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Labor Market Adjustment to Third Party Competition: Evidence from Mexico

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Abstract: China's exports reduce wages in importing countries, but few studies have looked at competition in third party markets. We examine labor market outcomes in Mexico's apparel and textile sectors associated with U.S. apparel and textile imports from China. Using the Bartik (1991) approach, we find that U.S. imports from China are associated with a reduction of wages and employment in Mexico's textile and apparel sector. Our results suggest that the adjustment to falling labor demand had larger effects on employment, which is consistent with relatively small firm-level employment adjustment costs, and that low-wage workers are more tied to local markets.

Keywords: Apparel, China, Mexico, Trade, Wages, Inequality

JEL Codes: F16,J31

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I. Introduction

Over the last two decades, China's growth has profoundly changed global trade. Mounting evidence has shown that rising Chinese trade has been associated with significant changes in wages and employment in Chinese trading partner countries. For example, rising Chinese exports to the United States have substantially lowered wages and employment among the low-skilled (Autor, Dorn, and Hanson 2013). In addition, China's commodity imports from Latin America corresponded with a period of economic growth and falling inequality for many Latin American countries. Mexico, however, was an exception. Trade with China remains small relative to trade with the United States, and therefore Mexico did not benefit much from the commodity boom.[1] At the same time, Mexican imports from China were relatively small, limiting the potential labor market effects.

Mexican labor markets, however, were not immune from China's trade. After the North American Free Trade Agreement (NAFTA), Mexico's apparel sector increased exports to the United States. By 2000, Mexico's apparel exports were 16% of total U.S. apparel imports. Figure 1a shows that China's share was about 6% of total imports in 2000. By 2016, however, the situation had changed dramatically. Figure 1b shows that China's share of total U.S. apparel imports had increased to 42%. Mexico's share had fallen to 3% by 2016. Related, Figure 2 shows that the relative prices of Chinese apparel fall when China enters the World Trade Organization in 2001 until 2005.[2] Mexican prices rise slightly between 2000 and 2017. The change in prices and quantities are consistent with a substitution away from Mexican to Chinese textiles and apparel.

China's growth was clearly an exogenous change for Mexico and offers the opportunity to explore the relatively unexamined question of how domestic labor markets change when competition in an export destination increases.[3] Figure 3a offers some initial impressions by showing the strong association between Mexican exports to the US in apparel and employment

[1] For the 2007-2017 period, the U.S. share of total Mexican imports averaged 48.5% and the share of Mexico's total annual exports sent to the United States averaged 80.2%. See http://www.inegi.org.mx/sistemas/bie/cuadrosestadisticos/GeneraCuadro.aspx?s=est&nc=566&c=24791.

[2] We use average unit values calculated from U.S. apparel import value divided by quantity imported. Quantity is measured by square-meter equivalent. See also Harrigan and Barrows (2009) for evidence of apparel price changes.

[3] Carillo Garcia, Chen, and Goodman (2011) note the asymmetry in China and Mexico's political and economic ties. China is much more relevant to Mexico's economic ambitions than Mexico is to China's.

shares in apparel.[4] Figure 3b does the same for textiles. The two figures show that Mexican exports to the US and employment shares are highly correlated in both industries. The decline in US clothing and textile imports from Mexico was primarily driven by increases in exports from China in these industries as shown in Figures 4a and 4b.

Mexico's experience also offers an opportunity to address several other questions as well. For example, there is some debate about whether the change in labor demand (for example, due to a change in exports or imports) affects wages or employment. The results help to inform the debate about the type and importance of adjustment costs in trade models. Second, we can estimate the relative speed of adjustment by estimating the dynamic response of outcomes to trade shocks. Third, it is possible that changes in the apparel and textile sectors have spillovers into other industries. That is, it is also possible to estimate cross-industry effects of trade-induced demand shocks to the apparel or textile industries. Finally, given the relatively high levels of inequality in Latin America, generally, and Mexico, in particular, the Mexican case also offers the opportunity to contribute to the debate about trade and inequality but from a very different angle than the vast majority of previous studies that focus on the link between trade liberalization and inequality.[5]

Several recent papers estimate the effects of Chinese competition on Mexican production. Many of these focus on assembly plants located along the U.S.-Mexican border known as *maquiladoras*. For example, Ma and Wooster (2009) and Utar and Torres Ruiz (2013) consider increased Chinese exports to the United States and their effect on the *maquiladoras* with respect to employment and wages along the U.S.-Mexico border. Using industry data from four border metropolitan areas between 1992 and 2006, the authors deduce that more Chinese imports to the United States are "significantly related to lower employment and wages in U.S.-Mexico border counties." The only border county area that showed insignificant effects was San Diego, which has a diversified economy much less dependent on manufacturing. In addition, Mendoza (2010, 2016) shows that the maquiladora industry has experienced slower growth, lower employment, and reduced productivity since the turn of the century. While Mexico's proximity to the United States continues to be a boon to maquiladora activities, the benefit has been limited to only a

[4] Note that throughout this manuscript, we will use the words apparel and clothing interchangeably.

[5] Chiquiar (2008) finds that the results are consistent with Stolper-Samuelson. Wages, both overall and unskilled, increased in regions with strong ties to the United States.

small number of industries (*e.g.* automobile manufacturing). The reason is that China's comparative advantage in the average wages of its manufacturing personnel has cost Mexico in exports where labor costs are a more significant factor than transportation costs (*e.g.* electronic equipment production). Next, Utar, et al. (2013) studies the response of Mexican export processing plants to increased competition from Chinese products from 1990 to 2006 and they find that increased competition from Chinese products hampers plant growth and employment in maquiladoras. These impacts are shown to be stronger in unskilled, labor-intensive sectors. Related, Iacovone, Rauch, and Winters (2013) explore the impact of trade shocks from a surge in Chinese textile imports over a period from 1994-2004. Their study indicates that while smaller companies experienced reduced sales due to competition and ceased their production, larger companies were either relatively unaffected or benefitted from the trade shock through their improved access to cheaper intermediate inputs.

The papers most similar to ours are Mendez (2015) and Chiquiar *et al.* (2016) who use a similar approach as ours to study region-specific effects of Mexican competition in the U.S. market. Using two points in time (2000 and 2010, from Census data), Mendez (2015) finds falling manufacturing employment shares but no effects on wages. Chiquiar *et al.* (2016) find that, while increased access to the U.S. market through NAFTA led to higher real wages and greater employment for unskilled workers in manufacturing in Mexico, increased Chinese exports to the United States had the opposite effect. They find that these effects were felt most strongly in regions that border the United States, suggesting that geography should be considered when studying the consequences of trade in Mexico.

Our paper differs from theirs in several ways. First, we focus on the post MFA-period (2005-2015). Until 2005, the textile and clothing industry in Mexico remained exempt from the rules of General Agreement on Tariffs and Trade (GATT) and was instead subject to the quotas established by the Multi-Fiber Arrangement (MFA) in 1974 (Ernst and Ferrer and Zult 2005). This arrangement imposed quotas restricting the imports of textiles and apparel from developing countries like China and Mexico into the United States. Second, their results do not focus on particular industries, while our paper focuses on textiles and apparel, specifically. Since we have high-frequency data, we can analyze adjustment in more detail. Finally, we investigate any possible equilibrium and distributional effects that the expiration of the MFA may have had.

Our approach, however, is similar to Chiquiar et al. (2016) and other papers that apply a Bartik (1991) approach[6] to estimate local labor-market effects of globalization. This approach uses geographic heterogeneity on production or employment to construct weights that are applied to trade flows. We then apply this approach and explore the differences in the effects across education and decile groups.

Our main results are that third-market competition had significant adverse effects on Mexican labor market outcomes. Employment is more responsive than wages, which is consistent with workers having relatively small adjustment costs resulting in a relatively elastic labor supply. In addition, estimation of dynamic models indicate that the employment adjustment happens in less than six months, which points to low firm-level adjustment costs and is consistent with Robertson and Dutkowsky (2002). Unlike Mendez (2015), however, we find evidence of wage effects for lower wage workers, which is consistent with higher relative adjustment costs at the low end of the wage distribution. To the extent that worker-level adjustment costs[7] are high for poorer workers, the changes in employment and wages may imply significant welfare implications for Mexican workers. Low-wage workers also often experience larger changes in employment, which is consistent with firms having lower adjustment costs for these kinds of workers.

The balance of this paper is organized as follows. To provide context for these results, section II describes changes in apparel and textile trade policies that are especially relevant for Mexico. After that, we discuss the data. We then discuss our empirical methodology. This is followed by a discussion of our core results and then some extensions. We then conclude.

II. Apparel and Textile Trade Policies

Apparel and textiles are considered highly sensitive industries throughout the world. In the 1970s, developed countries restricted apparel and textile trade through the Multi-Fibre Arrangement. Towards the end of the Uruguay Round of GATT in 1994, it was agreed that trading in apparel and textiles would fall under the jurisdiction of the World Trade Organization

[6] This approach actually has roots at least as far back as Freeman (1980).
[7] Worker-level adjustment costs are costs borne by workers, such as search for a new job, or moving to a new city, or learning skills specific to a new industry. These are distinct from firm-level adjustment costs such as posting a position, interviewing, and legally-mandated hiring and firing costs.

(WTO). The round implementing the Agreement on Textiles and Clothing (ATC) came into effect in 1995 and phased out most of the quotas under the MFA over the following 10-year period, ending on 1 January 2005.

During this time, Mexico was implementing its own trade liberalization program and had its eye on China. Following its economic liberalization and subsequent signing of the General Agreement on Tariffs and Trade (GATT) in 1986, Mexico was compelled to create mechanisms to implement anti-dumping policies in-line with other GATT countries. The 1993 passing of the Foreign Trade Law and its Regulations contributed to the development of these institutions and represented the zenith of anti-dumping policy in Mexico. China, in particular, felt the brunt of these measures. It was targeted primarily for two reasons. First, Mexico could target Chinese industries with which it had low trade to minimize the domestic economic consequences. Second, by directing anti-dumping efforts towards China, Mexico's partnerships with other GATT countries would remain unaffected. These measures, however, proved unsustainable once China joined the WTO in 2001. The subsequent decline in Mexican anti-dumping policy towards China was not replaced by new policies targeting other Chinese industries or other international partners (Robertson 2011). The lack of new temporary trade barriers and anti-dumping policies suggests that Mexico no longer considers these measures a viable long-term economic strategy.

A series of subsequent policy changes paved the way for the US to commence textile and apparel imports from China at the levels seen today. Initially, after the implementation of the North American Free Trade Agreement (NAFTA) in 1994, Mexico was able to expand its trade of textile and apparel products to the United States and Canada. In effect, while the MFA restricted the access of the US market to China and other developing countries to a specified quantity, Mexico was free to expand its markets without the fear of competition from other developing countries.

China gained entry into the WTO in the midst of this process in 2001. While it was expected that the Chinese textile and apparel exports would increase at the conclusion of the phase-out period, the extent to which it would increase its market share was unclear. In 2005, the first year without quotas, Chinese textile and clothing exports to the United States rose by 40 percent in quantity and 26 percent in market share.[8] The dramatic jump in imports compelled the United States to impose targeted quotas over a three-year period, in an effort to limit the effect on American industry. Despite this, China continued to expand its exports to the United States market.

Repealing the MFA in stages resulted in significant shifts in the patterns of trade and employment structures within and between countries. For example, Spener (2002) finds that shifting the regulatory environment for apparel industries led to the decline of apparel plants in El Paso, Texas, and increased lay-offs among the Mexican immigrant population in the US. This situation has further been impacted by high production costs and poor market diversification in Mexico, which exports nearly all of its textile products to the United States market, leaving little space to adjust to demand shocks from the USA.

III. **Data**

Our trade data focus on the apparel and textile sectors. In apparel manufacturing (NAICS 315), firms trade in knit or woven apparel. They consist of manufacturing from two distinct processes: (1) purchasing fabric, cutting, and sewing to make a garment, and (2) manufacturing garments in establishments that first knit fabric and then cut and sew the fabric into a garment. The Textile Mills (NAICS 313) sector includes manufacturing yarn and textile fabrics, consisting of cotton, wool, and manmade fibers to name the major ones. Textile Product Mills (NAICS 314) include carpeting, bed linens, curtains, towels, as well as textile bags, rope, cordage, twine, canvas, and tire cord and fabric.

