Local Economic and Political Effects of Trade Deals: Evidence from NAFTA

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Abstract

Why have white, less educated voters left the Democratic Party over the past few decades? Scholars have proposed racial resentment, social issues and deindustrialization as potential answers. We highlight the role played by the 1994 North American Free Trade Agreement (NAFTA). In event-study analysis, we demonstrate that counties whose 1990 employment depended on industries vulnerable to NAFTA suffered large and persistent employment losses relative to other counties. These losses begin in the mid-1990s and are only modestly offset by transfer programs. While exposed counties historically voted Democratic, in the mid-1990s they turn away from the party of the president (Bill Clinton) who ushered in the agreement and by the 2000s are among the most Republican. Employing a variety of micro-data sources, including 1992-1994 respondent-level panel data, we show that protectionist views predict movement toward the GOP in the years that NAFTA is debated and implemented. This shift among protectionist respondents is larger for whites (especially men and those without a college degree) and those with conservative social views, suggesting an interactive effect whereby racial identity and social-issue positions mediate reactions to economic policies.

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1 Introduction

In September of 1993, the Clinton administration released a letter signed by 283 economists, including twelve Nobel laureates, urging Congress to ratify the North American Free Trade Agreement (NAFTA). "[T]he assertions that NAFTA will spur an exodus of U.S. jobs to Mexico are without basis," the economists wrote. "The letter is part of a concerted White House campaign to rebut the criticisms of the trade agreement made by Texas billionaire Ross Perot, who has begun spending large amounts of his considerable fortune to promote his view that NAFTA will destroy American jobs," reported the *Los Angeles Times*.[1]

The White House indeed succeeded in passing NAFTA in a close and bi-partisan vote a few months later, and it was implemented on January 1st, 1994. However, a quarter of a century later, it remains controversial. Donald Trump made opposition to NAFTA a key part of his successful 2016 presidential campaign, claiming in the first presidential debate that "NAFTA is the worst trade deal maybe ever signed anywhere, but certainly ever signed in this country." While his presidential administration ultimately took pro-trade positions, Senator Barack Obama campaigned against NAFTA in the 2008 Democratic primary, tying Hillary Clinton to her husband's championing of the policy. "[T]rade deals like NAFTA ship jobs overseas and force parents to compete with their teenagers to work for minimum wage at Wal-Mart. That's what happens when the American worker doesn't have a voice at the negotiating table, when leaders change their positions on trade with the politics of the moment."[2]

In this paper we study NAFTA's local economic effects as well as its political impact. Ever since the seminal work of Autor *et al.* (2013a) on the local employment effects of the "China shock," a growing literature has documented the struggles of communities faced with Chinese import competition in the late 1990s and early 2000s. By contrast, the work on local employment effects of NAFTA is more limited.

We begin by showing in an event-study analysis that NAFTA had a significant, negative effect on employment in counties exposed to Mexican import competition. By 2000, counties in the top quartile of our measure of NAFTA exposure saw a 5-8 log point decline in total employment, relative to the bottom quartile. These losses were concentrated in manufacturing and, importantly, exhibit no pre-trends from the mid 1980s to 1993. While we begin all of

[1] See "283 Top Economists Back Trade Pact, Letter Shows," *Los Angeles Times*, September 4, 1993, `https://www.latimes.com/archives/la-xpm-1993-09-04-mn-31519-story.html`.

[2] For the Trump quote, see the transcript to the first presidential debate in 2016: `https://www.washingtonpost.com/news/the-fix/wp/2016/09/26/the-first-trump-clinton-presidential-debate-transcript-annotated/`. For the Obama quote, see the transcript to a February 12, 2008 speech: `https://www.nytimes.com/2008/02/12/us/politics/12text-obama.html`.

our analysis by showing trends with raw data, the basic shape of our event-study coefficients are unchanged as we add a large number of controls: pre-period county-level measures (e.g., 1990 manufacturing share of employment, 1990 share with a college degree) interacted with year fixed effects, to control flexibly for other secular changes (e.g., automation, skill biased technological change) that may affect communities differentially across time; the "China shock" measure from Autor *et al.* (2013a) interacted with year fixed effects, to ensure we isolate the NAFTA effect from the rise of Chinese imports; and fixed effects at the $state \times year$ level, to pick up any policy or other unobserved variation within states across time.

The large employment losses might lead to population declines (as in Blanchard *et al.*, 1992, though they examine data from an earlier period), so we examine annual population measures. We find no population response to NAFTA-driven employment losses, at least through 2008 when we end our sample period. We have the power to reject even small effects. Note that Autor *et al.* (2013a) also find limited migration response to the China shock, so our result deepens the puzzle of why population does not appear to respond to these large, trade-driven employment shocks. By contrast, transfer-programs—Trade Adjustment Assistance (TAA), Disability Insurance (DI), and Supplemental Nutrition Assistance Program (SNAP)—exhibit significant increases in both applications and receipt. However, relative to the size of our estimated employment declines, the magnitude of these effects are small.

In the second half of the paper, we show that voters in the counties most impacted by NAFTA and voters who oppose free trade (independent of their area of residence) leave the Democratic party in large numbers beginning around the time of NAFTA's debate and implementation. NAFTA was a major issue in the 1992 U.S. presidential campaign, with Ross Perot making opposition to it the major motivation for his surprisingly successful third-party campaign.[3] President Bill Clinton eventually won the election and made passage of NAFTA an early goal of his administration, which he accomplished via a close, controversial and bi-partisan vote in November of 1993. Moreover, his support of NAFTA marked a major switch in Democratic-party policy toward trade, as in the 1970s and 1980s Democrats had been the more protectionist of the two major parties.

We begin our political analysis by showing that counties most exposed to NAFTA begin to turn away from the Democratic party in the mid 1990s. While the top quartile of NAFTA-

[3]In the second presidential debate of 1992, Perot memorably said about NAFTA: "We have got to stop sending jobs overseas. It's pretty simple: If you're paying $12, $13, $14 an hour for factory workers and you can move your factory South of the border, pay a dollar an hour for labor, ..., have no health care,...,no environmental controls, no pollution controls and no retirement, and you don't care about anything but making money, there will be a giant sucking sound going south." Perot captured 19 percent of the popular vote in 1992, making his campaign the most successful third-party effort since Theodore Roosevelt's 1912 run as the Bull Moose Party candidate.

exposed counties (many in the upper South) were the most likely to vote Democratic in elections before NAFTA, they begin to trend Republican just as NAFTA is being debated and then implemented. By the early 2000s, they vote as or more Republican than any other quartile. We find analogous results for House elections.

While the Presidential and House election outcomes are at the county level, the rest of our political analysis is at the individual level. We begin by showing that in the years since its passage, less than half of Americans approve of NAFTA, and disapproval is especially strong in the areas most vulnerable to it. Second, in repeated cross-section data from the American National Election Surveys (ANES) we show that, in each year of survey data from 1986 to 1992, Democrats enjoy a significant and steady advantage among those with protectionist views, but between 1992 and 1996 a significant number of protectionist voters move toward the GOP and remain there. Finally, in an ANES panel dataset from 1992 to 1994, we can look at the *same voters* over time during this key moment. We indeed find that a significant share of those who in 1992 express protectionist views have moved their party-identification toward the GOP by 1994. We show these effects are robust to flexibly controlling for a variety of demographic variables as well as views on other political and policy questions.

Our paper contributes to the literature on the local employment effects from exposure to import competition from low-income countries. Shortly after NAFTA's passage, Rodrik (1997) warned that academics and policy-makers were underestimating the effects of globalization on workers in rich countries. In the U.S. context, Autor *et al.* (2013a) highlighted the large and lasting employment effects of Chinese import competition on exposed U.S. communities.

There has been more limited work of this type for NAFTA. The closest is Hakobyan and McLaren (2016a). Like Autor *et al.* (2013a), they use Census data, so focus on longer (ten-year) differences than we do. In particular, they use decennial Census data and model industry-level effects of NAFTA (proxied as changes in earnings by industry from 1990 to 2000) as a function of both 1990 tariff levels and the *change* in tariff levels between 1990 and 2000.[4] We bring much less structure to our empirical approach, allowing each county's 1990-level of protection to have an unrestricted effect on employment (as well as myriad other outcomes) in every year of our sample period and then plot these estimated effects. Relative to both Hakobyan and McLaren (2016a) and Autor *et al.* (2013a), our use of annual

[4]A potentially important issue with including both the *change* in tariff levels from 1990 to 2000 and tariff *levels* in 1990 is that the two are nearly one-for-one (negatively) correlated, as tariffs are mostly stable from 1990 to 1993 and then from 1994 to 2000 almost all tariffs go to zero as a result of NAFTA. Thus, identification is reliant on the relatively small share of industries whose tariffs with Mexico do not go to zero by 2000.

data as opposed to Census microdata (which are available at lower frequency) allow us to visually test for pre-trends and moreover show that breaks in trend are highly correlated in time with NAFTA's implementation.

While there has been limited reduced-form work on local employment effects of NAFTA, there is a large trade literature that aims to quantify its welfare effects.[5] It is important to emphasize that our paper does *not* make aggregate welfare claims. We seek merely to document (a) local economic effects in the counties most exposed *relative* to other counties; and (b) any political response in those counties or among individuals, regardless of geography, opposed to free trade. However, one aggregate implication that emerges from our results is that NAFTA likely increased spatial inequality in the US, as the places most exposed were already lower-income and less educated in the pre-NAFTA period (see, e.g., Moretti, 2012 and Diamond, 2016 on rising spatial inequality in terms of wages and education levels in the US).

We also contribute to a recent literature on the political effects of trade shocks. To date, this literature has found mixed results in the U.S. context. Dorn *et al.* (2020) find over 2002-2010 a mix of right-ward movement alongside growing polarization in areas facing Chinese import competition. While they conclude that overall the movement is rightward, they also find that exposed areas that begin more Democratic send increasingly *liberal* candidates to Congress. Che *et al.* (2017) find that over 1990–2000, counties more exposed to competition via the granting of Permanent Normal Trade Relations with China become more likely to vote Democratic. Papers on Germany and France find that greater import competition results in a larger vote share for the far right party (Malgouyres, 2017 and Dippel *et al.*, 2015). In the British case, greater exposure to trade predicts votes for Brexit (Colantone and Stanig, 2018).

By contrast with the literature on the U.S. political response to the China shock, we

[5]The literature on the effect of NAFTA on the U.S. has focused on examining the policy's impact on prices and trade flows as well as measuring its aggregate wage and welfare impact. Krueger (1999) documents the expansion of trade flows among the three North American countries during the first four years of NAFTA, with a potential trade diversion away from non-NAFTA countries. Romalis (2007) uses detailed trade flow and tariff data to estimate import supply and demand elasticities and evaluates the price and welfare impact on the U.S. The paper finds a positive impact on the trade quantities but moderate impact on prices and welfare. Caliendo and Parro (2014) develop a structural general equilibrium model that incorporates the sectoral linkages (e.g., intermediate goods and input-output linkages) and show that NAFTA had a positive impact on U.S.'s welfare by 0.08 percent, while it increased Mexico's welfare by 1.31 percent and decreased Canada's welfare by 0.06 percent. There are papers that document the effect of NAFTA on Mexico, including Hanson (1998) that shows NAFTA affected the regional employment in Mexico by contracting manufacturing employment in Mexico City and increasing the manufacturing employment in northern Mexico.

find a clear shift in the Republican direction in places most exposed to NAFTA and among voters opposed to free trade. We suspect that the difference lies in the political saliency of NAFTA. The debate over NAFTA motivated a highly successful third-party presidential campaign in 1992 and remains a politically controversial point to this day. NAFTA also involved a president (Bill Clinton) breaking with the base of his party on a key issue. As we discuss in Section 6, NAFTA captured much more attention on network nightly news than did the later easing of trade relations with China. Why NAFTA captured media and public attention more than did easing of trade relations with China is an interesting question for future work.

The rest of the paper is organized as follows. Section 2 provides a short background on NAFTA's provisions and describes how we measure local vulnerability to NAFTA. Section 3 outlines the empirical strategy for our event-study analysis. Section 4 describes the employment results, Section 5, the demographic and transfer-program results and Sections 6 and 7 the political results. Section 8 concludes and offers ideas for future work.

2 Measuring local vulnerability to NAFTA

We begin with a very brief primer on NAFTA itself to motivate our vulnerability measure. We then define our measure, discuss its variation, and show its relationship to Mexican imports to the US before and after NAFTA.

2.1 Background on the agreement and trade with Mexico

By 1992, diplomats from Canada, Mexico and the US had hammered out the details of an historic agreement to substantially reduce trade barriers across the North American continent, though the agreement awaited ratification by the governments of the three countries. In fact, trade between the US and Canada had mostly been tariff-free due to earlier agreements in the 1980s, so the debate over NAFTA in the US focused on whether to liberalize trade with Mexico (and our analysis will similarly focus on import competition with Mexico).

Bill Clinton signed NAFTA into law in November 1993 after a close vote in both Houses of Congress (we defer the political history of NAFTA to Sections 6). Many of its provisions went into effect in January of 1994. While growing before NAFTA, Mexican imports enjoy more rapid growth beginning in 1994 (see Appendix Figure A.1). As we show in Section 2.5, post-NAFTA Mexican import growth is concentrated in industries in which U.S. industries had previously enjoyed tariff protection, as we would expect. Interestingly, despite the larger focus on China in the empirical labor economics literature, Appendix Figure A.1 also shows that it is not until 2004 that China supplants Mexico as the most important low-income source of imports.

2.2 Construction of our measure of NAFTA exposure

Our exposure measure draws heavily from Hakobyan and McLaren (2016a), though we create county-level measures, whereas they examine exposure at the Public-Use Micro-data Area (PUMA) level. In spirit, it is also very similar to that used by Autor *et al.* (2013a), as it takes a vector of industry-level measures of exposure to import competition and, for each community, multiplies it by a vector of pre-period industry employment shares.

Following Hakobyan and McLaren (2016a), we begin by creating Mexico's "revealed comparative advantage" (RCA) in a given industry $j \in \mathbf{I}$, using 1990 (pre-NAFTA) data:

$$\mathrm{RCA}^j = \frac{\left(x_{j,1990}^{MEX}/x_{j,1990}^{ROW}\right)}{\left(\sum_i x_{i,1990}^{MEX}/\sum_i x_{i,1990}^{ROW}\right)}. \tag{1}$$

In the numerator of the above expression, $x_{j,1990}^{MEX}$ is the 1990 value of Mexican exports (to all countries, not just the US) in industry j, $x_{j,1990}^{ROW}$ is the 1990 value of the rest of the world's (ROW) exports (again, to all countries) in j. The ratio of the two expressions is roughly equal to Mexico's share of exports in industry j. Of course, the share will be in part driven by Mexico's size. The denominator adjusts for Mexico's *overall* share of all exports, not just those in industry j. Thus, the overall expression in equation (1) captures, in 1990, Mexico's relative advantage in producing exports in industry j relative to other industries $i \in \mathbf{I}$.

We use data from the UN Comtrade bilateral export series to calculate the RCA for each industry j. Note that because we use so many different data sources in this paper (and most of them are well known to labor and trade economists) in the interest of space we do not have a separate data section nor describe the data in detail in the main text. Instead, in the main text we only briefly describe the data we use and refer readers to Appendix B for more detail.

How much a U.S. county is likely to be affected by NAFTA depends on its pre-period reliance on employment from industries with the following two characteristics: (a) Mexico has large RCA in that industry, *and* (b) the industry had previously enjoyed tariff protection before NAFTA.

We can now write our full county-level vulnerability measure:

$$\mathit{Vulnerability}_{c,1990} = \frac{\sum_{j=1}^{J} L_{1990}^{cj}\mathrm{RCA}^j \tau_{1990}^j}{\sum_{j=1}^{J} L_{1990}^{cj}\mathrm{RCA}^j}, \tag{2}$$

where L^{cj}_{1990} is employment of industry j in county c in year 1990 and τ^j_{1990} is the ad-valorem equivalent tariff rate of industry j in 1990. Note that the measure uses only *pre-period* measures of both Mexican RCA and community-level industrial composition, and thus does not pick up any endogenous reaction to NAFTA itself.[6]

Note that the *Vulnerability* expression in equation (2) is a constant within county—as we take the τ^j values and employment levels from 1990, it captures how much tariff protection from Mexican RCA a county enjoyed in 1990. As it will serve as the key explanatory variable in our event-study analysis, we essentially ask how this fixed-over-time characteristic covaries with local employment every year of our sample period (so any negative covariance *before* NAFTA's passage in the form of "pre-trends" would cast doubt on our hypothesis).

While our τ^j_{1990} measure is taken from the specific year of 1990 and thus are by construction constant across time, the τ^j_t values naturally can change over time. Figure 1 shows, separately by quartile of 1990 vulnerability, how the protection measure in equation (2) changes if we allow the τ^j_t to follow their *actual* course over time (all other variables in the expression are kept at their 1990 levels, so the value of the four series in 1990 is in fact the average county vulnerability measure, as defined in equation 2, for the four groups). Before 1993, there is little change, as tariff rates were largely stable in this pre-NAFTA period. Between 1993 and 1995, there is a large decline in protection, as indeed half of all tariffs on Mexican goods went to zero in the first year after NAFTA's January 1994 implementation.[7] By 2000, even the most protected quartile of counties by the 1990 measure have essentially zero tariff protection.

Because (*i*) tariffs change very little between 1990 and 1993 and (*ii*) most tariffs go to zero between 1994 and 2000, there is an extremely high correlation between 1990 tariffs and the 1990 to 2000 *change* in tariffs. Thus, "protection" from Mexican import competition in 1990 is essentially the same as "vulnerability" or "exposure" to NAFTA and we use these expressions interchangeably.

2.3 Geographic variation in the NAFTA exposure measure

While Figure 1 shows how tariff protection changed over time, Figure 2 shows how protection in 1990 (and thus vulnerability to NAFTA) varies geographically. NAFTA most affected low-

[6]County-level employment data come from County Business Patterns (CBP) and tariff data from the U.S. Tariff database from Feenstra *et al.* (2002), both described in more detail in Appendix B.

[7]See U.S. Information Agency (1998), p. 25. One claim in the 1993 letter signed by economists and circulated by the Clinton administration was that the tariff reductions would be too gradual to create employment losses, but in fact those reductions were mostly complete within the first two years.

wage, labor-intensive manufacturing industries—textiles, apparel, shoes and leather. Thus, the most vulnerable areas of the US are naturally the regions that specialized in these goods. The South exhibits the highest levels of vulnerability, but there are pockets of high-vulnerability areas within most states.

A natural question is how our measure of NAFTA vulnerability varies with exposure to the China shock in Autor *et al.* (2013a). Many of the same industries were affected (textiles and apparel, e.g.). However, the correspondence is hardly one-for-one. At the CZ level, the (1990 population-weighted) correlation is 0.172. As noted, ADH often use an instrumented version of their exposure measure, and the correlation in that case is 0.420. Thus, while positively correlated, they are not identical, though in all of our analysis we show results after flexibly controlling for the China-shock measures.

2.4 Characteristics of counties by NAFTA vulnerability

Even before NAFTA, those living in the most vulnerable quartile of counties were disproportionately the least educated and had the lowest per capita income, as we show in Table 1. They were also the most reliant on manufacturing employment. The differences in pre-NAFTA characteristics by exposure quartile highlights the importance of flexibly controlling for these attributes in order to isolate the effects of NAFTA from secular changes such as skill-biased technological change (Goldin and Katz, 2008) or the China shock.

As the most vulnerable quartile is disproportionately Southern, it is not surprising that it is less white than the other quartiles, as African-Americans have always disproportionately lived in the South. It also begins the period the least supportive of Republican candidates in House and Presidential elections. While the South was no longer a Democratic stronghold by 1990, Democrats still performed well in the region.[8]

2.5 Relationship between Vulnerability measure and Mexican imports to the US

While our *Vulnerability* variable is similar in spirit to the ADH measure, one departure is that we focus on statutory changes in tariff protection instead of changes in actual import penetration. We view this modification as preferable, as actual imports are potentially endogenous to domestic demand (Autor *et al.*, 2013a themselves note this concern, and

[8]See Kuziemko and Washington (2018) on the decline of Democratic party identification among Southern whites from the 1950s through the 1980s. See Black and Black (2009) on how Southern Democratic legislators and governors managed to survive well after Southern whites began to support Republicans in presidential elections.

thus use Chinese import flows to *other* rich countries as an instrumental variable in many specifications).

While we prefer to relate employment changes to statutory changes in tariffs instead of actual import penetration, here we use $industry \times year$ data to show that pre-NAFTA tariff levels (the large majority of which go to zero in the years immediately following NAFTA) do indeed predict Mexican import growth after NAFTA's implementation. To demonstrate this "first stage" relationship we estimate:

$$MexImports_{jt}^{US} = \beta_t Avg.Tariff_j^{1990} + \gamma_1 MexImports_{jt}^{ROW} + \gamma_2 ROWImports_{jt}^{US} \eta_j + \mu_t + e_{jt},$$

where $MexImports_{jt}^{US}$ is Mexican imports to the US in industry j in year t, $Avg.Tariff_j^{1990}$ is the average tariff level on Mexican imports in industry j in 1990 (pre NAFTA), $MexImports_{jt}^{ROW}$ are Mexican imports in industry j in year t to the rest of the world (ROW), $ROWImports_{jt}^{US}$ are the rest of the world's imports to the US in industry j in year t and e_{jt} is the error term. Including $MexImports_{jt}^{ROW}$ and $ROWImports_{jt}^{US}$ separates the NAFTA-triggered decline in industry j tariffs from, respectively, world demand for Mexican imports in j (not necessarily from the US) and U.S. demand for imports in j (not necessarily from Mexico).

Figure 3 shows a clear relationship in the expected direction between pre-NAFTA tariff levels and an increase in Mexican imports to the US after NAFTA's implementation. There is little trend in the relationship between the 1990 average tariff in industry j and U.S. imports from Mexico in j, but an increase beginning in 1994 that reaches its peak around 1997. We use U.S. International Trade Commission data in Figure 3 (which attempts to account for the value of re-exports) and show robustness to using UN Comtrade data (which does not) in Appendix Figure A.2.

3 Empirical strategy for event-study analysis

The next two sections examine local economic outcomes of those counties most exposed to NAFTA relative to other counties. For each outcome (employment, population, DI claims, etc.), we begin by showing trends for four groups of counties: four quartiles based on the NAFTA vulnerability measure that we defined in the previous Section. These trends are based on raw data, unadjusted except for normalization of each quartile to zero at 1993. While this approach is the most transparent, it is difficult to summarize and to adjust for covariates. We thus turn to a standard event-study approach for the bulk of our analysis, where instead of dividing NAFTA exposure into quartiles we simply use (linearly) the measure in equation (2), interacting it with year fixed effects. In particular, we estimate:

$$Y_{ct} = \alpha_c + \gamma_t + \sum_{\tilde{t} \neq 1993} \beta_t \left(\mathit{Vulnerability}_{c,1990} \right) \times \mathbb{1} \left(t = \tilde{t} \right) + \lambda X_{ct} + \epsilon_{ct}, \quad (3)$$

where Y_{ct} is a given outcome in county c in year t (employment, population, etc.); α_c are county fixed effects; γ_t are year fixed effects, $\text{Vulnerability}_{c,1990}$ is the vulnerability index in c (measured, as discussed in the previous section, using data from 1990); X_{ct} include controls that vary within community over time (which we vary to probe robustness); and ϵ_{ct} is the error term. The exact sample period depends on the outcome variable and data availability, but in general we begin in the mid-1980s and end in the early 2000s. We cluster standard errors at the state level.

Note that this equation does not directly use the schedule of tariff reductions implied by NAFTA (and plotted earlier in Figure 1). Instead, we allow the 1990 level of tariff protection to have an unrestricted effect in each year, captured by the β_t coefficients, and plot those estimated effects each year. We prefer to take a more agnostic approach to how the effects of tariffs play out over time and in particular prefer to allow unrestricted effects of the tariffs before 1994 to test for pre-trends.

4 Employment results

In this section we document large employment declines in the counties most exposed to NAFTA, relative to less exposed areas, beginning in the mid-1990s. In the next section, we examine common margins of adjustment to local economic downturn (e.g., out-migration and transfer-program application).

4.1 Main county-level event-study results

We begin by showing raw county data broken up into quartiles based on NAFTA exposure, though for the sake of space relegate these results to the Appendix. Appendix Figure A.3 shows these results for county-year log employment (all employment data in this section is taken from the Census' County Business Patterns data). The raw data suggest that county groups trended together before 1994, after which time the most exposed counties fell behind the other groups in terms of employment growth.

While the plots of raw data that we show as Appendix figures have the virtue of transparency, more parametric event-study figures can more succinctly show robustness to flexible controls and other specification choices. The first series in Figure 4 plots the β_t estimates from a version of equation (3) where we control only for county and year fixed effects (meaning the X_{ct} vector is empty). The coefficient values in the years before NAFTA are all indistinguishable from zero (note that 1993 is the omitted category and normalized to zero) and more importantly show no negative pre-trend. But beginning in 1994 there is a steady decline in the coefficient values. The event-study coefficient is roughly -1.0 by 2000. Multiplying this coefficient by 0.08 (the difference in exposure between the most- and least-exposed quartile) implies a relative effect of roughly eight log points.

The 1990s was an active moment for state policy experimentation (e.g., the AFDC welfare waivers preceding the 1996 federal welfare reform act, Medicaid expansions, and state-level EITC introductions and expansions), so in the second series we add state-year fixed effects, to capture these policy reforms or any other unobserved change within states across time. The coefficients do not move appreciably relative to the baseline series. We take this specification as our preferred specification.

As noted, an important alternative explanation is that these effects are in fact picking up early stages of the China shock. In the third series, we add (to the controls already noted in the previous specifications) the ADH measure (a constant at the CZ level) interacted with each year fixed effect.[9] To make the test more demanding, we use the IV version of their measure, as it happens to be more highly correlated with our NAFTA-exposure measure. In fact, controlling flexibly for the China shock makes little difference to our results. As we already discussed, NAFTA and China-shock vulnerability are positively correlated across space but not overwhelmingly so; moreover, the real acceleration of Chinese imports happens about eight years after NAFTA, meaning it is not hard to separate the short- and medium-run effects of NAFTA from the China shock. Another potentially confounding trade policy during the 1990s was the phase-out of the Multi-Fibre Arrangement (MFA) quotas (which was announced in the mid 1990s but did not become binding until the early 2000s, see Khandelwal *et al.*, 2013 and Chiron, 2004 for further detail and analysis). Appendix Figure A.4 show robustness of our results to flexibly controlling for the MFA phase-out.

As shown in Table 1, counties that would be more exposed to NAFTA were already different on important dimensions in 1990: for example, they had higher reliance on manufacturing employment and lower rates of college-degree completion. The fourth series in Figure 4 adds 1990 manufacturing share of county employment interacted with year fixed effects, which barely moves the coefficients. The final series substitutes the manufacturing controls used in the fourth series with a vector of interactions between county-level share of college-educated adults in 1990 with year fixed effects. Of all the controls we add, this one

[9]We use their IV defined for a period between 1990 and 2000, instead of between 2000 and 2007, as this period coincides more with the timing of NAFTA.

has the most appreciable effect. Nonetheless, the estimate effects of vulnerability remain large, negative and highly significant. We use a balanced panel of counties consistent across all specifications in Figure 4 as the analysis sample, which only includes counties with non-missing dependent variable for all years, non-missing vulnerability and control variables for 1990. This results in the balanced panel of 2924 counties, which accounts for 98 percent of U.S. population in 1990. We relegate to Appendix Figure A.5 parallel analysis that allows 1990 share Black, share foreign-born to have their own effects and that includes county-year varying controls (despite their potentially being "bad controls"). We also add an offshore-ability measure for each county's 1990 industry mix and interact it with year effects. Results remain robust in all of these additional analyses.

How large are these effects? In the year 2000, the estimates of the coefficient on *Vulnerability* in Figure 4 range from -0.97 to -0.51. Taking quartile *Vulnerability* estimates from Table 1, these coefficients translate into a 3.8 to 7.2 log-point decline in the most vulnerable quartile of counties relative to the least.[10] Taking employment-to-working-age-population ratios from Table 1, this decline roughly translates into 1.77 to 3.38 jobs per 100 working-age residents.[11] These magnitudes will be useful to keep in mind when we examine the response of transfer programs in the next section.

