The Impact of NAFTA on U.S. Local Labor Market Employment *

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Abstract

This paper studies the impact of the North American Free Trade Agreement on U.S. local employment outcomes based on cross-regional variation in exposure to U.S. and Mexico's tariff liberalization. I find that lower U.S. tariffs led to a relative decline in the share of the working-age population employed in manufacturing (especially among low-skilled workers) in more exposed regions, and increases in unemployment and in the share of the population employed in certain low-pay nonmanufacturing industries. Employment losses due to U.S. tariff liberalization were much larger among female and nonwhite workers. U.S. tariff cuts also induced changes in the task composition of employment, leading to a decline in employment in production-related routine occupations and an increase in abstract occupations. The contraction in manufacturing and total employment as a result of U.S. tariff liberalization was concentrated in parts of the South and Midwest with relatively lower human capital. While Mexico's tariff cuts did not have a statistically significant impact on manufacturing employment for the population as a whole, they did increase manufacturing employment among individuals with college education.

Keywords: NAFTA, Trade policy, Tariffs, Employment, Unemployment, Local Labor Markets

JEL classification: F1, J2

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1. Introduction

The consequences of the North American Free Trade Agreement (NAFTA) for U.S. workers have been hotly debated since its enactment. Key to this debate is the geographic dimension of NAFTA's impact, given that regions across the U.S. were differentially exposed to tariff liberalization. Despite NAFTA's prominence in the public debate, however, evidence on its consequences is still limited. This paper studies the impact of NAFTA on local employment outcomes.

Starting January 1st 1994, the U.S. and Mexico swiftly liberalized tariffs toward each other. Local labor markets across the U.S. were exposed to this liberalization to different extents, depending on their initial industrial composition. For example, textile and apparel industries were among those facing the largest tariff reductions by the U.S. Consequently, among the most exposed regions were areas in North and South Carolina with a large textile sector, such as Greensboro and Fayetteville. Following the cross-regional empirical approach of Autor et al. [2013] and Hakobyan and McLaren [2016], I relate measures of regional exposure to tariff cuts to changes in local labor market outcomes during 1990-2000.[1]

I start by documenting the effect of tariff liberalization on manufacturing employment. Regions at the 75th percentile of exposure to U.S. tariff cuts experienced a 0.20 percentage point decline in the share of manufacturing employment in the working-age population relative to regions at the 25th percentile of exposure. This implies that the reduction in U.S. tariffs toward Mexico can be associated with a 0.41 percentage point decline in the manufacturing employment to population ratio over 1990-2000. To benchmark it, this is equal to 18.6% of the decline in this ratio during the decade.[2]

Like with other shocks to U.S. local labor markets, I find no statistically significant adjustment in population.[3] In addition, I find U.S. tariff cuts led to small and statistically insignificant changes in the share of population employed in the nonmanufacturing sector. Consequently, there was a decline in total employment, coupled with a statistically significant increase in unemployment as well as a similar increase in labor force nonparticipation which is not statistically significant.[4,5]

This overall impact did not affect all workers in a region equally. The effect of U.S. tariff cuts

[1] The timelines of liberalization in the U.S. and Mexico's tariff schedules indicate that both countries eliminated tariffs on most goods either immediately in January 1st, 1994 or shortly thereafter. This justifies focusing on the period 1990-2000.

[2] The share of manufacturing employment in the working-age population evolved from 12.7% in 1990 to 10.5% in 2000.

[3] The lack of response in local population to tariff liberalization is consistent with similar findings in other contexts, such as rising import competition from China [Autor et al., 2013]. Yagan [2019] and Molloy et al. [2011] document little impact of the 2007-2008 recession on migration.

[4] This rise in unemployment adds to the evidence showing this is an important adjustment margin provided by [Autor et al., 2013] and Erten et al. [2019] based on other contexts.

[5] The lack of adjustment in nonmanufacturing employment hides substantial heterogeneity. U.S. tariff cuts led to increases in employment in both retail and wholesale trade and in construction, which are among the lowest-paying service subsectors.

on manufacturing employment is not statistically significant among workers with college education. In contrast, I find a large and statistically significant decline in manufacturing employment as well as increases in unemployment and labor force nonparticipation only among noncollege individuals.

The impact of U.S. tariff cuts also differs markedly by gender. While the effect on manufacturing employment is very small and not statistically significant among men, it is negative and very large among women. Constructing gender–specific measures of exposure to U.S. tariff cuts, I find that the larger impact of these tariff cuts on female manufacturing employment is not due to differences in exposure to the shock on the manufacturing sector, but rather in the response to it.

It is especially interesting to study differential effects by race, because sectors facing large tariff cuts, such as textiles and apparel, were concentrated in regions with a large black population, such as certain areas in North and South Carolina. I find that while the impact of U.S. tariff cuts on manufacturing employment (as a fraction of the working-age population) was similar for white and black workers, the impact on total employment was very different, and specifically, very negative for nonwhite workers. In line with this, nonwhite workers face a larger increase in unemployment than white workers. This suggests that nonwhite workers have fewer opportunities following displacement from manufacturing jobs.

While I have described a significant impact of U.S. tariff liberalization, Mexico's tariff cuts did not have a statistically significant effect on manufacturing employment or other adjustment margins for the population as a whole.[6] However, Mexico's tariff liberalization led to a relative increase in manufacturing employment among college workers.[7] In other words, those who faced the decline in employment due to increased import competition (i.e. those with no college education, women and nonwhite workers) are different than those who benefited from increased export demand (those with college education).

U.S. tariff cuts also had an impact on the task composition of employment, leading to an increase in employment in abstract occupations and a decline in production–related routine occupations. In addition, U.S. tariff cuts had very different effects across high and low human capital commuting zones.[8] In areas with low human capital, located mostly in the South and parts of the Midwest, U.S. tariff cuts

[6] The impact of Mexico's tariff cuts on U.S. manufacturing employment, while not statistically significant, has a magnitude that is larger (and, intuitively, an opposite sign) to that of U.S. tariff cuts. Thus, the impact of Mexico's tariffs on the population as a whole is estimated imprecisely, yet is not necessarily small. Note also that I show that U.S. exports to Mexico did respond to Mexico's tariff cuts.

[7] There is also some evidence of an increase in employment among men and white workers in response to Mexico's tariff cuts, but these effects are not robust.

[8] I interpret the impact of human capital endowments on the adjustment to tariff liberalization as descriptive rather than causal, given that there are other differences across commuting zones in addition to human capital endowments (such as their economic structure), and these other factors could be in turn determined by human capital endowments.

had a large negative effect on manufacturing employment and in total employment. In high human capital regions, in contrast, these effects were small and not statistically significant.[9] This implies a widening in regional disparities across the U.S., and gives support to the idea that high–skill regions are more resilient to shocks [Glaeser et al., 2004, Glaeser, 2005]. Finally, the effects of NAFTA were persistent beyond year 2000 (at which point tariff liberalization was almost complete). Looking up to 2007, I find that manufacturing employment kept declining at about the same rate than it did during 1990–2000 in response to U.S. tariff cuts. The decline in total employment, in contrast, was almost complete by 2000 because the growth in nonmanufacturing employment was slower than the decline in manufacturing employment. While the unemployment effects disappeared over the longer horizon, there was a statistically significant increase in labor force nonparticipation over 1990–2007.

The empirical setting in this paper corresponds to theoretical models designed to analyze the local effects of trade liberalization [Kovak, 2013]. In particular, the adjustment margins studied in the current paper speak to models incorporating unemployment and labor force nonparticipation into that framework [Kim and Vogel, 2021]. The prediction of that model is that groups of the population employed disproportionately in sectors with a higher exposure to U.S. trade liberalization will experience a decline in total employment (an increase in unemployment and labor force nonparticipation). This prediction thus extends Stolper–Samuelson type mechanisms to richer environments with non–wage adjustment margins. The empirical results found in this paper appear to be in general terms in support of those predictions, given that the sectors more exposed to U.S. trade liberalization (such as apparel) concentrate disproportionate amounts of low–skill workers, which is the group seeing a larger decline in employment.

The fact that the measures of regional exposure to tariff liberalization are shift–share regressors connects this paper to recent work that has formalized the conditions for inference in this type of setting. Borusyak et al. [2022b] develop a framework in which identification is based on exogenous shocks (i.e. industry–level tariff cuts) and possibly endogenous shares (i.e. employment weights). I show that the key assumptions for identification under this framework are met.

Finally, the results are robust to using different measures of regional exposure to tariffs, to controlling for rising import competition from China, and to controlling for a rich set of initial commuting zone characteristics used by Autor et al. [2013].[10]

[9] These results hold even when focusing on low-skill workers, such that low–skill workers in high human capital regions seem to be shielded from import competition.

[10] A potential concern with the empirical strategy is that Mexico experienced a devaluation in December 1994 as well as a recession. This crisis was temporary: while Mexico's GDP fell by 6.3% in 1995, it grew by 6.8% in 1996 and growth rates remained high during the rest of the decade. In fact, Burfisher et al. [2001] argue that trade between the U.S. and Mexico recovered promptly following this currency crisis. The empirical identification of the effect of NAFTA is based on varia-

Related Literature This paper contributes to a literature studying the local impact of trade shocks in the U.S. [Hakobyan and McLaren, 2016, Autor et al., 2013, 2015, 2019, Pierce and Schott, 2020].[11] While the literature has documented the impact of NAFTA on wages [Hakobyan and McLaren, 2016], understanding its effects on employment, unemployment, and labor force participation is critical, because changes in wages are not sufficient to assess the effects on individuals' welfare [Kim and Vogel, 2020].[12]

In addition, NAFTA is conceptually different than the China shock (rising Chinese import competition) [Autor et al., 2016]. Unlike the one–sided China shock, NAFTA involves an increase both in import competition due to U.S. tariff cuts as well as in export demand due to Mexico's tariff cuts. It is also worth noting that there is a positive but relatively low correlation across regions in exposure to the China shock and NAFTA tariff liberalization.[13] Thus, sectors, regions and people impacted by NAFTA are to a large extent different than those impacted by the China shock.

While the literature has studied the differential impact of trade shocks based on educational attainment and gender, the most novel contribution in this regard is documenting large differences in outcomes by race.[14,15] Understanding this heterogeneity in the impact of NAFTA is crucial for policymaking. This is true not only regarding the direct shock to the manufacturing sector, but especially so regarding differences in the adjustment to this shock, which entails moving to other sectors of the economy, into unemployment, or out of the labor force. The findings in this paper can thus be used to tailor policies designed to help with this adjustment, such as the Trade Adjustment Assistance program.

The literature has shown that the elimination of U.S. tariffs toward Mexico in the context of NAFTA led to a decline in blue–collar wages [Hakobyan and McLaren, 2016], especially among women [Hakobyan

tion in tariff cuts across manufacturing industries, which interacts with commuting zones' initial industrial composition. All regressions control for the initial share of manufacturing employment in total employment. A devaluation would affect the manufacturing sector as a whole, and should not interfere with the identification strategy. In addition, while Mexico's recession and devaluation might have temporarily impeded imports from the U.S., I show that Mexico's tariff liberalization boosted U.S. exports between 1990 and 2000, to a similar extent than the increase in U.S. imports due to U.S. tariff liberalization.

[11] There has also been important work studying the impact of trade shocks on local labor market outcomes in other countries including India [Topalova, 2010], Brazil, [Kovak, 2013, Dix-Carneiro and Kovak, 2017], Germany [Dauth et al., 2014], and South Africa [Erten et al., 2019].

[12] Kim and Vogel [2020] develop a sufficient statistic for welfare changes in response to trade shocks accounting for these adjustment margins. Studying growth in Chinese import competition, they find that a majority of the welfare change in more exposed relative to less exposed U.S. commuting zones is *not* due to changes in wages, but rather to changes in other adjustment margins such as unemployment.

[13] Regions with more exposure to growth in Chinese imports were also more exposed to U.S. and Mexico's tariff cuts, but the correlation coefficients are only 0.30 and 0.46 in absolute value.

[14] Hirata and Soares [2020] study Brazil's unilateral trade liberalization and show a compression in the wage gap between black and white workers that is not explained by differences in observables. Recent work by Batistich and Bond [forthcoming] focuses on import competition from Japan during the 1970s and 1980s in the U.S., and find it led to a decline in manufacturing employment among black workers only. See the survey by Harrison et al. [2011] regarding the differential impact of trade liberalization across groups by educational attainment and the work by Hakobyan and McLaren, 2018, Aguayo-Tellez et al., 2010, Black and Brainerd, 2004, Autor et al., 2019, Gaddis and Pieters, 2017, Benguria and Ederington, forthcoming, Juhn et al., 2014 and Sauré and Zoabi, 2014, among others regarding the differential impact of trade liberalization by gender.

[15] These findings are consistent with Gould [2018], which finds that deindustrialization in the U.S. during 1960-2010 has had a negative impact on black relative to white individuals.

and McLaren, 2018]. In addition, Choi et al. [2021] study the political effects of NAFTA, finding that counties more exposed to U.S. tariff cuts reduced their votes for the Democratic party. Like this paper, Choi et al. [2021] also document that U.S. tariff cuts led to a reduction in total employment. However, the main difference with Choi et al. [2021] is that using Census data allows me to focus on employment in different sectors, unemployment, and labor force participation, not only for the population as a whole but for different demographics based on educational attainment, gender and race.[16]

Finally, from a methodological perspective, this paper contributes to the literature by constructing much more disaggregate measures of exposure to U.S. tariffs than in previous work, by using newly–digitized data on Mexico's schedule of tariff preferences toward the U.S. under NAFTA to measure exposure to Mexican tariff cuts, and by engaging with recent work that formalizes the conditions for inference in regressions with shift–share regressors [Borusyak et al., 2022b].

2. Empirical Approach and Data

2.1. Empirical Approach

The empirical strategy exploits regional variation in exposure to NAFTA tariff cuts that originates in commuting zones' initial industrial composition. I construct regional measures of tariff changes between 1990 and 2000 weighing industry-level tariffs with industry employment shares in each region. These weights are computed in the initial year, 1990. This approach has been used in the case of NAFTA by Hakobyan and McLaren [2016] and Choi et al. [2021] and in other contexts by Topalova [2010], Kovak [2013], Dix-Carneiro and Kovak [2017], Erten et al. [2019], and Kis-Katos and Sparrow [2015] among others. Other work has constructed similar measures of regional exposure to trade flows instead of tariffs [Autor et al., 2013]. Specifically, the measure of U.S. tariff liberalization for region i is the following sum across manufacturing industries $j \, \epsilon \, J$:

$$\Delta\tau_i^{U.S.} = \sum_{j \, \epsilon \, J} \frac{L_{ij} \Delta\tau_j^{U.S.}}{L_i} \ . \tag{1}$$

[16]Other work on NAFTA has focused on trade flows and welfare. Romalis [2007] finds an increase in trade with Mexico, but negligible effects on U.S. welfare. Caliendo and Parro [2015] use a Ricardian model with sectoral linkages to find a small (0.08%) increase in U.S. welfare. My findings underscore the importance of incorporating unemployment and labor force nonparticipation into the full–employment models used to quantify welfare.

In this expression L_{ij} is employment in industry j in region i in 1990, L_i is total employment in region i in 1990, and $\Delta\tau_j^{U.S.} = \tau_{j\,2000}^{U.S.} - \tau_{j\,1990}^{U.S.}$ is the change in the U.S. tariff toward Mexico in industry j between 1990 and 2000. Variation in this measure of regional exposure to tariff liberalization stems from differences across regions in their initial industrial mix within the manufacturing sector, as well as from differences in the size of the manufacturing sector. The regressions I estimate will control for the initial share of manufacturing employment in total employment, so the identification will only be due to differences in the industrial mix within manufacturing. Following Autor et al. [2013], the denominator in equation (1) is total regional employment, which implies that (1) is equivalent to a weighted average across all industries assigning zero tariff changes to nontraded industries.

Others [Kovak, 2013, Hakobyan and McLaren, 2016] normalize by total regional employment in traded industries, under the assumption that nontraded prices move with the prices of traded goods, and Hakobyan and McLaren [2016] argue this is a debatable issue.[17] In Appendix A.5, I define an alternative tariff measure with total regional employment in the manufacturing sector in the denominator, and show that the results found using it are very similar to those found using the measure of exposure defined by equation (1).[18,19]

In addition, Hakobyan and McLaren [2016] point out that U.S. tariff cuts on Mexico should have a larger effect on trade flows in industries in which Mexico has comparative advantage, and define a measure of exposure to tariff liberalization that takes this into account. In Appendix A.5 I describe this measure in detail, and show later that the key results in the paper are robust to using this alternative.

A third alternative exposure measure discussed in Appendix A.5 is equivalent to (1) but instead of considering tariff changes in manufacturing industries, it considers all tradable industries including commodities (agriculture, etc.)

I also construct an equivalent measure of regional exposure to reductions in Mexican tariffs granted to the U.S. The equivalent to equation (1) is:

$$\Delta\tau_i^{\mathrm{MEX}} = \sum_{j\,\epsilon\,J} \frac{L_{ij}\Delta\tau_j^{\mathrm{MEX}}}{L_i} \quad . \tag{2}$$

[17] Kovak [2013] develops a model including the nontraded sector, showing nontraded prices move with traded prices. Kovak [2013]'s framework is designed to measure the impact of trade liberalization on wages, and Kovak [2013] states that his model does not have a message in the case of studying nonwage outcomes (see his footnote 4). Given that this paper studies nonwage outcomes, I show that the results are robust to the various approaches to measuring weighted tariffs used in the literature.

[18] Because regressions control for the initial share of employment in manufacturing, identification is based only on variation across regions in the composition across traded industries, so both tariff measures yield very close results.

[19] I choose to report results using a measure of exposure that implicitly assigns zero tariffs to nontraded industries in the main text because I am interested in comparing the effects of NAFTA tariff liberalization to that of rising Chinese import competition in Autor et al. [2013], who treat nontraded industries in the same way.

, where $\Delta\tau_j^{MEX} = \tau_{j\,2000}^{MEX} - \tau_{j\,1990}^{MEX}$ is the change in Mexico's tariff toward the U.S. in industry j between 1990 and 2000. Again, alternative measures of exposure for Mexico's tariff cuts are defined in the Appendix.

2.2. Data Sources and Measurement

Local labor market outcomes I measure employment outcomes using the 1970, 1980, 1990, and 2000 5% samples of the Decennial Census [Ruggles et al., 2019]. In some results I also use the 2007 American Community Survey (ACS) 3% sample to look at longer term outcomes. As in Autor et al. [2013], I restrict the sample to individuals aged 16 to 64.[20]

Recent work studying U.S. local labor markets has defined these using the concept of commuting zone. These geographical units were defined by Tolbert and Sizer [1996] based on commuting patterns. I use the approach developed by Dorn [2009] and used by Autor and Dorn [2013] and Autor et al. [2013] to assign individuals to commuting zones based on the geographical information observed in the census data.[21] The analysis is restricted to 722 commuting zones in the continental U.S.

I also construct measures of the task composition of local labor market employment. Following Autor et al. [2015] I classify occupations into those performing primarily abstract, routine, or manual tasks. Abstract occupations perform problem-solving and organizational tasks. Routine occupations perform codifiable tasks and can thus be potentially automated, while manual occupations require physical dexterity or interpersonal communication and are difficult to codify. The abstract category includes managerial, professional and technical occupations. The routine category consists of two quite distinct groups: clerical activities and retail sales occupations, and production-related occupations. Finally, mechanic, craft, agricultural and service occupations consist primarily of manual tasks. Autor and Dorn [2013] provide evidence in favor of this classification based on measures of job task intensity using the 1977 Dictionary of Occupational Titles.

Appendix Table A.4 reports summary statistics for all local labor market outcomes in 1990 and 2000, and for their change during 1990-2000.

Tariffs I construct measures of regional exposure to U.S. tariffs imposed on Mexico as well as Mexican tariffs imposed on the U.S. Previous work by Hakobyan and McLaren [2016] has analyzed the effect of

[20] Note that the 3–year ACS includes years 2006, 2007, and 2008. Further details on the sample selection are provided in Appendix A.1.

[21] The Census and ACS report individuals' Puma (Public Use Microdata Area) of residence.

U.S. tariff cuts on U.S. local labor markets (for wage outcomes), but not their response to Mexico's tariff reductions.

U.S. tariffs imposed on Mexico are obtained from Romalis [2007] at the 8-digit level of the U.S. tariff schedule. These are aggregated to HS 6-digit codes using U.S. HS 8-digit imports as weights.[22] I then construct industry-level tariffs for 397 4-digit SIC manufacturing industries using the concordance provided by Autor et al. [2013].[23] The method used to construct industry-level U.S. tariffs has the advantage of resulting in much more detailed variation than in Hakobyan and McLaren [2016]. Hakobyan and McLaren [2016] define tariffs for 89 industries, given that they use the set of industries in the 1990 Census of Population. The further disaggregation in this paper aids with the identification. I later discuss in Section 3 that key results are found to be statistically significant only with the further geographic and industry disaggregation used in this paper.

To construct the regional measure of exposure to tariff changes defined by equation (1), I compute weights using commuting zone by industry employment in 1990 from the Census Bureau's County Business Patterns (CBP). I follow Autor et al. [2013]'s procedure to impute missing employment and to aggregate the county-level data to commuting zones and to the industry classification described in the previous paragraph.[24]

I also assemble new data on Mexico's tariff preferences toward the U.S. under NAFTA. These data are obtained directly from Mexico's *Diario Oficial* (the official daily publication of the Mexican government, equivalent to the U.S. Federal Register) and then digitized. These data have not been used in previous work. Appendix A.2 describes the processing procedure for this novel dataset. Mexico's tariffs are reported by 8-digit codes of the Mexican tariff schedule. I first construct average tariffs at the HS 6-digit level, which I then translate into SIC industries using the same concordance described earlier.[25] The measure of regional exposure to Mexican tariff cuts defined by equation (2) is constructed with the same CBP employment weights used for U.S. tariffs. It is worth noting that there is a substantial spatial correlation in regional exposure to U.S. and Mexican tariff cuts. The correlation coefficient between these two measures is 0.75. This high correlation underscores the importance of including in the analysis

[22] Data on U.S. imports in 1990 used to construct weights are a product of the U.S. Census Bureau and obtained from Schott [2008].

[23] I use the classification of industries developed by Autor et al. [2013], which introduces a minor modification to the SIC 1987 classification. The goal of this modification is to avoid situations in which manufacturing SIC industries are not the main industry for any HS code and thus report zero trade.

[24] In some cases the CBP data reports ranges instead of precise employment values for some industry-county pairs in the interest of confidentiality. Autor et al. [2013] develop a procedure to impute employment to these cells.

[25] I construct HS 6–digit tariffs for Mexico to then match these to SIC codes. Note that HS codes are not internationally equivalent at any level more disaggregated than HS6. No weights are used to average tariffs by HS6 codes, given that Mexico's trade flows by HS8 (according to the Mexican HS classification) are not available for 1990.

both Mexico's and U.S. tariff cuts.

Panel A in Figure 1 maps the measure of regional exposure to U.S. tariff cuts. The largest reductions in U.S. tariffs impact commuting zones in the South Atlantic region and to a lesser extent in the North Atlantic and the Midwest. Panel B shows the regional variation in exposure to Mexico's tariff cuts and reflects the high correlation in regional exposure to U.S. and Mexico's tariff liberalization. While the analysis in the paper only uses measures of regional exposure to tariffs in 1990 and 2000, Appendix Table A.6 gives a sense of the evolution of tariffs over time. It tabulates the mean and various percentiles of the distribution of commuting zone exposure over time. Panels A refers to U.S. tariffs and indicates that the largest decline in tariffs occurs as soon as the agreement is enacted in January 1st, 1994, and that further tariff cuts lead to almost zero tariffs by 1999. In addition, it shows the skewness in the distribution of tariff exposure across regions. Panel B refers to Mexico's tariffs. While the initial level of tariffs is much higher in Mexico, the largest decline occurs immediately in 1994 and liberalization is almost complete by the late 1990s, as in the case of U.S. tariffs. In addition, Appendix Table A.5 reports summary statistics for the measures of regional exposure to 1990-2000 *changes* in tariffs and Appendix Figure A.1 plots an histogram of the distribution of these tariff cuts. The histograms again emphasize that the distribution of 1990-2000 changes in U.S. tariffs is left-skewed, with a large number of small tariff cuts and a long tail of larger tariff reductions.