To compute municipality-specific labor demand shocks, we employ data on the total value of US apparel and textile imports from Mexico and China. These data come from the US Census Bureau, Economic Indicators Division and are collected from the forms filed with the US Customs Service for shipments entering and exiting the United States. For this study, we use general imports, which is a measure of the total physical arrivals of merchandise from foreign

[8] Irene Brambilla, Amit K. Khandelwal, and Peter K. Schott, *China's Experience Under the Multifiber Arrangement (MFA) and the Agreement on Textile and Clothing (ATC)**, working paper (National Bureau of Economic Research, 2010).

countries to the US.[9] This includes all goods that physically arrive into the United States, whether they are consumed domestically or are used further in production. The trade data are collected monthly but we aggregated it to quarters to match the labor-force survey data described below. The import value excludes transportation, insurance, freight and other related charges incurred above the price paid. The data employ the North American Industry Classification System (NAICS) definitions for industries. The data are deflated using the Mexican CPI with 2010 as the base year.

U.S. and Chinese imports over time are shown for apparel in Figure 4a and textiles in Figure 4b (also discussed earlier) over the period 2005-2015. These figures show a precipitous drop in US apparel and textile imports from Mexico and a rise in Chinese exports to the United States. There was also a dramatic dip in the series during the fourth quarter of 2008 due to the Great Trade Collapse, but the recovery from this was swift.

To analyze Mexico's labor market, we employ the Encuesta Nacional de Ocupacion y Empleo (ENOE), which is a quarterly labor-force survey. We use data spanning the years 2005-2015 and extract a sample of people ages 18 to 65. We collapse the data by municipality for 32 large cities. The final collapsed data set that we use has 1408 observations for the 32 municipalities across 11 years and 4 quarters. When collapsing the data, we employed the ENOE sample weights. In Table A1 of the Appendix, we list the 32 municipalities with their sample sizes in the original ENOE extract.

The main variables that we use are average wages, wage percentiles, and employment shares per city/quarter both by industry and across all industries. Employment shares were computed as the percentage of a municipality between the ages 18 and 65 who report positive earnings and work in a given industry in a given quarter. Wages were computed on an hourly basis by taking monthly earnings and dividing by total hours worked during a typical week, multiplied by 4.2. Wages were only computed for people who reported non-zero hours. In addition, we trimmed the top two percent of nominal wages in the raw data files to eliminate outliers. Industries were defined at the 3-digit level by their North American Industry Classification System (NAICS) codes. A complete listing of the industries that we use is

[9] An alternative is to measure only the consumption imports measuring only the traded goods that enter the consumption channels after clearing the customs. For some results, we used this alternative measure and found no meaningful differences.

provided in Table A2 of the appendix. Wages were deflated using the Mexican CPI computed by the Banco de Mexico with 2010 as the base year and then converted to US Dollars using the average nominal exchange rate for 2010.

Employment shares and mean wages by industry for the collapsed data are reported in Table 1. Across all industries, we see that the average wage in the collapsed data is $1.87 and that 73 percent of 18 to 65 year-olds were employed. Average textile wages were slightly lower than the overall average aggregate wage at $1.64, and average apparel wages are just below that at $1.53. We also see that 0.38 percent of the ENOE sample was employed in the textile industry, but about 0.95% was employed in apparel. The industry with the highest employment share in the table is food manufacturing which employs 2.52 percent of the sample.

In Tables A3a and A3b, we report the value of imports from Mexico and China for the 20 industries listed in Table A2. In these tables, we see that apparel imports from Mexico are 2.03 percent of the total in these 20 industries over the period 2005-2015, while apparel imports from China are 7.79 percent. Textile imports from Mexico constitute 0.58 percent of U.S. imports from. The corresponding number for China is 2.69 percent.

IV. **Empirical Approach**

Our research design begins with a construction of local demand shocks that closely mimics the "Bartick" approach that has been used by Autor, Dorn, and Hanson (2013) and Chiquiar, *et al.* (2016). These shocks will serve as a proxy for a local labor market's exposure to the plausibly exogenous trade shock caused by the expiration of the MFA. Second, we will rely on temporal variation in these shocks within cities to estimate their impact on local labor markets.

Construction of demand shocks

We define $M_t^{r,j}$ denote the dollar value US imports from either Mexico or China (denoted by region $r \in \{MX, CH\}$) at time t for industry $j \in \{APP, TEX\}$. We convert these data to 100 million dollar units. Next, we let $l_{j,c}$ denote the labor share working in city c in industry j at baseline (*i.e.* the first quarter of 2005) and l_j denote the labor share in industry *j* in Mexico, also at baseline. Our labor demand shock is then defined as

$$S_{ct}^{jr} = M_t^{r,j} \times \frac{l_{j,c}}{l_j} \;\; for\ r \in \{MX, CH\}\ and\ \ j \in \{APP, TEX\}. \quad (1)$$

This shock consists of two components. The first is $M_t^{r,j}$, which measures US demand for imports in quarter/year t from region r in industry *j*. The second is a weight given by $\frac{l_{j,c}}{l_j}$ which measures how intensively city c was engaged in industry *j* at baseline. The role of this ratio is essentially to magnify or diminish the effects of temporal fluctuations in US imports from Mexico in a given city. We are careful to use this weight at baseline since subsequent innovations to our regression equations might impact labor shares in apparels or textiles at later dates. We employ the shock S_{ct}^{jMX}, which is the city-weighted impact of US demand for apparel imports from Mexico, as the primary right-hand side variable in our regressions. In addition, we employ the shock S_{ct}^{jCH} for the analogous shock that uses US imports from China as an instrumental variable for S_{ct}^{jMX}.

Main Estimation Equation

Throughout this paper, we will focus on variants of a simple, parsimonious econometric model given by

$$y_{ct} = \gamma_c + \gamma_t + S_{ct}^{MX}\beta + v_{ct} \quad (2)$$

where c is city and t is a quarter/year cell. Note that we omit the *j* subscripts for the ease of the exposition but estimate the equation separately for apparel and textiles. For our main results, the dependent variable y_{ct} is either mean wages or employment shares in the apparel or textile industries, although we consider other outcomes such as employment shares in other industries and wage quantiles as well. Because we include both city and quarter/year fixed effects, identification of β relies on variation in S_{ct}^{MX} across quarter/year cells within cities, as well as across cities within a quarter/year cell.

The city fixed effects adjust for time-invariant location-specific variables that are correlated with both apparel and textile exports to the United States and employment outcomes.

For example, border cities such as Juarez and Tijuana may attract both foreign direct investment and workers because of their proximity to the United States. The quarter/year fixed effects adjust for any shocks that affect the entire country in a given quarter/year. These time effects are critical for the validity of our design since they control for a host of macroeconomic variables. Given that our sample includes the Great Recession, this is vital. In addition, this adjustment will also include any aggregate effects that the trade shock may have had, so this specification with both the city and period fixed effects identifies the idiosyncratic (*i.e.* city-specific) impact of the trade shock. In other words, the coefficient β delivers the impact of the trade shock on apparel or textile wages and employment shares in the local labor market.

Estimation of equation (2) or variants of it can also shed light on other aspects of labor market adjustment. First, we estimate the extent to which the expiration of the MFA had effects beyond the apparel or textile industry by employing aggregate labor shares as the dependent variable. This would identify any spill-overs or general equilibrium effects. Second, and related, we use labor shares in other industries to identify cross-industry effects. This would elucidate the sources of any general equilibrium effects that we have identified. Third, we estimate a distributed-lag variant of the model to understand the length of time that it took the labor markets to adjust to the trade shocks. Fourth, equation (2) can also be used to identify distributional impacts of the trade shocks by employing labor shares in different education groups and wage percentiles as dependent variables.

We use Newey-West standard errors for a panel data set in all of our estimations. As discussed by Arellano (2003), since they rely on large-T asymptotics, these standard errors allow for arbitrary cross-sectional correlations and ergodicity or some degree of serial correlation that dissipates in the limit. Allowing for cross-sectional dependence is important as the shocks S_{ct}^{r} most likely are correlated across cities since changes in US import demand may have impacted numerous cities in a given time period. These standard errors do not impose any restrictions on the form of this cross-sectional dependence. Instead, they rely on ergodicity in the data generating process so that the observations are independent over time provided that they are spaced sufficiently far apart. We allow for first order serial correlation in the data generating process.

On the whole, we believe that (Ordinary Least Squares) OLS estimation of equation (2) is appropriate since S_{ct}^{MX} is most likely exogenous and OLS provides us with an efficient estimator.

There are, however, some lingering concerns with OLS estimation. First, if increases in labor demand due to the trade shock were accompanied by migration to these cities, then estimation of β will be biased downwards. Second, if there is classical measurement error in S_{ct}^{MX} due to mismeasurement in either import values or the weights calculated in the ENOE, then there will be attenuation bias in the OLS estimator. Once again, this will induce a downwards bias.

To assuage these concerns, we also estimate equation (2) using Instrumental Variables (IV). The US increase in imports of apparel from China in 2005 was accompanied by a dramatic decline in apparel imports from Mexico. This suggests a first stage of the form

$$S_{ct}^{MX} = \theta_c + \theta_t + S_{ct}^{CH}\pi + \varepsilon_{ct} \qquad (3)$$

so that Chinese apparel import penetration into the US crowds out apparel imports from Mexico. We then use this first stage to estimate equation (2) via IV. As with the OLS estimates, we also employ Newey-West standard errors when estimating the model via IV. One caveat is that over 96 percent of the variation in S_{ct}^{MX} is absorbed by the city fixed effects. As a consequence, there is not much room for the instrumental variable to maneuver which, as we will see, results in a somewhat weak instrument.

Because of this, we primarily focus on the OLS results in this paper. First, as we have argued, OLS is likely downward biased and so, the true impacts will be even greater than we have estimated. Second, due to concerns about weak instruments, some of the subtle aspects of the labor market adjustment (*e.g.* general equilibrium effects, dynamic adjustments) will be harder to detect using IV.

V. **Core Results**

In this section, we present our core results. For both the apparel and textile industries, we present the OLS estimates followed by the IV estimates. After that, we investigate cross-industry linkages between the apparel and textile industries.

OLS Estimates for Apparel

We begin with Table 2a, which reports OLS estimates of the effect of the trade shock on labor shares and wages in the apparel industry and in the aggregate. All columns include city fixed effects and the even columns include time effects. Because the estimates of β are hard to interpret, we also report the marginal effect of a one standard deviation increase in apparel imports on the outcome of interest. To place this marginal effect in perspective, we also report it as a percentage of the mean of the dependent variable towards the bottom of the table.

The effects of the trade shock on aggregate labor shares are reported in the first two columns. We see that the coefficient estimate is 0.0637 in the first column, but once the city fixed effects are included in the second column, the estimate drops substantially to -0.0006. The corresponding marginal effects are 2.6 percent and effectively zero. The first estimate is significant at the one percent level, but the second estimate is no longer significant once we include the time dummies.

The estimate without the time effects indicates one of two phenomena. The first is that the trade shock had massive aggregate employment effects that were spread out fairly evenly across Mexico. The second is that the trade shock is highly correlated with time dummies, so their inclusion greatly attenuates the estimate. We presume that this is certainly part of the reason for the large estimate in the first column given that the Great Recession happened shortly after the expiration of the MFA. Unfortunately, we cannot tease these two stories apart.

In the next two columns, we report the effects of the trade shock on labor shares in the apparel industry. In the absence of spill-overs, the estimates in the first two columns should be about the same as the estimates in columns three and four. They are, however, both substantially smaller. The estimates without and with the time effects are 0.0052 and 0.0047, respectively. Both parameters are tightly estimated and significant at the one percent level. Finally, we see that a one standard deviation increase in US apparel imports is associated with a reduction in apparel employment shares of about 16-18 percent which, not surprisingly, is a very large effect.

We report the effects on wages in the final four columns. In columns five and six, we look at wages across all industries and in the final two columns, we look at wages in the apparel industry. The wage effects are significant in both columns, but turn negative when the time effects are included. The same result occurs when we focus just on the wages in the clothing industry. Note that the negative effects on wages in columns 6 and 8 are at odds with what a positive demand shock should do to wages. The marginal effects as a percentage of the dependent variable mean, however, are small at -0.7 and -0.9 percent, respectively. Hence, they are small in economic terms. Taken together, these results suggest the following about the underlying structure of the labor market. First, they suggest that the elasticity of labor supply in the apparel industry is relatively elastic since the adjustment is occurring through employment and not wages. This high elasticity of labor supply could be the consequence of low adjustment costs on the supply side due to relative ease of internal labor mobility, for example. Second, if there were any impacts on wages, they were diffused throughout the country.

