Online Appendix

Local Economic and Political Effects of Trade Deals:

Evidence from NAFTA

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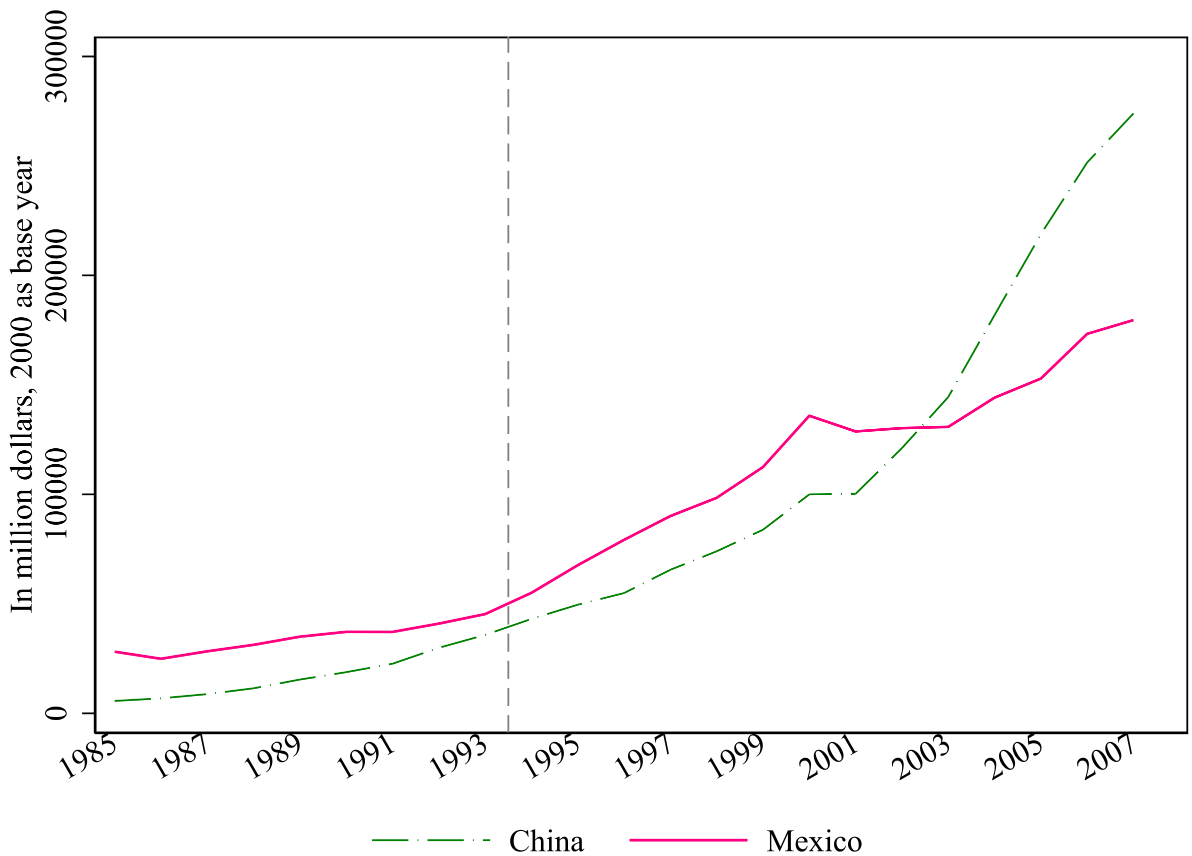
Appendix A. Supplementary Figures and Tables Noted in the Text

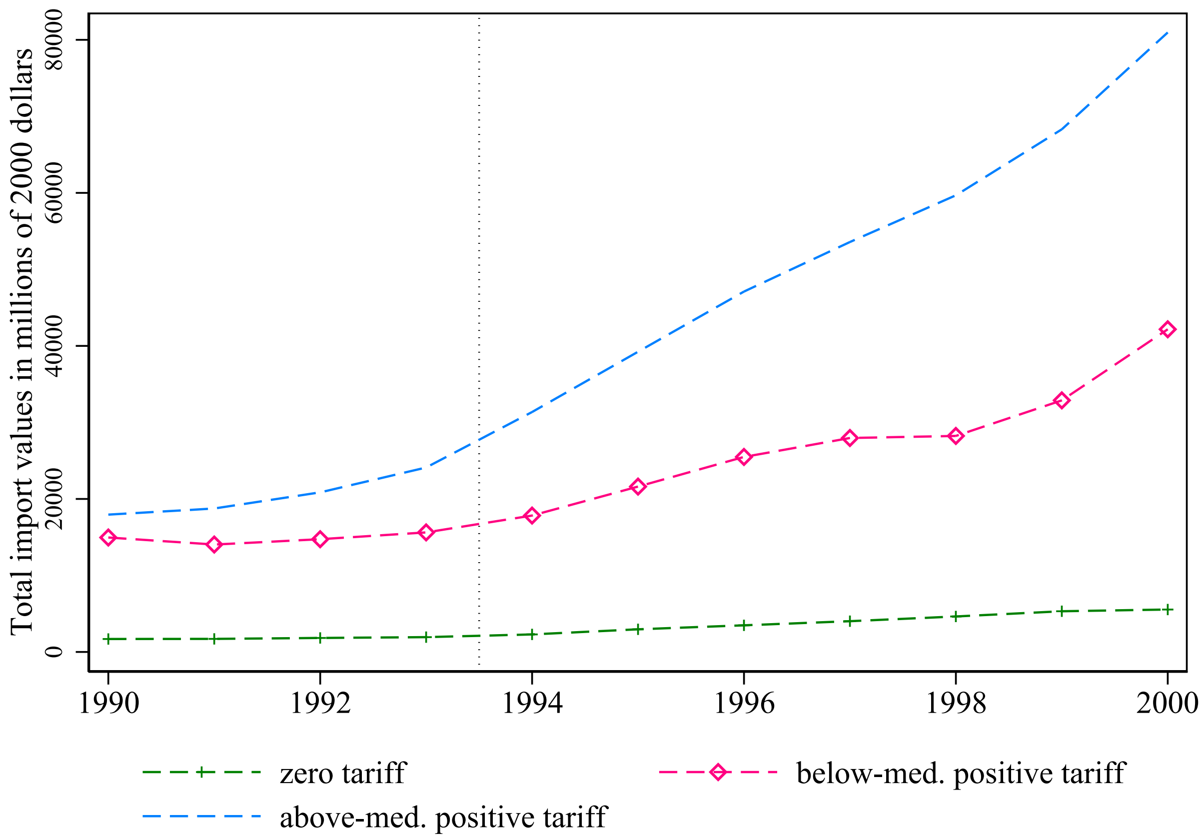
Appendix Figure A.1: U.S. imports from China and Mexico



Sources: Federal Reserve Economic Data Series (FRED).

Notes: The figure contains the time series of the value of goods imported by the US, based on the custom basis from China and Mexico. The import values are inflation-adjusted using the annual-level personal consumption expenditures available from FRED.

Appendix Figure A.2: Import values from Mexico by 1990 tariff level

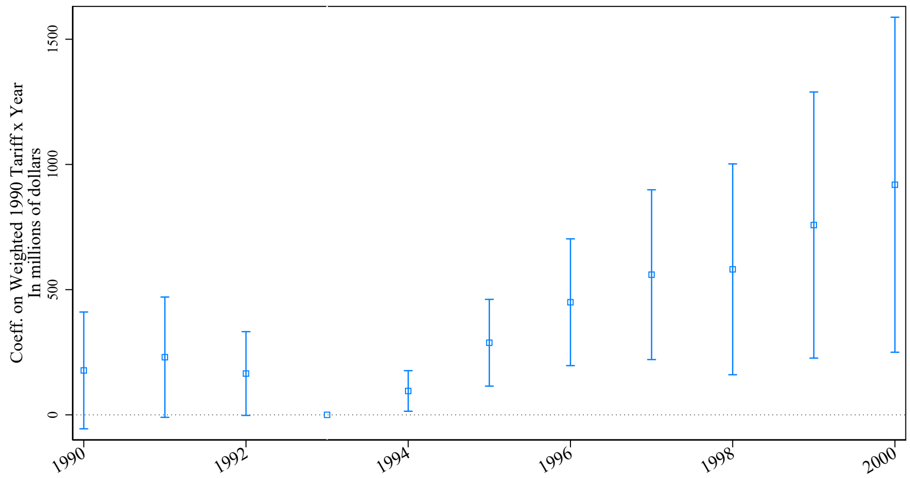


Sources: The import values are taken from the U.S. International Trade Commission (USITC).

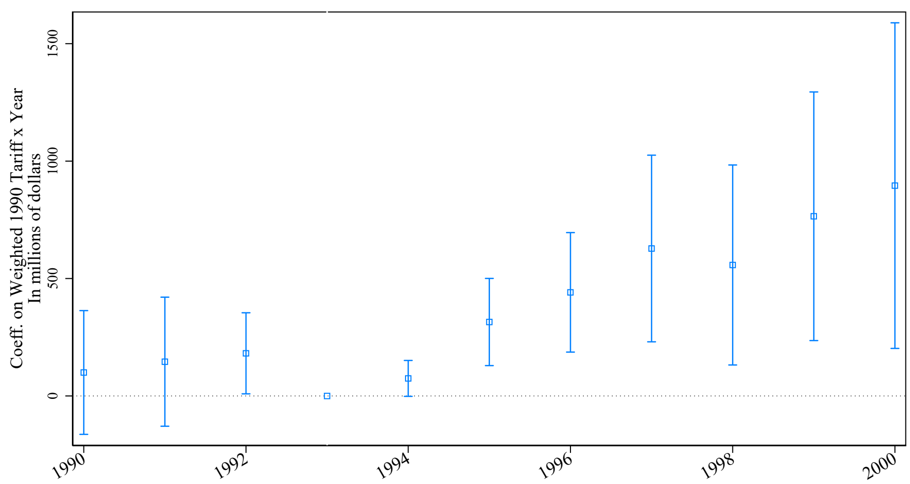
Notes: The figure shows the time series of average import values from Mexico by industries with zero tariff, industries with below-median tariff, and industries with above-median tariff based on 1990 industry-level tariff. The import values are inflation-adjusted using the annual-level personal consumption expenditures available from FRED. Data only available through 2000.

Appendix Figure A.3: Relationship (in levels) between Mexican imports to the US and pre-NAFTA tariffs

(a) U.S. ITC data



(b) U.N. data



Sources: U.S. International Trade Commission (panel a) and UN Comtrade data (panel b)

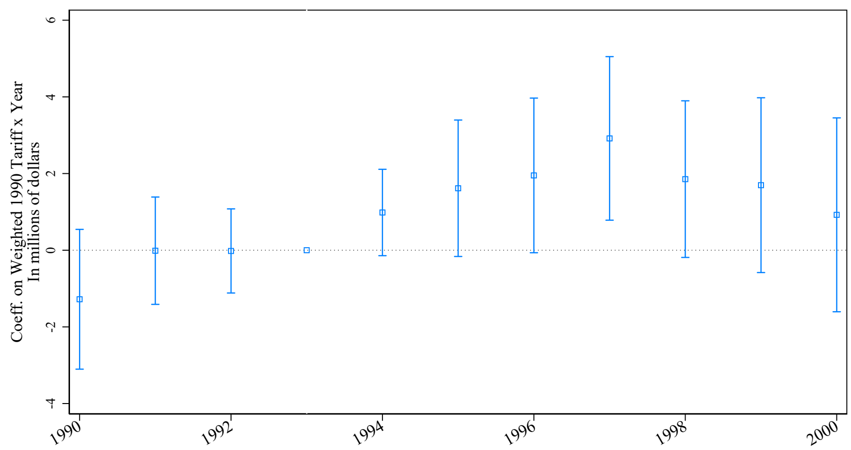
Notes: The figure shows the coefficients β^t from the following regression:

$$MexImports_{jt}^{US} = \beta^t Avg.Tariff_{j,1990} + \gamma_1 MexImports_{jt}^{ROW} + \gamma_2 ROWImports_{jt}^{US} + \eta_j + \mu_t + e_{jt},$$

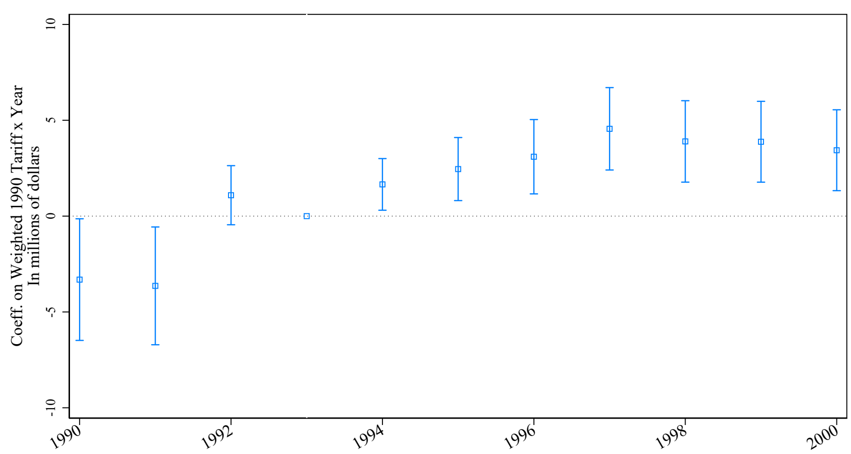
where $Avg.Tariff_{j,1990}$ is the weighted average tariff at the SIC four-digit industry level in 1990, $MexImports_{jt}^{US}$ are Mexican imports to the US for SIC four-digit industry j in year t, $MexImports_{jt}^{ROW}$ is Mexican imports to the rest of the world (ROW) for industry j in year t, $ROWImports_{jt}^{US}$ is the rest of the world's imports to the US for industry j in year t, and η_j and μ_t are industry and year fixed effects, respectively. All import values are in millions of current USD. The 95-percent confidence intervals are based on standard errors clustered at the industry level.

Appendix Figure A.4: Relationship (in logs) between Mexican imports to the US and pre-NAFTA tariffs

(a) U.S. ITC data



(b) U.N. data

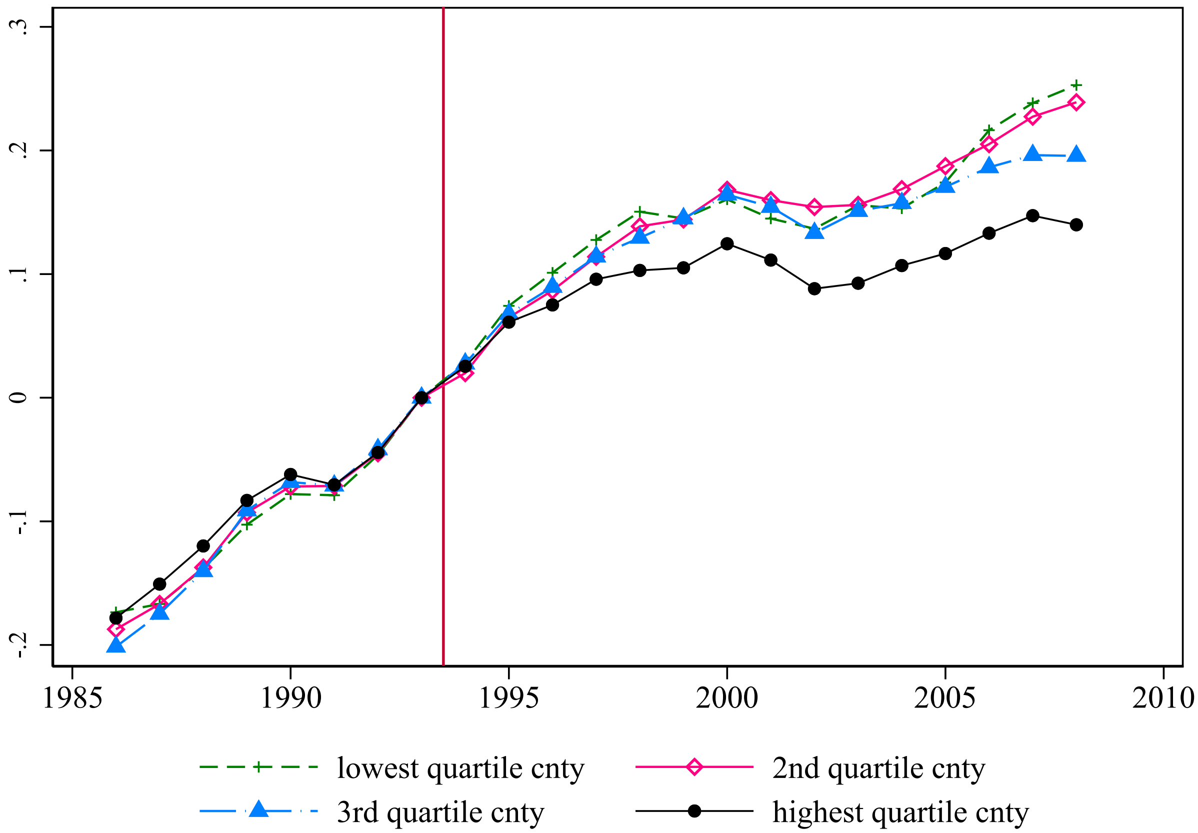


Sources: U.S. International Trade Commission (panel a) and UN Comtrade data (panel b)
Notes: The figures shows the coefficients β^t from the following regression:

$$\log(MexImports)^{US}_{jt} = \beta^t \log(1 + Avg.Tariff_{j,1990}) + \gamma_1 \log(MexImports^{ROW}_{jt}) + \gamma_2 \log(ROWImports)^{US}_{jt}) + \eta_j + \mu_t + e_{jt},$$

where $Avg.Tariff_{j,1990}$ is the weighted average tariff at the SIC four-digit industry level in 1990, $MexImports^{US}_{jt}$ are Mexican imports to the US for SIC four-digit industry j in year t, $MexImports^{ROW}_{jt}$ is Mexican imports to the rest of the world (ROW) for industry j in year t, $ROWImports^{US}_{jt}$ is the rest of the world's imports to the US for industry j in year t, and η_j and μ_t are industry and year fixed effects, respectively. All import values are in millions of current USD. The 95-percent confidence intervals are based on standard errors clustered at the industry level. Note that we use $\log(1 + Avg.Tariff_{j,1990})$ as our variable of interest because over forty percent of four-digit industry groups have zero average tariff in 1990.

Appendix Figure A.5: Average log employment for four vulnerability quartiles over time (normalized to zero in 1993)



Sources: The dependent variable is derived from the County Business Patterns (CBP). See Appendices B.1 and B.2 for more detail.

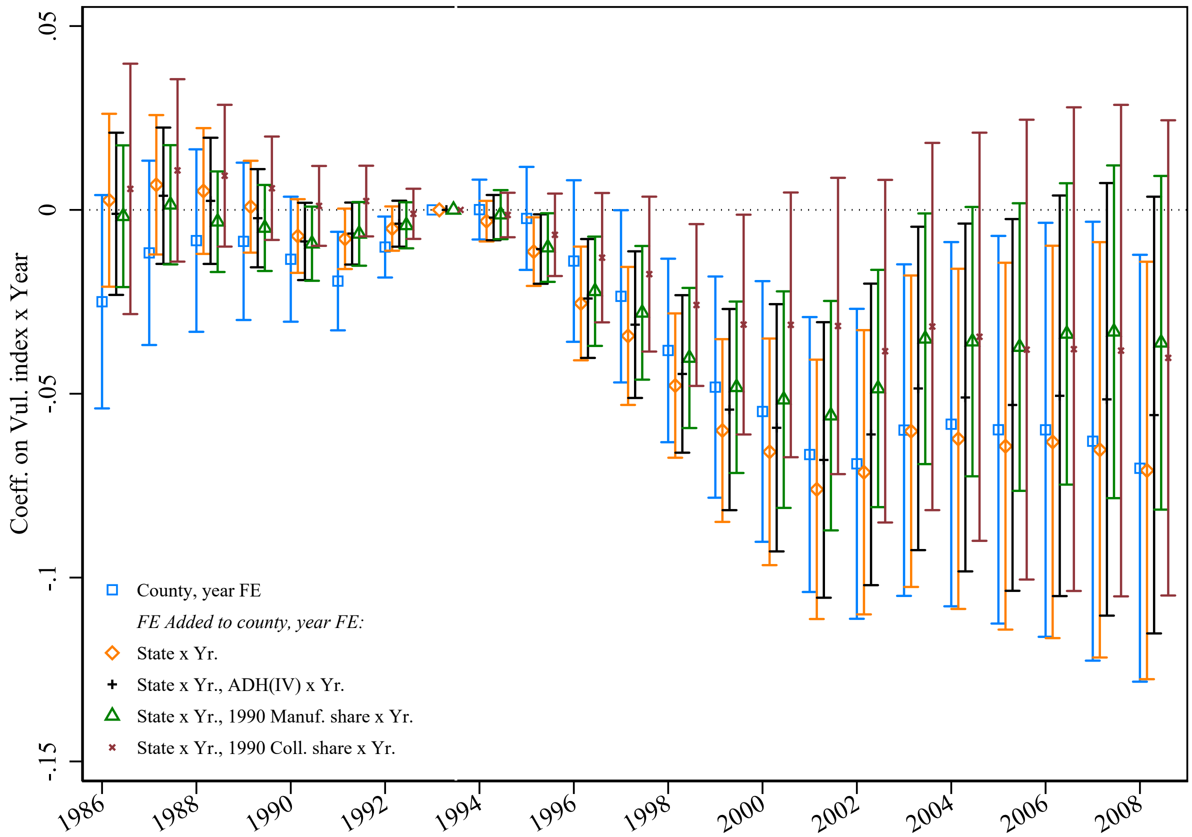
Notes: The figure shows log of total employment trends from 1986 to 2008, separately by 1990 county vulnerability quartiles. Log of total employment is computed using the CBPD. We do not weight and other than normalizing to zero in 1993, the data plotted are simply raw annual means within the quartiles.

Appendix Figure A.6: Log of employment as a function of NAFTA vulnerability using imputed CBP cells from Eckert et al. (2021)

Sources: The dependent variable is derived from the CBP.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2809 counties in each year of the sample. The figure shows the event-study coefficient estimates (plus 95%-confidence intervals, based on standard errors clustered by state) from specifications of equation (5), where log of county employment is the dependent variable. The first series uses our baseline vulnerability measure as the main independent variable. The second series uses the vulnerability measure using the imputed county-industry cells proposed by Eckert et al. (2021). Both specifications are weighted by 1990 county population, and they include county, year, and $state \times year$ fixed effects.

