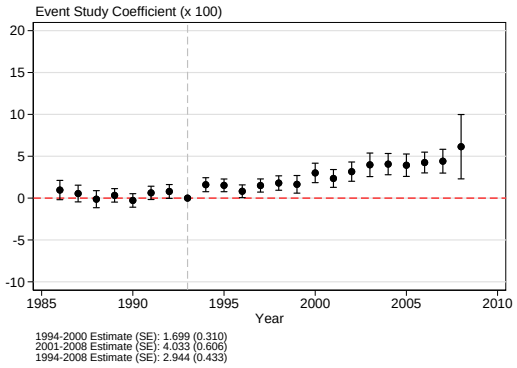
Notes: This figure displays 100 times the average estimate of β_t in equation (4) over the 1994-2008 post-period with the log mortality rate per 100,000 among all individuals for each cause of death as the outcome. Vertical lines denote 95% confidence intervals constructed using standard errors clustered at the CZ level. Observations are weighted by CZ population in 1990. The sample size is 722 CZs.

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

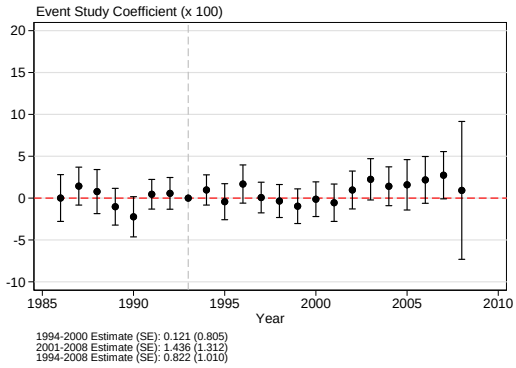
(a) Married



(b) Widowed



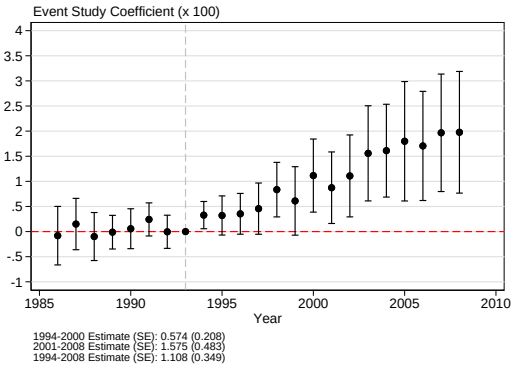
(c) Other



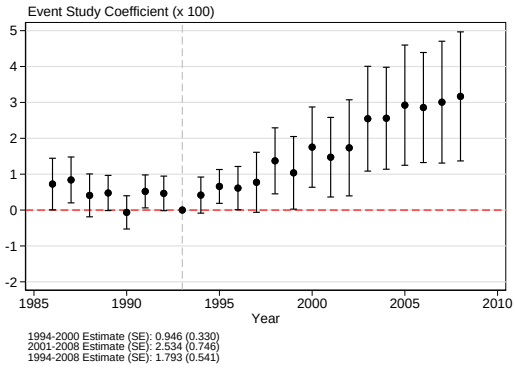
Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{gt} is the mortality rate per 100,000 for women aged 65+ in 1994 by marital status. A one-point increase in NAFTA vulnerability V_g corresponds to moving from the average CZ in the least vulnerable quartile 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 721 CZs.