In Figure 5a (apparel) and Figure 5b (textiles), we report the effects of the trade shock on employment shares in the 20 industries listed in Table A2. In each figure, we plot the estimate of β from equation (2) with the employment share in a given industry as the dependent variable along with the corresponding measures of confidence. Figure 5a shows that, by far, the largest impacts were in the apparel industry, which is not surprising (we discuss Figure 5b below). The industries that were the next most impacted were textiles, food, and agriculture. It is not surprising that there were large effects in the textile industry since it is highly complementary with the apparel industry. The large effects in the agricultural industry are somewhat more puzzling. This result, however, could be due to a supply of raw materials from that sector, but we do not formally evaluate that hypothesis because we do not have input-output tables. Comparatively, the effects on the other industries are much smaller and most are not significantly different from zero. The estimates that are significantly different from zero may be as a consequence of Type I error.

OLS Estimates for Textiles

In Table 2b, we report OLS estimates of the effect of the trade shock on labor shares and wages in the textile industry and across all industries. This table is structured exactly as Table 2a except that now we employ the textile shock as the primary independent variable. The effects of the textile trade shock on aggregate labor shares are reported in the first two columns. We see that the coefficient estimate is 0.451 in the first column, but once the city fixed effects are included in the second column, the estimate drops substantially to 0.0974. The corresponding marginal effects are 1.65 and 0.36 percent. Both estimates are significant at the 1 percent level. In contrast to Table 2a, the estimate in the second column with the time fixed effects is significant at the one percent level indicating stronger evidence of spill-overs than with the apparel shock.

In the next two columns, we report the effects of the trade shock on labor shares in the textile industry. Once again, in the absence of spill-overs, the estimates in the first two columns should be about the same as the estimates in columns three and four. However, we see that they are both substantially smaller. The estimates without and with the time effects are 0.0170 and 0.0173, respectively. Once again, both parameters are tightly estimated and significant at the one percent level. The ratio of the estimates in the second and fourth column is about 2.4. Hence, the aggregate effect is over twice as large as the direct effect. Note that we do not see equally strong evidence for cross-industry spillovers for the apparel shock in Table 2a. Finally, we see that a one standard deviation increase in U.S. textile imports is associated with a reduction in textile employment shares of about 28 percent which, not surprisingly, is a very large effect.

We report the effects on wages in the final four columns. In columns five and six, we look at wages across all industries and in the final two columns, we look at wages in the textile industry. The main result in both sets of columns is that there are only significant impacts on wages when the time effects are excluded. Once again, if there were any wage effects due to the expiration of the MFA, they were in the aggregate, but there is no evidence of any city-specific impact on wages.

In Figure 5b, we report the effects of the textile trade shock on employment shares in the same 20 industries as in Figure 5a. The large discrepancy between the effects of the textile shock on employment in the textile industry and across all industries strongly suggests that there were equilibrium impacts on other industries. In the figure, we plot the estimate of β from equation (2) with the employment share in a given industry as the dependent variable along with the corresponding measures of confidence. The figure shows that, by far, the largest impacts were in the apparel industry, which is not surprising. The industries that were the next most responsive were clothing and agriculture. The coefficient estimates in both industries are about two-thirds of the direct effect on textiles. It is not surprising that there were large effects in the clothing industry since it is highly complementary with the textile industry. The large effects in the agricultural industry are still somewhat more puzzling, but, again, could be linked to cotton supply. Comparatively, the effects on the other industries are much smaller and most are not significantly different from zero. As before, we suspect that the estimates that are significantly different from zero may be as a consequence of Type I error.

IV Estimates for Apparel

We begin our discussion of the IV estimates for the apparel industry by discussing the estimation of the first stage in Table 3a. In the specification in the first column, we include city fixed effects and, in the second column, we include city and time fixed effects. Importantly and as we have already discussed, the city fixed effects absorb over 90 percent of the variation in $\mathrm{S}_{\mathrm{ct}}^{\mathrm{MX}}$. Nevertheless, and as suggested by Figure 3, we still see that increases in Chinese apparel imports crowd-out Mexican apparel imports even after we adjust for city and fixed-period effects. As you may have anticipated, the instrument is still on the weaker side with F-statistics of 8.38 and 4.69 in columns one and two, respectively. The point estimates in both columns are virtually identical at -0.0226. This estimate implies that a one standard deviation increase in US imports of Chinese apparels reduces the trade shock, $\mathrm{S}_{\mathrm{ct}}^{\mathrm{MX}}$, by 0.63 percent.

In Table 3b, we report IV estimates of equation (2). The point-estimates of the impact of the trade shock on apparel labor shares are 0.0064 and 0.0041 without and with the period fixed effects. In contrast, the corresponding OLS estimates in Table 2 were 0.0052 and 0.0047. The range of IV estimates is larger, but the proportional marginal effects on the apparel sector are about 17 percent in both tables. In other words, the qualitative and quantitative results are very similar with and without instrumental variables. The IV results also indicate the same qualitative wage effects as the OLS estimates; we see significant impacts when the period effects are excluded but these effects go away with their inclusion.

IV Estimates for Textiles

We now turn to the corresponding estimates for the textile shock. We report the first stage in Table 4a. In the specification in the first column, we include city fixed effects and, in the second column, we include city and time fixed effects. Importantly and as we have already discussed, the city fixed effects absorb the vast majority of the variation in S_{ct}^{MX}. Nevertheless, we still see that increases in Chinese textile imports crowd-out Mexican textile imports even after we adjust for city and fixed-period effects. The instrument is still on the weaker side with F-statistics of 16.11 and 16.08 in columns one and two, respectively; however, it is stronger than in the case of apparel suggesting that, perhaps, the textile shock is more primitive than the apparel shock. The point estimates in both columns are virtually identical and are -0.0563. This estimate implies that a one standard deviation increase in US imports of Chinese textiles reduces the trade shock, S_{ct}^{MX}, by 1.95 percent.

In Table 4b, we report IV estimates of equation (2). First, looking at the effects on aggregate employment shares in the first two columns, we see significant effects without the time dummies in the first column but these estimates are no longer significant in the second column once we include the time effects. Next, the point-estimates of the impact of the trade shock on textile labor shares are 0.0402 and 0.0409 without and with the period fixed effects. In contrast, the corresponding OLS estimates in Table 6 were 0.0170 and 0.0173 and both are significant at the one percent level. Hence, the IV estimates are about 235 percent larger. The IV estimates imply a 65.6-65.8 percent increase in textile employment shares. Finally, the IV results also indicate the same qualitative wage effects as the OLS estimates; we see significant impacts when the period effects are excluded but these effects go away with their inclusion.

The Textile-Apparel Relation

In Figures 5a and 5b, we showed that the industry most impacted by the textile shock other than textiles was the apparel industry and *vise versa*. We now explore these effects in greater detail in Tables 5a-5d. Tables 5a and 5b contain the cross-industry associations for apparel and textiles, respectively, on labor shares. Tables 5c and 5d contain the cross-industry associations for apparel and textile, respectively, on wages.

Tables 5a and 5b show that the cross-industry regression coefficients are statistically significant and positive. As U.S. imports of apparel fall, so does Mexican textile employment. The estimated coefficients are larger for the textile shock and apparel labor share by a factor of between 10 and 20 for the OLS estimates in the first two columns and between 11 and 26 for the IV estimates. In addition, in both tables, we show that the estimated coefficients are robust to the inclusion of time effects.

These results together with the results from the previous subsection indicate that shocks to the textile industry are more primitive than shocks to the apparel industry. We show that reductions to labor demand that are driven by declines in textile imports from the United States have substantially larger effects on the apparel industry than the opposite. In addition, in previous results, we showed that the own effects of the textile shock was substantially larger than those for the apparel shocks.

In contrast, Tables 5c and 5d show that the same coefficients in the wage equations are not statistically significant when time controls are included. Including time effects in the wage equations generates coefficients that are much closer in magnitude across industries than the coefficients in the odd-numbered columns. This suggests once again that, if there were any impact on wages, that it was dissipated geographically. Hence, as before, when comparing the labor share results in Tables 5a and 5b with the wage equation results in 5c and 5d, we find results that are consistent with the hypothesis that the export demand shocks hit employment specifically and do not seem to have a statistically significant wage effect across regions.

VI. **Extensions**

In this section, we consider several extensions of the results from the previous section. First, while we showed that labor markets primarily adjusted by cutting employment share as opposed to wages, we still do not know how long it took this adjustment to take place. To shed light on this, we estimate some simple distributed lag models. Second, the previous section showed that there were no localized effects on wages at the mean, but this does not preclude localized wage impacts at other parts of the wage distribution. To shed light on this, we consider effects of our trade shocks on wages at various quantiles.

Dynamic Adjustment

We begin by considering the length of time that it takes for the labor market to adjust to a third-party trade shock. To do this, we estimate a distributed lag variant of equation (2). Specifically, we estimate

$$y_{ct} = \gamma_c + \gamma_t + S_{ct}^{MX}\beta(L) + \upsilon_{ct} \qquad (4)$$

where $\beta(L)$ is a qth order lagged polynomial. The goal of this exercise is to see how long the effects of the trade shocks persist which provides some indication of how long it takes the labor market to adjust to the shocks. We estimate equation (4) with the textile labor share as the dependent variable via OLS.

We report the results in Table 6a for apparel and Table 6b for textiles. We estimate six specifications which include the contemporaneous shock and up to five lags. Towards the bottom, we report the sum of the textile shock coefficient estimates. We also report an F-statistic of the null that the sum is zero along with its p-value.

We see the following salient patterns in the two tables. First, across all six columns, we see that the sum of the coefficient estimates is very stable at about 0.004 for apparel and 0.018 for textiles. Accordingly, the static models in Table 2 do an admirable job of summarizing the total of the dynamic effects from the distributed lag models. Second, both tables show that the adjustment is relatively rapid. Adding additional lags adds little information, and the first or second lags are most often significant. This suggests that the labor market adjustment to the apparel and textile shocks happens within roughly two quarters or six months.

Distributional Impacts

We now consider distributional impacts. First, we investigate the effects on labor shares in the apparel and textile industries by educational group. We consider two groups: people with 9 or fewer years of education and people with more than 9. This cutoff is important in Mexico because, unlike the United States population, the average education level for Mexican workers is close to 9 years. Thus, we roughly divide the sample using the mean education level.

In Tables 7a (apparel) and 7b (textiles), we report the results from using labor shares by education category. The table follows the same structure as many of the earlier tables in the sense that both the estimated coefficients and the marginal effects are reported. Several messages emerge from Tables 7a and 7b. First, the associated marginal effects for less educated workers are larger than for more educated workers, regardless of whether or not time effects are included. In the case of apparel, the marginal effects are about 80% higher and for textiles they are about 50% higher. Including time effects reduces the marginal effects, but does not affect the ratio much. In all cases (that is, including time effects) the employment effects are statistically significant.

Next, we consider impacts by wage percentile. In Figures 6a and 6b, we present the time trends of the 10th, 50th, and 90th percentiles of wages in the apparel (Figure 6a) and textile (Figure 6b) industries over the period 2005-2015. For the apparel industry, we see that the median hourly wage over this period was around \$1.35, but we also see that it declined slightly over the period. Specifically, in the first quarter of 2005, median wages were \$1.48 and during the last quarter of 2015, they were \$1.19 in constant 2010 dollars. This constitutes a 20.3 percent decline. In addition, looking at the difference between the 90th and the 10th percentiles, we see that wage inequality within the apparel industry also declined over this period. Similar results emerge for the textile industry in Figure 6b.

We now turn to the distributional impacts on wages in Tables 8a for the apparel industry and 8b for the textiles industry. In the odd numbered columns where we exclude the time effects, we see that, in absolute terms, the effects of the import shock are increasing in the percentile. Respectively, the apparel coefficient estimates are \$0.15, \$0.12, and \$0.21 for the 10th, 50th, and 90th percentiles. This is consistent with Figure 6a that shows that the discrepancy between the 90th and 10th percentiles declined over the period 2005-2015 since during this period U.S. imports from Mexico declined precipitously and this had large absolute impacts on the higher end of the wage distribution, at least in the aggregate. As a percentage of the mean of the dependent variable, these effects are higher at the low end of the wage distribution. For example, the marginal effect of the apparel shock on the 10th percentile of wages across cities is 22.4 percent of the mean in the first column, whereas at the 90th percentile it is 2.7 percent in the fifth column. In this sense, lower wage workers were more adversely affected and, in the case of apparel, higher-wage workers experienced an increase in wages when apparel exports fall (which is consistent with the Stolper-Samuelson prediction to the extent that apparel exports are a low-skill intensive good). Finally, we would like to note that in contrast to previous findings, the effects of the apparel shock on wages at the 10th and 90th percentile are robust to the inclusion of time effects suggesting that there were negative wage effects in local labor markets at the lower end of the wage distribution, and much smaller (and, in fact, positive) at the upper end of the distribution.

