NBER WORKING PAPER SERIES

LOOKING FOR LOCAL LABOR MARKET EFFECTS OF NAFTA

John McLaren
Shushanik Hakobyan

Working Paper 16535
http://www.nber.org/papers/w16535

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
November 2010

This research was supported by the Bankard Fund for Political Economy. For useful comments we thank seminar participants at the University of Virginia and Johns Hopkins University, as well as conference participants at the NBER International Trade and Investment Group, March 2011, the Empirical Investigations in Trade and Investment Conference, Tokyo, March 2011, and the ILO Globalization and Labor Market Outcomes Workshop, Geneva, June 2011. A special vote of thanks is owed to Kala Krishna and Andrew Bernard and to our discussants Carolyn Evans and Avraham Ebenstein. All remaining errors are ours. The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research.

Looking for Local Labor Market Effects of NAFTA
John McLaren and Shushanik Hakobyan
NBER Working Paper No. 16535
November 2010, Revised January 2012
JEL No. F13,F16,J31

ABSTRACT

Using US Census data for 1990-2000, we estimate effects of NAFTA on US wages. We look for effects of the agreement by industry and by geography, measuring each industry's vulnerability to Mexican imports, and each locality's dependance on vulnerable industries. We find evidence of both effects, dramatically lowering wage growth for blue-collar workers in the most affected industries and localities (even for service-sector workers in affected localities). 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.

John McLaren
Department of Economics
University of Virginia
P.O. Box 400182
Charlottesville, VA 22904-4182
and NBER
jmclaren@virginia.edu

Shushanik Hakobyan
Department of Economics
Middlebury College
505 Warner Hall
Middlebury, VT 05753
shakobyan@middlebury.edu

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; see Ruggles et. al. (2010)). 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 conspumas, whose boundaries are the same for both 1990 and 2000. Every worker in the data is identified as living in one of these conspumas, 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 elimination between the three countries, starting in 1994 and continuing for 10 years (with a few tariffs continuing to 15 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

[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.

sample period 1990-2000, but we would not 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 significantly slower wage growth compared to locations that had no protection against Mexico in the first place, particularly for blue-collar workers. For the most heavily NAFTA-vulnerable locations, a high-school dropout would have up to 8 percentage points slower wage growth from 1990 to 2000 compared to the same worker in a location with no initial protection. There is, however, an even larger industry effect, with wage growth in the most protected industries that lose their protection quickly falling 16 percentage points relative to industries that were unprotected to begin with.

To put it in concrete terms, the effect of the NAFTA on most workers and on the average worker is likely close to zero, but for an important minority of workers the effects are very negative. A high-school dropout living in an apparel and footwear dependent small town in South Carolina, even if she is employed in the non-traded sector such as in a diner where she would appear to be immune to trade shocks, would see substantially lower wage growth from 1990 to 2000 than if she were in, for example, College Park, Maryland, as the local workers in tradable sectors that do compete with Mexico start seeking jobs in the non-traded sectors. At the same time, if the same worker had actually been employed in those vulnerable tradables sectors when the agreement was signed, she would be hurt twice, with a much lower wage growth than fellow workers who were already working in the diner. These effects, however, are much smaller – and statistically insignificant – for college-educated workers.

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 input-output linkages, they find small 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 effects on US labor markets, summarized in Burfisher et. al. (2001), and have found only small effects. 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.

A number of studies have isolated effects of imports from a specific geographic origin on domestic labor markets. Bernard, Jensen, and Schott (2006) find that imports from low-wage countries have much more pronounced effects on the survival probabilities of US plants in the same product category than imports from other locations. Ebenstein et. al. (2009) show that offshoring to low-wage countries is associated with reductions in US employment in the same industry, while offshoring to high-wage countries has the opposite effect. Autor, Dorn and Hanson (2011) show that a rise in China's share of imports reduces wages in US localities where employment is concentrated in the affected industries. Although Mexico is not a low-wage country by the definition used in these papers, we do isolate Mexico-specific effects of imports on US workers in a similar manner.

In addition, Kennan and Walker (2011) 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. 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. To turn this into a measure of protection in geographic terms, we compute the initial average tariff in a given location, c, which we interpret as the 'vulnerability' of the location to the NAFTA. We define this similarly to the local average tariff in Topalova (2007), but we take into account that Mexico is not good at producing everything; a high tariff on imports of good j from Mexico makes no difference if Mexico has no comparative advantage in j and will not export it regardless of the tariff. We thus form an average local tariff, averaged across industries weighted by local employment in each industry and also by Mexico's revealed comparative advantage in each industry.

Weighted local average tariff ('vulnerability,' or anticipated local tariff drop) is defined as:

$$loc\tau_{1990}^{c} \equiv \frac{\sum_{j=1}^{N_{ind}} L_{1990}^{cj} RCA^{j} \tau_{1990}^{j}}{\sum_{j=1}^{N_{ind}} L_{1990}^{cj} RCA^{j}}, \tag{1}$$

where L_t^{cj} is the number of workers employed in industry j at conspuma c at date t, N_{ind} is the number of industries, and

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

is Mexico's revealed comparative advantage in j, a slight adaptation of Balassa's (1965) familiar formulation. Here, $x_{j,1990}^{MEX}$ is Mexico's exports of good j to the rest of the world excluding the US (ROW) and $x_{j,1990}^{ROW}$ is total exports of good j from countries excluding the US and Mexico to each other. Therefore, RCA^j is Mexico's share of ROW trade in good j, divided by Mexico's share in total ROW trade. The interpretation is that if $RCA^j > 1$, Mexico has more of a tendency to export j than the average product, and thus has a revealed comparative advantage in good j.

This gives rise to the realized local tariff change: $loc\triangle\tau^{c} \equiv \frac{\sum_{j=1}^{N_{ind}} L_{1990}^{cj} RCA^{j} \triangle\tau^{j}}{\sum_{j=1}^{N_{ind}} L_{1990}^{cj} RCA^{j}}$, where $\triangle\tau^j$ is the change in the tariff on good j imports from Mexico from 1990 to 2000.

Now, 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:

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

where i indexes workers; X_i is a set of individual characteristics; $j(i)$ is the index of worker i's industry; $ind_{i,j}$ 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; $\triangle\tau^j = \tau^j_{2000} - \tau^j_{1990}$; ϵ_i is a random disturbance term; and the α's and θ's are parameters to be estimated.[2]

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

[2] Note that our Census data, which we will describe in detail shortly, take the form of two cross sections rather than a panel. Each individual i in the sample is observed once; some are observed in 1990 and some in 2000.

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 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. This yields the richer regression equation:

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

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, to be consistent, in controlling for the level of protection by industry, we use the product of industry tariff with the revealed comparative advantage, $RCA^j \tau_{1990}^j$. We also allow for a different rate of wage growth for locations on the US-Mexico border, producing our main regression equation:

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

[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.

where $conspuma_{i,c}$ is a dummy variable that takes a value of 1 if worker i resides in conspuma c, $c(i)$ is the index of worker i's conspuma, and $loc\triangle\tau^{c(i)}$ is the change in tariff for location c, as defined at the beginning of this section.

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 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 (with its industries that compete with Mexican imports) would suffer a wage reduction due to NAFTA, while an import-competing worker in Arlington, VA (with only very few workers employed in industries that compete with Mexican imports) 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 workers from age 25 to 64 who report a positive income in the year before the census.[4] We include the personal characteristics age, gender, marital status, whether or not the worker speaks English, race, and educational attainment (less than high school,

[4]The sample includes individuals who report being employed, unemployed or not in labor force in the census year. We use the last industry of employment for the unemployed and those not in labor force.

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. Our sample size is 10,320,274 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.[5] We used Mexican trade data from the US International Trade Commission to obtain a trade-weighted average tariff for each Census industry.[6] To construct Mexico's revealed comparative advantage, RCA^j, we used data on exports by reporting countries from the UN Comtrade.

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)). After multiplying the tariff by RCA^j to correct for Mexico's pattern of comparative advantage, we obtain a product that ranges from 0 to 8.8% (for footwear). The initial average local tariff ranges across conspumas from approximately 0.09 to 4.74%, with a mean just above one 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

[5]Note that only 89 out of the 238 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.

[6]Trade data are obtained from the US International Trade Commission Trade and Tariff DataWeb at http://dataweb.usitc.gov.

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 Table 3 shows those with the highest value of the product of tariff and RCA^j and thus potentially the most vulnerable to NAFTA. The top two are footwear and oil and gas extraction, followed by carpets and rugs and plastics, all in the range of 7 to 8.8%. Comparison of Tables 2 and 3 shows that the correction for Mexican comparative advantage makes a fair amount of difference.[7] 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%). After adjusting for Mexico's revealed comparative advantage, tariffs in these industries still fell the slowest (see Figure 5). Four industries (*Dairy products*; *Cycles and miscellaneous transportation equipment*; *Printing, publishing, and allied industries*; *Agricultural chemicals*) experienced tariff increases between 1990 and 2000.