Appendix Table A.7 lists the commuting zones most and least exposed to U.S. and Mexico's tariff liberalization, among the 100 with the largest population in 1990. The most exposed are mostly concentrated among North and South Carolina, a region with a large textile and apparel sector in 1990.[26,27] Specifically, Fayetteville (North Carolina), Greenville (South Carolina) and Greensboro (North Carolina), are the top three and face a substantially larger shock than the following ones. This is consistent with the map of exposure described earlier. The regions that are most exposed to Mexico's tariff liberalization are more spread out throughout the U.S. However, Greensboro and Fayetteville are also the two most exposed to this shock. The reason is that in 1990 these two commuting zones had a large textile sector and both the U.S. and Mexico reduced textile tariffs substantially. Washington DC, in contrast, is among the least exposed to both U.S. and Mexico's tariff cuts.

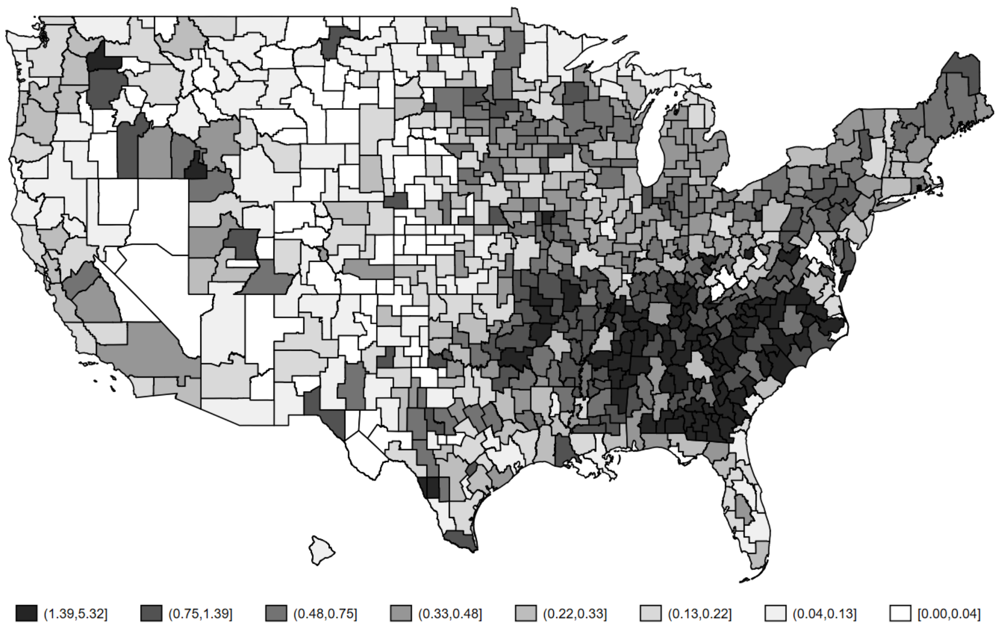
I also examine the variation across industries that generates the variation in regional exposure described earlier. Panel A in Appendix Table A.8 ranks SIC 2–digit industries from largest to smallest U.S.

[26]Some commuting zones cross state lines, and are assigned to the state in which they have the largest employment.

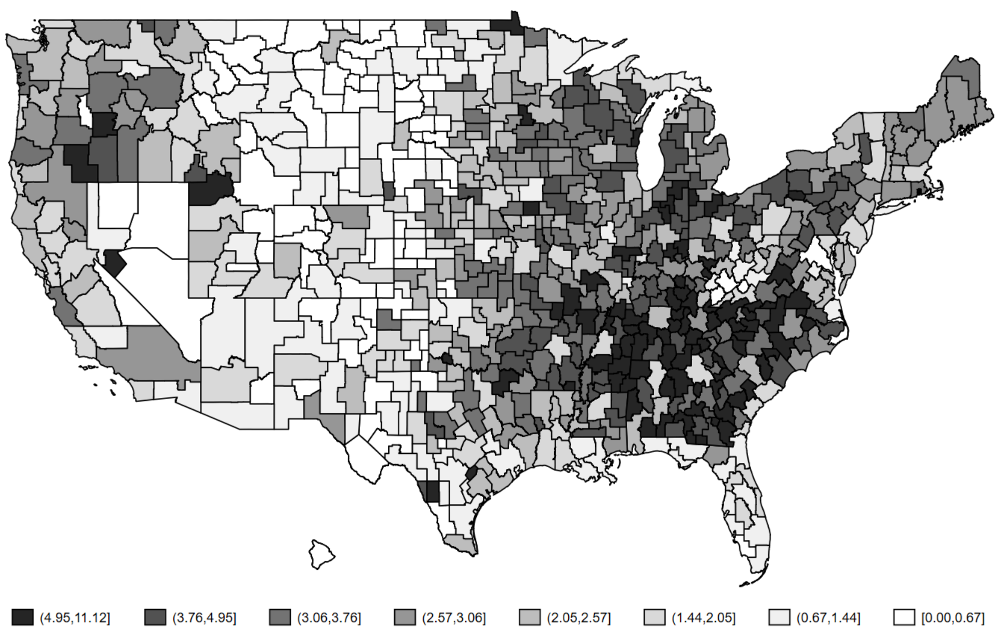
[27]South Carolina and North Carolina are the two states with the largest share of employment in textile and apparel industries in 1990, with 8.9% and 8.6% respectively.

Figure 1: Regional Exposure to Changes in Tariffs

Panel A: Commuting Zone Exposure to Change in U.S. Tariffs, 1990-2000



Panel B: Commuting Zone Exposure to Change in Mexico's Tariffs, 1990-2000



Notes: Panel A illustrates differences across commuting zones in exposure to U.S. tariff liberalization (defined by equation (1)) between 1990 and 2000. Panel B (in the next page) illustrates differences across commuting zones in exposure to Mexico's tariff liberalization (defined by equation (2)) between 1990 and 2000. Darker shades indicate larger tariff reductions.

tariff cuts. It shows that apparel, followed by textile mill products and leather and leather products are the most exposed sectors, while lumber and wood products and printing and publishing are the least exposed. Panel B ranks these sectors based on Mexico's tariff cuts, showing that tobacco products receive the largest tariff cuts followed by apparel, which received large tariff cuts from both countries.

The same table also gives a sense of the demographics of each manufacturing industry. It shows that industries facing the largest U.S. tariff cuts had a very high share of female and/or nonwhite employment in 1990. In particular, employment in apparel (which faced the largest U.S. tariff cut and the second largest Mexican tariff cut) was 78% female and 32% nonwhite; in both cases the highest share across all 2-digit industries.

Tariff liberalization and trade flows A pertinent question is whether U.S. tariff cuts increased U.S. imports from Mexico, and whether Mexico's tariff cuts increased U.S. exports to Mexico. In Appendix A.7, I show that this is indeed the case. Using product by country level data, I show that between 1990 and 2000 there was a 33% increase in U.S. imports from Mexico relative to the rest of the world in industries with initial high (i.e. above-median) tariff levels relative to other industries.[28] I also report a 24% increase in U.S. exports to Mexico relative to the rest of the world in industries with initial high tariff levels relative to other industries between 1990 and 2000.

Initial commuting zone characteristics The analysis includes a set of initial commuting zone variables measured in 1990, drawn from Autor et al. [2013] and used as control variables. These are the ratio of manufacturing employment over total employment, the share of college-educated population, the fraction of foreign born population, the share of the female population that is employed, the ratio of employment in routine occupations over total employment, and an index of the offshorability of the occupations in each commuting zone.

Growth in Chinese import competition During the time period under study, the U.S. labor market also faced rising import competition from China. I include in the analysis Autor et al. [2013]'s measure of commuting zone exposure to this shock during 1990-2000:

$$\Delta \text{IPW}_{ui} = \sum_{j} \frac{L_{ij}}{L_{uj}} \frac{\Delta M_{ucj}}{L_i} . \tag{3}$$

[28]This is consistent with the analysis in Romalis [2007].

In this expression, ΔM_{ucj} stands for the change in industry-level imports between 1990 and 2000, L_{ij} stands for employment in industry j in region i in 1990, L_{uj} stands for total employment in industry j in 1990, and L_i stands for total employment in region i in 1990. Unobserved shocks could have an impact on both U.S. local labor market outcomes and on imports, so following Autor et al. [2013] I use the following instrument to isolate the component due to supply shocks, stemming from China's rising productivity and transition to a market-oriented economy. This instrument is defined as a weighted average of 1990-2000 growth in industry-level imports from China by eight developed countries other than the U.S., ΔM_{ocj}:[29]

$$\Delta \text{IPW}_{oi} = \sum_j \frac{L_{ij,\,1980}}{L_{uj,\,1980}} \frac{\Delta M_{ocj}}{L_{i,\,1980}} \,. \tag{4}$$

Differently than in equation (3), employment is computed for 1980, to prevent a simultaneity bias resulting from commuting zone employment potentially being a function of anticipated Chinese imports. These variables are described by Autor et al. [2013] in detail.[30] Appendix Table A.9 reports summary statistics for these variables.

3. NAFTA and Manufacturing Employment

To assess the impact of NAFTA on manufacturing employment in U.S. local labor markets, I estimate regressions of the following form using OLS:

$$\Delta L_i^m = \beta_1 \Delta \tau_i^{U.S.} + \beta_2 \Delta \tau_i^{MEX} + X_i' \beta_3 + \epsilon_i \,. \tag{5}$$

The dependent variable is the change between 1990 and 2000 in the share of manufacturing employment in the working-age population in commuting zone i. $\Delta \tau_i^{U.S.}$ stands for the regional exposure to changes in U.S. tariffs toward Mexico between 1990 and 2000, defined by equation (1). $\Delta \tau_i^{MEX}$ represents exposure to changes in Mexican tariffs toward the U.S. during the same period, as defined by (2). The term X_i' contains a set of controls capturing the economic characteristics of each commuting zone in 1990, as well as dummy variables for nine census divisions. The sample consists of the 722 commuting zones in the continental U.S. Observations are weighted by each commuting zone's initial population in 1990.

[29] Specifically, this measure considers Chinese imports by Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland, based on data availability.

[30] These measures are constructed using HS 6-digit trade flows from UN Comtrade for 1990 and 2000, which are then translated to 4-digit SIC codes. Employment weights are computed using the CBP data described earlier, assigning counties to commuting zones.

Standard errors are clustered at the state level.[31] This regression resembles the main specification in Autor et al. [2013] but with measures of exposure to tariff liberalization as the regressors of interest.[32,33]

Table 1 reports the baseline results. Column 1 includes only a measure of exposure to U.S. tariff cuts, $\Delta\tau_i^{U.S.}$. Regions with higher exposure to tariff cuts see a relative decline in the share of manufacturing employment in the working-age population. The coefficient indicates that commuting zones at the 75th percentile of exposure experience a decline of 0.17 percentage points in the manufacturing employment share of the population relative to commuting zones at the 25th percentile.[34] An alternative way of interpreting this coefficient is that a one standard deviation increase in the measure of regional exposure to U.S. tariff cuts is associated with a decline of 0.42 percentage points in the manufacturing employment share of the population.

Column 2 adds the commuting zone exposure to Mexican tariff changes, $\Delta\tau_i^{MEX}$. The coefficient on the exposure to U.S. tariff cuts changes very little in comparison to column 1. Reductions in Mexico's tariffs toward the U.S. show no statistically significant impact on the share of manufacturing employment in the working-age population although the coefficient, intuitively, has the opposite sign to that for U.S. tariff exposure.

Next, column 3 also adds Autor et al. [2013]'s measure of rising import competition from China, defined by equation (3). In this case, I estimate equation (5) using two-stage least squares. I use the same instrument as Autor et al. [2013], regional exposure to rising imports from China by other non-U.S. developed countries, defined by equation (4). This is essentially the same specification used in Autor et al. [2013]. The only difference, other than the inclusion of exposure to NAFTA tariff cuts, is that Autor et al. [2013] stack differences between 1990-2000 and 2000-2007. Here, I focus on the period 1990-2000. The first stage estimates are shown in Appendix Table A.11 and indicate that U.S. imports

[31]Later, I also use [Borusyak et al., 2022b]'s procedure to compute exposure–robust standard errors that account for the fact that similar exposure shares across regions can lead to correlated residuals, as noted in Adao et al. [2019] and [Borusyak et al., 2022b].

[32]Consistent with most of the literature, I do not include a measure of regional exposure to the initial 1990 tariff level in the regression. First, it would be redundant, since the correlation between a measure of regional exposure to the initial 1990 tariff level and the measure of regional exposure to the 1990-2000 change in tariffs is -0.998 for the U.S. and -0.997 for Mexico. A possible reason to include a measure of exposure to the initial 1990 tariff level would be to control for anticipation effects in industries not fully liberalized by 2000. This is not a concern since liberalization was practically complete by 2000. In year 2000, the average (employment-weighted) tariff across manufacturing industries was 0.13% for U.S. tariffs and 1.3% for Mexican tariffs. Note, however, that I find similar results when including a measure of regional exposure to the initial 1990 tariff level, as shown in Appendix Table A.31.

[33]Note that this is a regression with two different shift—share regressors which have the same shares (employment weights) and different "shifts" or "shocks" (U.S. and Mexican tariff changes). To gain intuition, consider several regions with the same ratio of manufacturing employment over total employment. Assume the change in the U.S. tariff in a certain industry is particularly large. If one sees employment fall in regions with a particularly large share of employment in that industry, one could attribute it to the U.S. tariff shock.

[34]The 75th and 25th percentiles of the distribution of the measure of regional exposure to U.S. tariff cuts are -0.195 and -0.410, as shown in the first row in Appendix Table A.5. The difference between these two numbers, times the regression coefficient 0.790, is 0.17.

from China are highly correlated to Chinese imports by the set of other developed countries. Back to the 2SLS second-stage estimates in Table 1, the results show that the negative impact of U.S. tariff cuts on the manufacturing employment to population ratio persists after controlling for rising import competition from China and is quite stable across columns. Based on column 3, commuting zones at the 75th percentile of exposure experience a decline of 0.20 percentage points in the manufacturing employment share of the population relative to commuting zones at the 25th percentile.[35] Note also that, as Autor et al. [2013] found, rising import competition from China has a negative effect on commuting zone manufacturing employment. This effect, however, is not statistically significant at conventional levels during the period 1990-2000. This is not a result of controlling for tariff liberalization. Panel A in Appendix Table A.12 replicates Autor et al. [2013]'s main specification focusing exclusively on the period 1990-2000, without including measures of exposure to NAFTA tariff liberalization, finding a similar result.[36] In other words, Autor et al. [2013]'s result is driven primarily by the 2000-2007 period, even though in both the 1990-2000 and 2000-2007 periods there is substantial evidence of an impact of Chinese import competition on manufacturing employment.

How can these estimates of the impact of NAFTA on U.S. manufacturing employment be benchmarked? During the period 1990-2000 the mean U.S. tariff change across commuting zones based on the baseline definition in equation (1) was -0.447. Using the coefficient of 0.907 of column 3 in Table 1, this implies a decline of 0.41 percentage points in the share of manufacturing employment in the population. Over this period, this share went from 12.7 to 10.5 (a decline of 2.2 percentage points). This implies that U.S. tariff cuts toward Mexico account for 18.6% of the decline in the manufacturing employment to population ratio.[37] While the effect of Mexico's tariff cuts was found not to be statistically significant, the equivalent calculation implies an increase of 0.81 percentage points in the share of manufacturing employment in the population.[38] Thus, the overall effect of NAFTA on the manufacturing employment share is positive, resulting in a net 0.40 percentage point increase. This overall effect, however, is not statistically significant.

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[35]Note that this comparison of commuting zones at the 25th and 75th percentiles of exposure to U.S. tariff cuts assumes all else is held constant, including control variables as well as the measure of exposure to Mexico's tariff cuts. Because the measures of exposure to U.S. and Mexico's tariff cuts are both shift–share variables with identical weights but different shifts (industry–level tariff cuts), this is a restrictive ceteris paribus exercise which can be thought of as comparing commuting zones with a low vs. a high share of employment in industries facing large U.S. tariff cuts but small Mexican tariff cuts.

[36]The difference with Table 2 in Autor et al. [2013] in which they break down results by decade is that here all the control variables are included.

[37]This approach, however, uses relative effects obtained from the cross-regional empirical strategy to infer absolute effects. An alternative is to use a general equilibrium model to infer the impact of NAFTA, such as in Caliendo and Parro [2015].

[38]The mean change in Mexico's tariffs across commuting zones based on the definition in equation (2) was -2.499. Multiplying this by the coefficient of -0.325 of column 3 in Table 1 implies an increase of 0.81 p.p. in the share of manufacturing employment in the population.

Table 1: NAFTA Tariff Liberalization and Change in Share of Manufacturing Employment in the Working-Age Population

Dependent Variable: Change in manufacturing emp/working-age pop (in % pts)

	OLS (1)	OLS (2)	2SLS (3)
$\Delta\tau^{\text{US}}$	0.790** (0.325)	0.839** (0.334)	0.907*** (0.305)
$\Delta\tau^{\text{MEX}}$		-0.158 (0.268)	-0.325 (0.218)
ΔIPW			-0.216 (0.198)
Percentage of employment in manufacturing$_{1990}$	-4.407* (2.196)	-6.362* (3.601)	-6.939** (3.329)
Percentage of college-educated population$_{1990}$	-0.005 (0.018)	-0.004 (0.018)	-0.000 (0.018)
Percentage of foreign-born population$_{1990}$	-0.003 (0.014)	-0.003 (0.014)	0.001 (0.013)
Percentage of employment among women$_{1990}$	0.021 (0.027)	0.020 (0.027)	0.022 (0.026)
Percentage of employment in routine occupations$_{1990}$	-0.188*** (0.057)	-0.189*** (0.057)	-0.201*** (0.057)
Average offshorability index of occupations$_{1990}$	-0.622 (0.386)	-0.633 (0.393)	-0.641* (0.379)
Census division dummies	Yes	Yes	Yes

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variable is the change in manufacturing employment as a share of the working-age population. The measures of exposure to tariff liberalization are defined by equations (1) and (2). Columns 1 and 2 are estimated by OLS. In column 3, estimated by 2SLS, growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Robustness and Identifying Assumptions The first two columns in panel A in Appendix Table A.14 report results using an alternative definition of regional exposure to tariff cuts which additionally weighs U.S. industry–level tariff cuts by Mexico's revealed comparative advantage (and Mexico's tariff cuts by U.S. revealed comparative advantage), as defined in Appendix A.5 and following Hakobyan and McLaren [2016]. The results are very close to the baseline estimates in Table 1: commuting zones at the 75th percentile of exposure experience a decline of 0.16 percentage points in the manufacturing employment share of the population relative to commuting zones at the 25th percentile. In addition, the first two columns in panel B in Appendix Table A.14 use a measure of regional exposure to tariff cuts in which the denominator is employment in manufacturing rather than total regional employment (see equations (11) and (12) in Appendix A.5). The results again are quite similar to the baseline results discussed above; the coefficient in column 2 indicates that commuting zones at the 75th percentile of exposure experience a decline of 0.14 percentage points in the manufacturing employment share of the population relative to commuting zones at the 25th percentile. This is comparable to the 0.20 p.p. relative decline based on column 3 in Table 1 under the baseline tariff liberalization exposure measure. Next, while the baseline measures of exposure to tariff liberalization are based on tariff cuts in the manufacturing sector, panel C in Appendix Table A.14 reports the results with an equivalent measure taking into account tariff changes in all tradable industries, including tradable nonmanufacturing sectors such as agriculture or mining. The effect of U.S. tariff cuts on manufacturing employment is similar to the baseline results, while, like in panels A and B, the coefficient on exposure to Mexico's tariff cuts is not statistically significant.

Appendix Table A.13 examines the stability of the previous estimates to different sets of control variables. The first column excludes all the control variables in X_i'. These are introduced sequentially in columns 2 through 5. Column 2 adds the ratio of manufacturing employment over total employment in each commuting zone in 1990. This is a first step toward addressing the concern that the coefficient on the measure of exposure to tariff cuts might be capturing long-run trends in manufacturing employment (issue which is addressed further below). Column 3 adds the percentage of college-educated population, the percentage of foreign born population, and the share of working–age women that are employed, all measured in 1990. Column 4 adds the ratio of employment in routine occupations over total employment and the average offshorability of occupations. The share of routine occupations captures the possibility that the decline in manufacturing employment is driven by technological change, given that routine occupations are more susceptible to be substituted by automation. Finally, column 5 adds census division dummies and is equivalent to column 3 in Table 1. In columns 1 through 4, the magnitude of the impact of exposure to U.S. tariff cuts is fairly stable. The inclusion of census division dummies, which further control for trends in manufacturing employment, reduces the estimated coefficients compared to the previous columns.[39]

Recent work has formalized the conditions for inference when using shift–share regressors. Specifically, Borusyak et al. [2022b] show that identification is based on the industry–level shocks being exogenous, while exposure shares are allowed to be endogenous.[40] A first condition for consistency under Borusyak et al. [2022b]'s framework requires a large number of industries (i.e. shocks) and a small employment share for the largest industry. Appendix Table A.27 provides summary statistics on the industry–level variation in tariffs used to construct the measures of regional exposure, showing that these conditions are met in my setting.[41] A second assumption requires shocks to be as-good-as-randomly assigned. To this end, and following Autor et al. [2013] I estimate regression (5) with *past* changes in manufacturing employment as a share of the working–age population as the dependent variable. The results in Table 2 indicate that NAFTA tariff cuts are not correlated to changes in the lagged change in the share of manufacturing employment in the population during either 1980-1990, 1970-1980, or 1970-1990.[42,43] Also in favor of the as–good–as–random assumption, I assess the robustness of the results

[39]The reason for the substantial decline of the coefficient on exposure to U.S. tariff liberalization once census division dummies are included is that these dummies control for differences in industrial structure across divisions. This is seen by the fact that after controlling for industrial structure with measures of regional exposure to dummies for ten SIC groups (defined as employment– weighted averages following Borusyak et al. [2022b]), the inclusion or exclusion of census division dummies is not associated with large changes in the coefficient on exposure to U.S. tariff cuts.

[40]Note that while the baseline framework in Borusyak et al. [2022b] considers a regression with a shift–share regressor and a shift–share instrument, as they point out their setting nests the situation examined here in which the tariff exposure shift–share variables are treated as exogenous. Note also that Borusyak et al. [2022b] generalize their framework to the case with multiple shift–share regressors, as in the current setting.

[41]It is worth noting that the effective sample size (inverse of the HHI index of employment shares) and the share of the largest industry are similar to the case of Autor et al. [2013], which based on Borusyak et al. [2022b]'s analysis also meets their identifying assumption. The only difference in terms of the shares between the shocks in the current paper and Autor et al. [2013]'s is that they have shares in 1990 and 2000, whereas I only use 1990.

[42]It is worth noting that the lack of pre–existing trends is supportive of but does not prove the as–good–as–randomly assigned shocks assumption.

[43]Appendix Table A.30 shows that the results for exposure to U.S. tariff cuts in Table 1 are robust to controlling for these lagged changes in regional manufacturing employment during 1970–1980 and 1980–1990 (see columns 2 and 5). In addition and following Borusyak et al. [2022b], I report balance tests in which I regress each regional control variable used in Table 1 (as well as lagged growth in manufacturing employment) on the measures of regional exposure to U.S. or Mexico's tariff liberalization. These regressions control for the regional share of manufacturing employment in total employment in 1990 given that my setting corresponds to the incomplete shares case. I use Borusyak et al. [2022b]'s transformation to estimate equivalent industry–level regressions, with weights equal to employment shares and clustering standard errors by SIC 3–digit industries. In the case of exposure to U.S. tariffs, I find that two regional control variables, the percentage of college–educated population in 1990 and the share of working–age women that are employed in 1990 are correlated with the regional tariff measure. I follow the approach in Borusyak et al. [2022b] who find control variables that are not balanced in the case of the 'China shock"', and perform a sensitivity analysis. In Appendix Table A.29, I show that the coefficients in Table 1 essentially do not change when omitting these two control variables. In addition, I show that there is no statistically significant correlation between *all* the regional control variables and the tariff exposure measures when the balance tests control for regional exposure to ten SIC group dummy variables. In Appendix Table A.30 I show that the results in Table 1 are robust to controlling for exposure to these SIC group dummy variables. Finally, note that there is no statistically significant relationship between all regional control variables and exposure to Mexico's tariff cuts.

in Table 1 to controlling for a set of measures of regional exposure to industry–level control variables, such as changes in world demand, changes in employment in high income countries other than the U.S., changes in U.S. MFN tariffs, and dummy variables for ten SIC groups.[44] As shown in Appendix Table A.30, the results are quite close to the baseline case.

