The China Shock and Job Loss in Mexico[*]

Cristián Aguilera Arellano[†]

November 10, 2022

CLICK HERE FOR MOST RECENT VERSION

Abstract

I use administrative data from Mexico to examine the earnings losses and distributional effects of displaced workers from industries affected by China's entrance to the WTO, also known as the "China shock." By exploiting industry shocks to export competition with China, I find that displaced individuals in exposed industries have an initial job loss of 20 log points larger than displaced workers from non-exposed industries. Wage losses are larger for high-income workers than for low-income workers. I integrate sectoral choice, sector-specific human capital, severance payments, minimum wage schedule, and employment risk into a directed search model to rationalize the empirical patterns and quantify the contribution of labor market frictions and sector-specific human capital to the wage scarring effect. Finally, I use the model to assess the distributional effects of the China Shock.

JEL Codes: F14, J24.
Keywords: Labor market dynamics, distributional effects of trade shocks, adjustment costs, worker heterogeneity.

[*]I am very grateful to Mariacristina De Nardi, Fatih Guvenen, Kyle Herkenhoff, Loukas Karabarbounis, Jeremy Lise, Hannes Malmberg, and Joseph Mullins for their guidance on this project. In addition, I thank Fil Babalievsky, Serdar Birinci, Dhananjay Ghei, Egor Malkov, Nicolò Russo, David Wiczer, the participants at the SED 2022, and the participants of the De Nardi-Lise-Mullins and Guvenen workshops at the University of Minnesota for many helpful conversations. All errors are my own.

[†]University of Minnesota; aguil157@umn.edu

1 Introduction

It is well known that a country's exposure to international trade generates winners and losers. Understanding who the losers are is crucial to determine labor and trade policies that can maximize welfare. In the last three decades, numerous developing countries went through trade liberalization episodes that increased their exposure to international markets. This has also implied an increase in export competition among many developing countries across different industries. In this paper, I study the labor market effects of an increase in exposure to competition in export-competing industries. I specifically study how the entrance of China to the World Trade Organization (WTO) had an impact on Mexican labor markets.

After the entrance of China to the World Trade Organization (WTO) in 2001, its global share of world exports surged dramatically. Between 2001 and 2012, its share of world manufacturing exports rose from 6.9 percent to 15.8 percent (Figure 1). In the U.S., the share of imports coming from China increased from 4 percent in 2001 to around 14 percent in 2012. China's unprecedented rise in international markets had trade implications for other countries with significant presence in international markets. Countries producing goods China started exporting suffered a significant increase in competitive supply.

Mexico has been the U.S.'s top three trade partner since the early 1990s. In 1994, Mexico signed the North American Free Trade Agreement (NAFTA) between the U.S., Canada, and Mexico. This agreement represented an essential step in the integration of the Mexican economy into the international markets. Mexican exports have mainly concentrated in trade with the U.S. Between 1993 and 2001, 85.6 percent of total Mexican exports went to the U.S. The total share of U.S. imports coming from Mexico rose from 6.7 percent in 1993 to 11.5 percent in 2001. Contrary to what happened in the nineties, the total share of U.S. imports from Mexico declined to 10 percent in 2008. Similarly, the Mexican global share of world exports in the manufacturing sector steadily increased from 1.2 percent in 1993 to 2.5 percent in 2001 before dipping to 1.8 percent in 2008 (Figure 1). In the same period of steady decline in the global share of exports (2001 to 2008), the fraction of Mexican workers employed in manufacturing fell by around 20 percent.

A fact that resulted in a puzzling phenomenon during the entry of many developing countries into the world market is that distributional changes went in the opposite direction from the predictions of traditional theory. Trade liberalization is expected to help low-skilled workers who are, in theory, abundant factors in developing economies. However, substantial

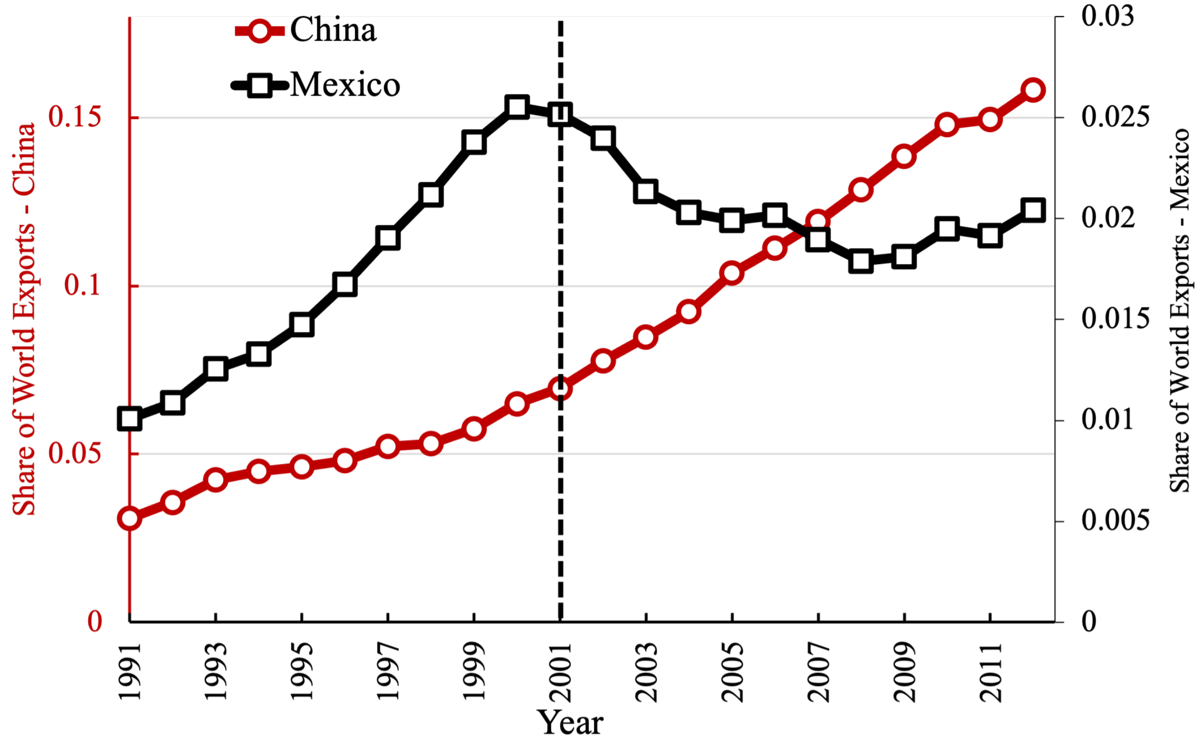


Figure 1: Share of world exports

Source: UN Comtrade.

evidence suggests that high-skilled workers in developing countries benefit the most from globalization. In this paper, I present evidence that this reverse effect happens in those industries affected by the China shock. High-skilled workers are more affected by the shock relative to low-skilled workers.

Trade theory has argued that long-run gains from trade are expected to be positive. However, a matter that requires more attention is how developing countries that compete in similar industries might experience adverse effects on their workers in the short and long run. In this paper, I examine the impact on employment and wage trajectories of Mexican workers in industries exposed to trade competition with China. I define trade exposure as the growth of U.S. imports from China in a given industry from 1991 to 2007. Then, using matched employer-employee data from the Mexican Social Security Administration (Instituto Mexicano del Seguro Social), I estimate the effects of Chinese export competition on wages and the reallocation of workers across industries. The nature of the data allows me to observe employment spells by firm and industry and to estimate the effects of the shock based on firm and worker characteristics.

It is well documented that job displacement has negative implications for future labor market outcomes. There is a large body of literature that documents that workers who lose their jobs experience large and highly persistent earnings losses.[1] In my empirical analysis, I document a persistent decline in earnings after a job loss for workers in Mexican industries exposed to Chinese export competition. Workers in those industries exposed to export competition suffer larger losses relative to workers in less exposed industries. To analyze heterogenous effects of the shock, I decompose the effects for workers with different levels of permanent income and find that workers that are at the bottom of the permanent income distribution do not suffer significant wage losses, as opposed to workers that are at the top, who experience a large drop in their wages relative to non-separators.[2]In the data, when we observe a worker who switched to a different sector, we have two potential alternatives: either the worker lost her job or she was looking for a new job while being employed. Multiple studies that estimate switching costs usually compare the wages of workers that continue in the same sector, independently of whether the worker was displaced or not, to workers that switched to a different sector. This distinction is relevant considering the displaced worker literature's main conclusions, which document that workers suffer wage losses after a displacement episode. In the extreme case that all switchers are displaced workers, comparing switchers to stayers would overestimate the switching costs. Instead, I depart from the literature and consider the future wages of displaced workers that reenter the same sector as a counterfactual for the future wages of those workers that switch out to a different sector.

A considerable concern among policymakers is how exposure to globalization has short and long-run effects on employment, wages, and income distribution. To assess the long-term effects of the exposure to the China shock, I develop and calibrate a dynamic two-sector competitive search model. Some key features of the model include employment risk, sectoral choice, labor search and matching, and sectoral human capital accumulation. I calibrate the model to aggregate and worker-level data from Mexico before the entrance of China to the WTO. The model allows me to analyze the distributional effects of the shock and to quantify the consequences of the shock coming from human capital accumulation and labor market frictions.

[1]See, e.g., Jacobson et al. (1993), Davis and von Wachter (2011), and Jarosch (2015).

[2]I define the permanent income as the past three-year average income before China entered to the WTO in 2001.

In the model, workers are endowed with an initial comparative advantage in each sector. When unemployed, workers decide to search for jobs in the sector and the wage that maximizes their lifetime utility. After matching with a firm in a given sector, the worker's human capital evolves stochastically and their human capital in the other sector evolves at a potentially different rate. The model predicts that the more time workers spend accumulating human capital in a given sector, the fewer incentives they have to reallocate to the other sector over time.

I calibrate the China shock by targeting the decline in value added in exposed industries from 2001 to 2008. The model allows me to study the reallocation of workers from the exposed to the non-exposed sector. The shock generates lower wages for all workers and job seekers in the exposed sector. After the shock, workers with low levels of human capital in the exposed sector have more incentives to reallocate and start accumulating human capital in the non-exposed sector. Furthermore, workers at the top of the human capital distribution have lower incentives to reallocate and suffer the largest losses from the shock. Additionally, I estimate the same reduced form empirical specifications in my model simulated data, and I show that it can successfully capture the heterogeneity of wage losses observed in the data.

Using the calibrated model, I perform the main quantitative experiment by examining the welfare effects for workers with different levels of permanent income. To compute the welfare effects along the transition path, I hit the model economy with a one-time unexpected permanent shock for the sector productivity of the exposed sector. I measure welfare along the transition path using a utilitarian welfare criterion for all individuals alive at the time of the shock. The block recursivity property of the model allows me to solve for the transition in a tractable way, once the distribution of agents across states does not enter in the equilibrium prices.

