Looking for Local Labor-Market Effects of the NAFTA*

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Abstract

Using US Census data for 1990 and 2000, we estimate effects of the NAFTA agreement on the US wages. We look for any indication of effects of the agreement on (i) local labor markets dependent on industries vulnerable to import competition from Mexico, and (ii) workers employed in industries competing with Mexican imports. We find evidence of only modest local labor-market effects, but evidence for a strong industry effect, dramatically lowering wage growth for blue-collar workers in the most affected industries. These distributional effects are much larger than aggregate welfare effects estimated by other authors. In addition, we find strong evidence of anticipatory adjustment in places whose protection was expected to fall but had not yet fallen; this adjustment appears to have conferred an anticipatory rent to workers in those locations.

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1 Introduction

Perhaps the most passionately debated issue in trade policy within the United States in a generation has been the signing and implementation of the North American Free Trade Agreement (NAFTA), signed by the governments of the US, Canada and Mexico in 1993. Opponents believe that it has devastated some parts of the country by encouraging multinationals to shift operations to Mexico, while proponents argue that it has boosted US exports and thus job growth. Despite the age of the agreement, as recently as 2008 it became the subject of intense political debate, with Democratic presidential candidates competing with each other in denunciations of the agreement in Ohio, a state in which many voters blame the agreement for local economic difficulties (Austen, 2008). Brown (2004, Ch. 6) presents a passionate example of the liberal non-economist's case against the NAFTA, arguing that it has destroyed millions of US jobs as well as causing environmental problems.

One aspect of popular opposition to the NAFTA has been the claim that it has had a disparate impact geographically, that it has devastated particularly vulnerable *towns* even as others have prospered. Leonhardt (2008) describes the anti-NAFTA sentiment in Youngstown, Ohio, which had suffered a long economic decline that many residents blamed partly on NAFTA. In particular, residents had recently seen the shuttering of the Youngstown Steel Door plant, which had been the leading supplier of steel doors for railway cars in North America for decades; the capital was purchased by a foreign firm and shipped to a plant in Mexico. Brown (2004, pp.156-7) argues that the agreement was a devastating blow to the towns of Nogales, Arizona and El Paso, Texas. At the same time, the town of Laredo, Texas enjoyed a dramatic economic boom based on traffic to and from Mexico following the agreement (Duggin, 1999). Kumar (2006) argues that the Texas economy as a whole has benefitted from exports to the Mexico as a result of the agreement.

Unfortunately, economists to date have not provided an answer to the question of whether or not NAFTA has indeed had the effects ascribed to it by its opponents. This paper is an attempt to do so. We ask whether or not we can identify subsets of US workers whose incomes were seriously diminished by the agreement, and if so, do they follow an identifiable geographic pattern.

Our approach is to do what seems like the simplest possible exercise to look for signs of the effects that NAFTA opponents claim. We try to identify local labor-market effects of the tariff reductions brought about by the NAFTA, using publicly available US Census data from 1990 and 2000, taken from the IPUMS project at the Minnesota Population Center (www.ipums.org). This data has enough richness to enable us to capture the features we need to capture.

Three features in particular that we need to capture should be highlighted.

(i) We need to be able to control for a worker's industry of employment, in order to allow for the likelihood that workers in industries that compete with imports from Mexico[1] will be affected differently than workers in other industries. The census data has a very coarse division of workers into industries that allows us to do so adequately.

(ii) The issue that has been foremost in much of the political debate is a geographic one: The claim that workers in some vulnerable locations have been harmed, relative to workers in other places. Thus, we need detailed geographic data, and a measure of how vulnerable a given location is likely to be to the effects of the NAFTA. The IPUMS data divide the country into 543 similar-sized, non-overlapping pieces, called Consistent Public-Use Microdata Areas, or CONSPUMA's, whose boundaries are the same for both 1990 and 2000. Every worker in the data is identified as living in one of these CONSPUMA's, and so this allows us to control for geography. In particular, in *addition* to controlling for what industry in which a worker is employed, we can control for *how many of the other workers within a worker's CONSPUMA* are employed in industries that will compete directly with imports from Mexico. This will be interpreted as the 'local vulnerability' of the labor market to the effects of NAFTA.

(iii) The agreement was framed as a gradual phase-in of tariff reductions between the three countries, starting in 1994 and continuing for 10 years. The negotiated schedule of liberalization was different for each sector of the economy. As a result, for some industries, the period from 1990 to 2000 would represent the period of an announcement of tariff reductions, most of which occurred after 2000. For other industries, the same period would be a period of rapid elimination of tariffs. Consider two hypothetical industries. Industry A benefitted from a 12% tariff in 1990; by 2000, the tariff on imports of that industry's products from Mexico had fallen to 9%, with the remaining 9% scheduled to be eliminated between 2000 and 2004. Industry B benefitted from a 3% tariff as of 1990, which was completely eliminated on imports from Mexico by 2000. Both of these industries saw a drop in their respective Mexico tariffs of 3 percentage points in the sample period 1990-2000, but we would not

[1]Note that we are not interested in imports from Canada, since tariffs between the US and Canada had already been eliminated by the Canada-US Free Trade Agreement.

expect the same economic effects in these two cases since in the case of Industry A, most of the tariff reduction is anticipated, rather than being realized over the period of the data. In any model of dynamic adjustment, anticipated tariff changes can have important effects over and above realized tariff changes. To deal with this, we measure the extent of anticipated tariff reduction by the initial tariffs (since all intra-NAFTA tariffs needed to be eliminated over the course of the agreement), and control for this in regressions in addition to the actual realized tariff reduction between 1990 and 2000.

To anticipate results, we find that NAFTA vulnerable locations that lost their protection quickly experienced modestly slower wage growth compared to locations that had no protection against Mexico in the first place. There is no evidence in these data of a very strong 'Youngstown' effect. There is, however, some evidence of a substantial industry effect, with wage growth in the most protected industries that lose their protection quickly falling 10 percentage points relative to industries that were unprotected to begin with. (These industry effects are, however, sensitive to small changes in specification.) Crudely, it looks as if, when NAFTA is announced, it is better to be a software worker in a textile-and-apparel town than a textile-and-apparel worker in a software town.

In addition, we find evidence of anticipatory effects. Comparing two locations that experience the same drop in weighted average tariff over the sample period, if one of them still has high tariffs on Mexican imports and thus expects further drops in protection soon, while the other is now unprotected, the location expecting further tariff drops on average sees wage *increases* as less-educated workers leave the area, making less-educated workers scarcer, as in Artuç, Chaudhuri and McLaren (2008).

2 Previous work

Post-NAFTA, much work on the economic effects of the agreement has focussed on trade creation and trade diversion. Romalis (2007) studies changes in trade flows following NAFTA and finds that trade diversion effects of the agreement were substantial, and swamped any benefits from trade creation, leaving a net aggregate welfare benefit for the US of about zero. Caliendo and Parro (2009) calibrate and simulate an Eaton-Kortum-type model of North American trade to estimate the effects of NAFTA. Taking full account of enhanced trade in intermediate inputs and inter-industry linkages created by the input-output table, they find substantial increases in welfare for each NAFTA country as a result of the agreement. Neither of these papers addresses within-country income distribution, which is the focus of this paper.

A few papers have looked at aggregate labor-market effects, summarized in Burfisher et. al. (2001), and have found only small effects. The focus here is on distributional effects among workers, particularly how the agreement may have affected inequality between workers living in different parts of the country. More work has been done on the Mexican side of the border. Hanson (2007) finds that in the most globalization-affected regions of Mexico over the introduction of NAFTA both inequality and poverty fell relative to the rest of the country. Prina (2009a,b) finds that Mexican small farmers tended to benefit from the agreement on balance, and that there does not seem to have been much of an effect on rural landless workers.

An important related study is Trefler (2004), who studied firm- and industry-level data on Canadian manufacturing to find effects of the earlier Canada-US Free Trade Agreement. That study found substantial employment reductions in Canadian industries whose tariff against US imports fell the fastest, but no reduction in wages and a substantial improvement in productivity growth. The study did not look for local labor-market effects.

We here borrow ideas from a number of sources. A number of studies identify effects of a national trade shock on local labor markets, most notably the pioneering paper by Topalova (2007), who constructed an employment-weighted average tariff for each Indian district to identify the differential effects of local labor-market shocks on different locations. Kovak (2010) uses a similar technique for Brazil. These studies indicate significant location-specific effects of trade shocks on wages, which of course implies mobility costs of some sort for workers that prevent them from arbitraging wage differences across locations. A rich literature examines the correlation of changes in industry tariffs or other industry-specific trade shocks with industry wages. Revenga (1992) finds effects of an industry's import price on that industry's wages in the US. Pavcnik, Attanasio and Goldberg (2004) find such effects for Columbia. Here, we allow for *both* local labor market effects *and* industry effects.

In addition, Kennan and Walker (forthcoming) and Artuç, Chaudhuri and McLaren (2010) estimate structural models of labor mobility, the former focussing on geographic mobility and the latter on inter-industry mobility. Both studies find large costs to moving, but not enough to keep a substantial number of workers from moving when economic shocks call for it. Our reduced-form regression can be interpreted as providing confirming evidence for such moving costs.

We also draw ideas from Artuç, Chaudhuri and McLaren (2008) on the effects of anticipated changes in trade policy on current labor-market outcomes, although in this paper we do not estimate a structural empirical model.

3 Empirical approach

The approach described above requires a measure of protection by industry and also by geographic location. We defer details on how these are computed until the next section; for now, note that for each industry j of the 89 Census traded-goods industries, we have an average tariff, τ_t^j, assessed on goods from industry j entering the US from Mexico. This measures protection at the industry level. For the measure in geographic terms, we compute the initial average tariff in a given location, k, which we interpret as the 'vulnerability' of the location to the NAFTA. We define this similarly to the local average tariff in Topalova (2007):

$$loc\tau_t^c \equiv \frac{\sum_{j=1}^{N_{ind}} L_t^{cj} \tau_t^j}{\sum_{j=1}^{N_{ind}} L_t^{cj}} \tag{1}$$

where N_{ind} is the number of industries, τ_t^j is the tariff on good j at time t, and L_t^{cj} is the number of workers employed in industry j at CONSPUMA c at date t.

First, to show how we attempt to deal with the dynamic issues mentioned as point (iii) above, for the moment set aside geography and focus on industry-level effects (which would be an appropriate approach if, for example, we were certain that geographic mobility costs were zero). Then we could run a regression as follows:

$$w_i = \alpha X_i + \sum_j \alpha_j^{ind} ind_{i,j} + \left\{ \theta_1 yr2000_i \tau_{1990}^j + \theta_2 yr2000_i \triangle\tau^j \right\} + \epsilon_i, \tag{2}$$

where i indexes workers; X_i is a set of individual characteristics; $ind_{i,j}$ is a dummy variable that takes a value of 1 if individual i is employed in industry j; $yr2000_i$ is a dummy that takes a value of 1 if individual i is observed in the year 2000; $\triangle\tau^j = \tau_{2000}^j - \tau_{1990}^j$; ϵ_i is a random disturbance term; and the α's and θ's are parameters to be estimated.[2]

[2]Note that the data take the form of two cross sections rather than a panel. Each individual i in the

In this specification, there are two factors that allow for wages to grow at different rates between 1990 and 2000 in different industries, both captured by the two terms in brace brackets. The more obvious of these is that the tariff on industry i's products imported from Mexico may fall at different rates for different industries; this is captured by the change in tariff in the second term in brace brackets. However, we also need to take into account that for some industries the tariff elimination was virtually complete by 2000, while for others it was ongoing, and so would generate expectations of future liberalization that would also affect wages. To capture this, we include the initial tariff separately from the change in tariff, in the first of the two terms in the brace brackets. The year-1990 tariff captures the scale of the anticipated total tariff reduction (since all tariffs on Mexican goods must be brought down to zero over the adjustment period of the agreement). Holding constant the *realized* change in tariff from 1990 to 2000, a higher value of the 1990 tariff indicates a larger *anticipated* reduction in tariffs following 2000.