Table 4 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 with agriculture omitted is used). The list is dominated by manufacturing areas of the Carolinas and southern Virginia. The least vulnerable locations include Washington, D.C. and its suburbs in northern Virginia and Maryland. Figure 5 shows a mostly linear relationship between the 1990 local tariff levels and the decline in local tariffs, but with plenty of variation. The largest differences between the initial local tariff and change in local tariff are observed in a conspuma in the state of Indiana (initial tariff is 3.32%; the change in tariff is -2.26%). 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.

[7] An earlier draft did not correct for Mexican comparative advantage at all. The results were qualitatively similar, but for the location variables the impact and anticipatory effects were larger, and the net effect was much smaller. Those details are available on request.

5 Results

Table 5 shows the results for the main regression with all right-hand-side variables and industry and conspuma fixed effects. This is the estimation of equation (4), with clustering of standard errors by conspuma, industry, and year, following Cameron, Gelbach and Miller (2006). 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 as 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 6, 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 10.28 for $\delta_{2,lhs}$ and 12.12 for $\delta_{4,lhs}$. Note first that the impact effect is larger than the anticipatory effect, and Table 6 shows that $\delta_{2,lhs} - \delta_{4,lhs}$ takes a value of -1.84, with a high level of significance. In other words, among conspumas that lost their protection quickly under NAFTA, those that appeared to be very vulnerable had substantially lower wage growth for high-school dropouts than those with low initial tariffs. Recalling that the most vulnerable conspumas had an initial local average tariff in the neighborhood of 4 or 5, this implies a drop in wage growth of around 8 percentage points in such a conspuma, a very substantial difference. Second, note that each of these terms individually is also very different from zero. The positive sign on the coefficient for the tariff change (12.12) 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 a conspuma with a 4% initial local average tariff, this anticipatory effect amounts to an increase in wage growth for high-school dropouts relative to the rest of the economy equal to 40 percentage points.

Similar comments apply for high-school graduates and for workers with some college but with smaller magnitudes, while college graduates show much smaller coefficients, as well as anticipatory and impact effects of opposite sign.

Briefly, the effect of the dummy for location on the Mexican border is both statistically insignificant and economically minuscule, implying half a 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 5, 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 6, 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). Recall that the most highly-protected industries had an initial value of tariff times RCA in the neighborhood of 8%; high-school dropouts in such an industry, if it lost its protection right away, would see wage growth 16 percentage points lower than similar workers in an industry that had had no protection. Again, the effect is much smaller for those with some college, and negligible (as well as statistically insignificant) for college graduates.

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 industry wage differences away.[8] 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. In addition, we find, for blue collar workers, a significant 'Youngstown' effect in the data: More vulnerable locations that lost their tariffs quickly had smaller wage growth compared with locations that had no NAFTA vulnerability at all, controlling for a broad range of personal

[8]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.

characteristics. 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 7. 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. The only significant coefficients are for high-school dropouts, and the main message is that a conspuma with a high level of protection tended to lose high-school dropouts over the 1990's relative to other conspumas whether the conspuma lost its protection right away (since $-43.20 + 38.49 < 0$) or merely anticipated losing it (since $-43.20 < 0$). This can be also seen in Figure 8, which plots the change in employment shares for each education class against initial local tariff. The figure shows that highly vulnerable conspumas tended to shed high-school dropouts over the 1990's.

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, 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.[9]

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 (with parallels in Ebenstein et. al. (2009) and Autor, Dorn and Hanson (2011)). 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 the Mexican tariff, we calculate this measure with and without agriculture by setting the change in Mexican import

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

share to zero for agricultural products. Figure 9 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 main results are shown in Table 8 (we suppress all coefficient estimates except for the interactions with the change in import share and year-2000 dummy, since those are the coefficients of interest).

In this regression the location effects essentially disappear. The location coefficients are mostly statistically insignificant, and the point estimates multiplied by even the largest change in location-average import share are economically negligible ($-0.46 \times 3.44\% = -1.58\%$ for high-school dropouts, for example, meaning less than 2 percentage points of reduced wage growth over 10 years for the most heavily-affected worker). The industry results, however, come out more strongly than in the tariff regression. 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% (an increase of 10 percentage points, about one standard deviation above the mean increase; 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 Controlling for trade with China

Autor, Dorn and Hanson (2011) show that increases in imports from China are correlated with reductions in employment and wages in the local US labor markets that are dependent on the industries whose imports are increasing. The effects of trade with China are substantial. A reader might be concerned that these increases in trade with China might be correlated with increases in trade or reductions in tariffs with Mexico. We therefore re-run the regression to control for Chinese imports. We add two variables to our basic regression: the share of imports for each industry that comes from China, and the employment-weighted local average of this share for each conspuma. We interact the first difference of both of these variables with the education class and year-2000 dummies. The results for the main coefficients of interest are listed in Tables 9 and 10. These correspond to Tables 5 and 6; again, only coefficients of interest are included. (The coefficients on Chinese import shares generally show that a higher rate of increase in that import share is correlated with lower wage growth. Full results are available from the authors on request.)

It is clear from Tables 9 and 10 that the results are barely affected by including trade with China. Trade with China and the NAFTA appear to have had quite separate, distinguishable effects.

7.3 Limiting the sample to service-sector workers

In interpreting the main regression results, we have interpreted the coefficients on the location variables as telling us about what happens to a worker who is not in the tradable sector but employed in close proximity to workers who are. In Table 11, we scrutinize that interpretation by limiting our sample only to workers in the service sector and running the main regression again. Of course, the industry-specific variables cannot be used in this exercise (apart from industry fixed effects), since those are all derived from tariffs, which do not apply to services. Again, standard errors are clustered by industry, conspuma and year.

Comparing the last four lines of Table 11 with Table 6 shows almost identical coefficients. The table therefore confirms that local labor market effects do indeed apply to workers who are not employed in the tradable sector. Thus, a worker waiting on tables in a town heavily dependent on NAFTA-vulnerable jobs, although he or she is not employed in an industry producing tradable output, is nonetheless harmed indirectly by NAFTA, plausibly due to workers who are in a contracting tradables industry and seek employment in local non-traded industries, pushing those wages down.

7.4 Employment effects

To this point, we have focussed on the wage effects of NAFTA. Here we explore effects on employment status. Table 12 reports the results from a linear probability model (Columns 1 and 2) and a logistic regression (Columns 3 and 4) for the determinants of the probability that a worker is unemployed (Columns 1 and 3) or not in the labor force (NILF; Columns 2 and 4). The right-hand-side variables are the same as in the main regression, and are arranged in the same way as in Table 5, so the first four rows can be interpreted as the 'anticipatory' effect, with the following four rows the 'impact' effect, and so on. Unfortunately, our data do not have as clear a story to tell on these employment issues as on wages. Ideally, we would have panel data for these questions, to see how each worker's employment status changes from 1990 to 2000, conditional on the worker's industry and location in 1990, but for a worker in 2000, we can condition only on year-2000 industry and location. Since it is likely that many workers have switched industry or moved in the intervening years, a decision influenced by trade policy as confirmed in Table 7, we are likely to be missing much of the story.

The NILF results are the most informative. Focussing on the estimated coefficients from the logistic model, the NILF coefficients in the top panel are all negative, with the coefficient for the 'anticipatory' effect for each educational category smaller in magnitude than the corresponding coefficient for the 'impact' effect (this is not true, however, for high-school dropout results in the linear probability model). The findings are the same for the other educational classes, and the pattern is broadly similar for unemployment (except for college graduates), but generally not statistically significant.

However, these estimates imply a truly negligible marginal effect of the tariff on the probability of being in the labor force, and a very small effect on unemployment. To illustrate this, we set the values of all right-hand side variables equal to their sample averages, and focus on the case of high-school dropouts for concreteness. Define a 'high' local tariff as the average local tariff (1.03% from Table 1) plus one standard deviation (0.67%, from Table 1). Call a conspuma 'high-impact' ('average impact') if it had a high (an average) initial tariff and lost all of its tariff by 2000. We can then use the estimated parameters to compute the probability of being NILF or unemployed at each date. The outcome of this calculation is that the change between 1990 and 2000 in the probability of being out of the labor force is only 0.07 percentage points higher in a high-impact conspuma than in an average conspuma (for the linear probability model, the corresponding figure is 0.08 of a percentage point in the other direction). The change between 1990 and 2000 in the probability of being unemployed is only 0.32 percentage points higher in a high-impact conspuma than in an average conspuma (for the linear probability model, the figure is 0.34 of a percentage point). These figures are small enough to treat as zero for practical purposes.

The industry effects are listed in the bottom half of the table. The overall story for the not-in-labor-force column is similar (while not precisely estimated) in that the impact effect dominates the anticipatory effect in each case, implying that workers in highly-protected industries that lost protection were more likely to leave the labor force. Defining the 'high' industry tariff to be the average industry tariff plus one standard deviation (as always, multiplying with the revealed comparative advantage term), we can compute the marginal effects of the tariffs. Call an industry 'high-impact' ('average impact') if it had a high (average) initial tariff and lost it all by 2000. The change between 1990 and 2000 in the probability of a high-school dropout being out of the labor force is 2.1 percentage points higher in a high-impact industry than in an average industry (for the linear probability model, the corresponding figure is 0.72 of a percentage point). By contrast, for all but high-school dropouts, the effect works in the opposite direction for unemployment, but the magnitudes are very small. For example, for the linear probability model, the change between 1990 and 2000 in the probability of being unemployed for a high-school graduate is 0.30 of a percentage point less for a high-tariff industry than for an average-tariff one (conditional on the worker still being in the same conspuma and not having switched industries).