Readers might find it surprising that there is not a negative pre-trend in our employment event-study graphs, given that the most NAFTA-exposed counties depended most on manufacturing and the sector has been in long-run decline in the US. Indeed, textile and other NAFTA-vulnerable industry lobbyists often complained—even before NAFTA—that politicians and economists acted as though these jobs were in "sunset industries" and were thus "not worth saving."[12] But at the time of NAFTA's passage, the apparel and textile industries alone still employed nearly two million people. Whether via a successful "Made-in-America" campaign pitched toward consumers in the 1980s or other factors, employment decline had also plateaued in these industries in the years leading up to NAFTA. We show in Appendix Figure A.6 that employment in textile mills was in fact quite stable in the early

[10]The relevant calculations are $-0.97 * (0.077 - 0.003) = -0.07178$ and $-0.51 * (0.077 - 0.003) = -0.03774$.

[11]The relevant calculation, using the summary statistics in Table 1, is $\frac{14638 * 0.07178}{31120} = 0.03376$ and analogously for the lower bound. Recall that these employment-to-population ratios are based on employment in the county (regardless of the residence of the worker) from the CBPD divided by working-age population in the county (from the Census) so is not directly comparable to the typical, survey-based measure of employment-to-population. When we put this employment-to-population ratio itself as the outcome variable in an event-study analysis, we find similar effects of roughly 2-3 percentage points.

[12]Much of the information provided in this paragraph is taken from Minchin (2012), a history of the decline of the U.S. textile industry.

1990s (at half a million workers) before beginning a rapid decline in the middle of the decade, coincident with NAFTA's package.

4.2 Robustness to randomization inference

Recent work has suggested that designs such as ours may over-reject the null hypothesis of no effect. In Appendix C we show all the main results of the paper are robust to using the correction provided by Adao *et al.* (2019b).

We also develop a related but more demanding randomization-inference test, again detailed further in Appendix C. The distribution of pre-NAFTA industry-level tariffs τ has a mass at zero and then a very long right tail. We retain $\tau = 0$ for all industries that have no tariff against Mexican imports in 1990. We then model the positive tariffs with a fourth-degree polynomial (the actual distribution of positive tariffs and our approximation is in Appendix C). One implication of this procedure is that the mean β of the distribution formed by permuting across the τ distribution need not be zero, because by retaining the actual tariff value when $\tau = 0$ the simulations contain some real information. As we show in the Appendix, our estimated $\hat{\beta}$ is in the extreme tails (often not even in the support) of the distributions of simulated $\hat{\beta}$ values after 1,000 draws.

4.3 Accounting for benefits of NAFTA to U.S. industries

So far, we have focused only on the heightened competition some U.S. industries faced due to NAFTA. But industries can benefit from NAFTA in at least two ways: they may rely on *inputs* that are now cheaper or they can export goods to Mexico more competitively due to reciprocal declines in Mexican tariffs on U.S. goods.

In Appendix D, we show that accounting for these potential benefits makes little difference to our employment results. While we go into detail in Appendix D, the key point is that NAFTA mostly helped and hurt the same industries (so that our *Vulnerability* measure largely picks up the *net* effect of NAFTA on local labor markets, accounting for both the local gains and losses). Input-output matrices demonstrate that most industries rely heavily on inputs from other industries in their same two-digit classification. Similarly, the sectors whose tariffs were reduced due to NAFTA were very similar in the US and Mexico, a point highlighted by policy-makers at the time (U.S. International Trade Commission, 1993).

4.4 Related results and additional robustness checks

So far, we have shown results at the county level. We prefer the county over the CZ as our unit of analysis because CZs can cross states and in the political analysis especially we would like to control flexibly for any effect of state-wide campaigns. While CZs have the advantage of better capturing labor markets, counties are in fact decent proxies for labor markets as well: in 1990 and 2000 census tabulations, 73 percent of workers lived and worked in the same county.[13] The employment results for CZs are very similar to those we find at the county level, as shown in Figure A.8, though the impact of NAFTA manifests more as a negative break in a positive pre-trend.

Some of the smallest industry-county cells in the CBP are imputed to protect confidentiality. Appendix Figure A.9 shows our main results are robust to using an alternative imputation proposed by Eckert *et al.* (2021).

A potential confounding event is the sudden devaluation of the Mexican Peso in December of 1994. The devaluation made Mexican goods relatively cheaper in the US and a natural concern is that it could have caused some of the employment effects that we attribute to NAFTA.[14] If the devaluation caused the local employment effects, then we should observe them in all counties reliant on industries for which Mexico is a strong exporter, *regardless of 1990 tariff levels*. A substantial share of SIC four-digit industries either had no tariff or a low tariff on the Mexican imports to the US, so we should be able to separate the two hypotheses. In Appendix Figure A.11, we replicate our employment results from Figure 4 but include as additional controls a *non-tariff-weighted* measure of vulnerability—that is, the expression in equation (2) but *excluding* the 1990 tariff industry tariff levels τ_j^{1990}—interacted with each year. Our results barely change, suggesting that the patterns we find in our main Figure 4 are driven by the decline in *tariffs*, not a more universal change in relative price levels between the two countries.[15]

[13]For the 1990 statistics, see `https://www2.census.gov/programs-surveys/commuting/tables/time-series/place-of-work/powstco.txt`. For the 2000 statistic, see Table 5 of the following Census publication: `https://www.census.gov/content/dam/Census/library/working-papers/2007/acs/2007_Jiles_01.xls`.

[14]Our read of the literature is that the devaluation (and the economic turmoil that followed) was triggered by a number of factors: a large capital account deficit funded via short-term loans; a large share of debt held by foreigners; and "euphoria" related to the future prospects of a liberalizing Mexican economy. NAFTA may have played a role in the final factor ("the 'euphoria' was linked to the country being a 'model reformer,' as well as its access to NAFTA and OECD," Griffith-Jones, 1998) and if so then the peso crisis is not a confounder but a mechanism.

[15]Another piece of evidence suggesting that our results are being driven by actual pre-period tariff levels and not a more general relative price decline is the randomization inference exercise described earlier in Section 4.2 and presented in Appendix C: we show in that exercise that a blunt "any positive tariff" measure does not pick up the same effects on county employment as using the

As further corroboration that NAFTA reduced relative employment in the most exposed counties, we break down our baseline employment effects by industry. That is, we ask, in NAFTA-exposed counties (those with employment concentrated in NAFTA-exposed industries), was it indeed manufacturing (the most NAFTA-exposed sector) that drive the employment losses we have documented? Appendix Figure A.10 shows that, at least through 1997, almost all of the employment losses were in the manufacturing sector, with losses in the non-manufacturing center small and not statistically significant. Unfortunately, this analysis cannot be extended seamlessly after 1997, because in 1998 the CBP data change from Standard Industrial Classification (SIC) codes to the North American Industry Classification System (NAICS) codes.[16] After a discontinuous jump in both series between 1997 and 1998, the relative downward trend in manufacturing employment in NAFTA-vulnerable counties continues.

4.5 Results at the individual level

Most of the analysis of trade-induced employment effects in the literature are, like our results so far, at the geographic level. Of course, county- or CZ-level results are of interest in their own right as they pick up potential effects on other industries or other types of local spillovers. But interpreting these results as informative of the individual-level effect of working in a NAFTA-vulnerable industry is subject to the ecological fallacy.

To more credibly estimate individual-level effects, we turn to the Panel Study of Income Dynamics (PSID). We define an *individual worker i's vulnerability* to NAFTA based on the industry j of their main job in 1990. That is:

$$Vulnerability_{j(i)} = \mathrm{RCA}^j \tau^j_{1990}. \tag{4}$$

We show results in Appendix Figure A.12 . While somewhat noisy, there is a clear decline in employment after 1993 for workers in more NAFTA-vulnerable industries.

5 Migration and transfer-program response

Our results so far show a large and robust loss of jobs in the counties whose 1990 employment was most reliant on NAFTA-affected industries. A natural question is how individuals and households respond to this negative local employment shock. The two margins we focus on

actual 1990 tariff levels).

[16] Somewhat ironically, NAFTA itself precipitated this switch, to better integrate data across the three countries. See `https://www.census.gov/eos/www/naics/`.

in this section are migration and (both applications to and receipt of) transfer programs.

5.1 Population estimates

Economists have long studied how migration responds to local economic shocks. Blanchard *et al.* (1992) found significant migration responses using data from the 1970s and 1980s. While *employment levels* often never recovered from economic shocks during this period, via the migration channel, *unemployment rates* generally did. But researchers studying more recent local employment shocks have found much smaller migration responses. The large employment effects of the China shock produced no (Autor *et al.*, 2013a) or small and delayed (Greenland *et al.*, 2019) population effects. Similarly, Yagan (2019) finds no statistically significant effect of the local severity of the Great Recession and out-migration from one's CZ. To the best of our knowledge, no one has examined the migration impact of NAFTA, which falls after the period studied by Blanchard and Katz but before the China Shock and Great Recession.

We use intercensal county population estimates from the Census. The Census produces these estimates by adjusting the decennial count interpolations for each county using annual vital statistics data on births and deaths as well as annual data from the IRS on residential address changes of tax-filers, so they are not merely interpolations between decennial Census counts.

Figure 5 is the analogue to Figure 4 except that log county population is the variable of interest. In contrast to the log-employment results, which showed a downward trend break in 1994 for all of our specifications, we find a series of null results. None of the specifications shows any break in 1994 or even any real change from 1990 to 2000—the confidence intervals of *all* post-period coefficients from all five specifications include zero. While we let the y-axis naturally adjust (ranging from -.5 to 1), note that the range is much smaller than for the employment results, masking in fact how small the coefficients are relative to the log employment results. In our preferred specification (the second series, with state-year fixed effects), the bottom of the confidence interval for the coefficient in 2000 is roughly at -0.2. We can thus reject with 95% confidence population declines between 1993 and 2000 in the most- versus least-exposed counties greater than $(0.077 - 0.003) * 0.2 \approx 1.48$ log points. Recall that the same calculation (using the point-estimate, not the edge of the confidence interval) suggested a four to seven log-point employment decline. While we do not include them in the interest of space, we find similar null results for various subgroups (e.g., working-age population, male and female population, the white and Black population).

We conclude that despite the large employment effects in NAFTA-vulnerable counties after 1993, their population growth tracks the rest of the country. This result echos historians' description of 1990s Southern mill towns after a major textile employer closed. "Workers' attachments to their jobs and communities—which had been so important as they endured the hardships of mill life—now made it harder for them to find opportunities. These workers failed to fulfill economists' predictions of a new, mobile workforce who would rationally relocate to find new jobs" Minchin (2012). This finding deepens the puzzle raised in recent papers that find no or limited migration response to large, negative local employment shocks.

5.2 Trade Adjustment Assistance

Of course, policy-makers are not completely naive to the possibility of local job losses due to import competition, from NAFTA or other sources. Legislation originating in the 1960s and further expanded in the 1970s created a series of measures collectively known as Trade Adjustment Assistance (TAA). Beyond income support, TAA provides opportunities for training, job search and relocation payments.[17]

TAA application and certification data by county-year is extremely skewed: the majority of observations are zero and a few outliers pull up the mean substantially. Log measures are thus not feasible and we instead begin by estimating per capita applications (dividing by 1990 county population) as the outcome in our usual event-study set-up. Figure 6 provides the results. We find no pre-trends in per capita applications. From 1994 until the early 2000s, the coefficient on vulnerability hovers between 0.005 to 0.01 (increasing from the zero baseline of 1993). The analogous results for TAA certification are in Appendix Figure A.13 and show a very similar pattern.

While these effects appear statistically significant in much of the late 1990s, the economic magnitudes are more modest. Translating these coefficients into our usual comparison of most- and least-exposed county quartiles and taking even the most generous estimates from the 1994-2003 period (a coefficient on *Vulnerability* of 0.0186), we estimate that most-exposed counties saw an increase of 0.13 TAA petitions per 100 workers relative to the least exposed.[18] The analogous calculation for TAA *certifications* is a 0.067 relative increase per 100 workers

[17]To receive TAA benefits, a group of three or more workers must first file a petition with the U.S. Department of Labor's TAA Program within a year of separation from the firm. If the group of workers meets the eligibility criteria, they will be issued a group eligibility certification. Each worker in the group then must make an individual application for TAA benefits through their local American Job Center. Hyman (2018) is one of the few economics papers that studies its efficacy. He uses assignment to investigators with varying leniency and finds that certification leads to short-run benefits that appear to fade within ten years.

[18]The relevant calculation is $0.0186 * (.077 - .003) = 0.001376$. The analogous calculation for certification is $0.0091 * (.077 - .003) = .0006734$.

(again, taking the most generous coefficient from 1998, the year with generally the largest estimated effects). Recall that we estimated a loss of approximately 1.77 to 3.38 jobs per one hundred people in the most- versus least-affected quartile group. Thus, even when we purposely use the most generous estimates for the TAA response, we see that TAA petitions cover only about five percent of job losses (note that Autor et al., 2013 also find a very small increase in TAA petitions in areas hit by the China shock). Of course, our definition of "NAFTA related" is an econometric one—county job loss correlated to 1990 county NAFTA vulnerability occurring from 1994 onward, conditional on a large set of controls—whereas the definition used by TAA investigators will be different. But these small effects motivate us to ask whether individuals in NAFTA-affected counties turned to other transfer programs.

5.3 Disability Insurance

At least since Autor and Duggan (2003), economists have studied whether individuals exposed to negative local economic shocks turn to the federal Disability Insurance (DI) program. Several mechanisms might operate. On the one hand, those with health issues but still capable of some gainful employment might turn to DI for income support if work opportunities dry up. So, holding health status constant, lack of jobs could push marginal candidates to apply to DI (what public finance economists would typically view as moral hazard). On the other hand, lack of employment could exacerbate health issues—mental health issues given the link between job search and depression (Krueger *et al.*, 2011); and physical health issues, given loss of employer health insurance. Minchin (2012) describes loss of employer insurance as one of the biggest concerns of those who lost textile jobs in the 1990s.

To test whether NAFTA led residents of exposed areas to apply to DI, we obtain office-year DI application and award counts, from 1989 to 2008, from the SSA.[19] We use contemporary district office locations to assign zip codes to district offices.[20] We then match those zip codes to counties based on 1990 geography to create a balanced panel of 762 counties, home to around three-quarters of the U.S. population in 1990.

Appendix Figure A.14 shows that our log-employment effects look similar, though some-

[19]We are deeply indebted to Manasi Deshpande for facilitating our access to these data and answering our many questions and to Melissa Kearney for sharing her extract.

[20]While the data do include zip code information for many district offices in *later* years (and thus in principle we do not need to match by office location for these years), to have a consistent matching methodology in all years, we match only by the zip code information we find using the contemporary district office locations. Using this methodology, we are unable to match to counties those district offices that closed before 2009, the earliest year to our knowledge that district office locations are available publicly.

what smaller in magnitude, when restricted to these counties as they do in Figure 4 for all counties. So any effects on DI applications in this subsample might serve as a lower bound for that on the full sample.

The event-study analysis shows a clear response to NAFTA along both the applications (Figure 7) and the awards (Appendix Figure A.16) margins (as usual, we show the patterns in the raw data as well, Appendix Figure A.15). There are no pre-trends suggesting a pre-NAFTA increase in DI applications (if anything, some evidence to the contrary). Depending on the exact specification, applications and awards begin to tick upward in NAFTA-vulnerable counties in 1994 or 1995 and remain high for several years.

Again, however, the magnitude of applications and awards relative to estimate job losses is modest. Taking the specification with the largest coefficient for the year 2000, we estimate that applications increased by 0.282 per 100 residents in the most affected counties relative to the least affected. The analogous estimate for actual awards is 0.174.[21] Even purposely choosing the largest estimate for DI awards and the smallest estimate for job losses, we find that by 2000 the increase in DI awards is less than ten percent of the size of the job losses.

5.4 Other outcomes

A natural implication of job loss is greater unemployment insurance (UI) payments. As UI eligibility typically lasts only 26 weeks, we would expect that UI payments would rise in the period of active job loss but not remain elevated in the longer run. Appendix Figures A.17 and A.18 show exactly this pattern. The decline in employment also suggests more families may gain SNAP eligibility. We find suggestive evidence of an increase in SNAP receipt in Appendix Figures A.19 and A.20. We do not emphasize these results more because NAFTA occurs just as states and eventually the federal government embark on major welfare reform, which among other changes ended automatic SNAP enrollment upon enrollment in AFDC.[22]

The increase in DI applications might reflect a deterioration of health, so it is natural to examine health outcomes, and mortality is the most widely available. An increase in DI applications reflects the health of the *working-age* population, since a sufficient work history is required for eligibility and the traditional (old-age) Social Security program, not its DI component, would cover those over age 65. We thus focus on this population, and

[21] The relevant calculation for applications is an increase of $2.915 * (0.077 - 0.003) = 0.216$ in log terms. As we saw earlier that population does not change as a result of NAFTA and taking the DI applications per capita from Table 1, we estimate an $0.216 * 1.308 = 0.282$ increase in applications per 100 residents. The analogous calculation for awards is $4.57 * (0.077 - 0.003) * 0.516 = 0.174$.

[22] This report articulates how many families eligible for food stamps did not receive them in the years following welfare reform: `https://www.brookings.edu/research/welfare-reform-reauthorization-an-overview-of-problems-and-issues/`.

in Appendix Figure A.21 regress log of total deaths between ages 25 and 55 by county and year in our usual event-study specification. While we see an increase beginning in 1996, it is sensitive to including flexible controls for pre-period college share. We believe these results are suggestive of declining health in NAFTA-vulnerable areas after 1994, but do not push them further.[23]

The evidence in this and the previous section suggest deterioration with respect to a number of important socio-economic indicators in NAFTA-vulnerable counties after 1994. Employment declines significantly. Transfer payments rise, but nowhere near enough to cover the estimated job losses. While the data are only suggestive, working-age mortality may also have increased.

6 The political response in areas vulnerable to NAFTA

This section begins the political analysis of the paper, focusing first on geographic variation in NAFTA vulnerability. We very briefly describe the politics of NAFTA's passage and then examine how areas most impacted by NAFTA responded politically. Section 7 also examines the political response to NAFTA, but instead of modeling any change in partisan identification as a function of geographic vulnerability to NAFTA, we model it as a function of individuals' views toward free trade.

6.1 The politics of trade and NAFTA

In the first few decades of the twentieth century, the Democratic Party (concentrated in the South and West) favored lowering tariffs, proposing a progressive federal income tax to make up for lost revenue. Republicans (concentrated in the industrial Northeast) preferred tariffs to protect their domestic manufacturing sales and, as the richest region of the country, opposed progressive income taxation. This debate lost its salience during World War II and during the first few decades of the Cold War, when a bi-partisan consensus maintained that expanded trade should be promoted to reduce the attraction of communism in low-income countries. That the US had few industrial rivals at this time also limited the salience of the issue. This consensus broke down in the 1970s as economic growth slowed and import competition grew, at which point the Democrats emerged as the more protectionist of the two major parties (not a surprise, given their base of union members and blue-collar workers

[23]We find similarly suggestive but not robust results when we examine "deaths of despair" (Case and Deaton, 2020). One complication is this analysis is that we have many zeros at the county-year level, so we cannot use a log specification without further aggregation.

threatened by liberalized trade regimes).[24]

As noted in the introduction, the debate over NAFTA was a major topic in the 1992 and 1994 national elections. While Bill Clinton avoided taking a clear stand on NAFTA during the 1992 presidential campaign, he made passing NAFTA in Congress a major goal of the first year of his administration, against the wishes of his party's base.

By no means are we the first to argue (as we do in this and the next section) that NAFTA led to lasting, negative effects on Democratic identification among regions and demographic groups once loyal to the party. Many historians and political scientists have made this argument, though more in narrative than quantitative terms. In general, a theme of *betrayal* emerges. Key groups that had once formed the base of the Democratic party—e.g., union members and other working-class voters—bitterly opposed NAFTA and the Democratic president pushing for it, in what became a highly emotional fight (e.g., anti-NAFTA groups organized candle-light vigils on the White House lawn as the vote in Congress approached). In his book on the 1994 midterm elections, Klinkner (2019) writes: "In a hotly contested and emotional vote, the critics of globalization, led by organized labor and environmental groups, were overcome by NAFTA's supporters, principally corporate lobbyists *and the Clinton administration* [emph. added]." Similarly, Stein (2010) writes about the more market-based shift in the Democratic Party's economic policy: "When it came to measures that the base of his party wanted, Clinton faltered... Clinton had made the NAFTA a priority....and this allowed the Republican opposition to mushroom."

A point emphasized by Minchin (2012) is that many Democratic voters opposing NAFTA already felt at home in the GOP with respect to social issues such as abortion and gun rights, but they remained Democrats because of economic issues such as protection from import competition. With NAFTA, a key reason to vote Democratic and thus against their own positions on social issues disappeared (we more formally test this idea in the next section).

The debate over NAFTA was not limited to economists and policy wonks but instead played out in the mass media and popular culture. A memorable event during the Clinton administration's push for NAFTA passage was Vice President Al Gore's nationally televised November 1993 debate against Ross Perot, who argued throughout the debate that the agreement would lead to blue-collar jobs leaving the US for Mexico. The debate set a viewership record for CNN that would stand for two decades (Kornacki, 2018).[25] Moreover, NAFTA was the subject of at least two *Saturday Night Live* sketches in 1993, both highlighting the

[24] This brief historical summary is drawn mostly from Weisman (2004) and Stein (2010).

[25] Over 38 percent of registered voters reported having watched all or part of the debate, with an additional thirty percent saying they watched at least a "little" or had since heard or read about it. These numbers are from the authors' calculations using November 1993 WSJ/NBC survey data.

potential American job losses claimed by detractors of the agreement.[26]

Interestingly, even though the easing of trade relations with China had a greater impact in terms of total import value, the topic did not garner much coverage on network news. In Figure 8 we plot, by year, the share of minutes that the three network nightly news programs devotes to stories with the words "trade" and "imports" and "jobs." From the 1980s until 2005, the only period where all three networks show a substantial increase is 1992-1993. In summary, both news programs and American popular culture focused on the issue of globalization, trade and jobs during the debate over NAFTA much more than in the ten years before or after. One possibility we find plausible is that the events of September 11th, 2001 and the resulting U.S. military campaigns in Afghanistan and Iraq crowded out media coverage of trade with China.

A final point we emphasize before moving on to the empirical work is that NAFTA did not turn out to be a one-time deviation from Democrats' traditional position on trade. It was instead the signal of a lasting shift toward promoting globalization. At the time of its 1993 passage, "Clinton told the national press that NAFTA was a 'job winner.' Staking a lot on passage of the agreement, Clinton even termed it 'the symbol of where we want to go in the world' (Minchin, 2017, p. 202)." In the 1996 presidential campaign, Clinton repeatedly cited his opening up the country to free trade as a major accomplishment of his first term.[27]

6.2 County-level event-study results

Figure 9 shows that NAFTA *Vulnerability* is associated with an increase (decrease) in Republican (Democratic) county-level presidential-election vote share in the mid 1990s, after a generally flat pre-NAFTA trend. Overall the pattern is more robust to controls for the Democratic share than the Republican.[28] Relative to the 1992 omitted baseline election and

[26]See `https://www.nbc.com/saturday-night-live/video/mexican-stereotype/n10486` and `https://www.nbc.com/saturday-night-live/video/united-we-stand-america/n10497` for the videos.

[27]In the first 1996 presidential debate, he emphasized that free trade was the right thing to do, even though it was controversial. "I've done a lot of things that were controversial. My economic plan, my trade position...Sometimes you just have to do that because you know it's right for the country over the long run." In the second debate, he emphasized that he had opened up the country to trade more than any of his predecessors. "[W]e've had over 200 separate trade agreements in the last four years. By far, the largest number in American history—not just the big ones you read about, but a lot of smaller ones." See `https://www.debates.org/voter-education/debate-transcripts/october-6-1996-debate-transcript/` and `https://www.debates.org/voter-education/debate-transcripts/october-16-1996-debate-transcript/` for transcripts from these debates.

[28]As usual, we show the raw relationships by NAFTA-vulnerability quartile in the Appendix. Given the importance of third-party voting in Presidential elections, especially in 1980 and in

using our preferred state-year-fixed-effects specification, by the early 2000s counties in the top quartile of vulnerability have moved in the Republican direction by roughly five percentage points (and moved away from the Democrats by a similar amount) compared to the least exposed quartile.[29] A top-quartile county that begins the early 1990s evenly split between the two major parties would be predicted to have more than a ten-percentage point GOP advantage within a few elections. In the famously close 2000 presidential election, some of the most NAFTA-vulnerable states switch from Democratic to Republican (Kentucky, Georgia, Louisiana, Arkansas, Missouri and even Al Gore's home state of Tennessee).

In the Appendix we show the analogous results for House elections, which yield similar patterns.[30]

A notable pattern for both panels of Figure 9 is the sensitivity to controlling flexibly for the 1990 college share (though the Democratic post-period coefficients remain largely statistically significant when we add this vector of controls). We will return to this point several times in the remainder of this paper. To summarize, independent of geography, those who self-report as being *against free trade* both (*i*) leave the Democratic party after NAFTA and (*ii*) are significantly less educated than those who support free trade. Thus, the 1990 county-level college share is correlated not only with NAFTA vulnerability (negatively so, see Table 1) but with county-level opinions on free trade, which as we show in the next section also predicts a turn away from the Democrats.

A limitation of any by-county analysis is that, by design, it will miss any institutional shifts precipitated by NAFTA that have nation-wide spillovers. Given the importance of unions to Democratic get-out-the-vote efforts (Feigenbaum *et al.*, 2018), scholars argue that the NAFTA fight may have caused lasting damage to the Democrats' ability to organize. "In aggressively pursuing passage of the agreement, the Clinton administration put itself in conflict with organized labor. By attacking one of the Democratic party's most important constituencies, the administration succeeded in further weakening the Democratic coalition and exacerbating the party's organizational decline" (Klinkner, 2019, p. 70).[31] As we know

1992-2000, we show results separately for both major parties when presidential vote share is the outcome. Third party voting is less common in Congressional elections, so in the Appendix we only show results for the Republican vote share in House elections.

[29]The coefficient in year 2004 is 0.75, so multiplying 0.75 by the interquartile difference in vulnerability, 0.074, yields 0.0555.

[30]One complication with House elections is that uncontested elections are not uncommon (whereas no presidential election since the early 1800s has gone uncontested). We drop such elections in our House analysis, meaning we have fewer counties in our strictly balanced sample and thus prefer the presidential-election results.

[31]As Minchin (2017) writes, NAFTA left a huge and lasting rift between the Democratic party and the labor movement: "For many in the labor movement, the resentment left by the administration's

of no data source for county-level union membership or organizing efforts during our sample period, we do not pursue union activity as either an outcome or a mechanism in this paper, but flag it as an important topic for future work.

6.3 Opinions of respondents in NAFTA-vulnerable states

Figure 9 shows that NAFTA-vulnerable counties shift away from the Democrats and toward the Republicans in the mid-1990s. While consistent with NAFTA driving this shift, the 1990s were a politically eventful period which witnessed a Democrat winning a presidential election for the first time in twelve years, the rise of ambitious Republican Congressional leaders such as Newt Gingrich and his 1994 Contract with America campaign, the continued decline of unions (key allies in Democratic get-out-the-vote efforts), and, slightly later in the decade, the growth of political media cable outlets such as C-Span and Fox News.