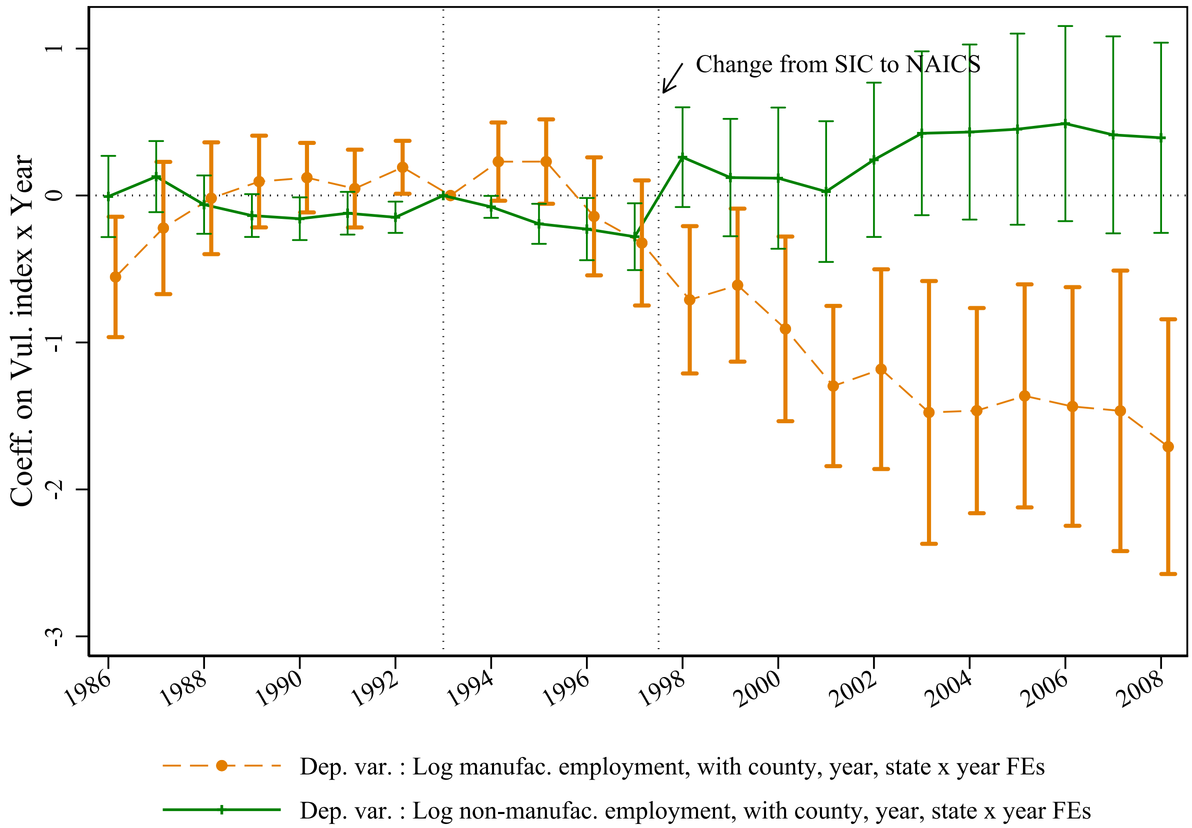
Appendix Figure A.7: Log employment as a function of county NAFTA vulnerability, varying controls



Sources: The dependent variable is computed from County Business Patterns. See Appendices B.1 and B.2 for more detail.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2912 counties in each year of the sample. This figure is analogous to Figure 2 but shows additional specifications after varying the controls. Observations are weighted by 1990 county population. The first series includes only county and year fixed effects. The second series adds to this specification $state \times year$ fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor, Dorn, and Hanson (2013) interacted with year fixed effects. The fourth specification adds to the second specification 1990 county-level manufacturing share of employment interacted with year fixed effects. The final specification adds to the second specification 1990 county-level college-graduate population share interacted with year fixed effects. Thus, the second and fourth specifications are identical to the first and second series of Figure 2.

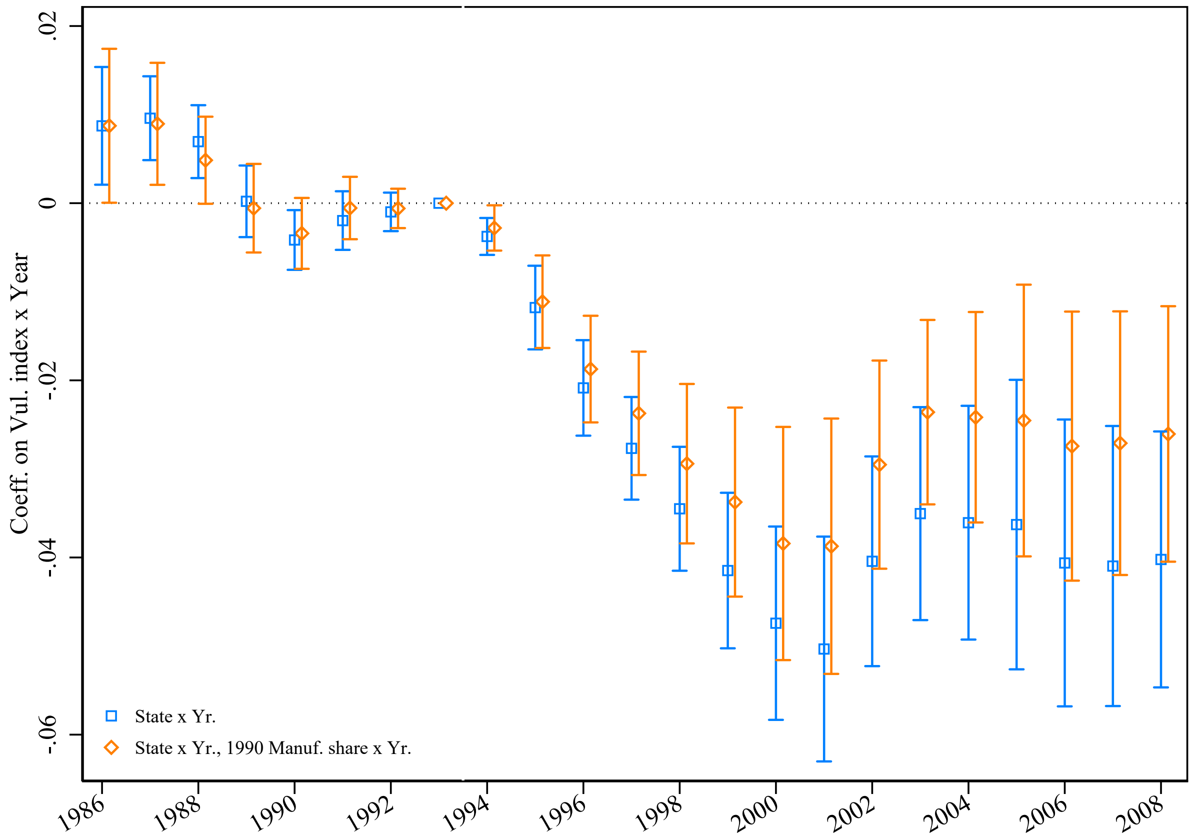
Appendix Figure A.8: Evolution of log employment as a function of NAFTA vulnerability, separating manufacturing v. other industries



Sources: The dependent variable and the codes to categorize manufacturing industries are derived from the CBP.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2926 counties in each year of the sample. The figure shows the event-study coefficient estimates (plus 95%-confidence intervals, based on standard errors clustered by state) from specifications of equation (5), where log of total manufacturing employment and log of total non-manufacturing employment at the county×year level are the dependent variable for the first and second series, respectively. Both specifications are weighted by 1990 county population, and they include county, year, and *state*×*year* fixed effects.

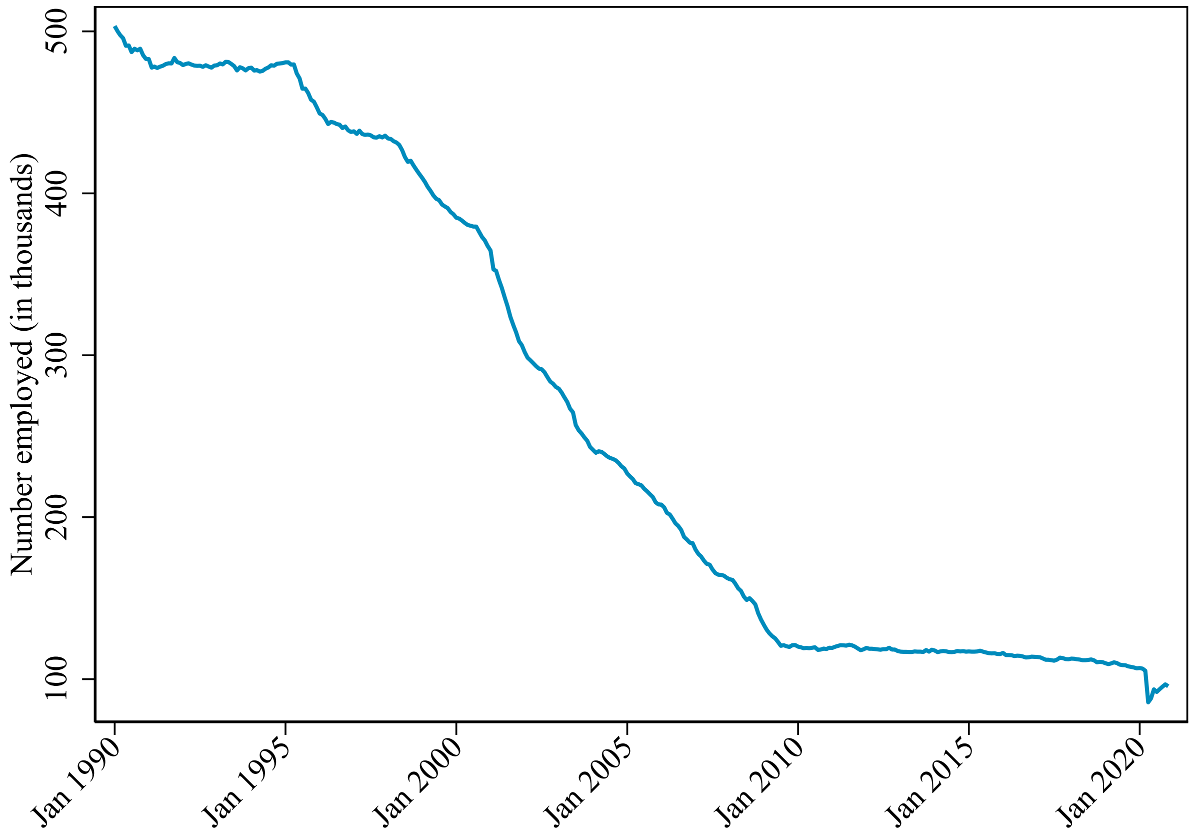
Appendix Figure A.9: Employment per capita as a function of NAFTA vulnerability



Sources: The dependent variable is derived from the CBP and the census PEP. Note that the denominator is 1990 working-age population.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2978 counties in each year of the sample. The figure is identical to Figure 2 except that the outcome variable is per capita employment and not log of total county employment. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (5), where per capita employment at the county×year level is the dependent variable. Observations are weighted by 1990 county population. The first series controls for county and year fixed effects, as well as *state*×*year* fixed effects. The second series adds to the first controls for 1990 county-level manufacturing share of employment interacted with year fixed effects.

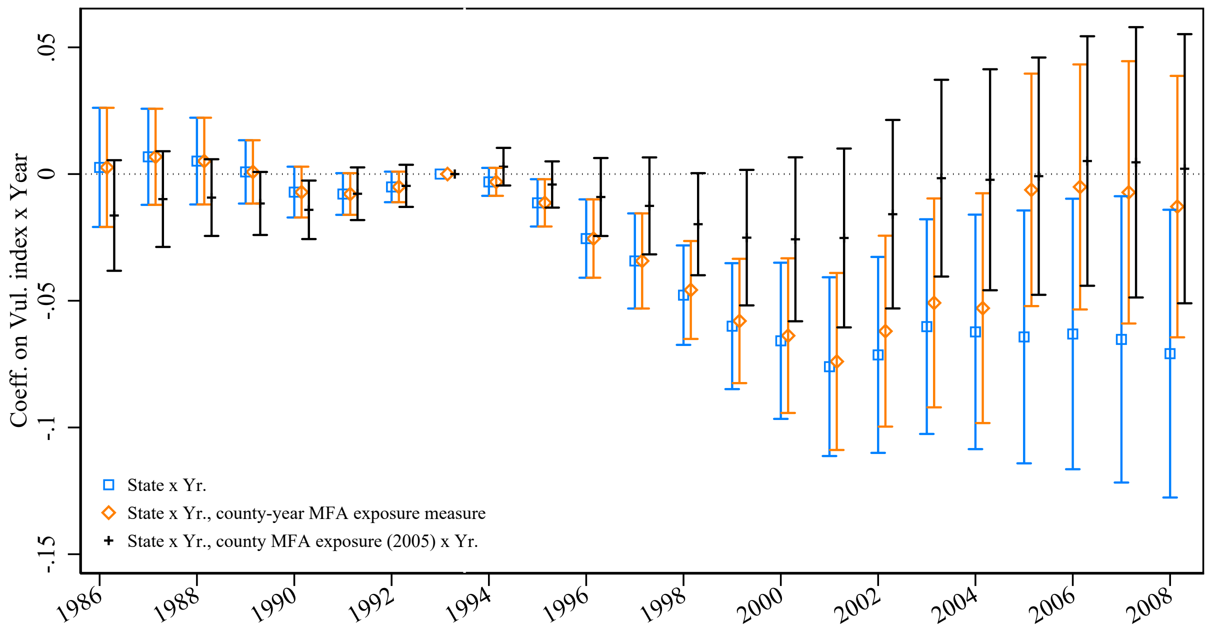
Appendix Figure A.10: Employment in textile mills, 1990-2020



Sources: U.S. Bureau of Labor Statistics, All Employees, Textile Mills [CES3231300001], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/CES3231300001`, December 7, 2020.

Notes: The data series provided by FRED begins only in 1990, so we cannot look earlier in time with this data series.

Appendix Figure A.11: Log employment as a function of NAFTA vulnerability, robustness to Multi-Fibre-Arrangement phase-out

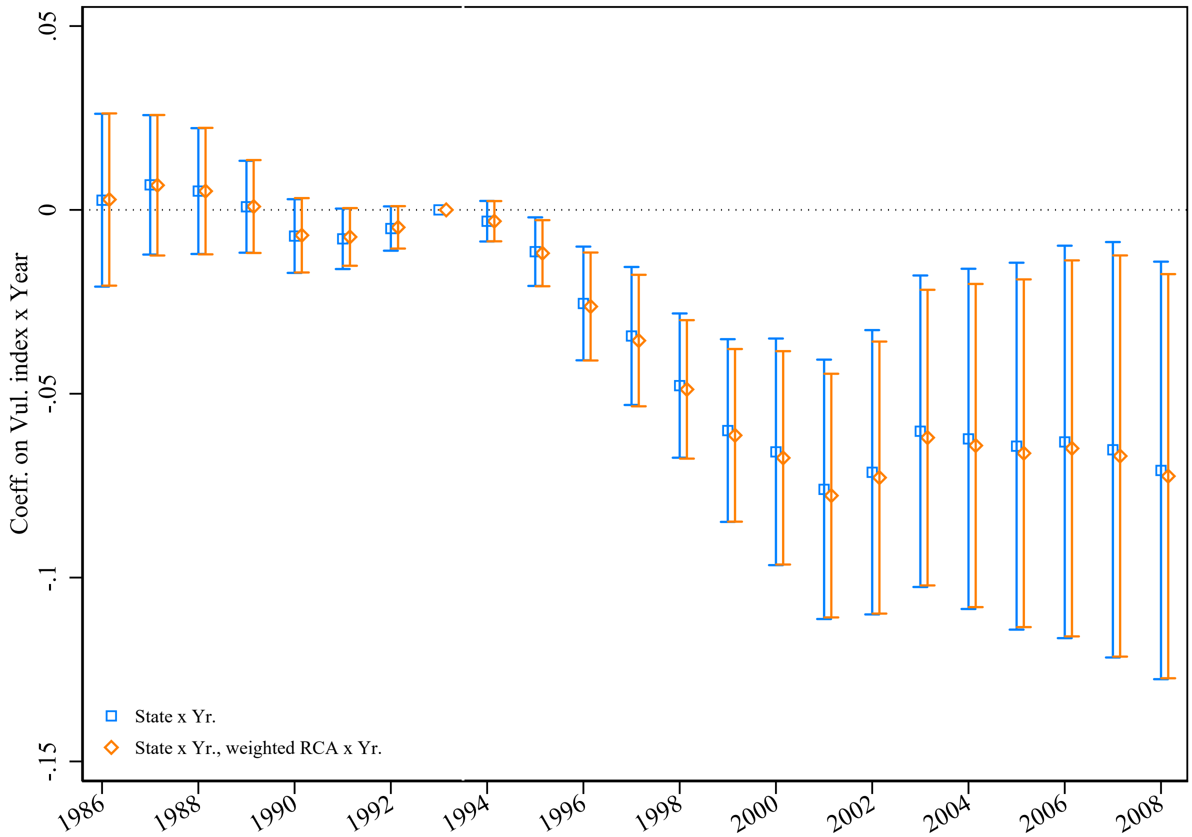


Sources: The dependent variable is derived from the CBP. A county-year-level measure of exposure to the MFA is drawn from Pierce and Schott (2020), which is based on the approach from Khandelwal, Schott, and Wei (2013).

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2914 counties in each year of the sample. Observations are weighted by 1990 county population. The first series controls for county and year fixed effects, as well as $state \times year$ fixed effects. The second series adds to the first controls for county-year-level measure of exposure to the MFA from Pierce and Schott (2020) interacted with year fixed effects. The third series adds to the first controls for county-level MFA exposure *based on 2005 average quota fill rates* from Pierce and Schott (2020) interacted with year fixed effects.

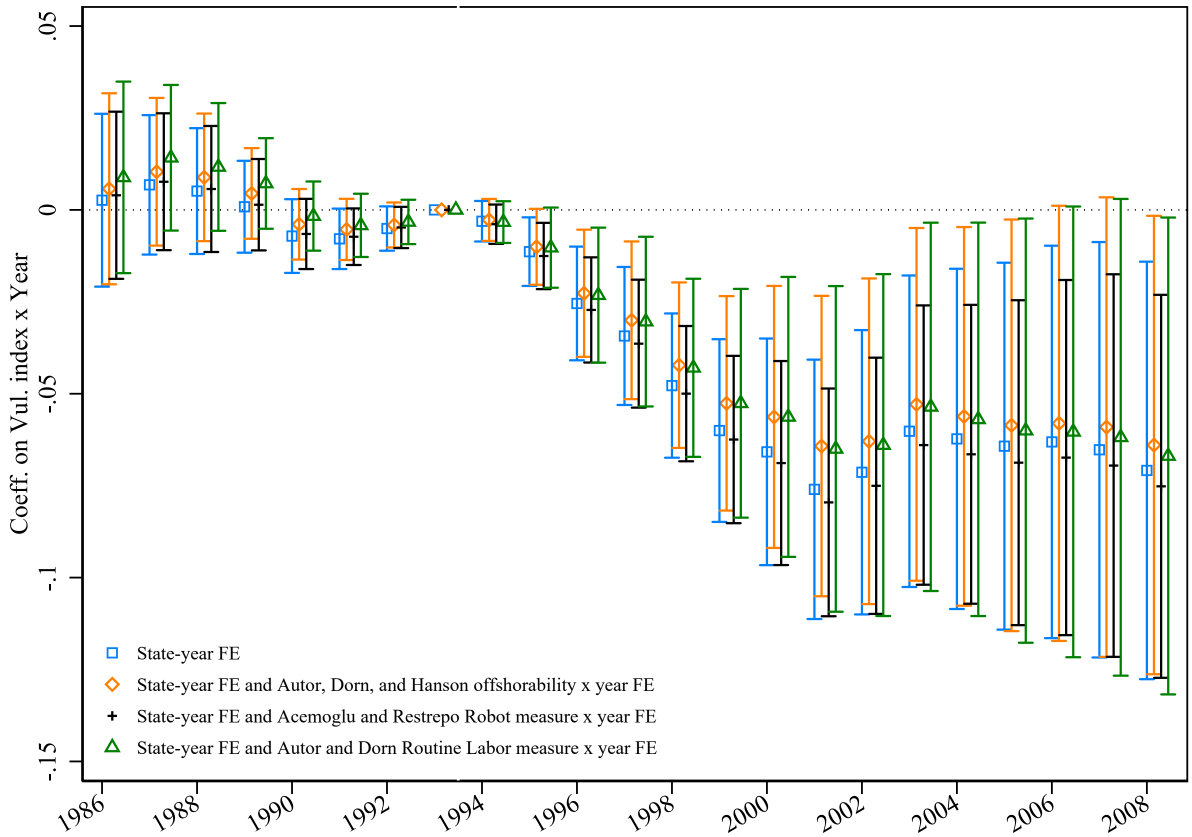
Under the Uruguay round of the General Agreement on Tariffs and Trade, the quotas under the Multi-Fibre Arrangement (MFA) were put on a phase-out schedule (the final year of the phase-out was announced as 2005). As there was little actual change in the "binding" quotas until the early 2000s, the *contemporaneous* quota fill rate is not a potential confounding variable in our NAFTA analysis, as can be seen by comparing the first and second series of this graph. However, to the extent that agents are perfectly forward-looking, the known end of the quotas by 2005 could potentially cause declines in protected industries many years earlier. We thus draw a county-level MFA vulnerability measure *based on 2005 average quota fill rates* from Pierce and Schott (2020) and interact it with every year in our sample period. That is, we let these future quota fill rates have arbitrary effects in all years. Comparing the second and third series shows that even after flexibly controlling for possible forward-looking effects of the MFA phase-out, we still identify a large, negative effect of NAFTA vulnerability on county employment that is statistically significant at the ten percent level in the late 1990s.

Appendix Figure A.12: Log of employment as a function of county NAFTA vulnerability, robustness to Peso crisis



Notes: The analysis sample is fixed across specifications and strictly balanced, with 2914 counties in each year of the sample. The figure shows the event-study coefficient estimates from different specifications of equation (5), where log of total employment is the dependent variable. Observations are weighted by 1990 county population. In the first series we replicated our usual specification with county, year, and $state \times year$ fixed effects. The second specification seeks to control for any effect of the 1994-1995 Mexican peso crisis, which we do as follows. The peso crisis made *all* Mexican goods cheaper, regardless of pre-NAFTA tariff status. Thus, we create a vulnerability measure that excludes the pre-NAFTA tariff level and simply weights pre-NAFTA 1990 county employment by its dependence on industries where Mexico has high revealed comparative advantage (as measured in 1990, regardless of tariff level). The second series adds as a control this county-level variable interacted with year fixed effects. Comparing the two series suggests that the estimated effect of NAFTA vulnerability does not change much after flexibly controlling for county-level exposure to the devalued peso.