Note that given that tariff exposure measures are weighted averages over manufacturing industries, the sum of the exposure shares is not constant across regions. In Borusyak et al. [2022b]'s framework, this does not pose a problem with identification as long as regressions control for the ratio of manufacturing employment over total employment, as I do throughout the paper.[45] In addition, Borusyak et al. [2022b] show that standard errors should take into account that similar exposure shares across regions can lead to correlated residuals. Column 1 in panel A in Table A.21 shows that the results in 1 are robust to using Borusyak et al. [2022b]'s "exposure–robust" standard errors.[46] When reporting exposure–robust standard errors (here and later in the paper), I cluster standard errors by SIC 3–digit industries as the baseline case. However, Appendix Table A.26 shows that the results are similar when clustering by SIC 3–digit, SIC 2–digit or by ten SIC groups.[47]

Finally, I show that the further disaggregation of industries and geographic units used to construct measures of exposure to tariff liberalization relative to the previous literature makes a difference. In Appendix A.12, I contrast the findings in Table 1 to the results of equivalent regressions with exposure measures based on more aggregate industries and geographic units.[48] I find the same sign for exposure to U.S. tariff cuts, but the coefficient is statistically significant only when using my more granular data.

[44] Borusyak et al. [2022b] extend their framework to cases in which the industry–level shocks are as–good–as–randomly assigned conditional on industry–level observables. Borusyak et al. [2022b]'s framework allows for the inclusion of control variables that are originally defined at the industry–level. These are included in the regional regressions by computing employment–weighted averages of these industry–level variables. Alternatively, when computing exposure–robust standard errors these industry–level control variables can be included directly in industry–level equivalent regressions that can be estimated after transforming the data as described in Borusyak et al. [2022b]. Details about the construction of these control variables is provided in Appendix A.10.

[45] This is the "incomplete shares" case in Borusyak et al. [2022b].

[46] This is achieved following Borusyak et al. [2022b]'s transformation to estimate an equivalent industry–level regression with standard errors clustered by 3–digit SIC industries. Adao et al. [2019] also make this point and have an alternative method to compute standard errors.

[47] Note that Borusyak et al. [2022b] cluster standard errors by SIC 3–digit industries in their application to the "China shock".

[48] Specifically, I construct exposure measures for 722 commuting zones using tariff changes for 397 manufacturing industries. I compare the results to those obtained with exposure measures as in Hakobyan and McLaren [2016], with 89 Census industries and 522 CONSPUMAs.

Table 2: NAFTA Tariff Liberalization and Change in Share of Manufacturing Employment in the Working-Age Population: 1970-1990

Dependent Variable: Change in manufacturing emp/working-age pop (in % pts)

	1970-1980	1980-1990	1970-1990
	(1)	(2)	(3)
$\Delta\tau^{\text{US}}$	-0.368	-0.431	-0.392
	(0.421)	(0.383)	(0.308)
$\Delta\tau^{\text{MEX}}$	-0.178	0.092	-0.046
	(0.185)	(0.183)	(0.130)

Notes: $N = 722$ (columns 1 and 2) or $N = 1444$ (column 3). This table reports the results of the OLS estimation of equation (5). The dependent variables are the change in the share in manufacturing employment in the working-age population between 1970-1980 (column 1), between 1980-1990 (column 2) or stacking 1970–1980 and 1980–1990 (column 3). Column 3 includes a time dummy. The measures of exposure to tariff liberalization are defined by equations (1) and (2). Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

4. The Impact of NAFTA Beyond Manufacturing

Having established the impact of NAFTA tariff cuts on manufacturing employment, I now document the adjustment of other margins – population, nonmanufacturing and total employment, unemployment and labor force participation – that characterize the overall response of a commuting zone to the shock. Throughout this section, I emphasize the heterogeneous impact of this shock based on education, gender, race, age and local characteristics.

I first examine the response of commuting zone population. Table 3 shows the results of estimating equation (5) with the log change in working-age population in each commuting zone as the dependent variable.[49] Clearly, the exposure to both U.S. and Mexico's tariff cuts did not have a statistically significant impact on commuting zone population. The coefficients are similar between columns 1 (which does not control for Chinese import competition) and column 2 (which does). Column 2 also shows that rising Chinese import competition does not lead to significant changes in commuting zone population, as discussed by Autor et al. [2013]. Columns 3 and 4 look separately at the population of those without and with a college education. The coefficients on the measures of exposure to tariff cuts remain statistically insignificant. This finding echoes a number of studies, which, in different contexts, have found that

[49]The working-age population consists of individuals aged 16-64.

Table 3: NAFTA Tariff Liberalization and Change in Working-Age Population

Dependent Variable: Change in log population counts (in log points)

	All	All	No College	College
	OLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
$\Delta\tau^{\text{US}}$	-0.167	-0.488	0.506	-1.608
	(1.115)	(1.043)	(1.204)	(1.091)
$\Delta\tau^{\text{MEX}}$	-1.543	-0.750	-1.352	-0.150
	(1.517)	(1.706)	(1.938)	(1.581)
ΔIPW		1.028	0.871	1.387
		(0.905)	(1.145)	(0.859)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variable is the log change in the working-age population considering all individuals (in columns 1 and 2), individuals with no college education (in column 3) or individuals with college education (in column 4) . The measures of exposure to tariff liberalization are defined by equations (1) and (2). Column 1 is estimated by OLS. In columns 2 through 4, estimated by 2SLS, growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

migration is fairly unresponsive to economic shocks.[50,51]

The results in the previous section document a decline in the manufacturing employment to population ratio as a result of U.S. tariff liberalization. This must be compensated by an increase in employment in nonmanufacturing sectors, unemployment, and/or the share of individuals not in the labor force. Table 4 estimates equation (5) with the changes in each of these outcomes as dependent variables. All these outcomes are expressed as a share of commuting zone population. Columns 1 and 2 refer to the share of manufacturing employment in the working–age population and are equivalent to columns 2 and 3 in Table 1 discussed earlier. Columns 3 and 4 refer to nonmanufacturing employment as a share of the working-age population. Column 3 is estimated by OLS and includes changes in exposure to both U.S. and Mexico's tariff cuts. Column 4 adds growth in Chinese imports and is estimated by 2SLS. The sign of the coefficients on regional exposure to changes in U.S. tariffs implies that tariff cuts lead to an increase

[50] For example, Yagan [2019] and Molloy et al. [2011] document that geographic mobility was not a relevant adjustment mechanism in response to the 2007-2008 Great Recession. Recent work by Borusyak et al. [2022a] argues that a possible reason for the lack of response of local population to local shocks found under different contexts in the literature is that location choices depend on shocks to both their current location as well as potential alternative locations. This implies that estimating the effects on population requires controlling for shocks to alternative locations, and Borusyak et al. [2022a] propose a model—based estimation procedure to address this issue.

[51] These results remain insignificant under exposure–robust standard errors following Borusyak et al. [2022b], as shown in Appendix Table A.22.

in employment in nonmanufacturing industries. In column 4, this coefficient is statistically significant, and implies a 0.09 percentage point increase in commuting zones at the 75th percentile of exposure relative to those at the 25th percentile. However, with exposure–robust standard errors (see panel A in Appendix Table A.21) the coefficient is not statistically significant. In addition, there is no statistically significant association between nonmanufacturing employment and exposure to Mexico's tariff cuts, nor to the growth in Chinese import competition. I will show later, however, that there are very different underlying impacts on various industries within nonmanufacturing. Columns 5 and 6 report the results for total employment, so the coefficients are equal to the sum of those obtained for manufacturing and nonmanufacturing employment. These columns show that U.S. tariff liberalization leads to a statistically significant decline in employment. Commuting zones at the 75th percentile of exposure experience a relative loss of 0.1 percentage points in the employment to population ratio relative to regions at the 25th percentile of exposure. These results for total employment can be benchmarked as follows. While the average change in U.S. tariffs across commuting zones is associated with a 0.21 p.p. decline in employment as a share of the working–age population, the average change in Mexico's tariffs implies a 0.03 p.p. increase in this share.[52] Consequently, the overall impact of NAFTA on total employment as a share of the working–age population is negative and corresponds to a 0.18 p.p. decrease.

Next, columns 7 (OLS) and 8 (2SLS) in Table 4 study unemployment (as a share of the working-age population). U.S. tariff cuts clearly lead to increases in unemployment. Regions at the 75th percentile of exposure see a rise in unemployment of 0.05 percentage points relative to regions at the 25th percentile of exposure.[53] Mexico's tariff cuts, in contrast, reduce unemployment, although the magnitude is also small and the coefficient is not statistically significant under exposure–robust standard errors (see panel A in Appendix Table A.21). Finally, in columns 9 (OLS) and 10 (2SLS) the dependent variable is the change in the number of individuals not in the labor force as a fraction of the working-age population. There is no statistically significant impact of U.S. or Mexico's tariffs on this outcome.[54]

Note finally that Appendix Tables A.14 illustrates the robustness of the results in Table 4 to using alternative measures of exposure to tariff cuts as discussed in detail in Appendix A.5.

[52] To assess the effect of U.S. tariff cuts, I multiply the average U.S. tariff cut across commuting zones (-0.447) by the coefficient of 0.458 in column 5 of Table 4. In the case of Mexico's tariff cuts, the average tariff cut is -2.499, which I multiply by the coefficient of -0.012 in the same column.

[53] Note that this coefficient is small. The mean tariff change across commuting zones during 1990-2000 is -0.447 and would be associated with a 0.11 percentage point decline in the unemployment to population ratio, which would imply a change of the average unemployment to population ratio in 1990 of 4.80% to 4.91%.

[54] Note that because all outcomes are expressed as shares of the working–age population and because the working-age population is the sum of those employed, unemployed, or out of the labor force, the coefficients across columns 5, 7 and 9 (or across columns 6, 8, and 10) in Table 4 add up to zero.

Table 4: NAFTA Tariff Liberalization and Change in Employment Status in the Working-Age Population

Dependent Variable: Change in population shares by employment status (in % pts)

	Manufacturing		Nonmanufacturing		Employment		Unemployment		Not in the Labor Force	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta\tau^{\text{US}}$	0.839**	0.907***	-0.374	-0.449**	0.466**	0.458*	-0.272***	-0.242**	-0.193	-0.216
	(0.334)	(0.305)	(0.250)	(0.208)	(0.216)	(0.250)	(0.089)	(0.101)	(0.179)	(0.201)
$\Delta\tau^{\text{MEX}}$	-0.158	-0.325	0.128	0.314	-0.030	-0.012	0.172**	0.097	-0.141	-0.085
	(0.268)	(0.218)	(0.345)	(0.353)	(0.340)	(0.297)	(0.077)	(0.103)	(0.321)	(0.300)
ΔIPW		-0.216		0.240		0.024		-0.097		0.073
		(0.198)		(0.250)		(0.215)		(0.099)		(0.160)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variables are the change in the share in the working-age population of manufacturing employment (columns 1-2), of nonmanufacturing employment (columns 3-4), of total employment (columns 5-6), of unemployment (columns 7-8) and of the number of individuals not in the labor force (columns 9-10). The measures of exposure to tariff liberalization are defined by equations (1) and (2). Columns 1, 3, 5, 7 and 9 are estimated by OLS. In columns 2, 4, 6, 8 and 10, estimated by 2SLS, growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Heterogeneity based on demographics Having established the impact of U.S. tariff cuts for the overall population, I now turn to exploring these effects for different subgroups based on education, gender, race and age. These results will show that there are wide differences across these groups in terms of both the impact on manufacturing employment as well as in the other adjustment margins. These findings can thus shape trade policy if equality across any of these dimensions is a goal of policymakers. Further, understanding the heterogeneity in the impact of NAFTA on different subsets of the population can help target mitigation policies such as Trade Adjustment Assistance. Finally, these results connect international trade to the large literature on gender or racial disparities in the labor market.[55]

Panels A and B in Table 5 divide each of the outcomes by educational attainment, showing important differences in the adjustment to tariff liberalization. Specifically, I divide the population into those with or without college education. For noncollege individuals (in panel A), the negative impact of tariff cuts on manufacturing employment is larger than that previously reported for the entire population. Commuting zones at the 75th percentile of exposure experience a decline of 0.26 percentage points in

[55] For the literature on gender disparities in the labor market see Altonji and Blank [1999] and Blau and Kahn [2000]. For the literature on racial disparities in the labor market see Altonji and Blank [1999], Fryer [2011] and Bayer and Charles [2018].

the manufacturing employment share of the working-age population relative to commuting zones at the 25th percentile. The results also indicate that Mexican tariff cuts do not have a large nor statistically significant impact on manufacturing employment for noncollege individuals.[56]

For the noncollege population I do not observe a statistically significant change in employment in nonmanufacturing industries (column 2). Adding up, the total effect on employment is statistically significant and indicates a relative decline of 0.21 percentage points in employment as a fraction of the working-age population for commuting zones in the 75th relative to the 25th percentile of exposure. This magnitude is about twice as large than the 0.1 p.p. found for the overall sample earlier. The increase in unemployment for noncollege workers as a result of U.S. tariff liberalization is also larger than for the population as a whole (column 3). Regions at the 75th percentile of exposure see a rise in unemployment of 0.08 percentage points relative to regions at the 25th percentile of exposure. Finally, U.S. tariff cuts lead to a large increase in the share of noncollege individuals out of the labor force, with a 0.13 percentage point difference between regions at the 75th and 25th percentiles of exposure. There is no significant impact of Mexican tariff cuts on any of these outcomes.

In contrast, for college workers (panel C) all results point to a lack of a significant response to U.S. tariff cuts. However, reductions in Mexico's tariffs do lead to an increase in manufacturing employment, as well as a decline in nonmanufacturing employment.[57] This portraits a very uneven impact of NAFTA across the college vs. noncollege population. While noncollege individuals see a decline in manufacturing and total employment due to U.S. tariff cuts, college individuals face an increase in manufacturing employment from Mexico's liberalization.

Next, panels C and D in Table 5 display impacts by gender. The results are striking. The effect of U.S. tariff liberalization on the manufacturing employment to population ratio is negative, large and statistically significant for women, and much smaller and not statistically significant among men. For women, commuting zones at the 75th percentile of exposure experience a decline of 0.37 percentage points in this outcome relative to commuting zones at the 25th percentile.[58] In addition, Appendix Table A.20 shows that the fact that women face a large and statistically significant decline in manufacturing and

[56] Note that the fact that the impact of U.S. tariff cuts on manufacturing employment is larger for those with lower educational attainment is similar to the response observed for rising import competition from China by Autor et al. [2013].

[57] Commuting zones at the 75th relative to the 25th percentile of exposure see a 1.06 percentage point increase in the manufacturing employment to working–age population ratio as a result of Mexico's tariff cuts. The decline in nonmanufacturing employment is not statistically significant with exposure–robust standard errors as shown in panel C in Appendix Table A.21.

[58] In this regard, there is a similarity with exposure to increasing Chinese import competition, which also impacts women more than men during 1990-2000. Note that Autor et al. [2013] show that stacking 1990-2000 and 2000-2007 the disproportionate impact of the "China shock" on women disappears; this pattern is only found in the 1990-2000 period and also holds after removing measures of tariff exposure from the regression. This is seen in columns 4 and 5 in panel A in Appendix Table A.12, which replicates Autor et al. [2013]'s analysis restricted to the 1990-2000 period.

total employment and men don't also holds among noncollege individuals. Note also that while Mexican tariff cuts appear to increase manufacturing employment among men, this effect is not statistically significant with exposure–robust standard errors as shown in panel E in Appendix Table A.21.

The difference in the impact of U.S. tariff liberalization on female and male manufacturing employment could be a result of being exposed to tariff cuts of different magnitude, if women are more likely to work on industries facing larger tariff cuts. Another possibility is that facing similar shocks, the response of female manufacturing employment is different. To some extent, the high concentration of female employment in the industries facing the largest tariff cuts suggests that exposure to the shock is larger for women. The top three industries in terms of U.S. tariff liberalization were apparel, textile mill products and leather products. As Appendix Table A.8 shows, these were also the manufacturing industries with the highest female employment shares (78%, 52% and 64% respectively). However, to address this issue more systematically, in Appendix A.13 I construct gender–specific measures of exposure to U.S. tariff liberalization, decomposing the baseline measure in equation (1). I find that, overall, women and men are similarly exposed to U.S. tariff cuts. I also show (see Appendix Table A.34) that female manufacturing employment falls in response to the female–specific measure of exposure only, while male manufacturing employment does not respond to either the male– or female–specific exposure measures. This points then to a different response to the shock of female manufacturing employment. Future work could examine differences by gender in displacement from the manufacturing sector in this or other contexts.

Moving on to other outcomes, the decline in the manufacturing employment to working-age population ratio among women is coupled with a large and statistically significant increase in the share of the population employed in nonmanufacturing industries, unemployed, and out of the labor force. Column 2 indicates that the share of nonmanufacturing employment to population ratio increases by 0.13 percentage points in a region at the 75th relative to the 25th percentiles of exposure. This increase in nonmanufacturing employment is not enough to compensate for the losses in manufacturing, so total employment as a share of the population falls by a very large 0.23 percentage points at the 75th relative to the 25th percentiles of exposure. Among men, there is an increase in unemployment due to U.S. tariff cuts, similar in magnitude to that for women, but no significant changes in employment. In addition, among men, U.S. tariff cuts cause a fall in the share of the population out of the labor force, which is the opposite that was found for women. An analysis using longitudinal data could perhaps shed more light on this difference.

An understudied aspect in the literature is the differential impact of trade shocks by race. As I dis-

Table 5: NAFTA Tariff Liberalization and Change in Employment Status in the Working-Age Population by Educational Attainment and by Gender

Dependent Variable: Change in population shares by employment status (in % pts)

	Manufacturing	Nonmanufacturing	Employment	Unemployment	Not in the Labor Force
	(1)	(2)	(3)	(4)	(5)
Panel A: No college education					
$\Delta\tau^{\text{US}}$	1.202***	-0.239	0.964***	-0.376***	-0.588**
	(0.342)	(0.254)	(0.344)	(0.124)	(0.288)
$\Delta\tau^{\text{MEX}}$	-0.129	0.049	-0.080	0.151	-0.071
	(0.270)	(0.425)	(0.429)	(0.141)	(0.410)
ΔIPW	-0.216	0.198	-0.018	-0.139	0.157
	(0.182)	(0.276)	(0.272)	(0.131)	(0.187)
Panel B: College education					
$\Delta\tau^{\text{US}}$	0.103	-0.283	-0.180	-0.068	0.248
	(0.311)	(0.290)	(0.228)	(0.097)	(0.227)
$\Delta\tau^{\text{MEX}}$	-0.791***	0.568**	-0.223	0.024	0.198
	(0.221)	(0.280)	(0.224)	(0.101)	(0.234)
ΔIPW	-0.147	0.257	0.110	-0.030	-0.080
	(0.258)	(0.211)	(0.163)	(0.068)	(0.160)
Panel C: Female					
$\Delta\tau^{\text{US}}$	1.703***	-0.617***	1.086***	-0.187**	-0.899***
	(0.252)	(0.212)	(0.253)	(0.080)	(0.220)
$\Delta\tau^{\text{MEX}}$	0.176	-0.151	0.026	0.029	-0.054
	(0.213)	(0.290)	(0.261)	(0.088)	(0.282)
ΔIPW	-0.476***	0.059	-0.418**	-0.105	0.523***
	(0.154)	(0.226)	(0.189)	(0.076)	(0.184)
Panel D: Male					
$\Delta\tau^{\text{US}}$	0.103	-0.246	-0.143	-0.293**	0.436*
	(0.373)	(0.280)	(0.291)	(0.137)	(0.223)
$\Delta\tau^{\text{MEX}}$	-0.871***	0.793*	-0.078	0.172	-0.094
	(0.291)	(0.482)	(0.437)	(0.141)	(0.418)
ΔIPW	0.059	0.402	0.461	-0.082	-0.379
	(0.302)	(0.325)	(0.340)	(0.142)	(0.263)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variables are the change in the share in the working-age population of manufacturing employment (column 1), of nonmanufacturing employment (column 2), of total employment (column 3), of unemployment (column 4) and of the number of individuals not in the labor force (column 5). The measures of exposure to tariff liberalization are defined by equations (1) and (2). All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

cussed in the introduction, while in other contexts the literature has examined differential effects by skill or gender, this paper is among the first to look at differential effects by race in the U.S. To this end, I split the population into white and nonwhite individuals.[59] Table 6 shows these results. Columns 1 and 2 in panel A indicate that the effect of U.S. tariff liberalization on the decline in manufacturing employment between white and nonwhite workers is similar.[60] The impact of U.S. tariff cuts on non-manufacturing employment (in columns 3 and 4), however, is radically different across racial groups. The coefficients indicate U.S. tariff cuts lead to a statistically significant increase in nonmanufacturing employment among whites only. Columns 5 and 6 report the impact on total employment for each group. Among nonwhites, U.S. tariff liberalization leads to a large decline in employment, such that regions at the 75th percentile of exposure experience a 0.23 percentage point decline relative to regions at the 25th percentile. In contrast, the effect is negative but much smaller (0.07 p.p.) and statistically insignificant for white individuals.[61]

This difference in the effect of NAFTA on employment across racial groups translates into large differences in the impact on unemployment (see columns 7 and 8). The increase in unemployment as a share of the population is 3.4 times larger for nonwhites than for whites. In addition, the impact of U.S. tariff liberalization on labor force nonparticipation is not statistically significant among either group. Finally, regarding the effect of Mexico's tariff cuts, the results indicate that they lead to an increase in manufacturing employment among white workers, yet those results are not robust to computing exposure–robust standard errors, as seen in panel G in Appendix Table A.21.

It is worthwhile to separate these effects by educational attainment, given that there are important differences in attainment by race.[62] These results are shown in panels B and C in Table 6. In the noncollege sample (see panel B), the decline in the manufacturing employment to population ratio in response to U.S. tariff cuts is larger among white workers, and statistically significant only for this group. In contrast, the decline in the total employment to population ratio is statistically significant for both groups and 52% larger for nonwhite workers. In line with this, there is also a much larger increase in unemployment rates for nonwhite workers. Regions at the 75th percentile of exposure face a

[59] I group all nonwhite individuals in a single category because some races have a very small population. At a national level, in the 1990 Census 80% of individuals are classified as white, 12% as black or African American, 3% are Asian or Pacific Islander and 5% belong to other groups. Note that being Hispanic is an ethnicity rather than a race.

[60] The coefficient implies a relative decline in manufacturing employment as a share of the population of 0.19 p.p. (for whites) and 0.15 p.p. (for nonwhites) between the 75th and 25th percentiles of exposure.

[61] The coefficient for total employment among white individuals is significant under exposure–robust standard errors, as shown in panel G in Appendix Table A.21.

[62] For instance, 28% of white workers and 20% of nonwhite workers have at least some college education in the 1990 Census.

0.17 percentage point decline in the unemployment to population ratio for nonwhite workers relative to regions at the 25th percentile, compared to a 0.06 p.p. relative decline for white individuals. Differently than with employment and unemployment, U.S. tariff liberalization leads to a statistically significant decline in labor force participation only among white individuals. Mexico's tariff cuts, in contrast, are not associated with statistically significant effects.[63] Last, the results in panel C show that tariff cuts by the U.S. do not lead to significant effects on all the outcomes analyzed among college individuals. In contrast, Mexico's tariff cuts are associated with an increase in manufacturing employment only among college whites.

Overall, these patterns of racial differences in the impact of U.S. tariff liberalization suggest that nonwhite workers find fewer opportunities when displaced from the manufacturing sector. A potential reason behind this could be the geographical sorting of white and nonwhite individuals, such that nonwhites concentrate in regions with fewer opportunities outside manufacturing available for those without college education. This paper takes the first step in the literature in uncovering these differences on the impact of tariff liberalization by race. However, a further exploration of the underlying mechanisms behind these differences faces the difficulty brought by the sample size of the Census data; in many commuting zones the share of nonwhite individuals is too small to allow for further breakdowns. Last, from a policymaking standpoint, these findings can be used to better target policies such as the Trade Adjustment Assistance program which helps relocate workers displaced from manufacturing. In this regard, an important conclusion for policy is that understanding how different groups are affected goes beyond looking at their direct exposure in the manufacturing sector.