Anticipated liberalization of this sort can have a wide range of effects. Artuç, Chaudhuri and McLaren (2008) show that in a model with costly labor adjustment, an anticipated liberalization of trade in one industry can lead to a steady stream of exiting workers, creating a labor shortage and rising wages in that sector. The way this works is illustrated in Figures 1 and 2, which illustrate the time path of employment and wages for a pair of hypothetical industries. Suppose that they both have the same level of τ^{j}_{1990}. In 1994, the agreement is made public and ratified, and the industry in Figure 1 loses its tariff right away. This leads to a sudden drop in wages in industry i, and a flow of workers out of the industry. As workers leave the industry, the equilibrium moves up and to the left along the industry labor-demand curve, increasing wages progressively toward the new steady state as shown in the second panel of Figure 1. The new steady state wage could be above or below the old one, and so the difference in wages between the sampled wages at 1990 and 2000 could be positive, negative or zero. Contrast this situation with the case of the delayed tariff elimination of Figure 2. Here, suppose that the tariff is scheduled in the agreement to be eliminated in 2004. Between 1994 and 2000, workers will be gradually leaving the industry in anticipation of this tariff elimination, moving the equilibrium up and to the left along the industry labor-demand curve, and therefore steadily increasing the wage. In this case, the sampled industry wage in 2000 will definitely be higher than the sampled industry wage in

sample is observed once; some are observed in 1990 and some in 2000.

1990. Note that in Figure 2, $\tau^i_{1990} > 0$ and $\triangle\tau^i = 0$, and the wage increases over the sample period. Compare that with another industry j that never had a tariff, and so expects no losses from NAFTA: $\tau^j_{1990} = \triangle\tau^j = 0$. Over the sample period, clearly industry i's wages rise relative to wages in industry j.

Clearly, in a model of that sort, θ_1 would be positive: Holding constant the *realized* tariff reduction during the sample period, the larger the tariff reduction *anticipated* during the sample period, the more workers will stream out of the industry and the more rapidly will wages in the industry rise during the sample period. A model with heterogeneous workers or firms might generate a similar effect, as workers or firms that are only marginally suited to the liberalizing industry leave it in anticipation, leaving only the higher-productivity producers and hence higher average wages. On the other hand, in a model with frictional job search and costly creation of vacancies as in Hosios (1990), anticipated liberalization will have the effect of curtailment of vacancies, which could occur more rapidly than worker exodus, leading to rising unemployment and falling wages in the industry. In this case, we would see $\theta_1 < 0$. We can parsimoniously say that θ_1 captures the 'anticipatory effect' of the liberalization, while θ_2 captures the 'impact effect.' Of course, in the event that an industry loses its tariff entirely during the sample period so that $\triangle\tau^j = -\tau^j_{1990}$, the effect on the wage during the sample period is then $\theta_1 - \theta_2$.

Equation (2) summarizes the essence of our approach to dynamics, but in practice we are interested in capturing more detail than it entails. In particular, we wish to allow the effects on wages to differ by educational class. We break the sample down into four classes, less than high school; high-school graduate; some college; and college graduate, and allow both the initial wage and the wage growth to vary by these categories.

$$\begin{aligned} log(w_i) &= \alpha X_i + \sum_j \alpha_j^{ind} ind_{i,j} \\ &+ \sum_{k \neq col} \gamma_{1k} educ_{ik} + \sum_k \gamma_{2k} educ_{ik} yr2000_i \\ &+ \sum_{k \neq col} \theta_{1k} educ_{ik} \tau^j_{1990} + \sum_k \theta_{2k} educ_{ik} yr2000_i \tau^j_{1990} \\ &+ \sum_{k \neq col} \theta_{3k} educ_{ik} \triangle\tau^j + \sum_k \theta_{4k} educ_{ik} yr2000_i \triangle\tau^j + \epsilon_i, \end{aligned} \tag{3}$$

where $educ_{ij}$ is a dummy variable taking a value of 1 if worker i is in educational category k.

The variables of interest here, corresponding to the anticipatory effect and the impact effect discussed in the context of equation (2), are θ_{2k} and θ_{4k}.[3]

Equation (3) allows for a rich characterization of dynamic response that varies by industry and education, but it does not yet allow for geography. To incorporate that, we include terms that treat local average tariffs as in (1), in a way that is parallel to the treatment of industry tariffs. In addition, we allow for a different rate of wage growth for locations on the US-Mexico border, producing our main regression equation:

$$\begin{aligned} log(w_i) &= \alpha X_i + \sum_j \alpha_j^{ind} ind_{i,j} + \sum_c \alpha_c^{conspuma} conspuma_{i,c} \\ &+ \sum_{k \neq col} \gamma_{1k} educ_{ik} + \sum_k \gamma_{2k} educ_{ik} yr2000_i \\ &+ \sum_{k \neq col} \delta_{1k} educ_{ik} loc\tau_{1990}^{c(i)} + \sum_k \delta_{2k} educ_{ik} yr2000_i loc\tau_{1990}^{c(i)} \\ &+ \sum_{k \neq col} \delta_{3k} educ_{ik} loc\triangle\tau^{c(i)} + \sum_k \delta_{4k} educ_{ik} yr2000_i loc\triangle\tau^{c(i)} \\ &+ \sum_{k \neq col} \theta_{1k} educ_{ik} \tau_{1990}^{j(i)} + \sum_k \theta_{2k} educ_{ik} yr2000_i \tau_{1990}^{j(i)} \\ &+ \sum_{k \neq col} \theta_{3k} educ_{ik} \triangle\tau^{j(i)} + \sum_k \theta_{4k} educ_{ik} yr2000_i \triangle\tau^{j(i)} \\ &+ \mu Border_{c(i)} yr2000_i + \epsilon_i, \end{aligned} \tag{4}$$

where $conspuma_{i,c}$ is a dummy variable that takes a value of 1 if worker i is in CONSPUMA number c and $loc\triangle\tau^{c(i)}$ is the change in tariff for location i, weighted by the year 1990 employment weights:

$$loc\triangle\tau^{c(i)} \equiv \frac{\sum_{j=1}^{N_{ind}} L_{1990}^{c(i)j} \triangle\tau^j}{\sum_{j=1}^{N_{ind}} L_{1990}^{c(i)j}}. \tag{5}$$

The parameters of primary interest here are $\delta_{2,k}$ and $\delta_{4,k}$, which measure the anticipatory effect and the impact effect, respectively, for the local average tariff change; and $\theta_{2,k}$ and $\theta_{4,k}$, which measure the anticipatory effect and the impact effect, respectively, for the industry tariff. If there is no dynamic adjustment, so that the labor market simply responds to current tariffs regardless of expectations, then we will observe $\delta_{2,k} = \theta_{2,k} = 0$.

If it is easy for workers to move geographically, so that local wage premiums are arbitraged

[3]The term with θ_{3k} is included only for consistency; it does not seem to have much economic meaning, and does not make much difference whether or not it is included in the regression.

away, but difficult for workers to switch industry, we will observe $\delta_{1,k}, \ldots, \delta_{4,k} = 0$ while $\theta_{1,k}, \ldots, \theta_{4,k} \neq 0$. In that case, industry matters, but location does not. This, together with the assumption that $\delta_{2,k} = 0$ is how the model in a number of studies such as Pavcnik, Attanasio and Goldberg (2004) are set up. On the other hand, if it is difficult for workers to move geographically but easy to switch industries within one location, we will see the opposite: $\delta_{1,k}, \ldots, \delta_{4,k} \neq 0$ while $\theta_{1,k}, \ldots, \theta_{4,k} = 0$. A 'pure Youngstown' effect would be indicated by $\delta_{4,k} > 0$ while $\delta_{2,k} = \theta_{2,k} = \theta_{4,k} = 0$. This would imply that an export-sector worker in Youngstown would suffer a wage reduction due to NAFTA, while an import-competing worker in Arlington, VA would not. This is how the model in Kovak (2010) is set up.

Finally, for a *location* that loses all of its protection within the sample period, the effect on wages within the sample period is equal to $\delta_{2,k} - \delta_{4,k}$, while for an *industry* that loses all of its protection within the sample period, the effect on wages within the sample period is equal to $\theta_{2,k} - \theta_{4,k}$.

4 Data

We use a 5% sample from the US Census for 1990 and 2000, collected from usa.ipums.org, selecting employed workers from age 25 to 64 who report a positive income in the year before the census and who do not report themselves as unemployed. We include the personal characteristics age, gender, marital status, whether or not the worker speaks English, race, and educational attainment (less than high school, high school graduate, some college, college graduate). In addition, we have the industry of employment and CONSPUMA of residence for each worker as well as the worker's pre-tax wage and salary income in the year of the census. Our sample size is 10,320,562 workers.

We use data on US tariffs on imports from Mexico collected by John Romalis and described in Feenstra, Romalis, and Schott (2002). We constructed a concordance to map the 8-digit tariff data into the 89 traded-goods industry categories of the Census in order to construct industry tariffs τ_t^j.[4] We used Mexican trade data from the US International Trade Commission to obtain a trade-weighted average tariff for each Census industry.[5]

[4]Note that only 89 out of the 239 Census industry categories produce tradable goods and can be mapped to trade data. The tariffs for the remaining non-traded-goods industries are treated as zeros.

[5]http://dataweb.usitc.gov

Table 1 shows descriptive statistics for the main control variables. The sample is 53% male and 80% white, with an average age of 41 years. High-school dropouts are 11% of the total, with the remainder about evenly split between high-school graduates, those with some college, and college graduates. The tariff in 1990 on Mexican goods ranged across traded-goods industries from 0 to 17%, with a mean of 2%. These tariffs are generally below the US Most-Favored-Nation (MFN) tariffs which are charged on imports from World Trade Organization (WTO) members as a default (see Figure 3). The difference is due to the Generalized System of Preferences (GSP), under which rich countries extend discretionary tariff preferences to lower-income countries (see Hakobyan (2010)). The initial average local tariff ranged across conspumas from approximately 0 to 2.7%, with a mean just above one half of a percent.

We actually have computed two versions of the local average tariff. In one, all industries are treated in the same way; in the second, we omit agriculture by setting its tariff equal to zero. The reason for doing this is that aggregation of industries is a particularly large problem for agriculture, as the Census makes no distinction between different crops. We know that corn, in particular, benefitted greatly from NAFTA due to elimination of Mexican corn quotas, while other crops, such as some vegetables, were likely hurt. However, with Census aggregation we are forced to apply the same tariff to all agriculture. This resulted in various farming areas of the great plains, where corn is king, appearing, implausibly, in the top ten most vulnerable conspumas (see Figure 6). To eliminate this problem, throughout, we have performed parallel regressions with agriculture omitted by artificially setting the agriculture tariff equal to zero, and reported the two sets of regressions side by side. The results are close to identical, but we refer to the version without agriculture as our preferred specification.

Table 2 shows which industries received the most protection against Mexican imports, and thus were potentially the most vulnerable to NAFTA. The top two are footwear and apparel, with average tariffs of 17%, followed by canned fruits and vegetables and knitting mills, with 16% each. Figure 4 shows that the relationship between the 1990 tariff levels and the decline in tariffs between 1990 and 2000 mostly follows a linear pattern, but with plenty of deviations. Industries whose tariffs fell more slowly than average include *Footwear* (initial tariff is 17%; the 2000 tariff is 11.2%) and *Structural clay products* (initial tariff is 14.5%; the 2000 tariff is 6.8%). Four industries (*Dairy products*; *Cycles and miscellaneous transportation equipment*; *Printing, publishing, and allied industries*; *Agricultural chemicals*) experienced tariff increases between 1990 and 2000.