Finally, I use my model to decompose the source of wage losses after displacement attributable to human capital accumulation and search frictions (including a minimum wage schedule). The minimum wage is a relevant component to explain the wage losses of workers at the bottom of the permanent income distribution. Although, it is not relevant to explain the relative losses of reallocation. It is the sector-specific human capital that explains the relative losses of displaced workers from export-competing industries.

Related Literature. My paper contributes to recent studies of the effects of China's entrance to the WTO on labor markets. In their seminal paper, Autor et al. (2013) analyze the effect of changes in exposure to Chinese import competition in U.S. labor market outcomes. In the following paper, Autor et al. (2014) use the U.S. administrative records to study the cumulative earnings losses of workers in manufacturing industries exposed to Chinese import competition. They find that earnings losses are larger for workers with low initial wages than those with high initial wages. In my paper, I use a different methodology to study how workers displaced from industries exposed to Chinese export competition in Mexico were affected in terms of earnings and wages. Surprisingly, the results are the opposite of what Autor et al. (2014) found. In Mexico, high-income workers are the ones who suffer the largest losses relative to low-income workers. Part of this effect might be explained by a previously documented phenomenon in Verhoogen (2008). In this paper, Verhoogen documents that the rise in income inequality following the trade liberalization in Mexico in 1994 obeyed the fact that most productive plants entered the export markets, producing higher-quality goods and raising wages to retain high-skilled workers. Using administrative records, I document the reverse effect in different measures of inequality after the trade shock. After the entrance of China to the WTO, there is a 20 log points decline in the 90/10 percentile ratio of the income distribution. Consistent with the fact that high-wage workers suffer the largest losses, the upper part of the distribution (90/50 ratio) experiences the most significant decline from 2001 to 2008.

My paper is also related to the trade literature that studies the effect of trade shocks and labor market dynamics. Two papers by Artuç et al. (2010) and Dix-Carneiro (2014) analyze workers' reallocation costs when moving across industries. To infer the reallocation costs, they use the flows of workers across sectors, which in the data are typically low. Both papers find high costs of reallocation, ranging from 1.4 to 6 times the average annual wages. In this paper, I argue that job displacement is an important component to explain the large costs observed by these papers. It is also related to Cosar et al. (2016), who study the effects of reducing trade frictions and firing costs on firm dynamics. In a different context, Kambourov (2009) shows that institutions are important to determine the reallocation of workers after a trade liberalization episode. In his model, he uses firing costs and sector-specific human capital to explain the lack of reallocation in Mexico after the trade liberalization. Motivated by the empirical findings, I add the minimum wage schedule to explain part of the relatively small scarring effect of workers that are at the bottom of the income distribution.

Finally, this work also contributes to the increasing literature that studies the persistent earnings decline following a job loss. In a different context, Jarosch (2015) finds that job security and human capital are the main drivers of worker's long-term losses, Braxton et al. (2019) show the importance of credit markets to smooth the income loss that follows a separation, or Birinci (2019) who studies the consequences of job loss and the role of the spouse to insure against unemployment risk. One of the differences is that I consider the distributional consequences for workers with different permanent income levels.

This paper is organized as follows. In Section 2, I document the facts that motivate the theoretical framework outlined in section 3. In section 4, I present the calibration and main results from the paper. Finally, I conclude the paper in section 5.

2 Empirical Analysis

2.1 Data

The main source of data I use in this paper is a confidential matched employer-employee panel data collected by IMSS (Instituto Mexicano del Seguro Social), the Mexican social security administration.[3] This data contains earnings records for all workers that received a Social Security number and for which employers pay payroll taxes but exclude government employees.[4] For the empirical analysis, I use a panel sample of 4 million workers, with an average of 400 thousand workers per year from 1980 to 2013.

Employers

In principle, every new company is required to file a tax return in Mexico. Each company is assigned a unique tax identification number called Registro Federal de Contribuyentes (RFC). Moreover, each company is required to register its employees with IMSS at the "establishment" level, which represents a single production geographic location. IMSS issues a unique identification number to each establishment (henceforth employer) named Registro Patronal (RP). Each employer reports their industry according to a 4-digit internal classification made in the spirit of the North American Industry Classification System (NAICS). The data contains information about the number of employees, geographic location, and the total wage bill of all registered employers.

Employees

All private-sector employers are required to pay payroll taxes. Employers have to report the daily wages of each of their employees. Furthermore, employers must notify any changes to employment contracts, including wage changes and termination. The data contains demographic information (sex, date of birth, geographic location, etc.) for every worker

[3] This data has been previously used, among others, by Frias et al. (2018) and Castellanos et al. (2004)

[4] Around 50 percent of the total labor force are under this regime, also considered as "formal workers" (e.g. Frias et al., 2018)

that an employer has registered from 1980 to 2013. The daily wage includes the base salary, commissions, annual bonuses, cash payments, employer-provided meals, housing benefits, and in-kind benefits. For the period of interest (1991 to 2012), wage income is top-coded to 25 times the minimum wage, which on average is binding for the top 1 percent of the wage distribution (e.g. Frias et al., 2018). Wages are converted to 2013 real values using the Mexican consumer price index, Indice Nacional de Precios al consumidor (INPC).

2.2 Motivating facts

In the late 1980s, Mexico adopted an export-oriented strategy. In 1994, the North American Trade Agreement (NAFTA) came into effect, and by 2005, tariffs dropped almost to zero between their members (see, e.g., Caliendo and Parro, 2014). As part of the global integration, total exports as a fraction of GDP increased from 15 percent in 1985 to 25 percent in 2000. Over the period 1996-2000, the manufacturing sector in Mexico accounted for 80 percent of total Mexican exports, and nearly half of these exports came from assembly plants engaged in production for foreign firms (also known as "Maquiladoras").[5] Mexican exports are mainly directed to the U.S. In the last three decades, Mexican exports to the U.S. averaged 82 percent of total exports. Figure 2 plots the share of U.S. imports from 1991 to 2015. Over the period 1991 to 2000, Mexico and China's share of U.S. imports steadily rose. However, there was an inflection point in 2001, when the Mexico's share of U.S. imports experienced a decline, and China's market share accelerated. In 2001, China joined the WTO, granting it the most favored nation trade status among its members. Mexico's failure to move into original-equipment manufactures and own-brand production has left it exposed to competition from China, whose abundance in low-skilled labor has provided it a comparative advantage in the production of manufacturing goods (see, e.g., Hanson, 2010).

From Figure 2, it is clear that China had spectacular growth from 2001 to 2012. A measure to compare relative Mexico's export performance to China is to use Balassa (1965) measure of revealed comparative advantage (RCA). The measure is defined as the ratio of a country's share of world exports in a given industry relative to the share of world exports of all goods. In figure 3, , I plot the gap between the China and Mexico RCA and between China and U.S. for the manufacturing sector. The relative comparative advantage between China and Mexico declined from 17 log points in 1991 to 7 log points in 2001. This trend

[5]The share of exports of the manufacturing sector stayed relatively stable from 1994 to 2006, roughly oscillating between 75 to 85 percent. These calculations are based on numbers reported in the UN Comtrade database.

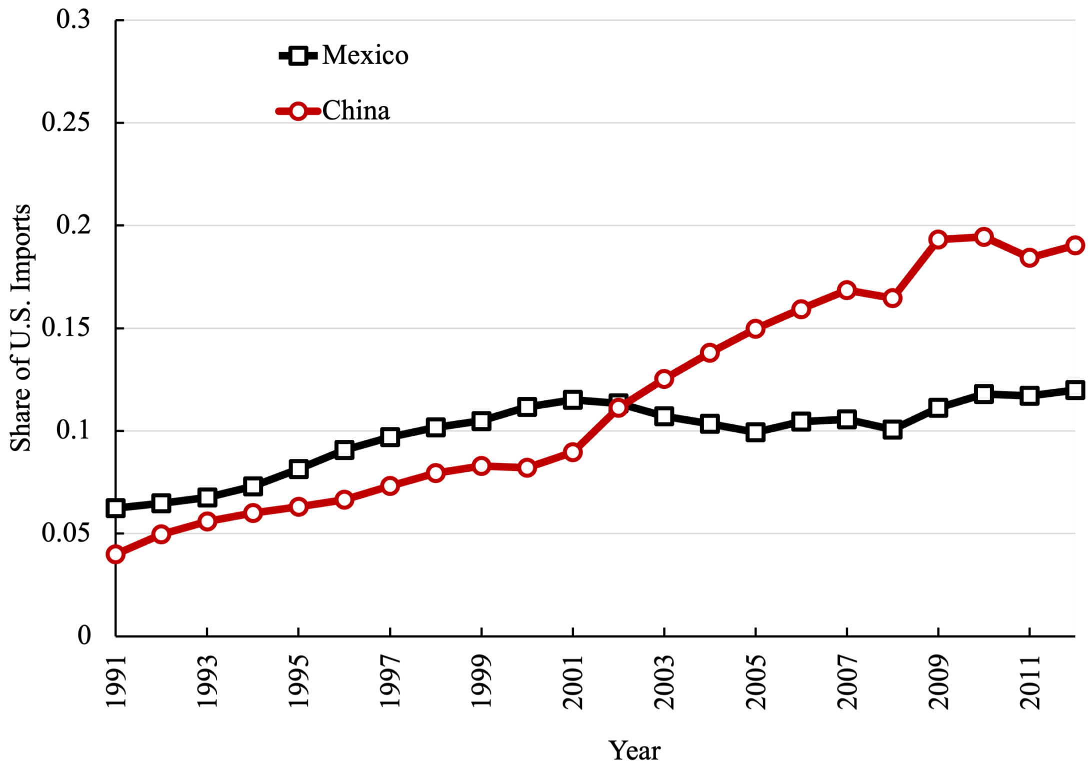


Figure 2: Share of U.S. Imports.

reflects the faster increase of the Mexican economy in the global share of exports relative to the Chinese increase over this period. We can observe that the pattern starts to reverse around 1998, reaching a peak of 22 log points in 2011. It is interesting to note that when comparing the RCA of China relative to the U.S., the trend is relatively stable before 2001. After this moment, the RCA of China relative to the U.S. increased from 4 log points in 2001 to 12 log points in 2012. The decline in the revealed comparative advantage of China relative to Mexico can be interpreted as part of the Mexican integration into international labor markets. However, it is after 2001 that the Mexican measure of comparative advantage starts to deteriorate relative to the Chinese economy. The change in RCA spreads at a faster rate between Mexico and China than between the U.S. and China. Given the fact presented in Figure 3 and in 1, we can interpret it as suggestive evidence about the export competition faced by Mexico.