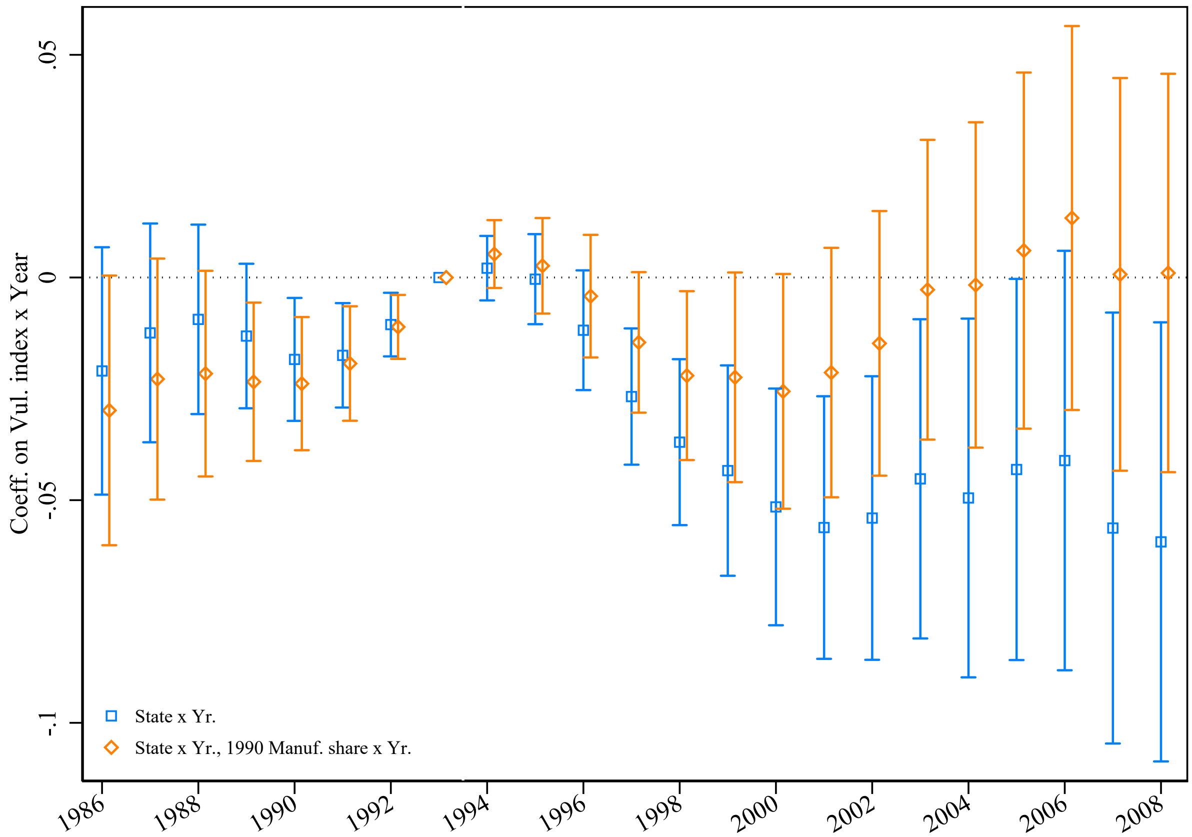
Appendix Figure A.13: Log employment as a function of county NAFTA vulnerability, robustness to automation, off-shoring and immigration



Sources: The dependent variable is derived from the CBP, and county-level demographics are from the Census PEP.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2914 counties in each year of the sample. This figure extends the analysis in Figure 2. The figure shows the point estimates (and 95% confidence intervals, based on standard errors clustered by state) for the coefficients on *Vulnerability* interacted with year (with 1993 the omitted year) from different specifications of equation (5).The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (5), where log of total employment at the county$\times$year level is the dependent variable. Observations are weighted by 1990 county population. The first series controls for county and year fixed effects, as well as *state*$\times$*year* fixed effects. The second specification adds to the first specification year fixed effects interacted with CZ-level "offshorability" based on 1980 occupation, as used in Autor, Dorn, and Hanson (2013). The third specification adds to the first specification year fixed effects interacted with CZ-level "robot" measure, as used in Acemoglu and Restrepo (2020). The final specification adds to the first specification year fixed effects interacted with CZ-level "routine labor" measure, as used in Autor and Dorn (2013).

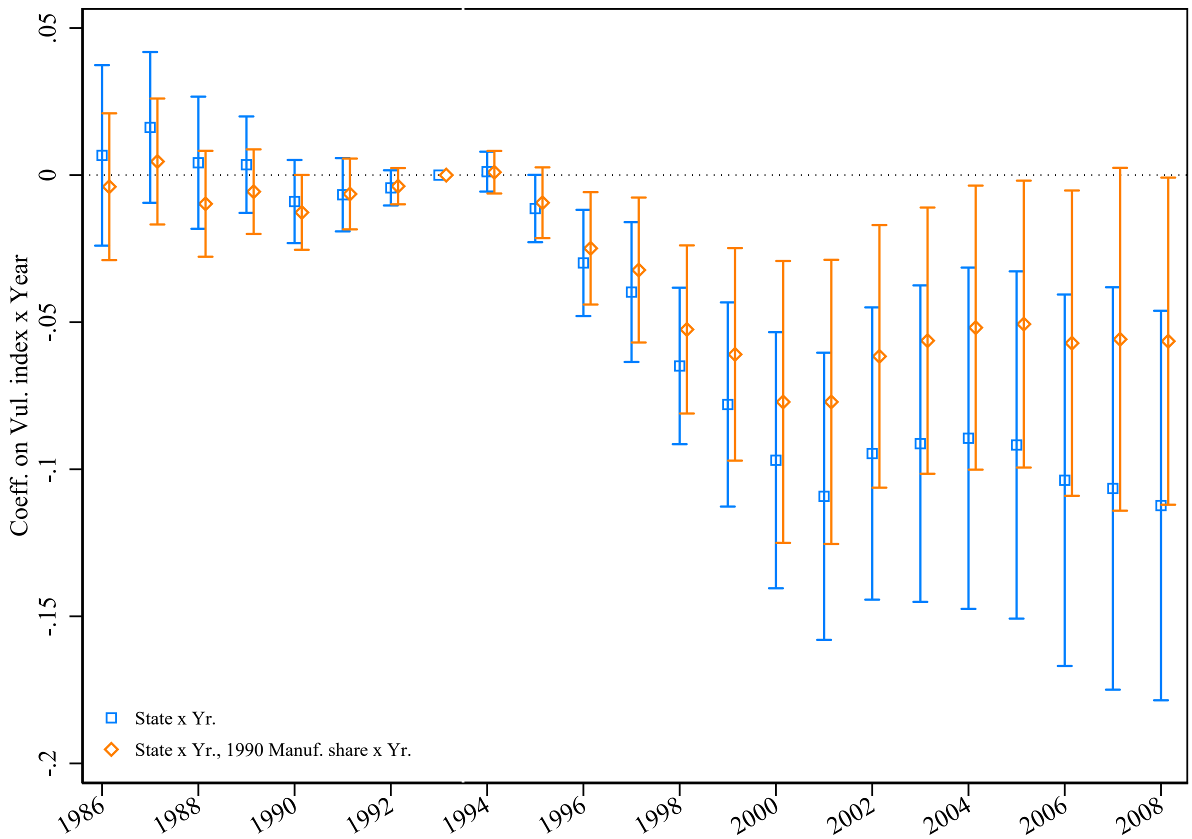
Appendix Figure A.14: Log of CZ employment as a function of CZ-level NAFTA vulnerability



Sources: The dependent variable is derived from the CBP.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 705 CZs in each year of the sample. This figure is the analogue to Figure 2 but at the CZ, not county, level. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by CZ) from different specifications of equation (5), where log employment at the CZ×year level is the dependent variable. Observations are weighted by 1990 CZ population. The first series controls for CZ, year fixed effects, and *state*×*year* fixed effects, where CZs are assigned to states using David Dorn's CZ-to-state crosswalk. Whenever a CZ crosses more than one state, the CZ is assigned to a state with the largest share of CZ's population. The second series adds to the first controls for 1990 CZ-level manufacturing share of employment interacted with year fixed effects.

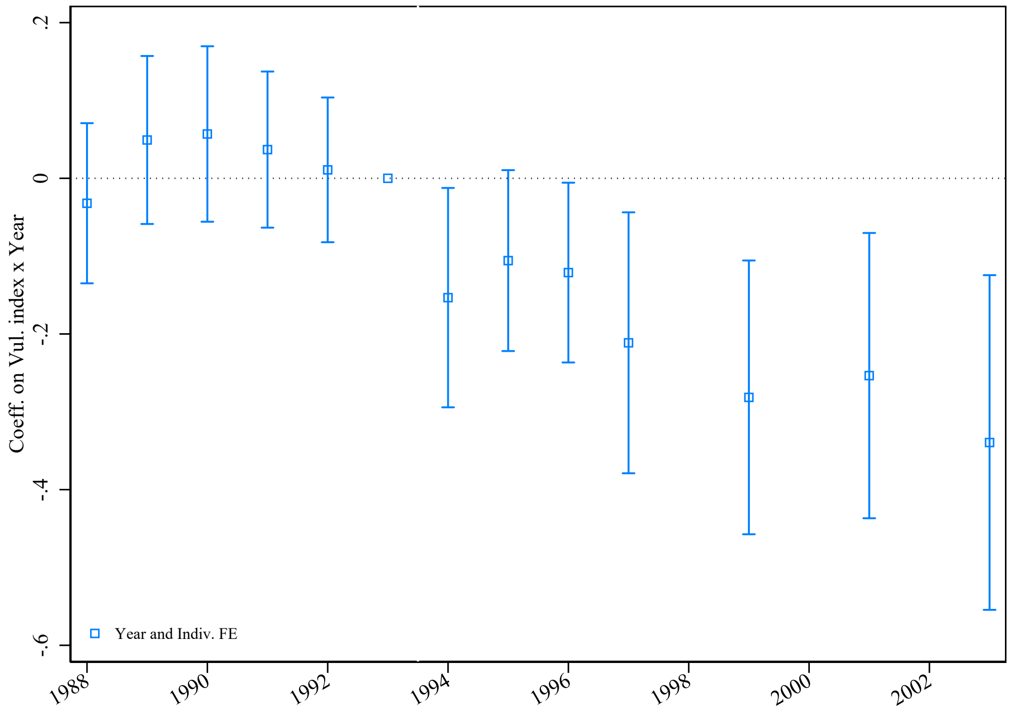
Appendix Figure A.15: Log total wage bill as a function of NAFTA vulnerability



Sources: CBP data.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2920 counties in each year of the sample. The figure is identical to Figure 2 except that the outcome variable is total log wage bill instead of total log employment. Observations are weighted by 1990 county population. The first series controls for county and year fixed effects, as well as $state \times year$ fixed effects. The second series adds to the first controls for 1990 county-level manufacturing share of employment interacted with year fixed effects.

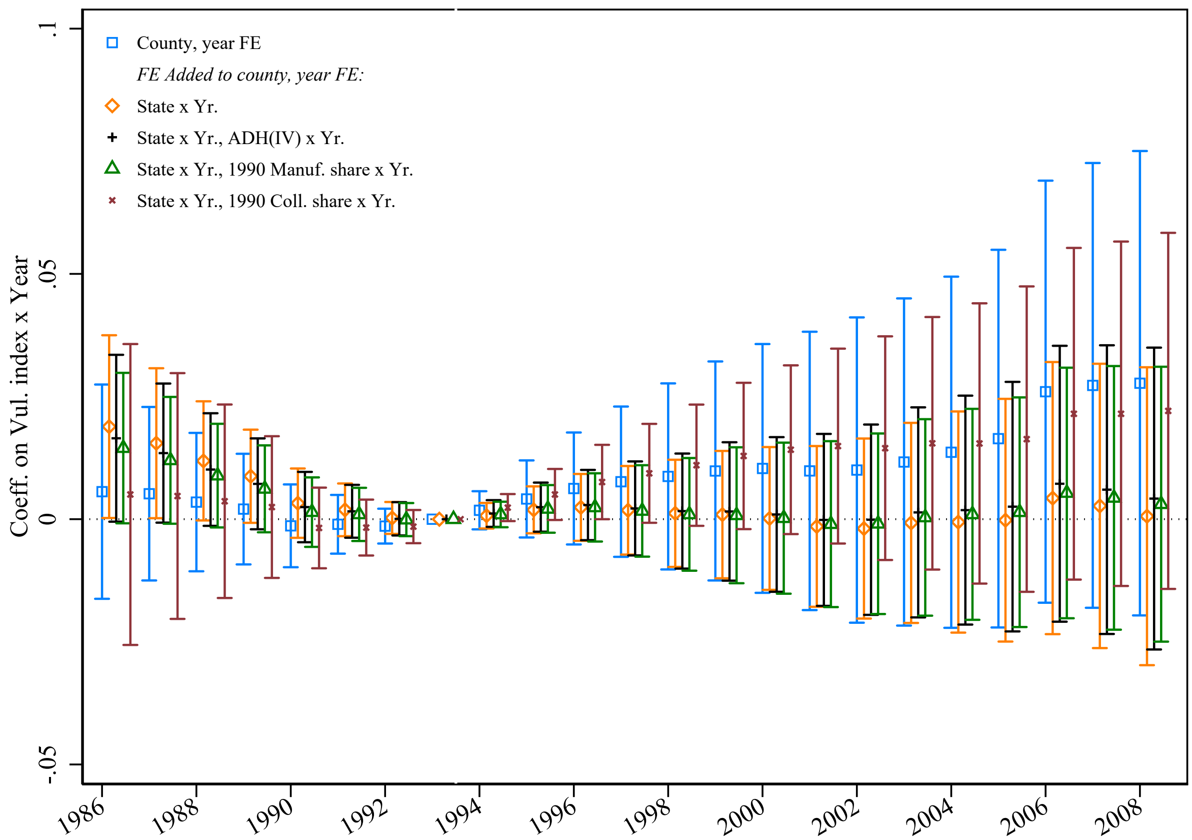
Appendix Figure A.16: Employment as a function of individual vulnerability, PSID sample



Sources: PSID panel data. See Appendix B.4 for more detail.

Notes: $N = 4352$ individuals. This figure does not use geography to assign vulnerability to NAFTA but instead the individual's industry in a baseline (1988) pre-NAFTA year. We define individual-level i's vulnerability to NAFTA as $Vulnerability_i = RCA_{j(i)} \cdot \tau_{j(i)}^{1990}$, where $j(i)$ is industry j of person i in 1988 (or, if unemployed that year, their most recent industry), $RCA_{j(i)}$ is Mexico's revealed comparative advantage in industry j, and $\tau_{j(i)}^{1990}$ is the U.S. tariff on Mexican imports in industry j in 1990. The specification regressed a dummy variable for being employed in year t on year fixed effects and $Vulnerability_i$ interacted with year and individual fixed effects (and reports the coefficients on these interaction terms).

Appendix Figure A.17: Log population as a function of county NAFTA vulnerability, varying controls

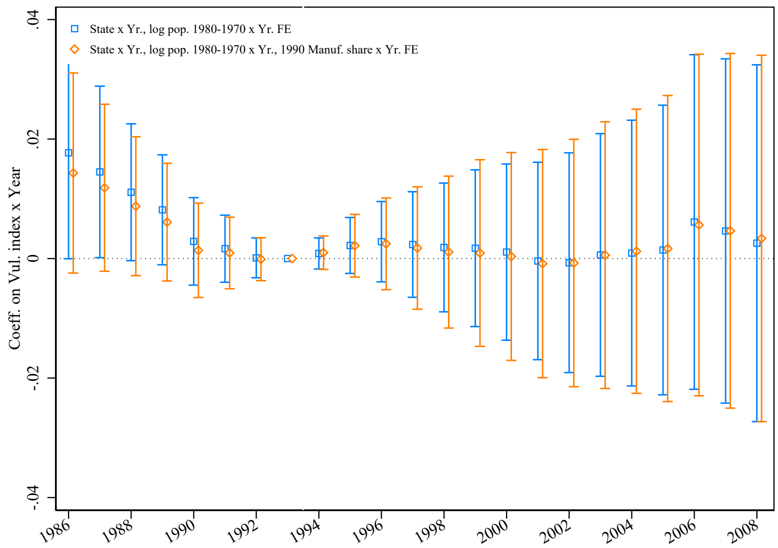


Sources: The dependent variable is taken from the Census Bureau's Population Estimates Program. See Appendix B.3 for more detail.

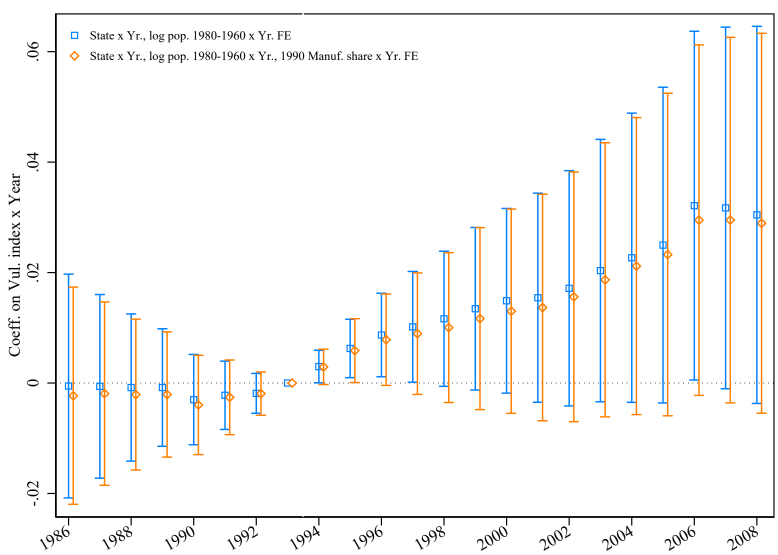
Notes: The analysis sample is fixed across specifications and strictly balanced, with 2978 counties in each year of the sample. This figure is analogous to Figure 3 but shows additional specifications after varying the controls. Observations are weighted by 1990 county population. The first series includes only county and year fixed effects. The second series adds to this specification $state \times year$ fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor, Dorn, and Hanson (2013) interacted with year fixed effects. The fourth specification adds to the second specification 1990 county-level manufacturing share of employment interacted with year fixed effects. The final specification adds to the second specification 1990 county-level college-graduate population share interacted with year fixed effects. Thus, the second and fourth specifications are identical to the first and second series of Figure 3.

Appendix Figure A.18: Log population as a function of NAFTA vulnerability, controlling for long population changes

(a) Controlling for 1970-1980 county pop change

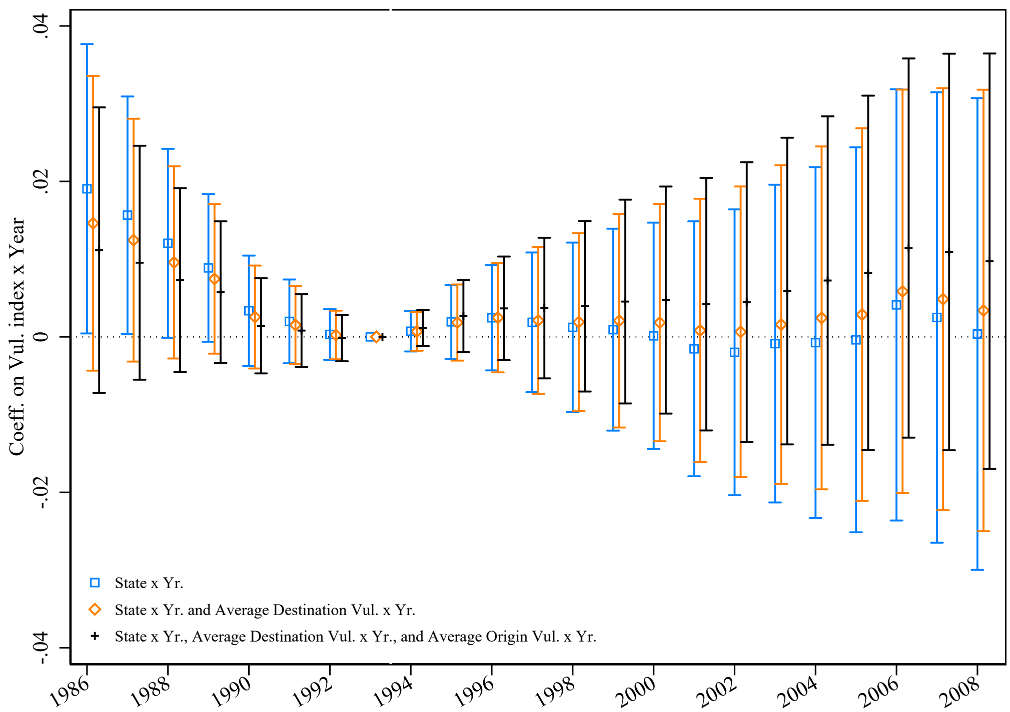


(b) Controlling for 1960-1980 county pop change



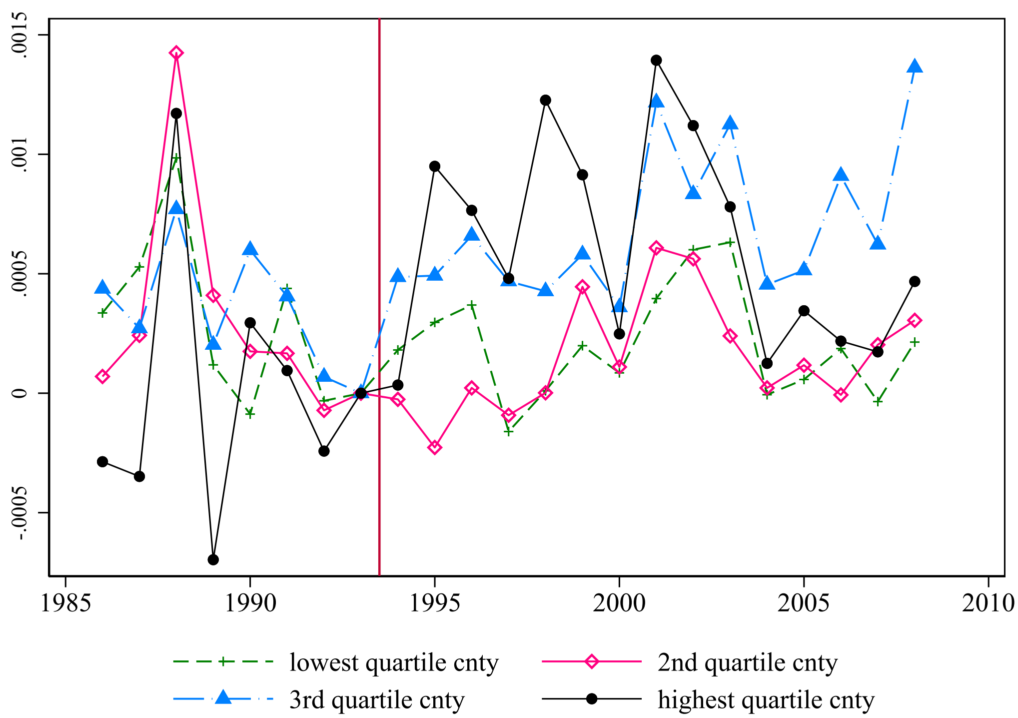
Notes: The analysis sample is fixed across specifications and strictly balanced, with 2967 counties in each year of the sample. These specifications mirror those in Figure 3 but control for 'long differences' in county population. Observations are weighted by 1990 county population. Panel (a) includes the 1970-1980 county population change interacted with year fixed effects in both specifications. Panel (b) includes the 1960-1980 county population change interacted with year fixed effects in both specifications.