Table 3 shows the conspumas with the highest and lowest 1990 local average tariffs on Mexican goods, and hence the most and least potential vulnerability to NAFTA (the local average tariffs agriculture omitted is used). The list is dominated by textile and apparel-manufacturing areas of the Carolinas and southern Virginia. The least vulnerable locations include Washington, D.C. and its suburbs in northern Virginia as well as Alaska. Figure 5 shows almost linear relationship between the 1990 local tariff levels and the decline in local tariffs. The largest difference between the initial local tariff and change in local tariff is observed in a conspuma in the state of Missouri (initial tariff is 1.9%; the 2000 tariff is 1.6%), followed by one in Indiana (initial tariff is 1%; the 2000 tariff is 0.7%). As will be seen, the variance of the differences between initial local tariffs and local tariff changes is sufficient to identify differential effects quite well.

5 Results

Table 4 shows the results for the main regression with all right-hand-side variables and industry and conspuma fixed effects. The worker controls have unsurprising coefficients. Married white men enjoy a wage premium; there is a concave age curve; and workers with more education earn higher wages, *ceteris paribus*. For each educational class k, the coefficients of interest are the equivalent of the key parameters in (4): $\delta_{2,k}$, which are listed in the table as the 'Anticipation Effect' for the Location-Specific Controls; $\delta_{4,k}$, listed at the 'Impact Effect' for the Location-Specific Controls; $\theta_{2,k}$, listed as the 'Anticipation Effect' for the Industry-Specific Controls; and $\theta_{4,k}$, listed as the 'Impact Effect' for the Industry-Specific Controls. In addition, the values of $\delta_{2,k} - \delta_{4,k}$ and $\theta_{2,k} - \theta_{4,k}$ for the case with agriculture excluded are reported in Table 5, together with the results of the test of the hypothesis that these differences are equal to 0. Throughout, we present results with and without agriculture excluded for comparison; the results are very similar, and we will focus on our preferred specification with agriculture excluded.

Looking first at the local variables, we find point estimates of 46.71 for $\delta_{2,lhs}$ and 46.51 for $\delta_{4,lhs}$. Note first that these are for all intents and purposes equal. In other words, $\delta_{2,lhs} - \delta_{4,lhs}$ is essentially zero (note that from Table 5 the p-value is 65%). In other words, among conspumas that lost their protection quickly under NAFTA, there is no perceptible difference between wage growth for high-school dropouts in the locations that had initially high Mexico tariffs, and that therefore appeared to be very vulnerable, and those that had low or zero tariffs. Second, note that each of these terms individually is very different from zero. The positive sign on the coefficient for the tariff change (46.51) indicates that for a given initial level of protection, locations that lost protection more quickly had more sluggish wage growth over the sample period – the impact effect. The positive sign on the coefficient for the initial level of protection $loc\tau^c_{1990}$ indicates that for a given realized tariff change during the sample period, the higher is the initial tariff (and thus the larger is the anticipated total tariff reduction), the higher is the wage growth over the sample period – the anticipation effect, just as described in Figure 2. The magnitudes are large. For the conspuma with the largest difference between $loc\tau^c_{1990}$ and $loc\triangle\tau^c$ (0.34 percentage points), namely a conspuma in Missouri that includes counties Ozark, Shannon, Howell, Wright, Oregon, Douglas, and Texas, this anticipatory effect amounts to an increase in wage growth for high-school dropouts relative to the rest of the economy equal to 16 percentage points.

Similar comments apply for high-school graduates and for workers with some college, while college graduates show coefficients with the opposite sign and insignificantly different from zero. The largest and most statistically significant value of $\delta_{2,k} - \delta_{4,k}$ is for workers with some college, with a point estimate of -1.7 from Table 5. This is still a very modest value. Recall that the largest value of the local average tariff is 2.7%, so workers with some college in a conspuma with that level of initial protection that lost it right away would suffer wage growth about 4.6 percentage points lower than the same workers would in a conspuma that never had protection. Since this is cumulative wage growth over a 10-year period, it amounts to less than half of a percentage point per annum.

Briefly, the effect of the dummy for location on the Mexican border is statistically significant but economically minuscule, implying less than a single percentage point of additional wage growth over a ten-year period. Evidently, the experience of towns like Laredo and towns like Nogales cancel each other out on average.

Turning now to the coefficients on the industry effects, the first feature to point out is that, from Table 4, the industry effects $\theta_{2,k}, \theta_{4,k}$ are not nearly as precisely estimated as the corresponding $\delta_{2,k}, \delta_{4,k}$ coefficients for the location effects were. However, from Table 5, the *differences* $\theta_{2,k} - \theta_{4,k}$ are precisely estimated (apart from college graduates, for whom the difference is not significantly different from zero). A worker with less than high school education working in the most protected industry (*Apparel and accessories, except knit*; initial tariff of 16.6%) experiences a wage growth rate almost 11 percentage points less than a worker in an unprotected industry, whereas a worker with the same education background working in an industry (*Structural clay products*) that loses the least of its protection experiences a wage decline of 15 percentage points. The wage decline for high school graduates is 4.5 and 8.3 percentage points, respectively.

In other words, unlike with the effect on local protection, the evidence suggests that a loss in a blue-collar worker's industry tariff substantially reduces that worker's wage growth. Note that both the anticipatory effect and the impact effect ($\theta_{2,lhs}$ and $\theta_{4,lhs}$ respectively in the case of high-school dropouts) have the opposite sign to the corresponding effect for the local labor-market variables ($\delta_{2,lhs}$ and $\delta_{4,lhs}$ respectively in the case of high-school dropouts). We need to be cautious about interpreting this, because, as noted above, these level effects, as opposed to the differences reported in Table 5, are estimated fairly imprecisely – none of the industry impact effects is significantly different from zero, for example. However, one could interpret these negative signs as indicating that the anticipatory response of vacancies and capital allocation occurs more quickly than that of workers ($\theta_{2,lhs} < 0$), and that loss of tariffs causes a shakedown within the industry that leaves only the most efficient worker-employer pairs ($\theta_{4,lhs} < 0$). Something similar to the latter appears to have been brought about in Canadian manufacturing following the Canada-US Free Trade Agreement; see Trefler (2004, pp. 884-6).

The fact that the industry effects hit blue-collar workers, especially high-school dropouts, but not college graduates suggests the possibility that the costs of switching industries are larger for less-educated workers, so that more-educated workers can arbitrage wage differences away.[6] This contrasts with the local labor-market effects, which suggest that blue-collar workers are quite mobile geographically.

To sum up, both locational variables and industry variables are highly statistically significant after controlling for a wide range of personal characteristics. This suggests that both costs of moving geographically and costs of switching industries are important. However, we find only a very modest 'Youngstown' effect in the data: More vulnerable locations that lost their tariffs quickly had either just the same or slightly smaller wage growth compared

[6]It should be noted that Artuç, Chaudhuri and McLaren (2010) looked for differences in inter-industry mobility costs and found no significant differences. However, they used only two skill categories (some college and no college), had a much smaller data set, and were not controlling for geographical mobility.

with locations that had no NAFTA vulnerability at all – across educational categories, and controlling for a broad range of personal characteristics. However, workers in vulnerable *industries* did see a substantial loss of income growth when their tariffs came down. The software engineer in Youngstown had better income growth during the period of NAFTA implementation than the footwear plant worker in Alexandria.

In addition, both by locality and by industry, anticipatory effects are in evidence, but the effect is more robust for the results by locality. Locations that were expected to lose protection but had not lost it yet saw wages *rise* relative to the rest of the country, possibly because of workers leaving the area and making labor more scarce. This applies across industries, so that even workers in a non-traded industry – waiting on tables in a diner, for example – benefitted from the (temporary) rise in wages.

6 Migration

The fact that wages rose more quickly in locations that anticipated a future drop in tariffs suggests the possibility that workers tend to leave such locations or to avoid moving to them, in anticipation of the future liberalization, thus driving up local wages temporarily much as in Artuç, Chaudhuri and McLaren (2008). We explore that possibility in Table 6. In the regression reported there, the dependent variable is the change in the log of the total number of workers of educational class k employed full time in conspuma c between 1990 and 2000. We regress this on $loc\tau^c_{1990}$ and $loc\triangle\tau^c$ to see if movements in workers are driven to a significant degree by the anticipated or realized tariff changes.

It should be pointed out that this exercise is illustrative; the employment growth figures are very volatile. This is likely due to the IPUMS sampling method; we draw a 5% sample from the Census, but there is no guarantee that 5% of the individuals from each conspuma are in the sample. Random variation in the location of sampled individuals creates large variations in the apparent size of conspumas over time. For example, the change between 1990 and 2000 in the log of employed high school dropouts within a conspuma ranges from -0.661 to 0.5728. It is hard to believe that the number of such workers rose or fell by two thirds in any location over 10 years.

Nonetheless, for our purposes this is nothing more than noise in the left-hand side variable, and although it makes it more difficult to measure a statistically significant relationship, it does not necessarily generate any bias in the regression. The regression does provide some information on the overall pattern of worker movements. *Ceteris paribus*, conspumas with more protection or a larger drop in protection against Mexican imports lost high-school dropouts more than other conspumas (since $-122.9 < 0$ and $-116.2 < 0$). Further, a conspuma with a high level of protection that lost it right away tended to lose high-school dropouts relative to other conspumas (since $-122.9 + 116.2 < 0$). Further, a conspuma like the Missouri one that contains Ozark county with the maximum difference between initial protection and drop in protection over the sample period would lose on average $122.9 * 0.027 - 116.2 * 0.017 = 0.61$ log points, or about half, of its high-school dropouts. By contrast, the same conspuma would gain an increase of 44% in the number of employed workers with some college. This can be also seen in Figure 7 which plots the change in employment shares for each education class against initial local tariff.

We interpret this as weak evidence in favor of the migration story, since anticipation of a drop in the local tariff leads to a drop in the number of local blue-collar workers. However, the (smaller) increase in the number of workers with some college certainly complicates the interpretation. A different dataset will be needed to explore this question in a more credible way.

7 Alternative approaches

We have explored some alternative ways of approaching the regression in order to check for robustness of the main results.

7.1 Import shares in place of tariffs

A natural concern is that NAFTA changed not only tariff but non-tariff barriers, border procedures, and dispute-resolution mechanisms, all of which can have a large effect on trade. As a result, our tariff measure is an imperfect measure of the policy changes brought about by NAFTA. In addition, there is the possibility that the tariff changes we track are correlated with other aspects of globalization, and so the effects that they are picking up are not specific to trade with Mexico. For instance, US MFN tariffs also saw decline over this period according to staged duty reductions under the Uruguay Round Agreements Act.[7]

[7] Uruguay Round Agreements Act was signed into law on December 8, 1994, as Public Law No. 103-465.