Overall, no strong message regarding employment effects emerges from these data, which is not surprising due to our inability to follow workers over time. The exception is modest evidence that high-impact industries saw a substantial rise in the likelihood that workers would leave the labor market.

7.5 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.[10] 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.

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. We find that reductions in the local average tariff are associated with substantial reductions in the locality's blue-collar wages, even for workers in the service sector, while a reduction in the tariff of the industry of employment generates additional substantial wage losses. In other words, found both a 'Youngstown' effect and 'textile' effect or a 'footwear' effect. The blue-collar diner worker in the footwear town is hurt by the agreement, as is the blue-collar footwear-factory worker in a town dominated with insurance companies. Worst hit of all is the blue-collar footwear worker in a footwear town, particularly if that worker never finished high school. College-educated workers skate away mainly unharmed.

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.

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

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 characterized by large redistributional effects and modest 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).

References

[1] Artuç, Erhan, Shubham Chaudhuri, and John McLaren (2008). "Delay and Dynamics in Labor Market Adjustment: Simulation Results." *Journal of International Economics* 75:1, pp. 1-13.

[2] ________ (2010). "Trade Shocks and Labor Adjustment: A Structural Empirical Approach." *American Economic Review* 100:3 (June), pp. 1008-1045.

[3] Austen, Ian (2008). "Trade Pact Controversy in Democratic Race Reaches Into Canadian Parliament." *The New York Times*, March 7.

[4] Autor, David H., David Dorn, and Gordon H. Hanson (2011). "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." Mimeo, February 2011.

[5] Balassa, Bela (1965). "Trade Liberalization and 'Revealed' Comparative Advantage." *The Manchester School* 33, pp. 99-123.

[6] Bernard, Andrew B., J. Bradford Jensen, and Peter K. Schott (2006). "Survival of the Best Fit: Exposure to Low-wage Countries and the (Uneven) Growth of U.S. Manufacturing Plants." *Journal of International Economics* 68, pp. 219-37.

[7] Brown, Sherrod (2004). *Myths of Free Trade: Why American Trade Policy has Failed.* New York: The New Press.

[8] Burfisher, Mary E., Sherman Robinson, and Karen Thierfelder (2001). "The Impact of NAFTA on the United States." *Journal of Economic Perspectives* 15:1 (Winter), pp. 125-144.

[9] Caliendo, Lorenzo and Fernando Parro (2009). "Estimates of the Trade and Welfare Effects of NAFTA." Working Paper, University of Chicago.

[10] Cameron, A. Colin, Gelbach, Jonah B., Miller, Douglas L. (2006). "Robust inference with multi-way clustering." NBER Technical Working Paper 0327.

[11] Duggan, Paul (1999). "NAFTA a Mixed Blessing for Laredo." *Washington Post*, Sunday, April 18, p. A17.

[12] Ebenstein, Avraham, Ann Harrison, Margaret McMillan, and Shannon Phillips (2009). "Estimating the Impact of Trade and Offshoring on American Workers Using the Current Population Surveys." NBER Working Paper 15107.

[13] Feenstra, Robert C., John Romalis, and Peter K. Schott (2002). "U.S. Imports, Exports, and Tariff Data, 1989-2001." NBER Working Paper 9387.

[14] Fukao, Kyoji, Toshihiro Okubo, and Robert Stern (2003). "An Econometric Analysis of Trade Diversion under NAFTA." *North American Journal of Economics and Finance* 14:1 (March), pp. 3-24.

[15] Gould, D. (1998). "Has NAFTA Changed North American Trade?" *Federal Reserve Bank of Dallas Economic Review*, First Quarter, pp. 12-23.

[16] Hakobyan, Shushanik (2010). "Accounting for Underutilization of Trade Preference Programs: U.S. Generalized System of Preferences." Mimeo, University of Virginia.

[17] Hanson, Gordon H. (2007). "Globalization, Labor Income, and Poverty in Mexico," in Ann Harrison (ed.), *Globalization and Poverty*. Chicago: University of Chicago Press.

[18] Harrison, Ann, John McLaren, and Margaret S. McMillan (2010). "Recent Findings on Trade and Inequality." NBER Working Paper 16425.

[19] Hosios, Arthur J. (1990). "Factor Market Search and the Structure of Simple General Equilibrium Models." *Journal of Political Economy* 98:2 (April), pp. 325-355.

[20] Hufbauer, Gary Clyde and Jeffrey J. Schott (2005). *NAFTA Revisited: Achievements and Challenges.* Washington, D.C.: Institute for International Economics.

[21] Kennan, John and James R. Walker (2011). "The Effect of Expected Income on Individual Migration Decisions." *Econometrica* 79:1 (January), pp. 211-251.

[22] Kovak, Brian K. (2010). "Regional Labor Market Effects of Trade Policy: Evidence from Brazilian Liberalization." Working Paper, Carnegie Mellon University.

[23] Kumar, Anil (2006). "Did NAFTA Spur Texas Exports?" *Southwest Economy* (Federal Reserve Bank of Dallas), March/April, pp. 3-7.

[24] Leonhardt, David (2008). "The Politics of Trade in Ohio." *The New York Times*, February 27.

[25] Pavcnik, Nina, Orazio Attanasio and Pinelopi Goldberg (2004). "Trade Reforms and Income Inequality in Colombia." *Journal of Development Economics* 74 (August), pp. 331-366.

[26] Prina, Silvia (2009(a)). "Who Benefited More from NAFTA: Small or Large Farmers? Evidence from Mexico." Working Paper, Department of Economics, Case Western Reserve University.

[27] ________ (2009(b)). "Effects of NAFTA on Agricultural Wages and Employment in Mexico." Case Western Reserve University.

[28] Revenga, Ana L. (1992). "Exporting Jobs?: The Impact of Import Competition on Employment and Wages in U.S. Manufacturing." *Quarterly Journal of Economics* 107:1 (February), pp. 255-284.

[29] Rodrik, Dani (1994). "The Rush to Free Trade in the Developing World: Why So Late? Why Now? Will It Last?" in Stephan Haggard and Steven B. Webb, (eds.), *Voting for Reform: Democracy, Political Liberalization, and Economic Adjustment*. New York, NY: Oxford University Press.

[30] Romalis, John (2007). "NAFTA's and CUSFTA's Impact on International Trade." *Review of Economics and Statistics* 89:3 (August), pp. 416-435.

[31] Ruggles, Steven, J. Trent Alexander, Katie Genadek, Ronald Goeken, Matthew B. Schroeder and Matthew Sobek (2010). Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]. Minneapolis: University of Minnesota.

[32] Sethupathy, Guru (2009). "Offshoring, Wages, and Employment: Theory and Evidence." Working Paper, Johns Hopkins University.

[33] Topalova, Petia (2007). "Trade Liberalization, Poverty and Inequality: Evidence from Indian Districts." Chapter 7 in Ann Harrison (ed.) *Globalization and Poverty*. Chicago: University of Chicago Press, pp. 291-336.

[34] Trefler, Daniel (2004). "The Long and Short of the Canada-U.S. Free Trade Agreement." *American Economic Review* 94:4 (September), pp. 870-895.