Appendix Figure A.19: Migration response to NAFTA, adjusting for NAFTA vulnerability of a county's pre-existing migration network



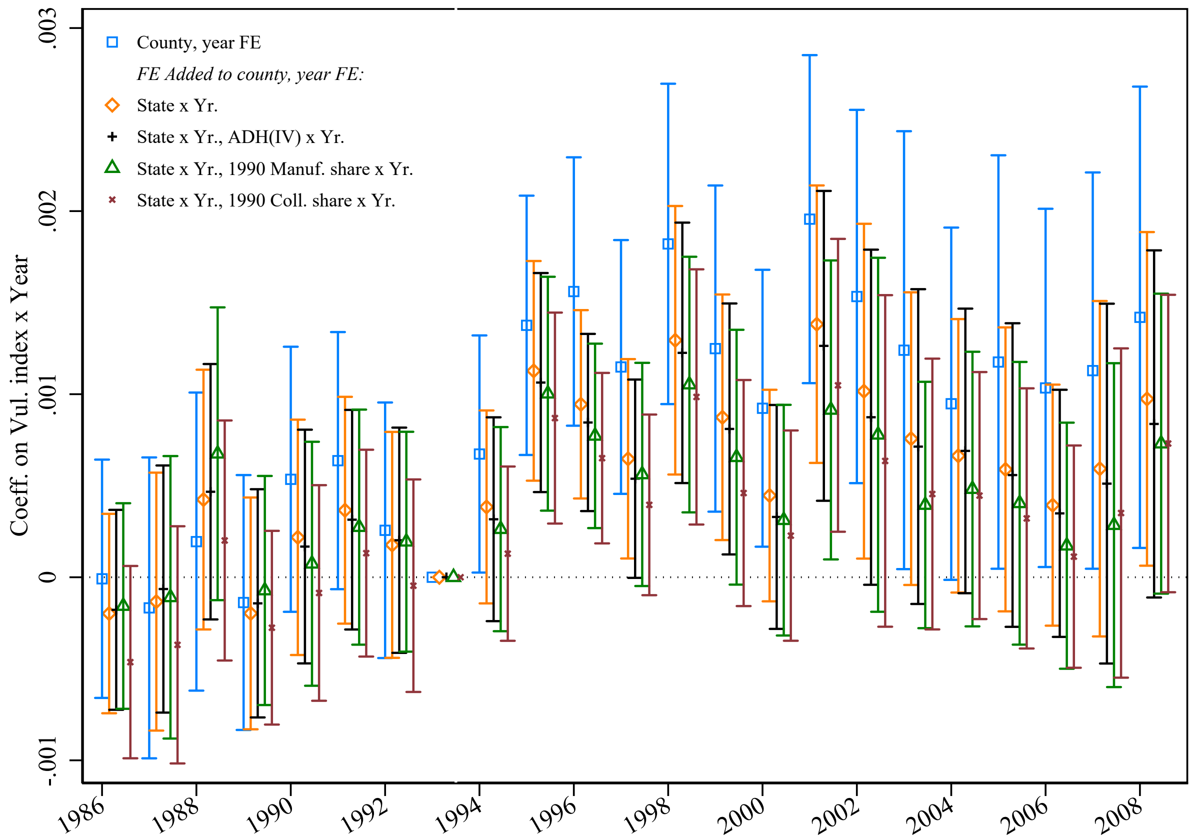
Notes: The analysis sample is fixed across specifications and strictly balanced, with 2866 counties in each year of the sample. We use the collapsed and cleaned version of the IRS migration data from Hauer (2023) to construct the pre-existing migration network. This figure is an extension of Figure 3. Observations are weighted by 1990 county population. The first series replicates the first specification of Figure 3. The second series adds to the first specification the average *Vulnerability* measure of destination counties based on 1990 migration patterns interacted with year fixed effects. The third series adds to the first specification the average *Vulnerability* measure of origin counties based on 1990 migration patterns interacted with year fixed effects.

Appendix Figure A.20: Trade Adjustment Assistance petitions per capita, by county *Vulnerability* quartile (normalized to zero in 1993)



Notes: $N = 2978$ counties for each year of the sample period. This figure uses the same data as in Figure 4 but simply shows raw averages (normalized to zero in 1993) by the four quartiles based on county *Vulnerability*.

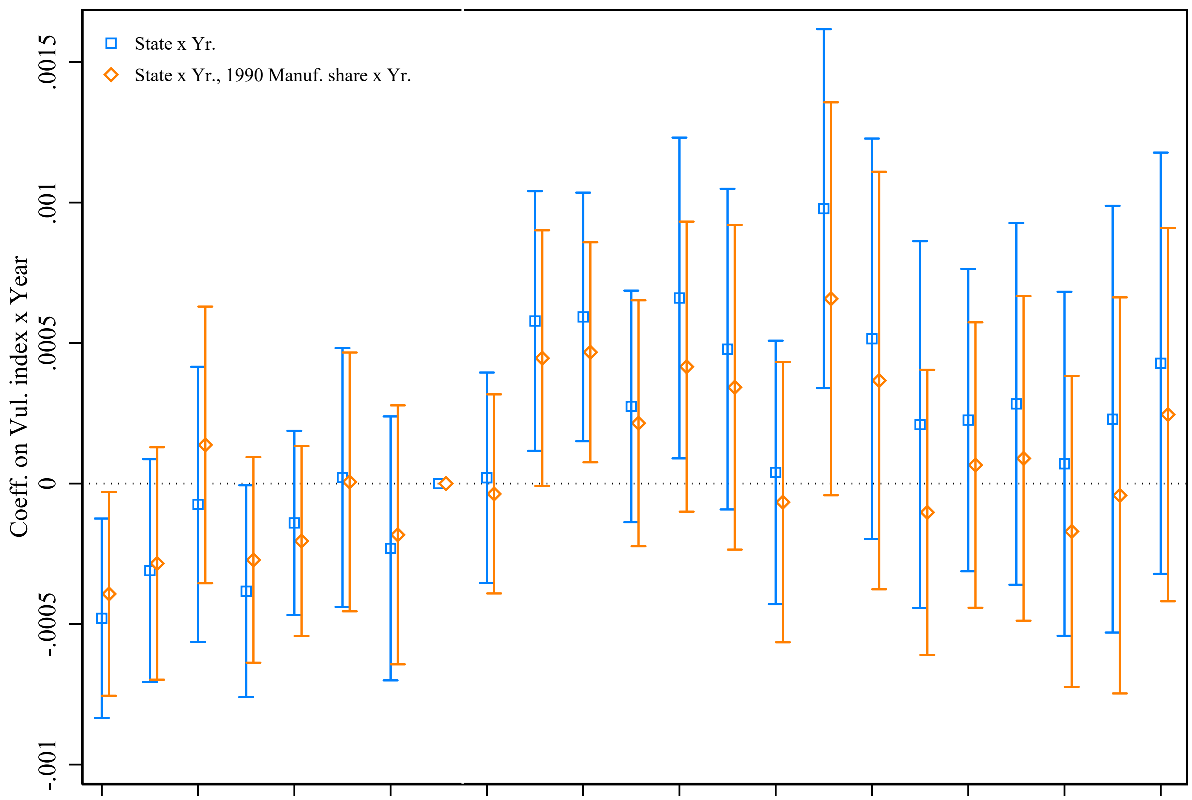
Appendix Figure A.21: Trade Adjustment Assistance petitions per capita as a function of county NAFTA vulnerability, varying controls



Sources: The dependent variable is taken from the U.S. Department of Labor TAA petition data, divided by 1990 working-age county population. See Appendix B.5 for more detail.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2978 counties in each year of the sample. This figure is analogous to Figure 4 but shows additional specifications after varying the controls. Observations are weighted by 1990 county population. The first series includes only county and year fixed effects. The second series adds to this specification $state \times year$ fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor, Dorn, and Hanson (2013) interacted with year fixed effects. The fourth specification adds to the second specification 1990 county-level manufacturing share of employment interacted with year fixed effects. The final specification adds to the second specification 1990 county-level college-graduate population share interacted with year fixed effects. Thus, the second and fourth specifications are identical to the first and second series of Figure 4.

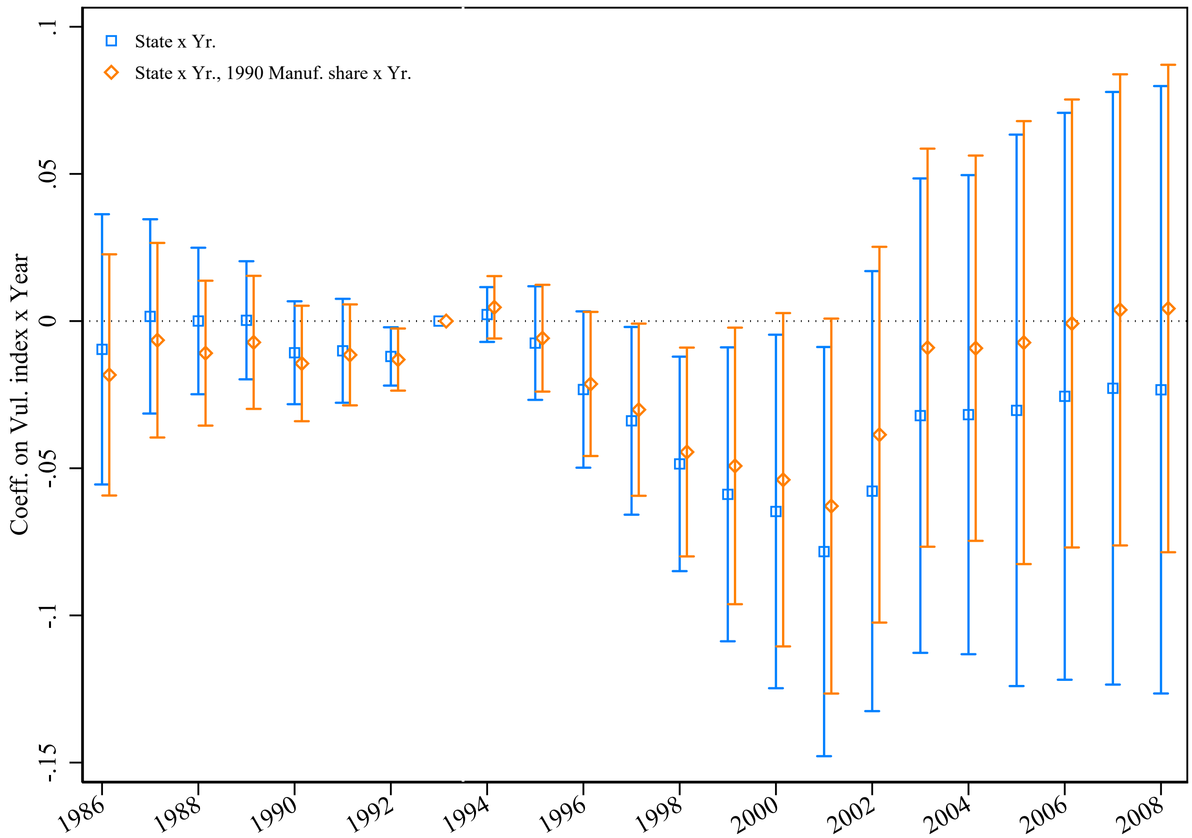
Appendix Figure A.22: Trade Adjustment Assistance *certifications* per capita as a function of county vulnerability



Sources: The dependent variable is taken from the U.S. Department of Labor TAA petition data. We divide by 1990 county working-age population. See Appendix B.5 for more detail.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2978 counties in each year of the sample. This figure is identical to Figure 4 except that the dependent variable is TAA *certifications* per capita instead of *petitions*. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (5), where per capita TAA certifications at the county×year level is the dependent variable. Observations are weighted by 1990 county population. The first series controls for county and year fixed effects, as well as *state*×*year* fixed effects. The second series adds to the first controls for 1990 county-level manufacturing share of employment interacted with year fixed effects.

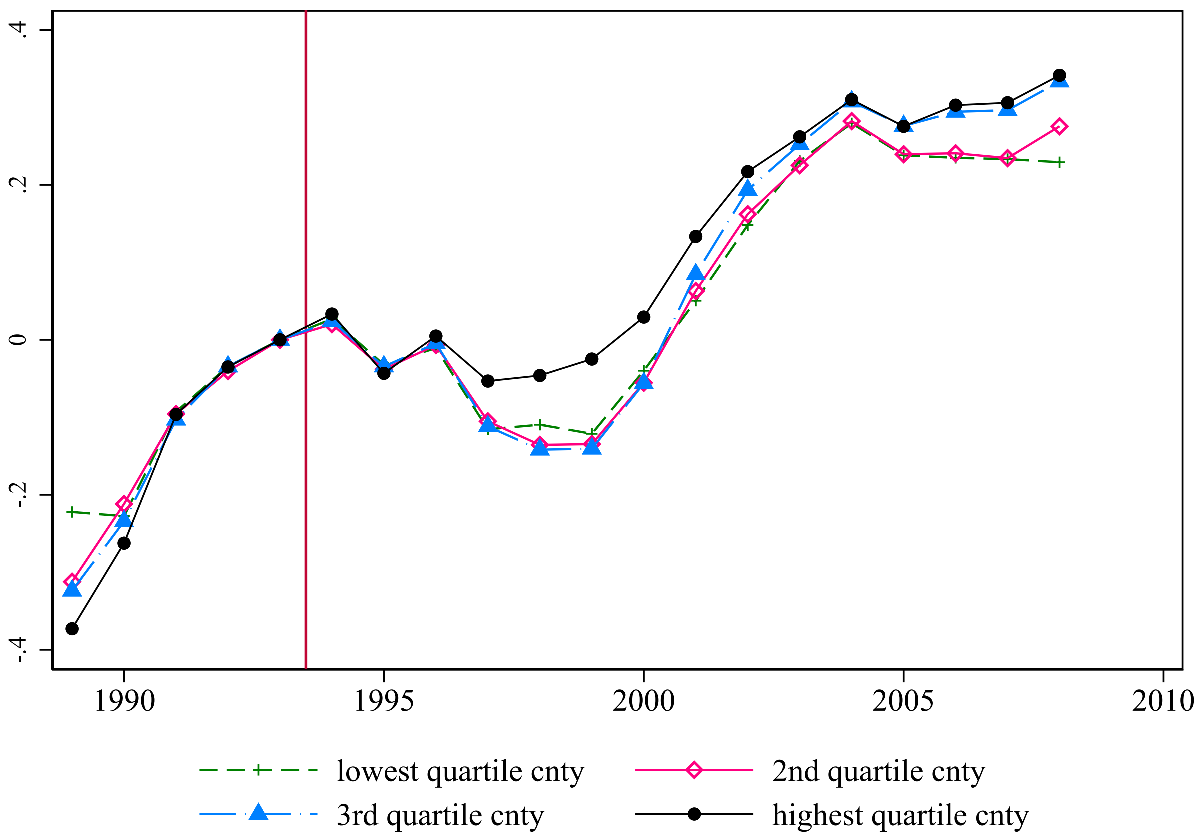
Appendix Figure A.23: Evolution of log employment as a function of county NAFTA vulnerability, for a balanced panel of 755 counties for which we have DI application data



Sources: The dependent variable is derived from the SSA. See Appendix B.8 for more detail.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 755 counties in each year of the sample. This figure is identical to Figure 2 but is restricted to the 755 counties (which account for around three-fourths of the U.S. population) for which we have DI data. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (5), where log of total employment at the county×year level is the dependent variable. Observations are weighted by 1990 county population. The first series controls for county and year fixed effects, as well as *state×year* fixed effects. The second series adds to the first controls for 1990 county-level manufacturing share of employment interacted with year fixed effects.

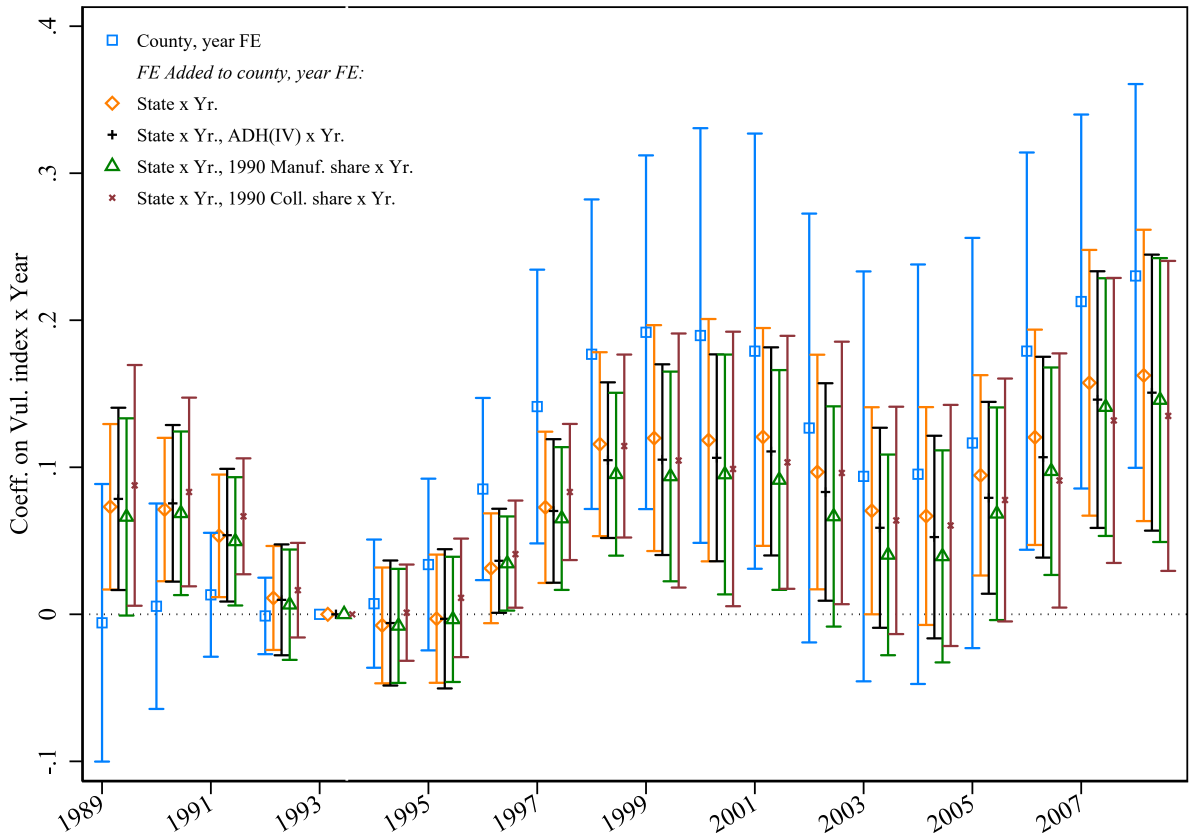
Appendix Figure A.24: Log DI applications, raw trends by four vulnerability quartiles (1993 normalized to zero)



Sources: The dependent variable is taken from the Social Security Administration (SSA). See Appendix B.8 for more detail.

Notes: The figure shows the log of annual county DI applications by 1990 county vulnerability quartiles. Observations are unweighted. Note that we can only perform this analysis for a subset of counties (see Section 5.3).

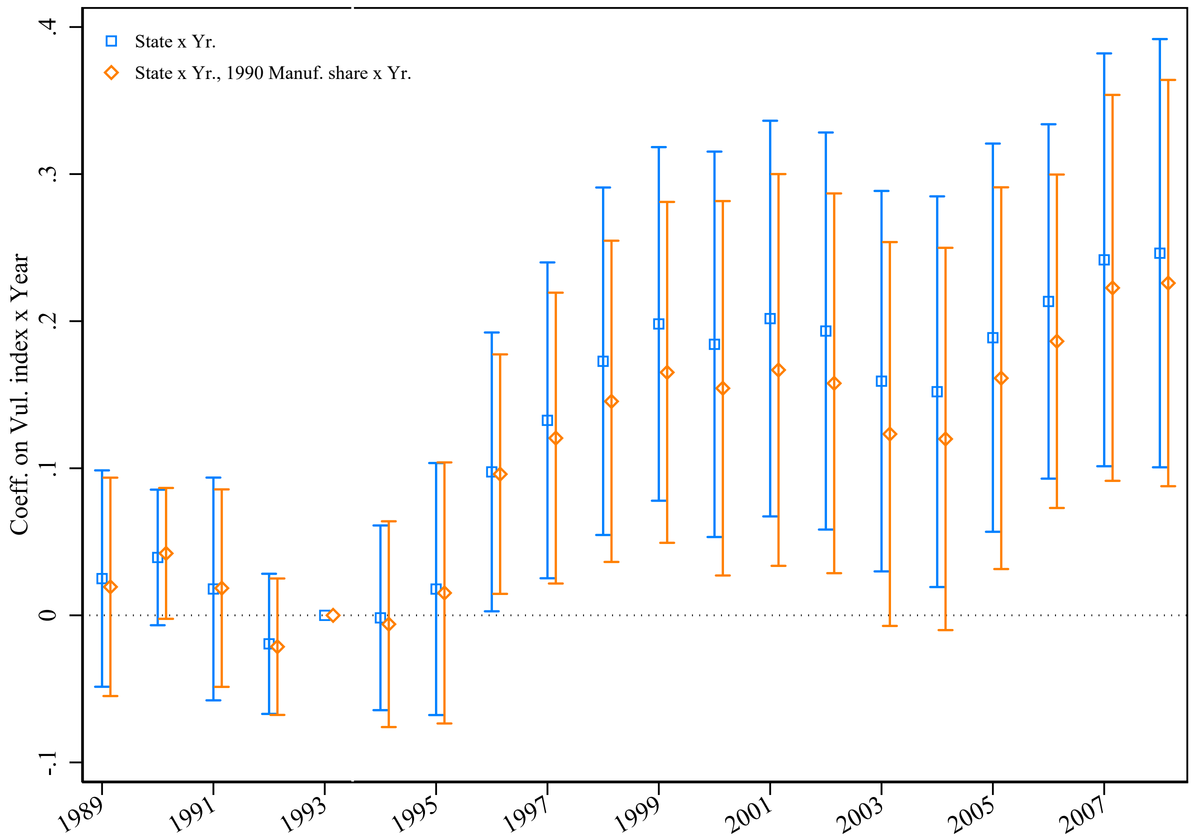
Appendix Figure A.25: Log of DI applications as a function of county NAFTA vulnerability



Sources: The dependent variable is taken from the Social Security Administration (SSA). See Appendix B.8 for more detail.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 759 counties in each year of the sample. This figure is analogous to Figure 5 but shows additional specifications after varying the controls. Observations are weighted by 1990 county population. The first series includes only county and year fixed effects. The second series adds to this specification $state \times year$ fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor, Dorn, and Hanson (2013) interacted with year fixed effects. The fourth specification adds to the second specification 1990 county-level manufacturing share of employment interacted with year fixed effects. The final specification adds to the second specification 1990 county-level college-graduate population share interacted with year fixed effects. Thus, the second and fourth specifications are identical to the first and second series of Figure 5.