As a final demographic characteristic, Appendix Table A.16 shows interesting differences in the adjustment to U.S. tariff liberalization across age groups. I divide the population into those aged 16-34, 35-49, and 50-64. The impact of U.S. tariff cuts on the manufacturing employment to population ratio is negative and statistically significant among all age groups. The estimated coefficient is somewhat larger among those aged 35-49, for which commuting zones at the 75th percentile of exposure experience a 0.22 percentage point decline in the manufacturing employment to population ratio relative to commuting zones at the 25th percentile of exposure. This interquartile difference is 0.16 percentage points for the 50-64 group. In contrast, Mexico's tariff cuts had a statistically significant impact raising manufacturing employment only among the 35–49 group. Regarding the other adjustment margins in response to U.S. tariff cuts, for individuals aged 16-34 there is a statistically significant increase in

[63] The statistically significant coefficient in column 9 in panel B for exposure to Mexico's tariff cuts is not statistically significant under exposure–robust standard errors.

Table 6: NAFTA Tariff Liberalization and Change in Employment Status in the Working-Age Population by Race

Dependent Variable: Change in population shares by employment status (in % pts)

	Manufacturing		Nonmanufacturing		Employment		Unemployment		Not in the Labor Force	
	Nonwhite	White	Nonwhite	White	Nonwhite	White	Nonwhite	White	Nonwhite	White
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: All education levels										
$\Delta\tau^{\mathrm{US}}$	0.690*	0.891***	0.373	-0.549**	1.063*	0.342	-0.625***	-0.186*	-0.438	-0.156
	(0.393)	(0.293)	(0.465)	(0.220)	(0.545)	(0.223)	(0.237)	(0.101)	(0.536)	(0.169)
$\Delta\tau^{\mathrm{MEX}}$	0.366	-0.518**	-1.227	0.606*	-0.861	0.088	-0.286	0.141	1.147	-0.229
	(0.424)	(0.209)	(0.907)	(0.316)	(0.794)	(0.257)	(0.363)	(0.089)	(0.741)	(0.272)
ΔIPW	-0.126	-0.258	-0.420	0.334	-0.546	0.076	0.177	-0.117	0.369	0.041
	(0.384)	(0.191)	(0.691)	(0.231)	(0.584)	(0.196)	(0.187)	(0.094)	(0.515)	(0.147)
Panel B: No college education										
$\Delta\tau^{\mathrm{US}}$	0.833	1.265***	0.608	-0.319	1.440**	0.945***	-0.796***	-0.296***	-0.644	-0.649**
	(0.548)	(0.322)	(0.605)	(0.254)	(0.614)	(0.312)	(0.272)	(0.112)	(0.604)	(0.255)
$\Delta\tau^{\mathrm{MEX}}$	0.532	-0.337	-1.618	0.400	-1.086	0.063	-0.318	0.182	1.404*	-0.245
	(0.489)	(0.259)	(1.018)	(0.406)	(0.891)	(0.422)	(0.392)	(0.126)	(0.828)	(0.406)
ΔIPW	-0.031	-0.243	-0.213	0.284	-0.243	0.041	-0.096	-0.139	0.340	0.098
	(0.425)	(0.166)	(0.515)	(0.264)	(0.573)	(0.244)	(0.254)	(0.130)	(0.515)	(0.167)
Panel C: College education										
$\Delta\tau^{\mathrm{US}}$	-0.062	0.081	0.478	-0.371	0.416	-0.289	-0.425	-0.031	0.009	0.320
	(0.563)	(0.294)	(0.659)	(0.308)	(0.655)	(0.228)	(0.337)	(0.104)	(0.614)	(0.227)
$\Delta\tau^{\mathrm{MEX}}$	0.139	-0.920***	-1.079	0.745***	-0.941	-0.175	-0.175	0.088	1.116	0.087
	(0.622)	(0.230)	(1.075)	(0.286)	(0.981)	(0.194)	(0.433)	(0.108)	(1.019)	(0.215)
ΔIPW	-0.187	-0.209	-0.428	0.371*	-0.615	0.162	0.413*	-0.068	0.202	-0.094
	(0.436)	(0.256)	(0.904)	(0.205)	(0.695)	(0.189)	(0.232)	(0.067)	(0.612)	(0.178)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variables are the change in the share in the working-age population of manufacturing employment (columns 1-2), of nonmanufacturing employment (columns 3-4), of total employment (columns 5-6), of unemployment (columns 7-8) and of the number of individuals not in the labor force (columns 9-10). The measures of exposure to tariff liberalization are defined by equations (1) and (2). All columns are estimated by 2SLS, and growth in Chinese imports ($\Delta\mathrm{IPW}_{ui}$, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

nonmanufacturing employment, and no overall employment effect. Those aged 35-49 and 50-64 see no increase in nonmanufacturing employment. The oldest group faces the largest decline in total employment, such that the employment to working-age population ratio falls by 0.28 p.p. at the 75th relative to the 25th percentile of exposure to U.S. tariff liberalization. While the increase in unemployment is larger among the middle-aged (those in the 35-49 group), older workers see a larger increase in labor force nonparticipation.

Which nonmanufacturing industries expand? The earlier results documented that U.S. tariff liberalization led to increases in nonmanufacturing employment among women and among young workers. This effect was not statistically significant for the population as a whole under exposure–robust standard errors, nor in the subsamples of noncollege and college individuals. Nonmanufacturing industries, however, can be quite different between them in terms of skill and pay. Here, I examine further the reallocation of employment toward nonmanufacturing, focusing on five narrower sectors. These are construction, transportation and utilities, wholesale and retail trade, other services, and government.

Table 7 reports the results of estimating equation (5) with the change in employment in each of these industries (as a share of the working-age population) as the dependent variable. U.S. tariff liberalization leads to a statistically significant increase in employment in construction and in wholesale and retail trade. Commuting zones at the 75th percentile of exposure experience an increase of 0.03 percentage points in the construction employment share of the working-age population relative to commuting zones at the 25th percentile. This magnitude is 0.05 percentage points for wholesale and retail trade. These coefficients are close to zero and not statistically significant for other nonmanufacturing industries. Overall, these results indicate that displacement from manufacturing leads workers to relocate to the lowest paying service-sector industries.[64]

Changes in the task composition of employment Next, I examine whether tariff liberalization under NAFTA induced a change in the task structure of U.S. local labor markets. The results here are related to Autor et al. [2015], who compare the impact of trade (captured by rising Chinese imports) and technology on the task composition of U.S. commuting zones.[65]

To this end, I estimate equation (5) with the dependent variable defined as the change in the share

[64]In the 1990 Census, the nonmanufacturing industries with the lowest average wage were wholesale and retail trade, personal services and construction. The average wage in wholesale and retail trade was only 75% of the average in all nonmanufacturing industries.

[65]More broadly, these results are related to the literature that has examined the causes of job polarization in advanced economies [Autor et al., 2006, Goos et al., 2009, Dustmann et al., 2009].

Table 7: NAFTA Tariff Liberalization and Change in Share of Industry Employment in the Working-Age Population

Dependent Variable: Change in industry emp/working-age pop (in % pts)

	Construction (1)	Transportation and Utilities (2)	Wholesale and Retail Trade (3)	Other Services (4)	Government (5)
$\Delta\tau^{\text{US}}$	-0.140*	0.033	-0.211**	-0.061	0.043
	(0.081)	(0.090)	(0.088)	(0.165)	(0.095)
$\Delta\tau^{\text{MEX}}$	-0.134	-0.060	-0.005	0.133	0.079
	(0.097)	(0.104)	(0.124)	(0.235)	(0.095)
ΔIPW	-0.117	-0.018	0.002	0.058	0.079
	(0.081)	(0.064)	(0.094)	(0.169)	(0.073)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variables are the change in the share in the working-age population of employment in the following non–manufacturing sectors: construction, in transportation and utilities, in wholesale and retail trade, in other services, or in government. The measures of exposure to tariff liberalization are defined by equations (1) and (2). All regressions are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

of commuting zone working-age population employed in primarily abstract, routine, or manual occupations. The classification of occupations and the logic behind it were described in Section 2.2. Recall that managerial, professional and technical occupations perform primarily abstract tasks. Routine occupations are divided into two distinct groups: i) clerical activities and sales-related occupations, and ii) production-related occupations. Finally, mechanic, craft, agricultural and service occupations primarily consist of manual tasks.

In these regressions, I control for the potential effect of technological change on the task composition of employment. Given that routine occupations are codifiable and thus subject to replacement by automation, I follow Autor et al. [2015] and represent exposure to technological change as the share of each labor market's initial employment in routine occupations. To isolate the long-run component of this routine employment share, I use an instrument based on the historical (1950) local industry mix proposed by Autor et al. [2015].[66] Note that the 1990 routine employment share was also included as a control variable in all previous regressions, but here I use Autor et al. [2015]'s instrument for this routine employment share, in order to be able to compare my results with those in Autor et al. [2015] and

[66] The instrument for the employment share in routine occupations is described in Appendix A.4. Appendix Table A.10 provides summary statistics for the 1990 share of routine employment and for this instrument.

to interpret the coefficient on the instrumented routine employment share as the effect of technological change.

Table 8 shows the results. Panel A focuses on abstract occupations. U.S. tariff liberalization is associated with an increase in employment in abstract tasks (as a share of the working-age population). The coefficient is very similar when I use the instrument for the start-of-period routine employment share (column 1) or not (column 2).[67] The magnitude is such that regions at the 75th percentile of exposure experience a 0.12 percentage point increase in the abstract employment to population ratio relative to those at the 25th percentile. Columns 3 and 4 indicate that the increase is almost five times larger among college workers. This effect on abstract employment has the same sign for the manufacturing and nonmanufacturing sectors, but is statistically significant only in the latter.[68] In contrast, I don't find a statistically significant effect of Mexico's tariff liberalization on abstract employment.[69,70] Finally, note that technological change, captured by the long-run component of the 1990 share of employment in routine occupations, led to an increase in employment in abstract occupations, both overall and in the nonmanufacturing sector.

These findings shed light on the transformation of local economies in response to import competition, with an expansion in managerial, professional and technical jobs. Note that this expansion could be driven by various margins. It could occur due to a reallocation across industries, with a relative increase in employment in abstract-intensive industries, or across firms within each industry, with a relative gain in employment in abstract-intensive firms, or even within firms. An analysis using firm-level data could further elucidate which of these margins is dominant.

Panel B in Table 8 focuses on the set of routine occupations consisting of clerical activities and sales jobs. Overall and among all subgroups, U.S. and Mexico's tariff cuts had little impact on these types of routine occupations. Next, in panel C, the dependent variable is the change in employment in production-related routine occupations as a share of the working-age population. In this case, the situation is very different: U.S. tariff liberalization has a large and clear negative impact. Overall, regions

[67] Appendix Table A.18 reports the first stage for the 2SLS regression. Also, note that the sum of the coefficients across all panels in column 2 is equal to the coefficient on total employment in column 6 of Table 4.

[68] In columns 5 and 6, for abstract employment in manufacturing and nonmanufacturing respectively, the measure of the initial share of routine employment (as well as the instrument) are constructed as shares of routine employment within each sector, in line with Autor et al. [2015].

[69] The exception is the coefficient for exposure to Mexico's tariff cuts in column 5 for abstract employment in manufacturing, but this is not statistically significant under exposure–robust standard errors (see Appendix Table A.24).

[70] Rising import competition from China only has a statistically significant effect on abstract employment in nonmanufacturing, such that more exposed regions see an increase in this share. This is consistent with Autor et al. [2015] who find a larger impact of trade during the 2000s. Appendix Table A.17 reports the results of these regressions excluding measures of exposure to tariff liberalization, finding similar results for the impact of rising Chinese imports during 1990-2000.

at the 75th percentile of exposure experience a 0.20 percentage point decline in the production-related routine employment to population ratio relative to those at the 25th percentile. The impact of U.S. tariff cuts is much larger among noncollege individuals (see columns 3 and 4). It is found only in the manufacturing sector, as shown in column 5. Mexican tariff liberalization, in contrast, had no statistically significant impact on these outcomes, nor does growth in Chinese import competition.[71,72] Finally, panel D looks at employment in manual occupations. In this case, U.S. tariff cuts do not appear to have statistically significant effects except when focusing on the nonmanufacturing sector in column 5, such that lower U.S. tariffs lead to an increase in employment in manual occupations in this sector. [73]

Overall, the results indicate that U.S. tariff liberalization leads to a reshuffling of employment away from production-related routine occupations and toward abstract occupations.

Regional heterogeneity in the adjustment to tariff liberalization Aside from differences based on worker characteristics, the literature has asked whether regional characteristics can shape the adjustment to shocks. In particular, the literature has focused on how the role of human capital shapes the resilience of regions or cities [Glaeser et al., 2004, Glaeser, 2005]. This is particularly important in a large country with substantial regional disparities in human capital like the U.S.

For this reason, I also study differences in the response of commuting zones to tariff liberalization based on initial human capital endowments. For this purpose, I define as high human capital commuting zones those with an above-median share of the population with college education in 1990, while the other half are defined as low human capital commuting zones. Appendix Figure A.2 maps high and low human capital commuting zones, showing that low human capital regions are concentrated in the South and parts of the Midwest, while high human capital regions are found in both coasts and in some northern and western parts of the interior. I will interpret these differences in the response to NAFTA by human capital endowments as descriptive, rather than causal, because there are other differences between these regions aside from human capital endowments (such as their economic structure), and these other differences could be in turn determined by human capital endowments.[74]

[71]Note that the coefficient for exposure to Mexico's tariffs in column 5 is not statistically significant under exposure–robust standard errors as shown in Appendix Table A.24.

[72]Note also that technological change (captured by the long–run component of the 1990 routine employment share) has a negative sign on routine employment, but this effect is not statistically significant except in column 2. This negative effect is consistent with the results by Autor et al. [2015] but the lack of statistical significance in my results compared to Autor et al. [2015]'s Table 5 is due to the larger set of control variables used here.

[73]Note also that the coefficient in column 5 in panel D for exposure to U.S. tariffs is not statistically significant under exposure–robust standard errors. In addition, technological change does appear to have a substantial positive impact on employment in manual occupations.

[74]It is worth noting that differences in labor market institutions between these two groups seem to be small along some dimensions. For example, unemployment insurance parameters seems to be similar, with replacement rates of 45% and

Table 8: NAFTA Tariff Liberalization and Change in Share of Task Employment in the Working-Age Population

Dependent Variable: Change in occupational emp/working-age pop (in % pts)

			By educ. attainment		By sector	
	All	All	Noncollege	College	Mfg.	Nonmfg.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Primarily abstract occupations.						
(Share of working-age population employed in managerial/professional/ technical occupations.)						
$\Delta\tau^{US}$	-0.535***	-0.393***	-0.132*	-0.601***	-0.130	-0.393***
	(0.177)	(0.136)	(0.074)	(0.183)	(0.099)	(0.121)
$\Delta\tau^{MEX}$	0.256	0.067	-0.096	0.178	-0.176*	0.361
	(0.275)	(0.161)	(0.096)	(0.300)	(0.105)	(0.235)
ΔIPW	0.279	0.121	0.041	0.257	-0.115	0.371*
	(0.230)	(0.154)	(0.080)	(0.171)	(0.080)	(0.189)
Share of 1990 Emp. in Routine Occs.	0.222**	-0.024	0.041	0.139	0.034	0.229**
	(0.107)	(0.042)	(0.040)	(0.106)	(0.028)	(0.092)
Panel B: Primarily routine occupations.						
(Share of working-age population employed in clerical/retail sales occupations.)						
$\Delta\tau^{US}$	-0.087	-0.023	-0.122	0.135	-0.060	0.003
	(0.151)	(0.119)	(0.177)	(0.180)	(0.060)	(0.132)
$\Delta\tau^{MEX}$	-0.088	-0.173	-0.022	-0.096	-0.021	-0.054
	(0.168)	(0.152)	(0.206)	(0.208)	(0.087)	(0.152)
ΔIPW	0.054	-0.018	0.260	-0.121	-0.020	0.055
	(0.138)	(0.111)	(0.184)	(0.138)	(0.043)	(0.117)
Share of 1990 Emp. in Routine Occs.	0.109	-0.002	0.212**	0.007	0.037*	0.055
	(0.094)	(0.031)	(0.103)	(0.103)	(0.021)	(0.075)
Panel C: Primarily routine occupations.						
(Share of working-age population employed in production occupations.)						
$\Delta\tau^{US}$	0.880***	0.894***	1.062***	0.290**	0.819***	0.007
	(0.150)	(0.147)	(0.244)	(0.119)	(0.166)	(0.027)
$\Delta\tau^{MEX}$	0.226*	0.207	0.276	-0.030	0.382**	0.004
	(0.136)	(0.136)	(0.210)	(0.142)	(0.187)	(0.040)
ΔIPW	0.055	0.040	-0.008	0.140	0.122	0.017
	(0.133)	(0.125)	(0.157)	(0.172)	(0.096)	(0.027)
Share of 1990 Emp. in Routine Occs.	-0.062	-0.086***	-0.053	-0.055	0.044	0.023
	(0.075)	(0.029)	(0.123)	(0.056)	(0.051)	(0.015)
Panel D: Primarily manual occupations.						
(Share of working-age population employed in craft/mechanics/agricultural/service occupations.)						
$\Delta\tau^{US}$	-0.127	-0.020	-0.218	-0.157	0.133*	-0.235*
	(0.117)	(0.114)	(0.203)	(0.104)	(0.073)	(0.130)
$\Delta\tau^{MEX}$	0.030	-0.113	0.259	-0.071	0.101	-0.119
	(0.208)	(0.180)	(0.355)	(0.178)	(0.104)	(0.204)
ΔIPW	0.001	-0.118	0.105	0.004	0.066	-0.092
	(0.118)	(0.102)	(0.257)	(0.104)	(0.047)	(0.123)
Share of 1990 Emp. in Routine Occs.	0.305***	0.120***	0.577***	0.056	0.066***	0.289***
	(0.088)	(0.030)	(0.138)	(0.055)	(0.021)	(0.072)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variables are the change in the share in the working-age population of employment in primarily abstract occupations (panel A), primarily clerical and sales-related routine occupations (panel B), primarily production-related routine occupations (panel C) and primarily manual occupations (panel D). The measures of exposure to tariff liberalization are defined by equations (1) and (2). All regressions are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). In columns 1 and 3 through 6 the share of employment in routine occupations in 1990 is instrumented by the measure of commuting zone historical industry structure defined by equation (6) in Appendix A.4. Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

I estimate equation (5) splitting the sample between high and low human capital areas. I include changes in manufacturing employment, nonmanufacturing employment, unemployment and the number of individuals out of the labor force as dependent variables, all expressed as a share of the working-age population. These results are shown in panel A in Table 9. There is a very sharp contrast in the impact of NAFTA between these two types of commuting zones. Among high human capital regions, the impact of U.S. and Mexico's tariff liberalization is small and not statistically significant for all outcomes, with the exception of a small increase in unemployment due to U.S. tariff cuts. In contrast, in low human capital regions, U.S. tariff liberalization has a large negative effect on manufacturing employment, a smaller positive impact on nonmanufacturing employment, and a negative impact on total employment. In addition, low human capital regions more exposed to U.S. tariff liberalization face increases in unemployment and in labor force nonparticipation.[75] All these effects are statistically significant. The impact among low human capital regions is such that commuting zones at the 75th percentile of exposure to U.S. tariff cuts experienced a 1.13 percentage point decline in manufacturing employment and a 0.58 p.p. decline in total employment (both as a share of the working-age population) relative to commuting zones at the 25th percentile of exposure. In addition, within the low human capital sample, regions at the 75th percentile of exposure face a 0.2 p.p. increase in unemployment and a 0.38 p.p. increase in labor force nonparticipation relative to regions at the 25th percentile.[76]

These differences across high and low human capital commuting zones could be due to the different share of college and noncollege workers in them. For this reason, it is useful to do this exercise separately for noncollege and college individuals. The results, in panels B and C in Table 9, show that there are key differences across high and low human capital commuting zones even within each of these groups. In low human capital regions (see the first five columns in panels B and C), there is a decline in manufacturing employment for both noncollege and college individuals. In the case of noncollege individuals, this translates into a decline in total employment as well. High human capital regions respond differently (see columns 6 through 10). The effect of U.S. tariff cuts for noncollege individuals are not statistically significant, although in terms of magnitude there is a decline in total employment that is similar to that

47% in high and low human capital commuting zones respectively (measured in 1997, which is the latest year available). Unionization rates are also similar, with coverage rates of 18% and 15% in high and low human capital commuting zones [Hirsch and Macpherson, 2003].

[75] Given that the magnitude of the shock is larger among low human capital regions (see panel B in Appendix Table A.5), one possibility is that the difference in responses across regions is explained by a nonlinear effect of tariff liberalization. However, including quadratic terms for the tariff exposure measures shows that this does not seem to be the case.

[76] The results in this section are related to Bloom et al. [2019], who study the response of firm employment to Chinese import competition during 1992-2012 and find a larger decline in manufacturing employment in low human capital regions. My results in Table 9 for the period 1990-2000 indicate a larger negative impact of Chinese import competition in high human capital commuting zones. This suggests Bloom et al. [2019]'s findings in this regard might be driven by the post 2000 part of their sample, which is consistent with their statement about finding stronger effects of Chinese import competition after 2000.

in the low human capital areas. However, there is an increase in manufacturing employment for college individuals, as well as an increase in total employment. This suggests that the manufacturing industry (as well as total employment) is able to transform itself in the high human capital regions, replacing low skill tasks and expanding high skill activities, and thus increasing the demand for college graduates. This is consistent with the earlier results regarding abstract tasks in Table 8. Regarding Mexico's tariff liberalization, the results do not show any statistically significant impacts.

Overall, these results imply a widening in regional disparities across the U.S. In 1990, low human capital regions had higher levels of unemployment and lower labor force participation than high human capital regions, and U.S. tariff liberalization extended that gap.[77] Further, the *decline* of manufacturing employment in low human capital commuting zones in contrast to its *transformation* in high human capital areas relate to the literature that argues that skilled places are more flexible in response to shocks and are more successful in reinventing themselves [Glaeser et al., 2004, Glaeser, 2005].

Persistence in the employment effects of NAFTA Finally, I examine the effects of tariff cuts over a longer horizon, given that the literature has established that the effect of trade shocks can be quite persistent [Autor et al., 2021]. To do so, I follow Autor et al. [2021] and estimate equation (5) replacing the dependent variable by changes in labor market outcomes computed over 1990–2007.[78] I choose 2007 as the final period because it falls right before the 2008–2009 financial crisis, which caused significant disruption to U.S. labor markets. In the baseline results, the regional measures of exposure to tariff cuts are still based on tariff cuts over 1990–2000, given that liberalization was nearly complete by 2000.[79] In robustness checks, however, I use difference in tariffs over 1990–2007, obtaining very similar results. It is important to take into account that the "China shock" accelerated starting with China's entry to the World Trade Organization in 2001. For this reason, I control for growth in Chinese imports over 1990–2007 (and instrumented by Chinese exports to high income markets also over 1990–2007), even though results are very similar when controlling for the China shock only over 1990–2000.

The results are shown in Table 10.[80] The odd–numbered columns reproduce the results in Table 4 earlier as a benchmark, while the even numbered columns report the new results, with longer–term

[77] In 1990, unemployment as a share of the working-age population was 0.052 in low human capital regions and 0.047 in high human capital regions. The number of individuals out of the labor force (also as a fraction of the working-age population) was 0.281 in low human capital regions and 0.238 in high human capital regions.

[78] Note that this approach is similar to Autor et al. [2021] who estimate the effect of growth in Chinese imports during 2000–2012 on changes in labor market outcomes at different horizons, up to 2019.

[79] In addition, measuring tariff changes over 1990–2000 makes the results comparable to those earlier in the paper. It allows me to determine how labor market outcomes adjust at different horizons to a same shock.

[80] Equivalent results with Borusyak et al. [2022b]'s exposure–robust standard errors are found in Appendix Table A.25.