I now proceed to analyze the share of workers in the manufacturing sector. Over the period 1986 to 1993, the fraction of Mexican workers employed in the manufacturing sector

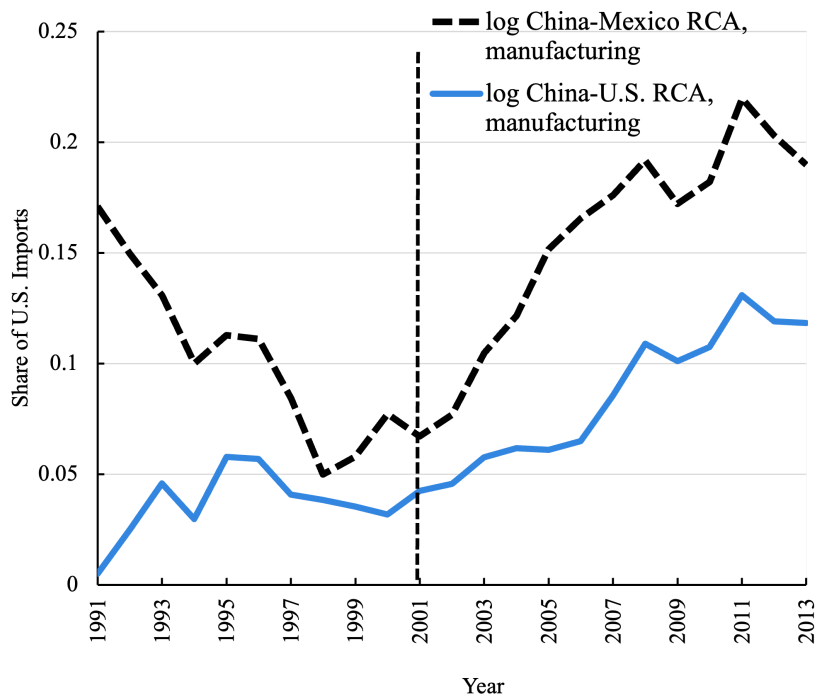


Figure 3: Share of workers in the manufacturing sector.
Notes: The figure displays the log difference in the revealed comparative advantage in the manufacturing sector between China and Mexico (black dashed line), and between China and the U.S. (blue solid line)
Source: *UN Comtrade.*

declined from 35 to 29 percent (Figure 4). In 1994, there is an inflection point that coincides with the year in which NAFTA went into effect. After this year, the share of workers in the manufacturing rose steadily and reached 32 percent in 2000, followed by a persistent decline that reached 25 percent by 2009, the lowest level since 1986. Although it can be argued that there is a general decrease in the fraction of workers in the manufacturing sector starting in 1982, in section 2.5, I present evidence on how the decline is driven by industries exposed to the China shock.[6]

2.3 The "Maquiladoras" case

An important component of the manufactured goods that Mexico exports to the U.S. is through "Maquiladoras." U.S. firms produce parts, export them as intermediate inputs to

[6] In the Appendix A, I extend the time series up to 2019 using public records from IMSS.

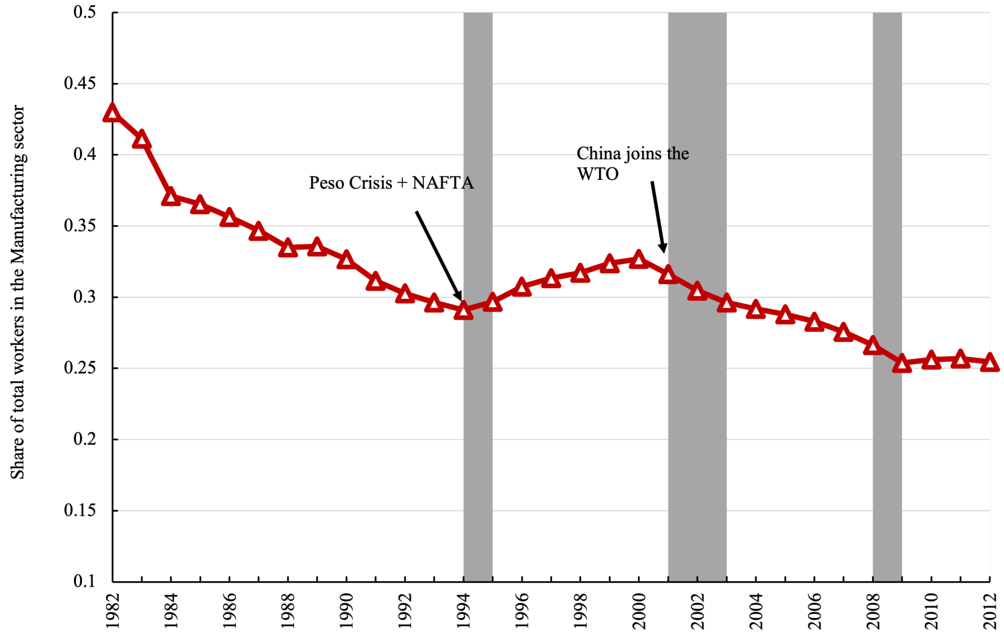


Figure 4: Share of workers in the manufacturing sector.
Notes: The shaded area reflects recessions in Mexico. Only employed workers aged 25 to 60 are included in the statistics. The data used in this graph are administrative records from IMSS.

Mexico, and goods are transformed into final goods, to finally be reimported by the U.S. (Bergin et al. (2009)). In 1983, the Mexican government designed the program "Decreto para el Fomento y Operación de la Industria Maquiladora de Exportación." This program was intended to provide support and help maquiladoras grow faster by providing tax benefits and tariff exemptions. The law defines maquiladoras as those firms that exported at least 80 percent of their produced goods in a given year. This requirement has gradually been loosened over time. In 1994, at least 55 percent of output had to be exported to be considered in the program. This program, together with the signing of the North American Free Trade Agreement in 1994, led to a substantial surge in Mexican exports. Employment in these firms also increased after the trade liberalization. The share of workers in "Maquiladoras" as a fraction of total employment experienced sustained growth going from 1.5 percent in 1991 to 3.5 percent in 2001 (Figure 5). After 2001, there was a clear decline in the number of workers displaced from "Maquiladoras." Around 10 percent of these workers stopped working in "Maquiladoras" firms. It can also be seen that the trend in the fraction of workers also suffered a permanent change after 2001. The share of workers in these firms stabilized at 2.8 percent per year and did not present a trend after this period.[7] Analogously, the total number of "Maquiladoras" firms experienced a similar trend to the workers. Figure 6 plots the number of "Maquiladoras" firms, and the value added generated by these firms. The number of "Maquiladoras" firms started with a relatively stable trend, with an average of 2,035 firms between 1991 and 1993. After this period, the number of firms almost doubled, reaching its peak of 3,735 firms in 2001. Consistent with the number of displaced workers after 2001, the number of firms declined, reaching an average of 2,800 firms between 2003 and 2006. Similarly, the value added of these firms had an inflection point in 2001, completely changing their trend to almost zero growth. This evidence provides support to the theory that the export-competing industries were heavily affected after 2001. One potential explanation for these phenomena is the fact that Mexico went through a recession between 2001 and 2002, which could have affected the exporting sector. However, one could argue that this could be the case in any other recession. By far, the largest financial crisis experienced in Mexico since the 1929 Great Depression took place in 1995. Just in 1995, the GDP decreased by 6.2 percent. If we observe the data, this financial crisis does not seem to affect the "Maquiladoras" firms. From this section, I conclude that "Maquiladoras" are suggestive evidence that export-competing industries were heavily affected after the entrance of China to the WTO.

2.4 Wage inequality

In Figure 7, I plot the log 90-10 ratio for workers from the administrative records. It is well documented that wage inequality in Mexico increased in the 1990s (Verhoogen, 2008). Using the social security administration data, I show that wage inequality increased by 27 log points from 1991 to 1995 and 6.5 log points from 1995 to 2001. This pattern is puzzling from the perspective of a Heckscher-Ohlin model, which predicts that low-skilled workers should win more relative txo high-skilled workers after trade liberalization. Goldberg and Pavcnik (2007) document inequality increased in multiple developing countries after their trade liberalization. Although their conclusions argue that the correlation between inequality and globalization seems country-specific, in the case of Mexico, Verhoogen (2008) provides substantial evidence on how globalization might had distributional effects on Mexican workers. Figure 7 shows that inequality started decreasing after 2001. The

[7]The survey stopped collecting information in 2006. Hence, it is not possible to present evidence after this period.

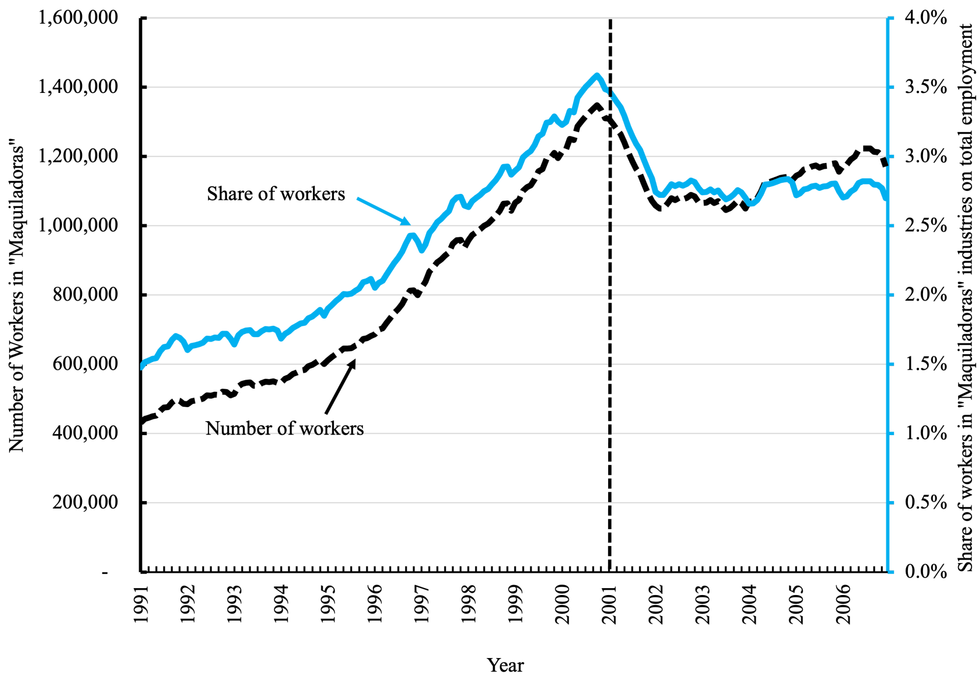


Figure 5: Workers in "Maquiladoras".

Notes: The number of workers in "Maquiladoras" from the Estadística de la Industria Maquiladora de Exportación (EIME). EIME is a survey conducted by INEGI (Instituto Nacional de Estadística y Geografía), The observation unit is a "Maquiladora" establishment. Inegi constructs the annual data from monthly surveys.