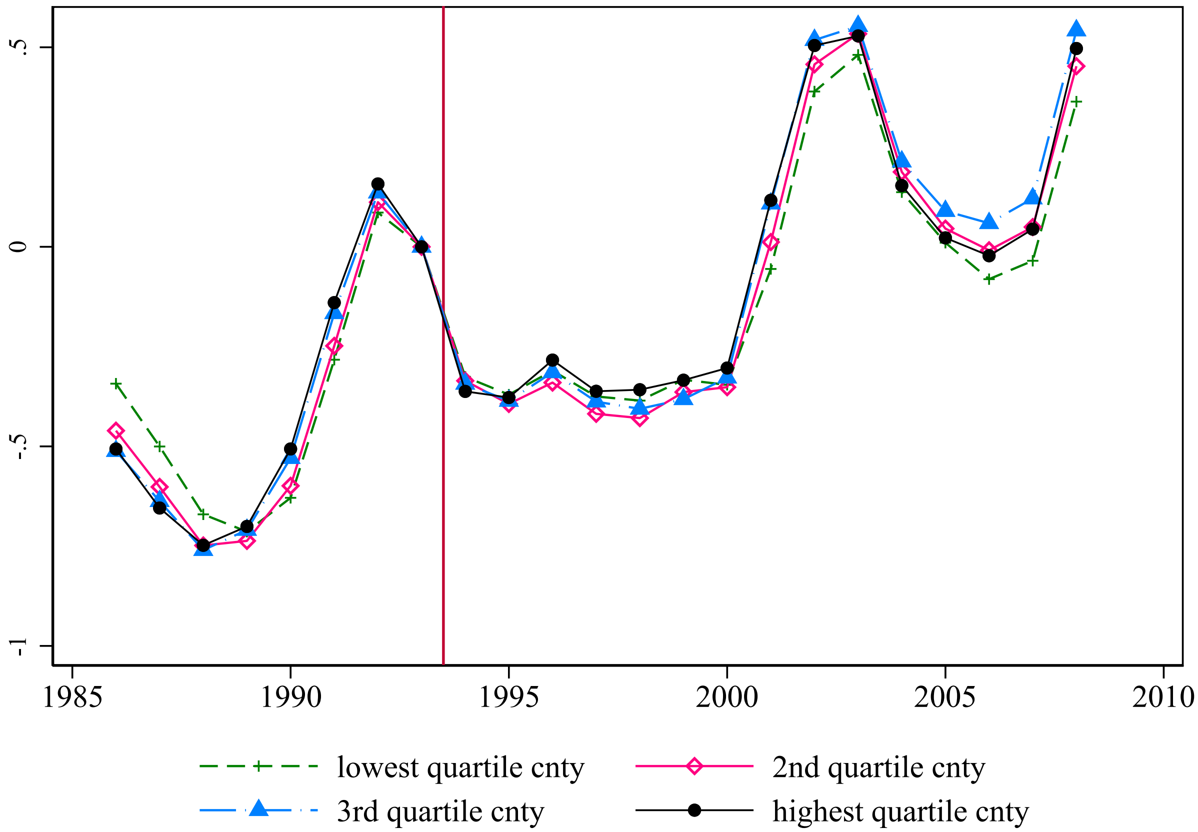
Appendix Figure A.26: Evolution of log DI final *awards* as a function of county vulnerability



Sources: The dependent variable is taken from the SSA. See Appendix B.8 for more detail.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 752 counties in each year of the sample. This figure is identical to Figure 5 except that the log of final awards instead of applications is the dependent variable. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (5), where log of Disability Insurance (DI) final awards is the dependent variable. As discussed in Section 5.3, we do not have all counties in this analysis, but the 752 counties we have in this balanced-panel analysis account for around three-fourths of the U.S. population. Observations are weighted by 1990 county population. The first series controls for county and year fixed effects, as well as *state*×*year* fixed effects. The second series adds to the first controls for 1990 county-level manufacturing share of employment interacted with year fixed effects.

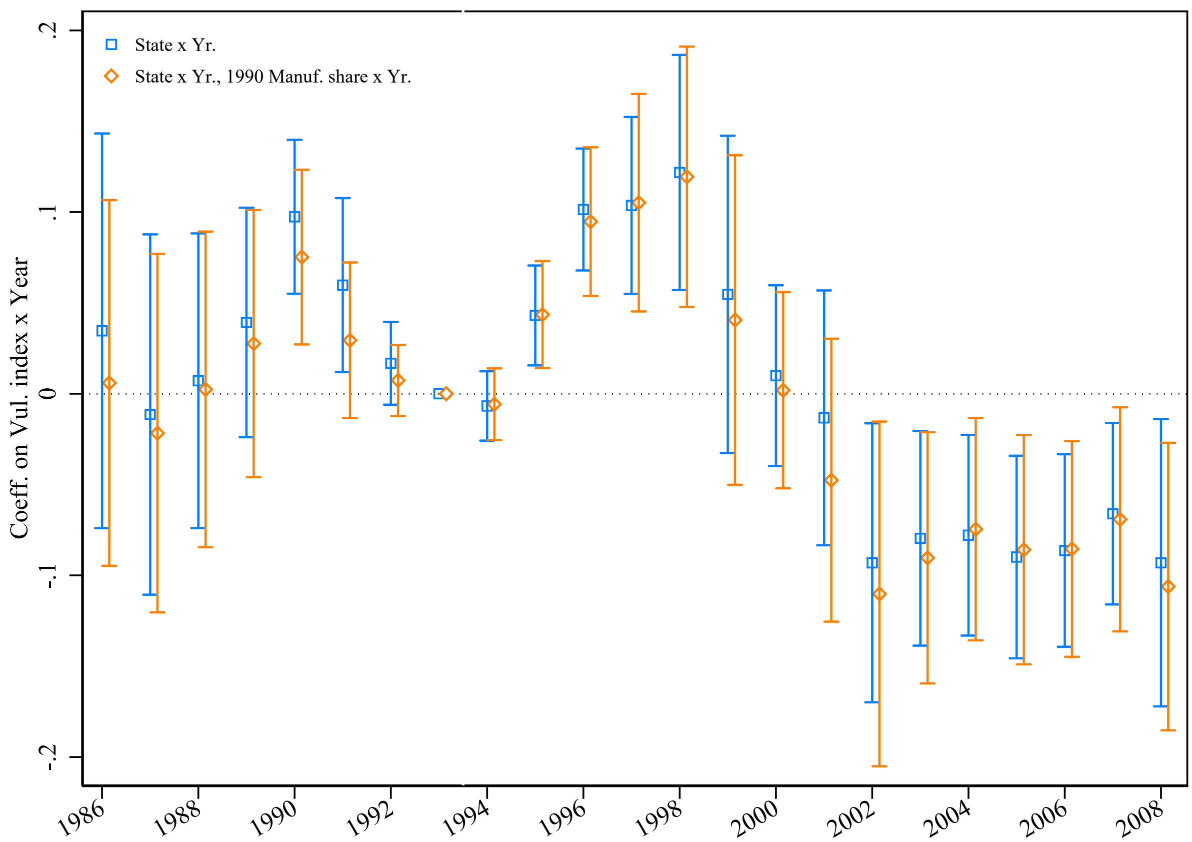
Appendix Figure A.27: Log of Unemployment Insurance benefits by county vulnerability, normalized



Sources: The U.S. Bureau of Economic Analysis (BEA) personal transfers data

Notes: The log of UI benefits is computed using the annual county-level personal transfers data from the U.S. BEA. The UI benefits in the series includes both state unemployment insurance compensation and other unemployment insurance payments, such as Trade Adjustment Assistance program.

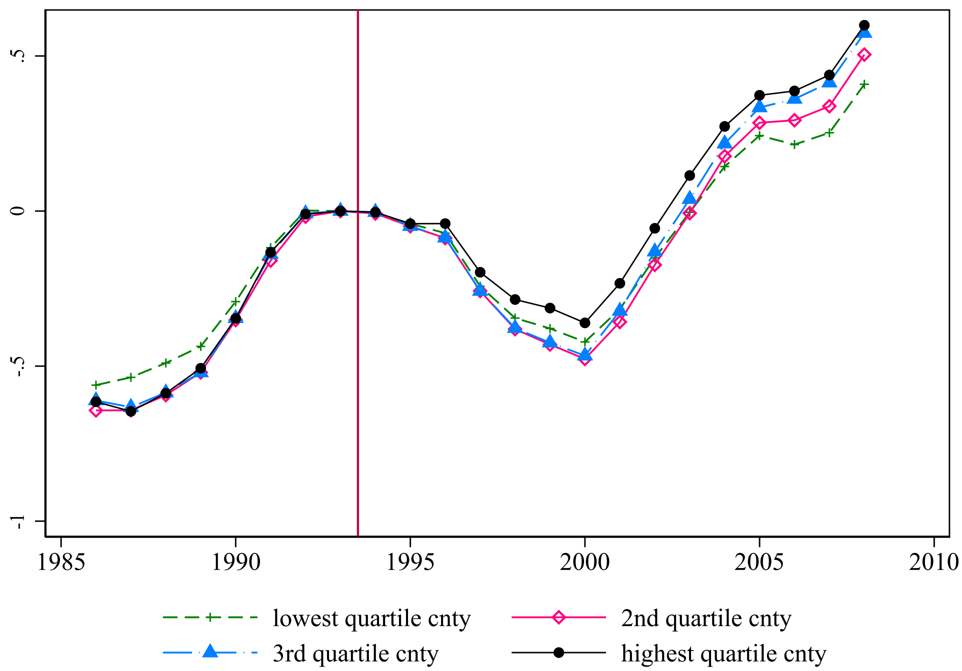
Appendix Figure A.28: Evolution of log UI benefits as a function of county vulnerability



Sources: The U.S. Bureau of Economic Analysis (BEA) personal transfers data

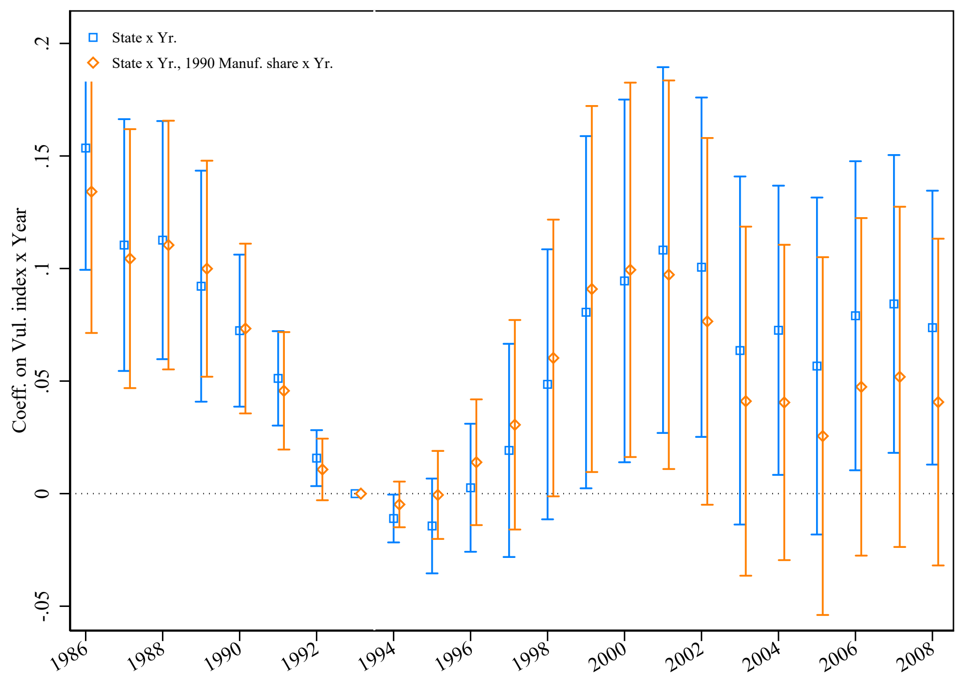
Notes: The analysis sample is fixed across specifications and strictly balanced, with 2925 counties in each year of the sample. The outcome variable is log of total UI benefits in each county. The log of UI benefits is computed using the annual county-level personal transfers data from the U.S. BEA. The UI benefits in the series include both state unemployment insurance compensation and other unemployment insurance payments, such as Trade Adjustment Assistance program. Observations are weighted by 1990 county population. The first series controls for county and year fixed effects, as well as *state*×*year* fixed effects. The second series adds to the first controls for 1990 county-level manufacturing share of employment interacted with year fixed effects.

Appendix Figure A.29: Log reported SNAP benefits, normalized



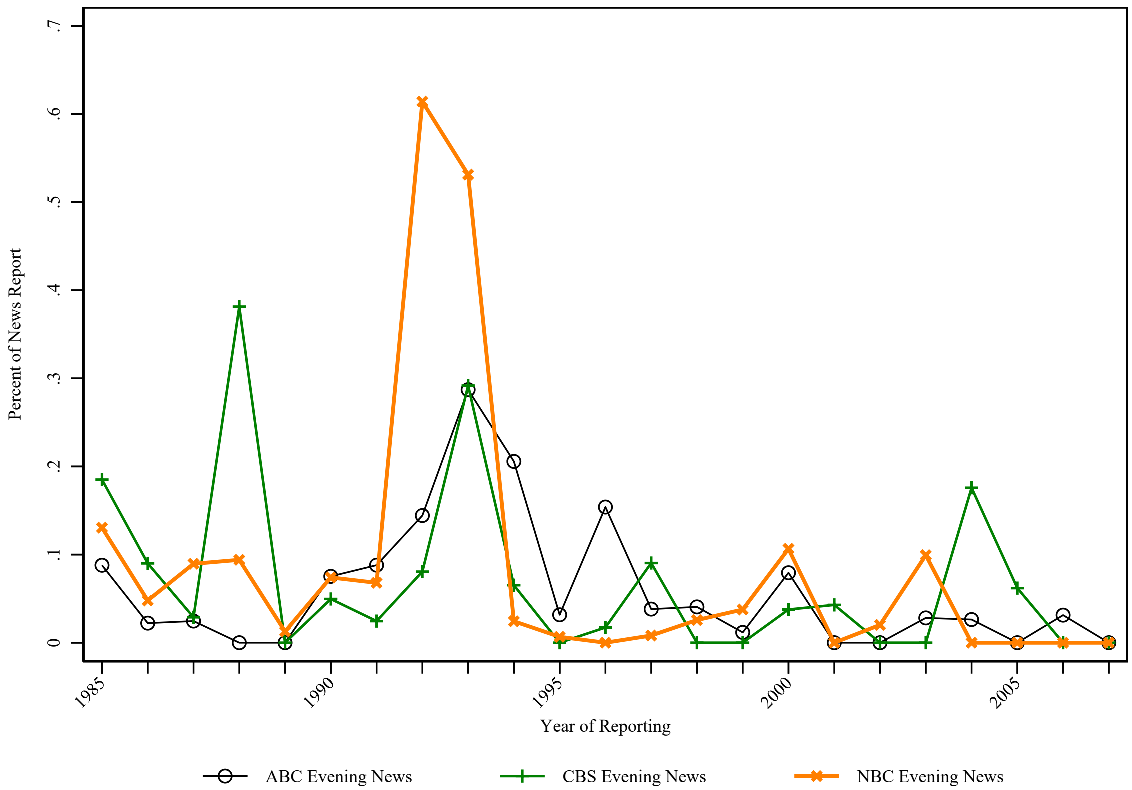
Notes: The log of reported SNAP benefits is computed using the annual county-level personal transfers data from the U.S. BEA. In the data, the SNAP benefits are estimated using the tabulations from the U.S. Department of Agriculture, payments data from state departments of social services, and the Census Bureau's Small Area Income and Poverty Estimates program. Observations are unweighted.

Appendix Figure A.30: Log reported SNAP benefits as a function of county vulnerability



Notes: The analysis sample is fixed across specifications and strictly balanced, with 2922 counties in each year of the sample. The outcome variable is log of reported SNAP benefits. The log of reported SNAP benefits is computed using the annual county-level personal transfers data from the U.S. BEA. In the data, the SNAP benefits are estimated using the tabulations from the U.S. Department of Agriculture, payments data from state departments of social services, and the Census Bureau's Small Area Income and Poverty Estimates program. Observations are weighted by 1990 county population. The first series controls for county and year fixed effects, as well as *state*×*year* fixed effects. The second series adds to the first controls for 1990 county-level manufacturing share of employment interacted with year fixed effects.

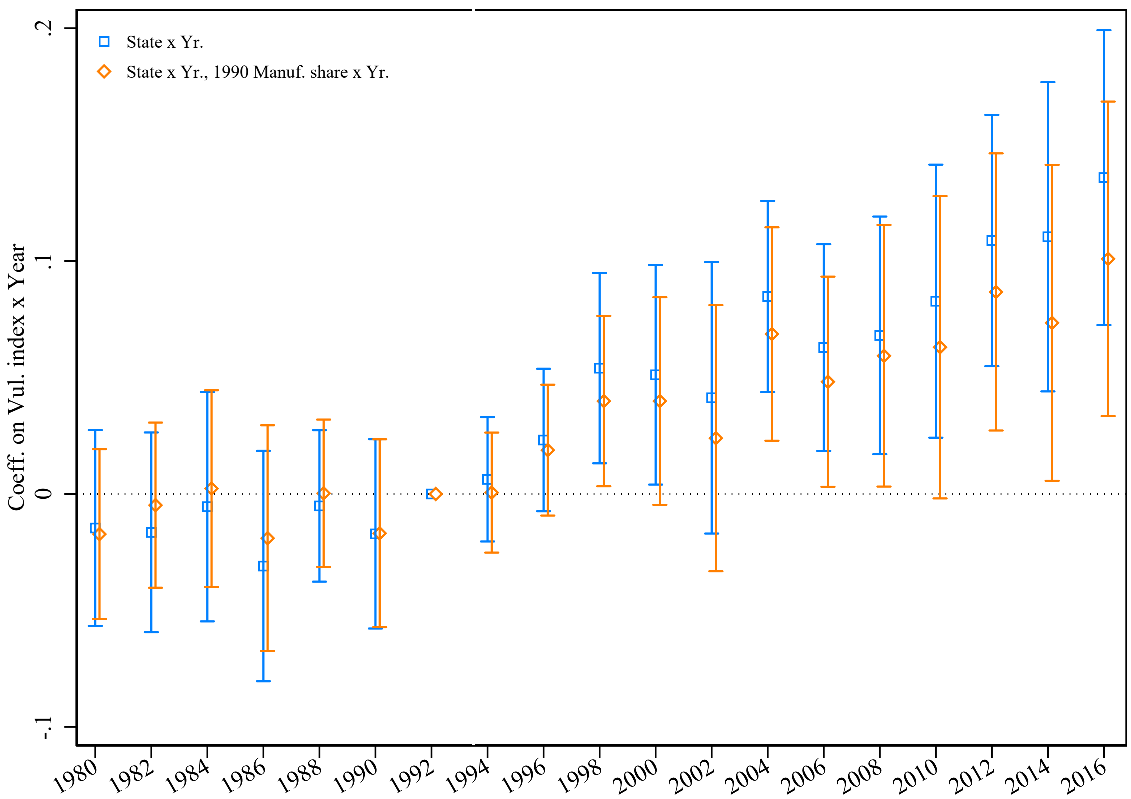
Appendix Figure A.31: Coverage of trade-and-jobs related stories by network nightly news programs



Sources: Data come from searching The Vanderbilt Television News Archive: `https://tvnews.vanderbilt.edu/search`. See Appendix B.9 for more detail.

Notes: For each year and network, we calculate the share of minutes on the nightly news dedicated to stories that include variants (plurals, capitalizations) the following words: "trade" and "imports" and "jobs" *or* "employment." We exclude any stories (in all years) that include the phrase "trade center" so as not to pick up stories related to the attacks on the World Trade Center buildings.