Figure 1: An Unanticipated Tariff Elimination

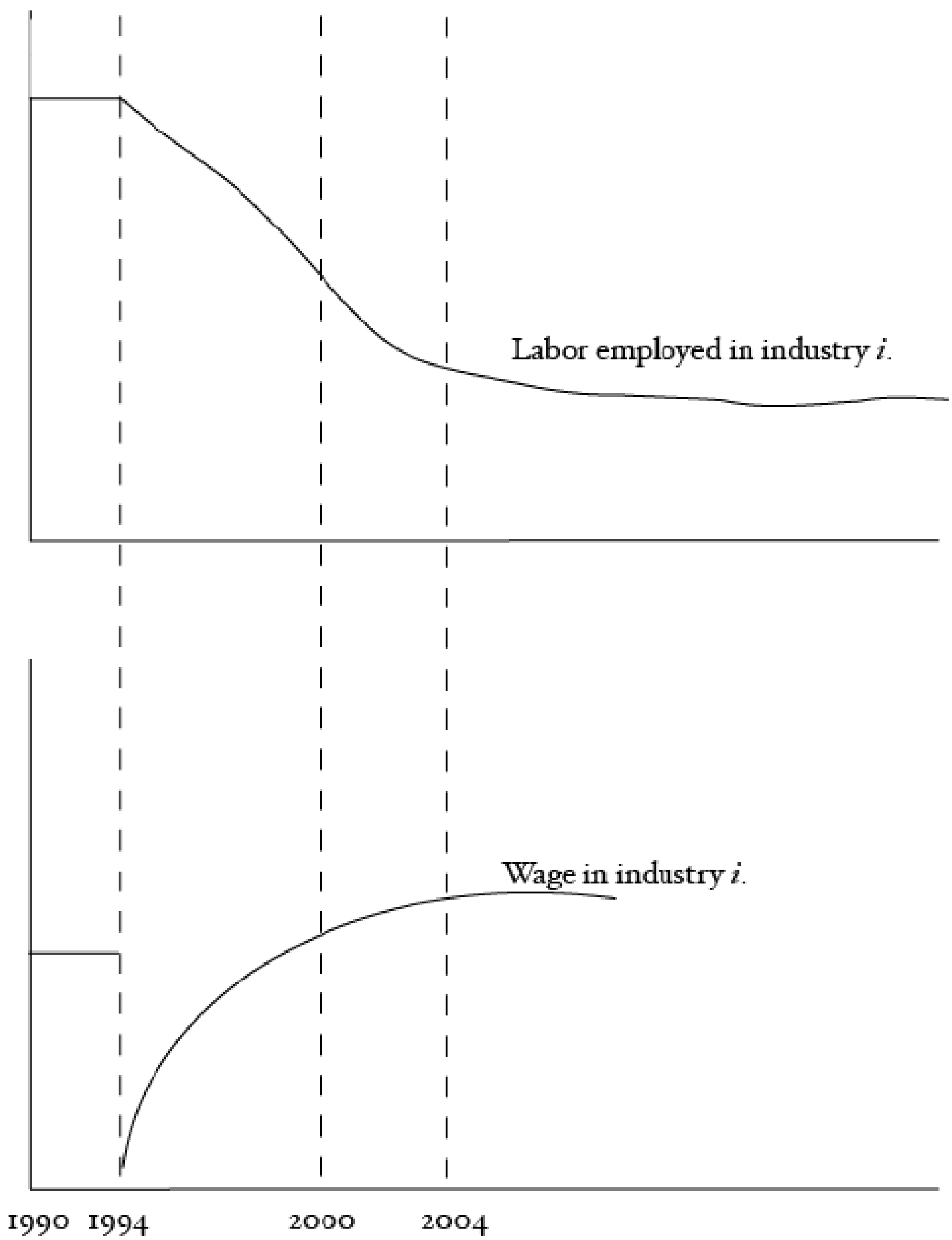


Figure 2: An Anticipated Tariff Elimination

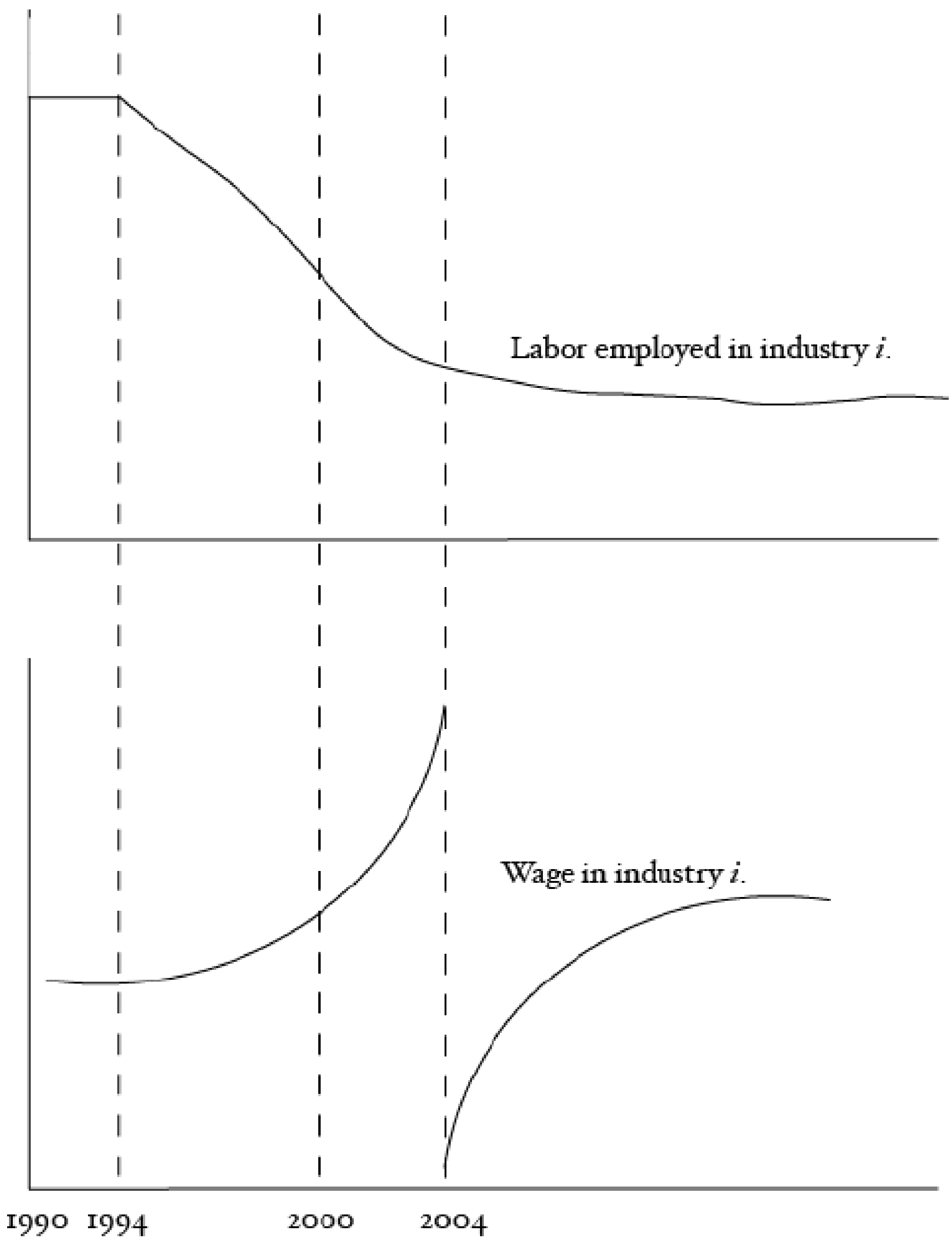
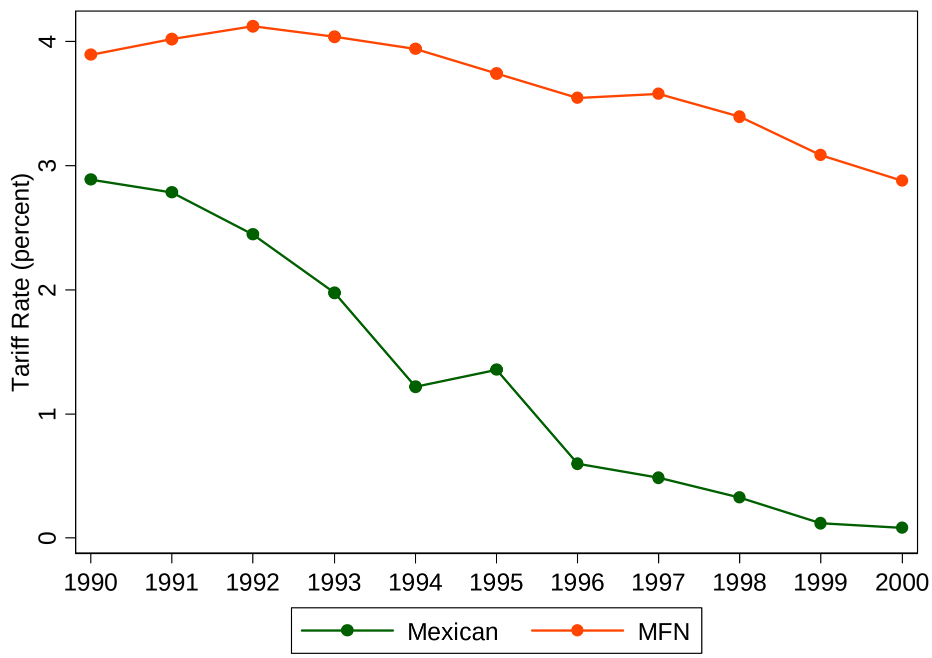