To address these issues, we have tried an alternative approach similar in spirit to Bernard, Jensen, and Schott (2006)'s use of import penetration by low-wage countries. Specifically, we perform a simple regression using changes in Mexican import shares as a proxy for the whole range of policy changes embodied in NAFTA that affect trade flows. For industry j, at date t, we compute Mexico's share, M_t^j, in US imports of industry-j goods. For each conspuma c, we find the local average value of M_t^j, with weights given by employment shares in 1990 within the conspuma, and denote that local average as M_t^c. Analogous to Mexican tariff, we calculate this measure with and without agriculture by setting change in Mexican import share to zero for agricultural products. Figure 8 shows considerable variation in the industry Mexican import shares between 1990 and 2000, with *Leather tanning and finishing* and *Railroad locomotives and equipment* experiencing the largest increase (35 and 31 percentage points, respectively). The largest drop in Mexican import share is observed for industries *Nonmetallic mining and quarrying, except fuels* and *Agricultural production, livestock*, 11.5 and 10.3 percentage points, respectively. From Table 1, the average change in Mexican import share across 89 traded-goods industries is 2.9 percentage points, and the average change in local Mexican import share across all conspumas is 0.7 percentage points.

We run a wage regression with the following right-hand side variables: the individual controls, industry and conspuma fixed effects as in the main regression; plus the change, $\triangle M^j$, in the industry Mexican import share interacted with education class and year-2000 dummies; and the change, $\triangle M^c$, in the local-average Mexican import share interacted with education class and year-2000 dummies. In effect, in a simplified form, the Mexican import shares take over the role of the Mexican tariffs in the main regression. Descriptive statistics are included in Table 1, and the results are shown in Table 7.

Once again, in this regression the industry results come out more strongly than the location results. For each education class except for college graduates, a rise in the Mexican share of imports of the workers' industry results in a statistically significant drop in wages relative to workers in other industries. The effects are of significant magnitude as well. For an industry whose Mexico share went from 10% to 20% (a drop about one standard deviation above the mean; see Table 1), they imply a drop in the cumulative growth of high-school dropout wages of 11 percentage points over the decade. For the maximum rise in an industry's Mexican import share, 35 percentage points, the implied drop in cumulative wage growth for a high-school dropout is 35.5 percentage points – an enormous deficit for a worker whose wages are already low.

7.2 Local correlation in error terms

Another issue of concern is the possibility that the error term for workers in the same conspuma and the same year may be correlated due to unobserved local shocks unrelated to trade policy. This is not a concern for observations from the year 1990 because we have included conspuma fixed effects in the regression, but it is a concern for observations from the year 2000. (If we had included conspuma-year fixed effects we clearly could not have included the year-2000 interactions with the local tariff variables that are our main variables of interest). This raises the possibility that our standard errors are underestimated and the statistical significance of our coefficients is spurious. The most straightforward way of dealing with this is clustering, but the large sample size makes this computationally difficult, so we have adopted a slightly different strategy. We regress wages on the set of individual characteristics with conspuma and industry fixed effects plus an interaction between the conspuma fixed effects and the year-2000 dummy. We then take these year-2000 conspuma fixed effects and regress them on the local tariff variables $loc\tau_{1990}^{c}$ and $loc\triangle\tau^{c}$. The results are reported in Table 8, again both for the version with agriculture included and the version with agriculture omitted. Clearly, the main features of the earlier results are repeated, with the coefficients of both local tariff variables positive, statistically significant, and very close to each other. We conclude that the significant values of the coefficients is not an artifact of ignoring correlation in the error term at the conspuma level.

7.3 Some additional qualifications

A few issues that are beyond our control should be mentioned. First, our measures of location and industry are both coarse, because of the nature of Census data. We would ideally prefer to have information on the county of residence for each worker, since a conspuma typically encompasses multiple counties.[8] By the same token, we have only 89 traded-goods industries, and so cannot make use of the rich variation in tariff changes across tariff codes. Because of these issues, we are likely to underestimate the effects of trade on wages in both geographic and industry dimensions.

[8]The Census does record county information, but the Publicly Available Microsamples do not consistently report it because of rules to protect confidentiality.

Second, it should be remembered that a change in wages brought about by trade policy will tend to overestimate the welfare change for the workers in question, because the welfare change depends on lifetime utility, which includes option value (Artuç, Chaudhuri and McLaren (2010)). To assess those welfare changes, we would need a structural model, which is beyond the scope of this paper.

8 Conclusions

We have tried to identify the distributional effect of NAFTA using US Census data. Our focus is on the effects of reductions in US tariffs on Mexican products under NAFTA on the wages of US workers.

Limitations on mobility of workers *both* geographically *and* across industries appear to be very important, because we find statistically and economically significant effects of both local employment-weighted average tariffs and industry tariffs on wages. However, we found that reductions in the local average tariff are associated with only very modest reductions in the locality's wages, while at least for blue-collar workers, a reduction in the tariff of the industry of employment generates substantial wage losses. In other words, we did not find much of a 'Youngstown' effect, but rather more of a 'textile' effect or a 'footwear' effect, and when the tariffs plunge it is better to be a programmer in a textile town than to be a textile worker in a software town.

In addition, we find strong evidence of anticipatory effects, at least for local average tariffs. When a location is about to receive a major tariff drop that has not occurred yet, wages there *rise* relative to locations with no current protection, possibly because of anticipatory movements of labor.

Perhaps the main finding is that the distributional effects of the NAFTA are large. Whether we define highly affected industries as industries that had been protected by a high tariff against Mexican imports, or as industries whose Mexican share of imports rose quickly, the result is the same: Blue-collar workers in highly-affected industries saw very substantially lower wage growth than workers in other industries. Since studies of aggregate welfare effects of the NAFTA such as Romalis (2007) and Caliendo and Parro (2009) find at most very small aggregate US welfare gains from NAFTA (the most optimistic estimate is 0.2% in Caliendo and Parro (2009)), these distributional effects suggest strongly that blue-collar workers in vulnerable industries suffered large absolute declines in real wages as a result of the agreement. This case study provides another example of the observation made by Rodrik (1994) that trade policy tends to be distinguished by large redistributional effects relative to aggregate welfare effects, and hence emphasizes once again the importance of identifying the effects of trade on income distribution (see Harrison, McLaren and McMillan (2010) for a recent survey).

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Figure 1: An Unanticipated Tariff Elimination