In the case of textiles, the story is similar. The coefficient estimates are larger, generally, as we have found consistently throughout this paper. The marginal effects are much smaller, but this is a primarily a consequence of higher low wage workers in the textile industry than in the apparel industry; the mean of the 10^{th} percentile of wages across cities and quarters is \$0.78 in the textile industry but \$0.26 in the apparel industry. Nevertheless, the results still show that it was the wages of the lowest-wage workers that declined the most. Finally, we do not find that the effects on the 10^{th} percentile are significant once the time effects are added in the second column of the table; however, the point estimate is still economically meaningful at 0.453 and has a t-statistic above unity. We presume that part of the reason for this is that many city/quarter observations did not have anybody working in the textile industries, whereas this was not the case for the apparel industry. Indeed, in Table 1, we show that the aggregate employment share in apparel is 0.0095, whereas it is 0.0038 in textiles. This is why the sample size is 873 in Table 8b, but 1408 in Table 8a. This difference should result in lower power in the textile estimates. Given this, we take the estimate in the second column of the table to be evidence (albeit weaker) of localized labor market effects on wages.

Hence, for both the apparel and textile results in Tables 8a and 8b, we find evidence for localized wage effects at the lower part of the wage distribution but not towards the top. One possible reason for this could be that the lowest-wage workers are the least mobile. This would makes sense in a classic Roy model of migration with migration costs; at the low-end of the distribution the wage premium from migrating may not offset the migration cost. This would suggest that there should be less-dispersion in city-specific wage premia at the high end of the wage distribution that at the low end of it. We explore this hypothesis in the next section.

Local Labor Market Wage Premiums

Worker-level adjustment costs are playing an increasingly prominent role in our understanding of how globalization affects wages. Worker-level adjustment costs inhibit labor mobility. One of the implications of labor mobility is that wages would be equalized across regions.[10] A lack of mobility would result in a dispersion of wages across regions. In other words, wages are set at the national level for mobile workers and at the local level for less mobile workers. We evaluate the hypothesis that the wage dispersion of lower-wage workers is higher than for higher-wage workers by estimating city-specific wage premiums by quantile. If our hypothesis is true, then there will be greater variation in these premiums for lower quantiles.

[10] Holding other factors constant, such as land costs.

To test this, using the raw (i.e., not the collapsed) ENOE data discussed above, we will estimate the following quantile regression

$$q_\alpha(w_i|I_i, X_i; c) = I_i\Delta_c + X_i\beta_c \quad (5)$$

where the function $q_\alpha(w_i|I_i, X_i)$ denotes the αth quantile of log real wages in city c conditional on a set of industry dummies denoted by $I_i$and a vector of individual characteristics denoted by $X_i$which parsimoniously includes age, sex, and years of schooling. The regression coefficients are all subscripted c to reflect that these regressions are estimated for each of the 32 cities in our data. We estimate the models for α equal to 0.1, 0.5, and 0.9 for each city for a total of 156 estimations. For each estimation, we collect the dummy for employment in the textile industry. We then report descriptive statistics for the estimated textile premium and report the kernel densities by quantile. If wages are set locally at the lower end of the distribution, then there will be less dispersion in the premium as we move towards the high end of the distribution.

In Tables 9a and 9b we report descriptive statistics for the estimated wage premium by quantile for apparel and textiles respectively. Each row of the table corresponds to a separate α from equation (5) and we report statistics based off of 32 separate estimates in each row. We see that the standard deviations of the wage premium decline as we move up the wage distribution in textiles. For α equal to 0.1, the standard deviation of the premium is 0.48; it is 0.34 at the median; and it is 0.31 at the 90th percentile. For apparel, we also see a decline with the percentile albeit one that is not entirely monotonic. The standard deviation moves from 0.16 to 0.07 to 0.09 as alpha increases.

We see a similar pattern when we look at the quantiles of the premiums for different values of α. For a given α, we report the 10th and 90th percentiles of the estimated textile dummies across the 32 cities. We also report the difference between the 90th and 10th percentiles. We see that these differences are 0.37 (0.97), 0.18 (0.76), and 0.22 (0.76) for the 10th, 50th, and 90th percentile quantile regressions for apparel (textiles). Finally, in Figures 5a and 7b, we plot the densities of the estimated premium for each α for apparel and textiles. The figure provides a visualization of the table. As can readily be seen, the dispersion in the city-specific premium declines as we move higher up the wage distribution.

The take-away of these exercises is that there is much more dispersion in wages within the textile industry across cities for low wage workers. This suggests that wages are set nationally for high wage works and locally for low wage workers. It also rationalizes the results in Tables 8a and 8b in which we showed evidence of city-specific wage effects for low wage workers. In general, the lowest-wage workers seem to exhibit the highest adjustment costs and also experienced the largest displacement.

VII. Conclusions

While the literature demonstrates that import competition can have direct adverse labor market effects, such as falling wages and rising displacement, there are few studies that illustrate how third-market competition can affect local labor markets. Understanding how competition in third markets affects local labor markets is an important dimension to the globalization debate. In the case of Mexico examined in this paper, the Chinese competition that Mexico faced in the U.S. market was strong in apparel and textiles. These two labor-intensive sectors experienced falling employment and wages as U.S. imports of Chinese apparel and textiles rose.

An important dimension of the debate surrounding the effects of globalization on labor markets centers around whether the effects are concentrated in prices (wages) or quantities (employment). Whether wages or employment are more likely to be affected is an especially important question for policy makers trying to alleviate the adverse effects of foreign competition. Using current techniques and detailed, high-frequency household surveys, we find that the drop in U.S. demand affected local employment more than local wages. We also explore the distributional effects and find that low-wage workers, who also seem to face the highest worker-level adjustment costs, also bore the brunt of the drop in U.S. demand.

One possible implication of our results is that, in the face of external demand shocks such as this one, adjustment is likely to occur in quantities (employment) rather than prices (wages). Employment adjustments may be inevitable, but they impose significant costs on workers when worker-level adjustment costs are high. Our paper supports several policy responses that have been put forth in the literature. Perhaps the most commonly suggested policy option is training, including vocational training. One leading example is the United States Trade Adjustment Assistance (TAA) program, which includes training support. Results of the TAA program have been mixed, however, which seems to be consistent with the evaluation of similar programs in both developed and developing countries. Employment subsidies may not be especially effective either, and some recent studies suggest that the effects seemed temporary when they were found.

Some other programs target matching and search but, again, findings of significant employment effects are rare. On the other hand, programs that target adjustment costs may present an effect alternative. Reducing the costs of obtaining information about jobs can directly address an important source of workers' adjustment costs. As McKenzie (2017) notes "On the labor supply side, the most promising interventions appear to be ones that help workers access different labor markets, overcoming sectoral and, especially, spatial mismatches…" In any case, the appropriate policy response may be to help workers offset these significant costs. Helping workers find other jobs can increase the efficiency of the economy as well as reduce the costs to workers and can help workers manage some of the adverse effects of rising globalization.

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Table 1: Employment Shares and Wages, ENOE

Industry	Mean Wage (SD)	Mean Employment Share (SD)
Agriculture	1.104	0.0040
	(0.081)	(0.0002)
Oil and Gas Extraction	2.782	0.0014
	(0.244)	(0.0002)
Minerals and Ores (except Oil and Gas)	2.048	0.0021
	(0.169)	(0.0001)
Food Manufacturing	1.530	0.0252
	(0.038)	(0.0002)
Textiles and Mills	1.806	0.0038
	(0.074)	(0.0002)
Apparel Manufacturing	1.509	0.0095
	(0.040)	(0.0003)
Leather and Allied Product Manufacturing	1.438	0.0068
	(0.064)	(0.0008)
Wood Product Manufacturing	1.735	0.0018
	(0.090)	(0.0001)
Paper Manufacturing	1.731	0.0020
	(0.090)	(0.0001)
Printing and Related Support Activities	1.717	0.0029
	(0.068)	(0.0000)
Petroleum and Coal Products Manufacturing	2.720	0.0010
	(0.190)	(0.0001)
Chemical Manufacturing	2.106	0.0031
	(0.076)	(0.0001)
Plastics and Rubber Products Manufacturing	1.776	0.0047
	(0.057)	(0.0001)
Nonmetallic Mineral Product Manufacturing	1.713	0.0053
	(0.052)	(0.0001)
Primary Metal Manufacturing	1.908	0.0018
	(0.099)	(0.0001)
Fabricated Metal Products Manufacturing	1.832	0.0096
	(0.045)	(0.0001)
Machinery Manufacturing	2.006	0.0016
	(0.093)	(0.0001)
Computers, Electrical Equipment, Appliance Manufacturing	1.905	0.0068
	(0.092)	(0.0003)
Transportation Equipment Manufacturing	1.994	0.0149
	(0.071)	(0.0006)
Furniture and Related Product Manufacturing	1.648	0.0067
	(0.042)	(0.0001)
All Industries	1.864	0.7303
	(0.044)	(0.0031)

Notes: Authors' calculations based on ENOE data. ENOE stands for the *Encuesta Nacional de Ocupaciòn y Empleo*, which is a labor-force survey conducted by Mexico's *Instituto Nacional de Estadistica Geografia y Informatica (INEGI).*

Table 2a OLS Apparel Estimates

VARIABLES	(1) Labor Share	(2) Labor Share	(3) LS Clothing	(4) LS Clothing	(5) Wage	(6) Wage	(7) Wage Clothing	(8) Wage Clothing
Apparel Shock	0.0637***	-0.000606	0.00518***	0.00473***	0.266***	-0.0343***	0.164***	-0.0335*
	(0.00680)	(0.00346)	(0.000272)	(0.000369)	(0.0352)	(0.0132)	(0.0241)	(0.0183)
Constant	0.536***	0.718***	0.00796***	0.00937***	1.223***	2.047***	1.101***	1.654***
	(0.0155)	(0.0136)	(0.000635)	(0.000949)	(0.0701)	(0.0485)	(0.0546)	(0.0717)
Observations	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408
Time Dummies	NO	YES	NO	YES	NO	YES	NO	YES
MFX	0.026	0.000	0.002	0.002	0.107	-0.014	0.066	-0.014
Dep.Var.Mean	0.730	0.730	0.012	0.012	1.965	1.965	1.579	1.579
MFX/MeanX100	3.521	-0.034	17.983	16.402	5.470	-0.704	4.195	-0.857

Notes: Newey-West standard errors reported in parentheses. MFX refers to the marginal effect corresponding to a one SD increase in US textile imports from Mexico. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. "LS" stands for Labor Share for either the location (share of workers in an area employed) or in the sector. "Wage" represents the mean wage for either the location or for the sector.

Table 2b: OLS Textile Estimates

VARIABLES	(1) Labor Share	(2) Labor Share	(3) LS Textiles	(4) LS Textiles	(5) Wage	(6) Wage	(7) Wage Textiles	(8) Wage Textiles
Textile Shock	0.451***	0.0974***	0.0170***	0.0173***	1.747***	0.0654	1.211***	0.219
	(0.0434)	(0.0211)	(0.00152)	(0.00158)	(0.192)	(0.0756)	(0.163)	(0.322)
Constant	0.582***	0.701***	0.00125***	0.00181***	1.427***	1.959***	1.453***	1.528***
	(0.0151)	(0.0112)	(0.000222)	(0.000316)	(0.0612)	(0.0398)	(0.0713)	(0.168)
Observations	1,408	1,408	1,408	1,408	1,408	1,408	873	873
Time Dummies	NO	YES	NO	YES	NO	YES	NO	YES
MFX	0.012	0.003	0.000	0.000	0.047	0.002	0.032	0.006
Dep.Var.Mean	0.730	0.730	0.002	0.002	1.965	1.965	1.634	1.634
MFX/MeanX100	1.653	0.357	27.794	28.215	2.381	0.089	1.986	0.359

Notes: Newey-West standard errors reported in parentheses. MFX refers to the marginal effect corresponding to a one SD increase in US textile imports from Mexico. ***p<0.01, **p<0.05, *p<0.1. “LS” stands for Labor Share for either the location (share of workers in an area employed) or in the sector. “Wage” represents the mean wage for either the location or for the sector.