Figure 3: Evolution of Tariffs



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

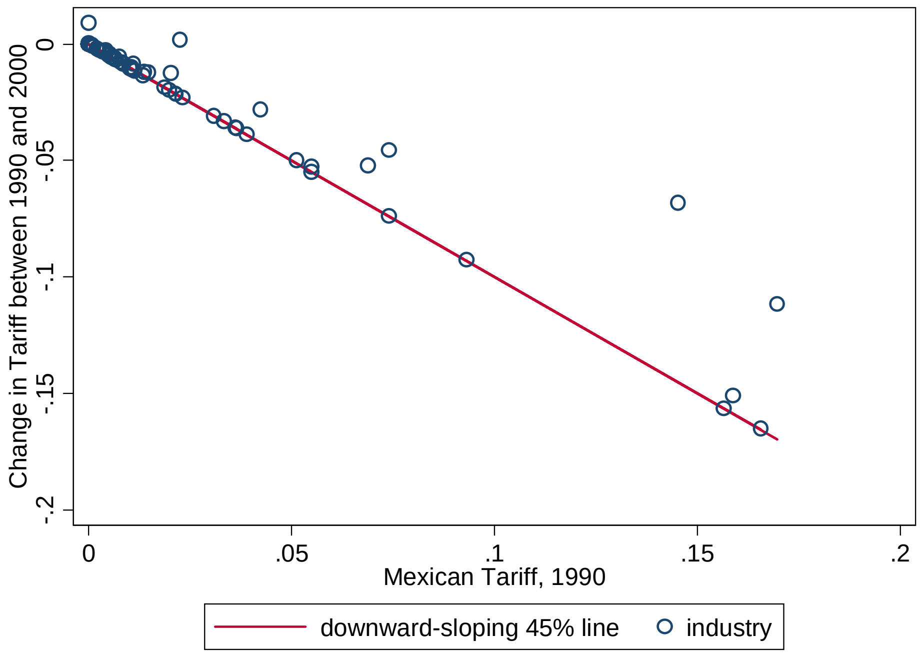


Figure 5: RCA-adjusted Industry Tariff in 1990 and Tariff Decline

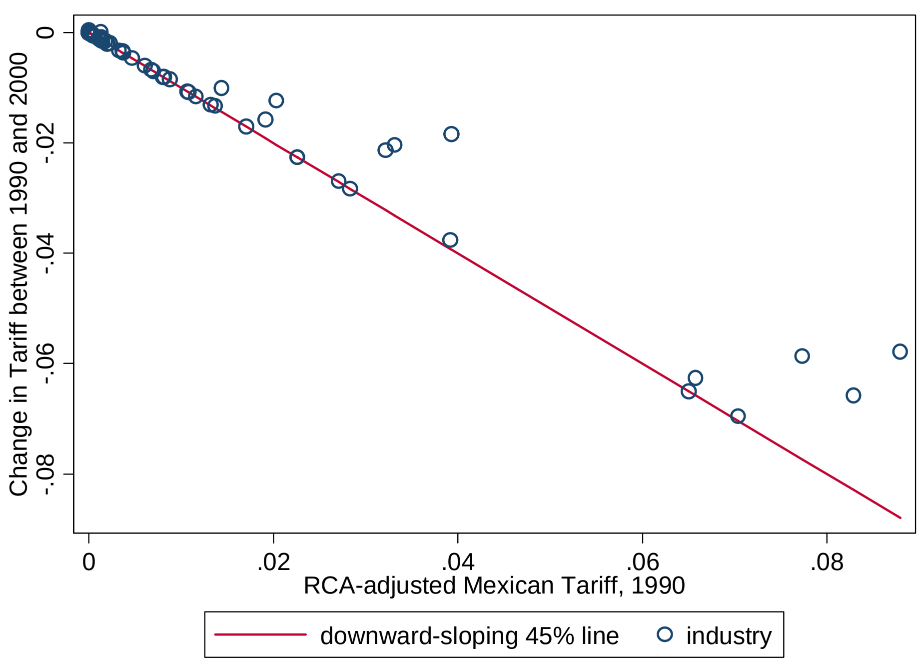
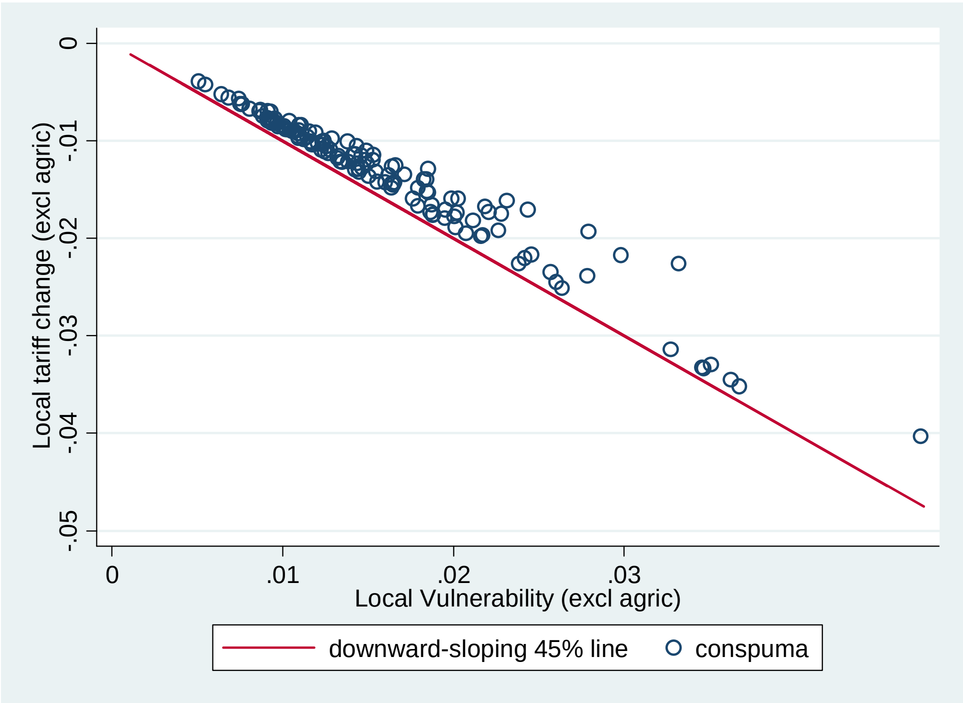
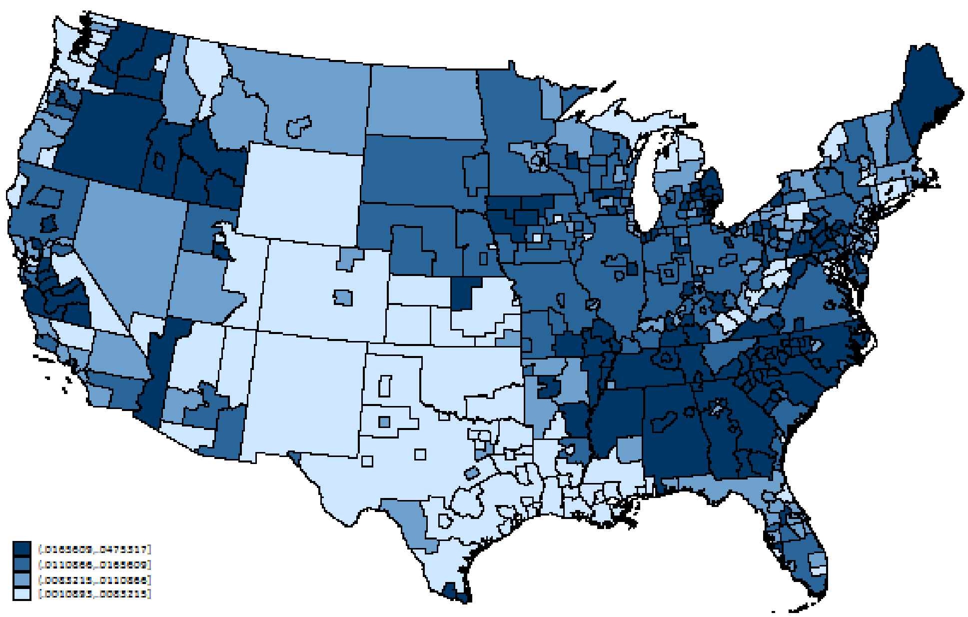


Figure 6: Local Tariff in 1990 and Local Tariff Decline

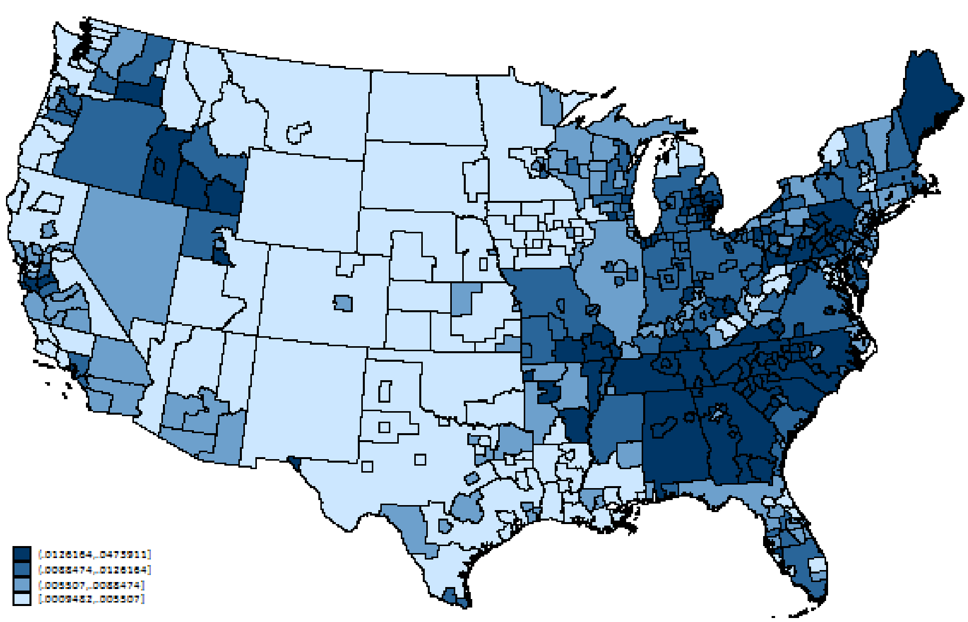


Note: Only conspumas with $loc\tau^c_{1990} - |loc\triangle\tau^c| > 0.0012$ are plotted. Excludes agriculture.