P90/P10 fell by 17.5 log points between 2001 and 2006. After this period, the measure of inequality was relatively stable. As pointed out by Song et al. (2019), the variance can mask differential trends in inequality across the earnings distribution. To gain additional insights, Figure 8 plots selected percentiles (10th, 20th, 50th, 80th, and 90th) of the overall log earnings distribution in each year, expressed as log deviations from their 2001 values. The figure confirms the patterns in the variance and P90/P10 measures of inequality after 2001. At the same time, the higher percentiles experience lower wage changes between 2001 and 2008, and the 80th and 90th percentile of the income distribution experience low wage changes relative to their 2001 value.

One potential explanation of the inequality patterns after the shock is that workers are receiving lower compensations within their firm, but wages of high-income workers are reduced in a larger proportion than their low-skilled coworkers. Another explanation is that

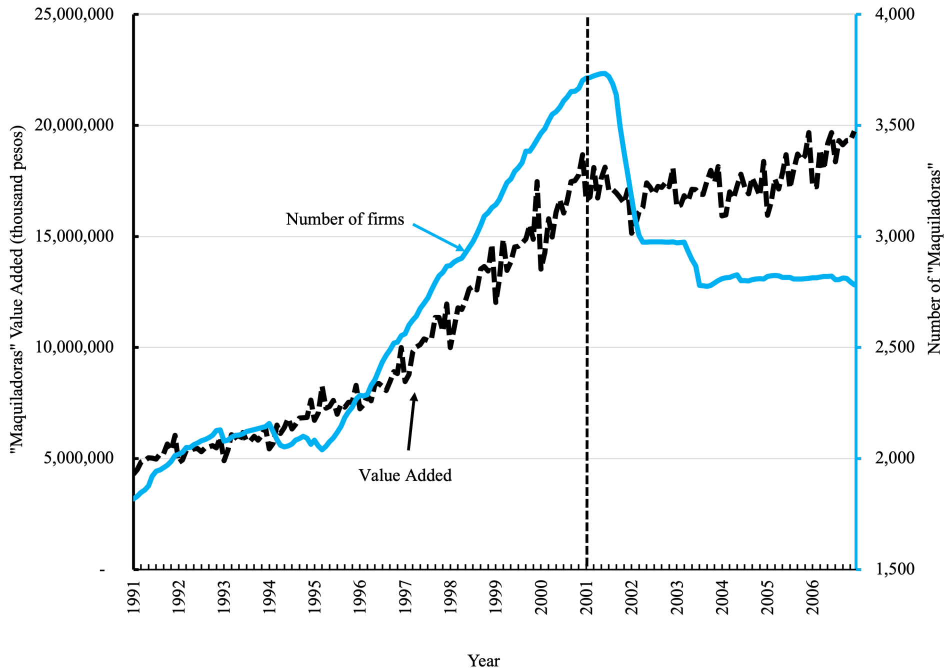


Figure 6: Value Added and Number of Establishments in “Maquiladoras”. .
Notes: The value added and number of establishments in “Maquiladoras” from the Estadística de la Industria Maquiladora de Exportación (EIME). EIME is a survey conducted by INEGI (Instituto Nacional de Estadística y Geografía), The observation unit is a “Maquiladora” establishment. Inegi constructs the annual data from monthly surveys.

high-skilled workers suffer wage losses when moving across firms, generating a compression in the earnings distribution. To explore tthese potential channels, I decompose the overall cross-sectional variance of log earnings into a between-firm and within-firm components. Let $w_t^{i,j}$ be the log earnings of worker i employed by firm j in a given period t. Following Song et al. (2019), the overall variance can be decomposed into a between-firm and within-firm component in the following way,

$$\underbrace{Var(w_t^{i,j})}_{\text{Overall}} = \underbrace{var(\bar{w}_t{}^j)}_{\text{Between}-\text{Firm}} + \underbrace{\sum_{j \in J} \theta_j Var(w_t^{i,j} | i \in j)}_{\text{Within}-\text{Firm}} \quad (1)$$

The first term is the between-firm dispersion of average earnings, and the second term is the employment-weighted mean of within-firm variance of log earnings, where θ_j is the

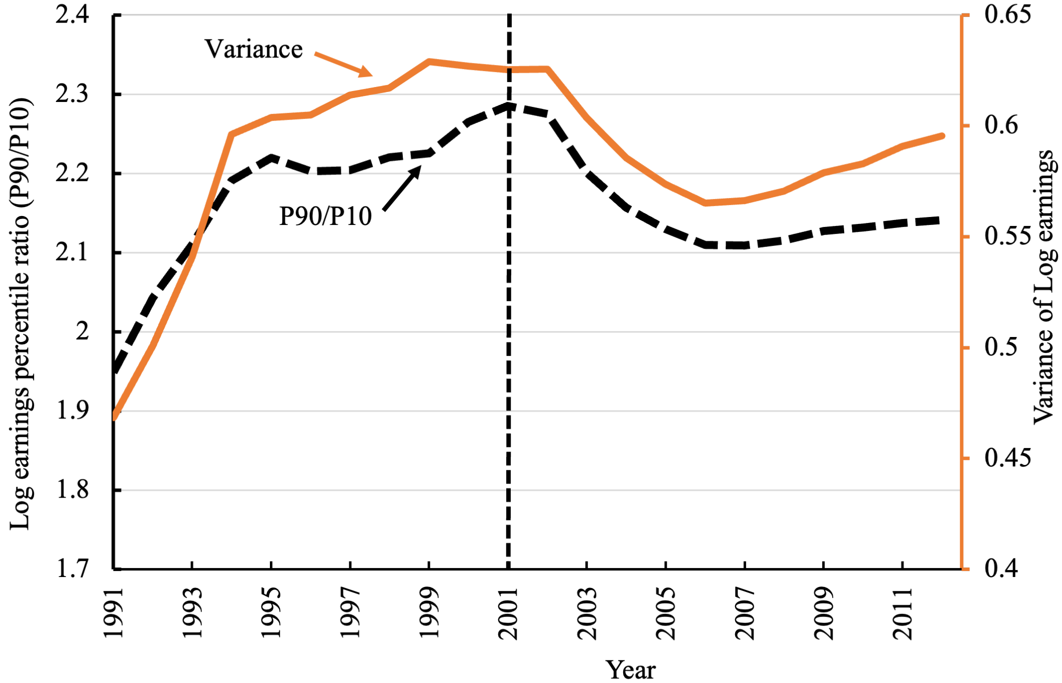


Figure 7: Wage Inequality in Mexico.

Notes: Log 90-10 is for annual earnings from administrative records. Only workers in firms with at least 5 employees are included. Only employed workers aged 25 to 60 are included in the sample.

employment share of firm j. Based on these definitions, we can explore if the decrease in inequality is due to the fact that workers within the firm are receiving different wages or if the compression obeys a change in the between-firm component. Figure 9 shows the variance decomposition of these channels over time. Two main insights can be noted from the figure. First, there is a significant level of within-firm variance, but it remains at a relatively stable level of 0.2 from 1990 to 2012. Second, the increase in inequality between 1991 and 2001 and the decrease after 2001 is mainly driven by the between-firm component. Of the 6 log point decrease in the overall variance of log earnings, about 5 log points were due to the between-firm component and 1 log point due to the within-firm component. We can conclude from these patterns that the decline in inequality is not driven by the fact that high-skilled workers are reducing their earnings within the firm relative to low-skilled workers.

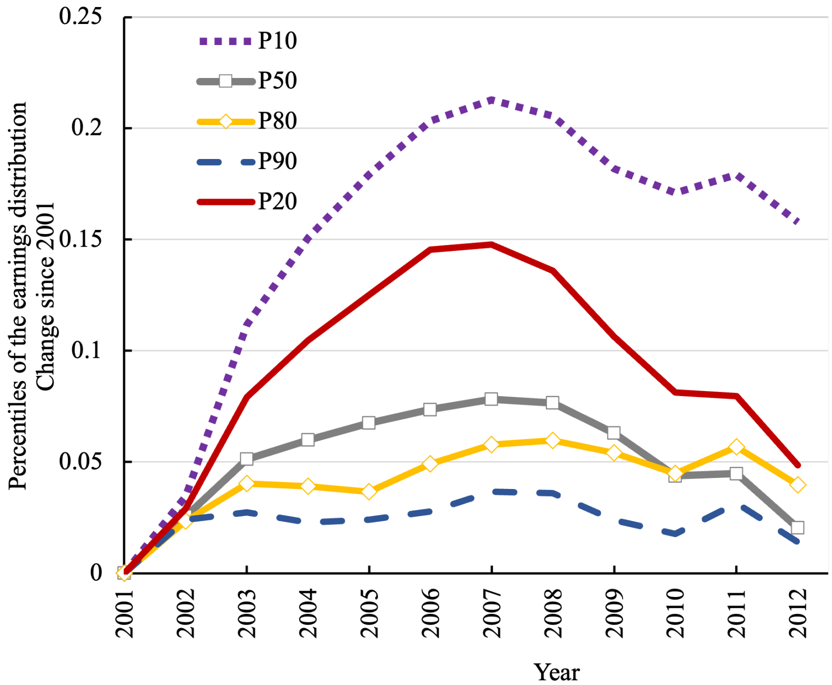


Figure 8: Change in Percentiles of Earnings relative to 2001.
Notes: Only workers in firms with at least 5 employees are included.Only employed workers aged 25 to 60 are included in the statistics.

2.5 Empirical strategy

To capture the effects in Mexico of export competition with China, I use the changes in U.S. imports from China by industry. Following Autor et al. (2014), I define the import penetration index for a given U.S. industry j over the period 1991 to 2007 as

$$\Delta IP_j \equiv \frac{\Delta M_j^{US-Ch}}{Y_{j,0} + M_{j,0} - E_{j,0}}$$

where ΔM_j^{US-Ch} is the change in U.S. imports from China from 1991 to 2007 in industry j, $Y_{j,0}$ are industry shipments, $M_{j,0}$ are industry imports, and $E_{j,0}$ are industry exports in 1991. Therefore, the denominator is the measure of initial absorption in industry j. I use this index as an instrumental variable for the change in Mexican exports goinf to the

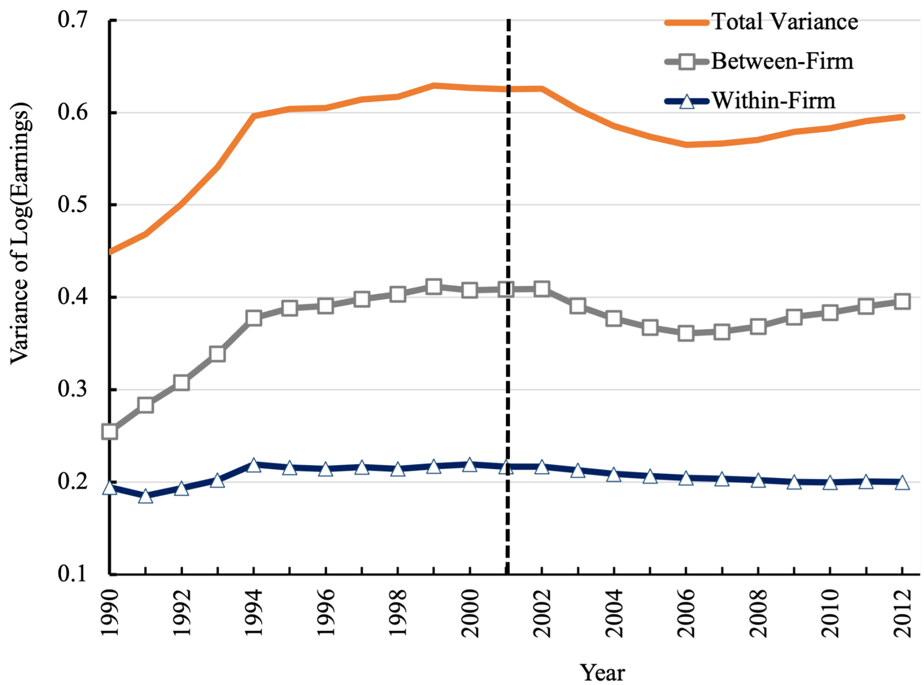


Figure 9: Variance Decomposition of Log Earnings
Notes: Only workers in firms with at least 5 employees are included.Only employed workers aged 25 to 60 are included in the statistics.