The first piece of evidence we provide to further our hypothesis that NAFTA played a significant role in this shift is to show that in NAFTA-vulnerable areas, NAFTA was and indeed remains unpopular. We gather surveys that (*a*) ask a generic sentiment question regarding NAFTA and (*b*) include state identifiers. Very few surveys include county identifiers and none that we know of are representative at the county level, so in this subsection we examine how *state*-level vulnerability to NAFTA predicts residents' views toward the trade agreement. Appendix B provides details on the surveys included in this sample.[32]

Table 2 documents a robust, negative relationship between the NAFTA vulnerability of the respondent's state of residence and her approval of NAFTA. Col. (1) regresses a dummy coded as one if the respondent supports NAFTA on the state-year vulnerability measure, survey (which subsumes year) fixed effects and no other controls. For now, we include and code as "zero" those who answer that they don't know or don't have an opinion. The coefficient on state-level vulnerability is negative and highly significant. For our state-level measure, the most vulnerable quartile of states have an average vulnerability of 0.04 (compared to essentially zero for the least vulnerable quartile), so the coefficient suggests support is over five percentage points lower in the most versus least vulnerable quartile. Given that only 38 percent of our respondents voice an affirmatively positive view of NAFTA,

support of NAFTA was long-lasting. Even many years later, some staffers felt that Clinton had betrayed them...'We had just managed to elect a Democratic president, Bill Clinton,' recalled [AFL-CIO economist] Mark Anderson. 'The lousy son of a bitch.' Anderson felt 'terrible' after the NAFTA vote, which he viewed as 'hugely personal' (pp. 203-204)."

[32] About half are from Pew, though we also include CNN/Gallup, CBS/NYT and Newsweek. Many other surveys (ABC and NBC for example) do not consistently include state identifiers in their public-use files, limiting their usefulness for this exercise. Most of these surveys are free to use via iPoll or ICPSR.

our estimate suggests support is 14 percent lower in the top versus bottom quartile.

Columns (2) and (3) show that the results are unchanged after adding controls for race, sex, education, income, age and union status. These controls themselves have highly significant effects and serve to absorb some variation and thus in fact shrink the standard error on the coefficient of interest. Note that even conditional on these other controls, lacking a college degree has a significant negative association with NAFTA support. Recall that adding education controls attenuated the effect of NAFTA vulnerability in Figure 9; these regressions suggest that education is proxying for protectionist or anti-NAFTA sentiment.

In col. (4) we add nine Census-division fixed effects, which in fact increases the magnitude of our coefficient of interest. While not as granular as our county-level analysis, the result in col. (4) suggests that individual-level opposition to NAFTA reflects the vulnerability of state of residence, not simply broader regional differences. The final column shows robustness to dropping those without a stated opinion on NAFTA.

In this section we have documented a remarkable shift in voting patterns in NAFTA-vulnerable counties: while they are the most reliably Democratic in terms of Presidential and House elections from 1980-1990, beginning in the mid-1990s they begin a long shift in the GOP direction. Consistent with NAFTA driving this effect, survey respondents in states more vulnerable to NAFTA oppose it more than respondents in other states.

7 The political response among individuals averse to free trade

Much of the existing literature on the political reaction to trade policy estimates, as we do in Section 6.2, ecological regressions at the geographic level, with the implicit assumption that the areas most affected by trade deals would exhibit the greatest shifts in political outcomes. In this final section of empirical analysis, we focus on individuals' self-reported views toward free trade and test whether those who report more protectionist sentiment shift away from the Democrats around the time of NAFTA's passage.

7.1 Evidence from repeated cross-sectional data

7.1.1 Data and empirical approach

In this section, we make heavy use of the ANES. Since 1986 it has asked in most of its surveys a question capturing general protectionist sentiment. In almost all years, the question reads as follows: "Some people have suggested placing new limits on foreign imports in order to protect American jobs. Others say that such limits would raise consumer prices and hurt American exports. Do you favor or oppose placing new limits on imports, or haven't you thought much about this?" We create a *Favor import limits* dummy variable, coded as one if you agree with placing new limits on imports and zero for all others. We will sometimes describe individuals coded as "one" for this dummy variable as having "protectionist views" or being "protectionist."[33] In all years, the ANES asks partisan ID, a scale variable from 1-7, increasing in support for the GOP, which we use to measure partisan identity. We provide information on the ANES repeated cross-sectional data in the Data Appendix.

We take two approaches in this section. We begin by estimating the following equation, separately by each year t in our sample period:

$$\textit{Partisan scale}_i = \beta_t \textit{Favor import limits}_i + \gamma \mathbb{X}_i + e_i. \tag{5}$$

We then plot the resulting β_t coefficients over time. Note that estimating this equation separately for each year t in our sample period allows the coefficients on the control variables to be unrestricted across years.

We then collapse our sample period into a pre- and post-period, in a differences-in-differences (DD) analysis:

$$\textit{Partisan scale}_{it} = \beta^{DD} \textit{Favor limits}_i \times \textit{After 1992} + \beta^{main} \textit{Favor limits}_i + \gamma \mathbb{X}_{it} + \mu_t + e_{it}, \tag{6}$$

where the β^{DD} is the coefficient on the variable of interest, $\textit{Favor import limits}_i \times \textit{After 1992}$, β^{main} captures how protectionist views predicted party identify *before* NAFTA, and the μ_t term is a vector of year fixed effects. This more parametric equation helps facilitate sub-sample analysis in a more succinct manner.

7.1.2 Main results

We show the results of estimating the event-study equation (5) in Figure 10. The first series shows the coefficient estimates from an equation with no controls (an empty vector $\mathbb{X}_i$), so the plotted points are just raw differences between protectionist versus other voters. We see that pre-NAFTA, those with protectionist views were *less* supportive of the GOP. Sometime between 1992 and 1996 (the favor-import-limits question is not asked in 1994) a significant number of protectionist voters moved toward the GOP, so that the raw difference disappears. In the second series, we add standard demographic and socioeconomic controls: race, sex, age, education, and income. The same 1992-1996 shift toward the GOP among protectionist voters remains, even after allowing these characteristics to have their own effect each year.

[33] Note that the ANES cumulative file codes as missing anyone who says they do not know enough about NAFTA or otherwise do not have an opinion. We thus use the individual survey files, which preserve this detail.

Recall, again, from Section 6 that controlling flexibly for the county's 1990 share of college graduates muted our event-study results. These results help explain why. This graph shows that, even conditional on individual-level, time-varying controls for education, individuals with protectionist views turn away from the Democrats between 1992 and 1996. Moreover, there is a strong, negative correlation between education and protectionist views (which we already saw in Table 2 on the question of NAFTA; see Appendix Table A.1 for evidence of this correlation regarding free trade more generally). As protectionist views are stronger in NAFTA-vulnerable areas (as we show in Table 2), our education controls in Figure 9 are likely picking up the (unobserved) anti-trade sentiment. But in this micro-data analysis, when we can in fact observe individual-level protectionist sentiment, controlling flexibly for education does not help explain any of the post-NAFTA negative effect of protectionist sentiment on Democratic partisan identity.

In the third series, we add controls for trust in the federal government, views (a "thermometer" going from cold to warm) toward African Americans (given the importance of race in U.S. politics), views on abortion, and weekly religious attendance. We choose these controls in particular because they are asked in all or most years of our sample period. The pattern of protectionist voters shifting in the GOP direction after 1992 holds. In the final series, we add a control for views toward immigration levels, which is not asked in the ANES in 1986 or 1988. For the years it is available, controlling for this variable separately by survey year yields coefficients almost identical to those in the third series.

Table 3 shows estimates of the differences-in-differences equation. Col. (1) has no additional controls beyond year fixed effects. Consistent with Figure 10, the coefficient on the main effect of *Favors import limits* suggests that from 1986 to 1992, protectionist views pushed against identifying as a Republican. The coefficient on the interaction term is positive and statistically significant, essentially erasing the pre-period effect. To give a sense of its practical significance, the shift is over one-half the size of the partisan gender gap (as estimated in our sample), a key divide in U.S. politics.

Col. (2) adds state fixed effects, which we add with the caveat that the ANES warns users it is not representative at the state level. Col. (3) drops state fixed effects and adds instead the same demographic controls in the second series of Figure 10. We do not report the coefficients to save space, but they are of the expected sign. Note that they indeed add significant explanatory power to the estimation (the R-squared values jumps up by ten percentage points), but if anything they only increase the magnitude on the coefficient of interest. A similar dynamic occurs in col. (4), when we add to the col. (3) specification the controls for other political and social issues included in the third series of Figure 10.[34]

[34]Note that we do not add views toward immigration, the extra control in the fourth series of

Col. (5) replicates col. (4) after dropping all observations that respond "don't know" to the *Favor import limits* question.

In column (6), we add *After 1992* interactions with all the controls in cols. (3) and (4), so that these variables, like our protectionist dummy, can have different effects before and after NAFTA. Adding these controls in cols. (3) and (4) significantly increased the R-squared value, consistent with their having large explanatory power *in the cross-section*, but they add only minimal explanatory power in col. (5), suggesting they have limited explanatory power *over changes*. Put differently, those who, say, oppose abortion or distrust government are for the most part already Republican by 1992.[35]

7.1.3 Heterogeneity

As noted earlier, Minchin (2012) and others have argued that for many white Democrats in the 1980s, economic issues such as trade policy were key to their party loyalty because on social issues such as guns, affirmative action and abortion they sided with the GOP. We thus hypothesize that for these voters, the response to NAFTA will be stronger. For, say, a Black voter opposed to NAFTA but who is also strongly pro-choice and suspicious of Republicans on Civil Rights, the Democrats' position on free trade would be just one of many issues that binds them to the party.

To test this idea, we examine our results in a series of splits that create mutually exclusive and exhaustive subsamples. For each subsample, we estimate the specification in col. (4) of Table 3. While we cannot examine each of the issues highlighted by past work, we try to proxy many of them with questions in the ANES.

First, we examine our results by race, estimating the col. (4) specification separately for whites and all others, and plotting the resulting coefficients and 95% confidence intervals in Figure 11. As the large majority group, the point-estimate for whites is close to that of the full sample, depicted by the vertical line in the graph. But that for non-whites is much smaller in magnitude, with a (wide) confidence interval that includes zero.

We have already noted the large gender gap in modern U.S. politics, and beginning with the women's liberation movement in the 1960s and 1970s, the Democratic party has highlighted more than Republicans issues of gender equality. We thus hypothesize that white *men* might feel especially at home with the GOP on cultural issues. Indeed, when we split

the figure, as it is missing for most of the pre-NAFTA period.

[35]Readers may wonder why we have not yet examined support for Ross Perot, given his importance in the anti-NAFTA movement. As he only ran in the 1992 and 1996 presidential races, focusing on him would limit the sample period relative to using party identification. But Appendix Table A.2 indeed shows that, in both years, approval of Perot is significantly higher among protectionist voters.

the sample into white men versus all others, the former group exhibits a substantially larger shift toward the GOP among protectionist voters. A similar result holds among whites without a college degree versus all other respondents.

We next show that the protectionist response is substantially larger in the South than elsewhere, perhaps because the South has more conservative social views or because the South was more vulnerable to NAFTA. While splitting further by race results in very small samples, we do indeed find (though do not report) that the effect is driven among whites in the South, even though whites and non-whites in our sample have similar views on free trade, in the South and elsewhere. But non-white, protectionist voters in the South are less responsive, consistent with many other issues binding them to the Democrats.

The final cuts we examine are along two key cultural markers: opposition to abortion and weekly church attendance. Both of these splits of the data reveal large differences in the responsiveness of protectionist voters after 1992. Among respondents who do not oppose abortion or do not attend church weekly, the "protectionist response" that we propose still exists and pushes in the hypothesized direction, but is much smaller and not always distinguishable from zero.

We conclude from the analysis of repeated cross-sectional data that between 1992 and 1996, voters with protectionist views exhibited a significant shift rightward. As hypothesized by historians, this shift was especially pronounced among individuals who already shared cultural positions with the GOP (at least to the extent we can measure them in our data, namely abortion and religious attendance) and in the South.

7.2 Evidence from panel data

There are at least two limitations to the repeated cross-sectional analysis. First, views on trade could be endogenous to party identification, whereas our analysis in Figure 10 and Table 3 implicitly assumes that views on trade cause changes in party identification. NAFTA signaled that key Democratic leaders were taking a new position on trade, and thus some Democratic voters may change their views on trade to limit cognitive dissonance. Second, while the analysis in the previous subsection controls for respondent views on some key issues besides free trade, we are limited in that we need those issues to be asked in most surveys in our sample period. For this reason, we turn to a 1992-1994 panel dataset that follow the same voters across time (so we can model any partisan shift as a function of pre-NAFTA trade views) and ask a number of question about other salient political issues of the early 1990s.

7.2.1 Data and empirical approach

The ANES generally fields repeated cross-sectional surveys, but on occasion they run panel studies as well. We are fortunate that once such time is in 1992. That year, they designate roughly 1,000 respondents for a follow-up survey two years later; about 750 in fact take the follow-up survey in 1994. We use the weights provided by the ANES to adjust for attrition.

We use the same "do you favor imports question" in 1992 that we use in the repeated-cross-section analysis earlier in this section.[36] We model changes in partisan identification between 1992 and 1994 (recall, NAFTA is passed in late 1993) as a function of 1992 views toward free trade:

$$Moved\,Right_{i,94\text{-}92} = \beta Favor\ Import\ Limits_{i,92} + \gamma \mathbb{X}_{i,92} + e_i, \tag{7}$$

where $Moved\,Right_{i,94\text{-}92}$ is a dummy for having moved toward the GOP on the seven-point scale and all other variables are defined as before.

As noted, a key advantage to this analysis is that we only need to observe control variables in 1992, not in all sample years, as we are zooming in on 1992-1994. We can thus control for a richer set of control variables, including the "hot button" issues of the early- and mid-1990s (e.g., gays in the military, the "small-government" initiatives of Newt Gingrich's Contract with America, and health reform). Views toward free trade are captured in 1992, *before* the emotional battle within the Democratic party over NAFTA. Thus, we can address the earlier concern with the cross-sectional data that party identification is causing respondents to change their views on trade instead of (as we hypothesize) views on trade causing changes in party identification.

7.2.2 Main results

Table 4 shows the results from estimating variants of equation (7). Note that we multiply the outcome variable by 100, so the reported mean of the dependent variable indicates that about 26 percent of individuals moved in the GOP direction on the seven-point partisan scale (consistent with the poor showing of Democrats in the 1994 midterm election). Col. (1) shows the results with no controls, and suggests that those with protectionist views had an eight percentage-point higher likelihood of shifting rightward. This effect increases in magnitude when we drop those without an opinion (col. 2).

Col. (3) adds to the col. (1) specification standard demographic controls, which have a negligible effect on the coefficient of interest. Recall, from the repeated-cross-section analysis

[36]The question is not asked in 1994 (neither in the 1994 follow-up survey nor in the standard ANES 1994 cross-section survey).

in Table 3, that these variables had important predictive power *in the cross-section* but not in explaining *changes* between 1992 and 1996. Consistent with that earlier result, adding these variables in an effort to explain changes between 1992 and 1994 increases the R-squared only modestly. In col. (4) we add some standard political control variables. The coefficients on views toward the government helping Blacks, demand for a generally active government, abortion rights and immigration are all close to zero. Again, these views have strong predictive power in any given year, but by 1992, most people who are, say, opposed to affirmative action are already Republican, so these controls will have little ability to explain *changes* from 1992 to 1994.[37]

A nice feature of the panel analysis is that we can control for key issues of the day in 1992, which may not have stood the test of time in order to be asked repeatedly in the ANES but which could correlate with views on trade. In the final column, we control for views about gays in the military and health reform (two controversial policies during Clinton's first term) and Congressional term limits (a key item on the Contract with America developed in 1993 by Newt Gingrich, the soon-to-be Speaker of the House). Interestingly, none of these issues have a significant effect, despite their attention in the media. In the final column, we add state fixed effects (although the ANES warns that its samples are not representative at the state level). Results are unchanged.

We can replicate this analysis using a 1993 question on support for NAFTA *per se*, instead of our 1992 question on protectionist sentiment. Two issues arise. First, the sample becomes smaller. Second, as the question is asked in the fall of 1993 (the peak of the debate over NAFTA as the vote in Congress neared) it is also much more likely to be endogenous to party identity than our 1992 measure. Nonetheless, in Appendix Table A.3 we find very similar results in terms of magnitude, though less precisely estimated.

7.2.3 Heterogeneity

Our final empirical exercise of the paper, Figure 12, examines heterogeneity in the 1992-1994 response of protectionist respondents that we documented in Table 4. We begin with the same cuts of the data we examined in our heterogeneity analysis of the repeated cross-sectional data in Figure 11, finding the same results directionally. We also split the sample by responses to questions in the panel survey specific to the 1992 political environment and

[37] An important and interesting exception is weekly religious attendance, which has a coefficient nearly equal to that on protectionist views. The inclusion of this variable has little effect on our coefficient of interest because the two are nearly perfectly uncorrelated ($\rho = -0.0099$). Thus, the religious represent a distinct group moving toward the GOP around the same time, an important reminder that NAFTA is not the only issue triggering potential political realignment during this moment and an interesting topic for future work.

find large gaps in how protectionist respondents shift their partisan identity. Protectionist respondents who oppose affirmative action and especially those who oppose gays openly serving in the military are especially likely to move toward the GOP.

8 Conclusion

In this paper, we provide evidence that NAFTA substantially reduced employment in counties most exposed to Mexican important competition, and that these areas (as well as voters opposed to free trade, regardless of geographic residence) turned away from the Democratic party as a result.

The movement of working-class whites away from the Democratic party is one of the most debated topics in U.S. politics. As Piketty (2020) documents, it is part of a larger trend in the rich democracies, as less-educated voters have abandoned the traditional center-left parties in Europe. The 2016 election of Donald Trump in the US, the successful Brexit campaign in the UK and the rise of right-wing populist parties in Europe have prompted a recent debate about whether these events are best explained by "economic dislocation" or "ethnocentrism."

The results in this paper point to an interactive effect between economic dislocation and ethnocentrism or other aspects of social conservatism, at least during the NAFTA era. The trigger for this movement toward the right was indeed an economic one—a trade deal that increased import competition for many low-wage domestic industries, which had been opposed by labor unions and less educated voters. But the movement appeared to manifest most significantly among those voters who already had conservative views on many social issues.

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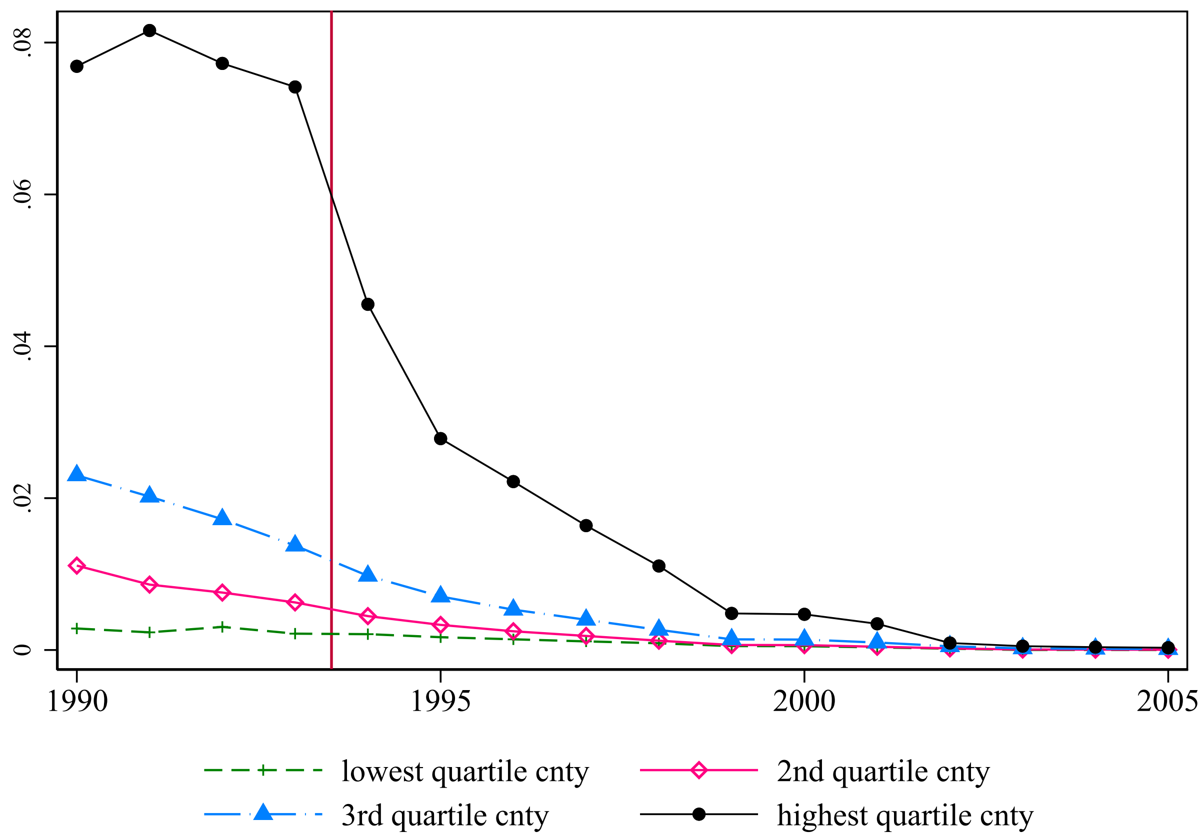
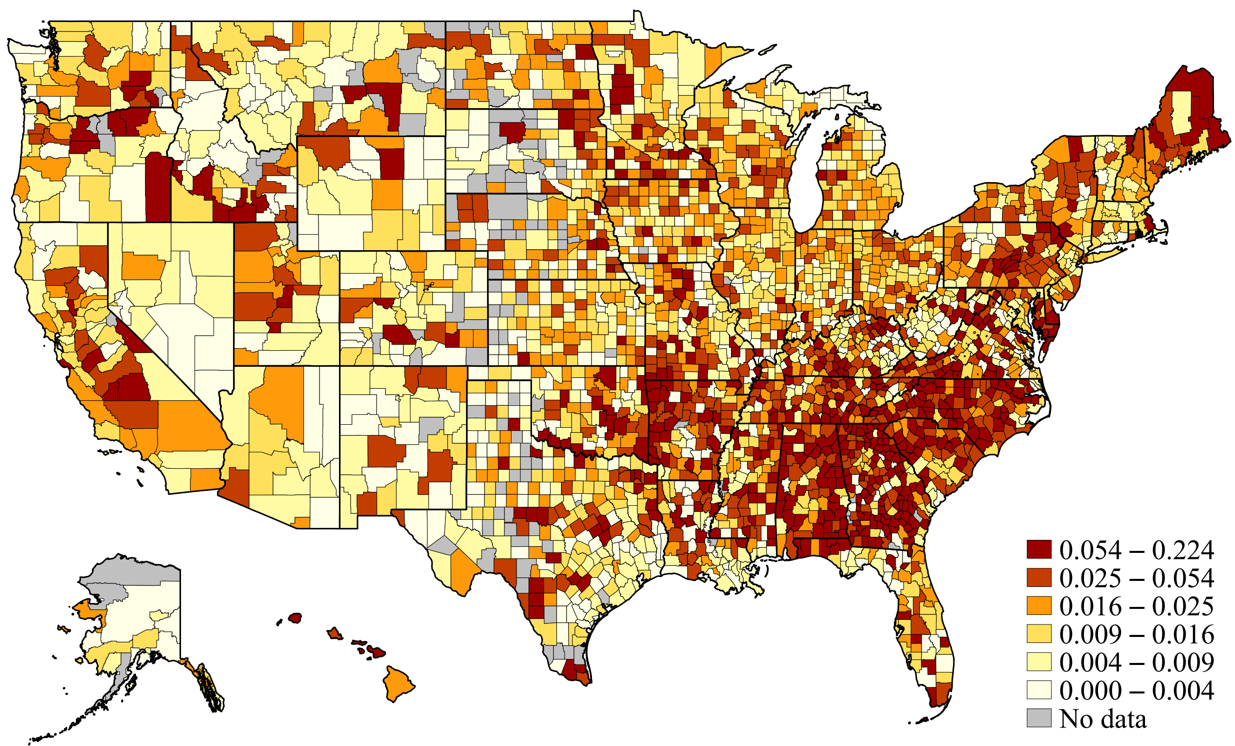
Figure 1: Protection across time, by 1990 NAFTA vulnerability quartiles



Sources: The vulnerability measure is constructed using three data sources: Ad-valorem equivalent tariffs from Feenstra *et al.* (2002) and USITC annual tariff data; export series from the UN Comtrade bilateral export series and Hakobyan and McLaren (2016b); and annual county employment by industry from County Business Patterns.

Notes: The figure shows the weighted average tariff protection across time by each quartile of 1990 county-level vulnerability. That is, for each county-year, we take baseline (1990) county employment by industry and multiply by Mexico's revealed comparative advantage (RCA) for that industry (in 1990) scaled by τ^t, the U.S. tariff on Mexican goods in that industry in year t. Note that the values of the series in 1990 are in fact the 1990-based county-level *Vulnerability* variable we use in much of the paper, as they use 1990-level tariffs τ^{1990}. See Section 2.2 for more detail on constructing this measure.

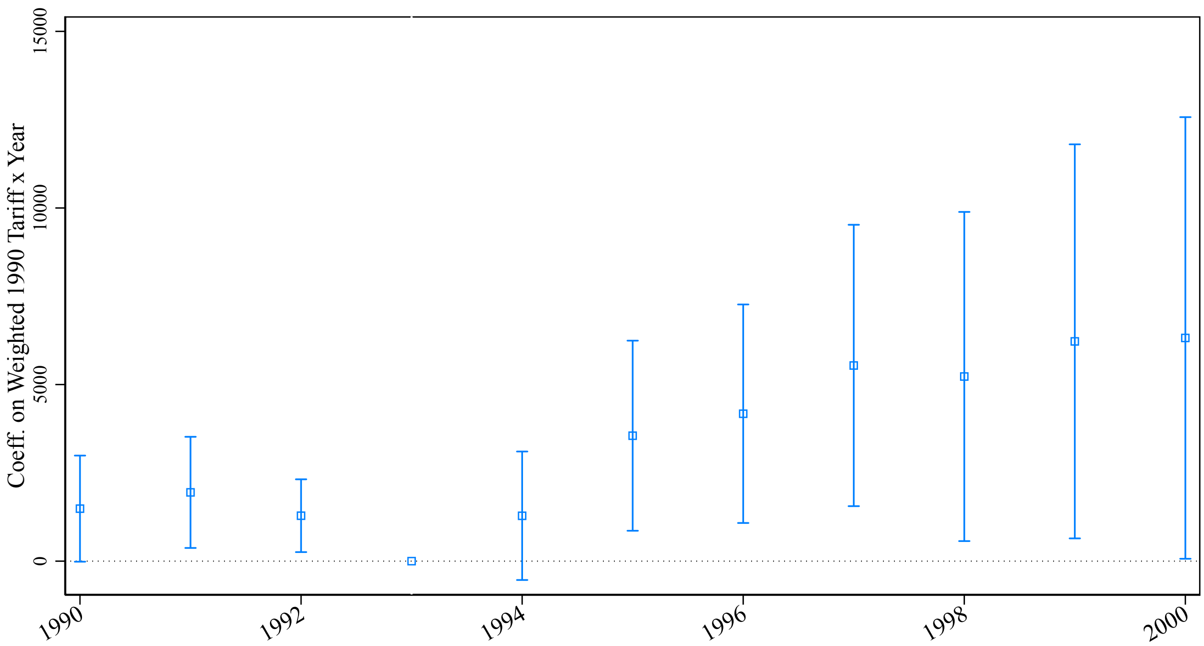
Figure 2: NAFTA vulnerability across counties



Sources: The vulnerability measure is constructed using three data sources: Ad-valorem equivalent tariffs from Feenstra *et al.* (2002); export series from the UN Comtrade bilateral export series and Hakobyan and McLaren (2016b); and annual county employment by industry from County Business Patterns.

Notes: The map graphs the geographic variation in our county-level *Vulnerability* measure. County-level vulnerability is calculated by taking the county's 1990 employment shares by industry and multiplying by Mexico's revealed comparative advantage (RCA) for that industry (in 1990) scaled by τ^{1990}, the U.S. tariff on Mexican goods in that industry in 1990. See Section 2.2 for more detail on constructing this measure.