Figure 7: Variation in Local Vulnerability

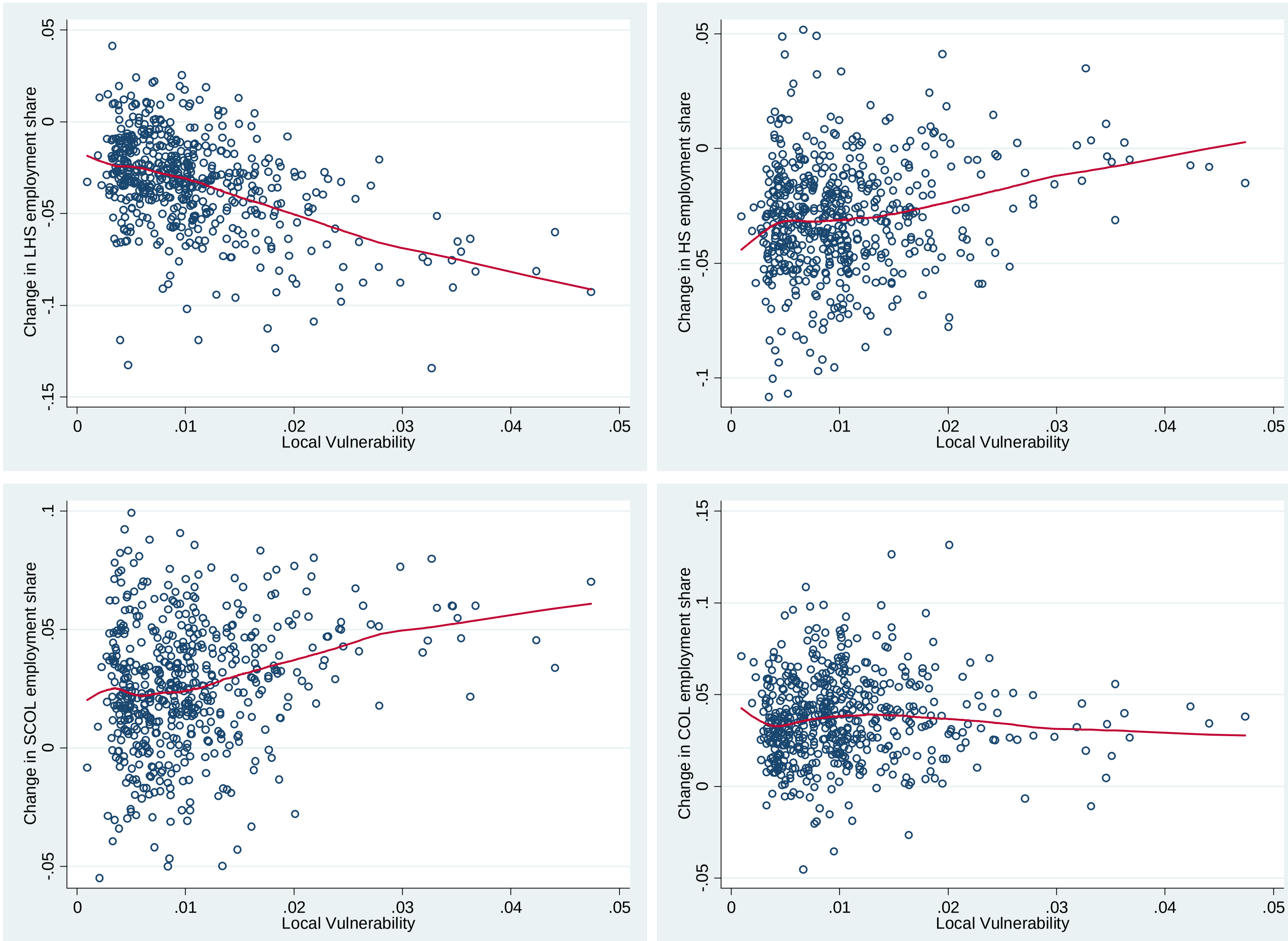


(includes agriculture)



(excludes agriculture)

Figure 8: Change in Employment Shares by Education Group



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

Figure 9: Change in Mexican Import Share and Initial Share in 1990

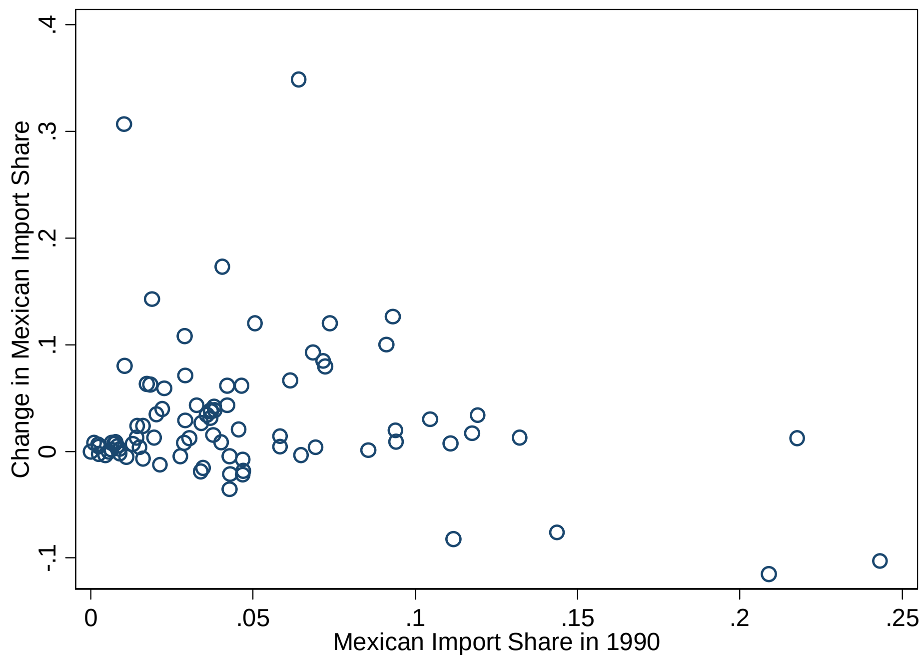


Table 1: Summary Statistics

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
$\triangle\tau^j$ (%)	-1.8	3.4	-16.5	0.9
RCA_{1990}	0.8	2.5	0	22.1
$RCA\tau^j_{1990}$ (%)	1.0	2.0	0	8.8
$RCA\triangle\tau^j$ (%)	-0.9	1.7	-7.0	0.04
$\triangle M^j$ (%)	2.9	6.5	-11.5	34.9
Conspuma-level (excludes agriculture)				
$loc\tau^c_{1990}$(%)	1.03	0.67	0.09	4.74
$loc\triangle\tau^c$ (%)	-0.92	0.61	-4.30	-0.08
$\triangle M^c$(%)	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: Top 20 Most Protected Industries in 1990 (adjusted for RCA)

Rank	Industry Name	$RCA\tau^j_{1990}$ (%)	$RCA\triangle\tau^j$
1	Footwear, except rubber and plastic	8.8	-5.8
2	Oil and gas extraction	8.3	-6.6
3	Carpets and rugs	7.7	-5.9
4	Plastics, synthetics, and resins	7.0	-7.0
5	Canned, frozen, and preserved fruits and vegetables	6.6	-6.3
6	Dyeing and finishing textiles, except wool and knit goods	6.5	-6.5
7	Structural clay products	3.9	-1.8
8	Agricultural production, crops	3.9	-3.8
9	Leather products, except footwear	3.3	-2.0
10	Blast furnaces, steelworks, rolling and finishing mills	3.2	-2.1
11	Knitting mills	2.8	-2.8
12	Yarn, thread, and fabric mills	2.7	-2.7
13	Nonmetallic mining and quarrying, except fuels	2.3	-2.3
14	Engines and turbines	2.3	-2.3
15	Glass and glass products	2.0	-1.2
16	Beverage industries	1.9	-1.6
17	Apparel and accessories, except knit	1.7	-1.7
18	Industrial and miscellaneous chemicals	1.4	-1.0
19	Pottery and related products	1.4	-1.3
20	Motor vehicles and motor vehicle equipment	1.3	-1.3