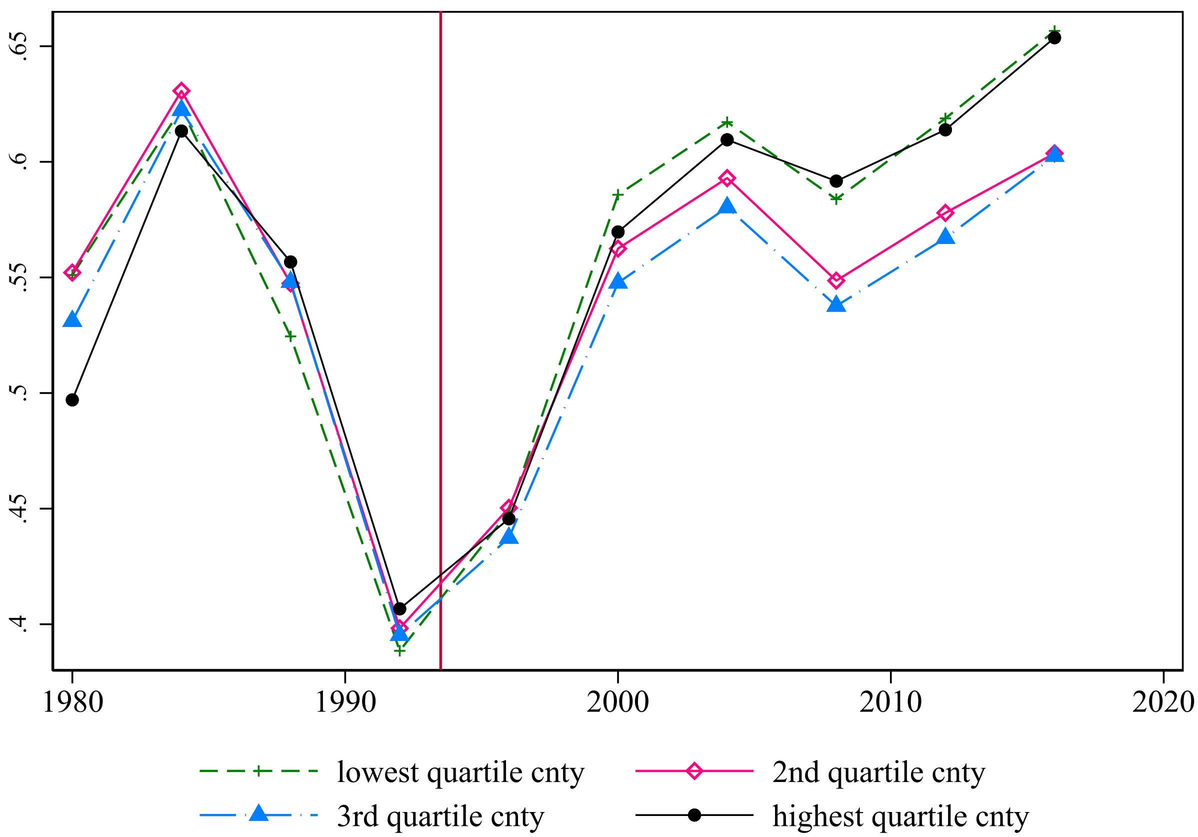
Appendix Figure A.32: Republican two-party share of House-election votes, by county NAFTA vulnerability



Sources: The dependent variable is computed from ICPSR general election data for the United States (1980-1990) and David Leip's Atlas of U.S. elections (1992-2008). Note that "Republican two-party share" is defined as $\frac{Repub.\,votes}{Repub.\,votes+Dem.\,votes}$ for each county-year. See Appendix B.10 for more detail.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2522 counties in each year of the sample. This figure is analogous to Figure 6 but for House elections which fall only on even years. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (5), where the two-party Republican vote share in House elections is the dependent variable. Observations are weighted by 1990 county population. The first series controls for county and year fixed effects, as well as *state*×*year* fixed effects. The second series adds to the first controls for 1990 county-level manufacturing share of employment interacted with year fixed effects.

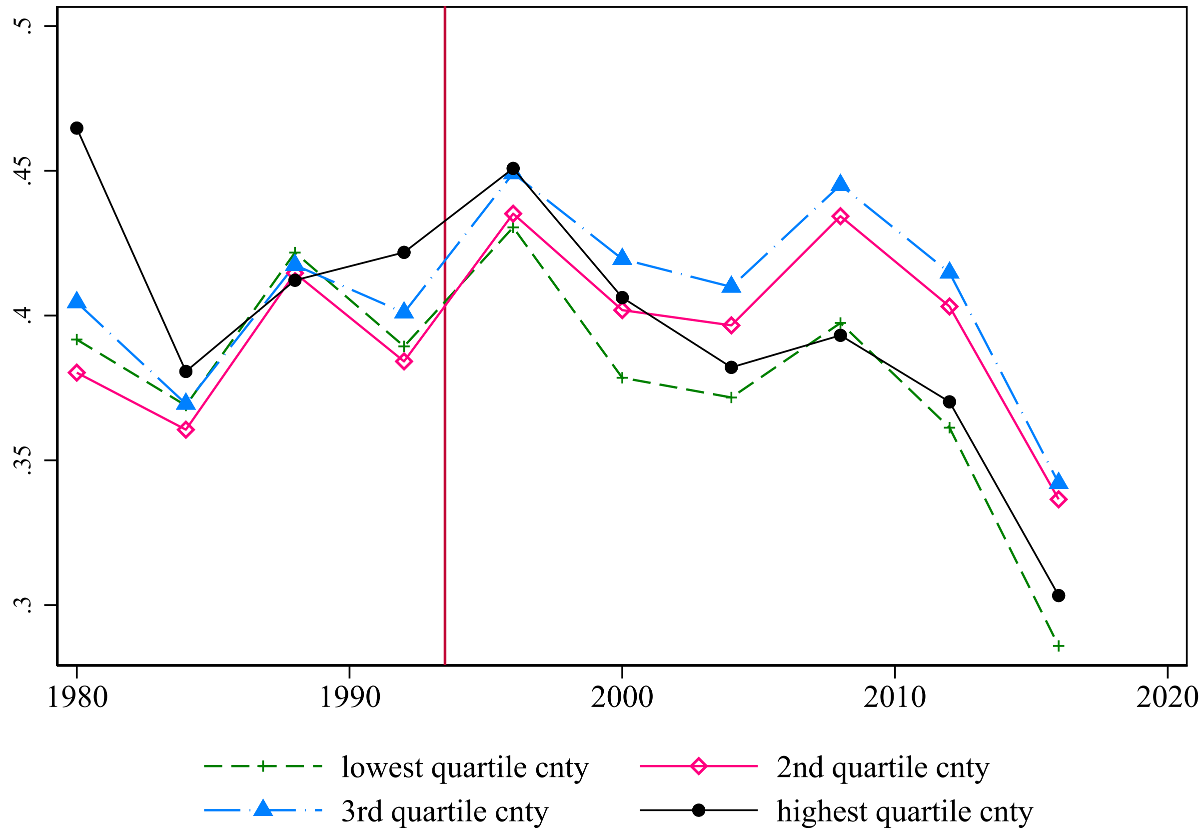
Appendix Figure A.33: Republican vote share in Presidential elections, separately by vulnerability quartile (raw means, not normalized)



Sources: The dependent variable is computed from ICPSR general election data for the United States (1980-1990) and David Leip's Atlas of U.S. elections (1992-2008).

Notes: The figure shows average total Republican Presidential vote share trends from 1980 to 2016 by 1990 county vulnerability quartiles. The total vote share is computed using ICPSR general voting data and Dave Leip's Atlas of U.S. Elections data. Observations are unweighted.

Appendix Figure A.34: Democratic vote share in Presidential elections, separately by vulnerability quartile (raw means, not normalized)

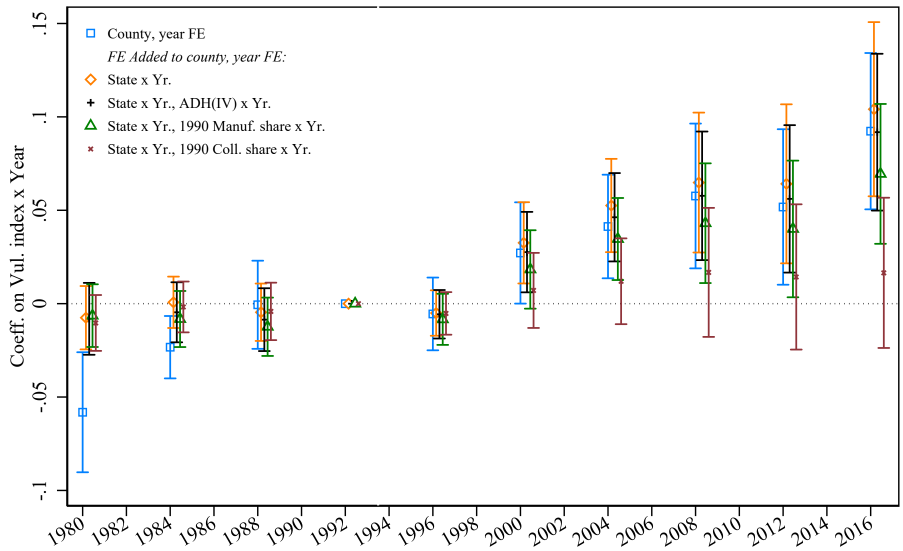


Sources: The dependent variable is computed from ICPSR general election data for the United States (1980-1990) and David Leip's Atlas of U.S. elections (1992-2008).

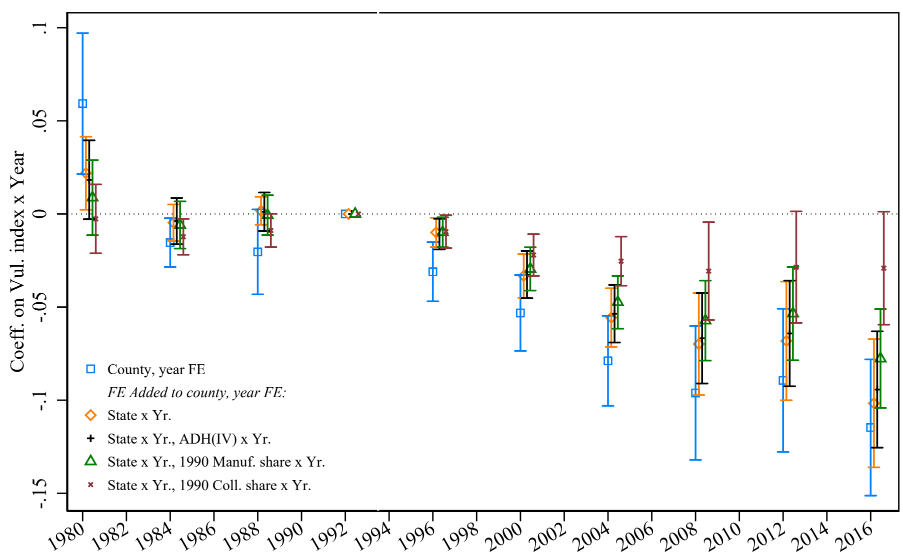
Notes: The figure shows average total Republican Presidential vote share trends from 1980 to 2016 by 1990 county vulnerability quartiles. The total vote share is computed using ICPSR general voting data and Dave Leip's Atlas of U.S. Elections data. Observations are unweighted.

Appendix Figure A.35: Presidential election vote shares as a function of county vulnerability, varying controls

(a) Republican share of county votes



(b) Democratic share of county votes

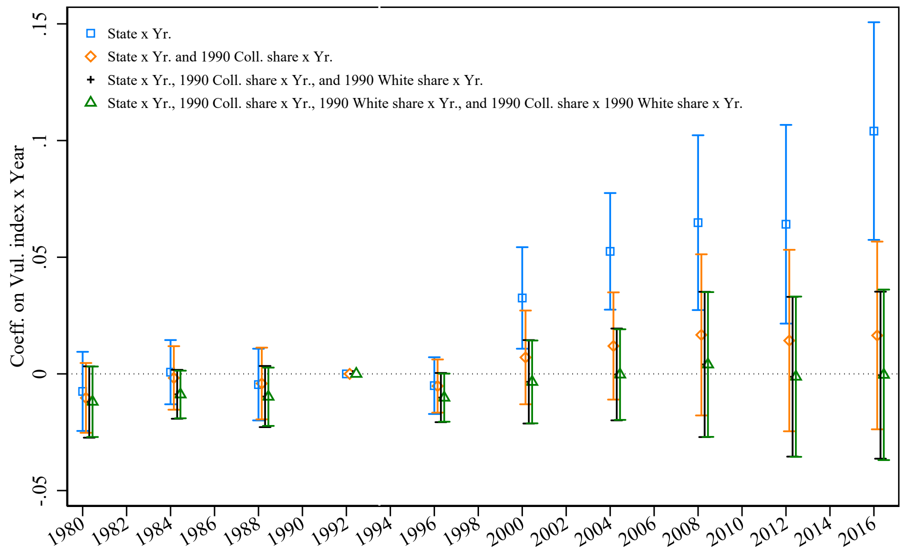


Sources: The dependent variable is taken from ICPSR general voting data and Dave Leip's Atlas of U.S. Election data.
Notes: The analysis sample is fixed across specifications and strictly balanced, with 2949 counties in each year of the sample.

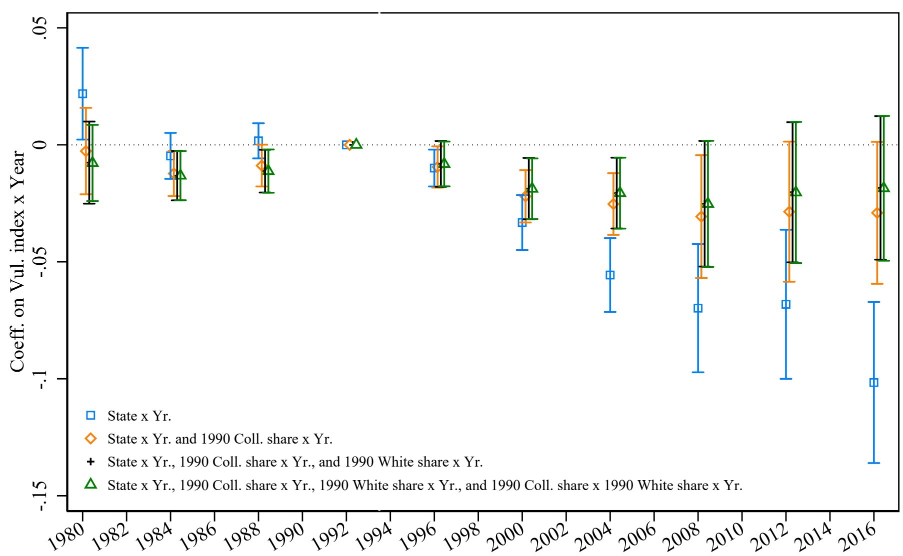
This figure is analogous to Figure 6 but shows additional specifications after varying the controls. Observations are weighted by 1990 county population. The first series includes only county and year fixed effects. The second series adds to this specification $state \times year$ fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor, Dorn, and Hanson (2013) interacted with year fixed effects. The fourth specification adds to the second specification 1990 county-level manufacturing share of employment interacted with year fixed effects. The final specification adds to the second specification 1990 county-level college-graduate population share interacted with year fixed effects. Thus, the second and fourth specifications are identical to the first and second series of Figure 6.

Appendix Figure A.36: Presidential election vote shares as a function of county vulnerability, additional white and college-share controls

(a) Republican share of county votes



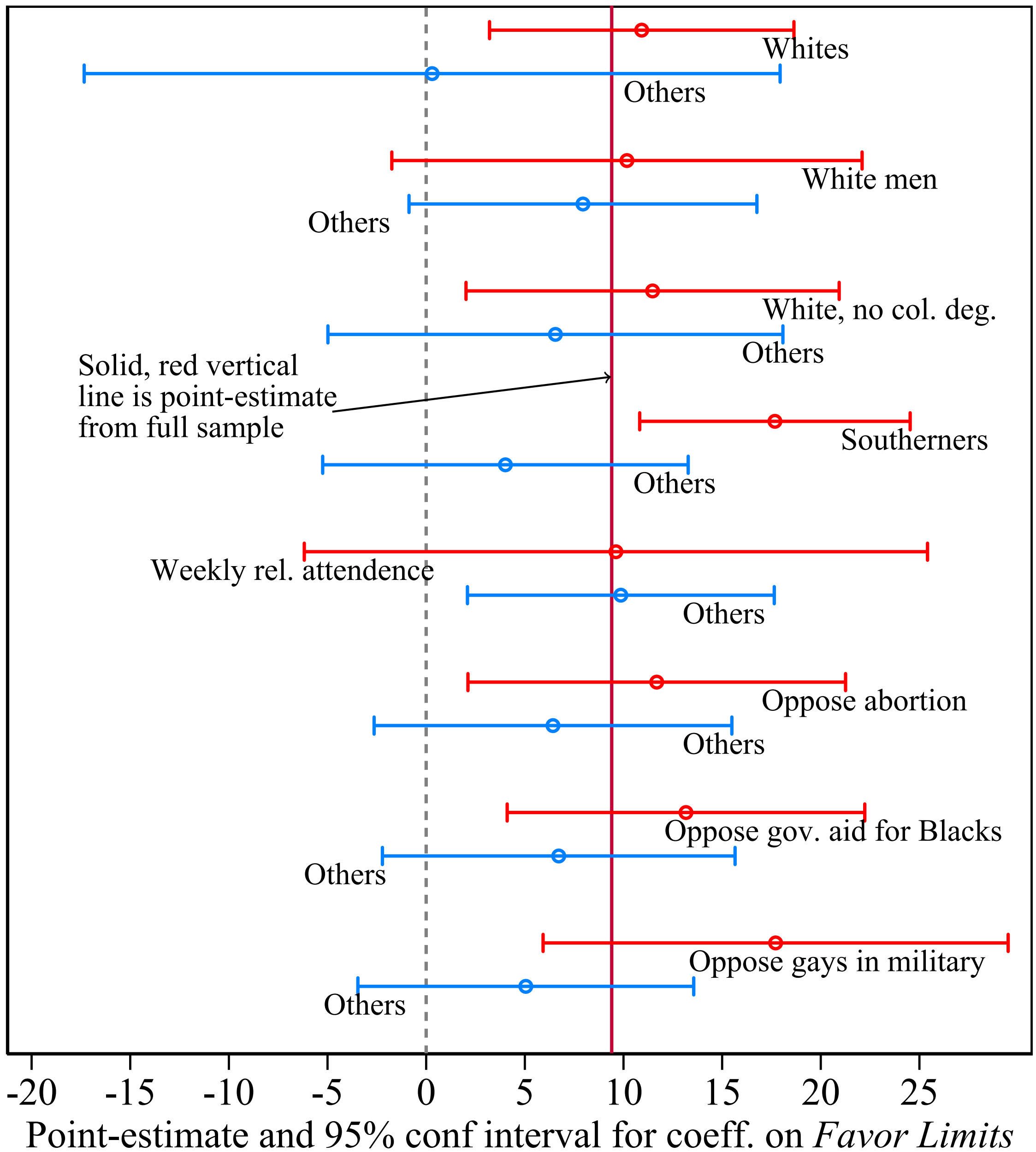
(b) Democratic share of county votes



Sources: The dependent variable is taken from ICPSR general voting data and Dave Leip's Atlas of U.S. Election data.
Notes: The analysis sample is fixed across specifications and strictly balanced, with 2955 counties in each year of the sample.

This figure is analogous to Figure 6 but shows additional specifications with white and college-share controls. Observations are weighted by 1990 county population. The first series controls for county and year fixed effects, as well as $state \times year$ fixed effects. The second series adds to the first controls for 1990 county-level college-graduate population share interacted with year fixed effects. The third specification adds to the second specification controls for 1990 county-level white population share interacted with year fixed effects. The fourth specification adds to the third specification controls for 1990 county-level white and college-graduate population share interacted with year fixed effects.

Appendix Figure A.37: Heterogeneity in 1992-1994 shift toward GOP among protectionist respondents



Sources: ANES panel data, 1992-1994.

Notes: This figure estimates, for mutually exhaustive and distinct subgroups of the sample, equation (7) from the text: $Moved\,Right_{i,94\text{-}92} = \beta Favor\,Import\,Limits_{i,92} + \gamma \mathbb{X}_{i,92} + e_i$. It uses the same control vector $\mathbb{X}_{i,92}$ as in col. (4) of Table 4, namely demographic and political-issue controls. We report the coefficient and 95% confidence interval (clustered by state) of our estimate of β.

Appendix Table A.1: Education predicts less protectionist views

	Dept. var: Favor more limits on trade					
	(1)	(2)	(3)	(4)	(5)	(6)
Has BA degree	-0.0824	-0.0822	-0.0970	-0.0974	-0.0938	-0.213
	[0.00971]	[0.0127]	[0.00954]	[0.00895]	[0.00802]	[0.0106]
Some college, no BA degree		0.000419				
		[0.0131]				
Dept. var. mean	0.382	0.382	0.382	0.382	0.382	0.643
Demog. covars	No	No	Yes	Yes	Yes	Yes
Issue covars	No	No	No	Yes	Yes	Yes
State FE	No	No	No	No	Yes	No
Ex. DK	No	No	No	No	No	Yes
Observations	18825	18825	18732	18732	18732	11118

Sources: ANES individual time series files, 1986–2012.

Notes: The dependent variable is a dummy coded as one for respondents who report favoring import limits (and zero otherwise, including no opinion). “Demographic controls” include indicators for white, and male; log of family income and age. “Issue controls” include views toward African-Americans, trust in government, and views toward abortion.

Appendix Table A.2: Simulating presidential elections removing the NAFTA effect (based on 2949 counties for which we have all needed variables)

	2000		2004		2008		2012	
	Flipped	Closer	Flipped	Closer	Flipped	Closer	Flipped	Closer
	NH	AR	IA	FL	GA	MT	NC	GA
	NM	MO	NM			SC		
		OH	OH					
		TN						
Electoral votes	9	49	32	27	15	11	15	16
Pivotal?	Yes		Yes		No		No	

Sources: Election data from David Leip.
Notes: Note that we cannot perform this analysis on the full voting population as we have missing data on a small share of counties. In state-years with very close presidential elections, the actual outcome will occasionally be different on our set of counties than in the full set of counties (e.g., approximately 3150). So, this exercise can only speak to the comparison between actual and counterfactual results in the 2949 balanced set of counties.

The counterfactual no-NAFTA Democratic vote count in election year t is calculated as: $Dem\,vote_c^t - \beta_t^D \cdot Vulnerability_c$, where β_t^D is the event-study coefficient estimating the effect of NAFTA vulnerability on Democratic vote share in election year t, using the baseline $state \times year$ specification. We perform a parallel calculation for the Republican vote share. We then aggregate up to the state-election level to determine the counterfactual state winners and electoral-vote allocations. "Flipped" means that the no-NAFTA counterfactual would have *changed* the state's winner in that election year (in all cases, the Democrat would have won instead of the Republican). "Closer" means that under the no-NAFTA counterfactual, the Democrat was within 2.5 percentage points (but would not have won) whereas in reality he lost the state by more that 2.5 percentage points. "Pivotal" indicates that the "flipped" states would have changed the outcome of the entire presidential election (again, as determined using only our 2949 set of counties).

Appendix Table A.3: How protectionist views predict approval of Ross Perot, 1992 and 1996

	Dept. variable: Approves of Perot					
	(1)	(2)	(3)	(4)	(5)	(6)
Favor import limits	0.0628 [0.0200]	0.0586 [0.0191]	0.0597 [0.0193]	0.0602 [0.0200]	0.0574 [0.0287]	0.0555 [0.0196]
Dept. var. mean	0.365	0.360	0.360	0.360	0.456	0.270
Demog. covars	Yes	Yes	Yes	Yes	Yes	Yes
Issue covars	No	No	Yes	Yes	Yes	Yes
State FE	No	No	No	Yes	No	No
Sample criteria	None	None	None	None	1992 only	1996 only
Observations	2990	2940	2940	2940	1422	1518

Sources: ANES, 1992 and 1996.