Figure 3: Relationship between Mexican imports to the US and pre-NAFTA tariffs



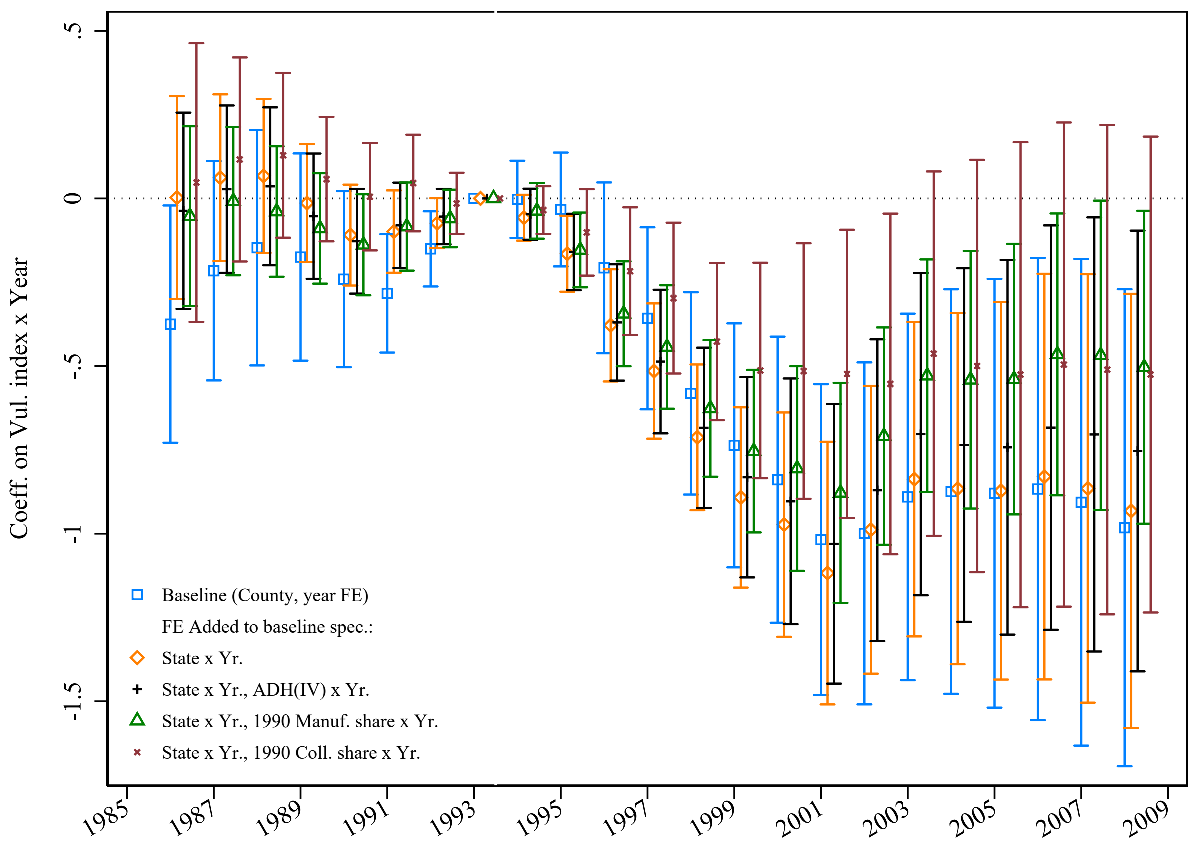
Sources: U.S. International Trade Commission

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.

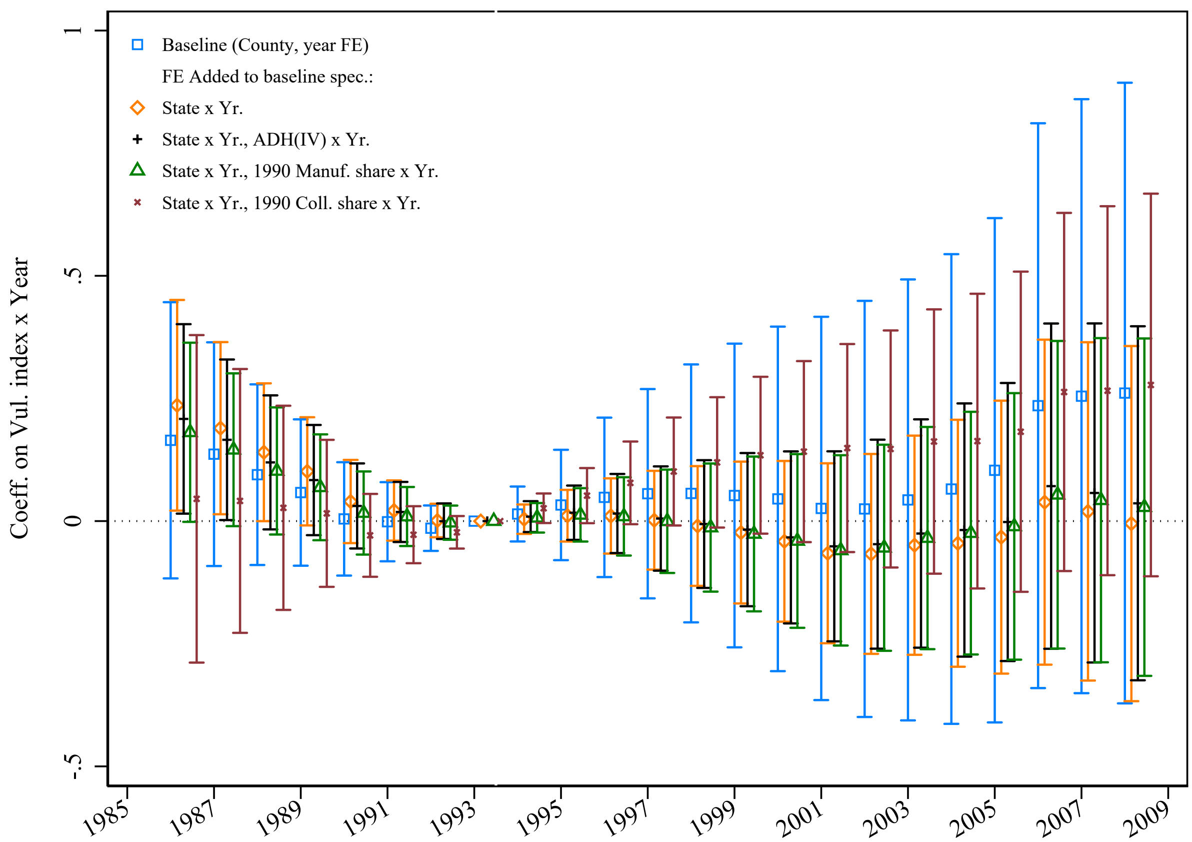
Figure 4: Log employment as a function of county NAFTA vulnerability



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 2924 counties in each year of the sample. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (3), where log of total employment at the county×year level is the dependent variable. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification *state*×*year* fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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.

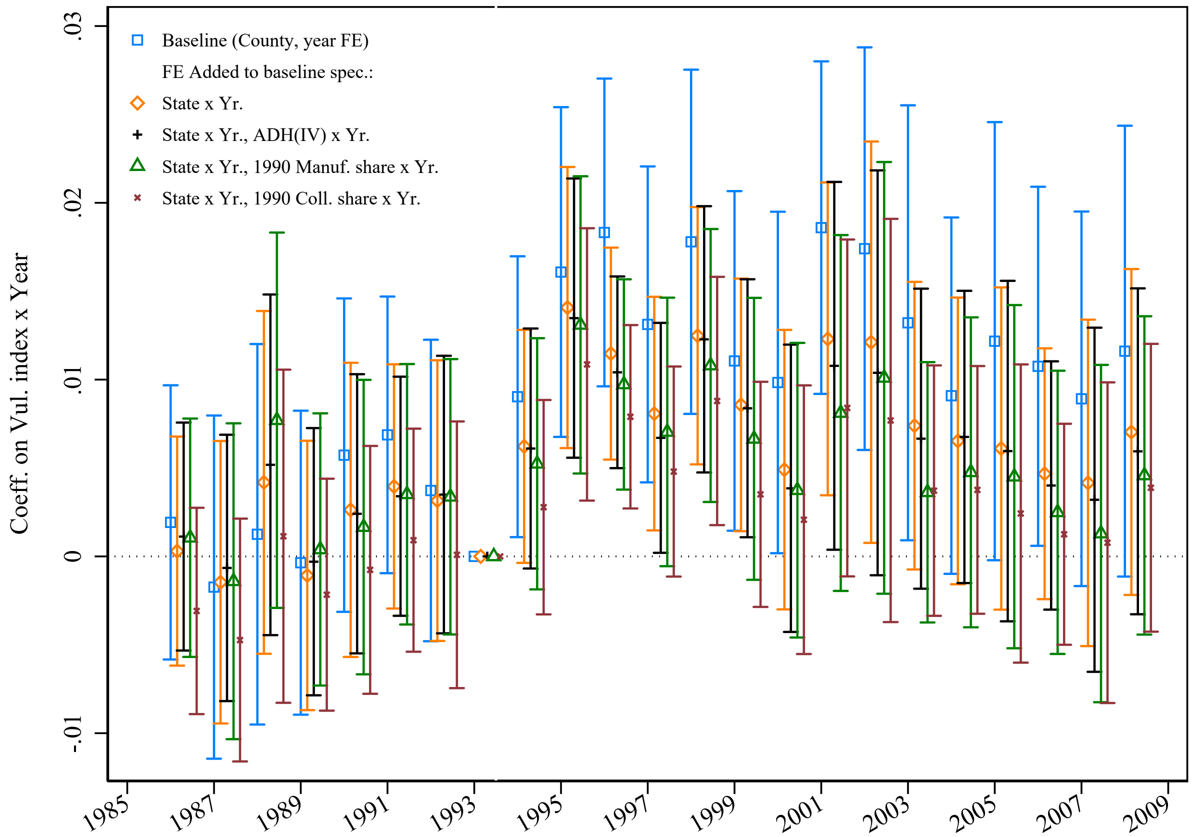
Figure 5: Log population as a function of county NAFTA vulnerability



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

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2924 counties in each year of the sample. This figure is identical to Figure 4 but with log of population as the outcome 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 (3), where log of total population at the county×year level is the dependent variable. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification *state*×*year* fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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.

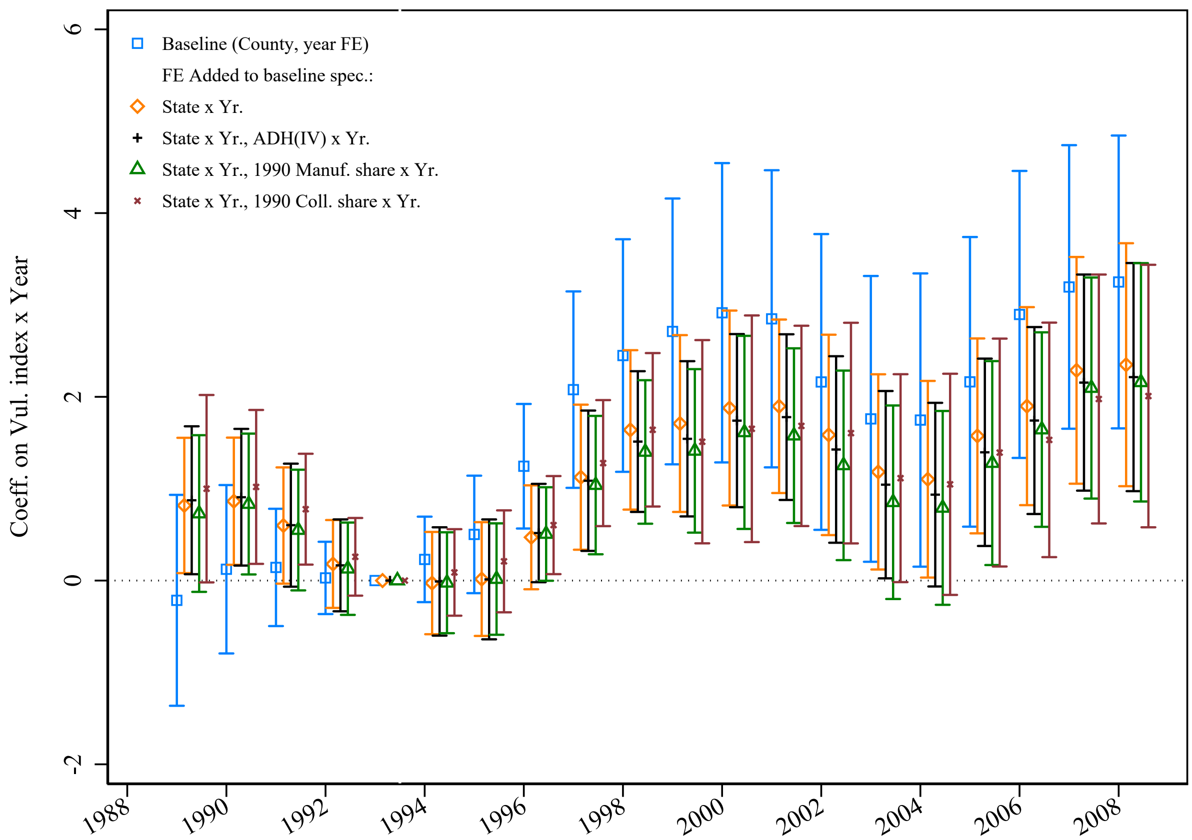
Figure 6: Trade Adjustment Assistance petitions per capita as a function of county NAFTA vulnerability



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 2914 counties in each year of the sample. This figure is similar to Figure 4 except for the outcome variable. Instead of log employment we use TAA petitions at the county-year level divided by the working-age population. Because this variable has many zeros we do not use logs. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (3). All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification $state \times year$ fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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.

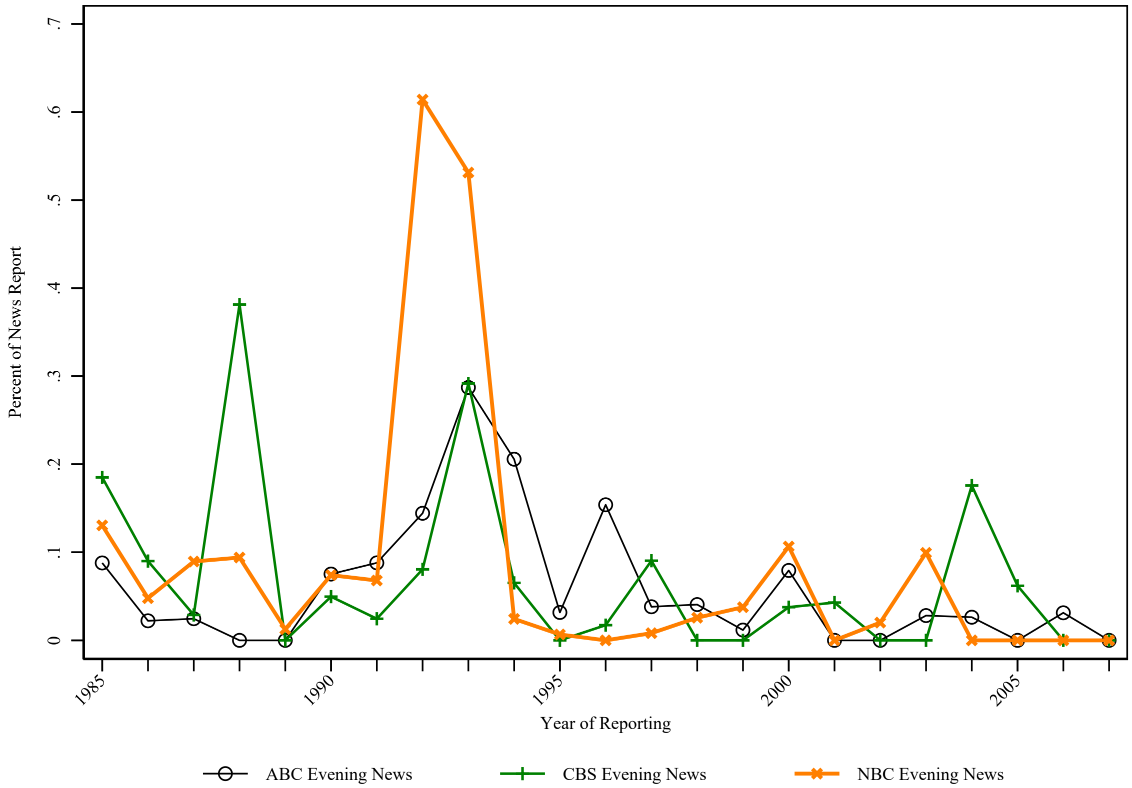
Figure 7: Log of DI applications as a function of county NAFTA vulnerability



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 762 counties in each year of the sample. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (3), where log of Disability Insurance (DI) applications is the dependent variable. As discussed in Section 5.3, we do not have all counties in this analysis, but the 762 counties we have in this balanced-panel analysis account for around three-fourths of the U.S. population. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification *state*×*year* fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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. Appendix Figure A.16 shows the same analysis for final awards of DI.

Figure 8: Coverage of trade-and-jobs related stories by network nightly news programs

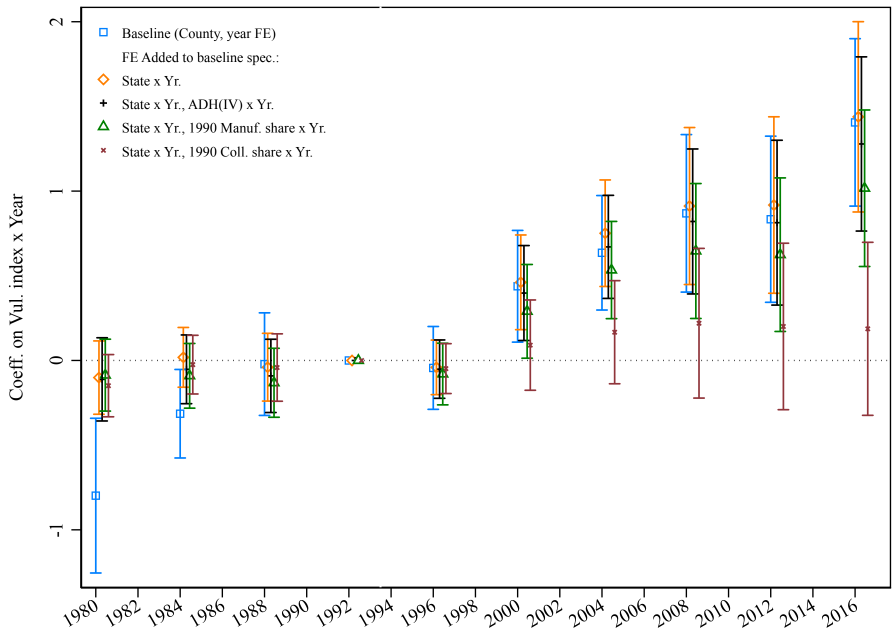


Sources: Data come from searching The Vanderbilt Television News Archive: `https://tvnews.vanderbilt.edu/search`. See Appendix B.10 for more detail.

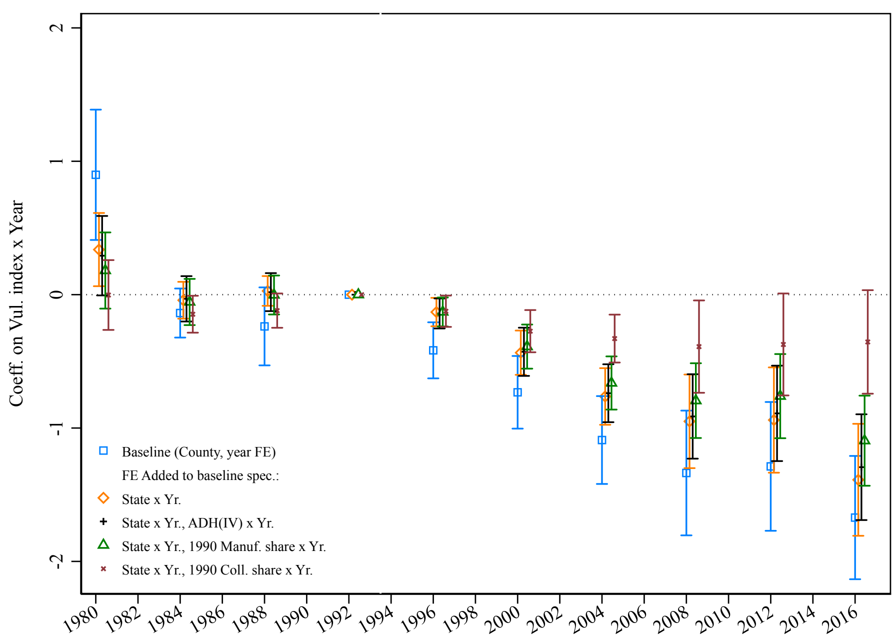
Notes: For each year and network, we calculate the share of minutes on the nightly news dedicated to stories that include variants (plurals, capitalizations) the following words: "trade" and "imports" and "jobs" *or* "employment." We exclude any stories (in all years) that include the phrase "trade center"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

Figure 9: Presidential election vote shares as a function of county vulnerability

(a) Republican share of county votes

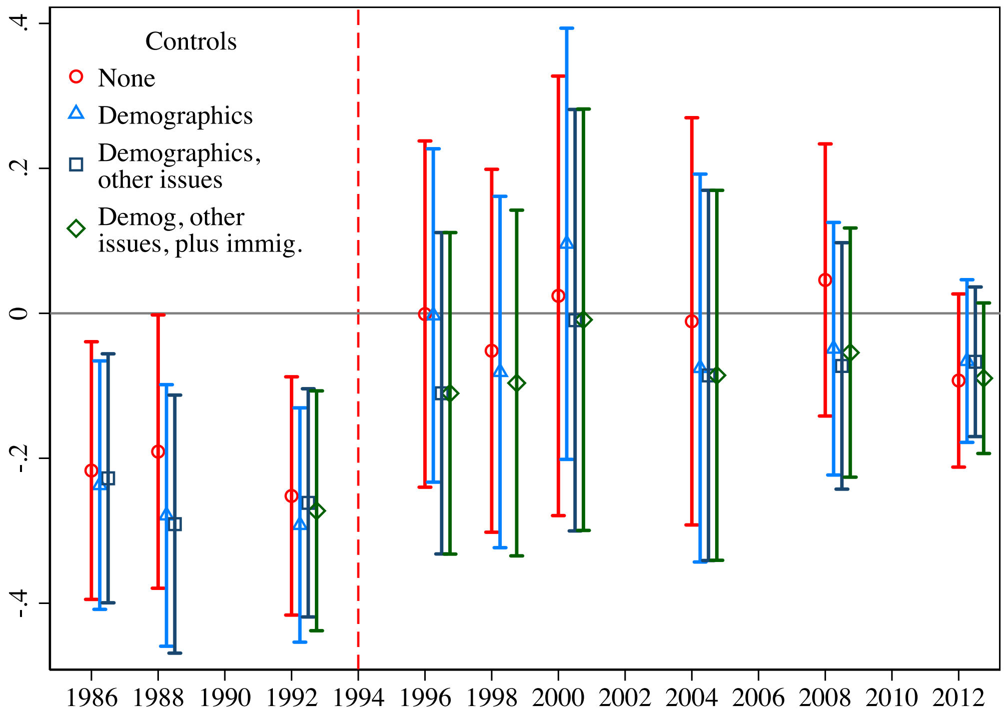


(b) Democratic share of county votes



Sources: The dependent variable is taken from ICPSR general voting data and Dave Leip's Atlas of U.S. Election data. *Notes*: $N = 2880$ counties. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (3), where the Republican (a) or Democratic (b) vote share in presidential elections is the dependent variable. It follows Figure 4 though obviously cannot be analyzed annually because elections fall only on every four years. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification $state \times year$ fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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.

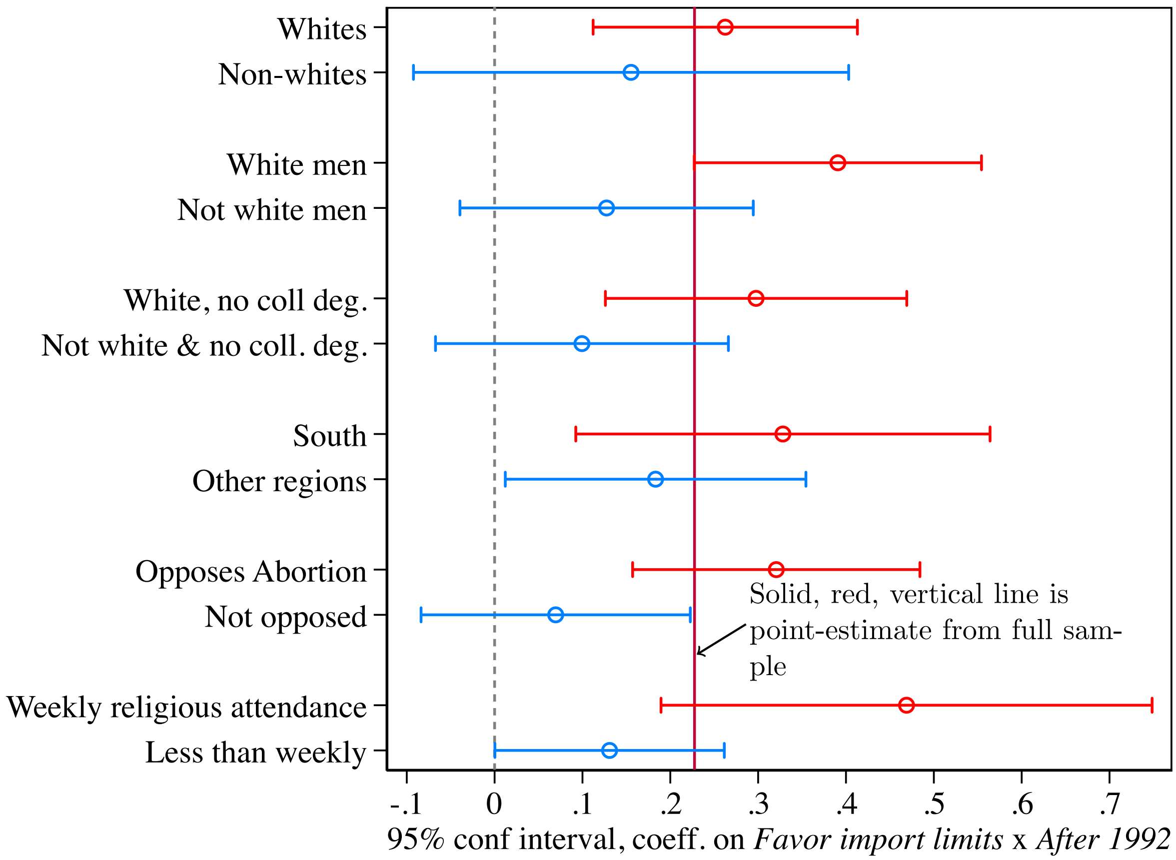
Figure 10: Party identification (increasing in Republican direction) as a function of views toward trade



Sources: ANES repeated cross-sectional data. See Appendix B.13 for more detail.

Notes: Separately for each year in our sample period, we regress the party-ID scale (a 1-7 categorical variable, increasing in allegiance to the GOP) on the *Favor Import Limits*$_i$ dummy variable (coded as one if the respondent says that they support additional limits on imports and zero otherwise). The first series includes no other controls, so is equivalent to raw differences. In the second series, we control for gender, age, race, education, and family income. In the third series, we add controls for views on other political and social issues, namely: abortion, trust in government, views toward Blacks and views toward welfare recipients (note that not all of these variables are available in 1998, so the third series is missing that year). The fourth series adds to the third series a control for wanting immigration to increase (this question is not asked in 1986 and 1988). Note that the analysis underlying the second through fourth series always estimates regressions separately by year, so the coefficients on the controls are unrestricted across years. We plot 95-percent confidence intervals based on standard errors adjusted for clustering by state.