U.S., which allows me to isolate potential supply shocks in the Mexican labor market.[8] To perform the econometric analysis, I rank industries in Mexico according to this index and categorize them into two groups: the "exposed" sector, which I define as the top 25 percent of this trade exposure index, and the "non-exposed" sector, which is defined as the bottom 75 percent of the index. Figure 10 plots the fraction of workers in the exposed sector relative to the workers in the non-exposed sector each year. Between 1986 and 1994, the ratio of exposed relative to non-exposed was relatively stable. The ratio climbed from 41 percent in 1994 to 49 percent in 2000. From 2000 to 2012, the ratio persistently declined, reaching a value of 33 percent by 2012.[9] This suggests that workers in the exposed industries

[8]Notice that the index might be correlated with the change in Mexican imports from China. However, the ratio of Mexican imports from China relative to Mexican exports to U.S. are relatively low, with an average of 12.3 percent over the period 2001 to 2012. Throughout the paper, I will ignore this potential channel. An analogous argument has been made by Autor et al. (2013), where they ignore the effect of the export from U.S. to China under the argument that U.S. imports from China largely exceed exports (the ratio of exports to imports is 17 percent in 2007).

[9]An alternative is to show the share of workers in the exposed industries relative to the total labor

potentially had to relocate to other industries.

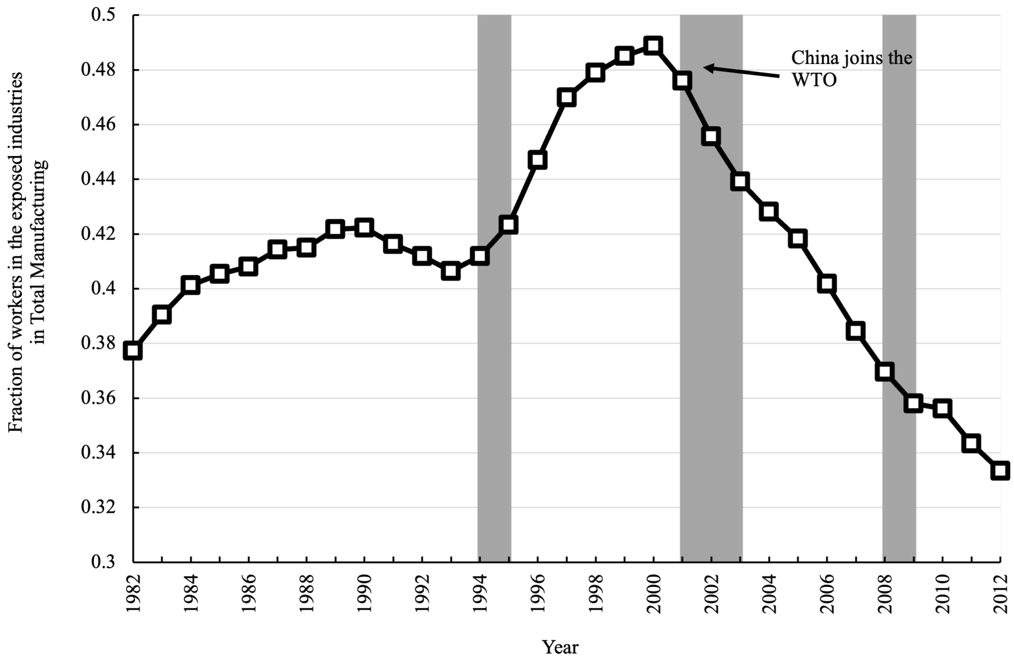


Figure 10: Share of workers in the exposed manufacturing sector relative to the non-exposed workers.
Notes: The shaded area reflects recessions in Mexico.

Sample and Variable construction

The data set is constructed at a daily level. To turn the daily level into an annual panel, I compute the earnings for each worker in a given year. If the individual works in more than one firm in a given year, I compute the fraction of earnings that each firm paid to that worker and assign her to the firm that had the largest fraction of earnings in that year. I restrict the sample to employed individuals aged 25 to 60, defined as working 13 weeks in a year. This restriction allows me to study workers with a high level of attachment to the labor market.[10] To construct annual wages, I divide the annual labor earnings by the number of days worked in a given year. For the permanent income, I add labor earnings

force. The ratio of exposed workers relative to the total workers reaches its peak in 2000, with a value of 11 percent, and starts its decline reaching a value of 6 percent by 2012.

[10]This also helps me to focus on workers that are attached to the formal sector, which is around 50 percent of the total labor force in Mexico.

from 1998 to 2000 and rank workers according to their average income. This measure helps me consider the intensive margin that captures income conditional on participation and the extensive margin that captures the worker's participation in the formal labor market. Following the job loss literature, I consider a separation between a worker and a firm if the firm fires at least 70 percent of its workers. This allows me to deal with the selection of workers at the time of the separation and to isolate layoffs from quits.

The effect on displaced workers: Exposed vs Non-Exposed

To examine the effect on displaced workers from the exposed and the non-exposed sector, I follow Jacobson et al. (1993) to estimate the following distributed-lag model on annual wages:

$$w_{it}^u = \mu_i^u + \eta_t^u + \gamma_X^u X_{it} + \sum_{m=-3}^{9} \delta_m^u D_{it}^m + \epsilon_{it} \tag{2}$$

where w_{it}^u is the average wage of the worker i in year t, and each u represent a displacement year. The dummy variables D_{it}^m, $m = -3, -2, ..., 9$, take the value of one if the worker was displaced in year u and $t - u = m$. Hence, δ_m^u represents the effect of displacement on workers' wages, m years after or m years before the displacement year u. On the other hand, D_{it}^m take zero for all m and t if the worker did not separate in year u.[11] The μ_i^u are individual fixed effects that capture unobserved characteristics among individuals. The η_t^u is the coefficient of a dummy variable for each year t that captures the time effects. The vector X_{it}, includes a quadratic polynomial in age, tenure accumulated in the exposed and non-exposed sector, and geographical dummies at the state level. I run these regressions for each separation year $u = 2001, 2002, ...2007$. I run a separate regression for displaced workers from the exposed sector and the non-exposed sector, each of them with the same control group; non separators from all the industries in the economy. Following Figure 11 plots the coefficients of the regression (δ_m^{2001}, $m = -3, -2, ..., 9$), in terms of log deviations with respect to the control group, for the displacement year $u = 2001$.[12] To validate the estimated parameters, notice that the treatment and control groups have parallel trends before the displacement year $u = 0$. While the wages of non-exposed workers fall 15 log

[11] A worker is considered to be separated from the firm if the match breaks as a consequence of a mass-layoff event. Following Davis and von Wachter (2011) I define mass-layoff event if the firm fires at least 90 percent of their workers in a given year.

[12] I find similar results for the rest of the separation years, I leave to Appendix A.4 the figures for the rest of the years. I also run regressions including unemployment spells in a given year. See appendix A.2 for further details.

points after one year of being displaced, the workers in exposed industries fall 37 log points relative to non-separators. Nine years after the shock, non-exposed workers almost recover from the shock. However, workers in the exposed sector do not recover.[13]

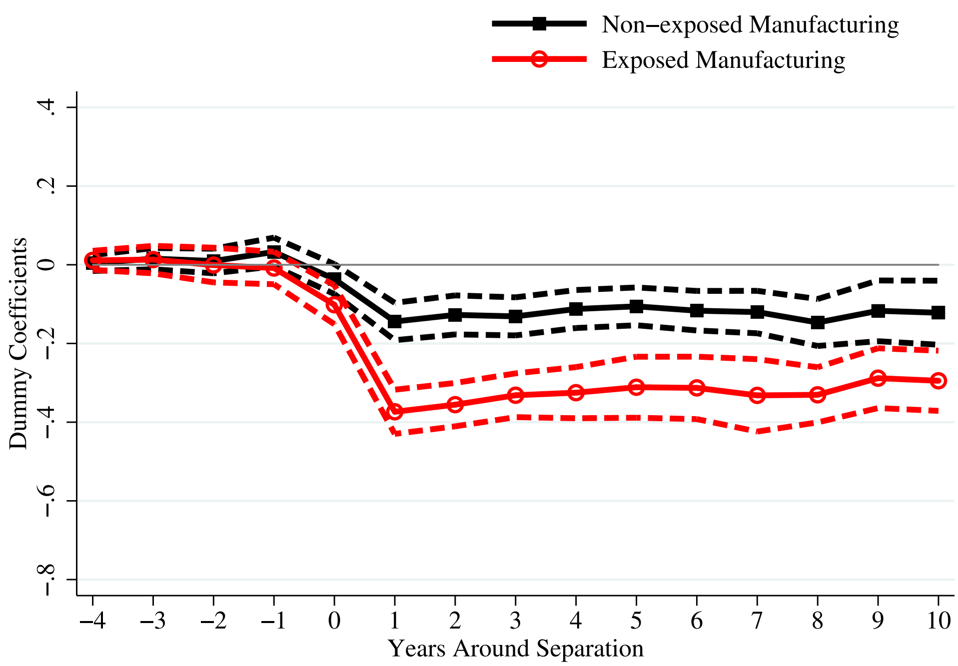


Figure 11: Job loss for the exposed and non-exposed sector.
Notes: The graph displays the relative deviation in logs of displaced workers in each sector relative to non separators in year 2001. The dashed lines represent 95 percent confidence intervals. Standard errors are clustered at the level of the firm where the worker was displaced. The 0 represent the displacement year.