Table 9: NAFTA Tariff Liberalization and Change in Employment Status in the Working-Age Population in High and Low Human Capital Regions

Dependent Variable: Change in population shares by employment status (in % pts)

	Low human capital					High human capital				
	Mftg. (1)	Nonmftg. (2)	Emp. (3)	Unemp. (4)	NILF (5)	Mftg. (6)	Nonmftg. (7)	Emp. (8)	Unemp. (9)	NILF (10)
Panel A: All education levels										
$\Delta\tau^{\text{US}}$	1.328***	-0.641***	0.687***	-0.236***	-0.452***	-0.003	-0.163	-0.166	-0.345*	0.511
	(0.211)	(0.196)	(0.154)	(0.083)	(0.106)	(0.632)	(0.706)	(0.409)	(0.194)	(0.356)
$\Delta\tau^{\text{MEX}}$	-0.119	-0.026	-0.145	0.155*	-0.010	-0.314	0.700	0.387	0.202	-0.589
	(0.302)	(0.348)	(0.286)	(0.093)	(0.241)	(0.350)	(0.446)	(0.426)	(0.211)	(0.427)
ΔIPW	0.178	-0.329	-0.151	0.075	0.076	-0.452**	0.600**	0.148	-0.151	0.003
	(0.237)	(0.341)	(0.194)	(0.056)	(0.184)	(0.227)	(0.265)	(0.305)	(0.143)	(0.248)
Panel B: No college education										
$\Delta\tau^{\text{US}}$	1.579***	-0.469*	1.110***	-0.296***	-0.814***	0.768	0.081	0.849	-0.392	-0.457
	(0.291)	(0.253)	(0.255)	(0.115)	(0.219)	(0.771)	(0.730)	(0.550)	(0.257)	(0.406)
$\Delta\tau^{\text{MEX}}$	0.107	-0.243	-0.135	0.151	-0.016	-0.281	0.804	0.523	0.368	-0.891
	(0.393)	(0.375)	(0.394)	(0.106)	(0.349)	(0.395)	(0.571)	(0.607)	(0.267)	(0.555)
ΔIPW	0.031	-0.286	-0.255	0.050	0.205	-0.330	0.568*	0.238	-0.160	-0.078
	(0.201)	(0.352)	(0.292)	(0.073)	(0.278)	(0.238)	(0.309)	(0.413)	(0.184)	(0.319)
Panel C: College education										
$\Delta\tau^{\text{US}}$	0.625***	-0.530**	0.095	-0.142*	0.047	-1.310**	-0.100	-1.410***	-0.262	1.672***
	(0.165)	(0.214)	(0.198)	(0.083)	(0.215)	(0.602)	(0.566)	(0.400)	(0.210)	(0.471)
$\Delta\tau^{\text{MEX}}$	-0.536	0.169	-0.367	0.119	0.248	-0.478	0.539	0.062	0.064	-0.125
	(0.350)	(0.332)	(0.339)	(0.131)	(0.337)	(0.428)	(0.359)	(0.314)	(0.221)	(0.428)
ΔIPW	0.471	-0.225	0.246	0.082*	-0.328	-0.537**	0.546*	0.009	-0.126	0.117
	(0.380)	(0.235)	(0.253)	(0.046)	(0.259)	(0.253)	(0.293)	(0.196)	(0.108)	(0.211)

Notes: $N = 361$ in each panel. This table reports the results of the estimation of equation (5), splitting the sample between low and high human capital commuting zones. High (low) human capital commuting zones are those with an above (below) share of working-age population with college education in 1990. The dependent variables are the change in the share in the working-age population of manufacturing employment (columns 1-6), of nonmanufacturing employment (columns 2-7), of total employment (columns 3-8) of unemployment (columns 4-9) and of the number of individuals not in the labor force (columns 5-10). The measures of exposure to tariff liberalization are defined by equations (1) and (2). All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

outcomes. Columns 1 and 2 focus on changes in manufacturing employment (as a ratio of working–age population). The fact that the coefficient for U.S. tariff cuts in column 2 is 77% larger than the coefficient in column 1 implies that the 1990–2000 tariff cuts kept reducing manufacturing employment substantially after 2000, at the same annual rate approximately than during 1990—2000. This finding echoes the persistent effects of the China shock documented by Autor et al. [2021]. Columns 3 and 4 examine nonmanufacturing employment. The effect of U.S. tariff cuts again persists strongly after 2000, even more so than for manufacturing employment. As a result, the coefficient indicating a decline in total employment is only slightly higher for 1990–2007 (column 6) than for 1990–2000 (column 5). In other words, nonmanufacturing employment increases more slowly than the decline in manufacturing employment, such that the decline in *total* employment is mostly done by 2000.

Next, columns 7 and 8 shows that while unemployment increases as a result of U.S. tariff cuts over 1990–2000, it is close to zero and not statistically significant over 1990–2007, implying that the unemployment effects eventually disappear. In contrast, there is a statistically significant increase in labor force nonparticipation over 1990–2007 (column 10), while this coefficient was not statistically significant over the shorter 1990–2000 horizon (column 9).[81] This suggests that workers displaced from manufacturing spend some time searching for new jobs, but eventually leave the labor force. In the case of Mexican tariff cuts, the negative coefficient for manufacturing employment, which was not statistically significant for 1990–2000, becomes statistically significant over the longer 1990–2007 horizon. This result, however, is not statistically significant under exposure–robust standard errors as shown in Appendix Table A.25. Note finally that as a robustness check Appendix Table A.19 reports very close results using exposure to tariff changes over 1990–2007 instead of tariff changes over 1990–2000.[82]

Overall, looking at longer horizons shows that while tariff liberalization was nearly complete by 2000, the adjustment of labor markets persisted well over then, and that the reallocation toward nonmanufacturing is slower than the decline in manufacturing employment.

5. CONCLUSIONS

This paper has provided a detailed portrait of the employment effects of U.S. and Mexican tariff liberalization under the North American Free Trade Agreement on U.S. local labor markets. A first key finding

[81] Labor force nonparticipation increases by 0.13 percentage points over 1990–2007 in regions at the 75th relative to the 25th percentile of exposure to U.S. tariff cuts.

[82] The same is found when using tariff levels in 1990 instead of tariff changes.

Table 10: NAFTA Tariff Liberalization and Change in Employment Status in the Working-Age Population: 1990–2007

Dependent Variable: Change in population shares by employment status (in % pts)

	Manufacturing		Nonmanufacturing		Employment		Unemployment		Not in the Labor Force	
	1990–2000	1990–2007	1990–2000	1990–2007	1990–2000	1990–2007	1990–2000	1990–2007	1990–2000	1990–2007
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta\tau^{\text{US}}$	0.907***	1.606***	-0.449**	-1.041***	0.458*	0.565**	-0.242**	0.027	-0.216	-0.592***
	(0.305)	(0.373)	(0.208)	(0.379)	(0.250)	(0.261)	(0.101)	(0.139)	(0.201)	(0.221)
$\Delta\tau^{\text{MEX}}$	-0.325	-0.545*	0.314	0.666	-0.012	0.121	0.097	-0.176	-0.085	0.055
	(0.218)	(0.284)	(0.353)	(0.421)	(0.297)	(0.391)	(0.103)	(0.174)	(0.300)	(0.305)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variables are the change in the share in the working-age population of manufacturing employment (columns 1-2), of nonmanufacturing employment (columns 3-4), of total employment (columns 5-6), of unemployment (columns 7-8) and of the number of individuals not in the labor force (columns 9-10). In columns 1, 3, 5, 7, and 9 the dependent variable is computed over 1990–2000 and the results are equivalent to Table 4. In columns 2, 4, 6, 8, and 10 the dependent variable is computed over 1990–2007. The measures of exposure to tariff liberalization are defined by equations (1) and (2) and are computed over 1990–2000. All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Growth in Chinese imports (and its instrument) is computed over 1990–2000 in columns 1, 3, 5, 7, and 9 and over 1990–2007 in columns 2, 4, 6, 8, and 10. Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

is that commuting zones with a higher exposure to U.S. tariff liberalization have seen a relative decline in the share of population employed in manufacturing. This has been coupled with increases in employment in certain low-pay service-sector industries, in unemployment, and in labor-force nonparticipation, and has not led to changes in population. At the same time, the impact of Mexican tariff cuts on U.S. local labor markets is not statistically significant across most of these outcomes for the population as a whole.

These effects of U.S. tariff liberalization are very uneven across different groups of the population. The decline in manufacturing employment is concentrated among individuals with low educational attainment and among women. I also provide some of the first evidence on differences between races in the impact of trade shocks in the U.S., finding that the decline in employment due to U.S. tariff liberalization is substantially larger among nonwhite workers. In addition, the impact of U.S. tariff liberalization has had a very disparate effect across geography. While low human capital commuting zones (located mostly in the South and parts of the Midwest) have seen declines in manufacturing and total employment, and increases in unemployment and labor force nonparticipation, the impact of tariff cuts on high human capital commuting zones has been small and not statistically significant. Mexico's tariff cuts, while not having a statistically significant for the population as a whole, do impact some groups. Specifically, they raise manufacturing among those with college education. In addition, there is some less robust evidence that they raise manufacturing employment among men and white workers. In sum, those who face the consequences of increased import competition due to U.S. tariff cuts are different than those who receive the opportunities from Mexico's tariff cuts, which underscores the distributional consequences of trade liberalization.

Finally, U.S. tariff liberalization under NAFTA has also led to changes in the task structure of local labor markets, with an increase in employment in abstract tasks which partially compensates a large decline in employment in production-related routine tasks. While the increase in employment in abstract tasks is larger among college-educated workers, the decline in employment in production-related routine tasks is concentrated among noncollege workers, again highlighting the uneven effects of trade liberalization.

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A. Appendix

A.1. Sample Selection and Local Labor Market Outcomes

The sample selection follows Autor et al. [2013]. I restrict the sample to individuals aged 16 to 64. Unpaid family workers and those living in institutional group quarters are excluded. Labor supply weights are constructed multiplying usual hours worked times weeks worked in the year preceding each survey. All employment outcomes are constructed weighing by these labor supply weights and by the Census person sampling weight.

A.2. Mexico's NAFTA Tariff Schedule

I digitize and process the schedule of Mexico's NAFTA tariffs toward the U.S. These data are obtained from Mexico's *Diario Oficial* (the official publication of Mexico's government). Products, listed at the 8-digit level of Mexico's version of the Harmonized System, are classified into several different categories according to the timeline of liberalization. The main categories are the following. Tariffs on category A products are eliminated immediately and entirely on January 1st, 1994. Category B products are liberalized in five equal steps starting January 1st, 1994, and become duty free on January 1st, 1998. Tariffs on category B6 products (a subset of textile and apparel products) are eliminated first by a percentage equal to the base rate on January 1st, 1994 and then in five equal steps, becoming duty free by January 1st, 1999. Tariffs on category C products are liberalized in ten equal steps starting January 1st, 1994, and become duty free on January 1st, 2003. Tariffs on category C+ products are liberalized in fifteen equal steps starting January 1st, 1994, and become duty free on January 1st, 2008. Category D products are duty free before NAFTA and remain as such. These categories account for more than 98% HS 8-digit products. The rest follows various exceptions which I process on a case by case basis.

Table A.1 reports the number of HS8 products under each category. Consistent with the pattern shown in Appendix Table A.6, most products are liberalized entirely or substantially shortly after January 1st, 1994.

Table A.1: Tariff Liberalization Categories: Mexico's Schedule

Category	Number of Products	% of Products
A	5815	47.4%
B	1747	14.2%
B+	3	0.0%
B6	762	6.2%
C	3436	28%
C+	3	0.0%
D	277	2.3%
Other	220	1.8%

Notes: This table reports the number of HS 8-digit products under each category of tariff liberalization in Mexico's tariff schedule.

A.3. U.S. NAFTA Tariff Schedule

Table A.2 describes the number of products under each category of U.S. tariff liberalization toward Mexico. While the tariff data in the analysis is obtained from Romalis [2007], here I use data from Besedes et al. [2020] to tabulate the liberalization categories.

The details are as follows. Tariffs on category A products are eliminated immediately and entirely on January 1st, 1994. Category B products are liberalized in five equal steps starting January 1st, 1994, and become duty free on January 1st, 1998. Tariffs on category B6 products (a subset of textile and apparel products) are eliminated first by a percentage equal to the base rate on January 1st, 1994 and then in five equal steps, becoming duty free by January 1st, 1999. Tariffs on category C products are liberalized in ten equal steps starting January 1st, 1994, and become duty free on January 1st, 2003. Tariffs on category C+ products are liberalized in fifteen equal steps starting January 1st, 1994, and become duty free on January 1st, 2008. Category D products are duty free before NAFTA and remain as such. Tariffs on category C10 fall to 80% of the original rate in January 1st, 1994 then to 70% in January 1st, 1996, and then in seven equal steps becoming duty free on January 1st, 2003. The rest of the products are labeled by Besedes et al. [2020] as mixed category products, such that within each HS8 product there are several subproducts indexed by letters (not by HS10 codes) that fall under different liberalization categories.

Overall, this table shows that at least 66.3% of HS8 products were duty free on January 1st 1994, at least 76.5% were duty free before January 1st, 1999, 10% were duty free beyond 2000 (but their tariff rates in most cases had fallen by two thirds by 2000) and 13.45% were under the mixed category situation which means I don't have the data to determine which fraction was duty free before 2000.

Table A.2: Tariff Liberalization Categories: U.S. Schedule

Category	Number of Products	% of Products
A	4526	50.7%
B	179	2.0%
B6	728	8.2%
C	752	8.4%
C+	74	0.8%
C10	71	0.8%
D	1402	15.7%
Other	1202	13.45%

Notes: This table reports the number of HS 8-digit products under each category of tariff liberalization in the U.S. tariff schedule. Source: Besedes et al. [2020].

A.4. Instrument for Routine Employment Share

Here I describe the instrument for the commuting zone share of employment in routine occupations in 1990, introduced by Autor et al. [2015] and used in columns 1 and 3 through 6 in Table 8. This instrument is a measure of commuting zone historical industry structure defined as a weighted average of industries' share of employment in routine occupations in 1950, with weights equal to employment shares. Define $E_{i,j,1950}$ as the employment share of industry j in region i in 1950 and $R_{-i,j,1950}$ as the share of employment in routine occupations in industry i in all U.S. states except the state that includes region i. Then this instrument is:

$$\widetilde{RSH}_i = \sum_j E_{i,j,1950} \times R_{-i,j,1950} \,. \tag{6}$$

A.5. Alternative Measure of Regional Exposure to Tariff Liberalization

In this section I describe alternative measures of regional exposure to tariff liberalization and discuss the results obtained using these alternative measures.

■ Hakobyan and McLaren [2016] construct a measure of exposure to tariff liberalization that takes this into account Mexico's revealed comparative advantage. They measure Mexico's revealed comparative advantage in each industry j following Balassa [1965] and use it as an additional weight for industry-level tariffs:

$$\text{RCA}_j^{\text{MEX}} = \frac{x_{j\,1990}^{\text{MEX}} \Big/ x_{j\,1990}^{\text{ROW}}}{\sum_k x_{k\,1990}^{\text{MEX}} \Big/ \sum_k x_{k\,1990}^{\text{ROW}}} \ . \tag{7}$$

In this expression, $x_{j\,1990}^{\text{MEX}}$ stands for exports from Mexico to the rest of the world (i.e. all countries excluding Mexico and the U.S.) in industry j in 1990. $x_{j\,1990}^{\text{ROW}}$ stands for exports between all countries excluding the U.S. and Mexico. This measure of revealed comparative advantage captures Mexico's share of rest of the world trade in industry j relative to all industries. An alternative measure of regional exposure to U.S. tariff liberalization weighing by revealed comparative advantage is then the following:

$$\Delta\tau_i^{U.S.} = \frac{L_i^J}{L_i} \sum_{j\,\epsilon\,J} \frac{L_{ij}\text{RCA}_j^{\text{MEX}} \Delta\tau_j^{\text{U.S.}}}{L_{ij}\text{RCA}_j^{\text{MEX}}} \ . \tag{8}$$

In this expression, the denominator in the term $\sum_{j\,\epsilon\,J} \frac{L_{ij}\text{RCA}_j^{\text{MEX}} \Delta\tau_j^{\text{U.S.}}}{L_{ij}\text{RCA}_j^{\text{MEX}}}$ corresponds to the sum of employment across manufacturing industries weighed by Mexico's revealed comparative advantage. To be consistent with the baseline tariff measure defined by equation (1) in the main text, I multiply this term by the ratio of total regional employment in manufacturing industries over total regional employment $\frac{L_i^J}{L_i}$.

An equivalent measure of regional exposure to Mexico's tariff cuts accounting for U.S. revealed comparative advantage is the following.[83]

$$\Delta\tau_i^{MEX} = \frac{L_i^J}{L_i} \sum_{j\,\epsilon J} \frac{L_{ij}\text{RCA}_j^{\text{US}} \Delta\tau_j^{\text{MEX}}}{L_{ij}\text{RCA}_j^{\text{US}}} \ . \tag{9}$$

[83] Just as before, the assumption behind this measure is that Mexico's tariff cuts toward the U.S. should have a larger effect on U.S. exports in industries in which the U.S. has comparative advantage.

In this expression, U.S. revealed comparative advantage is defined as:

$$\text{RCA}_j^{\text{US}} = \frac{x_{j\,1990}^{\text{US}} \Big/ x_{j\,1990}^{\text{ROW}}}{\sum_k x_{k\,1990}^{\text{US}} \Big/ \sum_k x_{k\,1990}^{\text{ROW}}} \,, \tag{10}$$

where $x_{j\,1990}^{\text{US}}$ stands for exports from the U.S. to the rest of the world (i.e. all countries excluding Mexico and the U.S.) in industry j in 1990. Note that Appendix A.6 describes the data used to construct the measures of revealed comparative advantage.

The tariff exposure measures in equations (8) and (9) are highly correlated with the baseline tariff measures in equations (1) and (2) in the main text (with correlation coefficients 0.93 for U.S. tariffs and 0.99 for Mexico's tariffs).

■ An alternative measure of exposure to U.S. tariff liberalization does not normalize by the ratio of total regional employment in manufacturing industries over total regional employment $\frac{L_i^J}{L_i}$ This is the exact same measure used by Hakobyan and McLaren [2016]:

$$\Delta\tau_i^{US} = \frac{\sum_{j\,\epsilon\,J} L_{ij}\text{RCA}_j^{\text{MEX}}\Delta\tau_j^{\text{US}}}{\sum_{j\,\epsilon\,J}\text{RCA}_j^{\text{MEX}} L_i} \,. \tag{11}$$

The following equation shows the equivalent to (11) but for exposure to Mexico's tariff liberalization, in which tariffs are weighted by U.S. revealed comparative advantage:

$$\Delta\tau_i^{MEX} = \frac{\sum_{j\,\epsilon\,J} L_{ij}\text{RCA}_j^{\text{US}}\Delta\tau_j^{\text{MEX}}}{\sum_{j\,\epsilon\,J} L_{ij}\text{RCA}_j^{\text{US}}} \,. \tag{12}$$

Again, these tariff exposure measures in equations (11) and (12) are highly correlated with the baseline tariff measures in equations (1) and (2) in the main text (with correlation coefficients 0.78 for U.S. tariffs and 0.59 for Mexico's tariffs).

Finally, while the baseline tariff exposure measures defined in the main text (in equations (1) and (2)) consider tariff changes for manufacturing industries, I also consider an equivalent measure including nonmanufacturing tradable industries. Note that there are 397 SIC 4-digit manufacturing industries and 419 SIC 4-digit tradable industries. Again, these tariff exposure measures are highly correlated with the baseline tariff measures in equations (1) and (2) in the main text (with correlation coefficients 0.99 for U.S. tariffs and also 0.99 for Mexico's tariffs).

Results Appendix Table A.14 shows that key results in the paper are robust to using these alternative measures of regional exposure to tariff liberalization.

Panel A replicates Table 4 in the main text using the exposure measures in equations (8) and (9). Panel B uses the exposure measures in equations (11) and (12). Finally, panel C uses the baseline measures in equations (1) and (2) but considering tariff changes in all tradable industries instead of only manufacturing industries.

The 0.907 coefficient on U.S. tariffs in column 2 in Table 4 implies a 0.20 percentage point decline in manufacturing employment as a share of the working-age population in regions at the 75th percentile of exposure relative to regions at the 25th percentile. The equivalent in panels A, B and C of Appendix Table A.14 is statistically significant in all cases and implies 0.16, 0.14 and 0.18 percentage point declines respectively.

For nonmanufacturing employment, the coefficient on U.S. tariffs in column 4 of Table 4 is statistically significant.[84] It is also statistically significant in panels B and C in A.14, and it has the same sign but is not statistically significant in panel A. In panel B, or example, the coefficient implies a 0.09 percentage point increase in nonmanufacturing employment as a share of the working-age population in regions at the 75th percentile of exposure relative to regions at the 25th percentile, which is the same magnitude implied by Table 4.

The 0.458 coefficient in column 6 in Table 4 implies a 0.1 percentage point decline in total employment as a share of the working-age population in regions at the 75th percentile of exposure relative to regions at the 25th percentile. The equivalent in panel A of Appendix Table A.14 is also a 0.10 percentage point decline. The coefficient in panels B and C have the same sign but are not statistically significant.

The results for the effect of U.S. tariff cuts on unemployment and labor force nonparticipation are also quite similar with the alternative tariff measures.

Finally, in all panels in Table A.14 exposure to Mexican tariff cuts does not have a statistically significant impact on most outcomes, except for a small decline in unemployment.

A.6. Construction of Revealed Comparative Advantage

The measures of revealed comparative advantage defined by equations (7) and (10) require industry-level trade flows in 1990. Specifically, I use exports from Mexico to the rest of the world excluding the U.S.,

[84] Recall that this result in Table 4 was also not statistically significant under exposure–robust standard errors.

exports from the U.S. to the rest of the world excluding Mexico, and exports among the rest of the world excluding the U.S. and Mexico. I use a concordance provided by Autor et al. [2013] to assign trade flows from the 1988/1992 version of the Harmonized System ("H0") to SIC industries. The trade data are obtained from the UN's Comtrade database through the World Bank's World Integrated Trade Solution (WITS). They are downloaded using the SITC revision 2 classification, given that in 1990 only some countries report trade using the Harmonized System. I then use a concordance between SITC Tier 4 codes and the 1988/1992 HS Classification 6-digit codes.

A.7. Did NAFTA Increase Trade Flows?

This section shows that both U.S. and Mexico's tariff liberalization under NAFTA led to increased trade. To assess the effect of U.S. tariff liberalization, I use data on U.S. imports by HS 6-digit product and source country in 1990 and 2000.[85] I estimate the following difference in differences regression with country-year, product-country and product-year fixed effects:

$$\log(\text{Value})_{pct} = \gamma_{pc} + \nu_{pt} + \eta_{ct} + \beta \cdot \text{Mexico}_c \cdot \text{High Tariff}_p \cdot \text{Post}_t + \epsilon_{pct}\,. \tag{13}$$

The effect of U.S. tariff liberalization is captured by the triple interaction between a dummy variable High Tariff$_p$ equal to one for products with above-median tariffs in 1990 and zero otherwise, a dummy Mexico$_c$ equal to one for imports sourced from Mexico and zero otherwise, and a dummy Post$_t$ equal to one for year 2000 and zero for 1990. The results are shown in column 1 in Table A.3 and the 0.286 coefficient implies a 33% increase between 1990 and 2000 in U.S. imports from Mexico relative to imports from the rest of the world in industries with high initial tariff levels relative to other industries.

Similarly, I estimate an equivalent regression using data on U.S. exports to Mexico and all other countries. In this case the High Tariff$_p$ dummy variable is equal to one for products with above-median Mexican tariffs in 1990 and zero otherwise, and Mexico$_c$ is equal to one for exports to Mexico. The coefficient in column 2 in Table A.3 implies a 24% increase between 1990 and 2000 in U.S. exports to Mexico relative to exports to the rest of the world in industries with high initial tariff levels relative to other industries.