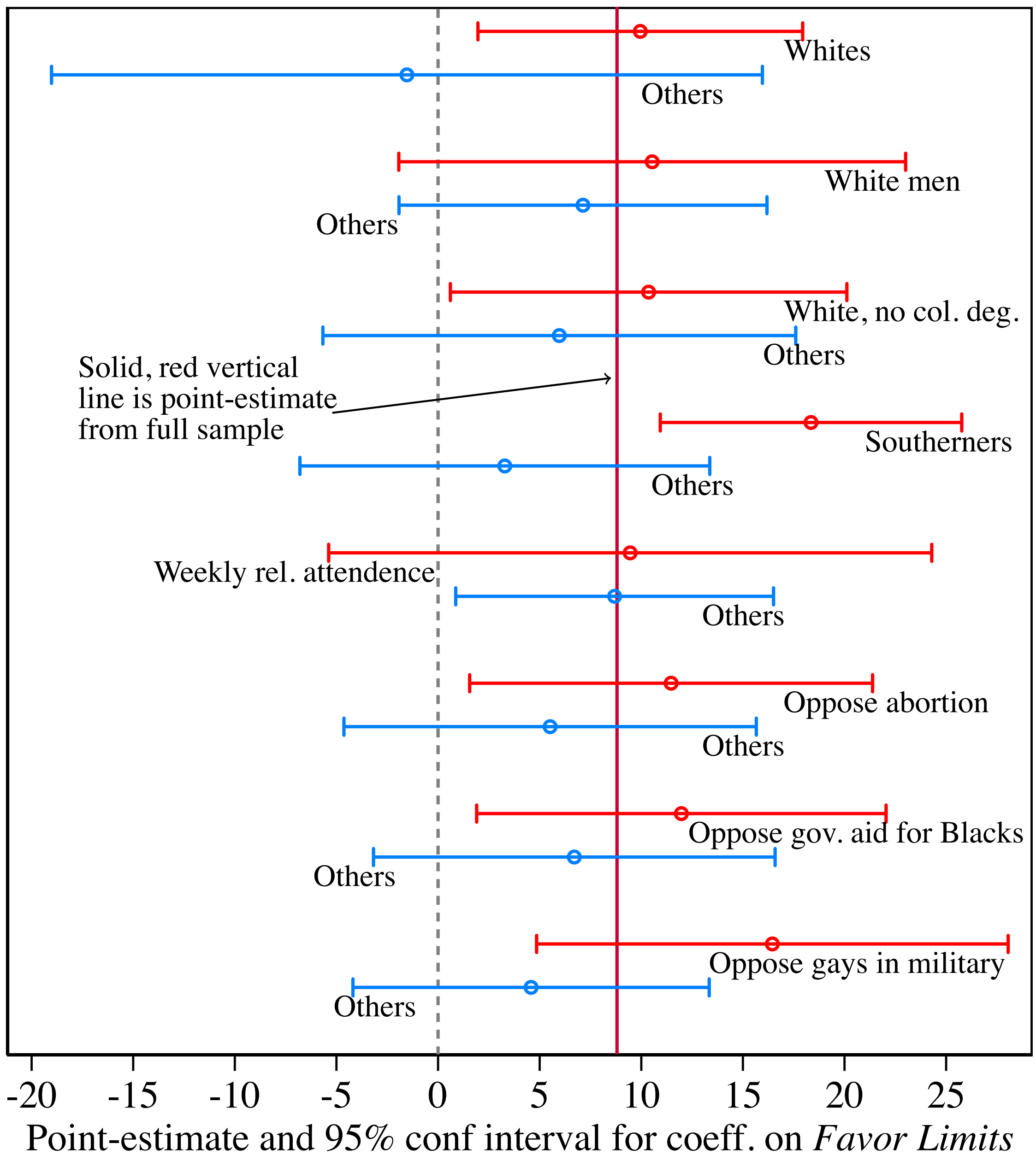
Figure 11: Heterogeneity in the shift toward GOP after 1992 among protectionist respondents



Sources: ANES repeated cross-sectional data, 1986-2012.

Notes: We estimate, for mutually exhaustive and distinct subgroups of the sample, equation (5) from the text: $Party\ ID_{it} = \beta^{DD} Favor\ limits_i \times After\ 1992_t + \beta^{main} Favor\ limits_i + \gamma \mathbb{X}_{it} + \mu_t + e_{it}$. *Party ID* is a 1–7 scale variable increasing in Republican-party identification. We use the same control vector $\mathbf{X}_{it}$ as in col. (4) of Table 3, namely demographic and political-issue controls. We report the coefficient and 95% confidence interval from the estimate of β^{DD}.

Figure 12: 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.

Table 1: Pre-NAFTA characteristics of counties, by vulnerability quartile

	Quartile (lower quartile : less vulnerable)			
	1	2	3	4
Demographics (1990)				
Population (in thousands)	35.388	139.239	103.993	48.041
Working-age population (in thousands)	22.825	92.521	68.441	31.120
Household income (in thousands)	23.439	26.262	24.591	22.121
Number of jobs (in thousands)	10.707	57.021	39.476	14.638
Emp-to-Pop ratio	0.353	0.434	0.428	0.403
White share of population	0.907	0.905	0.904	0.845
Manufacturing share of employment	0.085	0.132	0.135	0.175
College-grad share of population	0.132	0.158	0.139	0.113
Political preference (1980-1990)				
Republican House two-party vote share	0.461	0.475	0.479	0.387
Republican Presidential vote share	0.568	0.569	0.573	0.554
Democratic Presidential vote share	0.394	0.392	0.391	0.420
DI and TAA takeup per thousand (1990)				
TAA petition	0.356	0.768	0.874	1.076
TAA certification	0.152	0.437	0.347	0.831
DI application	12.242	9.133	9.837	13.083
DI awards	4.777	3.699	4.012	5.162
NAFTA vulnerability				
Vulnerability based on tariff in 1990	0.003	0.011	0.023	0.077
Exposure to Chinese imports				
ADH (2013) China shock measure (IV)	0.756	0.912	1.064	1.596
Number of counties	757	756	755	755

Sources: County-level demographics are from the Census Population Estimates Program (PEP), House election results are from ICPSR general election data for the United States (1980-1988), pre-NAFTA DI and TAA takeup are computed using the Social Security Administration (SSA) data and the U.S. Department of Labor TAA petition data, and the "China Shock" variable is from Autor *et al.* (2013a) .

Notes: The table contains average county characteristics by quartiles of the *Vulnerability* variable, a county-level variable that is increasing in vulnerability to NAFTA. See Section 2.2 for details on its construction. The first panel shows demographic differences among these four county groups. Note that employment-to-population ratio comes from dividing employment in the county (from the CBPD) by population in the county (from the Census) and thus cannot be compared to the usual employment-to-population ratios based on whether residents are employed. The second panel documents political differences as captured by House elections. The third panel shows how the TAA and DI petitions and awards differ by the four county groups.The final panel shows how the "China shock" in Autor *et al.* (2013a) varies across our four groups (we use their "IV" version as it is more highly correlated with our NAFTA vulnerability measure.

Table 2: Approval of NAFTA as a function of state-level NAFTA vulnerability

	Dept. var: Supports NAFTA				
	(1)	(2)	(3)	(4)	(5)
State-level vulnerability	-1.368**	-1.532**	-1.510***	-1.703***	-2.910***
	[0.583]	[0.620]	[0.499]	[0.490]	[0.619]
White			-0.0290**	-0.0206*	-0.0201
			[0.0111]	[0.0111]	[0.0157]
Black			-0.0130	-0.00507	0.0121
			[0.0144]	[0.0140]	[0.0165]
Male			0.0138*	0.0138*	-0.0587***
			[0.00785]	[0.00799]	[0.00857]
No college degree			-0.0696***	-0.0682***	-0.0619***
			[0.00831]	[0.00811]	[0.0114]
Log family income			0.0322***	0.0307***	0.0149*
			[0.00727]	[0.00706]	[0.00753]
Union household			-0.0817***	-0.0758***	-0.104***
			[0.0126]	[0.0120]	[0.0129]
Age / 100			-0.374***	-0.375***	-0.429***
			[0.0255]	[0.0250]	[0.0292]
Dept. var. mean	0.381	0.415	0.415	0.415	0.538
Drop if missing covars	No	Yes	Yes	Yes	Yes
Division FE	No	No	No	Yes	Yes
Drop DK / no opinion	No	No	No	No	Yes
Observations	23297	16143	16143	16143	12431

Sources: Opinion polls from 1993-2015, many of which are from Pew. See Appendix B.12 for survey dates, exact question wording, and other details.

Notes: Survey (which subsume year) fixed effects in all regressions. Col. (1) includes no other controls. Col. (2) replicates the col. (1) specification but on the subsample that has no missing values for the covariates used in subsequent columns. Col. (3) adds the covariates reported in the table. Col. (4) adds Census-division fixed effects. Col. (5) drops respondents who say they do not know enough about NAFTA or do not have an opinion. Standard errors clustered by state.
$^{*}p = 0.1,^{**}p = 0.05,^{***}p = 0.01$.

Table 3: Partisan identity and views toward free trade, 1986-2012 repeated cross-sections

	Dep't var.: Party ID (1-7, increasing in Republican dir)					
	(1)	(2)	(3)	(4)	(5)	(6)
Favor import limits x After 1992	0.182** [0.0719]	0.190** [0.0718]	0.216*** [0.0699]	0.228*** [0.0648]	0.155** [0.0771]	0.209*** [0.0653]
Favor import limits	-0.222*** [0.0706]	-0.227*** [0.0709]	-0.265*** [0.0713]	-0.278*** [0.0708]	-0.385*** [0.0837]	-0.269*** [0.0695]
Dep't var. mean	3.619	3.619	3.620	3.620	3.737	3.620
Controls						
–Demographic	No	No	Yes	Yes	Yes	Yes
–State FE	No	Yes	No	No	No	No
–Issues	No	No	No	Yes	Yes	Yes
–Demogr. x Aft	No	No	No	No	No	Yes
–Issues x Aft	No	No	No	No	No	Yes
Excl. DK	No	No	No	No	Yes	No
R-sq. x 100	0.680	2.787	11.988	16.271	15.462	17.176
Observations	18770	18770	18497	18497	11031	18497

Sources: ANES time-series files (repeated cross-sections), 1986–2012. We include all surveys in this interval that ask the *Favor Import Limits* question (see Section 7.1).

Notes: Year fixed effects are in all regressions. Col. (1) includes no other controls. Col. (2) replicates the col. (1) specification but adds state fixed effects. Col. (3) adds to the col. (1) specification controls for race, gender, education, age, and log of family income. Col. (4) adds to the col. (3) specification views toward abortion, trust in government and feelings towards African-Americans. Col. (5) replicates col. (4) but drops any respondent who says "don't know" in response to the *Favor Import Limits*$_i$ question (they are otherwise coded as zero). Col. (6) adds to col. (4) interactions between *After 1992* and each of the controls in col. (3) and col (4). Standard errors clustered by state. $^{*}p = 0.1,^{**} p = 0.05,^{***} p = 0.01$.

Table 4: Partisan identity and views toward free trade, 1992-1994 panel data

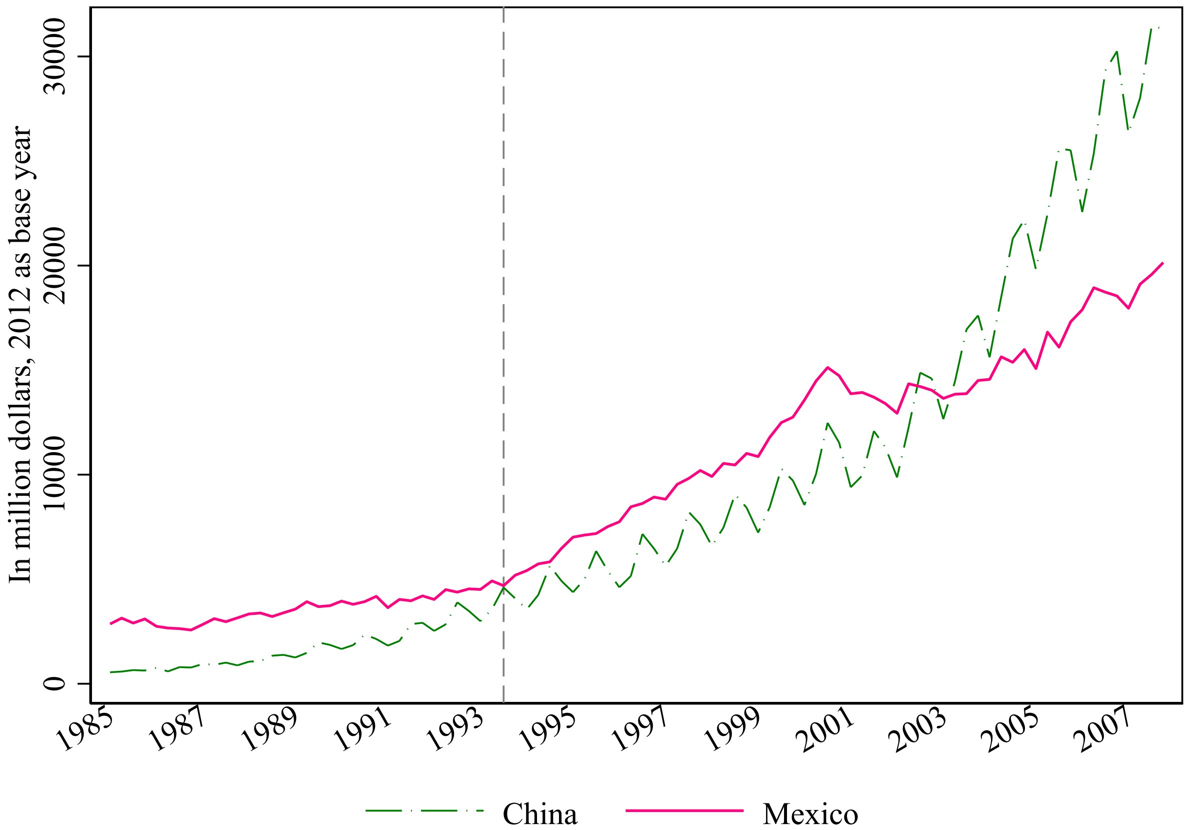
	Move in Repub direction dummy x 100					
	(1)	(2)	(3)	(4)	(5)	(6)
Favor import limits	8.304**	9.530**	8.301**	8.065**	8.833**	8.512**
	[3.325]	[4.108]	[3.443]	[3.580]	[3.715]	[4.041]
Minorities sd help self				1.388	1.474	1.600
				[1.071]	[1.037]	[1.026]
Wants active gov't				-0.923	-0.911	-1.820
				[1.121]	[1.281]	[1.439]
Support abortion				-1.770	-1.089	-1.254
				[1.872]	[2.159]	[2.281]
Attend church weekly				7.772**	8.211**	6.940*
				[3.632]	[3.819]	[3.937]
Favors increased immigr.				0.222	-2.946	-4.598
				[5.899]	[6.579]	[7.056]
Oppose gays in military					3.408	2.745
					[7.246]	[7.841]
Oppose gov't health care					-0.544	-0.928
					[0.782]	[0.847]
Favor term limits					-6.178*	-5.557
					[3.620]	[4.138]
Dept. var. mean	26.52	26.76	26.49	26.49	26.54	26.54
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	0.00887	0.0104	0.0388	0.0607	0.0660	0.103
Observations	739	553	736	736	731	731

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. "Ex. DK" means that respondents who did not have an opinion 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. $^{*}p = 0.1,^{**}p = 0.05,^{***}p = 0.01$.

Appendix A. Supplementary Figures and Tables Noted in the Text

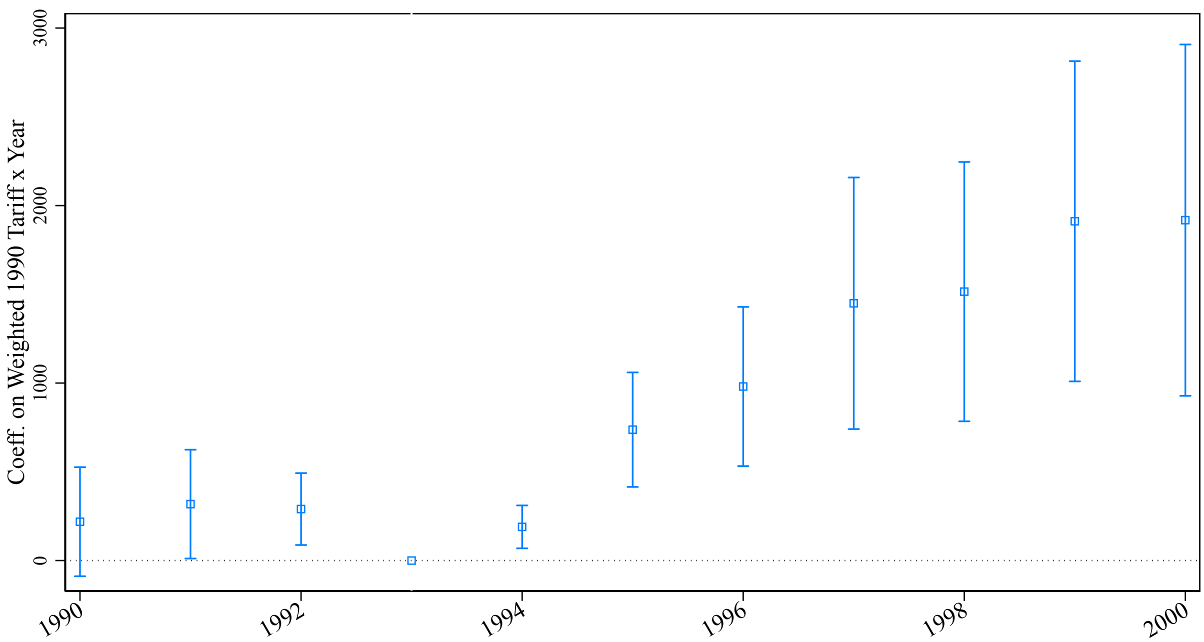
Appendix Figure A.1: U.S. imports from China and Mexico



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 quarterly-level personal consumption expenditures available from FRED.

Appendix Figure A.2: Relationship between Mexican imports to the US and pre-NAFTA tariffs (using UN Comtrade data instead of USITC data)



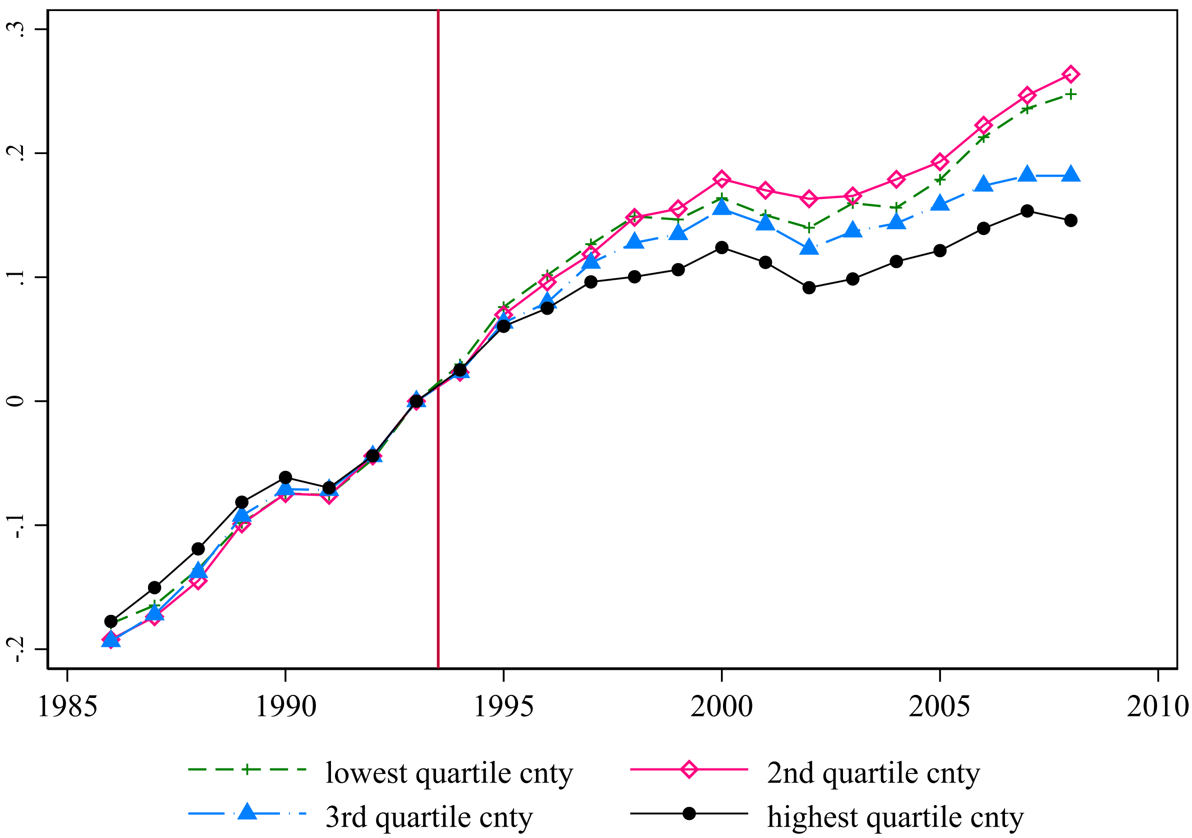
Sources: UN Comtrade data

Notes: This figure is identical to Figure 3 but uses UN Comtrade data instead of USITC data. 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, respecitvely. All import values are in millions of current USD. The 95-percent confidence intervals are based on standard errors clustered at the industry level.

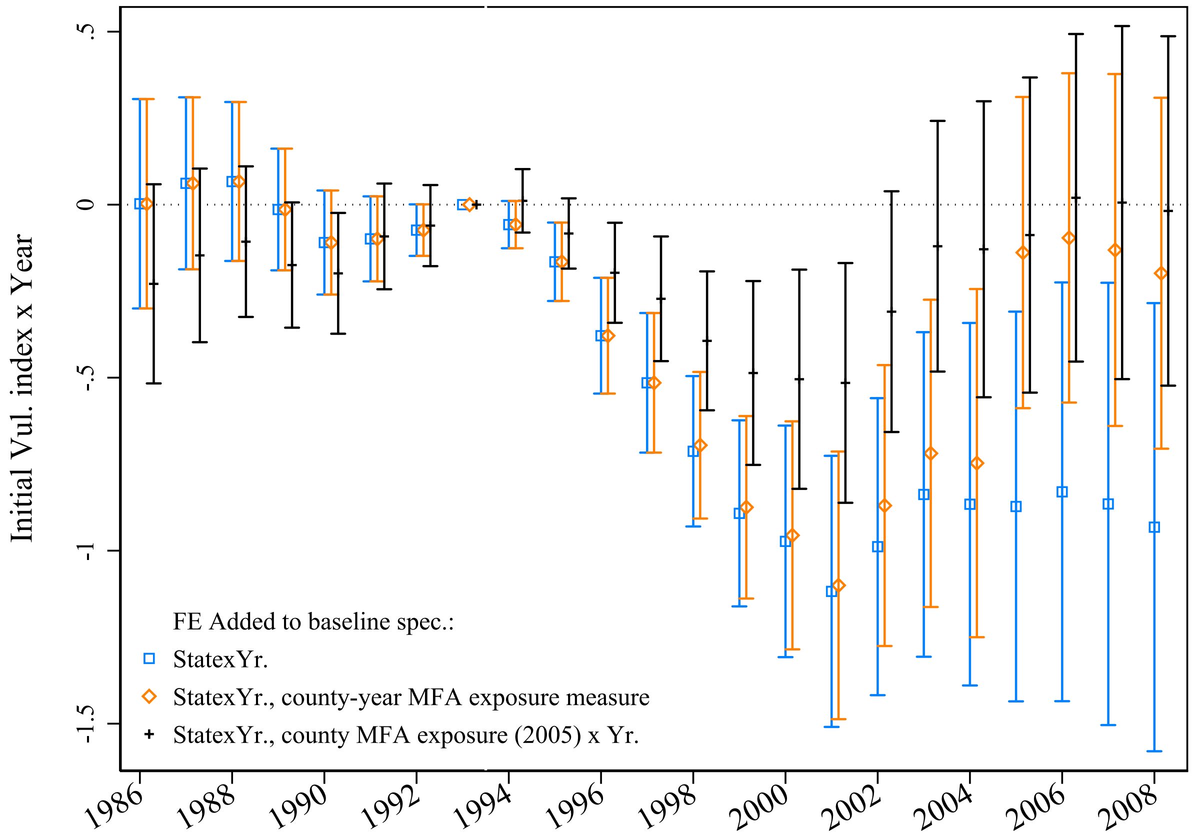
Appendix Figure A.3: Average log employment for four vulnerability quartiles over time (normalized to zero in 1993)



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.

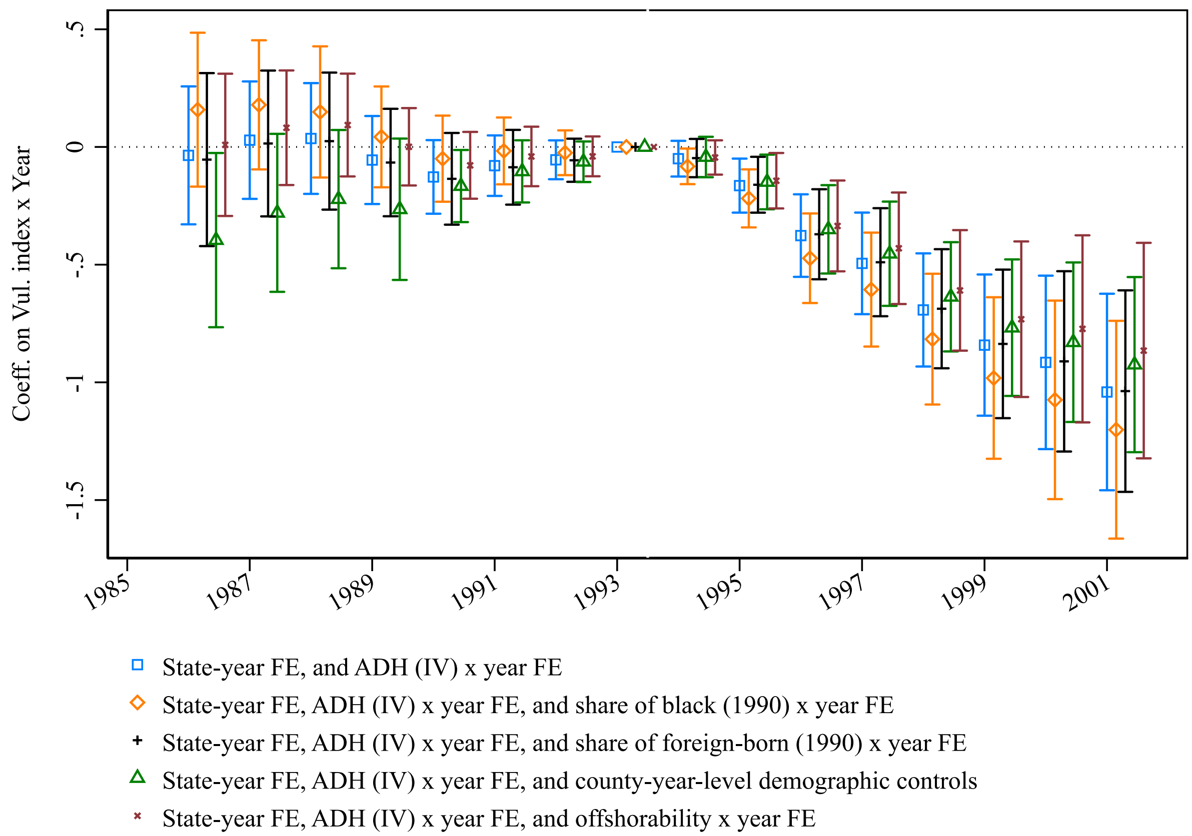
Appendix Figure A.4: Log employment as a function of NAFTA vulnerability, robustness to Multi-Fibre-Arrangement phase-out



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 (2020b), which is based on the approach from Khandelwal *et al.* (2013).

Notes: $N = 2926$ counties.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. However, to the extent that agents are 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 effects in all years. In this graph, the first series are identical to the second series in Figure 4. Comparing the second and third series shows that even after flexibly controlling for any forward-looking effects of the MFA phase-out, we still identify a large, negative effect of NAFTA vulnerability on county employment.