Figure OA.10: Impact of NAFTA on Mortality: Robustness Checks

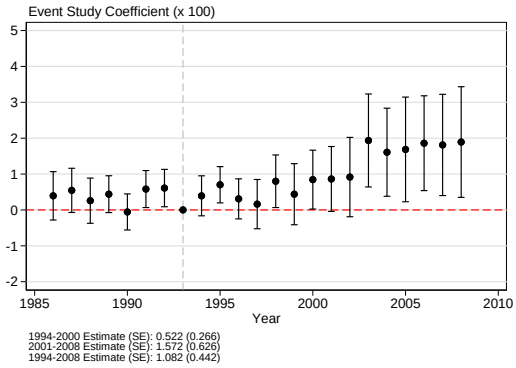
(a) County Level



(b) With Import Penetration-By-Year FE



(c) Separately Manufacturing Clusters

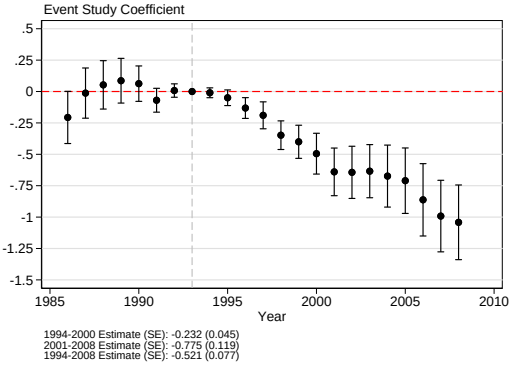


Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{gt} is the log age-adjusted mortality rate per 100,000. A one-point increase in NAFTA vulnerability V_g corresponds to moving from the average county or CZ in the least vulnerable quartile to the average county or CZ in the most vulnerable quartile. Panel (a) estimates the specification at the county level. Panel (b) estimates it at the CZ level, controlling for 1990-2000 Autor et al. (2013) Chinese import penetration. Panel (c) controls for three separate k-means clusters of the 1980 manufacturing share in addition to 3-kmeans clusters of our other control variables. 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) and (c). The sample size is 3,096 counties in panel (a) and 722 CZs in panels (b) and (c).

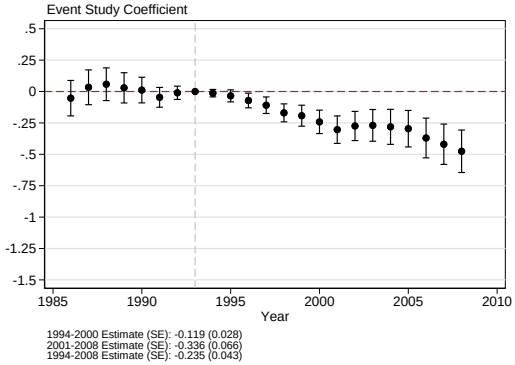
Figure OA.11: NAFTA Employment Impacts by Birth Cohort and Sex

Born 1950-1969 (Ages 25-44)

(a) Male

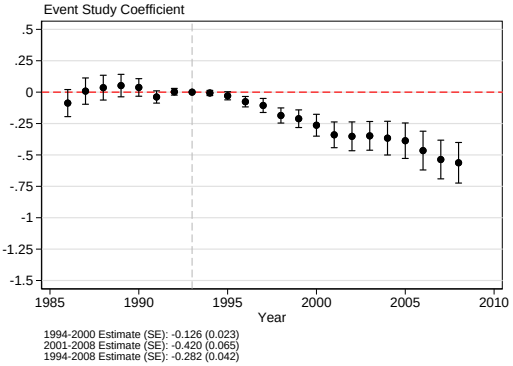


(b) Female

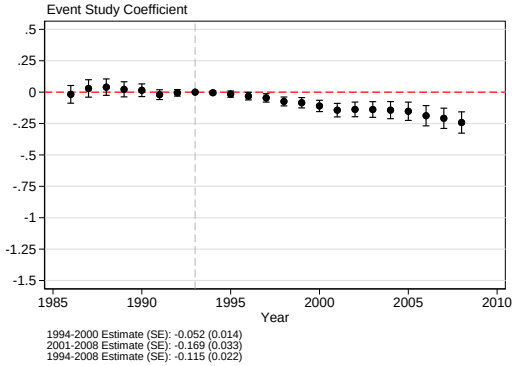


Born 1930-1949 (Ages 45-64)

(c) Male

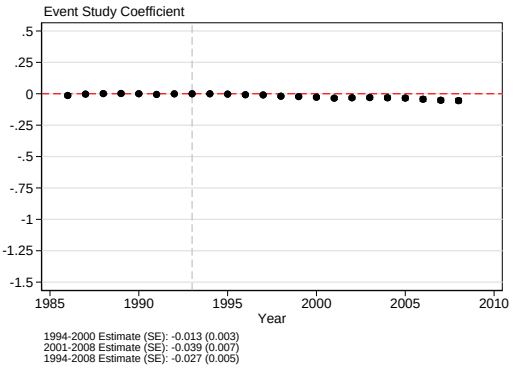


(d) Female

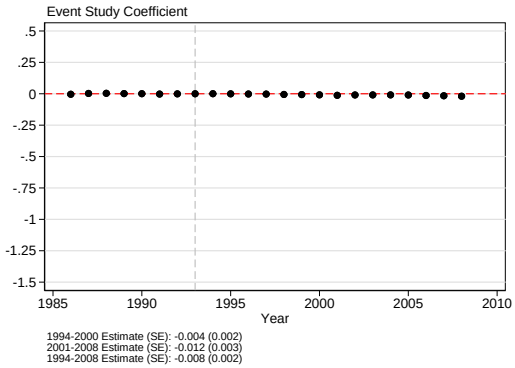


Born Before 1929 (Ages 65+)