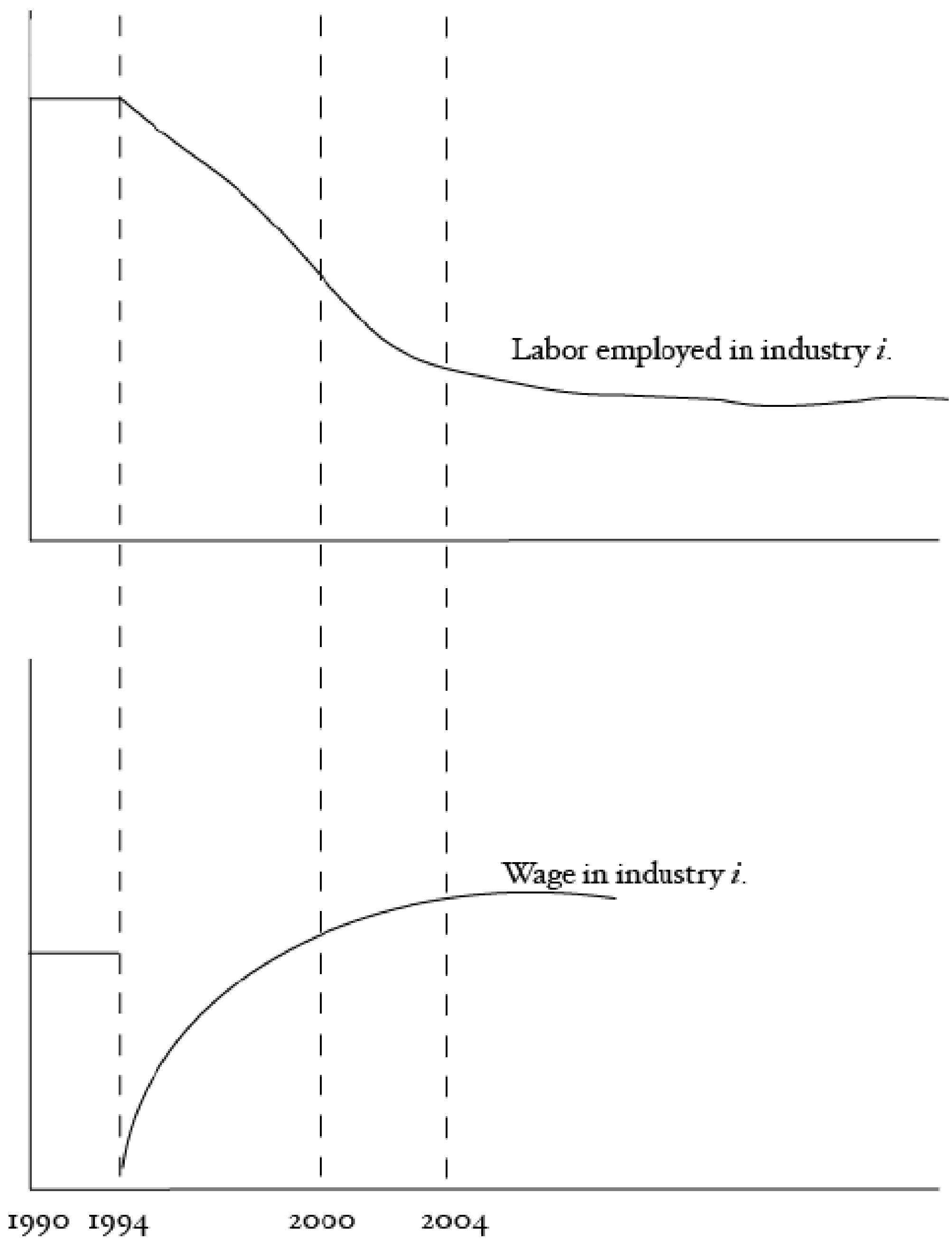


Figure 2: An Anticipated Tariff Elimination

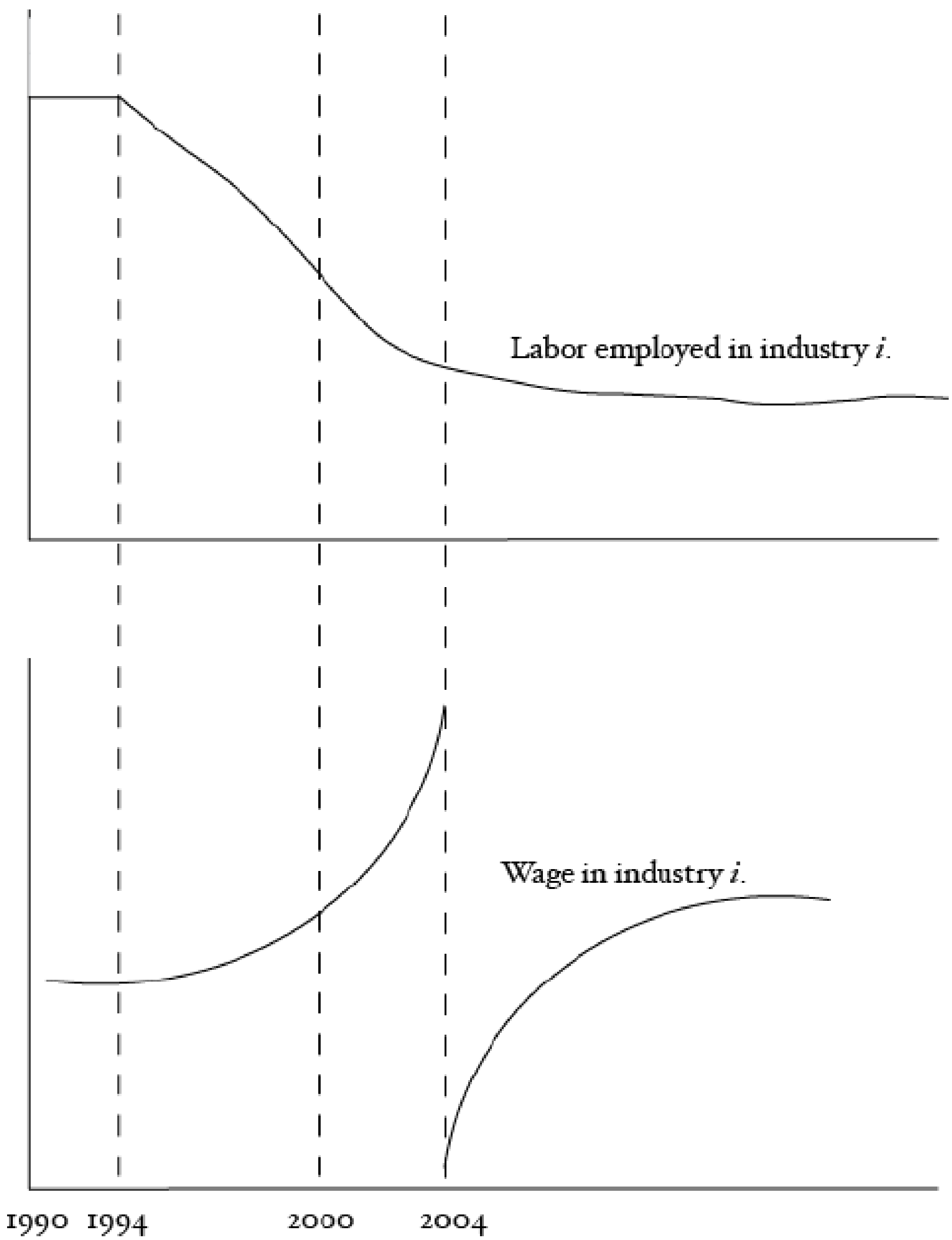
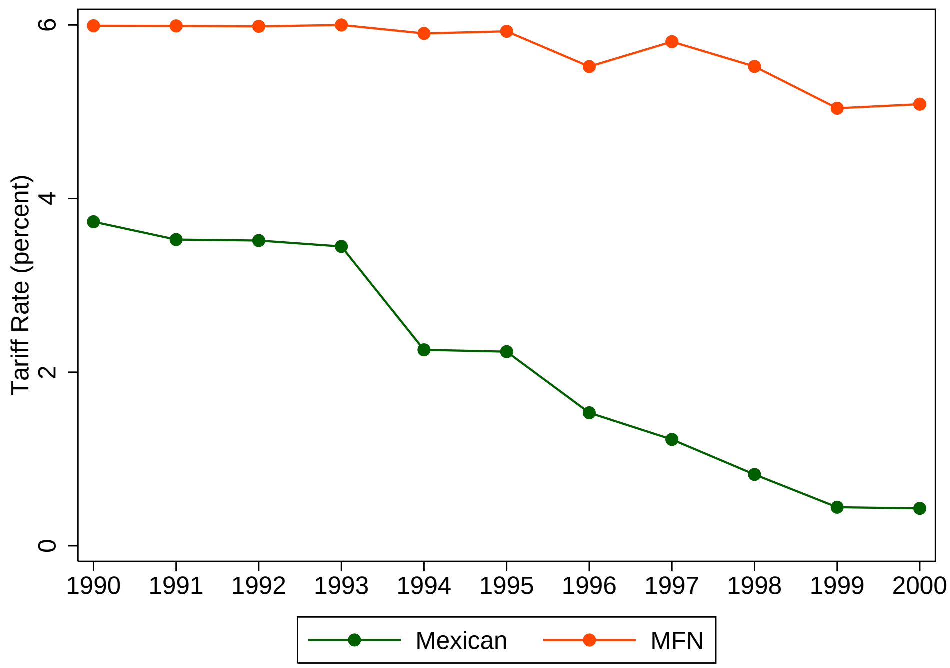


Figure 3: Evolution of Tariffs



Note: MFN and Mexican tariffs are weighted by world and Mexican imports, respectively. (Harmonized System 8-digit level)

Figure 4: Industry Tariff in 1990 and Tariff Decline

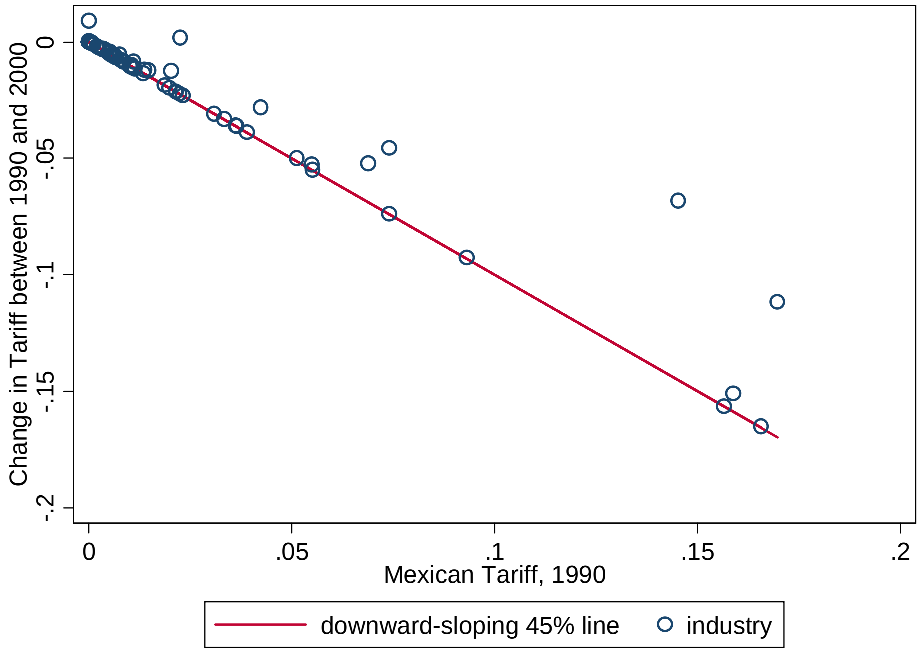
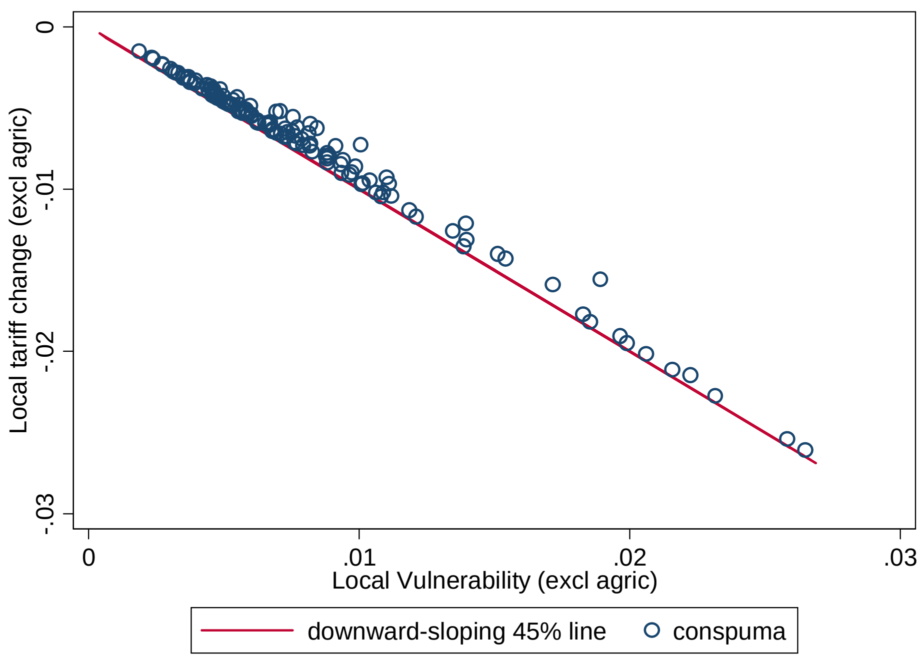
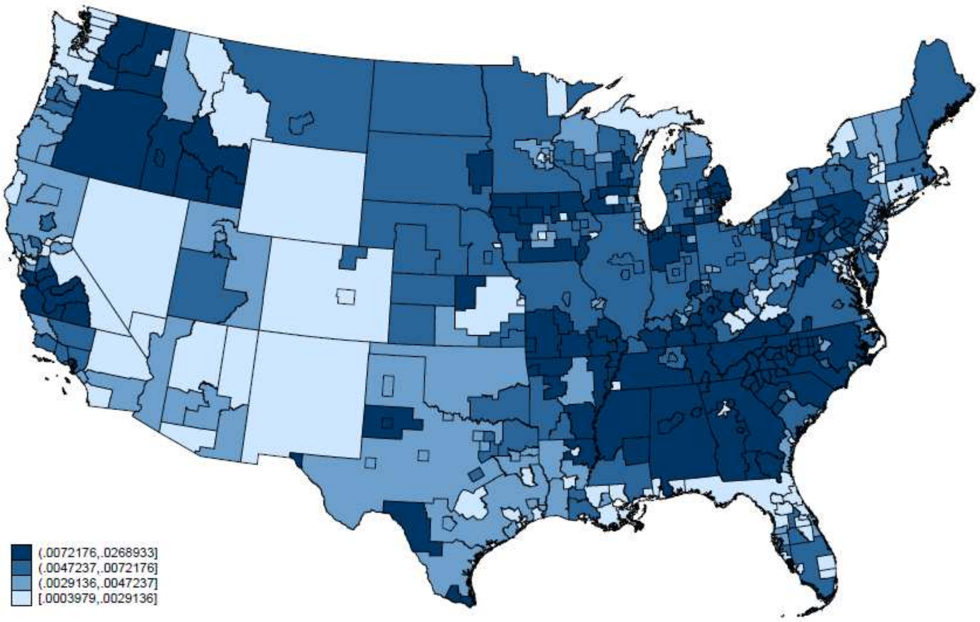


Figure 5: Local Tariff in 1990 and Local Tariff Decline

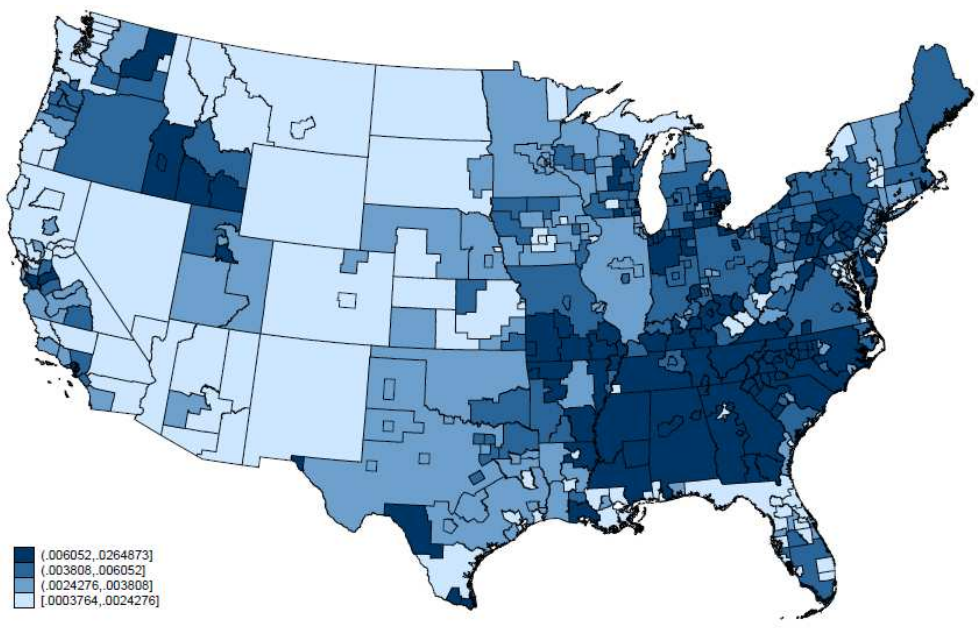


Note: Only conspumas with $loc\tau^c_{1990} - |loc\triangle\tau^c| > 0.0003$ are plotted. Excludes agriculture.