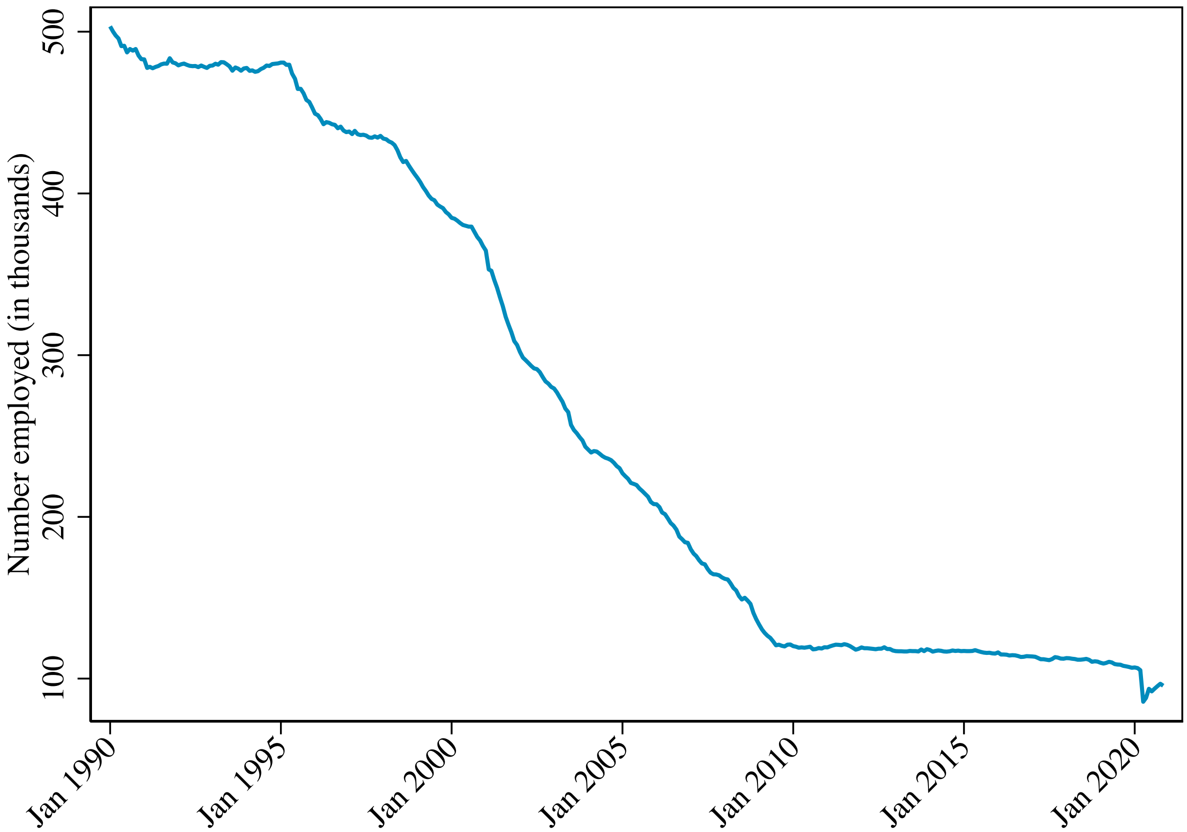
Appendix Figure A.5: Log employment as a function of county NAFTA vulnerability, adding additional controls



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

Notes: Sample contains $N = 2957$ counties for each year of the sample period. This figure extends the analysis in Figure 4. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (3), where log of total employment at the county$\times$year level is the dependent variable. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for county and year fixed effects, and CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) interacted with year fixed effects. The specification for the second series adds to the first specification share Black in 1990 interacted with year fixed effects. The third specification adds to the first specification the foreign-born share of county population in 1990 interacted with year fixed effects. The fourth specification includes share Black, share "other" (not Black nor white), log of working-age population, and share of college graduates (the final control is not available annually at the county level, so we interpolate between Census years). Note that these controls vary at the county year level and thus might be themselves subject to NAFTA and thus "bad controls." The final specification adds to the first specification the CZ-level "offshorability" based on 1980 occupation, as used in Autor *et al.* (2013a).

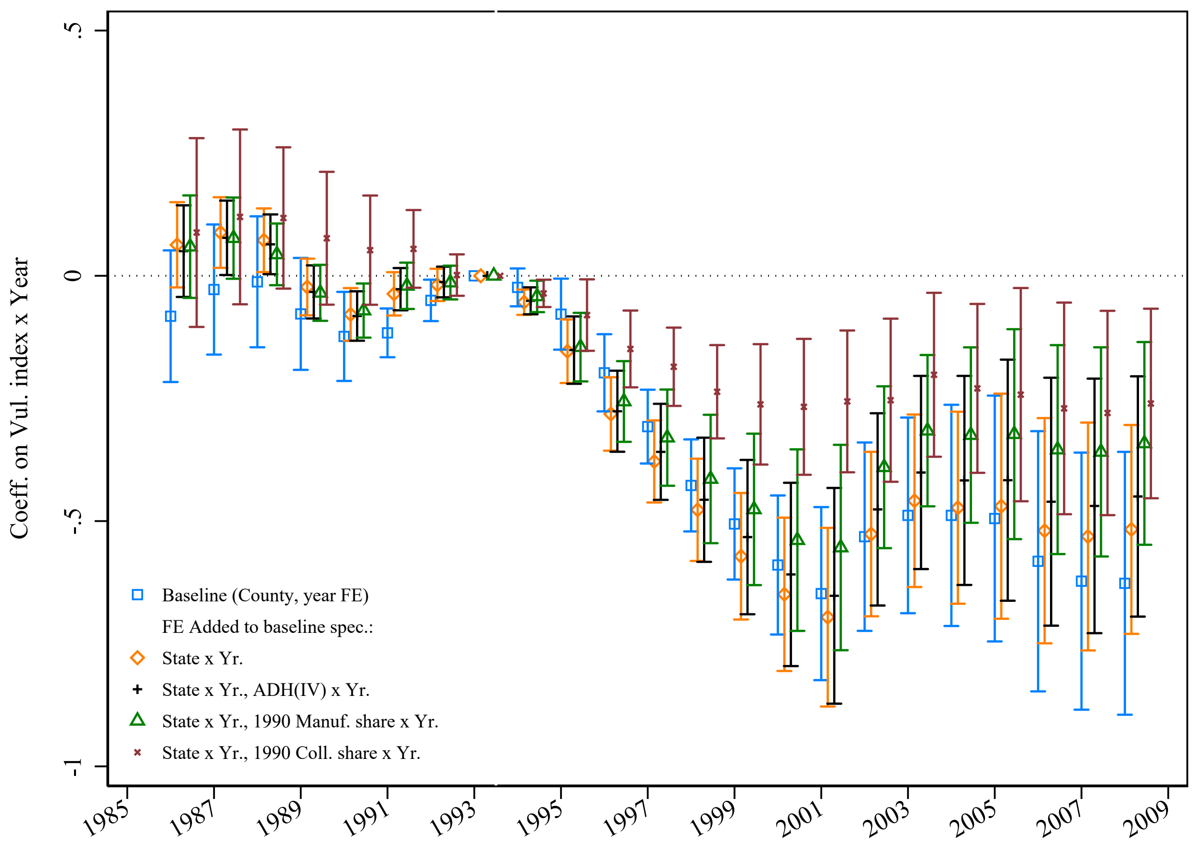
Appendix Figure A.6: Employment in textile mills, 1990-2020



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.

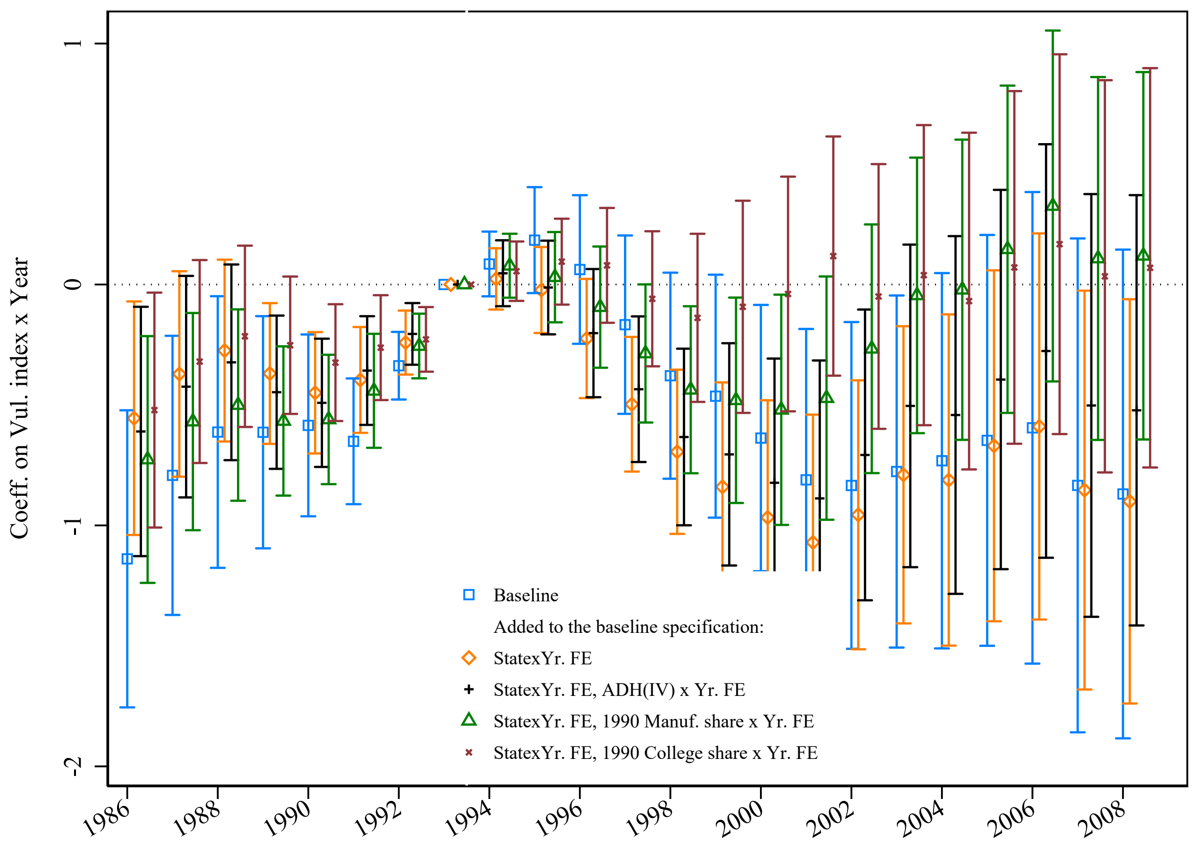
Appendix Figure A.7: Employment per capita as a function of NAFTA vulnerability



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

Notes: $N = 2990$ counties for each year of the sample. The figure is identical to Figure 4 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 (3), where per capita employment at the county×year level is the dependent variable. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification *state×year* fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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.

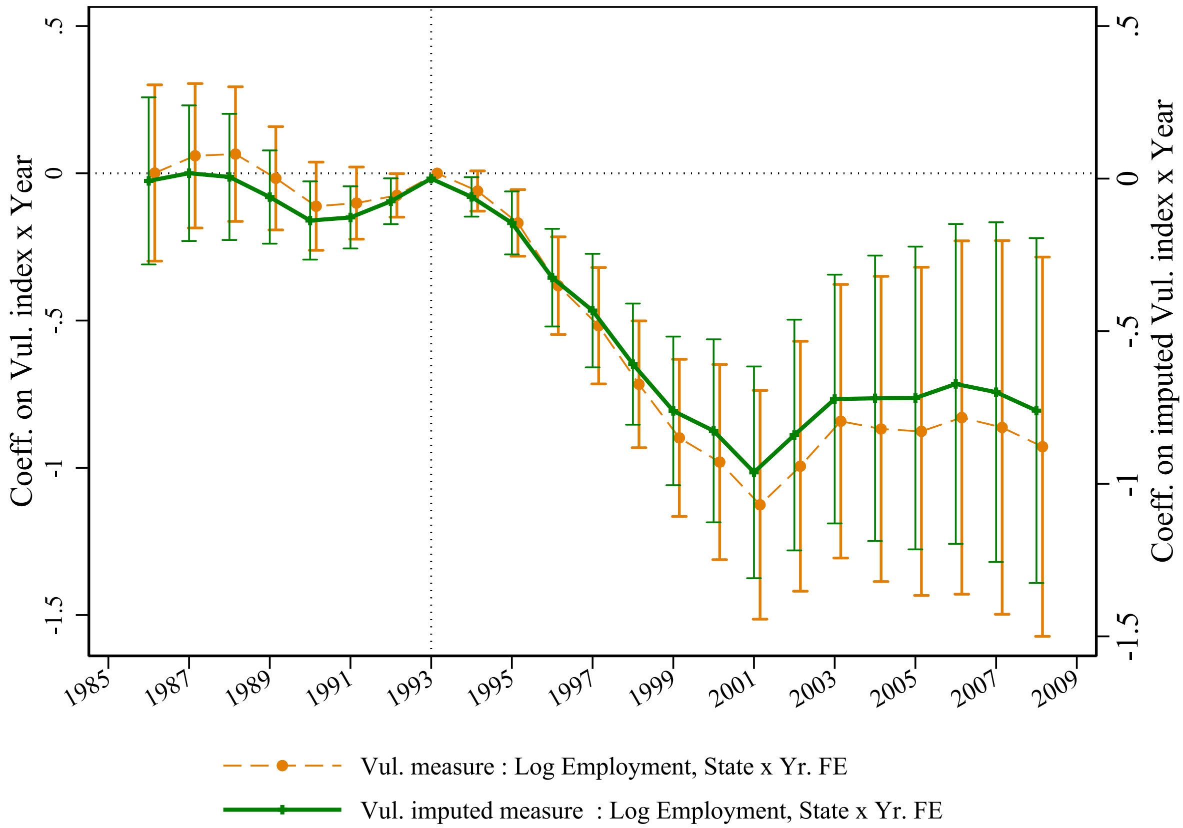
Appendix Figure A.8: Log of CZ employment as a function of CZ-level NAFTA vulnerability



Sources: The dependent variable is derived from the CBP.

Notes: $N = 705$ CZs for each year of the sample period. This figure is the analogue to Figure 4 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 (3), where log employment at the CZ×year level is the dependent variable. All specifications are weighted by 1990 CZ population. The first series shows the coefficient estimates from a specification where we control for only CZ and year fixed effects. The specification for the second series adds to this baseline specification *state×year* fixed effects, where CZs are assigned to state 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 third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) interacted with year fixed effects. The fourth specification adds to the second specification 1990 CZ-level manufacturing share of employment interacted with year fixed effects. The final specification adds to the second specification 1990 CZ-level college-graduate population share interacted with year fixed effects.

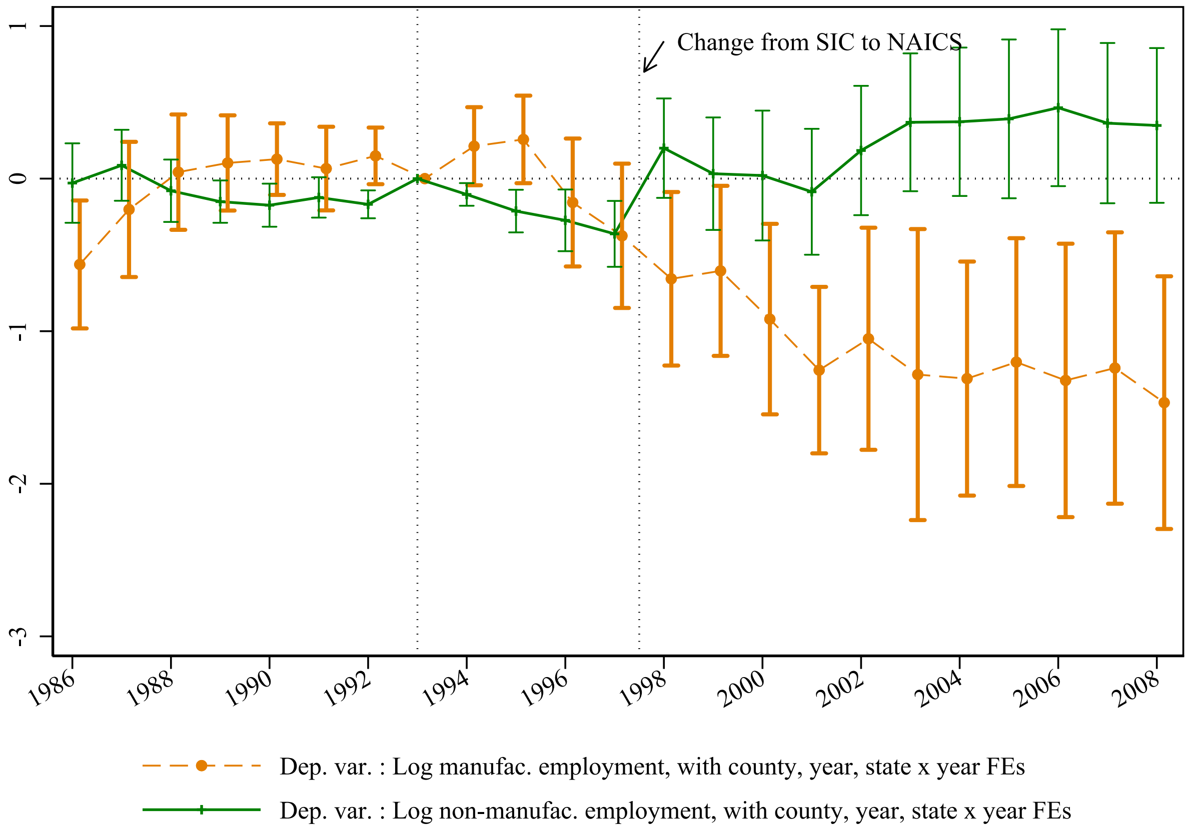
Appendix Figure A.9: Log of employment as a function of NAFTA vulnerability using imputed CBP cells from Eckert *et al.* (2021)



Sources: The dependent variable is derived from the CBP.

Notes: $N = 2822$ counties. The figure shows the event-study coefficient estimates (plus 95%-confidence intervals, based on standard errors clustered by state) from specifications of equation (3), where log of county employment is the dependent variable. The first series uses our baseline vulnerability measure as the main independent variable, and the specification includes county and year fixed effect and $state \times year$ fixed effects. The second series uses the vulnerability measure using the imputed county-industry cells proposed by Eckert *et al.* (2021), and the specification includes county and year fixed effect and $state \times year$ fixed effects.

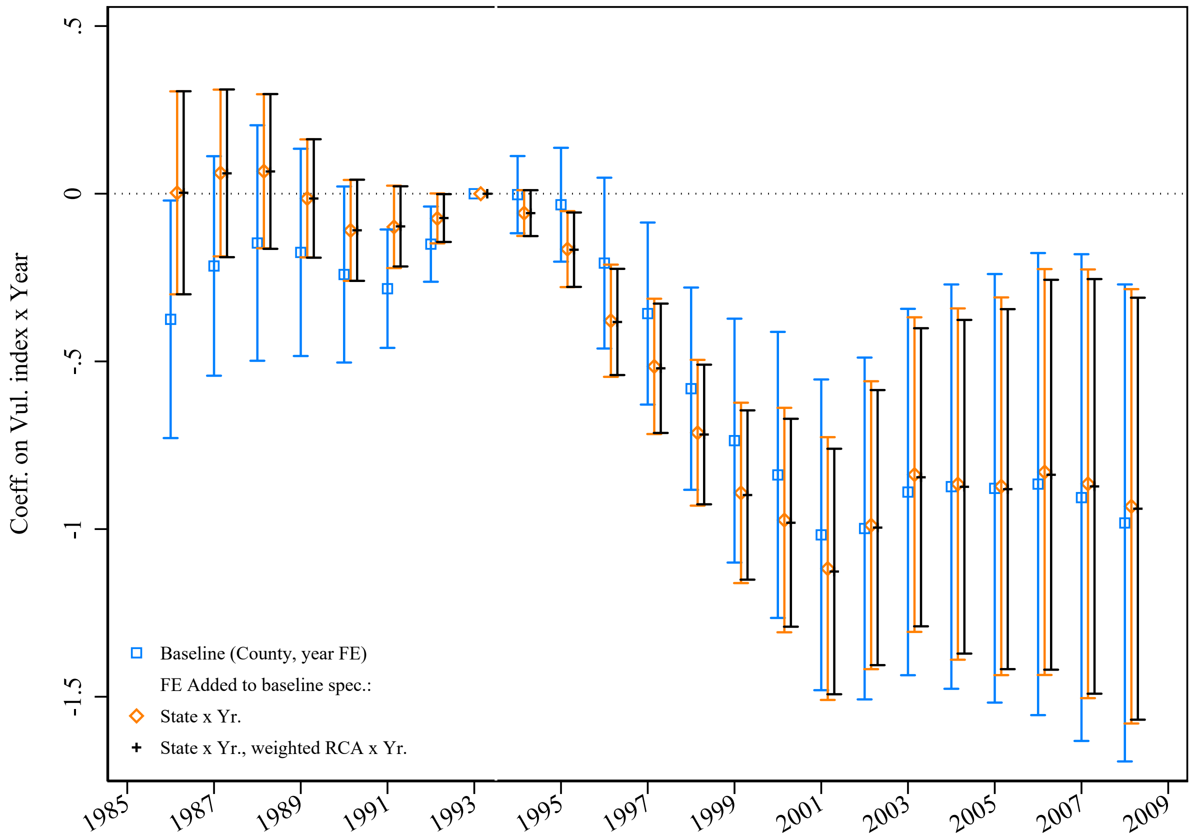
Appendix Figure A.10: Evolution of log employment as a function of NAFTA vulnerability, separating manufacturing v. other industries



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

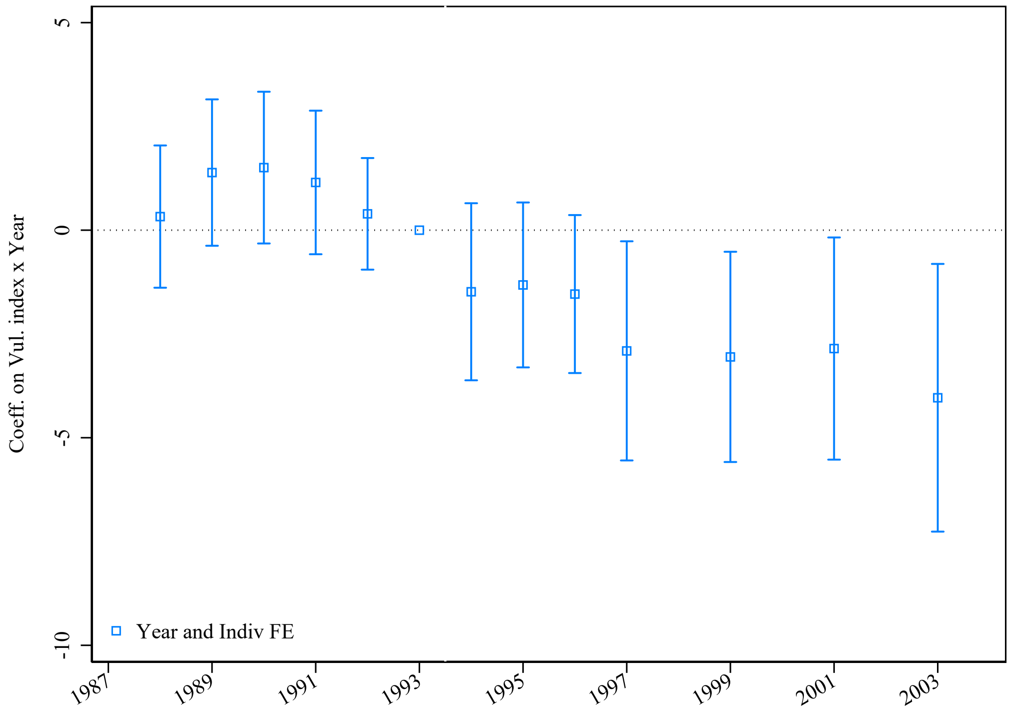
Notes: $N = 2960$ counties. The figure shows the event-study coefficient estimates (plus 95%-confidence intervals, based on standard errors clustered by state) from specifications of equation (3), where log of total manufacturing employment and log of total non-manufacturing employment at the county$\times$year level are the dependent variable for the first and second series, respectively. Both specifications are weighted by 1990 county population, and they include county and year fixed effects and $state \times year$ fixed effects.

Appendix Figure A.11: Log of employment as a function of county NAFTA vulnerability, robustness to Peso crisis



Notes: $N = 2926$ counties for each year of the sample period. The figure shows the event-study coefficient estimates from different specifications of equation (3), where log of total employment is the dependent variable. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series add to this baseline specification $state \times year$ fixed effects. The third 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 third series adds as a control this county-level variable interacted with year fixed effects. Comparing the second and third series suggests that the estimated effect of NAFTA vulnerability does not change much after flexibly controlling for county-level exposure to the devalued peso.

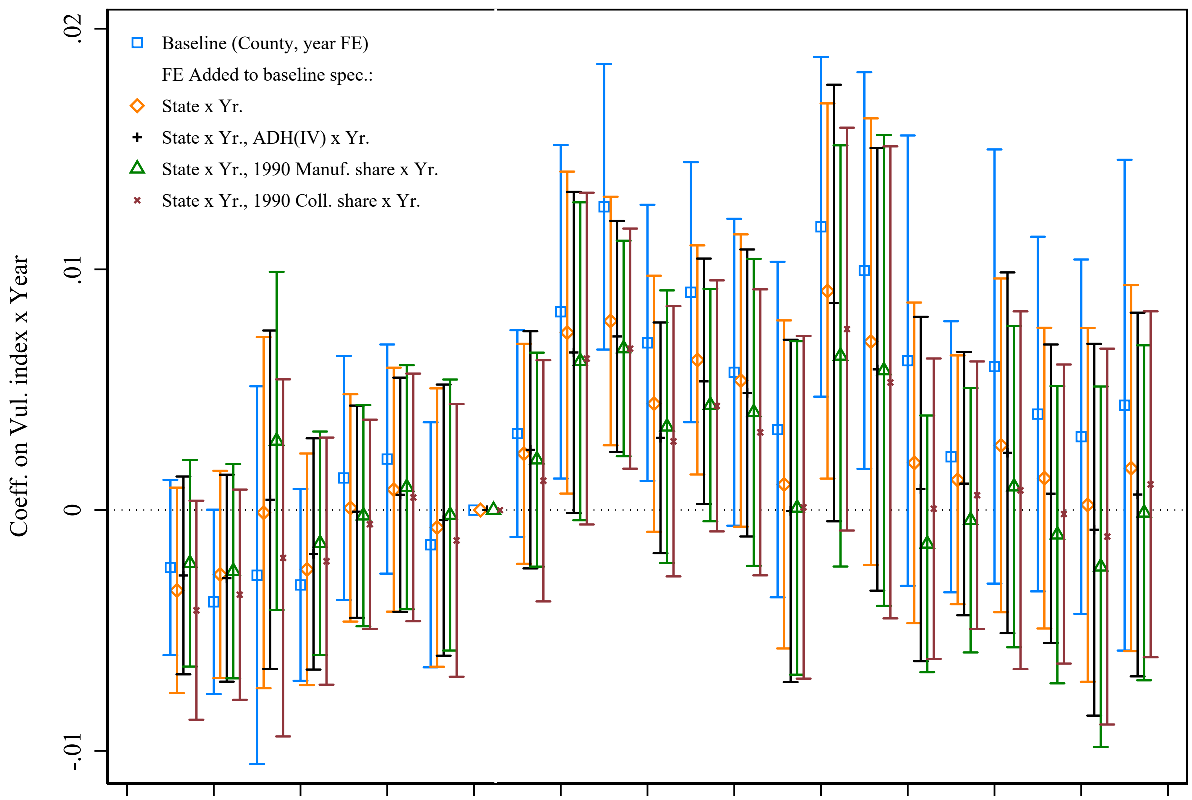
Appendix Figure A.12: Employment as a function of individual vulnerability, PSID sample



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

Notes: $N = 4373$ 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).