Table A.3: NAFTA Tariff Liberalization and Trade Flows

Dependent Variable: (log) U.S. imports from Mexico or U.S. exports to Mexico

	U.S. Imports (1)	U.S. Exports (2)
$1[\text{Mexico}_c] \cdot 1[\text{High Tariff}_p] \cdot 1[\text{Post}_t]$	0.286*	0.216*
	(0.038)	(0.028)
N	137352	277878

Notes: This table reports the results of the estimation of equation (13). Column 1 corresponds to U.S. imports and column 2 corresponds to U.S. exports. Standard errors are clustered by HS 6-digit product, year and origin (or destination) using multiway clustering. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

[85] These data on U.S. imports and exports are produced by the U.S. Census Bureau and obtained from Schott [2008].

A.8. Descriptive Statistics

Table A.4: Summary Statistics for Local Labor Market Outcomes

Percentage of working-age population employed in manufacturing	1990	2000	1990-2000	Percentage of working-age population employed in nonmanufacturing	1990	2000	1990-2000
All	12.7	10.5	-2.1	All	57.8	59.2	1.3
	(4.8)	(4.5)	(1.6)		(5.9)	(5.2)	(2.4)
Noncollege	13.4	11.0	-2.3	Noncollege	48.9	49.1	0.0
	(5.4)	(5.1)	(1.9)		(5.8)	(5.3)	(2.7)
College	11.6	9.9	-1.7	College	67.9	68.5	0.5
	(4.2)	(4.0)	(1.6)		(4.5)	(4.0)	(2.0)
Female	8.3	6.7	-1.5	Female	55.4	57.7	2.3
	(3.7)	(3.0)	(1.6)		(5.9)	(5.4)	(2.8)
Male	17.3	14.5	-2.6	Male	60.2	60.7	0.2
	(6.4)	(6.1)	(2.0)		(6.8)	(6.1)	(2.6)
Nonwhite	13.3	11.2	-2.0	Nonwhite	47.9	49.9	1.8
	(6.2)	(5.6)	(3.1)		(8.2)	(6.5)	(4.1)
White	13.9	11.6	-2.1	White	58.6	60.7	2.0
	(5.2)	(4.9)	(1.7)		(6.2)	(5.5)	(2.2)

Percentage of working-age population employed	1990	2000	1990-2000	Percentage of working-age population unemployed	1990	2000	1990-2000
All	70.4	69.7	-0.8	All	4.8	4.3	-0.5
	(5.0)	(5.0)	(2.8)		(1.0)	(0.9)	(0.7)
Noncollege	62.3	60.1	-2.2	Noncollege	6.3	5.7	-0.6
	(5.4)	(5.9)	(3.3)		(1.2)	(1.2)	(0.9)
College	79.5	78.4	-1.1	College	3.1	3.0	-0.2
	(3.9)	(3.6)	(2.4)		(0.7)	(0.7)	(0.7)
Female	63.6	64.3	0.8	Female	4.2	4.0	-0.3
	(5.5)	(5.5)	(3.2)		(0.9)	(0.9)	(0.7)
Male	77.5	75.2	-2.4	Male	5.4	4.6	-0.8
	(4.9)	(4.9)	(2.8)		(1.3)	(1.1)	(0.9)
Nonwhite	61.1	61.1	-0.2	Nonwhite	8.4	6.9	-1.4
	(6.7)	(4.6)	(4.8)		(2.2)	(1.6)	(1.8)
White	72.4	72.3	-0.1	White	4.0	3.5	-0.5
	(4.8)	(4.7)	(2.5)		(0.9)	(0.8)	(0.7)

Percentage of working-age population not in the labor force	1990	2000	1990-2000
All	24.8	26.1	1.3
	(4.3)	(4.4)	(2.6)
Noncollege	31.4	34.2	2.8
	(4.6)	(5.2)	(3.0)
College	17.4	18.7	1.3
	(3.6)	(3.3)	(2.2)
Female	32.1	31.7	-0.5
	(4.9)	(4.9)	(3.0)
Male	17.1	20.2	3.2
	(4.5)	(4.3)	(2.6)
Nonwhite	30.5	31.9	1.6
	(5.6)	(3.9)	(4.4)
White	23.6	24.2	0.6
	(4.3)	(4.2)	(2.2)

Notes: This table reports the mean and standard deviation (in parenthesis under the mean) for local labor market outcomes studied throughout the paper. These statistics are weighted by 1990 population in each commuting zone.

Table A.4: Summary Statistics for Local Labor Market Outcomes (*Continued*)

Percentage of working-age population employed in construction	1990	2000	1990-2000	Percentage of working-age population employed in transportation and utilities	1990	2000	1990-2000
All	4.6	5.0	0.4	All	5.5	5.5	0.0
	(0.9)	(1.0)	(0.8)		(1.1)	(1.1)	(0.5)
Noncollege	62.3	60.1	-2.2	Noncollege	62.3	60.1	-2.2
	(5.4)	(5.9)	(3.3)		(5.4)	(5.9)	(3.3)
College	79.5	78.4	-1.1	College	79.5	78.4	-1.1
	(3.9)	(3.6)	(2.4)		(3.9)	(3.6)	(2.4)
Female	0.9	1.0	0.1	Female	3.2	3.3	0.1
	(0.3)	(0.3)	(0.2)		(1.0)	(1.0)	(0.4)
Male	7.7	8.6	0.8	Male	7.6	7.6	-0.0
	(1.6)	(1.7)	(1.4)		(1.4)	(1.4)	(0.7)
Nonwhite	30.5	31.9	1.6	Nonwhite	30.5	31.9	1.6
	(5.6)	(3.9)	(4.4)		(5.6)	(3.9)	(4.4)
White	23.6	24.2	0.6	White	23.6	24.2	0.6
	(4.3)	(4.2)	(2.2)		(4.3)	(4.2)	(2.2)

Percentage of working-age population employed in wholesale and retail trade	1990	2000	1990-2000	Percentage of working-age population employed in other services	1990	2000	1990-2000
All	13.9	13.2	-0.8	All	26.5	29.0	2.4
	(1.5)	(1.4)	(0.9)		(4.5)	(4.5)	(1.4)
Noncollege	62.3	60.1	-2.2	Noncollege	62.3	60.1	-2.2
	(5.4)	(5.9)	(3.3)		(5.4)	(5.9)	(3.3)
College	79.5	78.4	-1.1	College	79.5	78.4	-1.1
	(3.9)	(3.6)	(2.4)		(3.9)	(3.6)	(2.4)
Female	12.5	12.0	-0.5	Female	33.7	36.6	3.0
	(1.6)	(1.6)	(0.9)		(4.3)	(4.2)	(1.9)
Male	15.4	14.4	-1.0	Male	20.9	22.7	1.8
	(2.0)	(1.7)	(1.0)		(4.9)	(5.3)	(1.5)
Nonwhite	30.5	31.9	1.6	Nonwhite	30.5	31.9	1.6
	(5.6)	(3.9)	(4.4)		(5.6)	(3.9)	(4.4)
White	23.6	24.2	0.6	White	23.6	24.2	0.6
	(4.3)	(4.2)	(2.2)		(4.3)	(4.2)	(2.2)

Percentage of working-age population employed in government	1990	2000	1990-2000
All	3.6	3.5	-0.1
	(1.9)	(1.6)	(0.7)
Noncollege	62.3	60.1	-2.2
	(5.4)	(5.9)	(3.3)
College	79.5	78.4	-1.1
	(3.9)	(3.6)	(2.4)
Female	3.1	3.3	0.1
	(1.9)	(1.6)	(0.7)
Male	4.1	3.8	-0.3
	(2.0)	(1.6)	(0.8)
Nonwhite	30.5	31.9	1.6
	(5.6)	(3.9)	(4.4)
White	23.6	24.2	0.6
	(4.3)	(4.2)	(2.2)

Notes: This table reports the mean and standard deviation (in parenthesis under the mean) for local labor market outcomes studied throughout the paper. These statistics are weighted by 1990 population in each commuting zone.

Table A.4: Summary Statistics for Local Labor Market Outcomes (*Continued*)

Percentage of working-age population employed in abstract occupations	1990	2000	1990-2000	Percentage of working-age population employed in routine (clerical and sales) occupations	1990	2000	1990-2000
All	25.0	26.0	0.9	All	16.7	16.4	-0.3
	(4.8)	(4.9)	(1.3)		(2.3)	(1.8)	(1.2)
Noncollege	8.9	7.7	-1.3	Noncollege	15.2	14.8	-0.4
	(1.4)	(1.1)	(0.7)		(2.9)	(2.4)	(1.4)
College	42.8	42.2	-0.6	College	18.5	18.0	-0.6
	(4.9)	(4.8)	(1.6)		(1.8)	(1.4)	(1.2)
Female	22.7	24.5	1.8	Female	23.3	22.3	-1.1
	(4.1)	(4.1)	(1.5)		(2.9)	(2.2)	(1.9)
Male	27.5	27.4	-0.1	Male	9.8	10.3	0.5
	(5.7)	(5.9)	(1.5)		(2.0)	(1.7)	(0.8)

Percentage of working-age population employed in routine (production) occupations	1990	2000	1990-2000	Percentage of working-age population employed in manual occupations	1990	2000	1990-2000
All	7.3	6.1	-1.1	All	21.4	21.2	-0.2
	(2.9)	(2.7)	(1.0)		(3.2)	(3.1)	(1.0)
Noncollege	9.8	8.5	-1.3	Noncollege	28.3	29.1	0.7
	(3.6)	(3.4)	(1.3)		(3.1)	(3.0)	(1.6)
College	4.3	3.9	-0.4	College	13.9	14.3	0.4
	(1.7)	(1.8)	(0.7)		(2.9)	(3.0)	(1.0)
Female	4.7	4.0	-0.7	Female	12.9	13.6	0.7
	(2.8)	(2.1)	(1.3)		(2.4)	(2.3)	(0.9)
Male	9.9	8.3	-1.5	Male	30.3	29.1	-1.2
	(3.5)	(3.5)	(1.0)		(4.3)	(4.1)	(1.6)

Notes: This table reports the mean and standard deviation (in parenthesis under the mean) for local labor market outcomes studied throughout the paper. These statistics are weighted by 1990 population in each commuting zone.

Table A.5: Summary Statistics for Measures of Regional Exposure to Tariff Liberalization

	Defined by equation	Mean	St. Dev.	p10	p25	p50	p75	p90
Panel A: Across all commuting zones								
$\Delta\tau^{\text{US}}$	1	-0.45	0.53	-0.90	-0.41	-0.30	-0.20	-0.13
$\Delta\tau^{\text{US}}$	8	-0.44	0.56	-0.87	-0.44	-0.24	-0.18	-0.12
$\Delta\tau^{\text{US}}$	11	-1.91	1.43	-3.69	-1.99	-1.56	-1.12	-0.81
$\Delta\tau^{\text{MEX}}$	2	-2.50	1.24	-3.98	-2.91	-2.34	-1.57	-1.32
$\Delta\tau^{\text{MEX}}$	9	-2.32	1.18	-3.85	-2.77	-2.23	-1.51	-1.16
$\Delta\tau^{\text{MEX}}$	12	-11.55	1.56	-12.68	-11.96	-11.55	-10.91	-9.97
Panel B: By human capital								
$\Delta\tau^{\text{US}}$ (low human capital)	1	-1.00	0.87	-2.07	-1.26	-0.72	-0.41	-0.21
$\Delta\tau^{\text{US}}$ (high human capital)	1	-0.29	0.20	-0.43	-0.36	-0.24	-0.17	-0.12
$\Delta\tau^{\text{MEX}}$ (low human capital)	2	-3.70	1.70	-5.73	-4.75	-3.50	-2.51	-1.81
$\Delta\tau^{\text{MEX}}$ (high human capital)	2	-2.16	0.80	-3.10	-2.69	-2.12	-1.47	-1.32

Notes: This table reports summary statistics of the distribution of the measures of exposure to NAFTA tariff liberalization between 1990 and 2000. High (low) human capital commuting zones are those with an above (below) share of working-age population with college education in 1990. These statistics are weighted by 1990 population in each commuting zone.

Table A.6: Regional Exposure to Tariff Liberalization Over Time

Year	Mean	St. Dev.	p10	p25	p50	p75	p90
Panel A: Regional Exposure to U.S. Tariffs (equation (14))							
1993	0.35	0.47	0.09	0.14	0.20	0.33	0.75
1994	0.21	0.30	0.04	0.08	0.12	0.20	0.44
1997	0.11	0.15	0.02	0.03	0.06	0.10	0.24
2000	0.03	0.04	0.00	0.01	0.02	0.02	0.06
Panel C: Regional Exposure to Mexico's Tariffs (equation (15))							
1993	2.76	1.37	1.48	1.77	2.55	3.27	4.48
1994	1.27	0.69	0.61	0.77	1.13	1.53	2.24
1997	0.71	0.42	0.34	0.42	0.64	0.84	1.29
2000	0.27	0.15	0.13	0.16	0.24	0.32	0.47

Notes: Panel A tabulates the mean, standard deviation, and 10th, 25th, 50th, 75th and 90th percentiles of the distribution across commuting zones of the following measure of regional exposure to U.S. tariff liberalization, in which employment is computed in 1990 and tariffs vary by year. L_{ij} stands for employment in commuting zone i in industry j. $\tau_{tj}^{U.S.}$ is the U.S.' tariff toward Mexico in industry j in year t.

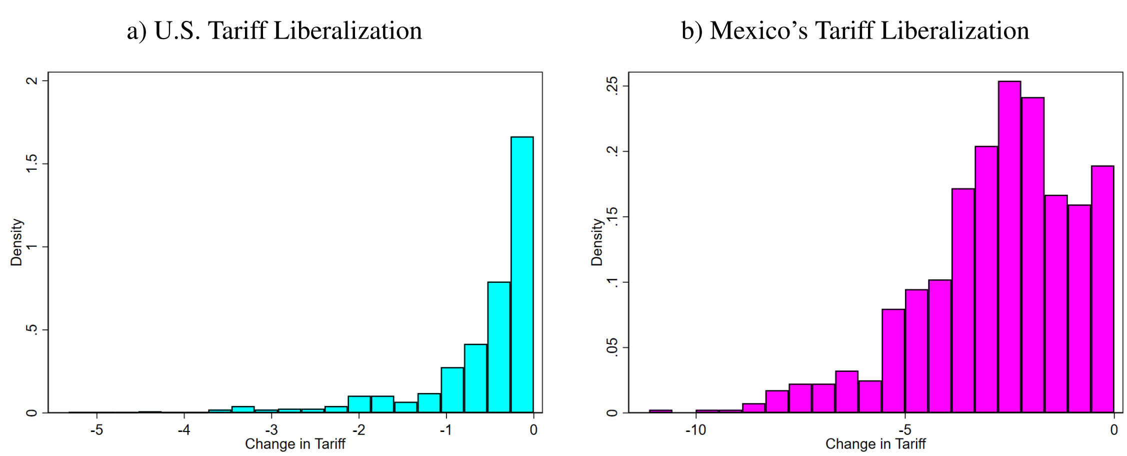
$$\tau_{it}^{U.S.} = \sum_j \frac{L_{ij}\tau_{tj}^{\text{U.S.}}}{L_{ij}} \ . \tag{14}$$

Panels B tabulates equivalent summary statistics of the distribution across commuting zones of the following measure of regional exposure to Mexico's tariff liberalization. τ_{tj}^{MEX} is Mexico's tariff toward the U.S. in industry j in year t.

$$\tau_{it}^{MEX} = \sum_j \frac{L_{ij}\tau_{tj}^{\text{MEX}}}{L_{ij}} \ . \tag{15}$$

These summary statistics are weighted by commuting zone population in 1990.

Figure A.1: Distribution of Changes in Regional Exposure to Tariff Liberalization



Notes: These histograms show the distribution of the measures of regional exposure to tariff liberalization. Figure a) corresponds to exposure to U.S. tariff liberalization, defined by equation (1). Figure b) corresponds to exposure to Mexico's tariff liberalization, defined by equation (2).

Table A.7: Largest and Smallest Exposure to Tariff Liberalization Among 100 Largest Commuting Zones

Panel A: U.S. Tariffs

Rank	CZ Name	State	Change in Tariff	Rank	CZ Name	State	Change in Tariff
1	Fayetteville	NC	-2.770	91	Denver	CO	-0.137
2	Greenville	SC	-2.060	92	Des Moines	IA	-0.136
3	Greensboro	NC	-2.055	93	Jacksonville	FL	-0.127
4	Charlotte	NC	-1.289	94	Houston	TX	-0.121
5	El Paso	TX	-1.256	95	New Orleans	LA	-0.116
6	Johnson City	TN	-1.141	96	Orlando	FL	-0.109
7	Allentown	PA	-1.030	97	Tucson	AZ	-0.089
8	Reading	PA	-0.997	98	Port St. Lucie	FL	-0.086
9	Scranton	PA	-0.981	99	Las Vegas	NV	-0.036
10	Brownsville	TX	-0.975	100	Washington DC	MD	-0.033

Panel B: Mexico's Tariffs

Rank	CZ Name	State	Change in Tariff	Rank	CZ Name	State	Change in Tariff
1	Greensboro	NC	-5.594	91	Tucson	AZ	-1.273
2	Fayetteville	NC	-5.343	92	Orlando	FL	-1.270
3	Johnson City	TN	-4.972	93	San Antonio	TX	-1.260
4	Reading	PA	-4.797	94	Toms River	NJ	-1.210
5	Grand Rapids	MI	-4.567	95	Jacksonville	FL	-1.150
6	Rockford	IL	-4.493	96	New Orleans	LA	-1.108
7	Greenville	SC	-4.438	97	Port St. Lucie	FL	-0.930
8	Kenosha	WI	-4.168	98	Bakersfield	CA	-0.910
9	Canton	OH	-3.978	99	Washington DC	MD	-0.523
10	Erie	PA	-3.893	100	Las Vegas	NV	-0.459

Notes: This table reports the list of commuting zones facing the largest and smallest reductions in regional tariff exposure among the largest 100 commuting zones in terms of 1990 population. Panel A corresponds to exposure to U.S. tariff liberalization (defined by equation (1)). Panel B corresponds to exposure to Mexico's tariff liberalization (defined by equation (2)). States listed correspond to the state in which a commuting zone has the largest share of population. Commuting zone names are obtained from Chetty et al. [2014].

Table A.8: Employment by Gender and Race Across Manufacturing Sectors

Rank	Sector Name	Number of Workers (thousands)	Share Female	Share Nonwhite	Change in Tariff
Panel A: Sectors ranked by change in U.S. tariffs					
1	Apparel And Other Textile Products	1360	0.78	0.32	-12.48
2	Textile Mill Products	927	0.52	0.26	-11.94
3	Leather And Leather Products	158	0.64	0.16	-7.39
4	Food And Kindred Products	1745	0.38	0.25	-3.69
5	Chemicals And Allied Products	1367	0.33	0.17	-1.45
6	Tobacco Products	63	0.36	0.30	-1.37
7	Industrial Machinery And Equip., Electronic And Electric Equip.	4460	0.32	0.15	-1.31
8	Transportation Equipment	2899	0.23	0.17	-1.22
9	Stone, Clay, And Glass Products	639	0.26	0.16	-1.21
10	Primary Metal Industries And Fabricated Metal Products	2262	0.21	0.16	-0.97
11	Rubber And Misc. Plastics Products	797	0.37	0.18	-0.90
12	Miscellaneous Manufacturing Industries	1523	0.43	0.25	-0.58
13	Instruments And Related Products	577	0.46	0.15	-0.34
14	Petroleum And Coal Products	214	0.21	0.16	-0.32
15	Paper And Allied Products	733	0.27	0.16	-0.25
16	Furniture And Fixtures	679	0.33	0.20	-0.24
17	Lumber And Wood Products	840	0.17	0.17	-0.17
18	Printing And Publishing	2228	0.47	0.13	0.00
Panel B: Sectors ranked by change in Mexico's tariffs					
1	Tobacco Products	63	0.36	0.30	-35.00
2	Apparel And Other Textile Products	1360	0.78	0.32	-19.06
3	Miscellaneous Manufacturing Industries	1523	0.43	0.25	-15.96
4	Stone, Clay, And Glass Products	639	0.26	0.16	-15.38
5	Textile Mill Products	927	0.52	0.26	-14.92
6	Lumber And Wood Products	840	0.17	0.17	-14.80
7	Furniture And Fixtures	679	0.33	0.20	-14.72
8	Leather And Leather Products	158	0.64	0.16	-14.09
9	Food And Kindred Products	1745	0.38	0.25	-13.63
10	Rubber And Misc. Plastics Products	797	0.37	0.18	-13.36
11	Industrial Machinery And Equip., Electronic And Electric Equip.	4460	0.32	0.15	-13.05
12	Instruments And Related Products	577	0.46	0.15	-12.34
13	Transportation Equipment	2899	0.23	0.17	-12.09
14	Primary Metal Industries And Fabricated Metal Products	2262	0.21	0.16	-11.91
15	Chemicals And Allied Products	1367	0.33	0.17	-10.94
16	Petroleum And Coal Products	214	0.21	0.16	-8.24
17	Paper And Allied Products	733	0.27	0.16	-8.03
18	Printing And Publishing	2228	0.47	0.13	-6.44

Notes: Panel A lists the 18 SIC 2-digit manufacturing industries sorted based on the size of the reductions in U.S. tariffs toward Mexico between 1990 and 2000. Panel B sorts these sectors according to the reductions in Mexico's tariffs toward the U.S. between 1990 and 2000. To construct this table, I use Autor et al. [2013] concordance between the industries in the 1990 Census and their modified SIC-87 classification. For that reason, I group together the 2-digit industries "Industrial Machinery And Equip.," and "Electronic And Electric Equip." as well as the 2-digit industries "Primary Metal Industries" and "Fabricated Metal Products".

Table A.9: Summary Statistics for Growth in Chinese Import Competition

	Defined in equation	Mean	St. Dev.	p10	p25	p50	p75	p90
ΔIPW_{ui}	3	1.14	0.99	0.38	0.62	0.89	1.32	2.05
ΔIPW_{oi}	4	1.00	0.70	0.33	0.53	0.92	1.26	1.87

Notes: This table reports summary statistics of the distribution of the measure of growth in Chinese imports between 1990 and 2000, ΔIPW_{ui} and the instrument used for it, growth in Chinese imports by other eight developed countries ΔIPW_{oi}. These statistics are weighted by 1990 population in each commuting zone.

Table A.10: Summary Statistics for Initial Routine Employment Share

	Mean	St. Dev.	p10	p25	p50	p75	p90
Share of 1990 Empl. in Routine Occs.	32.23	2.83	28.13	30.44	32.85	34.45	35.01
$\widetilde{RSH}_i$	24.11	4.76	17.28	21.47	25.04	26.96	28.19

Notes: The first row reports summary statistics for the distribution of the share of employment in routine occupations in 1990. The second row reports summary statistics for the instrument used for the initial routine employment share, which is defined by equation (6). These statistics are weighted by 1990 population in each commuting zone.