Notes: The dependent variable is a dummy coded as one for respondents who answer "Yes" to the following question: "Is there anything about Mr. Perot that might make you want to vote for him?" (1992) or "Is there anything in particular about MR. PEROT that might make you want to vote FOR him?" (1996). All columns except the final two include year fixed effects. "Demographic controls" include indicators for white, male, and college completion; fixed effects for age rounded to the nearest ten, and log of family income and age. "Issue controls" include views toward African-Americans, trust in government, and views toward abortion.

Appendix Table A.4: Partisan identity and views toward NAFTA, 1992-1994 panel data

	Move in Repub direction dummy x 100					
	(1)	(2)	(3)	(4)	(5)	(6)
Oppose NAFTA	7.777	11.09	6.428	6.071	6.884	6.918
	[5.095]	[5.853]	[4.617]	[4.592]	[4.696]	[4.954]
Minorities sd help self				9.137	9.961	10.19
				[2.896]	[2.854]	[3.027]
Wants active gov't				-4.522	-4.016	-6.234
				[3.531]	[3.796]	[3.991]
Support abortion				-3.552	-2.398	-2.428
				[3.737]	[3.884]	[4.017]
Attend church weekly				3.969	4.448	1.515
				[3.419]	[3.536]	[3.696]
Favors increased immigr.				-1.866	-5.454	-8.008
				[5.965]	[6.883]	[7.336]
Oppose gays in military					2.670	3.412
					[7.522]	[8.483]
Oppose gov't health care					-2.423	-3.387
					[3.795]	[3.998]
Favor term limits					-5.886	-5.428
					[3.953]	[4.557]
Dept. var. mean	25.93	25.69	25.89	25.77	25.77	25.77
Ex. DK	No	Yes	No	No	No	No
Demog. covars	No	No	Yes	Yes	Yes	Yes
State FE	No	No	No	No	No	Yes
R-squared	0.00489	0.0155	0.0489	0.0686	0.0722	0.121
Observations	621	288	618	617	613	613

Sources: ANES panel data, 1992-1994.

Notes: The dependent variable is a dummy (multiplied by 100) for whether the respondent moved in the GOP direction in the 1-7 partisan identity scale. All explanatory variables were asked in 1992, except for the NAFTA question, which was asked in the fall of 1993. "Excl. DK" means that respondents who did not have an opinion on NAFTA are dropped (they are otherwise coded as zero). Demographic controls include race, gender, education, age, log family income, and urbanicity. Standard errors clustered by state.

Appendix B. Data appendix

B.1. Data used to construct the vulnerability measure

Our county-level vulnerability measure is constructed using three components defined prior to NAFTA's implementation (our base year is 1990): (i) average tariff on imports from Mexico by industry, (ii) Mexico's revealed comparative advantage (RCA) by industry, and (iii) industrial composition of each county.

The average tariff on imports from Mexico is drawn from the U.S. Tariff database created by Feenstra, Romalis, and Schott (2002).[37] The dataset contains ad-valorem, specific and estimated ad-valorem equivalent (AVE) tariff rates for Most-Favored-Nations (MFNs), Canada, and Mexico by eight-digit Harmonized Tariff Schedule (HTS) industries. Whenever the Mexico-specific tariff rates are not defined for industries, we apply the MFN tariff rates.

We compute Mexico's revealed comparative advantage using the UN Comtrade bilateral export series, available from Hakobyan and McLaren (2016b)'s replication directory. The data from the replication directory contains the dollar value of Mexican and World exports in a six-digit Harmonized Tariff Schedule code. When aggregating eight-digit industries into six-digit industries and computing the weighted average of tariffs, we use Mexican import values from the USITC, which we drew from Hakobyan and McLaren (2016b)for each of the eight-digit industries as the weights. The USITC Mexican Imports data is drawn from Hakobyan and McLaren (2016b)'s replication directory. We further compute the average tariffs by four-digit industries, using the crosswalk from David Dorn's data webpage.[38]

We accessed the Feenstra, Romalis, and Schott, 2002 database in March 2017, the Hakobyan and McLaren, 2016b data in October 2017, and additional UN Comtrade export data in January 2022.

We utilize the County Business Patterns data to compute the industry composition of each county, which is further described in Appendix B.2.

B.2. County Business Patterns

County Business Patterns (CBP) provide county-level economic data by industry, including the number of establishments, employment, and annual payroll. The dataset is based on

[37] We also use the same dataset to create the vulnerability for years other than 1990. This is not used in the analysis, but to illustrate the change of vulnerability measure over time.

[38] In the crosswalk, a small number of adjacent four-digit SIC industries in the crosswalks are aggregated into four-digit SIC industries. However, we do not aggregate the adjacent four-digit industries in computing the county-level industrial composition calculation. Our results are robust to using the "slightly" aggregated industrial composition.

the week of March 12th every year. We use CBP from 1986 to 2008 to compute county-level annual employment size as the main outcome variable in our employment analysis. We use industry employment share in 1990 to construct the vulnerability measure. When employment counts by industry are withheld to avoid disclosure, we impute the employment count by the median value in the range of the employment flag. [39] County-level industry employment shares in 1990 are computed for each four-digit SIC industry. When we are combining average tariffs of six-digit HTS industries with county-level employment shares of four-digit SIC industries, we use crosswalk from David Dorn's data webpage. We accessed the CBP data in January 2017 and Dorn's crosswalk in April 2018.

B.3. Data on county-level annual population

We utilize county-level annual intercensal population estimates from the Census Bureau's Population Estimates Program (PEP). The PEP calculates population estimates using the most recent Census and data on births, deaths, and migration. The county-level estimates are broken down by race, sex, age, and educational attainment. The PEP estimates are obtained from the NBER website (`https://data.nber.org/data/census-intercensal-population/`) and the U.S. Department of Agriculture Economic Research Service website (`https://www.ers.usda.gov/data-products/county-level-data-sets/download-data/`). We accessed both data sources on August and November 2022, respectively.

We use the annual intercensal population estimates as the outcome variable of our population response event-study analysis. We derive county-level pre-NAFTA demographic controls from the PEP, such as the working-age population defined by population estimates of age 15-64 and share college-educated among age 25-64.

B.4. PSID data used for individual-level NAFTA vulnerability analysis

We use the Panel Survey of Income Dynamics (PSID) data to examine the employment effect of NAFTA on an individual level for 1988 to 2003.[40] The sample comprises 68,814 individuals with information on their demographics (i.e., sex, age, and race), education

[39] We use the published version of CBP county-industry-level employment counts when constructing our vulnerability measure. Eckert et al. (2021) point out that some of these county-industry-level employment cells are missing or imputed when the cell sizes are too small, due to the CBP's disclosure rules. We construct the vulnerability measure using a version of the dataset from Eckert et al. (2021), where the missing county-industry cells are imputed, and we end up with very similar vulnerability measure and analysis results.

[40] The data set is available at `https://simba.isr.umich.edu/data/data.aspx`

level, labor status, state of residency, and employment industry code. We construct the vulnerability measure for each 1990 Census industry code (ind1990) and assign the measure to each worker in the following steps. First, we use tariffs and import information at the four-digit SIC level. We then use the crosswalk from SIC industries to the 1990 Census industries by Autor, Dorn, and Hanson (2019) to create the ind1990-level RCA and weighted tariffs as described in Appendix B.2. Then, the industry-level vulnerability is the product of the RCA and the weighted tariffs. Individuals' industry is recorded in the 1970 Census industry code (ind70), so we use the crosswalk between the 1970 and 1990 Census industry code to assign each individual a vulnerability measure that varies by the 1990 Census industry code. Second, when individuals didn't have an industry code associated, we assigned them the value of zero as their vulnerability measure. We accessed the PSID data on June 2020 and October 2021.

B.5. Data on county-level annual Trade Adjustment Assistance petition and certifications

We acquire the universe of TAA petition data from 1975 to 2020 from the U.S. Department of Labor to examine the effect of NAFTA on the TAA take-up. For each petition, the dataset contains information on the name, address, zipcode, and industry code of the firm, the product or service that the worker group is engaged with, and the institution date, which is the date the investigation started.[41] We calculate the number of workers included in certified (approved) petitions in a county from 1975 to 2020, based on the petitions' institution date.[42] We assign a zero number of affected workers for counties with no petitions filed at a given year. We accessed the data on August 2020.

B.6. Data on county-level SNAP benefits

We acquire annual county-level SNAP benefits data from the U.S. Bureau of Economic Analysis (BEA) personal transfers data, available on the BEA website, to examine whether vulnerability to NAFTA is associated with the change in the SNAP take-up.[43] The series

[41]These data also include the date of the petition, which may be a better variable to use to "date" each observation, but the variable is available only starting 1994. However, the gap between the petition and investigation is, on average, less than a month in the post-1994 data.

[42]We assign all the petition cases to three categories: certification, denial, and termination. Termination is not an actual decision but an administrative closing of the case due to petition withdrawal or because another petition covers the case. Thus we only look at the cases that are either certificated or denied.

[43]The series is available for download at `https://apps.bea.gov/regional/downloadzip.cfm`

is available from 1969-2020, and we use the data from 1986 to 2008. In the data, the SNAP benefits are estimated using the tabulations from the U.S. Department of Agriculture, payments data from state departments of social services, and the Census Bureau's Small Area Income and Poverty Estimates program. We accessed the data in November 2021.

B.7. Data on county-level UI benefits

We acquire annual county-level UI benefits data from the U.S. Bureau of Economic Analysis (BEA) personal transfers data, available on the BEA website, to examine the effect of NAFTA on the take-up of UI.[44] The series is available from 1969-2020; we use the data from 1986 to 2008. The UI benefits data include both state unemployment insurance compensation and other unemployment insurance payments, such as the Trade Adjustment Assistance program. In the data, the county-level benefits are estimated using data from the U.S. Department of Labor, Employment and Training Administration, payment data from the state employment security agencies, and the Local Area Unemployment Statistics program of the Bureau of Labor Statistics (BLS). We accessed the data on November 2021.

B.8. Data on county-level annual Disability Insurance approvals

We use the annual statistics of Disability Insurance approvals to examine whether NAFTA increased the county-level DI take-up. We acquire summary statistics of Social Security Disability Insurance (SSDI) and Supplemental Security Income (SSI) applications and approvals by county and year from the Social Security Administration (SSA). The application-level SSDI and SSI data contain the application and decision dates, the district office where the application was received, and the zipcode of the district office. We accessed the data in January 2020.

The zipcode information for each application is not completely populated until mid-1990s, so we focus on the applications with non-missing district office codes where we can locate the zipcode of the district office. We utilize the 2009 and 2019 SSA district office lists to create a set of district offices which existed both in 2009 and 2019 to keep the most consistent set of district offices and sample of applications. We keep the applications from these 1180 district offices and recover the zipcode of each application submitted to the offices. With the recovered zipcode for each application, we tabulate the number of applications and approvals by county using the 1990 geographic correspondence engine from Missouri Census Data Center. We end up with 755 counties as our "matched district office" sample, which accounts for around 75 percent of the U.S. population in 1990.

[44] The series is available for download at `https://apps.bea.gov/regional/downloadzip.cfm`

B.9. Data on news coverage

To identify the timing and intensity of news coverage on NAFTA, we measure how much NAFTA was covered in the news by computing the share of total news minutes (including commercials, intro, and outro of the news programs) allocated to the news with keywords trade, import, and jobs, excluding "Trade Center" in CBS, ABC, and NBC evening news from 1985 to 2010. We acquire the text data by web-scraping Vanderbilt's TV news archive (`https://tvnews.vanderbilt.edu/`). We did not include news sources such as Fox News that were created during our main analysis years. We accessed the data on August and September 2020.

B.10. Data on county-level House and Presidential election votes

We use county-level voter election votes from ICPSR general election data for the United States (1980-1990) and David Leip's Atlas of U.S. presidential elections (1992-2008) to examine the local political effects of NAFTA. We compute the two-party Republican vote share by the share of Republican votes among the votes received by Republican and Democratic candidates, and the republican vote share among the total votes cast in each county. We accessed the ICPSR data in August 2019 and Leip's in July 2017.

B.11. Survey data on NAFTA favorability

We obtained all available survey data in ICPSR and iPoll as of April 2020 that (a) asked a generic sentiment question on NAFTA; (b) contained state identifiers; (c) took place before 2016 (so as not to be affected by the anti-NAFTA presidential campaign of Donald Trump). The datasets always contained information on basic demographics and often union status and family income.

B.12. American National Election Studies (ANES) repeated cross-sectional data

We use the *individual* files for each year, *not* the cumulative file that ANES creates for convenience. The individual files have questions that are not included in the cumulative file. We use every year of data from 1986 to 2012 that includes the *Favor Import Limits* question. We do not include the year 1990 survey because this question is asked in a different format (a seven-category Likert scale instead of a binary yes/no question). We accessed the data on November 2019.

Appendix Table B.1: Datasets used in Table 2 (NAFTA approval by state-level vulnerability)

Organization conducting the survey	Date	Sample size
ANES	1993	742
CBS	Oct 1996	1528
Pew	Sep 1997	2000
CNN/Gallup	Aug 1997	481
Pew	Sep 2001	1000
Pew	Dec 2003	553
Pew	Jul 2004	1003
CNN/Gallup	Jan 2004	455
Pew	Mar 2004	1703
Pew	Dec 2004	2000
Newsweek	Feb 2004	1019
Program on International Policy Attitudes	Jun 2005	812
Pew	Oct 2005	1003
Pew	Dec 2006	1502
Pew	Apr 2008	1502
Pew	Mar 2009	2031
Pew	Oct 2009	2000
Monmouth	Oct 2015	1012
CBS/NYT	May 2015	1022

The key variables on views toward trade and party ID have different labels across the individual ANES files. For the "favor import limits" question, we use the variables *V860521*, *V880376*, *V923802*, *V961327*, *V980490*, *V000511a*, *V045114*, *V085081*, and *imports_limit*, for 1986, 1988, 1992, 1996, 1998, 2000, 2004, 2008 and 2012, respectively. Note that in 2000 there is an "experimental" version of the question, which we do not use. We do not drop respondents who say "I don't know" or variants thereof, but do drop if ANES suggests that the question was not posed to them (e.g., "not ascertained").

For "party ID," we use *V860300*, *V880274*, *V923634*, *V960420*, *V980339*, *V000523*, *V043116*, *V083098x*, and *pid_x*.

B.13. ANES panel data

We use the ANES panel data to examine whether the individuals with protectionist views changed their political alignment between 1992 and 1994. The panel data comprises a subset of the 1992 ANES survey respondents who were interviewed in 1993 and 1994. We use the provided weights to adjust for attrition. We accessed the data on July 2020.

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Appendix C. Assessing main results with randomization inference

Recent literature has shown that in shift-share regression designs, the standard errors could be underestimated even after being clustered by geography (e.g., state) or estimated under heteroskedastic assumptions, since the regression residuals could be correlated across local labor markets with similar industrial compositions (Adão, Kolesár, and Morales 2019; AKM from here on). Our vulnerability measure is an average of industry-level tariff shocks weighted by county industrial composition, so such downward bias may occur when computing standard errors in our event-study analysis.

In order to check the robustness of our employment and Presidential election results to the above issue, we perform two exercises: (1) we first conduct a placebo exercise where we simulate county-level vulnerability measures by randomly assigning tariffs to each industry drawn from various distributions; and (2) we also compute the standard errors based on the inference methods introduced in AKM (2019), where the shifters are assumed to be as good as randomly assigned and independent across clusters of sectors, allowing for arbitrary correlation within three-digit SIC sectors.

As the inference discussion in the aforementioned literature is based on a cross-sectional regression approach, we modify our main analysis to be the first-difference regression specification below :

$$Y_{c,t} - Y_{c,t-7} = \beta \text{Vulnerability} c^{1990} + \gamma X c + e_c \tag{8}$$

where $Y_{c,t} - Y_{c,t-7}$ is the first-differenced outcome variable such as change in the log of employment and change in two-party republican vote share, Vulnerabilityc^{1990} is the vulnerability of county c in 1990, X_c is a vector of county-level characteristics which always includes state dummies and in some specifications also includes the share of workers in manufacturing.

For the placebo exercise, we use simulated vulnerabilities instead of the actual Vulnerability$_c^{1990}$, using the simulation procedure described in the following paragraph. For the AKM inference exercise, we use the actual Vulnerability$_c^{1990}$ as the main independent variable and report the AKM standard errors along with robust and state-clustered standard errors. We run equation (8) separately for the pre-NAFTA and post-NAFTA periods. We define 1986-1993 as the pre-NAFTA period and 1993-2000 as the post-period in our employment analysis, and we use 1984-1992 and 1992-2000 for the pre-NAFTA and post-NAFTA periods in the Presidential election analysis, respectively.

We draw simulated tariffs from three distributions: (i) one that follows the empirical distribution of actual industrial tariffs applied to industries with positive tariffs in 1990; (ii) uniform distribution with range [0, 0.4] applied to industries with positive tariffs in 1990; and (iii) uniform distribution with range [0, 0.4] applied to all industries.[45] For (i), we generate the empirical cumulative distribution of all positive tariffs in 1990 by fitting a fifth-degree polynomial, as shown in Appendix figure C.1. We take a random draw from U[0, 1] for each sector with a positive tariff and use our modeled CDF to generate a simulated tariff for the sector. We then use this vector of simulated tariffs to generate a simulated $\text{Vulnerability}_c^{1990}$, using the county employment composition in 1990 from the CBP. We construct simulated vulnerability measures from the uniform distribution U[0, 0.4] for (ii) and (iii) in an analogous way.

For each distribution, we repeat the simulation of county vulnerability and estimation of the equation (8) 1000 times and create 1000 placebo analysis samples. The outcome variables, change in the log of county employment and change in Republican Presidential vote share, are constructed using the observed data in each county and are identical for all placebo samples. We then compute the estimate of β in equation (8) for each sample and report the mean and standard deviation of the estimates across the placebo samples. In order to appropriately apply state fixed effects in our simulated samples, we resample observations in each sample with replacement, using states as the clustering unit.

The average and standard deviation of the estimates are reported in Appendix tables C.1, C.2, C.3, and C.4 for the employment analysis and Appendix tables C.5, C.6, C.7, and C.8 for the Presidential election analysis. The pre-NAFTA employment analysis shows that both original and simulated vulnerabilities have no significant impact on log of county employment in all specifications. The post-period analysis indicates that the original vulnerability measure is associated with a significant decline in log of county employment while simulated vulnerabilities are not significantly associated with the change in county employment. Note that the coefficients on the simulated vulnerabilities using the actual tariff distribution and U[0,0.4] are positive while insignificant, as industries with zero tariffs continue to have zero tariffs in the simulation, the simulated vulnerabilities retain some information on the true industry tariffs and employment shares (e.g., service industries with zero tariffs will continue to have zero tariffs, and counties with high share of service industries will continue to have low simulated vulnerability). When the tariffs are simulated for all industries from U[0, 0.4], the coefficients become more precisely zero.

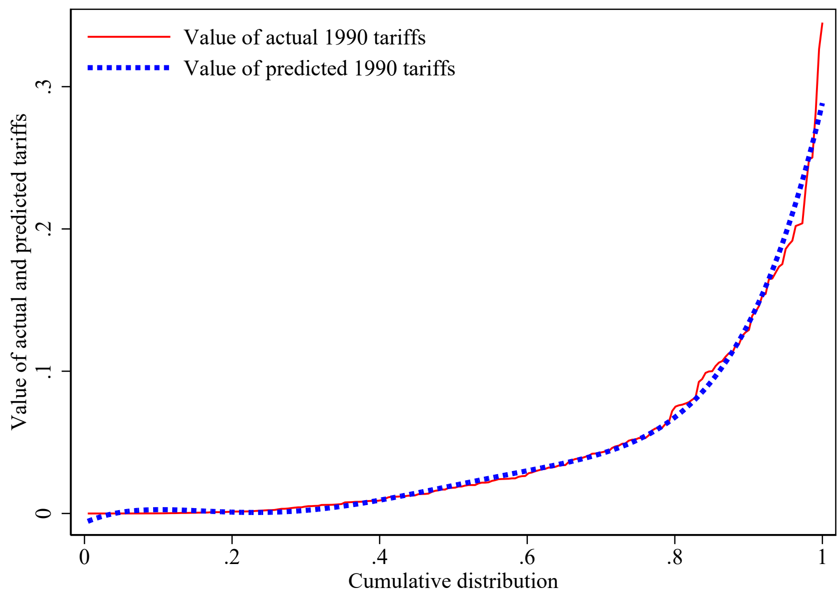
Similarly, the pre-NAFTA election analysis indicates that both original and simulated vulnerabilities are not associated with the change in county two-party Republican vote share. In post-period analysis, only the original vulnerability measure is associated with a significant

[45] We set the range of uniform distribution 0.4 based on the rough maximum of the actual 1990 tariffs.

increase in the Republican vote share.

In Appendix tables C.9 and C.10, we report the estimates of equation (8) with robust, state-clustered, and the AKM standard errors for the employment analysis. The estimates of Equation (8) for the election analysis are reported in Appendix tables C.11 and C.12. For both employment and election analysis in the pre-NAFTA period, not including state fixed effects overstates the effect of tariff protections. When implementing state fixed effects, we find that the pre-period coefficients are not significant, and the post-period effects of vulnerability are significant and robust to allowing for correlation across industry composition of local labor markets, as the coefficients are still significant under the AKM inference exercise.

Appendix Figure C.1: Empirical distribution of industrial tariffs in 1990



Notes: The figure plots the empirical cumulative distribution of positive tariffs of four-digit SIC industries in 1990. The dashed line is a predicted cumulative distribution of positive tariffs, generated by fitting a five-degree polynomial to the empirical CDF.

Appendix Table C.1: Estimates from the first-difference model: Change in log of employment (1986-1993) and simulated county vulnerability

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	uniform [0,0.4]
Coefficient	-.035	.034	.02	.004
(SE)	(.154)	(.215)	(.082)	(.124)
state FE	yes	yes	yes	yes
tariffs simulated	none	positive tariff industries	positive tariff industries	all

Notes: The table reports the estimates from the first-difference model shown in equation (8). The dependent variable is change in log of county employment between 1986 and 1993. The first column uses the original county vulnerability. In column 2, the simulated tariffs for industries with positive tariffs are drawn from the estimated tariff distribution plotted in Appendix figure C.1. In column 3, the simulated tariffs for industries with positive tariffs are drawn from U[0, 0.4]. In column 4, the tariffs for all industries are drawn from U[0, 0.4]. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. The industry-level tariffs are simulated 1000 times and the corresponding county-level vulnerability measure is used as the main regressor for the first-difference analysis. All specifications are weighted by 1990 county population and include state fixed effects. We compute the average and standard deviation of the 1000 estimates and report them as the bootstrapped coefficient and standard error.