Table 4: 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	Georgia	Catoosa, Dade, Walker	4.74	-4.04
2	North Carolina	Alamance, Randolph	4.41	-4.30
3	South Carolina	Oconee, Pickens	4.24	-4.12
4	South Carolina	including Cherokee, Chester, Chesterfield, Clarendon	3.67	-3.52
5	South Carolina	Anderson	3.62	-3.45
6	North Carolina	Cabarrus, Rowan	3.54	-3.45
7	North Carolina	Alexander, Burke, Caldwell	3.51	-3.30
8	South Carolina	including Abbeville, Edgefield, Fairfield	3.47	-3.33
9	North Carolina	Cleveland, McDowell, Polk, Rutherford	3.46	-3.32
10	Indiana	Gary	3.32	-2.26
11	Virginia	Danville, Pittsylvania	3.27	-3.14
12	North Carolina	Catawba	3.23	-3.15
13	South Carolina	Spartanburg	3.19	-3.07
14	Missouri	including Douglas, Howell, Oregon, Ozark, Shannon	2.98	-2.17
15	Indiana	Hammond, Whiting, East Chicago	2.79	-1.93
16	Georgia	including Appling, Baldwin, Banks, Barrow, Bartow	2.78	-2.39
17	Michigan	Flint	2.71	-2.67
18	North Carolina	including Alleghany, Ashe, Avery, Mitchell	2.64	-2.51
19	South Carolina	including Greenville, Greer, Mauldin, Simpsonville	2.60	-2.45
20	Pennsylvania	Schuylkill	2.57	-2.35
Panel B: Top 20 Least Vulnerable Conspumas				
1	D.C.	Washington	0.09	-0.08
2	Washington	Kitsap	0.19	-0.17
3	Virginia	Arlington	0.21	-0.18
4	Maryland	Calvert, Charles, St. Mary's County	0.23	-0.19
5	Montana	including Flathead, Lincoln, Missoula, Ravalli	0.27	-0.24
6	Maryland	including College Park, Hyattsville, Prince George's	0.28	-0.25
7	Virginia	Alexandria	0.29	-0.26
8	Montana	including Big Horn, Blaine, Carter, Chouteau	0.30	-0.24
9	South Dakota	including Aurora, Beadle, Bennett, Brule, Buffalo	0.30	-0.28
10	Iowa	Calhoun, Hamilton, Humboldt, Pocahontas, Webster	0.30	-0.28
11	Washington	Whatcom	0.32	-0.28
12	Montana	Yellowstone	0.32	-0.26
13	Oregon	Clatsop, Columbia, Lincoln, Tillamook	0.32	-0.28
14	California	Humboldt	0.33	-0.28
15	Kansas	including Clark, Finney, Ford, Grant, Gray, Wichita	0.33	-0.26
16	Kansas	including Cheyenne, Decatur, Graham, Russell	0.33	-0.26
17	Virginia	Fairfax County, Fairfax city, Falls Church city	0.33	-0.31
18	Oregon	Jackson	0.33	-0.29
19	South Dakota	including Brookings, Clark, Codington, Hamlin	0.33	-0.31
20	North Dakota	including Adams, Barnes, Benson, Billings, Burke	0.34	-0.28

Table 5: Regression Results
Individual Characteristics

Dependent Variable: Log Wage	Including Agriculture	Excluding Agriculture
Age	0.08***	0.08***
	(0.004)	(0.004)
Age squared	-0.001***	-0.001***
	(4.05e-05)	(4.08e-05)
Male	0.51***	0.51***
	(0.062)	(0.063)
Married	0.069***	0.069***
	(0.02)	(0.021)
White	0.16***	0.16***
	(0.016)	(0.016)
English speaking	0.30***	0.30***
	(0.021)	(0.022)
Less than high school	-0.78***	-0.78***
	(0.031)	(0.039)
High school	-0.51***	-0.51***
	(0.032)	(0.039)
Some college	-0.35***	-0.36***
	(0.030)	(0.036)
Less than high school * (Year = 2000)	0.36***	0.38***
	(0.016)	(0.017)
High school * (Year = 2000)	0.36***	0.37***
	(0.008)	(0.008)
Some college * (Year = 2000)	0.38***	0.39***
	(0.012)	(0.012)
College graduate * (Year = 2000)	0.40***	0.40***
	(0.016)	(0.019)

Standard errors in parentheses, clustered by conspuma, industry and year.

*** indicates significance at the 1% 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)	8.49***	10.28***
		(1.598)	(1.594)
	High school * $loc\tau^c_{1990}$ * (Year = 2000)	4.07***	5.91***
		(0.778)	(0.752)
	Some college * $loc\tau^c_{1990}$ * (Year = 2000)	-1.016	1.50**
		(0.652)	(0.656)
	College * $loc\tau^c_{1990}$ * (Year = 2000)	-5.74*	-5.30
		(3.024)	(3.368)
Impact effect	Less than high school * $loc\triangle\tau^c$ * (Year = 2000)	8.97***	12.12***
		(1.574)	(1.525)
	High school * $loc\triangle\tau^c$ * (Year = 2000)	3.96***	7.05***
		(0.843)	(0.950)
	Some college * $loc\triangle\tau^c$ * (Year = 2000)	-1.23*	3.15***
		(0.679)	(0.824)
	College * $loc\triangle\tau^c$ * (Year = 2000)	-5.09*	-4.34
		(3.052)	(3.359)
	Less than high school * $loc\tau^c_{1990}$	-20.55***	-19.95***
		(3.751)	(3.999)
	High school * $loc\tau^c_{1990}$	-19.29***	-18.92***
		(3.387)	(3.534)
	Some college * $loc\tau^c_{1990}$	-14.02***	-15.50***
		(2.767)	(3.024)
	Less than high school * $loc\triangle\tau^c$	-21.15***	-20.16***
		(3.623)	(4.105)
	High school * $loc\triangle\tau^c$	-18.90***	-18.29***
		(3.017)	(3.442)
	Some college * $loc\triangle\tau^c$	-12.95***	-15.62***
		(2.260)	(2.896)
	Border * (Year = 2000)	0.005	0.001
		(0.016)	(0.017)

Standard errors in parentheses, clustered by conspuma, industry and year.

***, ** 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 * $RCA\tau^j_{1990}$ * (Year = 2000)	-3.90	2.21
		(2.956)	(1.540)
	High school * $RCA\tau^j_{1990}$ * (Year = 2000)	-2.19	-0.27
		(2.146)	(1.856)
	Some college * $RCA\tau^j_{1990}$* (Year = 2000)	-2.09	0.15
		(1.933)	(1.603)
	College * $RCA\tau^j_{1990}$ * (Year = 2000)	-2.93	-1.21
		(2.280)	(2.345)
Impact effect	Less than high school * $RCA\triangle\tau^j$ * (Year = 2000)	-4.68	4.28**
		(4.133)	(1.700)
	High school * $RCA\triangle\tau^j$ * (Year = 2000)	-2.14	0.67
		(2.685)	(2.140)
	Some college * $RCA\triangle\tau^j$ * (Year = 2000)	-1.87	1.36
		(2.487)	(1.906)
	College * $RCA\triangle\tau^j$ * (Year = 2000)	-3.21	-0.98
		(2.803)	(3.024)
	Less than high school * $RCA\tau^j_{1990}$	0.60	3.15
		(2.473)	(2.411)
	High school * $RCA\tau^j_{1990}$	1.69	5.20*
		(2.774)	(2.724)
	Some college * $RCA\tau^j_{1990}$	-1.58	2.01
		(2.147)	(1.868)
	Less than high school * $RCA\triangle\tau^j$	1.29	4.50
		(3.290)	(3.287)
	High school * $RCA\triangle\tau^j$	1.94	6.61*
		(3.522)	(3.429)
	Some college * $RCA\triangle\tau^j$	-1.98	2.78
		(2.982)	(2.603)

Standard errors in parentheses, clustered by conspuma, industry and year.

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

Table 6: Differences Between Anticipation and Impact Effect

Parameter difference	Point estimate	F Value	Pr > F
$\delta_{2,lhs} - \delta_{4,lhs}$	-1.843	10.39	0.001
$\delta_{2,hs} - \delta_{4,hs}$	-1.139	13.31	<0.001
$\delta_{2,scol} - \delta_{4,scol}$	-1.646	10.79	0.001
$\delta_{2,col} - \delta_{4,col}$	-0.957	1.23	0.27
$\theta_{2,lhs} - \theta_{4,lhs}$	-2.066	16.46	<0.001
$\theta_{2,hs} - \theta_{4,hs}$	-0.939	4.40	0.036
$\theta_{2,scol} - \theta_{4,scol}$	-1.206	6.12	0.013
$\theta_{2,col} - \theta_{4,col}$	-0.228	0.07	0.791

Table 7: Employment Growth Regression Results

Dependent Variable: $\triangle$ in Log Employment of	Including Agriculture	Excluding Agriculture
High School Dropouts		
$loc\tau^c_{1990}$	-50.20***	-43.20***
	(8.667)	(8.696)
$loc\triangle\tau^c$	-50.68***	-38.49***
	(9.494)	(9.236)
High School Graduates		
$loc\tau^c_{1990}$	-3.069	-1.473
	(4.009)	(4.232)
$loc\triangle\tau^c$	-6.701	-3.302
	(4.256)	(4.529)
Some College Education		
$loc\tau^c_{1990}$	8.312	10.56
	(6.649)	(6.973)
$loc\triangle\tau^c$	3.254	8.094
	(7.009)	(7.355)
College Graduates		
$loc\tau^c_{1990}$	-8.176	-7.969
	(7.923)	(8.056)
$loc\triangle\tau^c$	-11.65	-10.79
	(8.402)	(8.631)

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

Table 8: 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)	-2.05***	-0.45
	(0.48)	(0.48)
High school * $\triangle M^c$ * (Year = 2000)	-0.01	1.20***
	(0.13)	(0.17)
Some college * $\triangle M^c$ * (Year = 2000)	-0.99***	0.23
	(0.15)	(0.15)
College * $\triangle M^c$ * (Year = 2000)	-0.36	-0.14
	(0.33)	(0.42)
Industry-specific controls		
Less than high school * $\triangle M^j$ * (Year = 2000)	-1.01***	-1.07***
	(0.10)	(0.09)
High school * $\triangle M^j$ * (Year = 2000)	-0.56***	-0.60***
	(0.10)	(0.08)
Some college * $\triangle M^j$ * (Year = 2000)	-0.50***	-0.52***
	(0.10)	(0.10)
College * $\triangle M^j$ * (Year = 2000)	-0.10	-0.07
	(0.20)	(0.16)

Standard errors in parentheses, clustered by conspuma, industry and year.