Heterogeneous effects across the income distribution

In this section, I explore the heterogeneity of the shock depending on different levels of permanent income, which I define as the average income from 1998 to 2000. I rank workers according to the percentiles across the permanent income distribution, independently of their sector. To assess the impact over different permanent income levels, I run regression 2 conditioning the treatment and the control group on different percentiles. I run a regression

[13]To verify that this result is not specific to the sector, in other words, that for any year this difference is present, I run a regression for a separation year $u = 1994$ and find the values overlap and we cannot reject the coefficients are different. I show the results of this regression in the Appendix A.3.

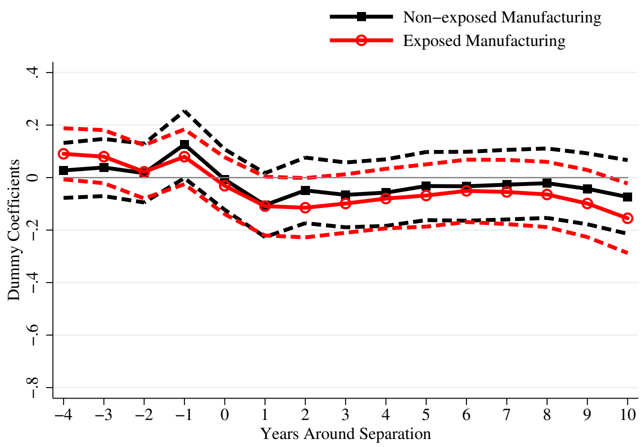
conditioning on workers from both sectors to be below the 20th percentile of the permanent income distribution, and in Figure 12a, I plot the loss of displaced workers relative to non-separators. We can observe that displaced workers at the bottom of the distribution have almost no losses in terms of relative wages to non-separators. Analogously, I run a regression for workers between the 50th and 60th percentile of the permanent income distribution. Figure 12b plots the relative difference between separators in each sector to the non-separators. Although it is not possible to reject the hypothesis that the wage trajectories of workers in the middle of the distribution who are displaced from exposed and non-exposed industries are different, the point estimates after displacement are, on average, 6 log points lower for workers in exposed industries..[14] Finally, I use the same strategy to evaluate the impact at the top 20th percentile of the permanent income distribution. The comparison between exposed and non-exposed workers at the top of the permanent income distribution, displayed in Figure 12c, shows a more dramatic difference than workers in the middle of the distribution. While workers in the exposed sector suffer an initial loss of about 70 log points, non-exposed workers' wages decrease by around 15 log points following displacement.

Part of the interest of the paper is to explore the mechanisms under the observed patterns. Figure 12a suggests that workers at the bottom of the distribution are better insured against a sector-specific shock, as opposed to workers at the top. I will study two potential mechanisms that might explain these patterns. The first mechanism is the minimum wage schedule, which might help low-skilled workers to reallocate across sectors without suffering large wage losses. The second mechanism works through the sector-specific human capital component. In particular, workers at the top have accumulated more human capital in a given sector and find it harder to relocate across sectors without incurring large losses in their wages.

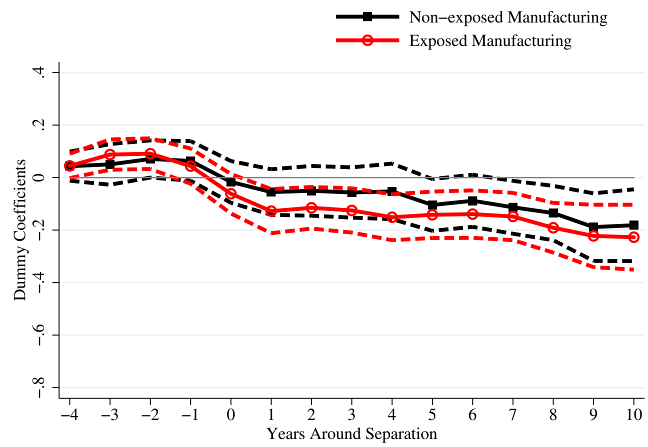
3 Model

My framework is a labor model with directed search (e.g. Menzio and Shi, 2011) with the following features. First, workers accumulate human capital in each sector. Second, workers lead their search for jobs across sectors and across piece-rate wages (e.g. Braxton et

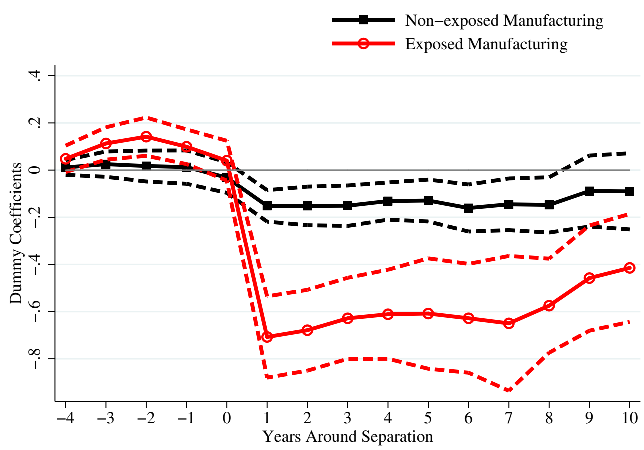
[14] In the appendix I run a regression with log annual earnings including the unemployment spells and find a job loss coming from an unemployment channel. Consistent with the results of wages, the earnings losses of exposed workers are the same as the earnings losses of non-exposed workers.



(a) 10th to 20th percentile.



(b) 50th to 60th percentile.



(c) 90th to 100th percentile.

Figure 12: Job loss for different percentiles

Notes: The graph displays the relative deviation in logs of displaced workers in each sector relative to non separators in year 2001. The dashed lines represent 95 percent confidence intervals. Standard errors are clustered at the level of the firm where the worker was displaced. The 0 represent the displacement year.

al. (2019), Menzio et al. (2016)), which is defined as the fraction that the worker keeps from what is produced in the match. Third, workers are subject to a minimum wage schedule and they receive severance payments if they are laid off. Finally, workers face exogenous employment risk. My model abstracts from incorporating tariffs and international trade, as in Dix-Carneiro (2014).

3.1 Environment

Time is discrete and runs forever. There is a unit measure of workers and a continuum of potential entrant firms. Each worker maximizes the present discounted utility with discount factor $\beta \in (0,1)$. Each firm operates under a constant returns-to-scale technology, and maximizes the expected sum of periodical profits discounted by the same discount factor as households, β. [15]

There are two sectors in the economy: the exposed sector (M) and the non-exposed sector (N), modeled in the spirit of Lucas and Prescott (1974). There is an aggregate level of technology z_t at time t (common to all firms). For each sector, there is a productivity level η_{tj} common to all firms within the sector $j \in \{N, M\}$. At time t, all vacancies posted in sector $j \in \{N, M\}$ use technology level $A_{tj} = z_t \eta_{tj}$. Entrant firms pay cost κ_t to post a vacancy at time t, and choose the sector where they will post vacancies $j \in \{N, M\}$.

Workers are either unemployed ($s = \hat{U}$) or employed ($s = E$), where $s \in \{\hat{U}, E\}$ denotes the employment status. Individuals are heterogeneous in their human capital accumulated in each sector. I denote the human capital by the vector $\vec{h} = (h_M, h_N) \in \mathcal{H} \equiv [\underline{h}, \bar{h}] \times [\underline{h}, \bar{h}] \subset \mathbb{R}^2$, where h_M is the human capital in the exposed sector, and h_N is the human capital in the non-exposed sector. A worker permanently exits the market with probability $1 - \xi \in (0,1)$.

Unemployed individuals direct their search over sectors $j \in \{N, M\}$ and across piece-rate wages (ω) for the duration of the employment match. The labor matching technology is denoted by $M(u, v)$, and I define the labor market tightness to be the ratio of vacancies (v) to unemployment (u). In a directed search environment, there is a separate labor market tightness for each submarket. A worker searching in submarket $(\omega, \vec{h}, j)$, meets a vacancy with probability $p(\theta_t(\omega, \vec{h}, j))$, where $p : \mathbb{R}_+ \to [0,1]$ is a twice-differentiable, strictly increasing, and strictly concave function of labor market tightness $\theta_t(\omega, \vec{h}, j)$, with boundary conditions $p(0) = 0$ and $p(\infty) = 1$. In terms of the matching technology, the job-finding rate is such that,

$$p(\theta_t(\omega, \vec{h}, j)) = \frac{M(u_t(\omega, \vec{h}, j), v_t(\omega, \vec{h}, j))}{u_t(\omega, \vec{h}, j)}$$

Analogously, a vacancy posted in submarket $(\omega, \vec{h}, j)$, meets a worker with probability

[15] The utility function meets standard conditions $u' > 0$, $u'' < 0$, $\lim_{c \to \infty} u'(c) = 0$, and $\lim_{c \to 0} u'(c) = +\infty$.

$q(\theta_t(\omega, \vec{h}, j))$, where $q : \mathbb{R}_+ \to [0, 1]$ is a twice-differentiable, strictly decreasing function of labor market tightness $\theta_t(\omega, \vec{h}, j)$, with boundary conditions $q(0) = 1$ and $q(\infty) = 0$. In terms of the matching technology, the hiring rate is such that,

$$q(\theta_t(\omega, \vec{}h, j)) = \frac{M(u_t(\omega, \vec{h}, j), v_t(\omega, \vec{h}, j))}{v_t(\omega, \vec{h}, j)}$$

When a firm in sector j and a worker of type $\vec{h}$ meet, the firm offers the worker an employment contract where the firm commits to pay a share ω of what is produced. If the worker accepts the offer, she produces $f_t(A_j, h_j) : \mathcal{H} \to \mathbb{R}_+$ units of the consumption good in period t, and receives $\omega f_t(A_j, h_j)$ as her wage. I denote the minimum wage as w_{min}, and the workers search across ω such that $\omega f_t(A_j, h_j) \geq w_{min}$. The match continues to operate until it is exogenously destroyed at the exogenous rate $\delta \in [0, 1]$. After the separation, workers receive a severance payment that I denote with $\Omega(\omega, \vec{h}, j)$. I assume the human capital follows a Markov chain which depends on an individual's employment status.

Let $\Gamma = (s, \vec{h}, j) \to [0, 1]$ be the distribution of workers across employment status (s), the vector of human capital ($\vec{h}$), sectors (j). I denote $\vec{\psi} = (\Gamma, z, \eta)$ as the aggregate state of the economy. Each period t is divided into three stages. First, the aggregate productivity z is realized, and workers are laid-off with probability δ and remain unemployed for at least one period. In the second stage, unemployed workers search, and firms post vacancies in the submarket $(\omega, \vec{h}, j)$. In the third stage, workers produce $f_t(A_j, \vec{h})$.