Table 3a: Stage 1 of Apparel IV Estimation

VARIABLES	Apparel Shock	Apparel Shock
China Shock	-0.0226***	-0.0226**
	(0.00780)	(0.0104)
Constant	1.722***	2.459***
	(0.119)	(0.165)
Observations	1,408	1,408
Time Dummies	NO	YES
MFX	-0.056	-0.056
Dep.Var.Mean	8.936	8.936
MFX/MeanX100	-0.630	-0.630
F-Stat	8.379	4.692

Table 3b: Apparel IV Estimates

VARIABLES	(1) Labor Share	(2) Labor Share	(3) LS Clothing	(4) LS Clothing	(5) Wage	(6) Wage	(7) Wage Clothing	(8) Wage Clothing
Apparel Shock	0.1630***	-0.0272	0.00644***	0.00407**	0.819***	-0.147*	0.549***	0.0137
	(0.0484)	(0.0206)	(0.00153)	(0.00197)	(0.259)	(0.0751)	(0.187)	(0.114)
Constant	0.387***	0.778***	0.00608***	0.0109**	0.396	2.303***	0.525*	1.546***
	(0.0730)	(0.0473)	(0.00234)	(0.00451)	(0.389)	(0.172)	(0.281)	(0.267)
Observations	1,408	1,408	1,408	1,408	1,408	1,408	1,408	1,408
Time Dummies	NO	YES	NO	YES	NO	YES	NO	YES
MFX	0.066	-0.011	0.003	0.002	0.331	-0.059	0.222	0.006
Dep.Var.Mean	0.730	0.730	0.012	0.012	1.965	1.965	1.579	1.579
MFX/MeanX100	9.035	-1.503	22.337	14.111	16.830	-3.012	14.037	0.351

Notes: Newey-West standard errors reported in parentheses. MFX refers to the marginal effect corresponding to a one SD increase in US textile imports from Mexico. ***p<0.01, **p<0.05, *p<0.1. “LS” stands for Labor Share for either the location (share of workers in an area employed) or in the sector. “Wage” represents the mean wage for either the location or for the sector.

Table 4a: Stage 1

VARIABLES	(1) Textile Shock	(2) Textile Shock
China_shockGen_textiles_l	-0.0563***	-0.0563***
	(0.0140)	(0.0140)
Constant	0.128***	0.163***
	(0.00572)	(0.0125)
Observations	1,408	1,408
Time Dummies	NO	YES
MFX	-0.007	-0.007
Dep.Var.Mean	0.373	0.373
MFX/MeanX100	-1.952	-1.952
F-Stat	16.109	16.075

Table 4b: IV Estimates

VARIABLES	(1) Labor Share	(2) Labor Share	(3) LS Textiles	(4) LS Textiles	(5) Wage	(6) Wage	(7) Wage Textiles	(8) Wage Textiles
Textile Shock	1.023***	0.0451	0.0402***	0.0409***	4.712***	-0.389**	3.595***	-0.591
	(0.197)	(0.0727)	(0.00667)	(0.00702)	(0.920)	(0.194)	(0.811)	(1.426)
Constant	0.518***	0.709***	-0.00132*	-0.00178	1.098***	2.028***	1.188***	1.662***
	(0.0256)	(0.0155)	(0.000759)	(0.00109)	(0.114)	(0.0491)	(0.110)	(0.289)
Observations	1,408	1,408	1,408	1,408	1,408	1,408	873	873
Time Dummies	NO	YES	NO	YES	NO	YES	NO	YES
MFX	0.027	0.001	0.001	0.001	0.126	-0.010	0.096	-0.016
Dep.Var.Mean	0.730	0.730	0.002	0.002	1.965	1.965	1.634	1.634
MFX/MeanX100	3.753	0.165	65.592	66.766	6.423	-0.530	5.893	-0.969

Notes: Newey-West standard errors reported in parentheses. MFX refers to the marginal effect corresponding to a one SD increase in US textile imports from Mexico. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. "LS" stands for Labor Share for either the location (share of workers in an area employed) or in the sector. "Wage" represents the mean wage for either the location or for the sector.

Table 5a: Apparel's Effects on Textile Labor Share

VARIABLES	(1) Textiles Base	(2) Textiles Time	(3) Textiles IV Base	(4) Textiles IV Time
Clothing Shock	0.00156***	0.00205***	0.00300***	0.00400***
	(0.000156)	(0.000226)	(0.000855)	(0.00142)
Constant	0.000812***	-0.000232	-0.00135	-0.00466
	(0.000275)	(0.000517)	(0.00130)	(0.00322)
Observations	1,408	1,408	1,408	1,408

Table 5b: Textile's Effects on Apparel Labor Share

VARIABLES	(1) Apparel Base	(2) Apparel Time	(3) Apparel IV Base	(4) Apparel IV Time
Textile Shock	0.0330***	0.0207***	0.0781***	0.0517***
	(0.00301)	(0.00292)	(0.0150)	(0.0119)
Constant	0.0120***	0.0170***	0.00703***	0.0123***
	(0.000674)	(0.000845)	(0.00175)	(0.00193)
Observations	1,408	1,408	1,408	1,408

Notes: Authors’ calculations based on ENOE data. The first two columns in each table are estimates with OLS.

Table 5c: Apparel's Effects on Textile Wages

VARIABLES	(1) Textiles Base	(2) Textiles Time	(1) Textiles IV Base	(2) Textiles IV Time
Clothing Shock	0.167***	-0.0331	0.721**	0.315
	(0.0347)	(0.0501)	(0.366)	(0.395)
Constant	1.338***	1.643***	0.509	0.817
	(0.0819)	(0.202)	(0.550)	(0.960)
Observations	873	873	873	873

Table 5d: Textile's Effects on Apparel Wages

VARIABLES	(3) Apparel Base	(4) Apparel Time	(3) Apparel IV Base	(4) Apparel IV Time
Textile Shock	1.064***	0.0279	3.377***	-0.0101
	(0.136)	(0.104)	(0.687)	(0.345)
Constant	1.228***	1.573***	0.971***	1.579***
	(0.0484)	(0.0593)	(0.0872)	(0.0784)
Observations	1,408	1,408	1,408	1,408

Notes: Authors' calculations based on ENOE data. The first two columns in each table are estimates with OLS. The abbreviation "n.a." stands for "not applicable".

Table 6a: Distributed Lag Model for Apparel

VARIABLES	(1) LS Apparel	(2) LS Apparel	(3) LS Apparel	(4) LS Apparel	(5) LS Apparel	(6) LS Apparel	(7) LS Apparel
Apparel Shock	0.00473***	0.000330	0.000614	-0.00393	-0.00403	-0.00334	-0.00287
	(0.000376)	(0.00103)	(0.00120)	(0.00271)	(0.00259)	(0.00298)	(0.00294)
lag1 Apparel Shock		0.00449***	0.00298*	0.00688**	0.00155	0.000392	-0.00225
		(0.00108)	(0.00156)	(0.00316)	(0.00275)	(0.00337)	(0.00371)
lag2 Apparel Shock			0.00130	-0.00296	0.00244	0.00266	0.00531
			(0.000936)	(0.00306)	(0.00280)	(0.00294)	(0.00348)
lag3 Apparel Shock				0.00414*	-0.00175	-0.00218	-0.00136
				(0.00228)	(0.00226)	(0.00263)	(0.00252)
lag4 Apparel Shock					0.00522***	0.00502	0.00367
					(0.00171)	(0.00306)	(0.00291)
lag5 Apparel Shock						0.000708	0.00403
						(0.00247)	(0.00306)
lag6 Apparel Shock							-0.00305
							(0.00205)
Constant	0.00937***	0.00774***	0.00878***	0.0102***	0.0112***	0.00965***	0.00921***
	(0.000971)	(0.00101)	(0.00100)	(0.00107)	(0.00112)	(0.000936)	(0.00101)
Observations	1,408	1,376	1,344	1,312	1,280	1,248	1,216
Sum	n.a.	0.005	0.005	0.004	0.003	0.003	0.003
F Stat	158.004	226.001	198.931	88.421	32.297	24.721	23.373
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. LS stands for Labor Share. The abbreviation "n.a." stands for "not applicable".

Table 6b: Distributed Lag Model for Textiles

VARIABLES	(1) LS textiles	(2) LS textiles	(3) LS textiles	(4) LS textiles	(5) LS textiles	(6) LS textiles	(7) LS textiles
Textile Shock	0.0173***	0.00445*	0.00272	0.000155	-0.000763	0.00237	0.00269
	(0.00165)	(0.00242)	(0.00231)	(0.00260)	(0.00243)	(0.00262)	(0.00294)
lag1 Textile Shock		0.0133***	0.00645**	0.00811***	0.00622**	0.00284	0.00395
		(0.00230)	(0.00273)	(0.00275)	(0.00253)	(0.00297)	(0.00307)
lag2 Textile Shock			0.00850***	0.00359	0.00522*	0.00433	0.00308
			(0.00242)	(0.00312)	(0.00292)	(0.00308)	(0.00335)
lag3 Textile Shock				0.00591**	0.00135	0.00199	0.00113
				(0.00265)	(0.00259)	(0.00278)	(0.00297)
lag4 Textile Shock					0.00588***	0.000660	0.00123
					(0.00207)	(0.00292)	(0.00286)
lag5 Textile Shock						0.00623**	0.00353
						(0.00261)	(0.00272)
lag6 Textile Shock							0.00321
							(0.00239)
Constant	0.00181***	0.00128***	0.00130***	0.00109***	0.00111***	0.00170***	0.00135***
	(0.000324)	(0.000293)	(0.000303)	(0.000311)	(0.000329)	(0.000390)	(0.000338)
Observations	1,408	1,376	1,344	1,312	1,280	1,248	1,216
Sum	n.a.	0.018	0.018	0.018	0.018	0.018	0.019
F Stat	109.381	128.241	116.775	101.289	90.314	83.670	74.059
P-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. LS stands for Labor Share.

Table 7a: Apparel Estimates by Education Level

VARIABLES	(1) <=9 Yrs	(2) <=9 Yrs	(3) >9 Yrs	(4) >9 Yrs
Apparel Shock	0.00405***	0.00372***	0.00112***	0.000980***
	(0.000170)	(0.000213)	(0.000170)	(0.000263)
Constant	0.00469***	0.00566***	0.00330***	0.00378***
	(0.000468)	(0.000624)	(0.000315)	(0.000607)
Observations	1,408	1,408	1,408	1,408
Time Dummies	NO	YES	NO	YES
MFX	0.002	0.002	0.000	0.000
Dep.Var.Mean	0.008	0.008	0.004	0.004
MFX/MeanX100	20.404	18.742	12.438	10.934

Table 7b: Textile Estimates by Education Level

VARIABLES	(1) <=9 Yrs	(2) <=9 Yrs	(3) >9 Yrs	(4) >9 Yrs
Textile Shock	0.0132***	0.0134***	0.00383***	0.00388***
	(0.00137)	(0.00141)	(0.000674)	(0.000728)
Constant	0.000553***	0.00105***	0.000703***	0.000771***
	(0.000187)	(0.000271)	(0.000105)	(0.000144)
Observations	1,408	1,408	1,408	1,408
Time Dummies	NO	YES	NO	YES
MFX	0.000	0.000	0.000	0.000
Dep.Var.Mean	0.001	0.001	0.000	0.000
MFX/MeanX100	30.838	31.345	20.669	20.917

Notes: Authors' calculations based on ENOE data. The column headings are based on number of years of education. The cut-off of nine years of education was based on the distribution of education in the Mexican sample; 9 years is roughly the mean education level for the sample and was the compulsory requirement until 2013. In 2013 the Mexican Secretary of Education raised the compulsory limit to twelve years but full compliance was not expected until 2020. See https://wenr.wes.org/2016/08/education-in-mexico.

Table 8a: Apparel Estimates by Selected Deciles

VARIABLES	(1) 10th Pctile	(2) 10th Pctile	(3) 50th Pctile	(4) 50th Pctile	(5) 90th Pctile	(6) 90th Pctile
Apparel Shock	0.145***	0.0456**	0.116***	-0.0183	0.209***	-0.152***
	(0.0173)	(0.0223)	(0.0178)	(0.0166)	(0.0450)	(0.0534)
Constant	-0.202***	0.133*	1.087***	1.415***	2.216***	3.473***
	(0.0298)	(0.0780)	(0.0460)	(0.0641)	(0.0872)	(0.233)
Observations	1,408	1,408	1,408	1,408	1,408	1,408
Time Dummies	NO	YES	NO	YES	NO	YES
MFX	0.059	0.018	0.047	-0.007	0.084	-0.061
Dep.Var.Mean	0.262	0.262	1.359	1.359	3.158	3.158
MFX/MeanX100	22.380	7.018	3.434	-0.543	2.673	-1.947

Table 8b: Textile Estimates by Selected Deciles

VARIABLES	(1) 10th Pctile	(2) 10th Pctile	(3) 50th Pctile	(4) 50th Pctile	(5) 90th Pctile	(6) 90th Pctile
Textile Shock	0.804***	0.453	0.825***	0.0917	1.765***	-0.423
	(0.211)	(0.400)	(0.141)	(0.332)	(0.305)	(0.476)
Constant	0.0756	-0.113	1.403***	1.304***	2.897***	3.468***
	(0.0713)	(0.180)	(0.0620)	(0.165)	(0.191)	(0.345)
Observations	873	873	873	873	873	873
Time Dummies	NO	YES	NO	YES	NO	YES
MFX	0.022	0.012	0.022	0.002	0.047	-0.011
Dep.Var.Mean	0.780	0.780	1.587	1.587	2.585	2.585
MFX/MeanX100	2.762	1.556	1.393	0.155	1.829	-0.438

Notes: Newey-West standard errors reported in parentheses. MFX refers to the marginal effect corresponding to a one SD increase in US textile imports from Mexico. $^{***}p<0.01$, $^{**}p<0.05$, $^{*}p<0.1$. "LS" stands for Labor Share for either the location (share of workers in an area employed) or in the sector. "Wage" represents the mean wage for either the location or for the sector.