*** indicates significance at the 1% level.

Table 9: Robustness Check: Control for Changes in Chinese Import Share

Dependent Variable: Log Wage	Excluding Agriculture
Location-Specific Controls	
Less than high school * $loc\tau^c_{1990}$ * (Year = 2000)	9.92***
	(1.641)
High school * $loc\tau^c_{1990}$ * (Year = 2000)	4.82***
	(0.806)
Some college * $loc\tau^c_{1990}$ * (Year = 2000)	0.693
	(0.679)
College * $loc\tau^c_{1990}$ * (Year = 2000)	-5.90*
	(3.257)
Less than high school * $loc\triangle\tau^c$ * (Year = 2000)	11.60***
	(1.548)
High school * $loc\triangle\tau^c$ * (Year = 2000)	6.24***
	(0.918)
Some college * $loc\triangle\tau^c$ * (Year = 2000)	2.67***
	(0.861)
College * $loc\triangle\tau^c$ * (Year = 2000)	-4.494
	(3.283)
Industry-Specific Controls	
Less than high school * $RCA\tau^j_{1990}$ * (Year = 2000)	4.75***
	(1.806)
High school * $RCA\tau^j_{1990}$ * (Year = 2000)	1.328
	(2.194)
Some college * $RCA\tau^j_{1990}$* (Year = 2000)	0.631
	(1.774)
College * $RCA\tau^j_{1990}$ * (Year = 2000)	-1.026
	(2.430)
Less than high school * $RCA\triangle\tau^j$ * (Year = 2000)	6.99***
	(1.978)
High school * $RCA\triangle\tau^j$ * (Year = 2000)	2.331
	(2.432)
Some college * $RCA\triangle\tau^j$ * (Year = 2000)	1.722
	(2.020)
College * $RCA\triangle\tau^j$ * (Year = 2000)	-0.826
	(3.069)

Standard errors in parentheses, clustered by conspuma, industry and year.

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

Table 10: Robustness Check: Control for Chinese Import Share
Differences Between Anticipation and Impact Effect

Parameter difference	Point estimate	F Value	Pr > F
$\delta_{2,lhs} - \delta_{4,lhs}$	-1.678	9.39	0.002
$\delta_{2,hs} - \delta_{4,hs}$	-1.421	21.38	<0.001
$\delta_{2,scol} - \delta_{4,scol}$	-1.980	24.50	<0.001
$\delta_{2,col} - \delta_{4,col}$	-1.407	3.25	0.072
$\theta_{2,lhs} - \theta_{4,lhs}$	-2.233	20.50	<0.001
$\theta_{2,hs} - \theta_{4,hs}$	-1.003	4.32	0.038
$\theta_{2,scol} - \theta_{4,scol}$	-1.091	6.22	0.013
$\theta_{2,col} - \theta_{4,col}$	-0.200	0.05	0.819

Table 11: Sample sensitivity: Workers in Services (excludes agriculture)

Dependent Variable: Log Wage	
Location-Specific Controls	
Less than high school * $loc\tau^c_{1990}$ * (Year = 2000)	21.82***
	(2.12)
High school * $loc\tau^c_{1990}$ * (Year = 2000)	11.57***
	(1.29)
Some college * $loc\tau^c_{1990}$ * (Year = 2000)	4.03***
	(0.59)
College * $loc\tau^c_{1990}$ * (Year = 2000)	-4.00
	(3.33)
Less than high school * $loc\triangle\tau^c$ * (Year = 2000)	24.23***
	(2.03)
High school * $loc\triangle\tau^c$ * (Year = 2000)	12.87***
	(1.56)
Some college * $loc\triangle\tau^c$ * (Year = 2000)	5.65***
	(0.79)
College * $loc\triangle\tau^c$ * (Year = 2000)	-2.98
	(3.34)
Number of Observations	7,489,403
Differences Between Anticipation and Impact Effect	
Parameter difference	Point estimate
$\delta_{2,lhs} - \delta_{4,lhs}$	-2.41***
	(20.11)
$\delta_{2,hs} - \delta_{4,hs}$	-1.30***
	(11.06)
$\delta_{2,scol} - \delta_{4,scol}$	-1.62***
	(13.00)
$\delta_{2,col} - \delta_{4,col}$	-1.03
	(1.49)

Standard errors or F values in parentheses.

*** indicates significance at the 1% level.

Standard errors are clustered by conspuma, industry and year.

Table 12: Other employment outcomes (excludes agriculture)

	Linear probability model		Logistic model	
	Unemployed	NILF	Unemployed	NILF
	(1)	(2)	(3)	(4)
Location-Specific Controls				
Less than high school * $loc\tau^c_{1990}$ * (Year = 2000)	0.06	-6.71***	-1.07	-60.22***
	(0.605)	(1.679)	(10.70)	(7.54)
High school * $loc\tau^c_{1990}$ * (Year = 2000)	-1.11***	-3.26***	-25.04***	-32.75***
	(0.155)	(0.981)	(7.29)	(5.27)
Some college * $loc\tau^c_{1990}$ * (Year = 2000)	-0.27	-2.11***	-8.41	-29.31***
	(0.171)	(0.622)	(10.21)	(6.93)
College * $loc\tau^c_{1990}$ * (Year = 2000)	0.15	-1.56***	-7.81	-24.56***
	(0.230)	(0.452)	(17.81)	(9.30)
Less than high school * $loc\triangle\tau^c$ * (Year = 2000)	-0.44	-6.59***	-8.14	-63.58***
	(0.600)	(1.894)	(11.58)	(8.15)
High school * $loc\triangle\tau^c$ * (Year = 2000)	-1.27***	-3.93***	-27.75***	-42.78***
	(0.145)	(1.069)	(7.94)	(5.72)
Some college * $loc\triangle\tau^c$ * (Year = 2000)	-0.37**	-2.71***	-11.04	-39.87***
	(0.184)	(0.689)	(11.03)	(7.48)
College * $loc\triangle\tau^c$ * (Year = 2000)	0.16	-1.99***	-7.13	-32.56***
	(0.236)	(0.502)	(19.02)	(10.01)
Industry-Specific Controls				
Less than high school * $RCA\tau^j_{1990}$ * (Year = 2000)	-0.62	-0.34	-8.92*	2.38
	(0.455)	(0.425)	(4.89)	(3.36)
High school * $RCA\tau^j_{1990}$ * (Year = 2000)	0.18	-0.39	-2.14	-0.95
	(0.326)	(0.503)	(4.12)	(3.05)
Some college * $RCA\tau^j_{1990}$* (Year = 2000)	0.97***	-0.80**	21.20***	-13.42***
	(0.353)	(0.403)	(6.49)	(4.85)
College * $RCA\tau^j_{1990}$ * (Year = 2000)	0.99***	-0.37	39.13***	-9.99
	(0.263)	(0.299)	(10.58)	(7.44)
Less than high school * $RCA\triangle\tau^j$ * (Year = 2000)	-0.69	-0.70	-10.45*	-0.65
	(0.642)	(0.573)	(5.53)	(3.91)
High school * $RCA\triangle\tau^j$ * (Year = 2000)	0.33	-0.86	-0.76	-7.84**
	(0.437)	(0.649)	(4.75)	(3.58)
Some college * $RCA\triangle\tau^j$ * (Year = 2000)	1.23***	-1.32***	26.12***	-22.91***
	(0.468)	(0.505)	(7.50)	(5.69)
College * $RCA\triangle\tau^j$ * (Year = 2000)	1.18***	-0.65	44.70***	-17.50**
	(0.345)	(0.412)	(12.50)	(8.87)
Number of Observations	9,474,678	10,320,274	9,474,678	10,320,274

Robust standard errors in parentheses. In Column 1 and 2, standard errors are clustered by conspuma, industry and year. Column 3 and 4 report the estimated coefficients from the logistic model. ***, ** and * indicate significance at the 1%, 5% and 10% level.