Figure 6: Variation in Local Vulnerability

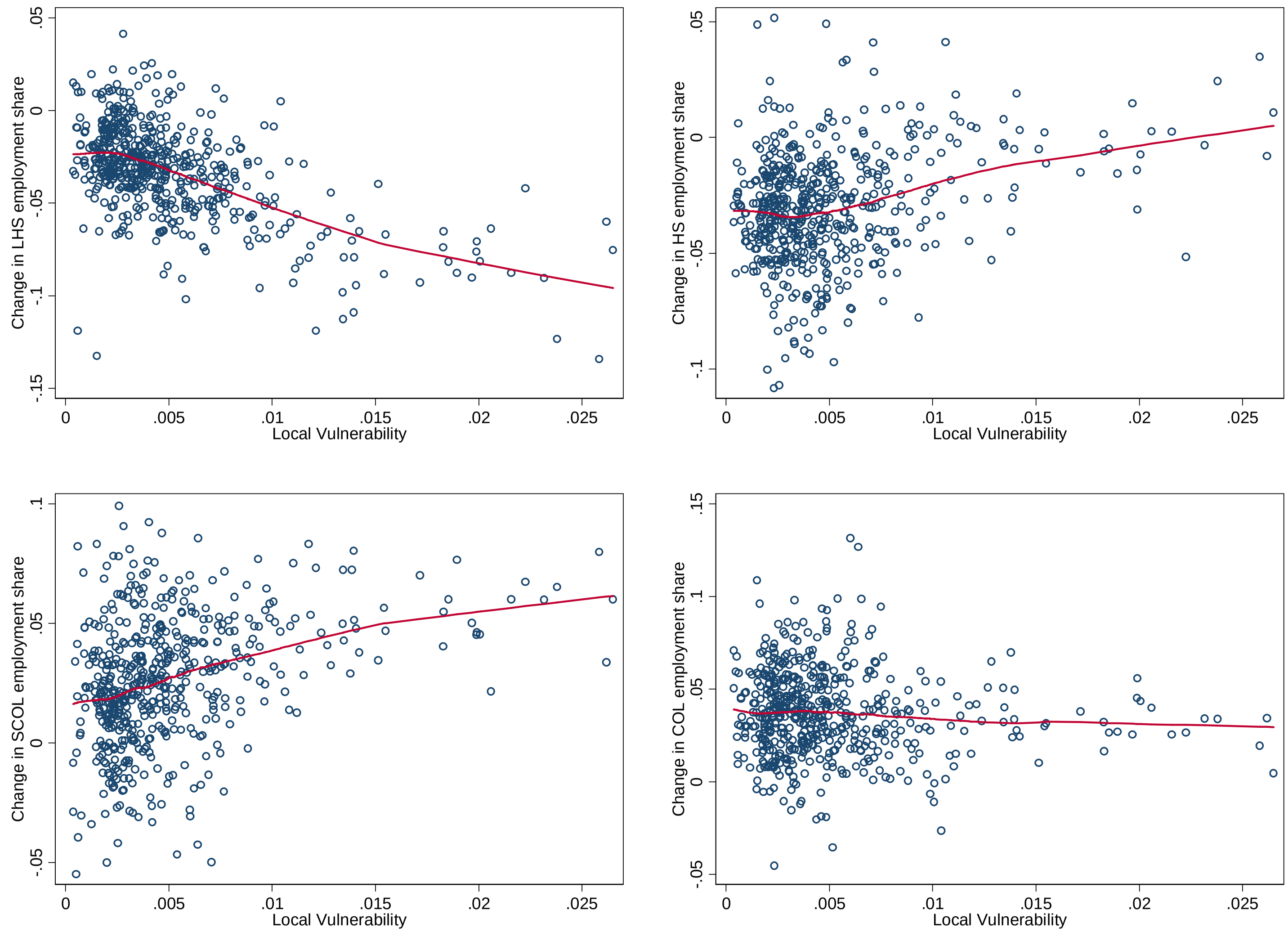


(includes agriculture)



(excludes agriculture)

Figure 7: Change in Employment Shares by Education Group



Note: Solid line represents fitted values from a locally weighted smoothing regression (bandwidth = 0.8).

Figure 8: Change in Mexican Import Share and Initial Share in 1990

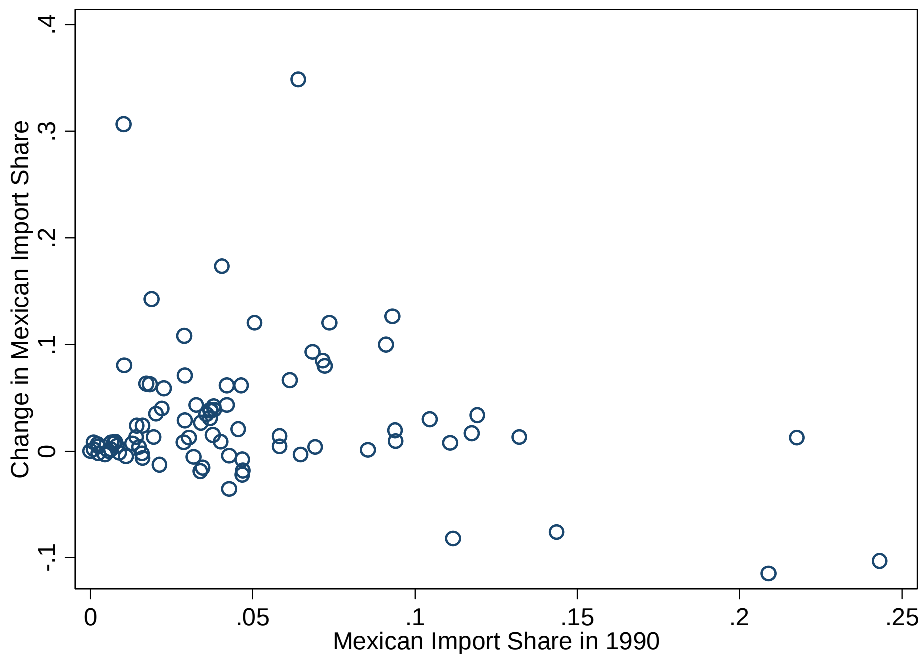


Table 1: Summary Statistics

Variable	Mean	St. Dev.	Min	Max
Individual-level				
Age	41	10	25	64
Male	0.53	0.50	0	1
Married	0.66	0.47	0	1
English speaking	0.99	0.09	0	1
White	0.80	0.40	0	1
High school dropouts	0.11	0.31	0	1
High school graduates	0.31	0.46	0	1
Some college	0.30	0.46	0	1
College graduates	0.28	0.45	0	1
Border	0.04	0.20	0	1
Industry-level				
τ^j_{1990} (%)	2.1	3.9	0	17
τ^j_{2000} (%)	0.3	1.1	0	7.7
$\triangle\tau^j$ (%)	-1.8	3.4	-16.5	0.9
$\triangle M^j$ (%)	2.9	6.5	11.5	34.9
Conspuma-level				
$loc\tau^c_{1990}$(%)	0.6	0.4	0.04	2.7
$loc\triangle\tau^c$ (%)	-0.5	0.4	-2.6	-0.04
$\triangle M^c$(%)	0.75	0.56	-0.40	3.44

Table 2: Top 20 Most Protected Industries in 1990

Rank	Industry Name	τ^j_{1990} (%)	$\triangle\tau^j$
1	Footwear, except rubber and plastic	17.0	-11.2
2	Apparel and accessories, except knit	16.6	-16.5
3	Canned, frozen, and preserved fruits and vegetables	15.9	-15.1
4	Knitting mills	15.7	-15.7
5	Structural clay products	14.5	-6.8
6	Yarn, thread, and fabric mills	9.3	-9.3
7	Leather products, except footwear	7.4	-4.6
8	Dyeing and finishing textiles, except wool and knit goods	7.4	-7.4
9	Carpets and rugs	6.9	-5.2
10	Grain mill products	5.5	-5.5
11	Agricultural production, crops	5.5	-5.3
12	Pottery and related products	5.1	-5.0
13	Blast furnaces, steelworks, rolling and finishing mills	4.2	-2.8
14	Electrical machinery, equipment, and supplies, n.e.c.	3.9	-3.9
15	Plastics, synthetics, and resins	3.6	-3.6
16	Miscellaneous textile mill products	3.6	-3.6
17	Motor vehicles and motor vehicle equipment	3.3	-3.3
18	Paints, varnishes, and related products	3.1	-3.1
19	Engines and turbines	2.3	-2.3
20	Cycles and miscellaneous transportation equipment	2.3	0.2

Table 3: Most and Least Vulnerable Conspumas (excludes agriculture)

Rank	State	Counties/Cities	$loc\tau^c_{1990}$ (%)	$loc\triangle\tau^c$
		Panel A: Top 20 Most Vulnerable Conspumas		
1	North Carolina	Cleveland, McDowell, Polk, Rutherford	2.65	-2.61
2	North Carolina	Alamance, Randolph	2.62	-2.59
3	Virginia	Danville, Pittsylvania	2.58	-2.54
4	Kentucky	including Adair, Casey, Clinton, Cumberland	2.38	-2.36
5	South Carolina	including Abbeville, Edgefield, Fairfield	2.32	-2.28
6	Pennsylvania	Schuylkill	2.22	-2.15
7	North Carolina	including Alleghany, Ashe, Avery, Mitchell	2.16	-2.11
8	South Carolina	Anderson	2.06	-2.02
9	South Carolina	Oconee, Pickens	2.01	-1.99
10	North Carolina	Cabarrus, Rowan	1.99	-1.96
11	North Carolina	Catawba County	1.99	-1.95
12	Tennessee	including Bledsoe, Bradley, Cannon, Cumberland	1.97	-1.91
13	Missouri	including Douglas, Howell, Oregon, Ozark, Shannon	1.89	-1.56
14	South Carolina	including Cherokee, Chester, Chesterfield, Clarendon	1.85	-1.82
15	North Carolina	Alexander, Burke, Caldwell	1.83	-1.77
16	South Carolina	including Campobello, Chesnee, Cowpens, Greer	1.83	-1.80
17	Georgia	Catoosa, Dade, Walker	1.72	-1.59
18	North Carolina	including Beaufort, Bertie, Carteret, Caswell, Craven	1.55	-1.52
19	Tennessee	including Bedford, Carroll, Chester, Decatur, Fayette	1.54	-1.43
20	Pennsylvania	Clinton, Juniata, Mifflin, Snyder, Union	1.51	-1.40
		Panel B: Top 20 Least Vulnerable Conspumas		
1	D.C.	Washington	0.04	-0.04
2	Virginia	Alexandria	0.04	-0.04
3	Maryland	Calvert, Charles, St. Mary's County	0.05	-0.04
4	Virginia	Arlington	0.05	-0.05
5	Alaska	Anchorage	0.05	-0.05
6	Maryland	including College Park, Hyattsville, Prince George's	0.06	-0.05
7	Alaska	Rest of Alaska	0.06	-0.05
8	Kentucky	Floyd, Johnson, Magoffin, Martin, Pike	0.06	-0.05
9	Virginia	Fairfax County, Fairfax city, Falls Church city	0.06	-0.06
10	Nevada	including Boulder City, Las Vegas, Spring Valley	0.07	-0.07
11	Washington	Kitsap	0.07	-0.07
12	Montana	Yellowstone	0.07	-0.06
13	Maryland	including Bethesda, Montgomery, Rockville	0.08	-0.07
14	Arizona	Apache, Navajo	0.09	-0.09
15	Kansas	including Cheyenne, Decatur, Graham, Russell	0.09	-0.08
16	Wyoming	State of Wyoming	0.09	-0.08
17	Montana	including Blaine, Carbon, Dawson, Glacier, Phillips	0.09	-0.09
18	Florida	Alachua	0.09	-0.09
19	Washington	Thurston	0.10	-0.09
20	New York	including Albany, Loudonville, Roessleville	0.10	-0.09

Table 4: Regression Results
Individual Characteristics

Dependent Variable: Log Wage	Including Agriculture	Excluding Agriculture
Age	0.08***	0.08***
	(0.0002)	(0.0002)
Age squared	-0.001***	-0.001***
	(2.53E-06)	(2.53E-06)
Male	0.51***	0.51***
	(0.001)	(0.001)
Married	0.07***	0.07***
	(0.001)	(0.001)
White	0.16***	0.16***
	(0.001)	(0.001)
English speaking	0.30***	0.30***
	(0.003)	(0.003)
Less than high school	-0.77***	-0.77***
	(0.003)	(0.002)
High school	-0.50***	-0.50***
	(0.002)	(0.002)
Some college	-0.34***	-0.35***
	(0.002)	(0.002)
Less than high school * (Year = 2000)	0.35***	0.36***
	(0.003)	(0.003)
High school * (Year = 2000)	0.35***	0.36***
	(0.002)	(0.002)
Some college * (Year = 2000)	0.37***	0.38***
	(0.002)	(0.002)
College graduate * (Year = 2000)	0.40***	0.40***
	(0.002)	(0.002)

Standard errors in parentheses.