Table 9a: City-Specific Wage Premiums in Apparel

	Mean	SD	10th Percentile	90th Percentile	90th – 10th Percentile
10th Percentile	-0.11	0.16	-0.32	0.05	0.37
50th Percentile	-0.15	0.07	-0.24	-0.06	0.18
90th Percentile	-0.19	0.09	-0.30	-0.08	0.22

Note: Each row corresponds to summary statistics from 32 quantile regressions for a given quantile. For each quantile of the regression, we report the mean, standard deviation, 10th and 90th percentiles, and the difference between the two percentiles of the dummy variable on the textile industry.

Table 9b: City-Specific Wage Premiums in Textiles

	Mean	SD	10th Percentile	90th Percentile	90th – 10th Percentile
10th Percentile	-0.11	0.48	-0.73	0.24	0.97
50th Percentile	-0.19	0.34	-0.72	0.04	0.76
90th Percentile	-0.20	0.31	-0.58	0.18	0.76

Note: Each row corresponds to summary statistics from 32 quantile regressions for a given quantile. For each quantile of the regression, we report the mean, standard deviation, 10th and 90th percentiles, and the difference between the two percentiles of the dummy variable on the textile industry.

Table A1: Municipalities in the ENOE

Group	Municipality	Freq.	Percent	Cum.
1	Ciudad de México	330,745	6.76	6.76
2	Guadalajara	220,170	4.50	11.26
3	Monterrey	218,163	4.46	15.71
4	Puebla	194,672	3.98	19.69
5	León	228,945	4.68	24.37
6	San Luís Potosí	143,999	2.94	27.31
7	Mérida	140,814	2.88	30.19
8	Chihuahua	126,207	2.58	32.77
9	Tampico	122,906	2.51	35.28
10	Veracruz	114,449	2.34	37.62
11	Acapulco	130,442	2.67	40.28
12	Aguascalientes	141,821	2.90	43.18
13	Morelia	138,157	2.82	46.00
14	Toluca	144,542	2.95	48.96
15	Saltillo	142,054	2.90	51.86
16	Villahermosa	140,111	2.86	54.72
17	Tuxtla Gutiérrez	146,763	3.00	57.72
18	Tijuana	131,121	2.68	60.40
19	Culiacán	150,525	3.08	63.47
20	Hermosillo	142,832	2.92	66.39
21	Durango	138,816	2.84	69.23
22	Tepic	145,066	2.96	72.19
23	Campeche	124,849	2.55	74.74
24	Cuernavaca	133,271	2.72	77.47
25	Oaxaca	148,015	3.02	80.49
26	Zacatecas	143,480	2.93	83.42
27	Colima	138,030	2.82	86.24
28	Querétaro	141,595	2.89	89.14
29	Tlaxcala	145,355	2.97	92.10
30	La Paz	117,481	2.40	94.51
31	Cancún	137,614	2.81	97.32
32	Pachuca	131,314	2.68	100.00

Table A2: Industries by NAICS Code

Group	Description	NAICS Code
1	Agricultural Products	111
2	Oil and Gas Extraction	211
3	Minerals and Ores (except Oil and Gas)	212
4	Food Manufacturing	311, 312
5	Textiles and Mills	313, 314
6	Apparel Manufacturing	315
7	Leather and Allied Product Manufacturing	316
8	Wood Product Manufacturing	321
9	Paper Manufacturing	322
10	Printing and Related Support Activities	323
11	Petroleum and Coal Products Manufacturing	324
12	Chemical Manufacturing	325
13	Plastics and Rubber Products Manufacturing	326
14	Nonmetallic Mineral Product Manufacturing	327
15	Primary Metal Manufacturing	331
16	Fabricated Metal Products Manufacturing	332
17	Machinery Manufacturing	333
18	Computer and Electronic Products, Electrical Equipment, Appliance and Component Manufacturing	334, 335
19	Transportation Equipment Manufacturing	336
20	Furniture and Related Product Manufacturing	337
21	Miscellaneous Manufacturing	338, 339

Table A3a: Imports from Mexico by Industry

Group No.	Product Description	Mean Imports (billions of US$)	Percent	Cum.
1	Agricultural Products	1.68	2.97	2.97
2	Oil and Gas Extraction	7.70	13.59	16.56
3	Minerals and Ores (except Oil and Gas)	0.08	0.15	16.71
4	Food Manufacturing	1.90	3.35	20.06
5	Textiles and Mills	0.32	0.58	20.64
6	Apparel Manufacturing	1.15	2.03	22.67
7	Leather and Allied Product Manufacturing	0.47	0.83	23.50
8	Wood Product Manufacturing	0.04	0.09	23.59
9	Paper Manufacturing	0.24	0.42	24.01
10	Printing and Related Support Activities	0.11	0.21	24.22
11	Petroleum and Coal Products Manufacturing	0.79	1.40	25.63
12	Chemical Manufacturing	1.16	2.05	27.67
13	Plastics and Rubber Products Manufacturing	0.80	1.43	29.10
14	Nonmetallic Mineral Product Manufacturing	0.61	1.08	30.18
15	Primary Metal Manufacturing	2.29	4.04	34.23
16	Fabricated Metal Products Manufacturing	1.54	2.72	36.94
17	Machinery Manufacturing	3.10	5.47	42.42
18	Computer and Electronic Products, Electrical Equipment, Appliance and Component Manufacturing	17.1	30.18	72.60
19	Transportation Equipment Manufacturing	15.1	26.65	99.25
20	Furniture and Related Product Manufacturing	0.42	0.75	100.00

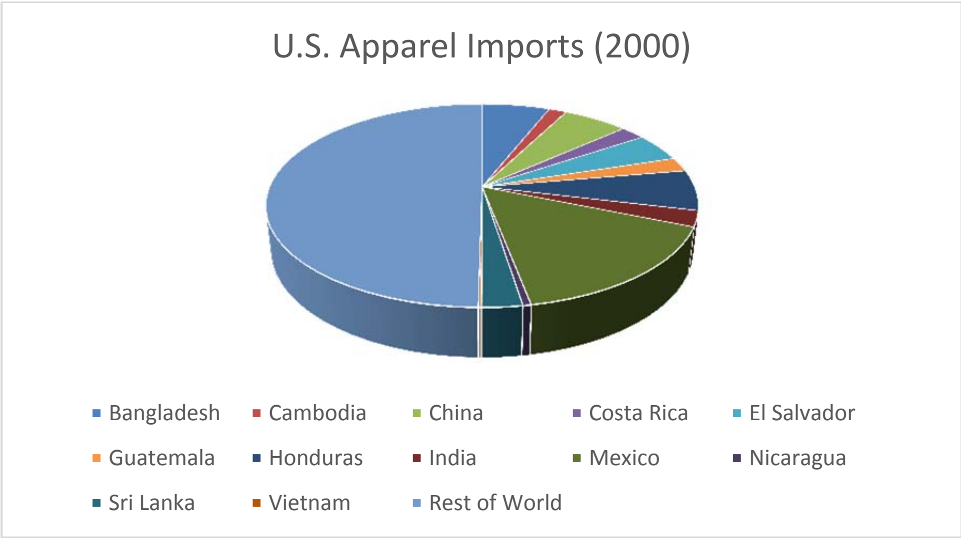
Note: This data source is the U.S. Census Bureau estimates from the Economic Indicators Division. Product groups are based on 3-digit level North American Industrial Classification System (NAICS) classification.

Table A3b: Imports from China by Industry

Group No.	Product Description	Mean Imports (in billions)	Percent	Cum.
1	Agricultural Products	6.55	7.38	7.38
2	Oil and Gas Extraction	0.07	0.08	7.46
3	Minerals and Ores (except Oil and Gas)	0.06	0.08	7.54
4	Food Manufacturing	0.75	0.85	8.38
5	Textiles and Mills	2.39	2.69	11.08
6	Apparel Manufacturing	6.92	7.79	18.87
7	Leather and Allied Product Manufacturing	5.66	6.37	25.24
8	Wood Product Manufacturing	1.12	1.26	26.50
9	Paper Manufacturing	0.66	0.75	27.25
10	Printing and Related Support Activities	0.58	0.65	27.91
11	Petroleum and Coal Products Manufacturing	0.11	0.12	28.03
12	Chemical Manufacturing	2.80	3.15	31.19
13	Plastics and Rubber Products Manufacturing	3.00	3.38	34.56
14	Nonmetallic Mineral Product Manufacturing	1.49	1.68	36.24
15	Primary Metal Manufacturing	1.38	1.55	37.80
16	Fabricated Metal Products Manufacturing	3.82	4.30	42.10
17	Machinery Manufacturing	5.29	5.96	48.05
18	Computer and Electronic Products, Electrical Equipment, Appliance and Component Manufacturing	39.40	44.37	92.42
19	Transportation Equipment Manufacturing	2.84	3.20	95.62
20	Furniture and Related Product Manufacturing	3.89	4.38	100.00

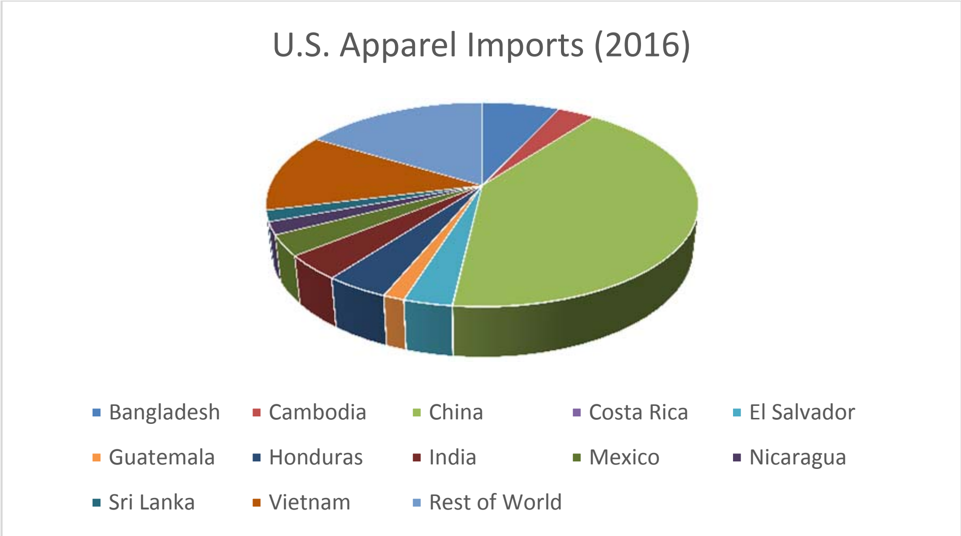
Note: Per Table A3b.