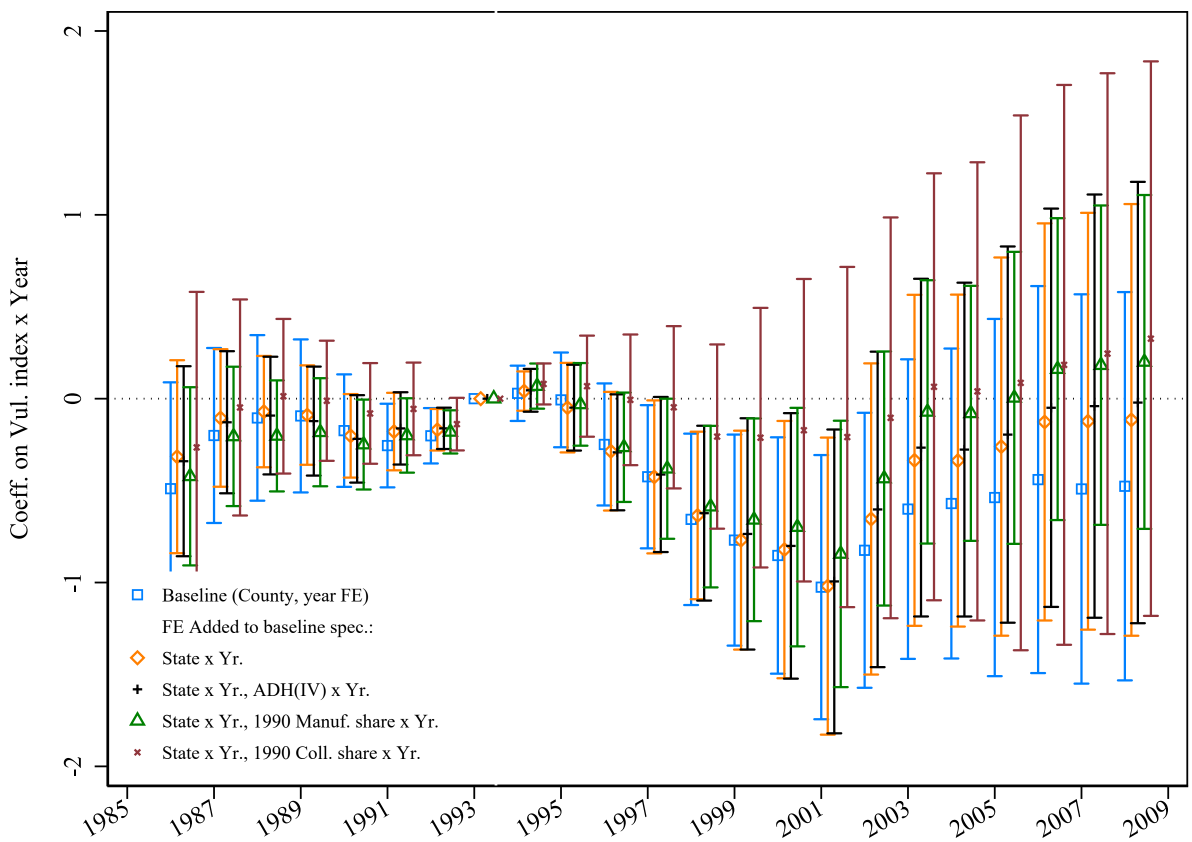
Appendix Figure A.13: Trade Adjustment Assistance certifications per capita as a function of county vulnerability



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: $N = 2914$ counties for each year of the sample period. This figure is identical to Figure 6 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 (3), where per capita TAA certifications at the county×year level is the dependent variable. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification *state*×*year* fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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.

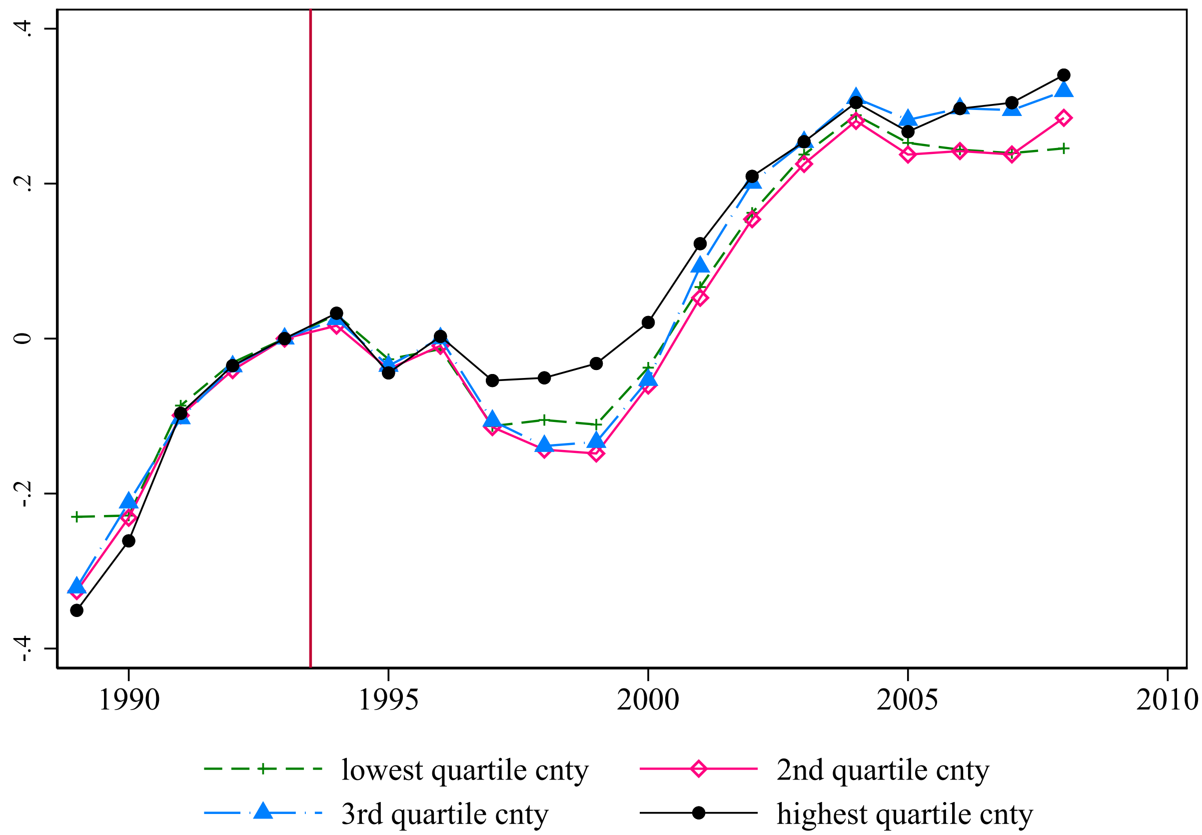
Appendix Figure A.14: Evolution of log employment as a function of county NAFTA vulnerability, for a balanced panel of 766 counties for which we have DI application data



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

Notes: $N = 766$ counties. This figure is identical to Figure 4 but is restricted to the 766 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 (3), where log of total employment at the county×year level is the dependent variable. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification *state*×*year* fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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.

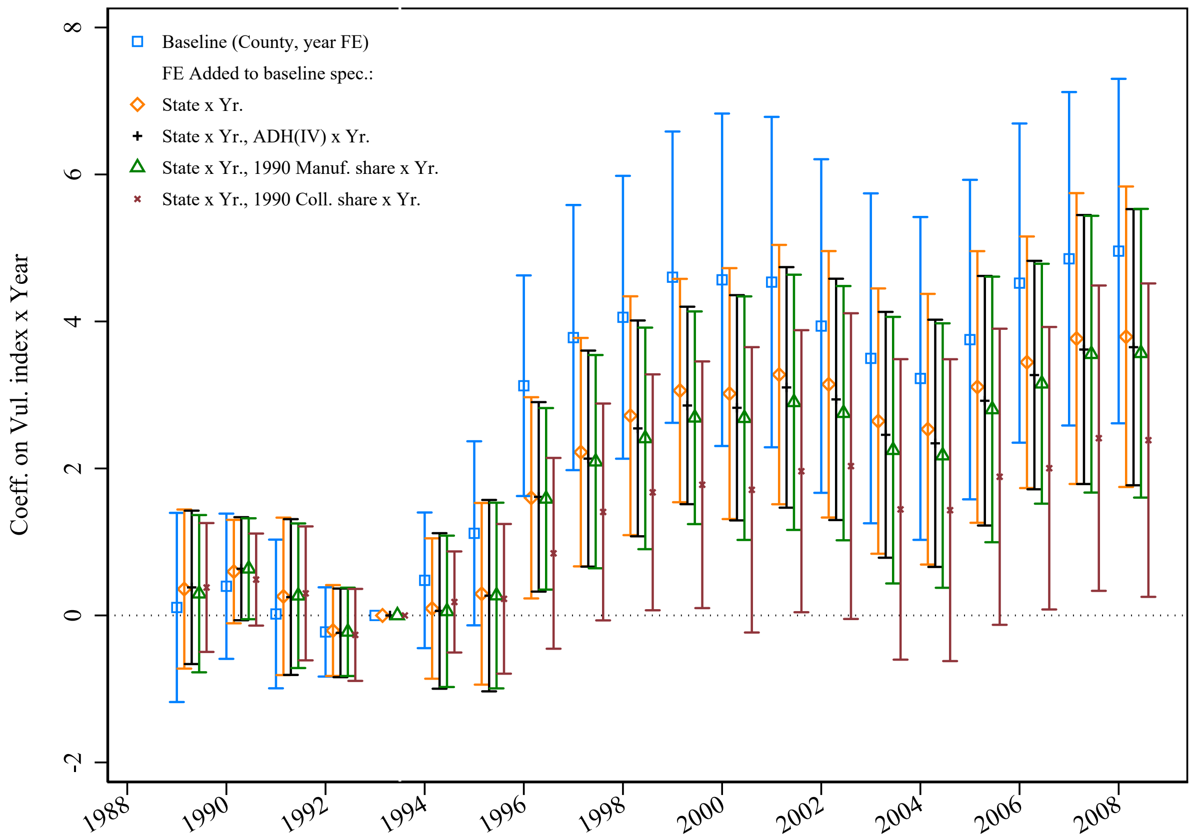
Appendix Figure A.15: Log DI applications, raw trends by four vulnerability quartiles (1993 normalized to zero)



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. Note that we can only perform this analysis for a subset of counties (see Section 5.3).

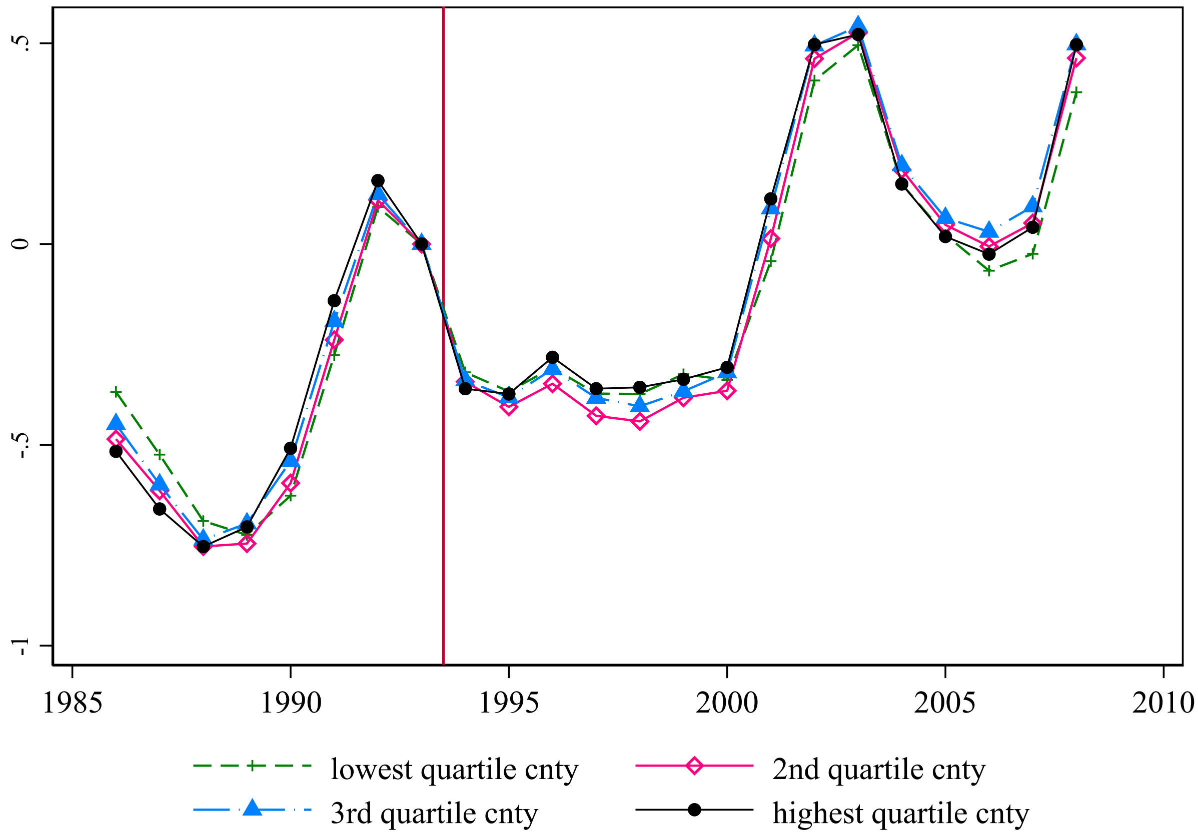
Appendix Figure A.16: Evolution of log DI final awards as a function of county vulnerability



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

Notes: $N = 755$ counties. This figure is identical to Figure 7 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 (3), 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 755 counties we have in this balanced-panel analysis account for around three-fourths of the U.S. population. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification $state \times year$ fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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.

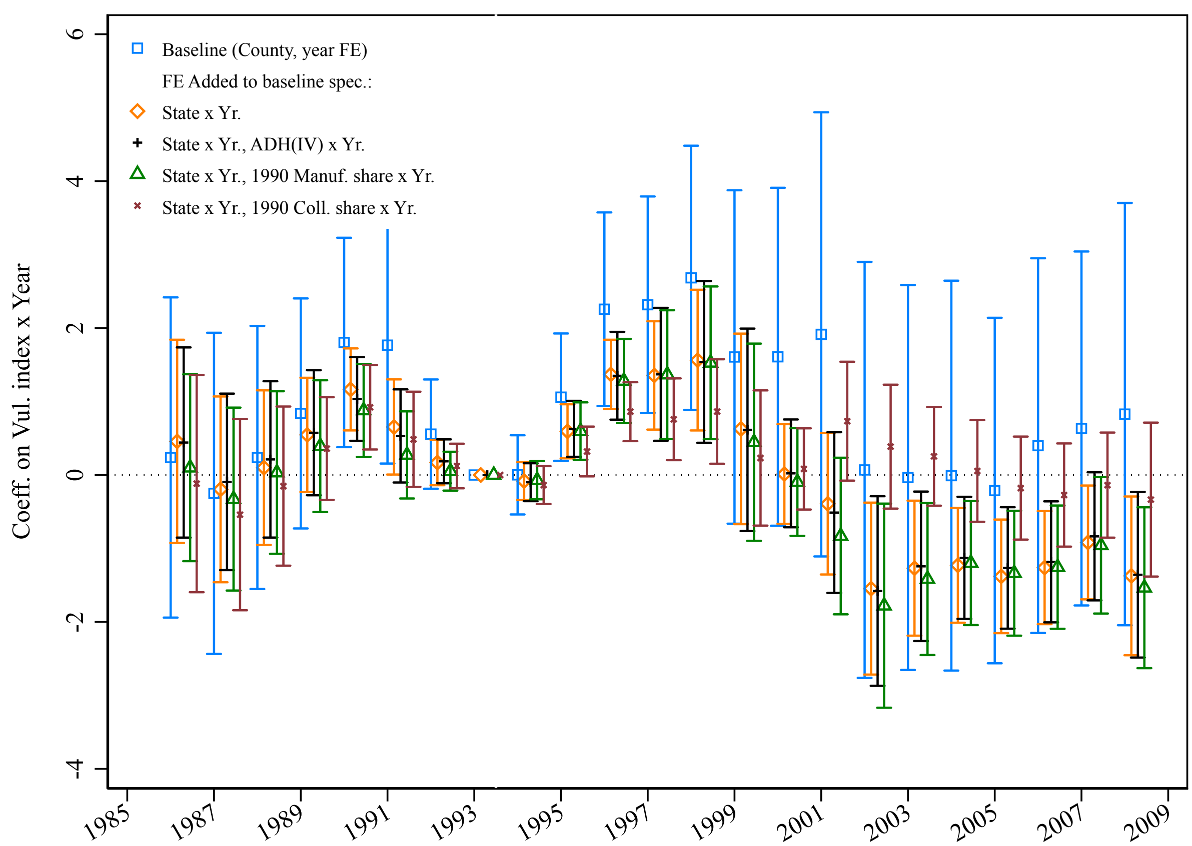
Appendix Figure A.17: Log of Unemployment Insurance benefits by county vulnerability, normalized



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.

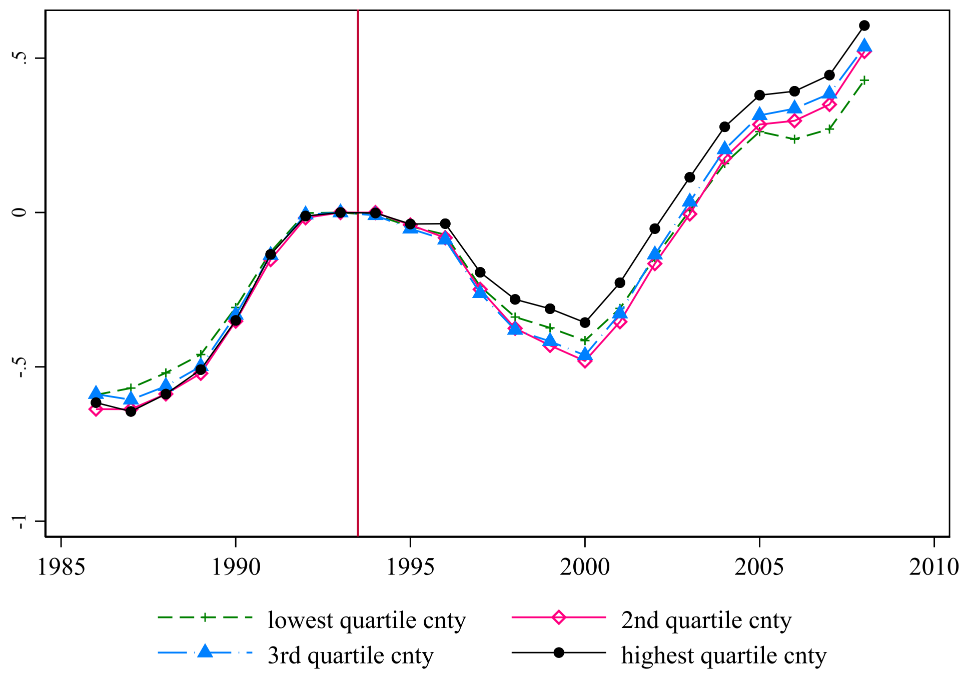
Appendix Figure A.18: Evolution of log UI benefits as a function of county vulnerability



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

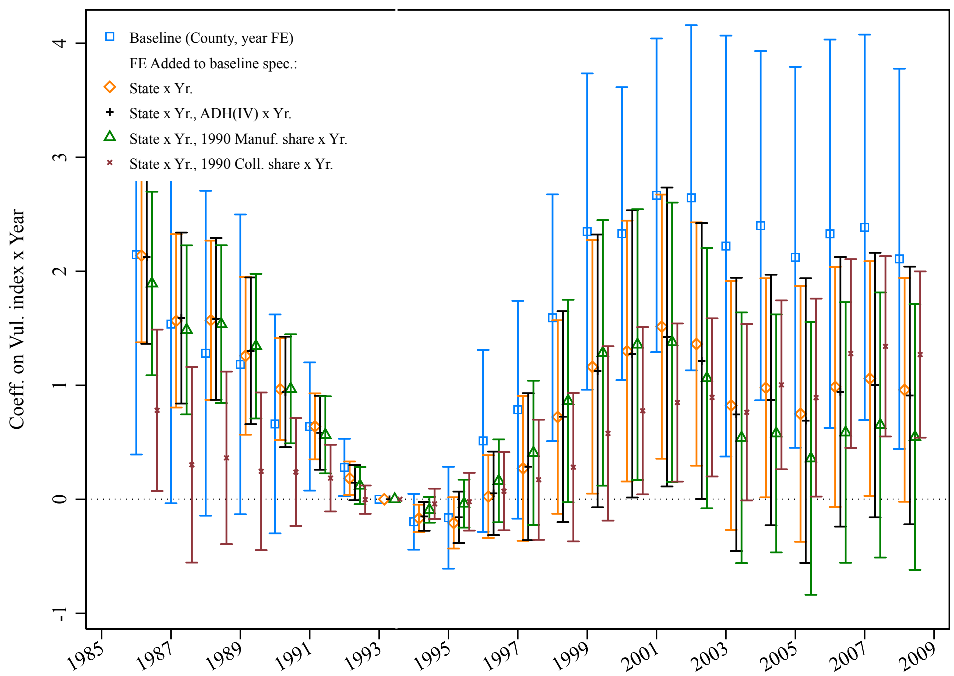
Notes: $N = 2957$ counties for each year of the sample period. The outcome variable is log of total UI benefits in each county. The log of UI benefits is computed using the annual county-level personal transfers data from the U.S. BEA. The UI benefits in the series include both state unemployment insurance compensation and other unemployment insurance payments, such as Trade Adjustment Assistance program. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification $state \times year$ fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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. Standard errors clustered at the state level.

Appendix Figure A.19: Log reported SNAP benefits, normalized



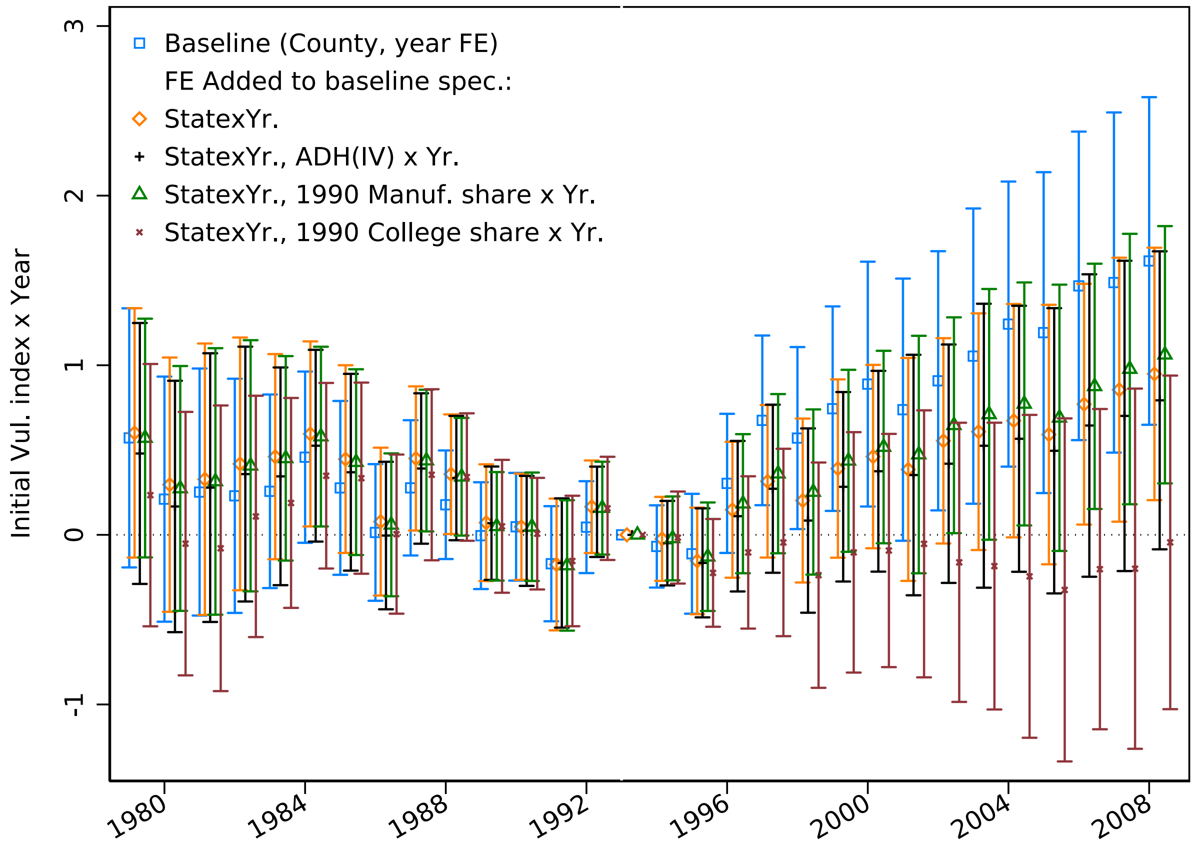
Notes: The log of reported SNAP benefits is computed using the annual county-level personal transfers data from the U.S. BEA. In the data, the SNAP benefits are estimated using the tabulations from the U.S. Department of Agriculture, payments data from state departments of social services, and the Census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

Appendix Figure A.20: Log reported SNAP benefits as a function of county vulnerability



Notes: $N = 2933$ counties for each year of the sample period. 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. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification $state \times year$ fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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. Standard errors clustered at the state level.

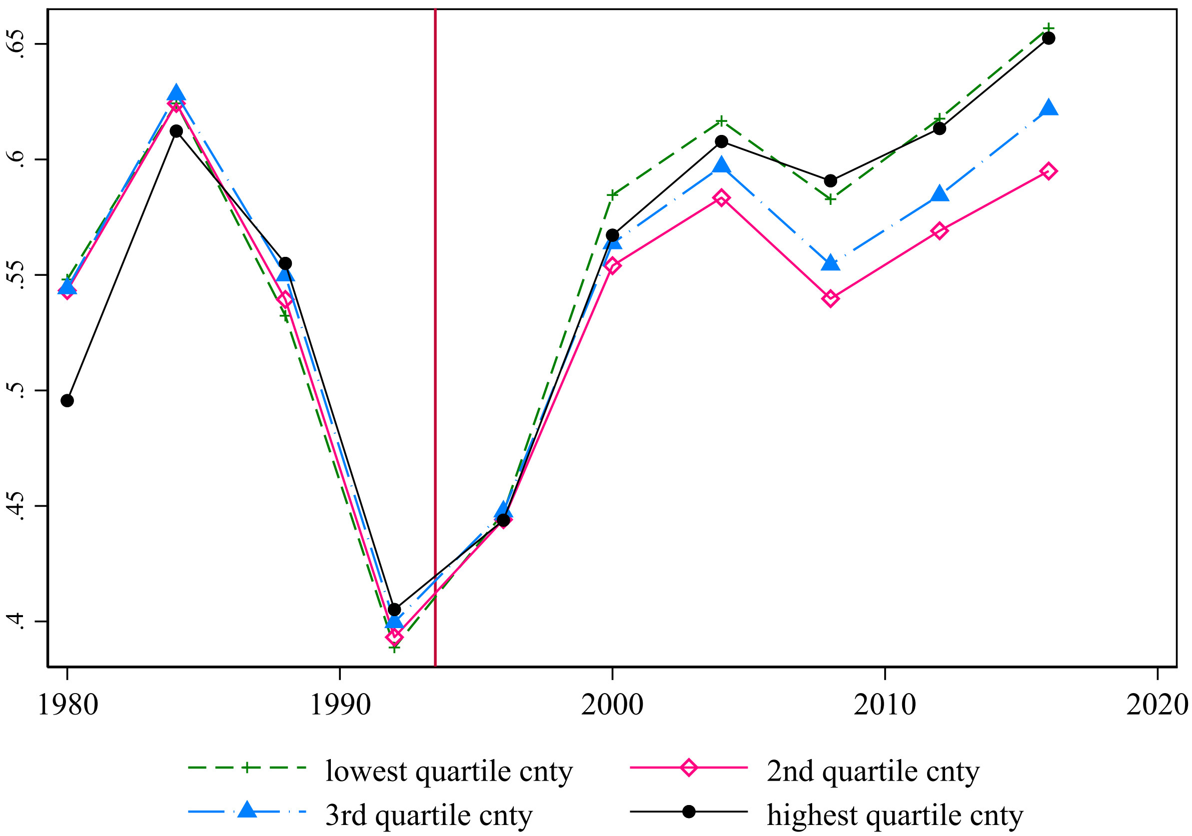
Appendix Figure A.21: Working-age mortality as a function of county NAFTA vulnerability



Sources: The dependent variable is derived from the National Center for Health Statistics (NCHS) public-use vital stats data (1979-1988) and restricted-use vital stats data (1988-2008).