3.2 Workers

First, consider an unemployed worker of type $\vec{h}$. The continuation value for this agent $U(\vec{h}; \vec{\psi})$ is such that,

$$\begin{aligned} U(\vec{h}; \vec{\psi}) = u(b) + \beta\xi\mathbb{E}_{\vec{\psi}'}\Bigg[\max_{j, \{\widehat{\omega} | \widehat{\omega} f(h_j, A_j) \geq w_{min}\}} &\{p(\theta(\widehat{\omega}, \vec{h}', j; \vec{\psi}'))V(\widehat{\omega}, \vec{h}', j; \vec{\psi}') \\ &+ (1 - p(\theta(\widehat{\omega}, \vec{h}', j; \vec{\psi}'))U(\vec{h}'; \vec{\psi}')\}\Bigg] \end{aligned}$$

Subject to the law of motion of human capital of unemployed workers,

$$\vec{h}' = H(\vec{h}, \hat{U})$$

where $\hat{U}$ denotes that the worker is unemployed. In the first period, the worker receives the utility of home production. In the next period, the worker chooses the sector and the piece-rate wage $\widehat{\omega}$ that maximizes the probability that the worker finds a job $p(\theta_t(\omega, \vec{h}', j; \vec{\psi}'))$ times the value to the worker of finding a job $(V(\omega, \vec{h}', x, j; \vec{\psi}') - U(\vec{h}', x; \vec{\psi}'))$. I denote the optimal choices by $\widetilde{\omega}(\vec{h}', x)$ and $\widetilde{j}(\vec{h}', x)$, associated with this equation.

Second, let $V(\vec{h}, x, j; \vec{\psi})$ denote the value of an employed worker of type $(\vec{h}, x)$ that meets with a firm in sector j that uses a known technology A_j. The worker's lifetime utility is such that,

$$V(\omega, \vec{h}, j; \vec{\psi}) = u(\omega f(A_j, h_j)) + \beta\xi\mathbb{E}_{\vec{\psi}'}\Big[(1-\delta(\vec{h}'))V(\omega, \vec{h}', j; \vec{\psi}') + \delta(\vec{h}')\big(U(\vec{h}'; \vec{\psi}') + \Omega(\omega, \vec{h}, j; \vec{\psi}')\big)\Big]$$

Subject to the law of motion for employed worker's human capital,

$$\vec{h}' = H(\vec{h}, E)$$

3.3 Firms

Consider a firm in sector j that is matched with a worker of type $(\vec{h}, x)$. After the match, the pair generates $f_t(A_j, h_j)$ and the firm's profit is $(1-\omega)f_t(A_j, h_j)$. At the beginning of the period, shocks to the technology and the human capital are realized. In the next period, with probability $1-\delta$ the match continues. The firm's lifetime profits, $J(\omega, \vec{h}, j; \vec{\psi})$, is such that

$$J(\omega, \vec{h}, j; \vec{\psi}) = (1-\omega)f(h_j, A_j) + \beta\xi\mathbb{E}_{\vec{\psi}'}\Big[(1-\delta(\vec{h}'))J(\omega, \vec{h}', j; \vec{\psi}') - \delta(\vec{h}')\Omega(\omega, \vec{h}, j; \vec{\psi}')\Big]$$

Subject to the law of motion for employed worker's human capital,

$$\vec{h}' = H(\vec{h}, E, x)$$

Potential entrants post vacancies at a cost κ in submarket $(\vec{h}, j)$ subject to the free-entry condition,

$$\kappa \geq q(\theta(\omega, \vec{h}, j; \vec{\psi}))J(\omega, \vec{h}, j; \vec{\psi})$$

This condition ensures that the unemployment-to-vacancy ratio in the submarket $(\vec{h}, j)$ is such that the firms have an incentive to create vacancies. Hence, in expectation, the owner of the firm makes zero profits. If the free-entry condition is slack, the cost is higher than the expected lifetime profits. Hence that submarket will have zero matches $(\theta_t(\omega, \vec{h}', j; \vec{\psi}') = 0)$. Analogously, if the free-entry condition binds, the market tightness satisfies $\theta_t(\omega, \vec{h}', j; \vec{\psi}') > 0$.

3.4 Equilibrium

Given the government policies w_{min} and $\Omega(\cdot)$, a recursive competitive equilibrium for this economy is a set of policy functions for piece-rate wages $\{\widetilde{\omega}(\vec{h}, x; \vec{\psi})\}$ and sectoral choice $\{\widetilde{j}(\vec{h}, x; \vec{\psi})\}$, a market tightness function $\{\theta(\omega, \vec{h}, x, j; \vec{\psi})\}$, a value function for unemployed workers $U(\vec{h}, x; \vec{\psi})$, for employed workers $V(\omega, \vec{h}, x, j; \vec{\psi})$, and for firms $J(\omega, \vec{h}, x, j; \vec{\psi})$, and a distribution of individuals across states $\vec{\psi}$ such that,

1. Given the shock processes, the government policies, and the aggregate law of motion, the policy functions for the individuals solve the dynamic programming problems.
2. The labor market tightness is consistent with the free-entry condition.
3. The aggregate law of motion of the aggregate state is consistent with the individual policy functions.

In the Appendix, I show that the model is Block Recursive (Menzio and Shi, 2011), which means that individuals' value and policy functions depend on the aggregate state of the economy $\vec{\psi}$, only through the aggregate productivity (z, η) and not through the distribution of agents across states $\Gamma(\cdot)$.

4 Calibration and Results

In this section, I describe how I calibrate the parameters of the model. I set the model period to be one quarter. I set the job destruction rate to a constant 10 percent ($\delta = 0.1$) as in Shimer (2005). I use the following constant returns to scale matching function (den Haan et al., 2000),

$$M(u, v) = \frac{uv}{[u^{\alpha} + v^{\alpha}]^{1/\alpha}}$$

which produces a well-defined job finding rate (bounded between 0 and 1):

$$p(\theta) = \theta(1 + \theta^{\alpha})^{-1/\alpha}$$

where α denotes the matching elasticity parameter, and is chosen to be $\alpha = 1.599$ as in Schaal (2017). I set the discount factor $\beta = 0.98$. I choose the cost of posting a vacancy κ to match the unemployment rate of 3.46%, which is the average unemployment rate from 1996 to 2000 in Mexico. [16]

Individual preferences over consumption are given by:

$$u(c) = \frac{c^{1-\sigma} - 1}{1 - \sigma}$$

I set the risk aversion parameter to a standard value, $\sigma = 2$.

The human capital in each sector $j \in \{N, M\}$ is assumed to lie on an equally spaced grid of 20 points $h_j \in [0.2, 0.28, ..., 1.8]$. The evolution of human capital of workers in sector j follows a Markov chain, governed by two probability parameters π^u and π^e. If the worker is unemployed, her human capital decreases with probability π^u, and stays with the previous human capital level with probability $1 - \pi^u$. If the worker is employed in sector j, the worker's human capital increases with probability π^e in that sector, and with probability $1 - \pi^e$ the human capital stays at the previous level. The process is given by

[16] I consider this period to capture the moment before the entrance of China to the WTO.

$$H(h_j, E) = h'_j = \begin{cases} h_j + \Delta^e & w.p.\ \pi^e \\ h_j & w.p.\ 1 - \pi^e \end{cases}$$

$$H(h_j, U) = h'_j = \begin{cases} h_j - \Delta^u & w.p.\ \pi^u \\ h_j & w.p.\ 1 - \pi^u \end{cases}$$

For the comparative advantage of workers in each sector, I assume that workers in sector j can substitute their human capital in sector $-j$, according to the following function,

$$h'_{-j} = h'_j e^{-\zeta h'_j}$$

where ζ is a parameter that reflects the degree of the worker's comparative advantage as a function of the sector-specific human capital where the worker is currently employed. Figure 13 provides the intuition of how the comparative advantage depends on the parameter ζ. If $\zeta = 0$, then the workers in sector j can use their accumulated human capital in a one-to-one relationship in sector $-j$. If the parameter ζ is greater than 0, then the comparative advantage of workers in sector j is amplified with the level of human capital. This means that the more time a worker spends in sector j, the larger is her comparative advantage with respect to sector $-j$. [17] In the model, this means that workers have less incentives to reallocate across sectors when they have high levels of human capital.

For the unemployed workers, I set the step size decline in the human capital, $\Delta^u = 0.34$. To estimate the probability (π^u) that the human capital decreases, I target the 14.4 log points decline in wages 1 year following the job loss independent of the sector of the worker. $\Delta^e = 0.084$ denotes the step size increase in the human capital of employed workers of type $\vec{h}$. The probability that a worker's human capital increases in sector j is denoted by π^e. To estimate this probability, I target the share of workers that experience a wage increase of 8.4% in a given year. I assume the step size Δ^e is independent of sector j. [18]

I assume the production function in each sector is linear in the human capital of the

[17] Notice that the function is strictly increasing in h'_j, as long as $1/h'_j > \zeta$.

[18] Although I could allow these parameters to differ by sector, I do not find substantial differences between sectors in terms of the fraction of workers who experience a wage increase of 8.4%.

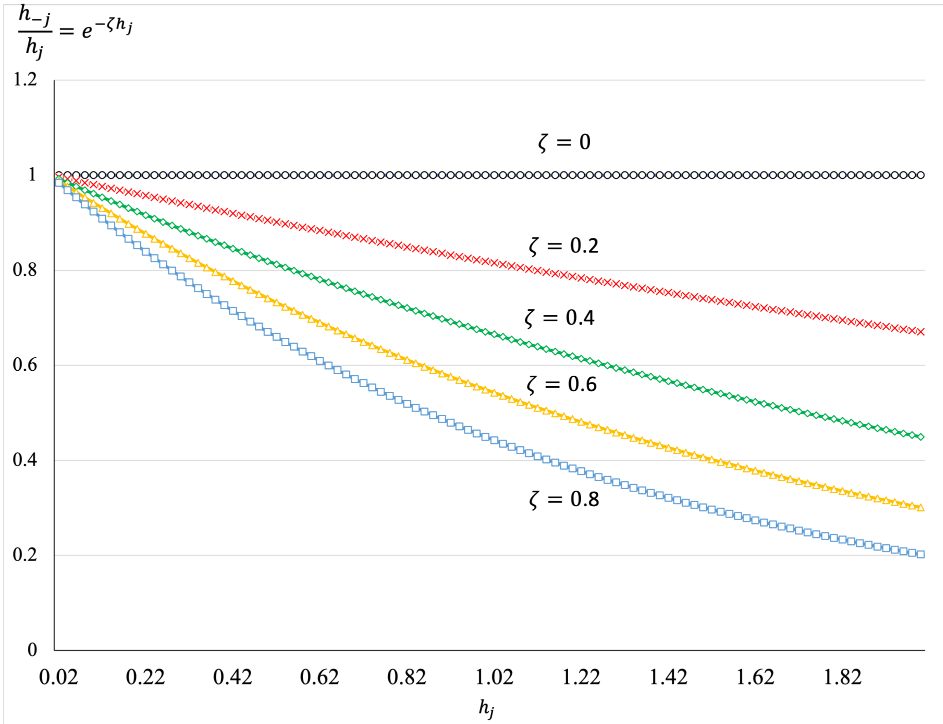


Figure 13: Comparative advantage (ζ) of workers in sector j.

worker $f(A_j,h_j) = A_j h_j = z\eta_j h_j$, where η_j is the sector-specific productivity. The aggregate productivity shock follows an AR(1) process in logs

$$\log(z_t) = \rho \log(z_{t-1}) + \epsilon_t \ , \ \ \epsilon_t \sim \mathcal{N}(0, \sigma_z^2),$$

where $\sigma_z = 0.008$ is the standard deviation, and $\rho = 0.75$ is the persistence of the innovation ϵ_t. I approximate the process using Rouwenhorst's method, using 4 grid points spread across ± 3 standard deviations of the mean,

For the severance payment, I assume $\Omega(\omega, \vec{h}, x, j; \vec{\psi}) = \iota\,(\omega f(A_j, h_j))$, where ι is the fraction of a quarterly wage that is paid to the worker, I choose this parameter to match the mandatory severance payment that any firm in Mexico has to pay in case of firing a worker. I assume that before the China shock the initial relative productivities between sectors is equal to one ($\eta_M = \eta_N = 1$) before the implementation of the China shock. To calibrate the productivity of the exposed sector after the shock η_M^{CS}, I target the relative change in value added of the non-exposed sector relative to the exposed sector from 2000 to 2008. The value added in the non-exposed sector increased 10.75 percent, while the exposed sector declined 24.1 percent. Since I normalized the productivity of both sectors to one before the shock, I target the relative change of 31.4 percent.