Figure 1a



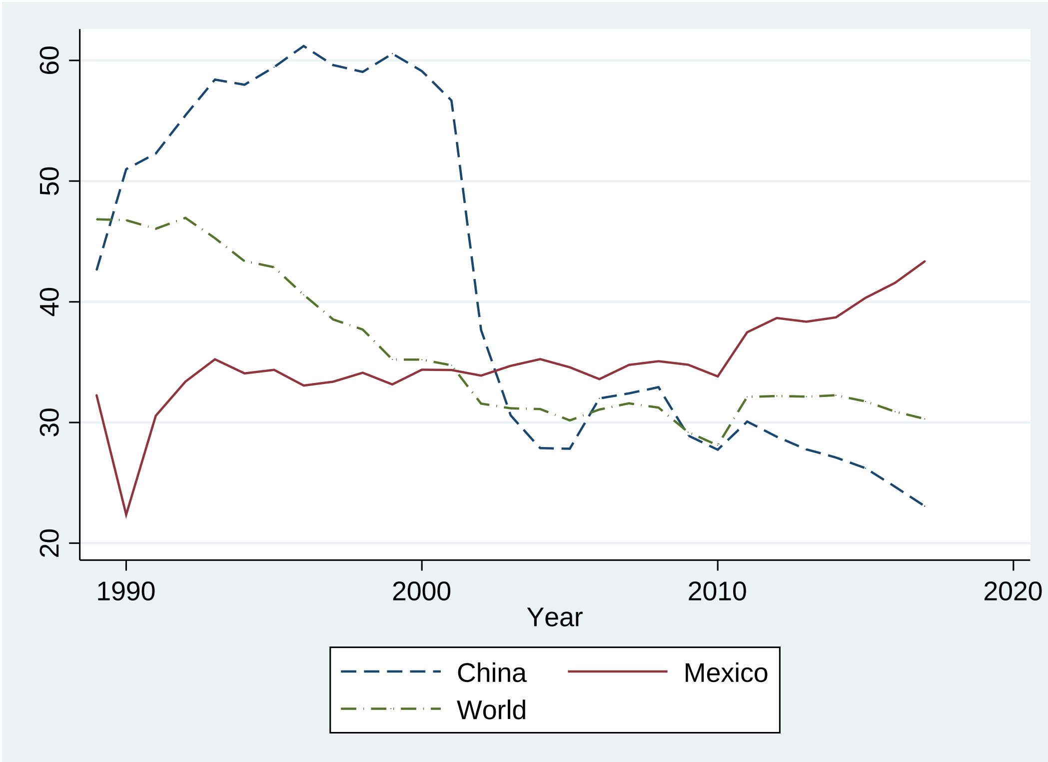
Notes: Authors' elaboration based on data from the International Trade Administration's Office of Textiles and Apparel (OTEXA). As seen, Mexico was the leading exporter of textiles and apparel to the United States in 2000 with 16% market share, and China comprised a mere a mere sliver of total imports (6%).

Figure 1b:



Notes: Authors' elaboration using data from the International Trade Administration's Office of Textiles and Apparel (OTEXA). By 2016, China had become the primary exporter of textiles and apparel to the United States, with close to a majority for all American imports within the industry (42%). Mexico's market share diminished considerably during this time period, falling from 16 percent in 2000 to 3 percent in 2016.

Figure 2: Average Unit Values of U.S. Apparel Imports 1989-2017



Notes: Authors' elaboration using data from the International Trade Administration's Office of Textiles and Apparel (OTEXA). Each series is the square-meter-equivalent-weighted mean unit value (total value divided by square meter equivalent quantity of imports) over all apparel goods imported from each country.

Figure 3a: U.S. Imports of Mexican Clothing and Mexican Employment Share in Clothin

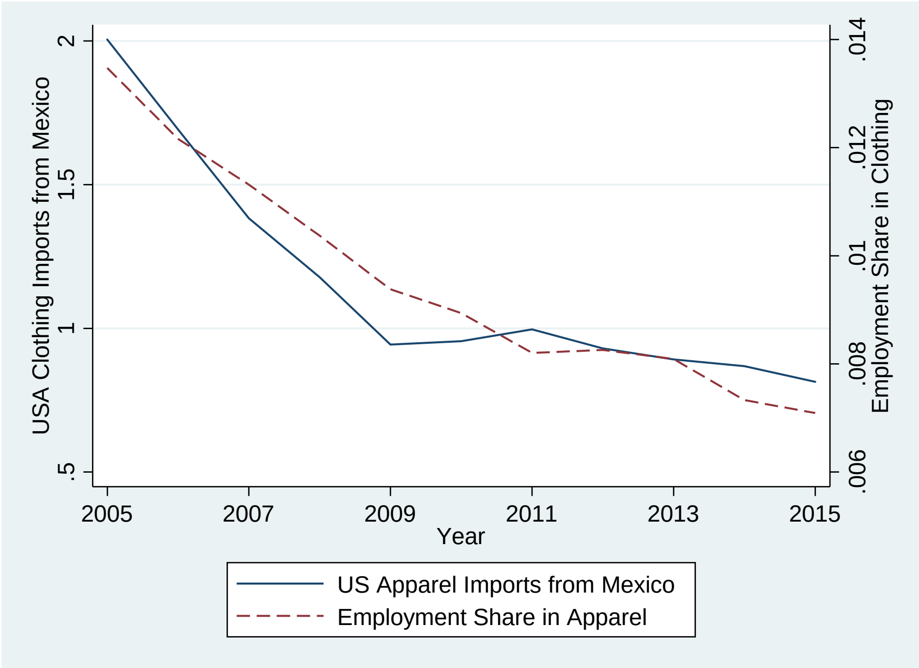
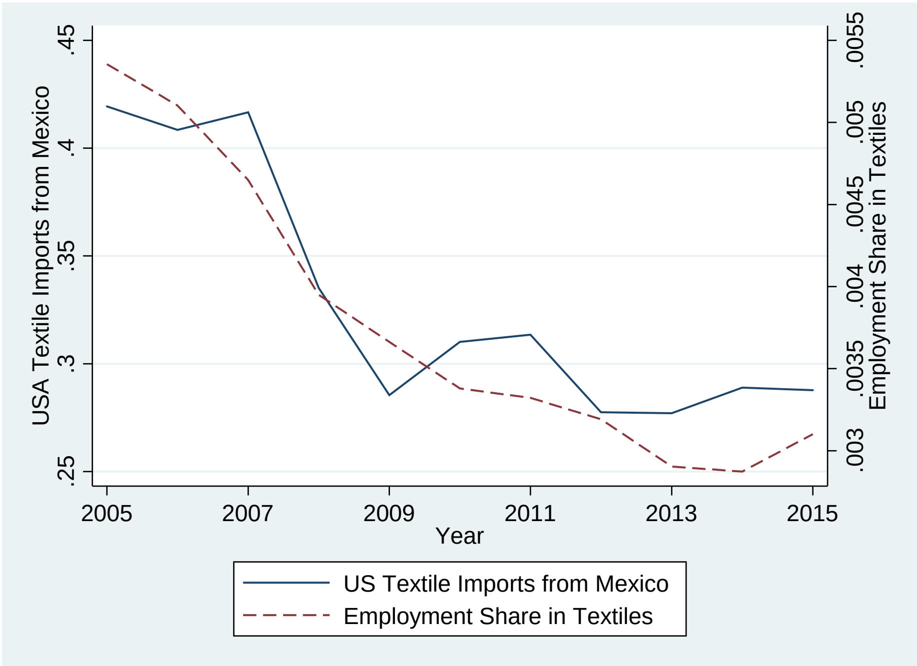


Figure 3b: U.S. Imports of Mexican Textiles and Mexican Employment Share in Textiles.



Notes: Authors' elaboration using data from the International Trade Administration's Office of Textiles and Apparel (OTEXA) and ENOE (from INEGI) as described in the text.

Figure 4a: U.S. Apparel Imports from Mexico and China

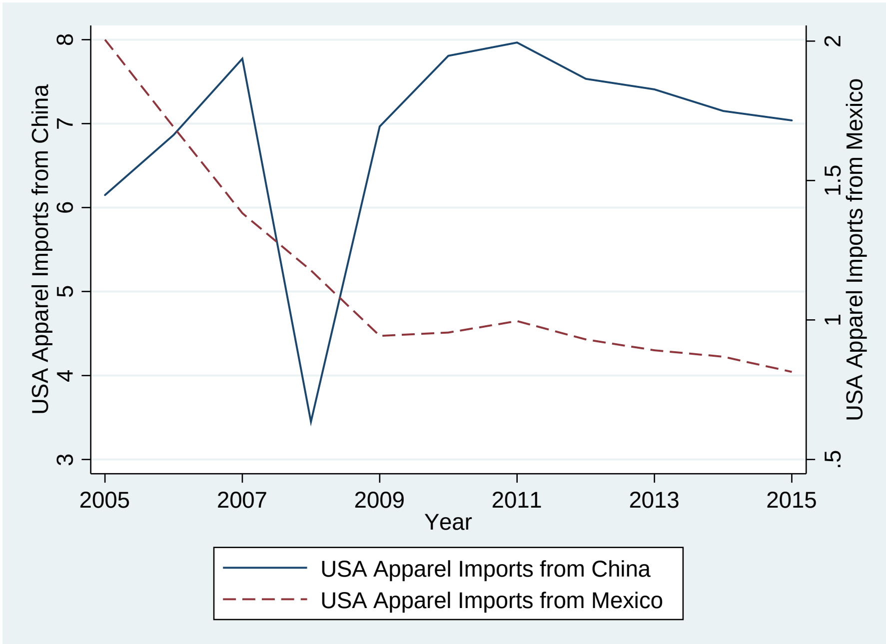
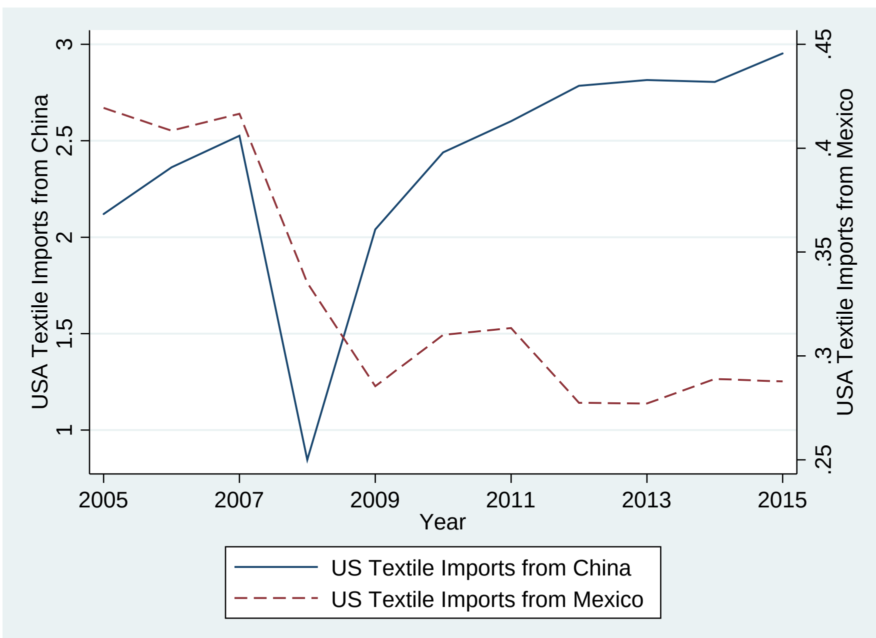
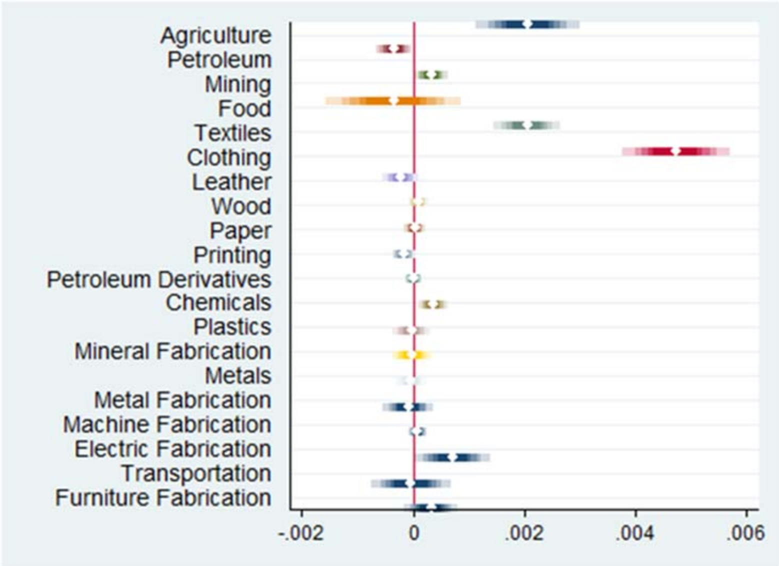