Notes: $N = 2801$ counties for each year of the sample period. This figure is identical to Figure 4 but with log of working-age mortality as the outcome 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 (3), where log of working-age mortality at the county×year level is the dependent variable. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification *state×year* fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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. Standard errors clustered at the state level.

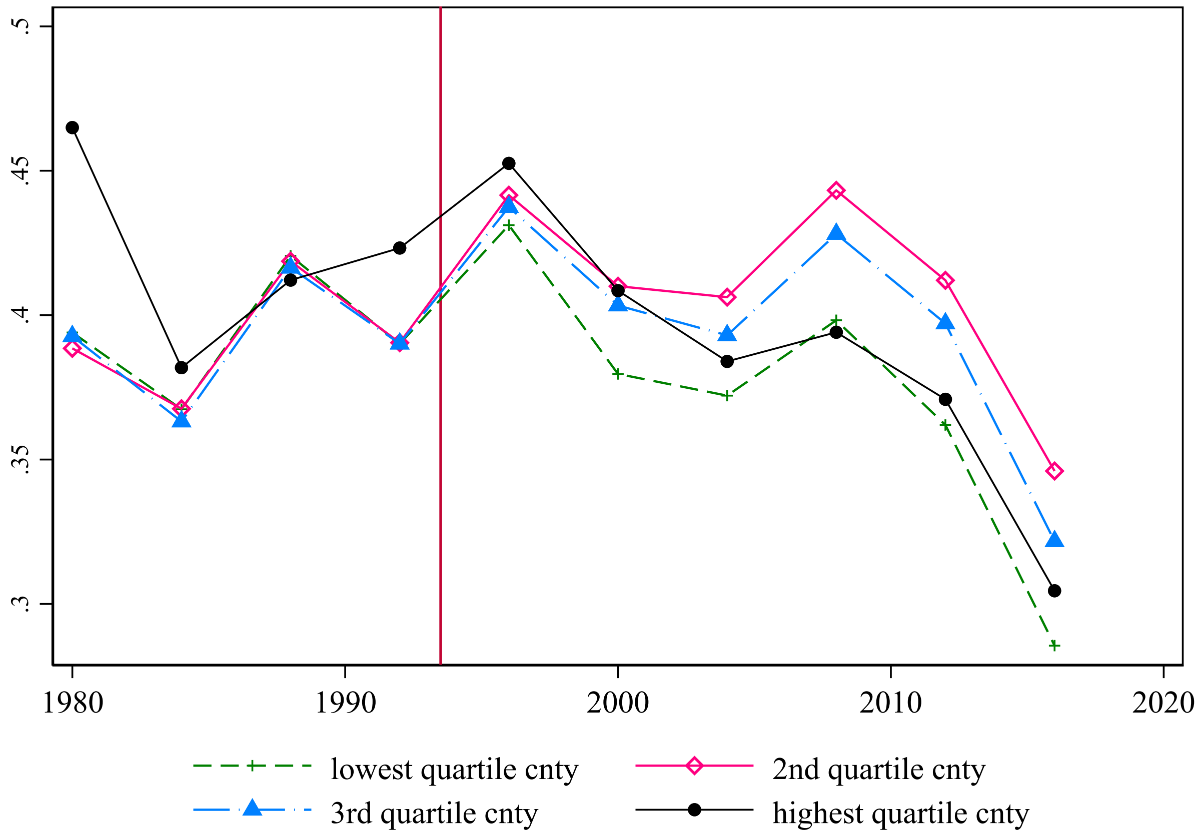
Appendix Figure A.22: Republican vote share in Presidential elections, separately by vulnerability quartile (raw means, not normalized)



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 two-party Republican House vote share trends from 1980 to 2016 by 1990 county vulnerability quartiles. The two-party vote share is computed using ICPSR general voting data and Dave Leip's Atlas of U.S. Elections data.

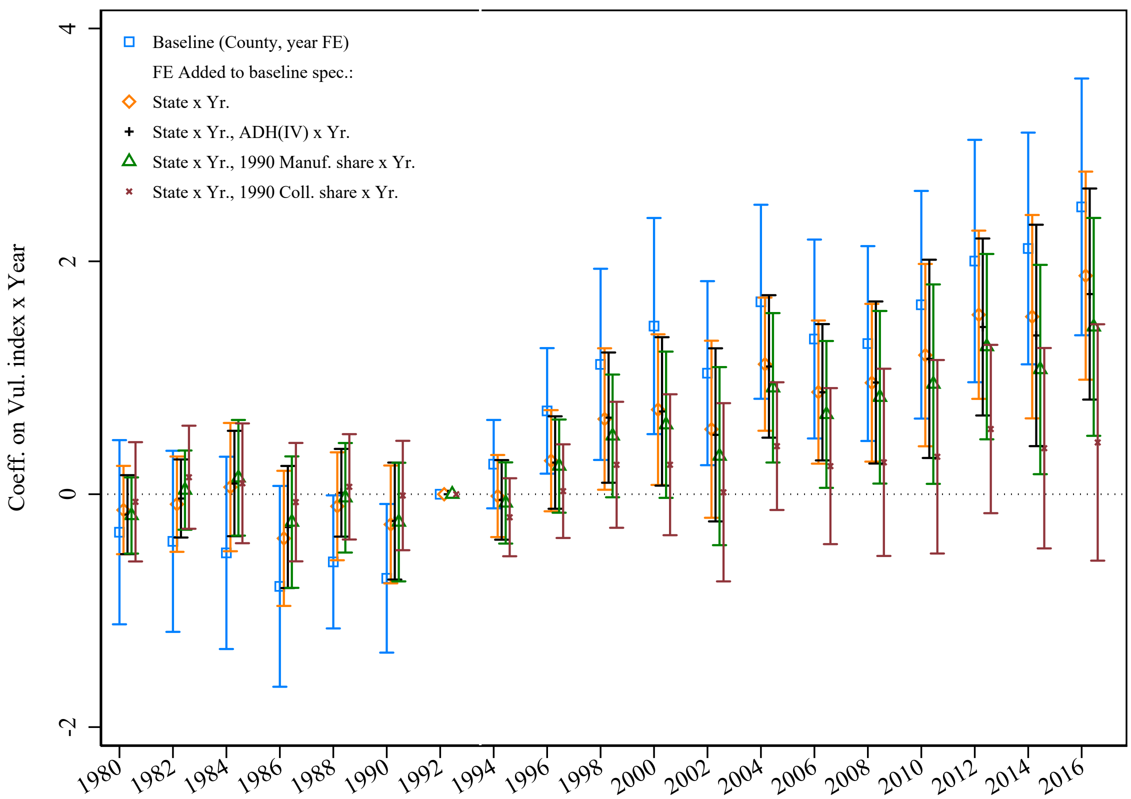
Appendix Figure A.23: Democratic vote share in Presidential elections, separately by vulnerability quartile (raw means, not normalized)



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 two-party Republican House vote share trends from 1980 to 2016 by 1990 county vulnerability quartiles. The two-party vote share is computed using ICPSR general voting data and Dave Leip's Atlas of U.S. Elections data.

Appendix Figure A.24: 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.11 for more detail.

Notes: The analysis sample is fixed across specifications and strictly balanced, with 2461 counties in each year of the sample. The figure shows the event-study coefficient estimates (and 95% confidence intervals, based on standard errors clustered by state) from different specifications of equation (3), where the two-party Republican vote share in House elections is the dependent variable. It follows Figure 4 though obviously cannot be analyzed annually because elections fall only on even years. All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects. The specification for the second series adds to this baseline specification $state \times year$ fixed effects. The third specification adds to the second specification CZ-level measure of Chinese import exposure from Autor *et al.* (2013a) 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.

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	-0.0823***	-0.0821***	-0.0969***	-0.0973***	-0.0938***	-0.213***
	[0.00970]	[0.0126]	[0.00953]	[0.00894]	[0.00801]	[0.0106]
Some college, no BA degree		0.000420				
		[0.0131]				
Dept v mean	0.382	0.382	0.382	0.382	0.382	0.643
Demog controls	No	No	Yes	Yes	Yes	Yes
Issue controls	No	No	No	Yes	Yes	Yes
State FE	No	No	No	No	Yes	No
Drop DKs	No	No	No	No	No	Yes
Observations	18836	18836	18743	18743	18743	11120

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.
$^{*}p = 0.1,^{**}p = 0.05,^{***}p = 0.01$.

Appendix Table A.2: 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]
Mean, dept var	0.365	0.360	0.360	0.360	0.456	0.270
Demog. controls?	No	Yes	Yes	Yes	Yes	Yes
Issue controls?	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.
$^{*}p = 0.1, ^{**}p = 0.05, ^{***}p = 0.01$.

Appendix Table A.3: 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 (asked in 1993)	7.777	11.09*	6.428	5.833	6.573	6.506
	[5.095]	[5.853]	[4.617]	[4.683]	[4.784]	[5.068]
Minorities sd help self				2.123*	2.301**	2.127**
				[1.049]	[1.025]	[0.999]
Wants active gov't				-0.282	-0.329	-1.335
				[1.337]	[1.539]	[1.758]
Support abortion				-1.164	-0.506	-0.569
				[1.935]	[2.248]	[2.460]
Attend church weekly				4.526	5.066	2.287
				[3.317]	[3.411]	[3.544]
Favors increased immigr.				-1.766	-5.217	-8.023
				[5.801]	[6.641]	[7.107]
Oppose gays in military					3.661	4.441
					[8.024]	[9.135]
Oppose gov't health care					-0.992	-1.507
					[0.961]	[1.042]
Favor term limits					-5.380	-4.651
					[4.177]	[4.872]
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	0.0685	0.0737	0.123
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. $^{*}p = 0.1,^{**}p = 0.05,^{***}p = 0.01$.

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 *et al.* (2002).[38] 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. When aggregating eight-digit industries into six-digit industries and computing the weighted average of tariffs, we use USITC import values for each eight-digit industries as the weights.

The UN Comtrade bilateral export series contains the dollar value of exports by origin and destination in six-digit Harmonized Tariff Schedule code. 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 the week of March 12th every year. We use CBP from 1986 to 2008 to compute county-level annual employment size and industry employment share in year 1990. [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.[40]

[38]For creating the vulnerability for years other than 1990-2001, we use the USITC annual tariff data. This is not used in the analysis, but to illustrate the change of vulnerability measure over time.

[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 try to 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 a very similar vulnerability measure and analysis results.

[40]The four-digit SIC industries in the crosswalks are the "slightly aggregated" version as used in ADH, but we decide not to add up the adjacent four-digit industries in the county-level industrial composition calculation as they did in the paper. When we use the same aggregation to the industrial composition, we still get a very similar vulnerability measure.

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 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 share of college-educated population and working-age population defined by population estimates of age 15-64.

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

We obtain individual characteristics from the Panel Survey of Income Dynamics (PSID)[41] for 1988 to 2003. The sample consists of 68,814 individuals with information on their demographics (i.e., sex, age, and race), education level, labor status, state of residency, and employment industry code. We follow a sequence of restrictions in order to keep a balanced panel for the relevant variables. First, we use the employment industry code of the individuals in 1990 to match the current NAFTA Vulnerability dataset we have constructed. The 1990 industry code available in the PSID is the 3-digit industry code from the 1970 Census of Population, and because our NAFTA vulnerability dataset includes a crosswalk between the 1970 and 1990 industry codes, we can keep working with the 1990 vulnerability measures seamlessly. Second, when individuals didn't have an industry code associated, we assigned them the value of zero as their vulnerability measure. Finally, the dependent variable is non-missing any year of analysis to guarantee a balanced panel.

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. 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 date the investigation starts.[42] We calculate the number of workers included in certified (approved) petitions in a county from 1975 to 2020, based on petitions' institution date.[43] For counties with no petitions filled at a given year, we assign a zero number of

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

[42] These data also include the date of the petition, which would appear to be a better variable to use to "date" each observation, but it only begins in 1994. However, the gap between petition and investigation is less than a month in the post-1994 data.

[43] 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

affected workers.

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[44]. The series 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.

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[45]. The series is available from 1969-2020, and 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 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, payments data from the state employment security agencies, and the Local Area Unemployment Statistics program of the Bureau of Labor Statistics (BLS).

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

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. The application is collapsed by zipcode and further by county using the 1990 geographic correspondence engine from Missouri Census Data Center.

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 list to create a set of district offices which existed both in 2009 and 2019. We keep the applications from these 1180 district offices and recover the zipcode of each application submitted to the offices. We end up with 755 counties as our "matched district office" sample, which accounts for around 75 percent of U.S. population in 1990. While the method allows us to keep a consistent set of district offices to be included, district offices that opened or closed between 1990 and 2009 are not included in this set.

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withdrawal or because the case is covered by another petition. We therefore only look at the cases that are either certificated or are denied.

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

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

B.9. Data on county-level annual mortality

We construct the number of working-age (age 15-64) deaths by county and year using the National Center for Health Statistics (NCHS) Vital Stats data. The individual-level mortality data contain the cause of death, age, sex, geographic location of each death (e.g., county and state). From 1979 to 1988, the vital stats data are publicly available. For 1989 and onward, the restricted version is acquired from the NCHS as the geographic identifiers are not publicly available.

B.10. Data on news coverage

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 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 the 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.

B.11. Data on county-level House election votes

We obtain county-level voter turnout and 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). 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 casted in each county.

B.12. Survey data on NAFTA favorability

We obtained all publicly available survey data in ICPSR and iPoll 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.13. 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. In 1990, this question is asked in a different format (a seven-category likert scale instead of a binary yes/no question) so we do not include that year.

B.14. ANES panel data

In 1992 that ANES fielded a small panel data set that followed a subset of the 1992 repeated cross-sectional dataset. We use the provided weights to adjust for attrition.

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

Appendix C. Assessing main results with randomization inference

Recent literature has shown that in shift-share regression design, 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 similar downward bias may occur when computing standard errors in our event-study analysis.

In order to check the robustness of our employment and House 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 apply the AKM inference procedures as in AKM (2019) and compute the standard errors that are robust to cross-sectional correlation across four-digit SIC industries and with three-digit SIC industry clusters.

As the inference discussion in the aforementioned literature is based on standard 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 first-differenced outcome variable such as change in log of employment and change in two-party republican vote share, Vulnerabilityc^{1990} is the vulnerability of county c in 1990, X_c is county-level characteristics including share of college grads in 1990 or a set of state dummy variables (thus state fixed effects).

For the placebo exercise, we use simulated vulnerabilities instead of the actual Vulnerability$_c^{1990}$, using 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 House election analysis, respectively, so that we are always comparing a midterm election to another midterm election.

For the placebo exercise, we draw simulated tariffs from three distributions: (i) one that follows the empirical distribution of actual industrial 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.[46] 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 Vulnerability$_c^{1990}$, using the

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

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.

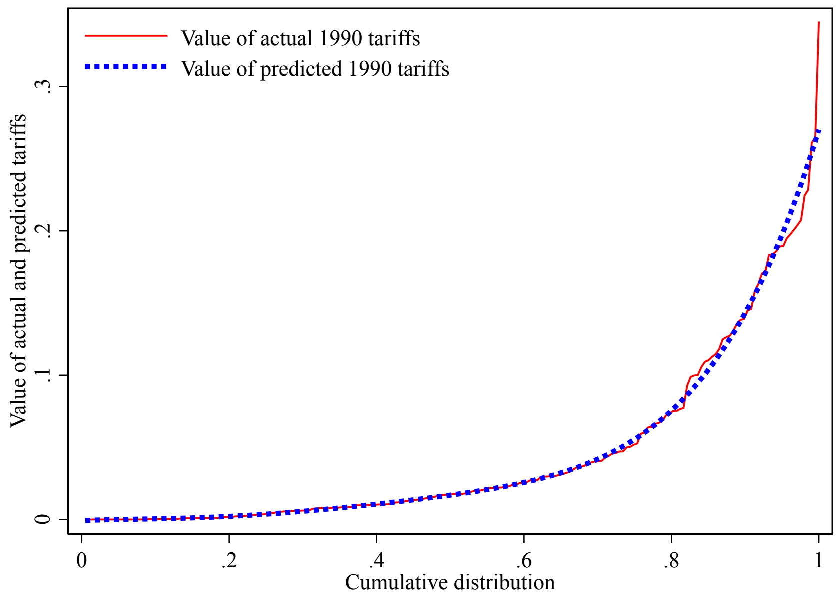
For each distribution, we repeat the simulation of county vulnerability and estimation of the equation (8) 1000 times and create 1000 placebo analysis samples. The outcome variables, change in log of county employment and change in Republican House vote share, are constructed using the observed data 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 House 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 the 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 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 on the county employment and Republican vote shares. 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 actual 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 vulnerabilities

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	all industry uniform
Coefficient	-.001	.071	.05	.004
(SE)	(.153)	(.231)	(.081)	(.129)
state FE	yes	yes	yes	yes

Notes: Number of simulation = 1000 times. 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]. 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. We compute the average and standard deviation of the estimates and report them as the bootstrapped coefficient and standard error. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. All specifications are weighted by 1990 county population and include state fixed effects.

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

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	all industry uniform
Initial vul.	-.044	.063	.043	.004
	(.206)	(.228)	(.079)	(.124)
state FE	yes	yes	yes	yes
share of colgrad (1990)	yes	yes	yes	yes

Notes: Number of simulation = 1000 times. 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]. 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. We compute the average and standard deviation of the estimates and report them as the bootstrapped coefficient and standard error. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. All specifications are weighted by 1990 county population and include share of college grads among 1990 county population as a control and state fixed effects.

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

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	all industry uniform
Initial vul.	-.993	-.172	-.128	.006
	(.171)	(.268)	(.091)	(.119)
state FE	yes	yes	yes	yes

Notes: Number of simulation = 1000 times. 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]. 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. We compute the average and standard deviation of the estimates and report them as the bootstrapped coefficient and standard error. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. All specifications are weighted by 1990 county population and include state fixed effects.

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

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	all industry uniform
Initial vul.	-.537	-.056	-.043	.005
	(.192)	(.231)	(.084)	(.111)
state FE	yes	yes	yes	yes
share of colgrad (1990)	yes	yes	yes	yes

Notes: Number of simulation = 1000 times. 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]. 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. We compute the average and standard deviation of the estimates and report them as the bootstrapped coefficient and standard error. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. All specifications are weighted by 1990 county population and include share of college grads among 1990 county population as a control and state fixed effects.

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

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	all industry uniform
Initial vul.	-.088	-.05	-.044	.003
	(.268)	(.247)	(.103)	(.128)
state FE	yes	yes	yes	yes

Notes: Number of simulation = 1000 times. The table reports the estimates from the first-difference model shown in equation (8). The dependent variable is change in county-level Republican House 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]. 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. We compute the average and standard deviation of the estimates and report them as the bootstrapped coefficient and standard error. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. All specifications are weighted by 1990 county population and include state fixed effects.

Appendix Table C.6: Estimates from the first-difference model with share of college grads (1990) control: Change in Republican House vote share (1984-1992) and simulated county vulnerabilities

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	all industry uniform
Initial vul.	-.102	-.053	-.047	.004
	(.249)	(.248)	(.1)	(.129)
state FE	yes	yes	yes	yes
share of colgrad (1990)	yes	yes	yes	yes

Notes: Number of simulation = 1000 times. The table reports the estimates from the first-difference model shown in equation (8). The dependent variable is change in county-level Republican House 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]. 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. We compute the average and standard deviation of the estimates and report them as the bootstrapped coefficient and standard error. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. All specifications are weighted by 1990 county population and include share of college grads among 1990 county population as a control and state fixed effects.

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

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	all industry uniform
Initial vul.	.732	.206	.16	-.002
	(.312)	(.333)	(.125)	(.168)
state FE	yes	yes	yes	yes

Notes: Number of simulation = 1000 times. The table reports the estimates from the first-difference model shown in equation (8). The dependent variable is change in county-level Republican House 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]. 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. We compute the average and standard deviation of the estimates and report them as the bootstrapped coefficient and standard error. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. All specifications are weighted by 1990 county population and include state fixed effects.

Appendix Table C.8: Estimates from the first-difference model with share of college grads (1990) control: Change in Republican House vote share (1992-2000) and simulated county vulnerabilities

Vulnerability :	Actual	Simulated		
Distribution :	N/A	poly. approx.	uniform [0,0.4]	all industry uniform
Initial vul.	.277	.091	.077	0
	(.293)	(.283)	(.109)	(.139)
state FE	yes	yes	yes	yes
share of colgrad (1990)	yes	yes	yes	yes

Notes: Number of simulation = 1000 times. The table reports the estimates from the first-difference model shown in equation (8). The dependent variable is change in county-level Republican House 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]. 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. We compute the average and standard deviation of the estimates and report them as the bootstrapped coefficient and standard error. We resample observations with replacement in each sample and use states as clustering units in order to employ state fixed effects. All specifications are weighted by 1990 county population and include share of college grads among 1990 county population as a control and state fixed effects.

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.	.378	-.001	-.044
robust SE	(.162)	(.14)	(.155)
AKM SE, three-digit SIC cl.	(.204)	(.144)	(.14)
state-clustered SE	(.176)	(.13)	(.208)
pop. weighted	yes	yes	yes
state FE	no	yes	yes
share colgrad (1990)	no	no	yes
Observations	2988	2988	2988

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 county population, and the second column reports the specification with state fixed effects, and the third column reports the specification with share of college grads in 1990 as a control and state fixed effects.

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.	-.854	-.993	-.537
robust SE	(.158)	(.139)	(.143)
AKM SE, three-digit SIC cl.	(.184)	(.186)	(.166)
state-clustered SE	(.214)	(.171)	(.192)
pop. weighted	yes	yes	yes
state FE	no	yes	yes
share colgrad (1990)	no	no	yes
Observations	2986	2986	2986

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 county population, and the second column reports the specification with state fixed effects, and the third column reports the specification with share of college grads in 1990 as a control and state fixed effects.

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

Dep. Var. :	First-difference in two-party Repub. vote share		
Initial vul.	.471	-.088	-.102
robust SE	(.223)	(.215)	(.208)
AKM SE, three-digit SIC cl.	(.256)	(.142)	(.15)
state-clustered SE	(.404)	(.268)	(.249)
pop. weighted	yes	yes	yes
state FE	no	yes	yes
share colgrad (1990)	no	no	yes
Observations	2565	2565	2565

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 House vote share between 1984 and 1992. All specifications are weighted by 1990 county population, and the second column reports the specification with state fixed effects, and the third column reports the specification with share of college grads in 1990 as a control and state fixed effects.

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

Dep. Var. :	First-difference in two-party Repub. vote share		
Initial vul.	1.445	.732	.277
robust SE	(.266)	(.26)	(.255)
AKM SE, three-digit SIC cl.	(.249)	(.133)	(.132)
state-cluster SE	(.453)	(.312)	(.293)
pop. weighted	yes	yes	yes
state FE	no	yes	yes
share colgrad (1990)	no	no	yes
Observations	2565	2565	2565

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 House vote share between 1992 and 2000. All specifications are weighted by 1990 county population, and the second column reports the specification with state fixed effects, and the third column reports the specification with share of college grads in 1990 as a control and state fixed effects.

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 account for changes in the economic condition of local labor markets.
One concern with the analysis in the main part of the paper is omitted-variables bias (from excluding the advantage measures) 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.[47]
We acquire industry-level Mexican tariff on imports from the US prior to NAFTA in 1993 from López-Córdova (2003).[48] The data contains tariff 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.[49] When aggregating the tariffs by SIC industries, we compute unweighted average tariffs of ISIC industries that correspond to each SIC industry.[50] 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

[47]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.

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

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

[50]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.

US HS-level imports and exports from Peter Schott's data webpage.[51] 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 for constructing 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*)-(*iii*) are identical to the data sources for computing the vulnerability measure. An additional data source we draw from is 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.)

In computing (*i*), we start by computing average tariff of industry groups, weighted by the import value of each industry group. Then we use the input cost composition for each industry group drawn from the I/O matrix to construct a measure of how each industry was affected by tariffs for the imported inputs prior to NAFTA. Computing (*ii*) and (*iii*) is exactly analogous to how we constructed Mexican 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 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.[52]

The correlation between our county-level input advantage measure and *Vulnerability*, constructed

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

[52] 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.

using the aggregation of 2-digit SIC industries, is 0.97.[53] 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.

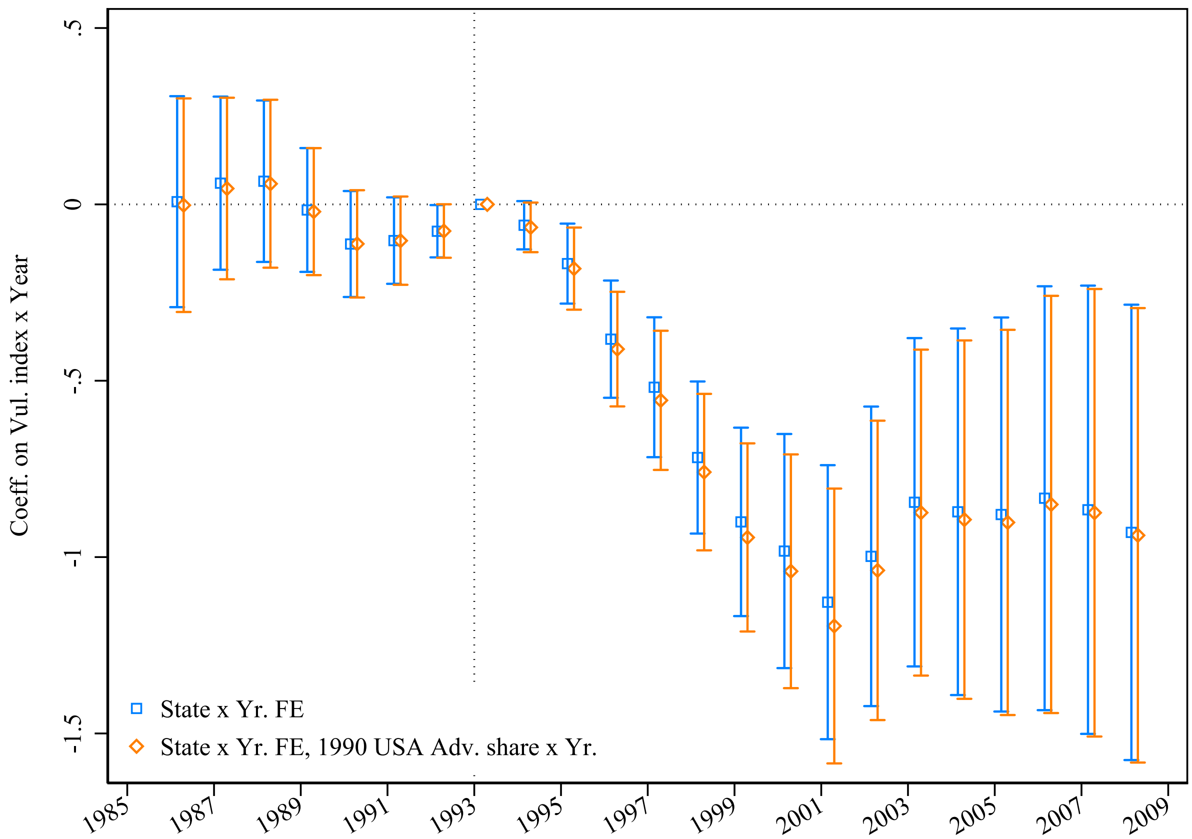
D.5. Is the Vulnerability effect robust to controlling for export advantage?

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*.

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 4 from the main paper). The second series adds the export-advantage measure interacted with year fixed effects. The coefficients on *Vulnerability* barely move.

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

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: $N = 2804$ counties. This figure is identical to Figure 4 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 (3). All specifications are weighted by 1990 county population. The first series shows the coefficient estimates from a specification where we control for only county and year fixed effects and state×year fixed effects, which is identical to the second series of Figure 4. The specification for the second series adds to this baseline specification 1990 county-level export advantage measure interacted with year fixed effects.