***, ** and * indicate significance at the 1%, 5% and 10% level.

Regression Results (continued)

Location-Specific Controls

	Dependent Variable: Log Wage	Including Agriculture	Excluding Agriculture
Anticipation effect	Less than high school * $loc\tau^c_{1990}$ * (Year = 2000)	51.44***	46.71***
		(6.87)	(6.93)
	High school * $loc\tau^c_{1990}$ * (Year = 2000)	35.43***	33.75***
		(3.76)	(3.77)
	Some college * $loc\tau^c_{1990}$ * (Year = 2000)	32.19***	28.25***
		(4.72)	(4.74)
	College * $loc\tau^c_{1990}$ * (Year = 2000)	-4.40	-5.73
		(5.61)	(5.64)
Impact effect	Less than high school * $loc\triangle\tau^c$ * (Year = 2000)	50.48***	46.51***
		(7.08)	(7.12)
	High school * $loc\triangle\tau^c$ * (Year = 2000)	35.31***	34.45***
		(3.89)	(3.89)
	Some college * $loc\triangle\tau^c$ * (Year = 2000)	32.62***	29.94***
		(4.87)	(4.88)
	College * $loc\triangle\tau^c$ * (Year = 2000)	-3.26	-4.39
		(5.80)	(5.82)
	Less than high school * $loc\tau^c_{1990}$	-31.65***	-33.49***
		(6.32)	(6.36)
	High school * $loc\tau^c_{1990}$	-43.02***	-45.10***
		(5.11)	(5.13)
	Some college * $loc\tau^c_{1990}$	-59.63***	-58.63***
		(5.60)	(5.63)
	Less than high school * $loc\triangle\tau^c$	-26.15***	-28.07***
		(6.52)	(6.54)
	High school * $loc\triangle\tau^c$	-38.55***	-40.84***
		(5.28)	(5.29)
	Some college * $loc\triangle\tau^c$	-55.64***	-55.81***
		(5.78)	(5.80)
	Border * (Year = 2000)	0.007***	0.006***
		(0.003)	(0.003)

Standard errors in parentheses.

***, ** and * indicate significance at the 1%, 5% and 10% level.

Regression Results (continued)

Industry-Specific Controls

	Dependent Variable: Log Wage	Including Agriculture	Excluding Agriculture
Anticipation effect	Less than high school * τ^j_{1990} * (Year = 2000)	-1.02**	-1.37***
		(0.47)	(0.47)
	High school * τ^j_{1990} * (Year = 2000)	-0.78**	-0.83**
		(0.33)	(0.33)
	Some college * τ^j_{1990}* (Year = 2000)	0.46	0.44
		(0.50)	(0.50)
	College * τ^j_{1990} * (Year = 2000)	-0.09	-0.14
		(0.73)	(0.73)
Impact effect	Less than high school * $\triangle\tau^j$ * (Year = 2000)	-0.64	-0.73
		(0.49)	(0.49)
	High school * $\triangle\tau^j$ * (Year = 2000)	-0.58*	-0.56*
		(0.34)	(0.34)
	Some college * $\triangle\tau^j$ * (Year = 2000)	0.69	0.76
		(0.52)	(0.52)
	College * $\triangle\tau^j$ * (Year = 2000)	-0.23	-0.19
		(0.76)	(0.76)
	Less than high school * τ^j_{1990}	2.21***	2.18***
		(0.60)	(0.60)
	High school * τ^j_{1990}	2.59***	2.49***
		(0.57)	(0.57)
	Some college * τ^j_{1990}	0.66	0.52
		(0.63)	(0.63)
	Less than high school * $\triangle\tau^j$	2.13***	2.24***
		(0.62)	(0.62)
	High school * $\triangle\tau^j$	2.76***	2.86***
		(0.59)	(0.59)
	Some college * $\triangle\tau^j$	0.62	0.71
		(0.66)	(0.66)

Standard errors in parentheses.

***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 5: Differences Between Anticipation and Impact Effect

Parameter difference	Point estimate	F Value	Pr > F
$\delta_{2,lhs} - \delta_{4,lhs}$	0.2030	0.21	0.6482
$\delta_{2,hs} - \delta_{4,hs}$	-0.6992	5.94	0.0148
$\delta_{2,scol} - \delta_{4,scol}$	-1.6944	25.95	<.0001
$\delta_{2,col} - \delta_{4,col}$	-1.3483	11.69	0.0006
$\theta_{2,lhs} - \theta_{4,lhs}$	-0.6391	135.26	<.0001
$\theta_{2,hs} - \theta_{4,hs}$	-0.2679	34.05	<.0001
$\theta_{2,scol} - \theta_{4,scol}$	-0.3285	22.08	<.0001
$\theta_{2,col} - \theta_{4,col}$	0.0506	0.27	0.6023

Table 6: Employment Growth Regression Results

Dependent Variable: $\triangle$ in Log Employment of	Including Agriculture	Excluding Agriculture
High School Dropouts		
$loc\tau^c_{1990}$	-117.7***	-122.9***
	(24.10)	(25.49)
$loc\triangle\tau^c$	-114.5***	-116.2***
	(24.76)	(26.03)
High School Graduates		
$loc\tau^c_{1990}$	4.748	4.587
	(10.86)	(11.30)
$loc\triangle\tau^c$	-3.062	-2.254
	(11.18)	(11.58)
Some College Education		
$loc\tau^c_{1990}$	57.23***	57.28***
	(17.78)	(18.49)
$loc\triangle\tau^c$	47.84***	49.12***
	(18.33)	(18.99)
College Graduates		
$loc\tau^c_{1990}$	-2.053	-1.499
	(22.79)	(22.97)
$loc\triangle\tau^c$	-6.267	-5.712
	(23.52)	(23.69)

Standard errors in parentheses. *** indicates significance at the 1% level.

Table 7: Robustness Check: Change in Mexican Import Shares

Dependent Variable: Log Wage	Including Agriculture	Excluding Agriculture
Location-specific controls		
Less than high school * $\triangle M^c$ * (Year = 2000)	-2.06***	-0.45
	(0.38)	(0.39)
High school * $\triangle M^c$ * (Year = 2000)	-0.01	1.20***
	(0.21)	(0.22)
Some college * $\triangle M^c$ * (Year = 2000)	-0.99***	0.24
	(0.22)	(0.23)
College * $\triangle M^c$ * (Year = 2000)	-0.37	-0.15
	(0.27)	(0.28)
Industry-specific controls		
Less than high school * $\triangle M^j$ * (Year = 2000)	-1.02***	-1.08***
	(0.05)	(0.06)
High school * $\triangle M^j$ * (Year = 2000)	-0.56***	-0.60***
	(0.03)	(0.04)
Some college * $\triangle M^j$ * (Year = 2000)	-0.50***	-0.52***
	(0.04)	(0.04)
College * $\triangle M^j$ * (Year = 2000)	-0.10*	-0.07
	(0.05)	(0.05)

Standard errors in parentheses.

***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 8: Conspuma-Year Fixed Effects Regression

Dependent Variable: Coefficient on conspuma-year fixed effects	Including Agriculture	Excluding Agriculture
$loc\tau^c_{1990}$	16.69**	15.81**
	(7.243)	(6.802)
$loc\triangle\tau^c$	15.70**	15.74**
	(7.406)	(6.931)

Standard errors in parentheses. ** indicate significance at the 5% level.

Table 1: Summary Statistics

Variable	Mean	St. Dev.	Min	Max
Individual-level				
Age	41	10	25	64
Male	0.53	0.50	0	1
Married	0.66	0.47	0	1
English speaking	0.99	0.09	0	1
White	0.80	0.40	0	1
High school dropouts	0.11	0.31	0	1
High school graduates	0.31	0.46	0	1
Some college	0.30	0.46	0	1
College graduates	0.28	0.45	0	1
Border	0.04	0.20	0	1
Industry-level				
τ^j_{1990} (%)	2.1	3.9	0	17
τ^j_{2000} (%)	0.3	1.1	0	7.7
$\triangle\tau^j$ (%)	-1.8	3.4	-16.5	0.9
$\triangle M^j$ (%)	2.9	6.5	11.5	34.9
Conspuma-level				
$loc\tau^c_{1990}$(%)	0.6	0.4	0.04	2.7
$loc\triangle\tau^c$ (%)	-0.5	0.4	-2.6	-0.04
$\triangle M^c$(%)	0.75	0.56	-0.40	3.44

Table 2: Top 20 Most Protected Industries in 1990

Rank	Industry Name	τ^j_{1990} (%)	$\triangle\tau^j$
1	Footwear, except rubber and plastic	17.0	-11.2
2	Apparel and accessories, except knit	16.6	-16.5
3	Canned, frozen, and preserved fruits and vegetables	15.9	-15.1
4	Knitting mills	15.7	-15.7
5	Structural clay products	14.5	-6.8
6	Yarn, thread, and fabric mills	9.3	-9.3
7	Leather products, except footwear	7.4	-4.6
8	Dyeing and finishing textiles, except wool and knit goods	7.4	-7.4
9	Carpets and rugs	6.9	-5.2
10	Grain mill products	5.5	-5.5
11	Agricultural production, crops	5.5	-5.3
12	Pottery and related products	5.1	-5.0
13	Blast furnaces, steelworks, rolling and finishing mills	4.2	-2.8
14	Electrical machinery, equipment, and supplies, n.e.c.	3.9	-3.9
15	Plastics, synthetics, and resins	3.6	-3.6
16	Miscellaneous textile mill products	3.6	-3.6
17	Motor vehicles and motor vehicle equipment	3.3	-3.3
18	Paints, varnishes, and related products	3.1	-3.1
19	Engines and turbines	2.3	-2.3
20	Cycles and miscellaneous transportation equipment	2.3	0.2

Table 3: Most and Least Vulnerable Conspumas (excludes agriculture)