(e) Male

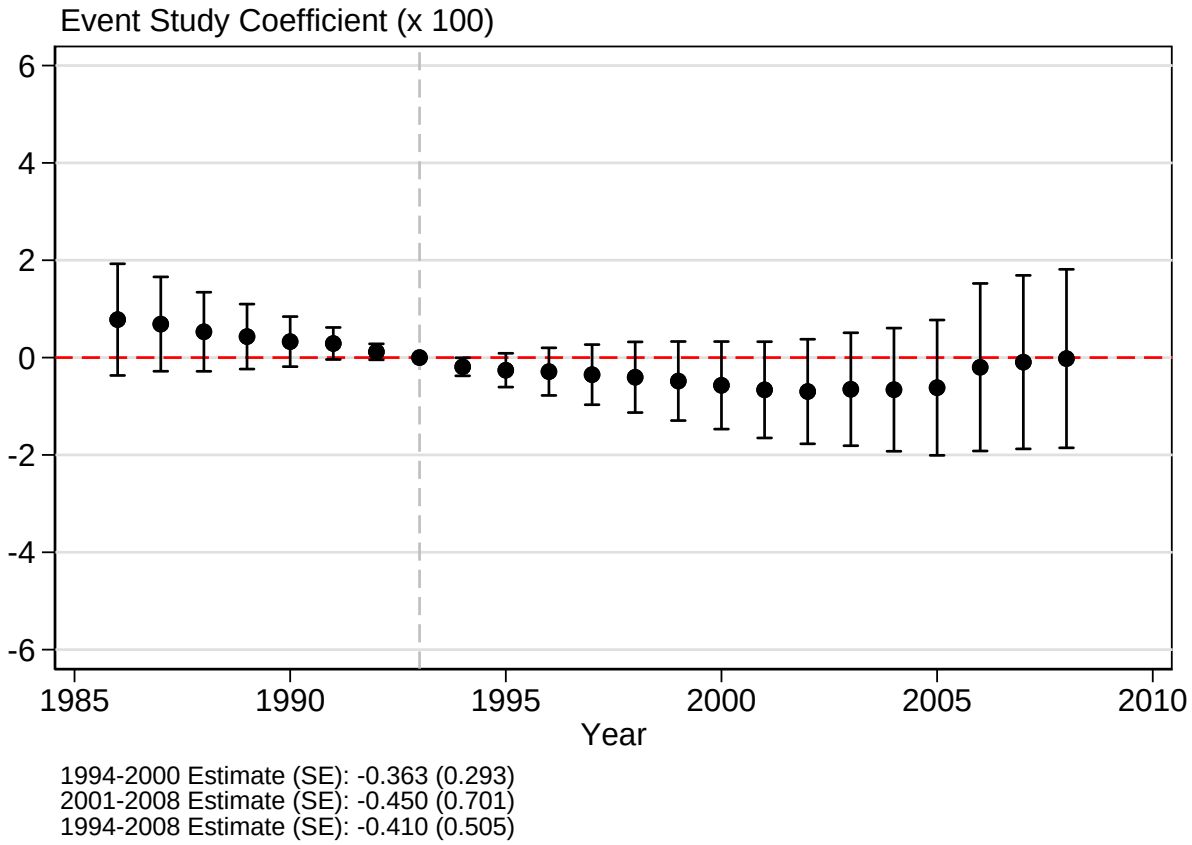


(f) Female



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.12: Impact of NAFTA Vulnerability on Population Aged 25+ Upon Implementation

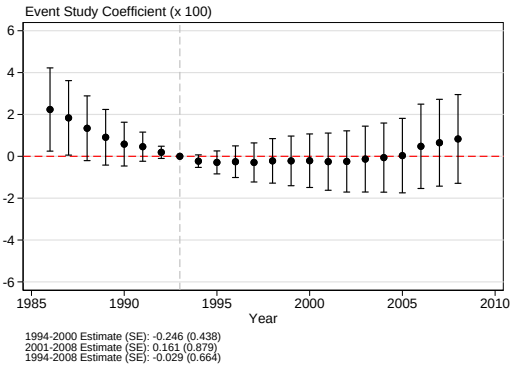


Notes: This figure displays 100 times estimates of β_t from equation (4), where the outcome y_{gt} is the log population aged 25 or older in 1994 in each CZ-year. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 722 CZs.