A.9. Additional Results

Table A.11: NAFTA Tariff Liberalization and Change in Share of Manufacturing Employment in the Working-Age Population: 2SLS First Stage Estimates

Dependent Variable: Change in Chinese import exposure per worker, ΔIPW_{ui}

	(1)
ΔIPW_{oi}	0.709^{***}
	(0.158)

Notes: $N = 722$. This table reports the results of the first stage for the 2SLS estimation of equation (5). The measures of exposure to tariff liberalization are defined by equations (1) and (2). Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.12: Growth in Chinese Imports and Change in Employment Status in the Working-Age Population

Dependent Variable: Change in population shares by employment status (in % pts)

		By Education		By Gender		By Age		
	All	Noncollege	College	Female	Male	16-34	35-49	50-64
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Manufacturing								
ΔIPW	-0.222	-0.263	-0.006	-0.627***	0.206	-0.197	-0.295*	-0.141
	(0.169)	(0.167)	(0.220)	(0.156)	(0.259)	(0.227)	(0.173)	(0.170)
Panel B: Nonmanufacturing								
ΔIPW	0.195	0.144	0.199	0.130	0.237	0.290	0.119	0.048
	(0.202)	(0.232)	(0.185)	(0.186)	(0.259)	(0.242)	(0.197)	(0.294)
Panel C: Employment								
ΔIPW	-0.028	-0.119	0.193	-0.498***	0.443	0.093	-0.176	-0.093
	(0.211)	(0.269)	(0.158)	(0.193)	(0.310)	(0.254)	(0.212)	(0.254)
Panel D: Unemployment								
ΔIPW	-0.052	-0.087	-0.006	-0.060	-0.041	-0.061	-0.043	-0.050
	(0.088)	(0.112)	(0.064)	(0.070)	(0.122)	(0.123)	(0.082)	(0.051)
Panel E: Not in the labor force								
ΔIPW	0.080	0.206	-0.187	0.557***	-0.402*	-0.032	0.218	0.143
	(0.157)	(0.196)	(0.148)	(0.177)	(0.242)	(0.190)	(0.152)	(0.236)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variables are the change in the share in the working-age population of manufacturing employment (panel A), of nonmanufacturing employment (panel B), of total employment (panel C), of unemployment (panel D) and of the number of individuals not in the labor force (panel E) overall (column 1) or for the subgroups listed in each column between 2 and 8. All regressions are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.13: NAFTA Tariff Liberalization and Change in Share of Manufacturing Employment in the Working-Age Population: Control Variables Introduced Sequentially

Dependent Variable: Change in manufacturing emp/working-age pop (in % pts)

	(1)	(2)	(3)	(4)	(5)
$\Delta\tau^{\text{US}}$	1.417***	1.357***	1.578***	1.667***	0.907***
	(0.404)	(0.376)	(0.333)	(0.342)	(0.305)
$\Delta\tau^{\text{MEX}}$	-0.474**	-0.207	-0.307	-0.565**	-0.325
	(0.225)	(0.307)	(0.269)	(0.265)	(0.218)
ΔIPW	-0.900***	-0.890***	-0.441*	-0.567**	-0.216
	(0.320)	(0.322)	(0.250)	(0.252)	(0.198)
Percentage of employment in manufacturing$_{1990}$		3.528	-3.062	-4.682	-6.939**
		(3.465)	(3.409)	(3.509)	(3.329)
Percentage of college-educated population$_{1990}$			-0.030	-0.018	-0.000
			(0.026)	(0.025)	(0.018)
Percentage of foreign-born population$_{1990}$			-0.055***	-0.029***	0.001
			(0.009)	(0.011)	(0.013)
Percentage of employment among women$_{1990}$			-0.044	0.000	0.022
			(0.029)	(0.032)	(0.026)
Percentage of employment in routine occupations$_{1990}$				-0.150***	-0.201***
				(0.052)	(0.057)
Average offshorability index of occupations$_{1990}$				-0.355	-0.641*
				(0.324)	(0.379)
Census division dummies	No	No	No	No	Yes

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variable is the change in manufacturing employment as a share of the working-age population. The measures of exposure to tariff liberalization are defined by equations (1) and (2). All regressions are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.14: NAFTA Tariff Liberalization and Change in Employment Status in the Working-Age Population: Alternative Measures of Regional Exposure to Tariff Liberalization

Dependent Variable: Change in population shares by employment status (in % pts)

	Manufacturing		Nonmanufacturing		Employment		Unemployment		Not in the Labor Force	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Alternative measure of exposure weighing by revealed comparative advantage										
$\Delta\tau^{\text{US}}$	0.601**	0.628***	-0.201	-0.229	0.400**	0.399*	-0.160**	-0.149*	-0.240	-0.250
	(0.254)	(0.238)	(0.190)	(0.172)	(0.192)	(0.206)	(0.075)	(0.080)	(0.161)	(0.171)
$\Delta\tau^{\text{MEX}}$	0.131	0.066	-0.151	-0.085	-0.020	-0.019	0.148**	0.122*	-0.128	-0.103
	(0.224)	(0.213)	(0.243)	(0.247)	(0.197)	(0.183)	(0.063)	(0.069)	(0.179)	(0.166)
ΔIPW		-0.220		0.223		0.003		-0.088		0.086
		(0.191)		(0.234)		(0.227)		(0.095)		(0.168)
Panel B: Alternative treatment of nontradable sector in measure of regional exposure to tariff liberalization										
$\Delta\tau^{\text{US}}$	0.156*	0.161*	-0.096	-0.101*	0.060	0.060	-0.049*	-0.047*	-0.011	-0.013
	(0.087)	(0.083)	(0.063)	(0.057)	(0.080)	(0.081)	(0.024)	(0.025)	(0.070)	(0.071)
$\Delta\tau^{\text{MEX}}$	0.018	0.005	-0.037	-0.026	-0.020	-0.021	0.043***	0.038***	-0.023	-0.017
	(0.051)	(0.045)	(0.056)	(0.055)	(0.051)	(0.048)	(0.013)	(0.014)	(0.047)	(0.044)
ΔIPW		-0.224		0.209		-0.015		-0.087		0.103
		(0.194)		(0.237)		(0.222)		(0.096)		(0.164)
Panel C: Baseline tariff measure including tariffs in nonmanufacturing tradable industries										
$\Delta\tau^{\text{US}}$	0.785**	0.829***	-0.412	-0.470**	0.373	0.359	-0.267***	-0.245**	-0.106	-0.115
	(0.340)	(0.320)	(0.255)	(0.220)	(0.227)	(0.250)	(0.090)	(0.097)	(0.200)	(0.215)
$\Delta\tau^{\text{MEX}}$	0.021	-0.080	0.271	0.404	0.292	0.324	0.157**	0.105	-0.449*	-0.429*
	(0.235)	(0.204)	(0.295)	(0.278)	(0.273)	(0.232)	(0.077)	(0.074)	(0.248)	(0.231)
ΔIPW		-0.188		0.247		0.059		-0.097		0.038
		(0.194)		(0.242)		(0.212)		(0.094)		(0.159)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variables are the change in the share in the working-age population of manufacturing employment (columns 1-2), of nonmanufacturing employment (columns 3-4), of total employment (columns 5-6), of unemployment (columns 7-8) and of the number of individuals not in the labor force (columns 9-10). The measures of exposure to tariff liberalization weigh tariffs by revealed comparative advantage, as defined by equations (8) and (9) in panel A, by equations (11) and (12) in panel B, and by equations (1) and (2) (but computed over all tradable industries instead of manufacturing industries) in panel C. Columns 1, 3, 5, 7 and 9 are estimated by OLS. In columns 2, 4, 6, 8 and 10, estimated by 2SLS, growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.15: NAFTA Tariff Liberalization and Change in Employment Status in the Working-Age Population: OLS Estimates

Dependent Variable: Change in population shares by employment status (in % pts)

	Manufacturing	Nonmanufacturing	Employment	Unemployment	Not in the Labor Force
	(1)	(2)	(3)	(4)	(5)
Panel A: All					
$\Delta\tau^{\text{US}}$	0.803**	-0.383	0.420*	-0.262***	-0.158
	(0.346)	(0.247)	(0.241)	(0.094)	(0.192)
$\Delta\tau^{\text{MEX}}$	-0.069	0.152	0.082	0.147*	-0.229
	(0.271)	(0.349)	(0.306)	(0.085)	(0.295)
Panel B: No college education					
$\Delta\tau^{\text{US}}$	1.111***	-0.208	0.902***	-0.405***	-0.497*
	(0.375)	(0.287)	(0.328)	(0.113)	(0.272)
$\Delta\tau^{\text{MEX}}$	0.097	-0.026	0.071	0.224**	-0.296
	(0.306)	(0.421)	(0.418)	(0.107)	(0.398)
Panel C: College education					
$\Delta\tau^{\text{US}}$	0.005	-0.164	-0.159	-0.073	0.232
	(0.351)	(0.308)	(0.237)	(0.096)	(0.238)
$\Delta\tau^{\text{MEX}}$	-0.547**	0.272	-0.275	0.037	0.238
	(0.266)	(0.284)	(0.255)	(0.103)	(0.246)
Panel D: Female					
$\Delta\tau^{\text{US}}$	1.564***	-0.609**	0.956***	-0.220***	-0.736***
	(0.274)	(0.236)	(0.239)	(0.076)	(0.198)
$\Delta\tau^{\text{MEX}}$	0.520**	-0.173	0.348	0.110	-0.458*
	(0.205)	(0.276)	(0.253)	(0.083)	(0.246)
Panel E: Male					
$\Delta\tau^{\text{US}}$	0.040	-0.126	-0.086	-0.298**	0.385*
	(0.436)	(0.322)	(0.280)	(0.131)	(0.229)
$\Delta\tau^{\text{MEX}}$	-0.716*	0.498	-0.218	0.184*	0.033
	(0.397)	(0.491)	(0.426)	(0.107)	(0.405)
Panel F: Nonwhite					
$\Delta\tau^{\text{US}}$	0.607	0.163	0.770	-0.603**	-0.167
	(0.453)	(0.461)	(0.466)	(0.237)	(0.443)
$\Delta\tau^{\text{MEX}}$	0.571	-0.708	-0.137	-0.341	0.478
	(0.452)	(0.735)	(0.643)	(0.339)	(0.644)
Panel G: White					
$\Delta\tau^{\text{US}}$	0.778**	-0.442*	0.337	-0.210**	-0.127
	(0.324)	(0.237)	(0.220)	(0.094)	(0.170)
$\Delta\tau^{\text{MEX}}$	-0.239	0.341	0.102	0.200**	-0.302
	(0.251)	(0.326)	(0.274)	(0.083)	(0.261)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variables are the change in the share in the working-age population of manufacturing employment (column 1), of nonmanufacturing employment (column 2), of total employment (column 3), of unemployment (column 4) and of the number of individuals not in the labor force (column 5). The measures of exposure to tariff liberalization are defined by equations (1) and (2). All columns are estimated by OLS. Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.16: NAFTA Tariff Liberalization and Change in Employment Status in the Working-Age Population by Age

Dependent Variable: Change in population shares by employment status (in % pts)

	Manufacturing	Nonmanufacturing	Employment	Unemployment	Not in the Labor Force
	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)
Panel A: Age 16-34					
$\Delta\tau^{US}$	0.739**	-0.863***	-0.125	-0.251	0.376
	(0.348)	(0.256)	(0.343)	(0.160)	(0.294)
$\Delta\tau^{MEX}$	-0.091	-0.062	-0.153	0.009	0.144
	(0.285)	(0.375)	(0.365)	(0.186)	(0.419)
ΔIPW	-0.172	0.201	0.030	-0.126	0.097
	(0.274)	(0.274)	(0.251)	(0.140)	(0.187)
Panel B: Age 35-49					
$\Delta\tau^{US}$	1.025**	-0.379	0.646***	-0.211**	-0.435***
	(0.420)	(0.315)	(0.214)	(0.097)	(0.160)
$\Delta\tau^{MEX}$	-0.826*	0.939**	0.113	0.168	-0.281
	(0.444)	(0.423)	(0.330)	(0.106)	(0.253)
ΔIPW	-0.380*	0.300	-0.080	-0.070	0.150
	(0.209)	(0.248)	(0.228)	(0.095)	(0.156)
Panel C: Age 50-64					
$\Delta\tau^{US}$	0.764**	0.533	1.296***	-0.193**	-1.104***
	(0.301)	(0.432)	(0.423)	(0.078)	(0.379)
$\Delta\tau^{MEX}$	-0.265	0.327	0.063	0.205**	-0.267
	(0.246)	(0.462)	(0.385)	(0.100)	(0.355)
ΔIPW	-0.134	0.243	0.110	-0.058	-0.052
	(0.195)	(0.349)	(0.271)	(0.058)	(0.252)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variables are the change in the share in the working-age population of manufacturing employment (column 1), of nonmanufacturing employment (column 2), of total employment (column 3), of unemployment (column 4) and of the number of individuals not in the labor force (column 5) by age-groups. The measures of exposure to tariff liberalization are defined by equations (1) and (2). All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW$_{ui}$, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.17: Growth in Chinese Imports and Change in Share of Task Employment in the Working-Age Population

Dependent Variable: Change in occupational emp/working-age pop (in % pts)

	Abstract	Routine: Clerical/Sales	Routine: Production	Manual
	(1)	(2)	(3)	(4)
ΔIPW	0.232	0.090	-0.069	0.029
	(0.191)	(0.120)	(0.118)	(0.100)
Share of 1990 Employment in Routine Occupations	0.229*	0.107	-0.056	0.304***
	(0.119)	(0.096)	(0.067)	(0.087)

Notes: $N = 722$. This table reports the results of the estimation of equation (5), excluding the measures of regional exposure to tariff liberalization. All regressions are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). The share of employment in routine occupations in 1990 is instrumented by the measure of commuting zone historical industry structure defined by equation (6) in Appendix A.4. Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.18: NAFTA Tariff Liberalization and Change in Share of Task Employment in the Working-Age Population: 2SLS First Stage Estimates.

Panel A: Dependent Variable: Change in Chinese import exposure per worker, ΔIPW_{ui}

	(1)
ΔIPW_{oi}	0.715***
	(0.156)

Panel B: Dependent Variable: Share of 1990 employment in routine occupations

	(1)
$\widetilde{RSH}_i$	14.824***
	(2.122)

Notes: $N = 722$. This table reports the results of the first stage for the 2SLS estimation of equation (5) corresponding to column 1 in Table 8, which uses growth in Chinese imports by eight developed countries (ΔIPW_{oi}) as an instrument for growth in Chinese imports by the U.S. (ΔIPW_{ui}) and historical industry structure defined by equation (6) in Appendix A.4 as an instrument for the 1990 share of employment in routine occupations. In both panels, the measures of exposure to tariff liberalization are defined by equations (1) and (2). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.19: NAFTA Tariff Liberalization and Change in Employment Status in the Working-Age Population: 1990–2007

Dependent Variable: Change in population shares by employment status (in % pts)

	Manufacturing		Nonmanufacturing		Employment		Unemployment		Not in the Labor Force	
	1990–2000	1990–2007	1990–2000	1990–2007	1990–2000	1990–2007	1990–2000	1990–2007	1990–2000	1990–2007
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
τ^{US}	-0.904***	-1.578***	0.518***	1.062***	-0.386	-0.516**	0.204**	-0.008	0.181	0.524**
	(0.285)	(0.349)	(0.200)	(0.361)	(0.246)	(0.248)	(0.098)	(0.132)	(0.194)	(0.207)
τ^{MEX}	0.531**	0.788***	-0.595*	-0.956**	-0.065	-0.168	-0.007	0.119	0.072	0.049
	(0.213)	(0.285)	(0.352)	(0.415)	(0.301)	(0.370)	(0.114)	(0.154)	(0.290)	(0.305)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variables are the change in the share in the working-age population of manufacturing employment (columns 1-2), of nonmanufacturing employment (columns 3-4), of total employment (columns 5-6), of unemployment (columns 7-8) and of the number of individuals not in the labor force (columns 9-10). In columns 1, 3, 5, 7, and 9 the dependent variable is computed over 1990–2000 and the results are equivalent to Table 4. In columns 2, 4, 6, 8, and 10 the dependent variable is computed over 1990–2007. The measures of exposure to tariff liberalization are defined by equations (1) and (2) and are computed over 1990–2007. All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Growth in Chinese imports (and its instrument) is computed over 1990–2000 in columns 1, 3, 5, 7, and 9 and over 1990–2007 in columns 2, 4, 6, 8, and 10. Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

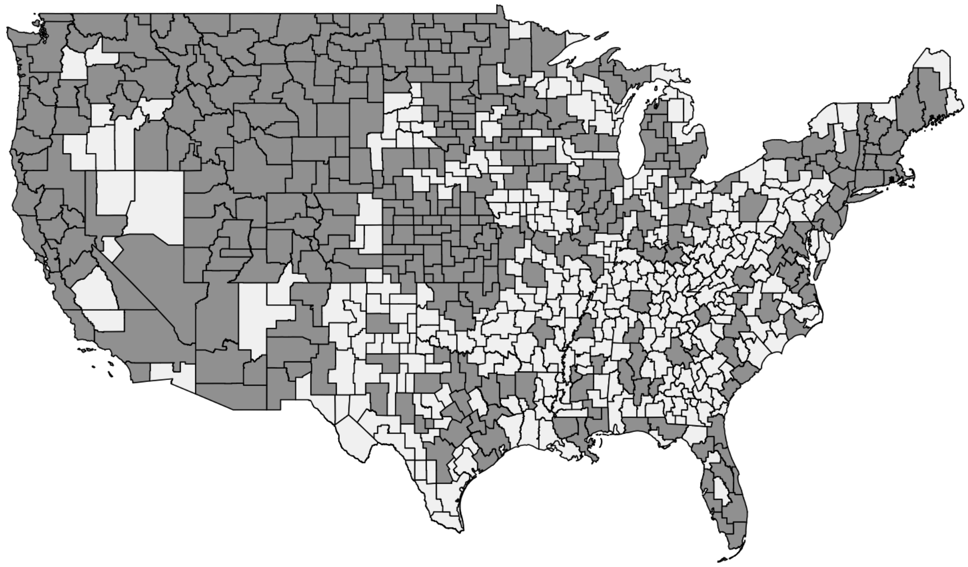
Table A.20: NAFTA Tariff Liberalization and Change in Employment Status in the Working-Age Population by Gender among the No College Sample

Dependent Variable: Change in population shares by employment status (in % pts)

	Manufacturing	Nonmanufacturing	Employment	Unemployment	Not in the Labor Force
	(1)	(2)	(3)	(4)	(5)
Panel A: No college education and female					
$\Delta\tau^{\text{US}}$	2.062***	-0.313	1.749***	-0.344***	-1.404***
	(0.329)	(0.303)	(0.337)	(0.098)	(0.298)
$\Delta\tau^{\text{MEX}}$	0.210	-0.324	-0.115	0.116	-0.001
	(0.297)	(0.451)	(0.412)	(0.131)	(0.388)
ΔIPW	-0.591***	0.053	-0.538**	-0.088	0.626***
	(0.177)	(0.266)	(0.247)	(0.103)	(0.231)
Panel B: No college education and male					
$\Delta\tau^{\text{US}}$	0.258	-0.032	0.226	-0.405**	0.178
	(0.394)	(0.271)	(0.411)	(0.176)	(0.352)
$\Delta\tau^{\text{MEX}}$	-0.561	0.398	-0.163	0.201	-0.038
	(0.360)	(0.501)	(0.555)	(0.194)	(0.534)
ΔIPW	0.232	0.259	0.491	-0.175	-0.316
	(0.306)	(0.358)	(0.405)	(0.181)	(0.296)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variables are the change in the share in the working-age population of manufacturing employment (column 1), of nonmanufacturing employment (column 2), of total employment (column 3), of unemployment (column 4) and of the number of individuals not in the labor force (column 5). The measures of exposure to tariff liberalization are defined by equations (1) and (2). All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Figure A.2: High and Low Human Capital Commuting Zones



Notes: A darker (lighter) shade indicates high (low) human capital in 1990. High (low) human capital commuting zones are those with an above (below) median share of working-age population with college education in 1990.

Table A.21: NAFTA Tariff Liberalization and Change in Employment Status in the Working-Age Population: Exposure–Robust Standard Errors [Borusyak et al., 2022b]

Dependent Variable: Change in population shares by employment status (in % pts)

	Manufacturing	Nonmanufacturing	Employment	Unemployment	Not in the Labor Force
	(1)	(2)	(3)	(4)	(5)
Panel A: All					
$\Delta\tau^{\text{US}}$	0.907***	-0.449	0.458**	-0.242***	-0.216
	(0.343)	(0.373)	(0.205)	(0.088)	(0.168)
$\Delta\tau^{\text{MEX}}$	-0.325	0.314	-0.012	0.097	-0.085
	(0.518)	(0.657)	(0.326)	(0.207)	(0.228)
Panel B: No college education					
$\Delta\tau^{\text{US}}$	1.202***	-0.239	0.964***	-0.376***	-0.588***
	(0.373)	(0.341)	(0.245)	(0.091)	(0.213)
$\Delta\tau^{\text{MEX}}$	-0.129	0.049	-0.080	0.151	-0.071
	(0.583)	(0.655)	(0.414)	(0.214)	(0.284)
Panel C: College education					
$\Delta\tau^{\text{US}}$	0.103	-0.283	-0.180	-0.068	0.248
	(0.314)	(0.323)	(0.199)	(0.097)	(0.199)
$\Delta\tau^{\text{MEX}}$	-0.791*	0.568	-0.223	0.024	0.198
	(0.457)	(0.486)	(0.229)	(0.203)	(0.249)
Panel D: Female					
$\Delta\tau^{\text{US}}$	1.703***	-0.617*	1.086***	-0.187**	-0.899***
	(0.283)	(0.354)	(0.202)	(0.078)	(0.175)
$\Delta\tau^{\text{MEX}}$	0.176	-0.151	0.026	0.029	-0.054
	(0.370)	(0.518)	(0.316)	(0.181)	(0.267)
Panel E: Male					
$\Delta\tau^{\text{US}}$	0.103	-0.246	-0.143	-0.293**	0.436*
	(0.424)	(0.422)	(0.253)	(0.117)	(0.223)
$\Delta\tau^{\text{MEX}}$	-0.871	0.793	-0.078	0.172	-0.094
	(0.711)	(0.818)	(0.406)	(0.268)	(0.319)
Panel F: Nonwhite					
$\Delta\tau^{\text{US}}$	0.690	0.373	1.063**	-0.625***	-0.438
	(0.507)	(0.662)	(0.439)	(0.187)	(0.453)
$\Delta\tau^{\text{MEX}}$	0.366	-1.227	-0.861	-0.286	1.147
	(0.774)	(1.210)	(0.797)	(0.322)	(0.768)
Panel G: White					
$\Delta\tau^{\text{US}}$	0.891***	-0.549*	0.342**	-0.186**	-0.156
	(0.299)	(0.291)	(0.165)	(0.085)	(0.158)
$\Delta\tau^{\text{MEX}}$	-0.518	0.606	0.088	0.141	-0.229
	(0.450)	(0.521)	(0.216)	(0.221)	(0.258)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). Exposure–robust standard errors are obtained estimating equivalent industry–level regressions using the procedure in [Borusyak et al., 2022b] and clustering standard errors by SIC 3–digit level. The dependent variables are the change in the share in the working-age population of manufacturing employment (column 1), of nonmanufacturing employment (column 2), of total employment (column 3), of unemployment (column 4) and of the number of individuals not in the labor force (column 5). The measures of exposure to tariff liberalization are defined by equations (1) and (2). All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.22: NAFTA Tariff Liberalization and Change in Working-Age Population: Exposure–Robust Standard Errors [Borusyak et al., 2022b]

Dependent Variable: Change in log population counts (in log points)

	All	No College	College
	(1)	(2)	(3)
$\Delta\tau^{\text{US}}$	-0.488	0.506	-1.608
	(1.286)	(1.601)	(0.988)
$\Delta\tau^{\text{MEX}}$	-0.750	-1.352	-0.150
	(2.106)	(2.514)	(1.830)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). Exposure–robust standard errors are obtained estimating equivalent industry–level regressions using the procedure in [Borusyak et al., 2022b] and clustering standard errors by SIC 3–digit level. The dependent variable is the log change in the working-age population. The measures of exposure to tariff liberalization are defined by equations (1) and (2). All columns are estimated by 2SLS and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.23: NAFTA Tariff Liberalization and Change in Share of Industry Employment in the Working-Age Population: Exposure–Robust Standard Errors [Borusyak et al., 2022b]

Dependent Variable: Change in industry emp/working-age pop (in % pts)

	Construction	Transportation and Utilities	Wholesale and Retail Trade	Other Services	Government
	(1)	(2)	(3)	(4)	(5)
$\Delta\tau^{\text{US}}$	-0.140***	0.033	-0.211**	-0.061	0.043
	(0.052)	(0.073)	(0.092)	(0.254)	(0.080)
$\Delta\tau^{\text{MEX}}$	-0.134	-0.060	-0.005	0.133	0.079
	(0.088)	(0.117)	(0.210)	(0.438)	(0.125)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). Exposure–robust standard errors are obtained estimating equivalent industry–level regressions using the procedure in [Borusyak et al., 2022b] and clustering standard errors by SIC 3–digit level. The dependent variables are the change in the share in the working-age population of employment in construction, in transportation and utilities, in wholesale and retail trade, in other services, or in government. The measures of exposure to tariff liberalization are defined by equations (1) and (2). All regressions are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.24: NAFTA Tariff Liberalization and Change in Share of Task Employment in the Working-Age Population: Exposure–Robust Standard Errors [Borusyak et al., 2022b]

Dependent Variable: Change in occupational emp/working-age pop (in % pts)