Rank	State	Counties/Cities	$loc\tau^c_{1990}$ (%)	$loc\triangle\tau^c$
		Panel A: Top 20 Most Vulnerable Conspumas		
1	North Carolina	Cleveland, McDowell, Polk, Rutherford	2.65	-2.61
2	North Carolina	Alamance, Randolph	2.62	-2.59
3	Virginia	Danville, Pittsylvania	2.58	-2.54
4	Kentucky	including Adair, Casey, Clinton, Cumberland	2.38	-2.36
5	South Carolina	including Abbeville, Edgefield, Fairfield	2.32	-2.28
6	Pennsylvania	Schuylkill	2.22	-2.15
7	North Carolina	including Alleghany, Ashe, Avery, Mitchell	2.16	-2.11
8	South Carolina	Anderson	2.06	-2.02
9	South Carolina	Oconee, Pickens	2.01	-1.99
10	North Carolina	Cabarrus, Rowan	1.99	-1.96
11	North Carolina	Catawba County	1.99	-1.95
12	Tennessee	including Bledsoe, Bradley, Cannon, Cumberland	1.97	-1.91
13	Missouri	including Douglas, Howell, Oregon, Ozark, Shannon	1.89	-1.56
14	South Carolina	including Cherokee, Chester, Chesterfield, Clarendon	1.85	-1.82
15	North Carolina	Alexander, Burke, Caldwell	1.83	-1.77
16	South Carolina	including Campobello, Chesnee, Cowpens, Greer	1.83	-1.80
17	Georgia	Catoosa, Dade, Walker	1.72	-1.59
18	North Carolina	including Beaufort, Bertie, Carteret, Caswell, Craven	1.55	-1.52
19	Tennessee	including Bedford, Carroll, Chester, Decatur, Fayette	1.54	-1.43
20	Pennsylvania	Clinton, Juniata, Mifflin, Snyder, Union	1.51	-1.40
		Panel B: Top 20 Least Vulnerable Conspumas		
1	D.C.	Washington	0.04	-0.04
2	Virginia	Alexandria	0.04	-0.04
3	Maryland	Calvert, Charles, St. Mary's County	0.05	-0.04
4	Virginia	Arlington	0.05	-0.05
5	Alaska	Anchorage	0.05	-0.05
6	Maryland	including College Park, Hyattsville, Prince George's	0.06	-0.05
7	Alaska	Rest of Alaska	0.06	-0.05
8	Kentucky	Floyd, Johnson, Magoffin, Martin, Pike	0.06	-0.05
9	Virginia	Fairfax County, Fairfax city, Falls Church city	0.06	-0.06
10	Nevada	including Boulder City, Las Vegas, Spring Valley	0.07	-0.07
11	Washington	Kitsap	0.07	-0.07
12	Montana	Yellowstone	0.07	-0.06
13	Maryland	including Bethesda, Montgomery, Rockville	0.08	-0.07
14	Arizona	Apache, Navajo	0.09	-0.09
15	Kansas	including Cheyenne, Decatur, Graham, Russell	0.09	-0.08
16	Wyoming	State of Wyoming	0.09	-0.08
17	Montana	including Blaine, Carbon, Dawson, Glacier, Phillips	0.09	-0.09
18	Florida	Alachua	0.09	-0.09
19	Washington	Thurston	0.10	-0.09
20	New York	including Albany, Loudonville, Roessleville	0.10	-0.09

Table 4: Regression Results
Individual Characteristics

Dependent Variable: Log Wage	Including Agriculture	Excluding Agriculture
Age	0.08***	0.08***
	(0.0002)	(0.0002)
Age squared	-0.001***	-0.001***
	(2.53E-06)	(2.53E-06)
Male	0.51***	0.51***
	(0.001)	(0.001)
Married	0.07***	0.07***
	(0.001)	(0.001)
White	0.16***	0.16***
	(0.001)	(0.001)
English speaking	0.30***	0.30***
	(0.003)	(0.003)
Less than high school	-0.77***	-0.77***
	(0.003)	(0.002)
High school	-0.50***	-0.50***
	(0.002)	(0.002)
Some college	-0.34***	-0.35***
	(0.002)	(0.002)
Less than high school * (Year = 2000)	0.35***	0.36***
	(0.003)	(0.003)
High school * (Year = 2000)	0.35***	0.36***
	(0.002)	(0.002)
Some college * (Year = 2000)	0.37***	0.38***
	(0.002)	(0.002)
College graduate * (Year = 2000)	0.40***	0.40***
	(0.002)	(0.002)

Standard errors in parentheses.

***, ** and * indicate significance at the 1%, 5% and 10% level.

Regression Results (continued)

Location-Specific Controls

	Dependent Variable: Log Wage	Including Agriculture	Excluding Agriculture
Anticipation effect	Less than high school * $loc\tau^c_{1990}$ * (Year = 2000)	51.44***	46.71***
		(6.87)	(6.93)
	High school * $loc\tau^c_{1990}$ * (Year = 2000)	35.43***	33.75***
		(3.76)	(3.77)
	Some college * $loc\tau^c_{1990}$ * (Year = 2000)	32.19***	28.25***
		(4.72)	(4.74)
	College * $loc\tau^c_{1990}$ * (Year = 2000)	-4.40	-5.73
		(5.61)	(5.64)
Impact effect	Less than high school * $loc\triangle\tau^c$ * (Year = 2000)	50.48***	46.51***
		(7.08)	(7.12)
	High school * $loc\triangle\tau^c$ * (Year = 2000)	35.31***	34.45***
		(3.89)	(3.89)
	Some college * $loc\triangle\tau^c$ * (Year = 2000)	32.62***	29.94***
		(4.87)	(4.88)
	College * $loc\triangle\tau^c$ * (Year = 2000)	-3.26	-4.39
		(5.80)	(5.82)
	Less than high school * $loc\tau^c_{1990}$	-31.65***	-33.49***
		(6.32)	(6.36)
	High school * $loc\tau^c_{1990}$	-43.02***	-45.10***
		(5.11)	(5.13)
	Some college * $loc\tau^c_{1990}$	-59.63***	-58.63***
		(5.60)	(5.63)
	Less than high school * $loc\triangle\tau^c$	-26.15***	-28.07***
		(6.52)	(6.54)
	High school * $loc\triangle\tau^c$	-38.55***	-40.84***
		(5.28)	(5.29)
	Some college * $loc\triangle\tau^c$	-55.64***	-55.81***
		(5.78)	(5.80)
	Border * (Year = 2000)	0.007***	0.006***
		(0.003)	(0.003)

Standard errors in parentheses.

***, ** and * indicate significance at the 1%, 5% and 10% level.

Regression Results (continued)

Industry-Specific Controls

	Dependent Variable: Log Wage	Including Agriculture	Excluding Agriculture
Anticipation effect	Less than high school * τ^j_{1990} * (Year = 2000)	-1.02**	-1.37***
		(0.47)	(0.47)
	High school * τ^j_{1990} * (Year = 2000)	-0.78**	-0.83**
		(0.33)	(0.33)
	Some college * τ^j_{1990}* (Year = 2000)	0.46	0.44
		(0.50)	(0.50)
	College * τ^j_{1990} * (Year = 2000)	-0.09	-0.14
		(0.73)	(0.73)
Impact effect	Less than high school * $\triangle\tau^j$ * (Year = 2000)	-0.64	-0.73
		(0.49)	(0.49)
	High school * $\triangle\tau^j$ * (Year = 2000)	-0.58*	-0.56*
		(0.34)	(0.34)
	Some college * $\triangle\tau^j$ * (Year = 2000)	0.69	0.76
		(0.52)	(0.52)
	College * $\triangle\tau^j$ * (Year = 2000)	-0.23	-0.19
		(0.76)	(0.76)
	Less than high school * τ^j_{1990}	2.21***	2.18***
		(0.60)	(0.60)
	High school * τ^j_{1990}	2.59***	2.49***
		(0.57)	(0.57)
	Some college * τ^j_{1990}	0.66	0.52
		(0.63)	(0.63)
	Less than high school * $\triangle\tau^j$	2.13***	2.24***
		(0.62)	(0.62)
	High school * $\triangle\tau^j$	2.76***	2.86***
		(0.59)	(0.59)
	Some college * $\triangle\tau^j$	0.62	0.71
		(0.66)	(0.66)

Standard errors in parentheses.

***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 5: Differences Between Anticipation and Impact Effect

Parameter difference	Point estimate	F Value	Pr > F
$\delta_{2,lhs} - \delta_{4,lhs}$	0.2030	0.21	0.6482
$\delta_{2,hs} - \delta_{4,hs}$	-0.6992	5.94	0.0148
$\delta_{2,scol} - \delta_{4,scol}$	-1.6944	25.95	<.0001
$\delta_{2,col} - \delta_{4,col}$	-1.3483	11.69	0.0006
$\theta_{2,lhs} - \theta_{4,lhs}$	-0.6391	135.26	<.0001
$\theta_{2,hs} - \theta_{4,hs}$	-0.2679	34.05	<.0001
$\theta_{2,scol} - \theta_{4,scol}$	-0.3285	22.08	<.0001
$\theta_{2,col} - \theta_{4,col}$	0.0506	0.27	0.6023

Table 6: Employment Growth Regression Results

Dependent Variable: $\triangle$ in Log Employment of	Including Agriculture	Excluding Agriculture
High School Dropouts		
$loc\tau^c_{1990}$	-117.7***	-122.9***
	(24.10)	(25.49)
$loc\triangle\tau^c$	-114.5***	-116.2***
	(24.76)	(26.03)
High School Graduates		
$loc\tau^c_{1990}$	4.748	4.587
	(10.86)	(11.30)
$loc\triangle\tau^c$	-3.062	-2.254
	(11.18)	(11.58)
Some College Education		
$loc\tau^c_{1990}$	57.23***	57.28***
	(17.78)	(18.49)
$loc\triangle\tau^c$	47.84***	49.12***
	(18.33)	(18.99)
College Graduates		
$loc\tau^c_{1990}$	-2.053	-1.499
	(22.79)	(22.97)
$loc\triangle\tau^c$	-6.267	-5.712
	(23.52)	(23.69)

Standard errors in parentheses. *** indicates significance at the 1% level.

Table 7: Robustness Check: Change in Mexican Import Shares

Dependent Variable: Log Wage	Including Agriculture	Excluding Agriculture
Location-specific controls		
Less than high school * $\triangle M^c$ * (Year = 2000)	-2.06***	-0.45
	(0.38)	(0.39)
High school * $\triangle M^c$ * (Year = 2000)	-0.01	1.20***
	(0.21)	(0.22)
Some college * $\triangle M^c$ * (Year = 2000)	-0.99***	0.24
	(0.22)	(0.23)
College * $\triangle M^c$ * (Year = 2000)	-0.37	-0.15
	(0.27)	(0.28)
Industry-specific controls		
Less than high school * $\triangle M^j$ * (Year = 2000)	-1.02***	-1.08***
	(0.05)	(0.06)
High school * $\triangle M^j$ * (Year = 2000)	-0.56***	-0.60***
	(0.03)	(0.04)
Some college * $\triangle M^j$ * (Year = 2000)	-0.50***	-0.52***
	(0.04)	(0.04)
College * $\triangle M^j$ * (Year = 2000)	-0.10*	-0.07
	(0.05)	(0.05)

Standard errors in parentheses.

***, ** and * indicate significance at the 1%, 5% and 10% level.

Table 8: Conspuma-Year Fixed Effects Regression

Dependent Variable: Coefficient on conspuma-year fixed effects	Including Agriculture	Excluding Agriculture
$loc\tau^c_{1990}$	16.69**	15.81**
	(7.243)	(6.802)
$loc\triangle\tau^c$	15.70**	15.74**
	(7.406)	(6.931)

Standard errors in parentheses. ** indicate significance at the 5% level.