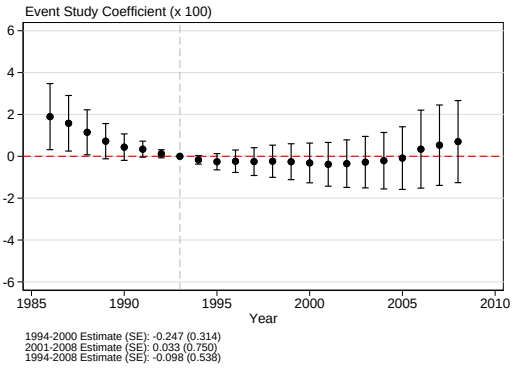
Figure OA.13: NAFTA Population Impacts by Birth Cohort and Sex

Born 1950-1969 (Ages 25-44)

(a) Male

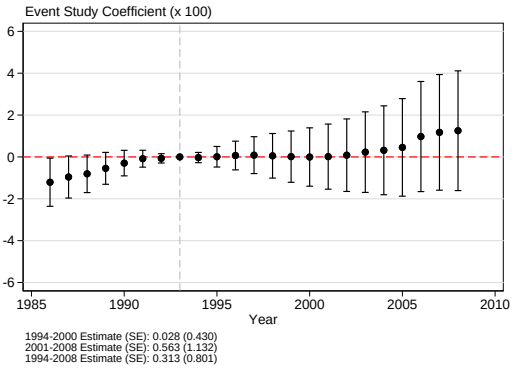


(b) Female

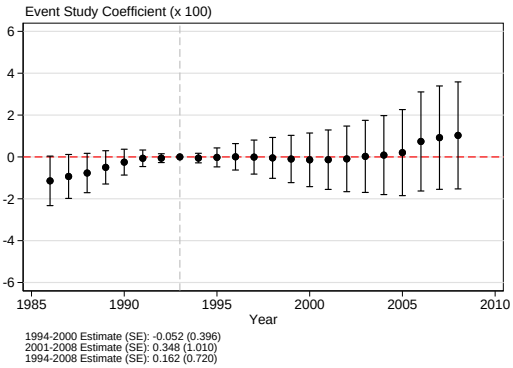


Born 1930-1949 (Ages 45-64)

(c) Male

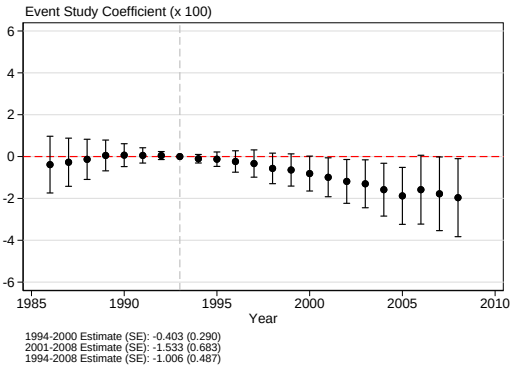


(d) Female

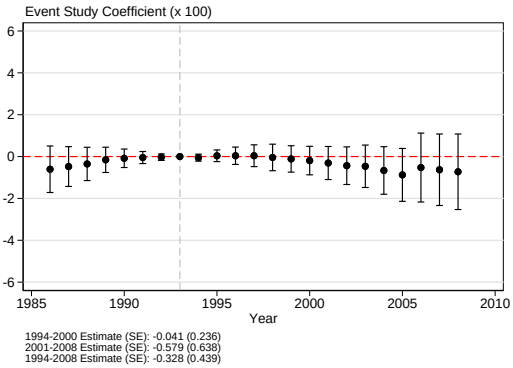


Born Before 1929 (Ages 65+)

(e) Male



(f) Female

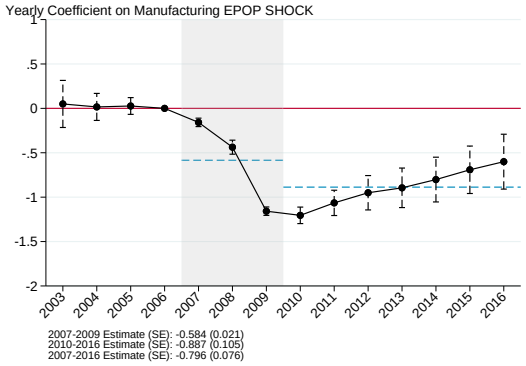


Notes: This figure displays estimates of β_t from equation (4), where the outcome y_{gt} is the log population of individuals in each demographic group within each CZ. Observations are weighted by CZ population in 1990. Vertical lines denote 95% confidence intervals computed using standard errors clustered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

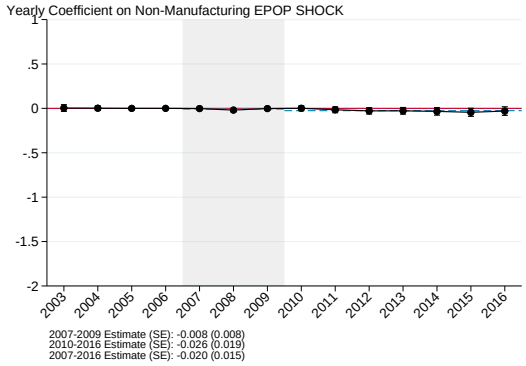
Figure OA.14: Great Recession Impacts on Sector-Specific EPOP