			By educ. attainment		By sector	
	All	All	Noncollege	College	Mfg.	Nonmfg.
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Primarily abstract occupations.						
(Share of working-age population employed in managerial/professional/ technical occupations.)						
$\Delta\tau^{\text{US}}$	-0.535***	-0.393***	-0.132*	-0.601***	-0.130	-0.393***
	(0.132)	(0.136)	(0.076)	(0.197)	(0.080)	(0.144)
$\Delta\tau^{\text{MEX}}$	0.256	0.067	-0.096	0.178	-0.176	0.361
	(0.198)	(0.207)	(0.116)	(0.274)	(0.139)	(0.237)
Panel B: Primarily routine occupations.						
(Share of working-age population employed in clerical/retail sales occupations.)						
$\Delta\tau^{\text{US}}$	-0.087	-0.023	-0.122	0.135	-0.060	0.003
	(0.146)	(0.136)	(0.164)	(0.155)	(0.056)	(0.152)
$\Delta\tau^{\text{MEX}}$	-0.088	-0.173	-0.022	-0.096	-0.021	-0.054
	(0.221)	(0.210)	(0.260)	(0.229)	(0.088)	(0.231)
Panel C: Primarily routine occupations.						
(Share of working-age population employed in production occupations.)						
$\Delta\tau^{\text{US}}$	0.880***	0.894***	1.062***	0.290***	0.819***	0.007
	(0.233)	(0.195)	(0.312)	(0.107)	(0.233)	(0.026)
$\Delta\tau^{\text{MEX}}$	0.226	0.207	0.276	-0.030	0.382	0.004
	(0.303)	(0.275)	(0.431)	(0.128)	(0.380)	(0.055)
Panel D: Primarily manual occupations.						
(Share of working-age population employed in craft/mechanics/agricultural/service occupations.)						
$\Delta\tau^{\text{US}}$	-0.127	-0.020	-0.218	-0.157	0.133	-0.235*
	(0.108)	(0.098)	(0.142)	(0.123)	(0.087)	(0.130)
$\Delta\tau^{\text{MEX}}$	0.030	-0.113	0.259	-0.071	0.101	-0.119
	(0.195)	(0.167)	(0.260)	(0.224)	(0.147)	(0.214)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). Exposure–robust standard errors are obtained estimating equivalent industry–level regressions using the procedure in [Borusyak et al., 2022b] and clustering standard errors by SIC 3–digit level. The dependent variables are the change in the share in the working-age population of employment in primarily abstract occupations (panel A), primarily clerical and sales-related routine occupations (panel B), primarily production-related routine occupations (panel C) and primarily manual occupations (panel D). The measures of exposure to tariff liberalization are defined by equations (1) and (2). All regressions are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). In columns 1 and 3 through 6 the share of employment in routine occupations in 1990 is instrumented by the measure of commuting zone historical industry structure defined by equation (6) in Appendix A.4. Each column includes all control variables used in Table 1. Observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.25: NAFTA Tariff Liberalization and Change in Employment Status in the Working-Age Population: 1990–2007; Exposure–Robust Standard Errors [Borusyak et al., 2022b]

Dependent Variable: Change in population shares by employment status (in % pts)

	Manufacturing		Nonmanufacturing		Employment		Unemployment		Not in the Labor Force	
	1990–2000	1990–2007	1990–2000	1990–2007	1990–2000	1990–2007	1990–2000	1990–2007	1990–2000	1990–2007
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\Delta\tau^{\text{US}}$	0.907***	1.606***	-0.449	-1.041**	0.458**	0.565*	-0.242***	0.027	-0.216	-0.592***
	(0.343)	(0519)	(0.373)	(0.474)	(0.205)	(0.298)	(0.088)	(0.104)	(0.168)	(0.220)
$\Delta\tau^{\text{MEX}}$	-0.325	-0.545	0.314	0.666	-0.012	0.121	0.097	-0.176	-0.085	0.055
	(0.518)	(0.602)	(0.657)	(0.769)	(0.326)	(0.571)	(0.207)	(0.161)	(0.228)	(0.459)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). Exposure–robust standard errors are obtained estimating equivalent industry–level regressions using the procedure in [Borusyak et al., 2022b] and clustering standard errors by SIC 3–digit level. The dependent variables are the change in the share in the working-age population of manufacturing employment (columns 1-2), of nonmanufacturing employment (columns 3-4), of total employment (columns 5-6), of unemployment (columns 7-8) and of the number of individuals not in the labor force (columns 9-10). In columns 1, 3, 5, 7, and 9 the dependent variable is computed over 1990–2000 and the results are equivalent to Table 4. In columns 2, 4, 6, 8, and 10 the dependent variable is computed over 1990–2007. The measures of exposure to tariff liberalization are defined by equations (1) and (2) and are computed over 1990–2000. All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Growth in Chinese imports (and its instrument) is computed over 1990–2000 in columns 1, 3, 5, 7, and 9 and over 1990–2007 in columns 2, 4, 6, 8, and 10. Each column includes all control variables used in Table 1. Observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.26: NAFTA Tariff Liberalization and Change in Share of Manufacturing Employment in the Working-Age Population: Alternative Levels of Clustering for Exposure–Robust Standard Errors [Borusyak et al., 2022b]

Dependent Variable: Change in manufacturing emp/working-age pop (in % pts)

	(1)	(2)	(3)
$\Delta\tau^{\text{US}}$	0.907***	0.907*	0.907*
	(0.343)	(0.504)	(0.483)
$\Delta\tau^{\text{MEX}}$	-0.325	-0.325	-0.325
	(0.518)	(0.645)	(0.701)
Std. errors clustered by:	SIC3	SIC2	SIC group

Notes: $N = 722$. This table reports the results of the estimation of equation (5). Exposure–robust standard errors are obtained estimating equivalent industry–level regressions using the procedure in [Borusyak et al., 2022b] and clustering standard errors by SIC 3–digit level, SIC 2–digit level, or by the ten SIC groups used in Borusyak et al. [2022b] and originally defined by Acemoglu et al. [2016]. The dependent variable is the change in the share in the working-age population of manufacturing employment. The measures of exposure to tariff liberalization are defined by equations (1) and (2). All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.27: Shock Summary Statistics Following Borusyak et al. [2022b]

	$\Delta\tau^{\text{US}}$	$\Delta\tau^{\text{MEX}}$
Mean	-2.269	-12.681
Standard deviation	4.168	6.256
Interquartile range	2.447	4.249
Effective sample size (1/HHI of $s_j = \frac{L_j}{L}$ weights)		
Across Industries	126.541	126.541
Across SIC3 groups	64.841	64.841
Largest $s_j = \frac{L_j}{L}$ weight		
Across Industries	0.031	0.031
Across SIC3 groups	0.041	0.041
Observation counts		
# of shocks	397	397
# of industries	397	397
# of SIC3 groups	136	136

Notes: This table summarizes the industry–level tariff changes between 1990 and 2000 across 397 manufacturing industries following Borusyak et al. [2022b]. All statistics are weighted by the employment shares of each industry over total employment $s_j = \frac{L_j}{L}$ in 1990. Following Borusyak et al. [2022b]'s terminology, the effective sample size refers to one over the Herfindahl–Hirschman index of employment shares $s_j = \frac{L_j}{L}$, normalized to add up to one (recall the nonmanufaturing sector is omitted).

Table A.28: Shock Balance Tests: Regional Balance

	$\Delta\tau^{\text{US}}$		$\Delta\tau^{\text{MEX}}$	
	(1)	(2)	(3)	(4)
Percentage of college–educated population$_{1990}$	3.083***	2.029	3.166	-0.389
	(0.602)	(4.022)	(3.294)	(3.114)
Percentage of foreign–born population$_{1990}$	-0.759	0.226	-5.265	-1.336
	(1.085)	(7.592)	(3.858)	(5.685)
Percentage of employment among women$_{1990}$	1.413**	2.427	-0.535	-3.474
	(0.650)	(4.645)	(2.656)	(3.425)
Percentage of employment in routine occupations$_{1990}$	0.469	0.628	-1.093	-2.653
	(0.342)	(2.195)	(1.575)	(2.072)
Average offshorability index of occupations$_{1990}$	0.023	0.051	-0.321	-0.483*
	(0.041)	(0.229)	(0.199)	(0.256)
Manufacturing employment growth, 1970–1980	-0.163	0.413	-0.073	0.936
	(0.121)	(0.790)	(0.890)	(0.868)
Manufacturing employment growth, 1980–1990	-0.264	-0.156	-1.261	-0.546
	(0.208)	(1.211)	(1.138)	(1.072)

Notes: $N = 722$. The first five rows report regressions of each regional control variable used in Table 1 as the dependent variable on the measures of regional exposure to U.S. (columns 1 and 2) or Mexico's (columns 3 and 4) tariff changes defined by equations (1) and (2). In the last two rows, the dependent variables are growth in manufacturing employment as a share of the working–age population in each commuting zone during 1970–1980 or 1980–1990 respectively. These regressions control for the regional share of manufacturing employment in total employment in 1990. I use Borusyak et al. [2022b]'s transformation to estimate equivalent industry–level regressions, with weights equal to employment shares, controlling for dummy variables for ten SIC groups in columns 2 and 4, and clustering standard errors at the SIC 3–digit level. The ten sic groups are used in Borusyak et al. [2022b] and originally defined by Acemoglu et al. [2016]. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

Table A.29: NAFTA Tariff Liberalization and Change in Share of Manufacturing Employment in the Working-Age Population: Excluding Percentage of College–Educated Population and Percentage of Employment Among Women

Dependent Variable: Change in manufacturing emp/working-age pop (in % pts)

	(1)	(2)
$\Delta\tau^{\text{US}}$	0.959***	0.959***
	(0.275)	(0.343)
$\Delta\tau^{\text{MEX}}$	-0.341	-0.341
	(0.220)	(0.523)
Exposure–robust S.E.:	No	Yes

Notes: $N = 722$. This table reports the results of the estimation of equation (5), without controlling for the percentage of college–educated population and the percentage of employment among women. In column 1, standard errors are clustered by state. In column 2, exposure–robust standard errors are obtained estimating equivalent industry–level regressions using the procedure in [Borusyak et al., 2022b] and clustering standard errors by SIC 3–digit level. The dependent variable is the change in manufacturing employment as a share of the working-age population. The measures of exposure to tariff liberalization are defined by equations (1) and (2). All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined in equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1 except for the percentage of college–educated population and percentage of employment among women. Observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

A.10. Additional control variables

The following table includes additional control variables to the estimation of equation (5). Since these are industry–level control variables, I define measures of regional exposure as employment–weighted averages following Borusyak et al. [2022b]. Weights are employment shares of each industry in each region in the initial period (1990). In addition, when computing exposure–robust standard errors, I use Borusyak et al. [2022b]'s procedure to transform the data and estimate equivalent industry–level regressions across 397 manufacturing industries, including the additional industry–level controls directly and clustering standard errors by SIC 3–digit industries.

These additional control variables are constructed as follows. Change in world demand between 1990 and 2000 is computed as the percent change in world imports in each SIC industry.[86] Change in world employment considers percent change in employment between 1990 and 2000 in a set of high income countries.[87] This is computed as a weighted average across countries for each industry, with weights equal to country–industry employment in 1990. Changes in U.S. MFN tariffs between 1990 and 2000 are computed using data from Romalis [2007] at the 8-digit level of the U.S. tariff schedule. These are aggregated to HS 6-digit codes using U.S. HS 8-digit imports as weights.[88] I then construct industry-level tariffs for 397 4-digit SIC manufacturing industries using the concordance provided by Autor et al. [2013]. The ten sic groups are used in Borusyak et al. [2022b] and originally defined by Acemoglu et al. [2016].

The results are shown in Table A.30.

[86] I use a concordance provided by Autor et al. [2013] to assign trade flows from the 1988/1992 version of the Harmonized System ("H0") to SIC industries. The trade data are obtained from the UN's Comtrade database through the World Bank's World Integrated Trade Solution (WITS). They are downloaded using the SITC revision 2 classification, given that in 1990 only some countries report trade using the Harmonized System. I then use a concordance between SITC Tier 4 codes and the 1988/1992 HS Classification 6-digit codes.

[87] Data on employment by industry and country is obtained from the Trade Production and Protection database [Nicita and Olarreaga, 2007], which uses ISIC revision 2 3–digit codes. These are then translated to SIC 2–digit industries. Countries considered correspond to all those classified as "high income" by the World Bank excluding those with no coverage in Nicita and Olarreaga [2007]. They include Austria, Australia, Belgium, Canada, Chile, Czech Republic, Denmark, Finland, France, Germany, Greece, Ireland, Israel, Italy, Japan, South Korea, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

[88] Data on U.S. imports in 1990 used to construct weights are a product of the U.S. Census Bureau and obtained from Schott [2008].

Table A.30: NAFTA Tariff Liberalization and Change in Share of Manufacturing Employment in the Working-Age Population: Additional Controls

Dependent Variable: Change in manufacturing emp/working-age pop (in % pts)

	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta\tau^{\text{US}}$	0.777**	0.890***	1.204***	0.777**	0.890***	1.204*
	(0.337)	(0.251)	(0.459)	(0.379)	(0.295)	(0.698)
$\Delta\tau^{\text{MEX}}$	-0.079	-0.160	-0.165	-0.079	-0.160	-0.165
	(0.213)	(0.204)	(0.280)	(0.545)	(0.420)	(0.307)
Controlling for:						
Regional Exposure to Change in World Demand	Yes	No	Yes	Yes	No	Yes
Regional Exposure to Change in US MFN Tariff	Yes	No	Yes	Yes	No	Yes
Regional Exposure to Change in World Employment	Yes	No	Yes	Yes	No	Yes
Lagged CZ Mftg Emp. Growth in 1970s and 1980s	No	Yes	Yes	No	Yes	Yes
Regional Exposure to ten SIC Groups	No	No	Yes	No	No	Yes
Exposure–robust S.E.:	No	No	No	Yes	Yes	Yes

Notes: $N = 722$. This table reports the results of the estimation of equation (5) with additional control variables. These include regional exposure to i) changes in industry–level world demand (defined as percent change in world imports) over 1990–2000, ii) changes in employment in high income countries other than the U.S. (defined as a weighted average across countries of percent change in employment in each industry), iii) changes in U.S. most favored nation (MFN) tariffs between 1990 and 2000, and iv) dummies for ten SIC groups used in Borusyak et al. [2022b] and originally defined by Acemoglu et al. [2016]. In addition, I control for growth in commuting zone manufacturing employment as a share of the working–age population during 1970–1980 and during 1980–1990. Note that in columns 1 through 3 standard errors are clustered by state and, following Borusyak et al. [2022b], the measures of regional exposure to industry–level variables (in columns 1 and 3) are employment–weighted averages of the industry–level variables. In columns 4 through 6, exposure–robust standard errors are obtained estimating equivalent industry–level regressions using the procedure in [Borusyak et al., 2022b] and clustering standard errors by SIC 3–digit level, such that industry–level controls in columns 4 and 6 can be included directly in the regression. The dependent variable is the change in manufacturing employment as a share of the working-age population. The measures of exposure to tariff liberalization are defined by equations (1) and (2). All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1 plus the additional control variables described earlier. Observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

A.11. Tariff level vs. tariff changes

Table A.31 revisits the estimation of equation (5) contrasting the results obtained using a measure of regional exposure to *changes* in tariffs as in the main text, a measure of exposure to the initial (1990) *level* in tariffs, or both simultaneously. The measure of exposure to the initial level in tariffs is defined as $\tau_i^{U.S.} = \sum_{j \epsilon J} \frac{L_{ij}\tau_j^{U.S.}}{L_i}$ where $\tau_j^{U.S.}$ stands for the tariff level in 1990 in industry j. I focus on exposure to U.S. tariff liberalization, which is the statistically significant coefficient in the main text results.

As argued in the main text, the preferred specification used throughout the paper uses exposure to the change in tariffs. Because tariff liberalization was nearly complete, the correlation between the measure with changes and the measure with levels is nearly (minus) one (-0.998). For that reason, the coefficients shown in Table A.31 with the share of manufacturing employment in the working–age population as the dependent variable are nearly identical (see columns 1 and 2). In contrast, the coefficient on the measures using tariff change and level are about four and three times larger when including both simultaneously (see column 3).

Table A.31: NAFTA Tariff Liberalization and Change in Share of Manufacturing Employment in the Working-Age Population: Tariff Change and Tariff Level

Dependent Variable: Change in manufacturing emp/working-age pop (in % pts)

	(1)	(2)	(3)
$\Delta\tau^{\text{US}}$	0.907***		3.860*
	(0.305)		(2.267)
τ^{US}		-0.840***	2.858
		(0.302)	(2.313)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variable is the change in manufacturing employment as a share of the working-age population. The measure of exposure to U.S. tariff liberalization is defined by equation (1) or alternatively by $\tau_i^{U.S.} = \sum_{j \epsilon J} \frac{L_{ij}\tau_j^{U.S.}}{L_i}$ where $\tau_j^{U.S.}$ stands for the tariff level in 1990 in industry j. The measures of exposure to Mexico's tariff liberalization is defined by equation (2). All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

A.12. Geographic and Industry Aggregation

By using data on 397 SIC 4-digit manufacturing industries and 722 commuting zones, I create more disaggregate measures of exposure to tariff liberalization than the previous literature [Hakobyan and McLaren, 2016], which uses data on 89 census industries and 540 CONSPUMAs. Table A.32 shows that this makes a difference for finding employment effects of NAFTA. To show this, I construct tariff exposure measures and control variables using the 89 census industries and 522 CONSPUMAs. I estimate regression (5) focusing on manufacturing employment as a share of the working–age population and on total employment as a share of the working–age population. Column 1 is equivalent to column 1 in Table 1 and shows a statistically significant decline in manufacturing employment for regions more exposed to U.S. tariff liberalization. Column 3 uses the more aggregate measure (with census industries and CONSPUMAs) and finds a coefficient of the same sign and magnitude but which is not statistically significant.[89] In the case of total employment, once again only the more disaggregate measure leads to a statistically significant coefficient, as shown in columns 2 and 4. In addition, there is a large difference in the magnitudes, which imply a 0.1 (column 2) or 0.04 (column 4) percentage point decline in total employment as a share of the working–age population in regions at the 75th percentile relative to the 25th percentile of exposure. Summing up, the further disaggregation of industries and geographic units plays a crucial role in establishing the employment effects of NAFTA.

Table A.32: NAFTA Tariff Liberalization and Change in Share of Manufacturing and Total Employment in the Working-Age Population: Aggregation

Dependent Variable: Change in manufacturing or total emp/working-age pop (in % pts)

	CZ+SIC4 Industries		CONSPUMA+Census Industries	
	Mftg. Emp.	Total Emp.	Mftg. Emp.	Total Emp.
	(1)	(2)	(3)	(4)
$\Delta\tau^{\text{US}}$	0.790**	0.456*	0.646	0.153
	(0.318)	(0.267)	(0.444)	(0.756)
Observations	722	722	540	540

Notes: This table reports the results of the estimation of equation (5). The dependent variable is the change in manufacturing employment or total employment as a share of the working-age population. The measure of exposure to U.S. tariff liberalization is defined by equation (1) using 327 industries and 722 commuting zones as in the main text (in columns 1 and 2) or 89 industries and 522 CONSPUMAs (in columns 3 and 4). All columns are estimated by OLS. Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone or CONSPUMA. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.

[89] These coefficients imply a 0.17 (column 1) or 0.16 (column 3) percentage point decline in manufacturing employment as a share of the working–age population in regions at the 75th percentile relative to the 25th percentile of exposure.

A.13. Gender–specific Exposure to Tariff Liberalization

The results in column 1 in panels C and D in Table 5 show that the effect of U.S. tariff cuts is large and statistically significant among women, and much smaller and not statistically significant among men.

One possibility is that tariff cuts are concentrated in industries which disproportionately employ women. Another option is that facing similar shocks, female employment responds different than male employment.

To shed light on this issue, it is convenient to decompose the measure of regional exposure to U.S. tariff liberalization in equation (1) into the following two additive components that weigh employment by the share of female and male employment by commuting zone and industry respectively:

$$\Delta\tau_i^{U.S.,f} = \sum_{j\,\epsilon\,J} \frac{(f_{ij})L_{ij}\Delta\tau_j^{U.S.}}{L_i} \ , \tag{16}$$

and

$$\Delta\tau_i^{U.S.,m} = \sum_{j\,\epsilon\,J} \frac{(1-f_{ij})L_{ij}\Delta\tau_j^{U.S.}}{L_i} \ . \tag{17}$$

This approach follows Autor et al. [2019] (see their equation (2)). To implement this, I define f_{ij} as the share of female employment in industry j and commuting zone i.[90]

Table A.33 shows descriptive statistics for each component. First, note the mean across commuting zones of $\Delta\tau_i^{U.S.,f}$ and $\Delta\tau_i^{U.S.,m}$ is nearly the same. These statistics are computed weighing by commuting zone population in 1990. Without these weights, the means are -0.34 for the female component and -0.28 for the male component.

Second, Table A.34 estimates equation (5) for female and male manufacturing employment as shares of the corresponding working–age population. Columns 1 and 3 are equivalent to column 1 in panels C and D in Table 5. Column 2 and 4 replace the measure of exposure to U.S. tariff liberalization in equation (1) into its two additive components in equations (16) and (17) . The results show that only the measure of tariff liberalization weighted by female employment shares leads to a decline in female manufacturing employment. For male employment, the coefficients on both measures are not statistically significant.

[90]Following Autor et al. [2019] these shares are computed from the U.S. Census. I use concordances provided by Autor et al. [2019] to go from 1990 Census industries to SIC 4–digit industries. Note that because gender employment shares are computed from Census data and employment weights are computed from CBP data, there are few cases in which the Census does not report employment for a certain industry and commuting zone while CBP does. In those cases I assign gender employment shares corresponding to the same commuting zone and the corresponding 3–digit SIC industry, the same commuting zone and the corresponding SIC 2–digit industry, or the corresponding SIC 3–digit industry at a national level, in that order of priority.

In conclusion, the large decline in manufacturing employment in response to U.S. tariff liberalization for women, and the lack of an effect for men, appears to be due not to the difference in the magnitude of the shock experienced by each group based on the industries in which they are employed in 1990. Instead, the response of female and male manufacturing employment is different. Future work could look at gender differences in displacement from the manufacturing sector in this or other contexts.

Table A.33: Summary Statistics for Measures of Regional Exposure to Tariff Liberalization by Gender

	Defined by equation	Mean	St. Dev.	p10	p25	p50	p75	p90
$\Delta\tau^{\text{US, f}}$	(16)	-0.223	0.34	-0.52	-0.21	-0.11	-0.08	-0.04
$\Delta\tau^{\text{US, m}}$	(17)	-0.224	0.32	-0.64	-0.36	-0.18	-0.07	-0.02

Notes: This table reports summary statistics of the distribution of the measures of exposure to U.S. tariff liberalization between 1990 and 2000 based on gender employment shares. These statistics are weighted by 1990 population in each commuting zone.

Table A.34: NAFTA Tariff Liberalization and Change in Share of Manufacturing Employment in the Working-Age Population with Gender–Specific Tariff Exposure Measures

Dependent Variable: Change in manufacturing emp/working-age pop (in % pts)

	Female		Male	
	(1)	(2)	(3)	(4)
$\Delta\tau^{\text{US}}$	1.703***		0.103	
	(0.252)		(0.373)	
$\Delta\tau^{\text{US, f}}$		2.436***		0.056
		(0.444)		(0.570)
$\Delta\tau^{\text{US, m}}$		0.552		0.176
		(0.555)		(0.844)

Notes: $N = 722$. This table reports the results of the estimation of equation (5). The dependent variable is the change in manufacturing employment as a share of the working-age population. The measure of exposure to U.S. tariff liberalization is defined by equation (1) in columns 1 and 3 and by equations (16) and (17) in columns 2 and 4. The measure of exposure to Mexico's tariff liberalization is defined by equation (2). All columns are estimated by 2SLS, and growth in Chinese imports (ΔIPW_{ui}, defined by equation (3)) is instrumented by growth in Chinese exports to non-U.S. high-income markets (defined by equation (4)). Each column includes all control variables used in Table 1. Standard errors are clustered by state and observations are weighted by 1990 population in each commuting zone. ***, **, and * indicate statistical significance at the 1%, 5% and 10% level.