Appendix Table C.2: Estimates from the first-difference model with manufacturing (1990) control: Change in log of employment (1986-1993) and simulated county vulnerability

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	uniform [0,0.4]
Initial vul.	.023	.04	.027	.003
	(.127)	(.223)	(.086)	(.127)
state FE	yes	yes	yes	yes
manuf. share (1990)	yes	yes	yes	yes
tariffs simulated	none	positive tariff industries	positive tariff industries	all

Notes: The table reports the estimates from the first-difference model shown in equation (8). The dependent variable is change in log of county employment between 1986 and 1993. The first column uses the original county vulnerability. In column 2, the simulated tariffs for industries with positive tariffs are drawn from the estimated tariff distribution plotted in Appendix figure C.1. In column 3, the simulated tariffs for industries with positive tariffs are drawn from U[0, 0.4]. In column 4, the tariffs for all industries are drawn from U[0, 0.4]. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. The industry-level tariffs are simulated 1000 times and the corresponding county-level vulnerability measure is used as the main regressor for the first-difference analysis. All specifications are weighted by 1990 county population and include 1990 county-level manufacturing share of employment as a control and state fixed effects. We compute the average and standard deviation of the 1000 estimates and report them as the bootstrapped coefficient and standard error.

Appendix Table C.3: Estimates from the first-difference model: Change in log of employment (1993-2000) and simulated county vulnerability

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	uniform [0,0.4]
Initial vul.	-.87	-.163	-.095	-.003
	(.202)	(.28)	(.105)	(.133)
state FE	yes	yes	yes	yes
tariffs simulated	none	positive tariff industries	positive tariff industries	all

Notes: The table reports the estimates from the first-difference model shown in equation (8). The dependent variable is change in log of county employment between 1993 and 2000. The first column uses the original county vulnerability. In column 2, the simulated tariffs for industries with positive tariffs are drawn from the estimated tariff distribution plotted in Appendix figure C.1. In column 3, the simulated tariffs for industries with positive tariffs are drawn from U[0, 0.4]. In column 4, the tariffs for all industries are drawn from U[0, 0.4]. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. The industry-level tariffs are simulated 1000 times and the corresponding county-level vulnerability measure is used as the main regressor for the first-difference analysis. All specifications are weighted by 1990 county population and include state fixed effects. We compute the average and standard deviation of the 1000 estimates and report them as the bootstrapped coefficient and standard error.

Appendix Table C.4: Estimates from the first-difference model with manufacturing employment share (1990) control: Change in log of employment (1993-2000) and simulated county vulnerability

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	uniform [0,0.4]
Initial vul.	-.682	-.118	-.067	-.005
	(.193)	(.283)	(.109)	(.136)
state FE	yes	yes	yes	yes
manuf. share (1990)	yes	yes	yes	yes
tariffs simulated	none	positive tariff industries	positive tariff industries	all

Notes: The table reports the estimates from the first-difference model shown in equation (8). The dependent variable is change in log of county employment between 1993 and 2000. The first column uses the original county vulnerability. In column 2, the simulated tariffs for industries with positive tariffs are drawn from the estimated tariff distribution plotted in Appendix figure C.1. In column 3, the simulated tariffs for industries with positive tariffs are drawn from U[0, 0.4]. In column 4, the tariffs for all industries are drawn from U[0, 0.4]. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. The industry-level tariffs are simulated 1000 times and the corresponding county-level vulnerability measure is used as the main regressor for the first-difference analysis. All specifications are weighted by 1990 county population and include 1990 county-level manufacturing share of employment as a control and state fixed effects. We compute the average and standard deviation of the 1000 estimates and report them as the bootstrapped coefficient and standard error.

Appendix Table C.5: Estimates from the first-difference model: Change in Republican presidential vote share (1984-1992) and simulated county vulnerability

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	uniform [0,0.4]
Coefficient	.004	.015	.012	.001
(SE)	(.066)	(.082)	(.03)	(.038)
state FE	yes	yes	yes	yes
tariffs simulated	none	positive tariff industries	positive tariff industries	all

Notes: The table reports the estimates from the first-difference model shown in equation (8). The dependent variable is change in county-level Republican Presidential vote share between 1984 and 1992. The first column uses the original county vulnerability. In column 2, the simulated tariffs for industries with positive tariffs are drawn from the estimated tariff distribution plotted in Appendix figure C.1. In column 3, the simulated tariffs for industries with positive tariffs are drawn from U[0, 0.4]. In column 4, the tariffs for all industries are drawn from U[0, 0.4]. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. The industry-level tariffs are simulated 1000 times and the corresponding county-level vulnerability measure is used as the main regressor for the first-difference analysis. All specifications are weighted by 1990 county population and include state fixed effects. We compute the average and standard deviation of the 1000 estimates and report them as the bootstrapped coefficient and standard error.

Appendix Table C.6: Estimates from the first-difference model with manufacturing employment share (1990) control: Change in Republican presidential vote share (1984-1992) and simulated county vulnerability

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	uniform [0,0.4]
Initial vul.	.037	.016	.017	.001
	(.079)	(.076)	(.03)	(.038)
state FE	yes	yes	yes	yes
manuf. share (1990)	yes	yes	yes	yes
tariffs simulated	none	positive tariff industries	positive tariff industries	all

Notes: The table reports the estimates from the first-difference model shown in equation (8). The dependent variable is change in county-level Republican Presidential vote share between 1984 and 1992. The first column uses the original county vulnerability. In column 2, the simulated tariffs for industries with positive tariffs are drawn from the estimated tariff distribution plotted in Appendix figure C.1. In column 3, the simulated tariffs for industries with positive tariffs are drawn from U[0, 0.4]. In column 4, the tariffs for all industries are drawn from U[0, 0.4]. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. The industry-level tariffs are simulated 1000 times and the corresponding county-level vulnerability measure is used as the main regressor for the first-difference analysis. All specifications are weighted by 1990 county population and include 1990 county-level manufacturing share of employment as a control and state fixed effects. We compute the average and standard deviation of the 1000 estimates and report them as the bootstrapped coefficient and standard error.

Appendix Table C.7: Estimates from the first-difference model: Change in Republican presidential vote share (1992-2000) and simulated county vulnerability

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	uniform [0,0.4]
Initial vul.	.412	.031	.017	.003
	(.099)	(.133)	(.047)	(.066)
state FE	yes	yes	yes	yes
tariffs simulated	none	positive tariff industries	positive tariff industries	all

Notes: The table reports the estimates from the first-difference model shown in equation (8). The dependent variable is change in county-level Republican Presidential vote share between 1992 and 2000. The first column uses the original county vulnerability. In column 2, the simulated tariffs for industries with positive tariffs are drawn from the estimated tariff distribution plotted in Appendix figure C.1. In column 3, the simulated tariffs for industries with positive tariffs are drawn from U[0, 0.4]. In column 4, the tariffs for all industries are drawn from U[0, 0.4]. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. The industry-level tariffs are simulated 1000 times and the corresponding county-level vulnerability measure is used as the main regressor for the first-difference analysis. All specifications are weighted by 1990 county population and include state fixed effects. We compute the average and standard deviation of the 1000 estimates and report them as the bootstrapped coefficient and standard error.

Appendix Table C.8: Estimates from the first-difference model with manufacturing employment share (1990) control: Change in Republican presidential vote share (1992-2000) and simulated county vulnerability

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	uniform [0,0.4]
Initial vul.	.307	.014	.003	.004
	(.088)	(.123)	(.045)	(.061)
state FE	yes	yes	yes	yes
manuf. share (1990)	yes	yes	yes	yes
tariffs simulated	none	positive tariff industries	positive tariff industries	all

Notes: The table reports the estimates from the first-difference model shown in equation (8). The dependent variable is change in county-level Republican Presidential vote share between 1992 and 2000. The first column uses the original county vulnerability. In column 2, the simulated tariffs for industries with positive tariffs are drawn from the estimated tariff distribution plotted in Appendix figure C.1. In column 3, the simulated tariffs for industries with positive tariffs are drawn from U[0, 0.4]. In column 4, the tariffs for all industries are drawn from U[0, 0.4]. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. The industry-level tariffs are simulated 1000 times and the corresponding county-level vulnerability measure is used as the main regressor for the first-difference analysis. All specifications are weighted by 1990 county population and include 1990 county-level manufacturing share of employment as a control and state fixed effects. We compute the average and standard deviation of the 1000 estimates and report them as the bootstrapped coefficient and standard error.

Appendix Table C.9: First-difference model with the AKM inference procedure: Change in log of county employment over pre-NAFTA control period (1986-1993)

Dep. Var. :	First-difference in log employment		
Initial vul.	.33	-.035	.023
robust SE	(.163)	(.141)	(.141)
AKM SE, three-digit SIC cl.	(.225)	(.153)	(.159)
state-clustered SE	(.191)	(.156)	(.128)
pop. weighted	yes	yes	yes
state FE	no	yes	yes
manufacturing share (1990)	no	no	yes
Observations	2912	2912	2912

Notes: The table reports the estimates of equation (8) with robust (Eicker-Huber-White) standard errors, the AKM standard error with three-digit SIC clusters, and state-clustered standard errors. The dependent variable is change in log of county employment between 1986 and 1993. All specifications are weighted by 1990 population. The second column adds state fixed effects. The third column adds manufacturing share of employment to the specification of column 2.

Appendix Table C.10: First-difference model with the AKM inference procedure: Change in log of county employment over treatment period (1993-2000)

Dep. Var. :	First-difference in log employment		
Initial vul.	-.725	-.87	-.682
robust SE	(.16)	(.146)	(.144)
AKM SE, three-digit SIC cl.	(.201)	(.191)	(.168)
state-clustered SE	(.233)	(.204)	(.195)
pop. weighted	yes	yes	yes
state FE	no	yes	yes
manufacturing share (1990)	no	no	yes
Observations	2912	2912	2912

Notes: The table reports the estimates of equation (8) with robust (Eicker-Huber-White) standard errors, the AKM standard error with three-digit SIC clusters, and state-clustered standard errors. The dependent variable is change in log of county employment between 1993 and 2000. All specifications are weighted by 1990 population. The second column adds state fixed effects. The third column adds manufacturing share of employment to the specification of column 2.

Appendix Table C.11: First-difference model with the AKM inference procedure: Change in Republican presidential vote share over pre-NAFTA control period (1984-1992)

Dep. Var. :	First-difference in two-party Repub. vote share		
Initial vul.	.13	.004	.037
robust SE	(.051)	(.047)	(.048)
AKM SE, three-digit SIC cl.	(.048)	(.035)	(.034)
state-clustered SE	(.088)	(.067)	(.079)
pop. weighted	yes	yes	yes
state FE	no	yes	yes
manufacturing share (1990)	no	no	yes
Observations	2949	2949	2949

Notes: The table reports the estimates of equation (8) with robust (Eicker-Huber-White) standard errors, the AKM standard error with three-digit SIC clusters, and state-clustered standard errors. The dependent variable is change in Republican Presidential vote share between 1984 and 1992. All specifications are weighted by 1990 population. The second column adds state fixed effects. The third column adds manufacturing share of employment to the specification of column 2.

Appendix Table C.12: First-difference model with the AKM inference procedure: Change in Republican presidential vote share over treatment period (1992-2000)

Dep. Var. :	First-difference in two-party Repub. vote share		
Initial vul.	.482	.412	.307
robust SE	(.073)	(.059)	(.056)
AKM SE, three-digit SIC cl.	(.123)	(.071)	(.067)
state-clustered SE	(.134)	(.1)	(.089)
pop. weighted	yes	yes	yes
state FE	no	yes	yes
manufacturing share (1990)	no	no	yes
Observations	2949	2949	2949

Notes: The table reports the estimates of equation (8) with robust (Eicker-Huber-White) standard errors, the AKM standard error with three-digit SIC clusters, and state-clustered standard errors. The dependent variable is change in Republican Presidential vote share between 1992 and 2000. All specifications are weighted by 1990 population. The second column adds state fixed effects. The third column adds manufacturing share of employment to the specification of column 2.

Appendix D. Accounting for industry-level benefits from NAFTA

D.1. Overview

There are two mechanisms by which NAFTA could have benefited U.S. industries and local labor markets. First, NAFTA decreased tariffs U.S. exporters face when U.S. goods are being exported to Mexico, which would have increased the demand of U.S. goods from Mexico (what we will call the *export advantage*). Second, the reduced tariffs on imports from Mexico could decrease the production cost of U.S. goods that use Mexican imports as inputs (what we will call the *input advantage*). We consider the possibility that counties could benefit from NAFTA through these channels, which could also impact economic conditions of local labor markets. Therefore, one concern with the analysis in the main paper is that omitted-variable bias (from excluding the benefits of NAFTA) is causing us to misinterpret the coefficient on *Vulnerability.* In the classic omitted-variables framework, if the export- or input-advantage variables were (*a*) negatively correlated with *Vulnerability* and (*b*) positively correlated with county employment, then our estimated coefficient on *Vulnerability* would be negatively biased.

To test this idea, we construct county-level measures of input advantage and export advantage based on county industrial composition in 1990. As we show below, these potential omitted variables are *positively* correlated with our county-level *Vulnerability* measure, suggesting little scope for omitted-variables bias in driving our result and instead that the *Vulnerability* measure is picking up the net effect of NAFTA on local labor markets, including any local benefits.

D.2. Constructing county-level measures of export advantage

Our county-level measure of *export advantage* is based on how much the drop in tariffs on U.S. products exported to Mexico can help U.S. industries and thus local labor markets with these industries. Similar to our vulnerability measure, we need three components for constructing the county export advantage measure: (*i*) Industry-level tariffs that are applied to U.S. exports to Mexico prior to NAFTA in year 1993; (*ii*) Revealed Comparative Advantage (RCA) of U.S. industries; and (*iii*) county-level industrial composition prior to NAFTA.[46]

We acquire industry-level Mexican tariffs on imports from the US prior to NAFTA in

[46]We ideally would want tariffs in 1990 to remain consistent with the construction of our *Vulnerability* variable, but our data source described below only has tariff data for year 1993.

1993 from López-Córdova (2003).[47] The data contains tariffs by four-digit ISIC industries, which we map to SIC codes using ISIC-to-SIC code crosswalk from the Industry Concordance website by Jon Haveman.[48] When aggregating the tariffs by SIC industries, we compute unweighted average tariffs of ISIC industries that correspond to each SIC industry.[49] RCA of U.S. industries is computed in an analogous way to how the Mexican RCA is constructed using Hakobyan and McLaren (2016a)'s replication data (which is from the UN Comtrade bilateral export series) and US HS-level imports and exports from Peter Schott's data webpage.[50] The county-level industrial composition prior to NAFTA is drawn from the 1990 CBP.

D.3. Constructing county-level measures of input advantage

Our county-level measure of *input advantage* captures how much the decline in tariffs on Mexican imports to the US could *help* U.S. producers by reducing production input costs (and thus local labor markets that rely on these industries whose input costs decline). We need three components to construct the county-level input advantage measure: (*i*) industry-level weighted average tariffs applied to production inputs prior to NAFTA; (*ii*) Mexican RCA; and (*iii*) county-level industrial composition. The data sources used in (*i*) include the U.S. Tariff database from Feenstra, Romalis, and Schott (2002) and the Input-Output matrix of the United States in 1990 from OECD Input-Output database. Input-output (I/O) matrix is a matrix that contains information about what share of production input costs of each industry is spent on each input industry. The OECD I/O matrix has information on 34 industries, which we map to groups of two-digit SIC industries (i.e., each group comprises one or more than one two-digit SIC industries.) The data sources used in (*ii*) and (*iii*) are identical to the data sources for computing the vulnerability measure.

In computing (*i*), we start by computing the average tariff of industry groups, weighted by the import value of their sub-industries. Then we construct a measure of how each industry was affected by tariffs for the imported inputs prior to NAFTA by creating an average of industry-group level tariffs, weighted across industry groups they take as inputs. The weights are created from the input cost composition for each industry group drawn from the I/O matrix. Computing (*ii*) and (*iii*) is exactly analogous to how we constructed Mexican

[47]We greatly appreciate the generous help from Jose Ernesto López-Córdova and Jose Ramon Morales Arilla in sharing the data.

[48]See `https://www.macalester.edu/research/economics/PAGE/HAVEMAN/Trade.Resources/TradeConcordances.html`.

[49]We would ideally compute the weighted average tariffs, weighted by the U.S. export values in each four-digit ISIC industry, but we do not have access to such information.

[50]See `https://sompks4.github.io/sub_data.html`.

RCA and county industrial composition for vulnerability measure, but with more aggregated industry groups. When using the input advantage measure in the analysis, we also build the vulnerability measure using same aggregated SIC industry categories for comparability.

D.4. Covariance between export- and input-advantage measures and *Vulnerability*

Whether the omission of county-level export or input advantages of NAFTA creates a negative bias in our estimates of the coefficient on *Vulnerability* depends on the covariances of these measures with *Vulnerability*. The correlation between our *Vulnerability* and export advantage measures is 0.15. It is not surprising to see that the export advantage measure is positively associated with the *Vulnerability* measure, as the main export industries in the US are often the main import industries in the US—the United States accounts for a large part of Foreign Direct Investments (FDI) to Mexico in the form of producing intermediate inputs and parts in Mexico and importing them to the US. The main export industries from the US to Mexico include autos and automotive parts, computers and electronics, textile and apparel, and the main import industries from Mexico to the US are also autos and automotive parts, computers and electronics, textiles and apparel, ceramic tile.[51]

The correlation between our county-level input advantage measure and *Vulnerability*, constructed using the aggregation of 2-digit SIC industries, is 0.97.[52] The high correlation is not only because industries heavily rely on own-industry inputs, but also because industry groups must be aggregated to include multiple two-digit SIC industries, making the share of own-industry input even higher.

D.5. Is the Vulnerability effect robust to controlling for export advantage?

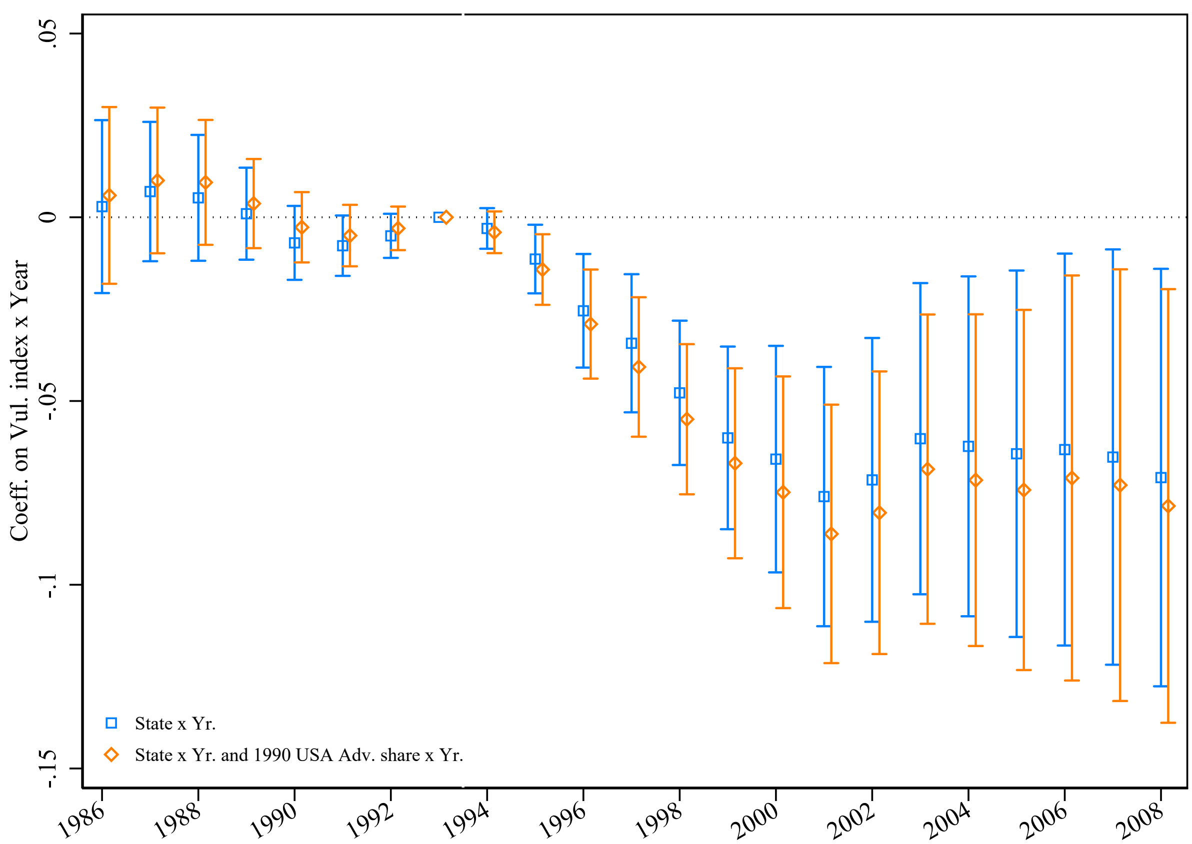
While the positive correlation between export advantage and *Vulnerability* makes it unlikely that omitted-variables bias is causing the negative coefficients on *Vulnerability* after 1993, we can nonetheless include export-advantage and its interaction with year fixed effects in our standard event-study regressions. We do not perform this exercise for the input-advantage measure given that it is nearly collinear with *Vulnerability*.

[51]This paragraph draws from USITC publication 2596 (1993), which provides a discussion of this strong overlap between import and export industries between the US and Mexico. See `https://www.usitc.gov/publications/332/pub2596.pdf` for the full report.

[52]The correlation between the *Vulnerability* constructed using 4-digit SIC industrial composition and the (two-digit) input-advantage measure is 0.56.

In Appendix Figure D.1, we test the robustness of our main log-employment result to including the flexible controls for export advantage. The first series merely reproduces the second series from our main log-employment figure (Figure 2 from the main paper). The second series adds the export-advantage measure interacted with year fixed effects. The coefficients on *Vulnerability* barely move.

Appendix Figure D.1: Log county employment as a function of county vulnerability, robustness to controlling for county export advantage from NAFTA



Sources: The dependent variable is log county employment drawn from the CBP. See Appendix B.2 for more detail.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2903 counties in each year of the sample. This figure is identical to Figure 2 except that we also use county export advantage measure as a flexible control on the second series along with the vulnerability measure as the independent variable. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (5). Observations are weighted by 1990 county population. The first series controls for county and year fixed effects, as well as *state*×*year* fixed effects. The second series adds to the first controls for 1990 county-level export advantage measure interacted with year fixed effects.