Effects on Manufacturing EPOP

(a) Manufacturing EPOP Shock

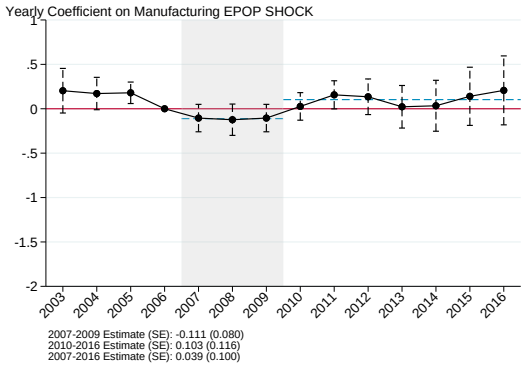


(b) Non-Manufacturing EPOP Shock

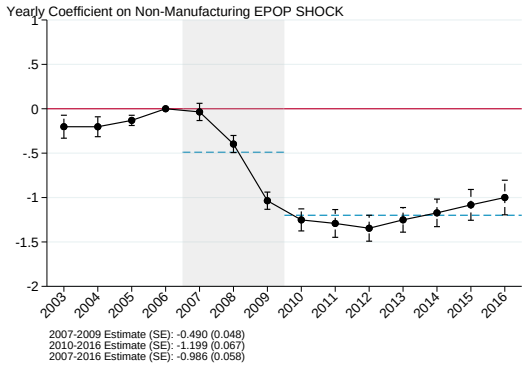


Effects on Non-Manufacturing EPOP

(c) Manufacturing EPOP Shock



(d) Non-Manufacturing EPOP Shock



Notes: This figure displays estimates of $\theta_{s,t}$ from equation (10), where the outcomes y_{ct} are the manufacturing EPOP (panels a and b) and non-manufacturing EPOP (panels c and d) in each CZ-year. Horizontal blue dashed lines indicate the point estimate for the average of coefficients from 2007-2009 and 2010-2016. These estimates (and corresponding standard errors) are reported in the lower left-hand corner, along with the corresponding estimate for the entire 2007-2016 period. Observations are weighted by CZ population in 2006. Vertical lines denote 95% confidence intervals computed using standard errors clustered at the CZ level. The sample size is 738 CZs.

G Appendix Tables

Table OA.1: Cause of Death Shares Pre-NAFTA

Cause of Death	Share of Deaths (1993)
Infectious Diseases	0.077
Cancer	0.128
Metabolic Diseases	0.081
Mental Illnesses	0.064
Nervous System Disorders	0.070
Circulatory Diseases	0.142
Respiratory Diseases	0.085
Digestive System Disorders	0.083
Genitourinary Disorders	0.069
External Causes	0.097
Others	0.105

Notes: This table displays the share of deaths attributable to each cause of death category in Figures OA.6 and OA.7 in 1993.

Table OA.2: U.S. Manufacturing Shares

Sector	Employment Share (1993)	Employment Share (2006)
Manufacturing	0.193	0.116
Non-Manufacturing	0.807	0.884

Notes: This table displays the share of national employment inside and outside of manufacturing in 1993 and 2006.

Table OA.3: China Shock Impacts on Mortality and EPOP

	Cumulative Mortality Rate	EPOP		
		Total	Manufacturing	Non-Manufacturing
	(1)	(2)	(3)	(4)
Import Penetration	215.0	-1.448	-1.319	-0.129
	(99.7)	(0.528)	(0.210)	(0.437)
Mean	8,922.8	47.7	5.7	41.9
First Stage F-Statistic	131.9	131.9	131.9	131.9
N	1,444	1,444	1,444	1,444

Notes: This table displays estimates of β_1 in equation (16) with the decadal 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 state level are given in parentheses. The sample size is 722 CZs.

Table OA.4: 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
	(417.5)	(392.9)	(145.8)	(85.4)	(46.9)	(22.4)	(16.6)	(9.4)
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	131.9	131.9	131.9	131.9	131.9	131.9	131.9	131.9
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 (16) with the cumulative mortality rate in each age and gender bin given in the column titles as outcomes. The regressions are weighted by the product of period length and start-of-period CZ populations shares. Standard errors clustered at the state level are given in parentheses. The sample size is 722 CZs.

Table OA.5: 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 E