Figure 4b: U.S. Textile Imports from Mexico and China



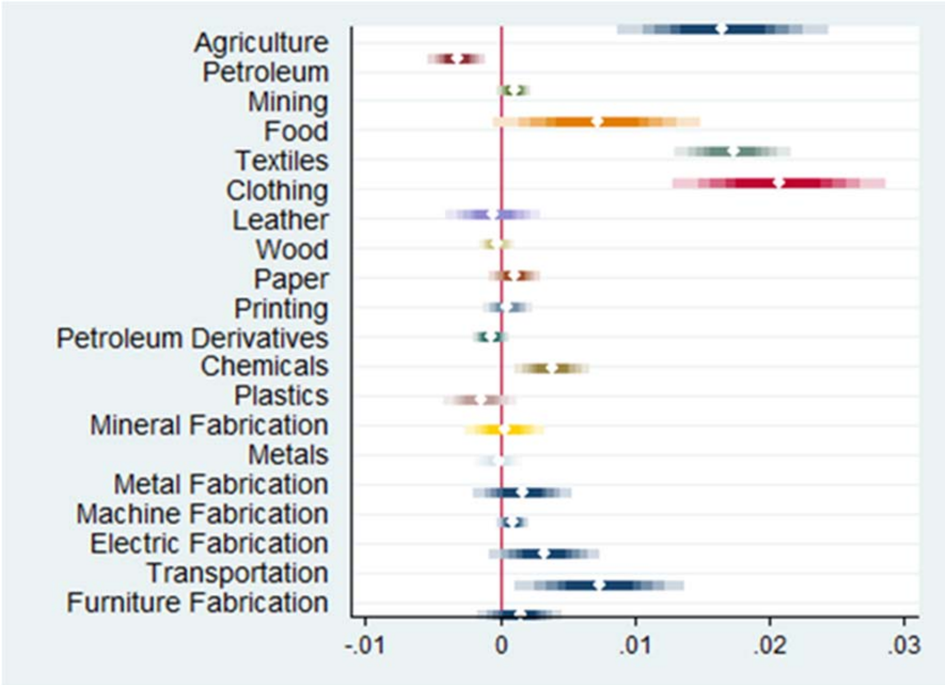
Notes: Authors' elaboration using data from the International Trade Administration's Office of Textiles and Apparel (OTEXA)

Figure 5a: Associated Industry Estimates from Apparel Exports



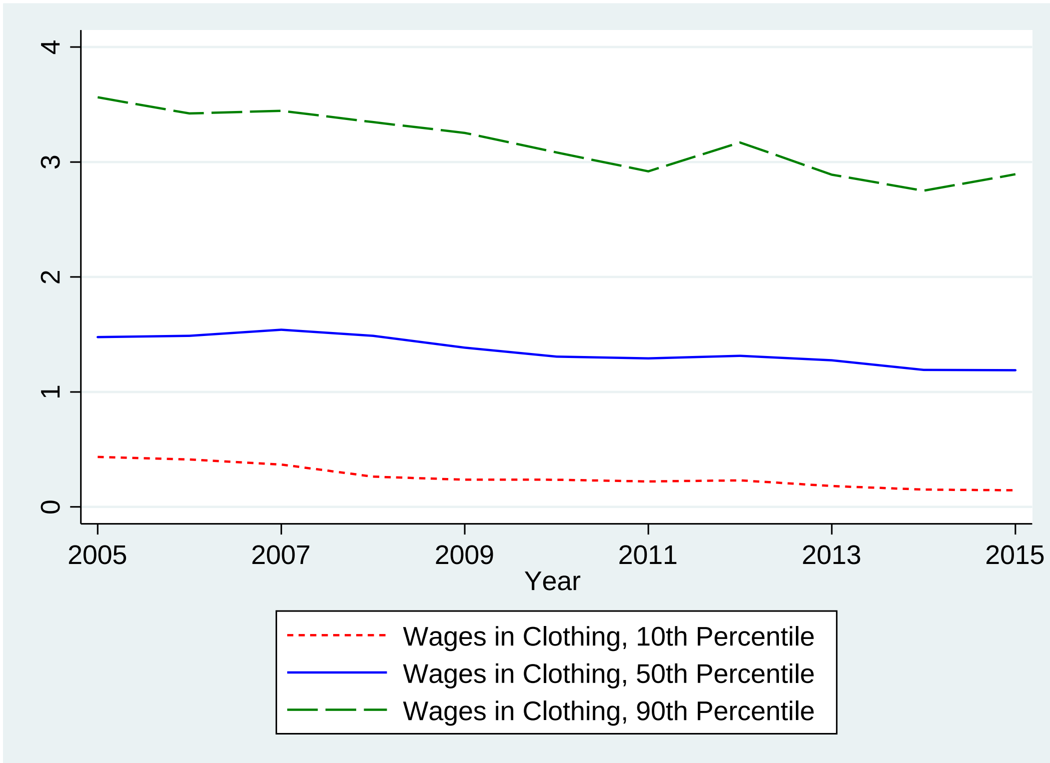
Notes: Authors' elaboration using data from the International Trade Administration's Office of Textiles and Apparel (OTEXA) and ENOE. The shaded areas represent confidence intervals around the hollow point estimates.

Figure 5b: Associated Industry Estimates from Textile Exports



Notes: Authors' elaboration using data from the International Trade Administration's Office of Textiles and Apparel (OTEXA) and ENOE. The shaded areas represent confidence intervals around the hollow point estimates.

Figure 6a: Apparel Wages over Time and Percentile

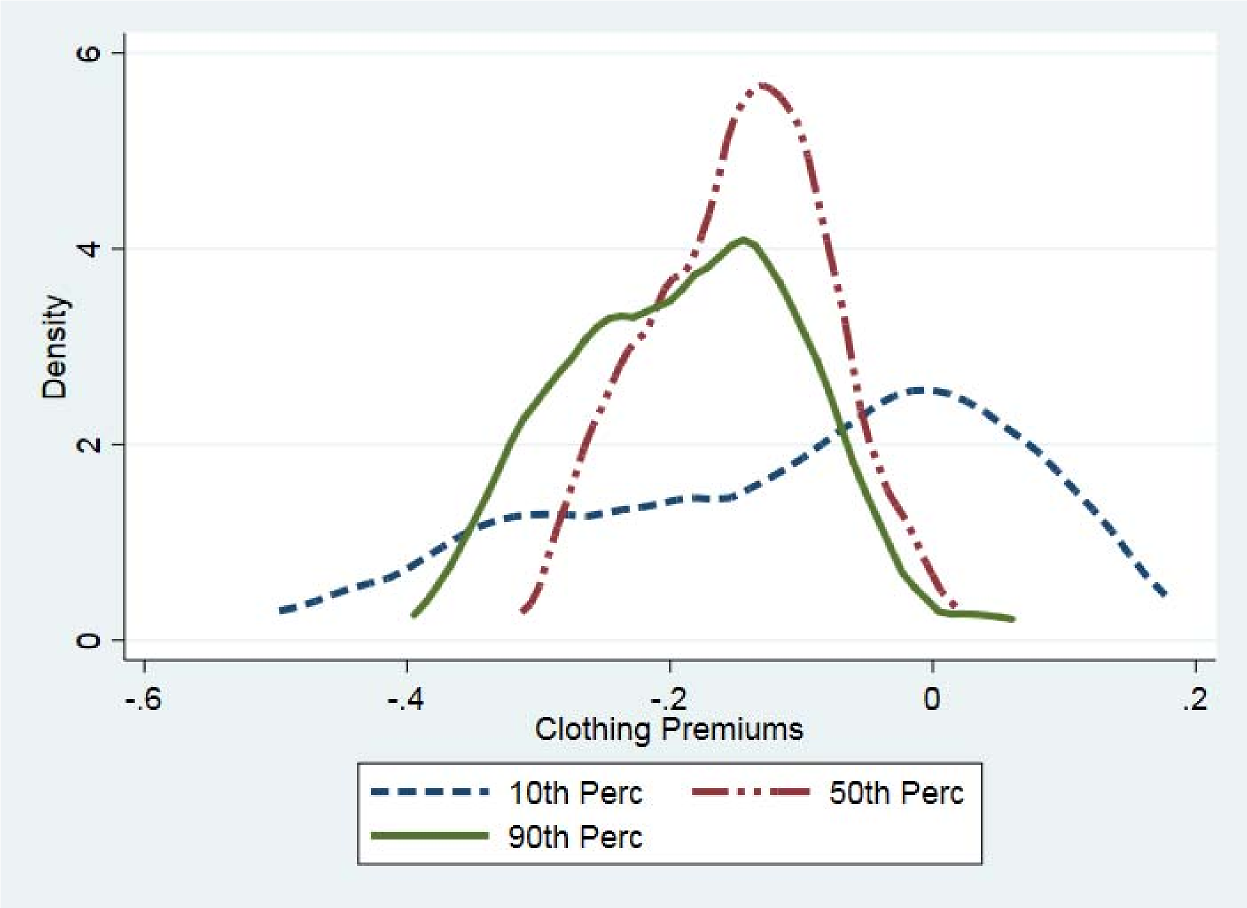


Notes: Authors' elaboration using data from ENOE.

Figure 6b: Textile Wages over Time and Percentile

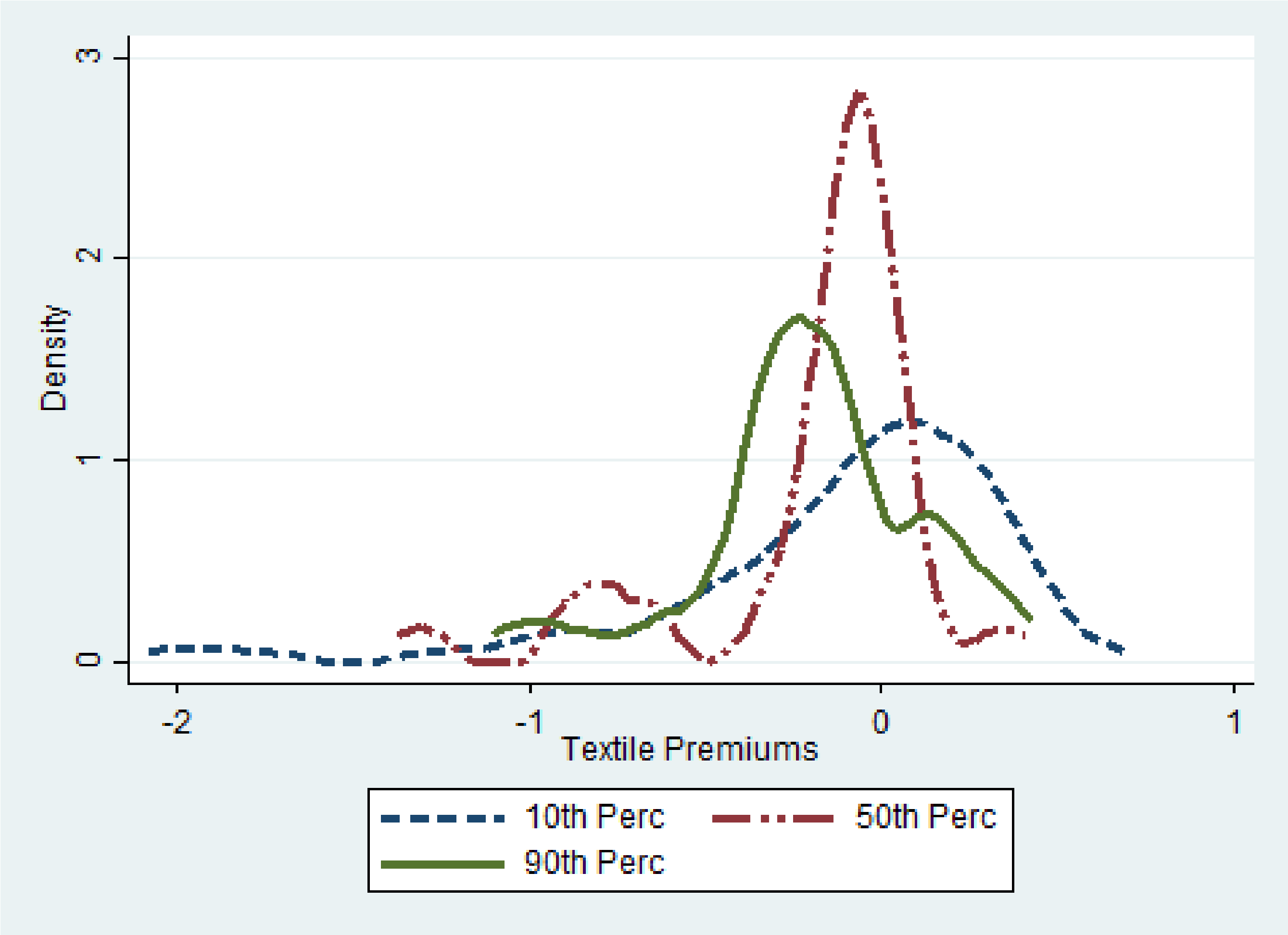
Notes: Authors' elaboration using data from ENOE.

Figure 7a: Apparel Wage Premiums



Notes: Authors' elaboration using data from ENOE. Figures represents the kernel density of the estimated city-specific apparel wage premiums for different points in the wage distribution. The apparel wage premiums are estimated using standard Mincerian log-wage equations.

Figure 7b: Textile Wage Premiums



Notes: Authors' elaboration using data from ENOE. Figures represents the kernel density of the estimated city-specific apparel wage premiums for different points in the wage distribution. The apparel wage premiums are estimated using standard Mincerian log-wage equations.