In Table 1 I summarize the non-estimated parameters of the model, and table 2 summarizes the estimated parameters using the simulated method of moments.

Table 1: Non-estimated parameters

Parameter	Value	Description
α	1.599	Labor search match elasticity
β	0.98	Discount factor
ζ	0.99	Survival probability
η_N	1	Non-exposed sector productivity before the China Shock
η_M	1	Exposed sector productivity before the China Shock
σ	2	Risk aversion parameter
b	0.2	Home production
Δ^e	0.084	Human capital increase when employed
Δ^u	0.34	Human capital decrease when unemployed
σ_z	0.008	Standard deviation of the aggregate productivity process
ρ	0.75	Persistence of the aggregate productivity process
δ	0.1	Exogenous job destruction rate
ι	25%	Severance payment as a fraction of the wage

Table 2: Estimated parameters

Parameter	Value	Description	Model	Data
w_{min}	0.32	Fraction of workers within 5% of the minimum wage	11.8	12.3
π_e	7.3%	Wage increase of 8.4% in a given year	14.2%	17.3%
π_u	32.8%	Decline in wages one year after displacement	-0.11	-0.144
ζ	0.41	Job Loss for the top 20th percentiles after the shock	-0.69	-0.72
κ	0.19	Unemployment rate	3.32%	3.46%
η_M^{CS}	0.61	Change in value added in the exposed sector	-0.35	-0.31

Notes: This summarizes all the parameters of the model. The moments are estimated usinig the Simulated Method of Moments.

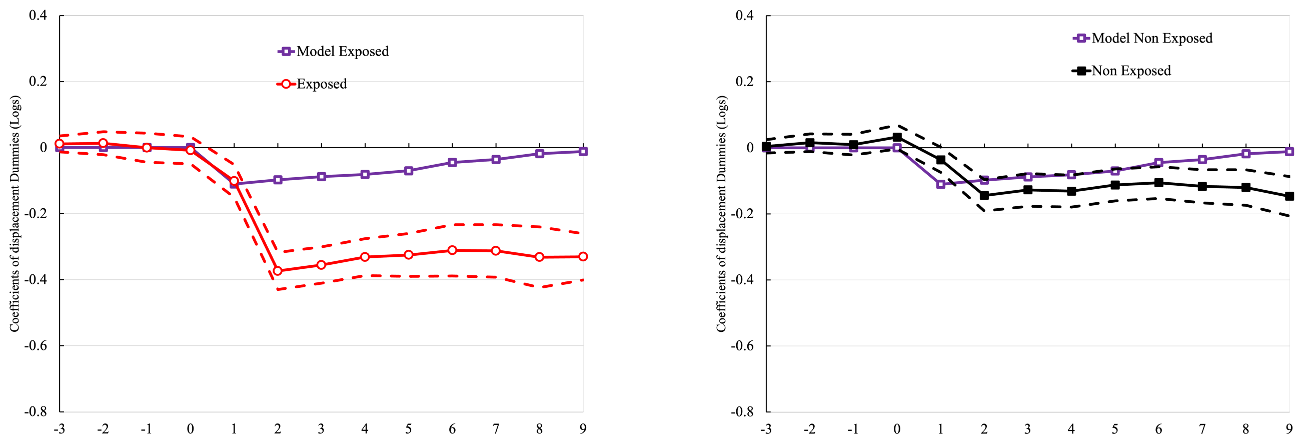
4.1 Comparison between the Model and the Empirical Findings

In this section, I compare the results of the quantitative exercise to the empirical findings from section 3. I simulate the model with 40,000 workers for 200 periods, burning the first 100 periods. To compare the model results to the empirical findings, I first construct annual wages in the same fashion as in the empirical part. Since each period is a quarter, I add the income of each worker in a given year and divide it by the number of quarters with positive income. I consider the model worker as displaced in a given year if she was unemployed for at least one quarter. Then, I run regression 2 for displaced workers in each sector relative to non-displaced workers in a given year. Figure 14 plots the comparison between the coefficients of the regression that comes from the model and the one that comes from the empirical part. The first thing to notice is that the model cannot explain the drop for the exposed workers (see Figure 14a). This result is expected, given the assumption that workers in both sectors have the same probability of decreasing human capital.[19] Figure 14b shows that the model is able to replicate the job loss, although it predicts a full recovery in wages after nine years.

I now explore how well the model can perform with respect to the distributional effects in a given displacement year. I follow the same procedure as in the empirical analysis. I rank workers according to the past three-year average income to the displacement year and run a separate regression for workers at the bottom 20th percentile of the income distribution and workers at the top 20th percentile.[20] Figure 15 plots the job loss for different percentiles of the permanent income distribution for each sector. Not surprisingly, figure 15b misses the large job loss observed in the data. In the China Shock section, I explore how the comparative advantage mechanism can account for the significant decline in wages of high-income workers. Notice that for workers at the bottom of the income distribution, the model is able to follow the wage recovery after a layoff closely. Part of this is explained by the minimum wage constraint that enables workers to find jobs above the minimum wage threshold. In the next section, we explore the role the minimum wage plays in the decline of low-income workers.

[19] This assumption is justified by replicating the econometric analysis for both sectors of displaced workers in 1994. I find that the gap between the job loss in both sectors is statistically equal to zero. As in 2001, this period experienced a contraction in the Mexican economy (also know as the "Peso Crisis").

[20] See section 3 for more details about how I run the regressions.



(a) Job loss in the Exposed Sector.

(b) Job loss in the Non-Exposed Sector.

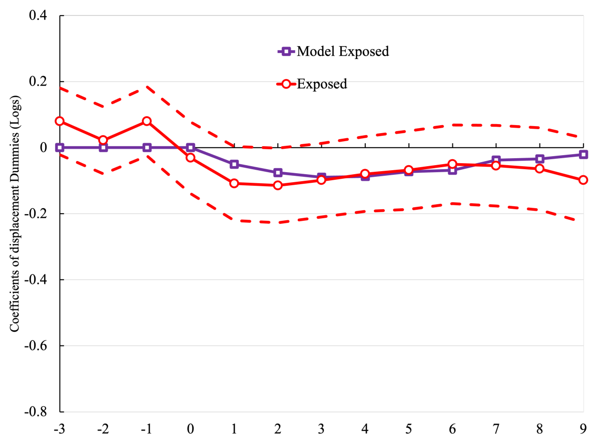
Figure 14: Job loss: Model vs Empirical

Notes: The black (red) lines represent the deviation in logs of non-exposed (exposed) displaced workers relative to non separators in year 2001. The dashed lines represent 95 percent confidence intervals. Standard errors are clustered at the level of the firm where the worker was displaced. The purple squared lines represent the log deviations of displaced workers relative to non-separators in the model. The 0 represents the displacement year.

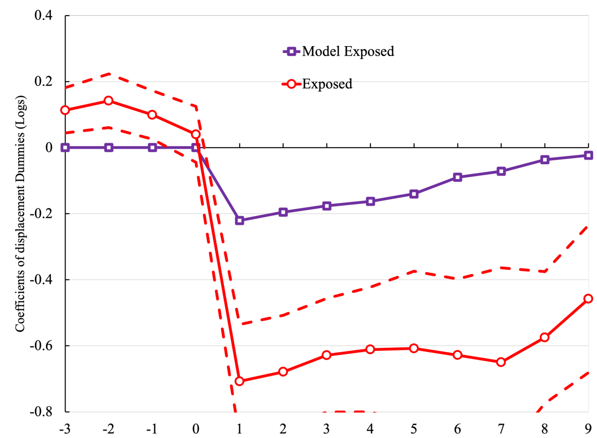
4.2 The effects of the Minimum Wage in the scarring effect

In this section, I use the model to decompose the effects of the minimum wage in the wage loss of workers. To quantify the minimum wage effects, I solve the model for an economy in which the minimum wage is zero ($w_{min} = 0$), holding the remaining parameters constant. Notice that before implementing the China shock, both sectors are treated equally. Hence, to explore the effects of the minimum wage, I plot the effects on job loss for the whole economy. Figure 16 plots the coefficients of the displaced workers for the calibrated minimum wage and for the economy without the minimum wage The minimum wage amplifies the scarring effect in 3 log points relative to an economy without the minimum wage.

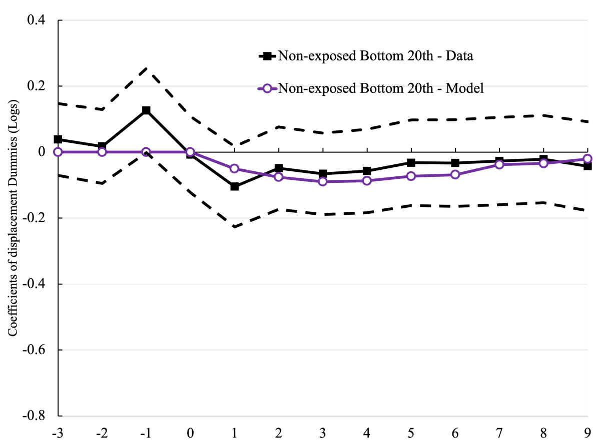
In Figure 17 I decompose the effect for low (bottom 20th percentile) and high-income workers (top 20th percentile) for each sector. From this figure, we can conclude that the minimum wage only explains around . One of the reasons is that workers at the bottom of the income distribution have wages closer to the minimum wage, so it is binding for a large fraction of them. Figure 17b shows how the minimum wage does not play a role in explaining the drop in the wage of workers at the top of the income distribution. For workers at the bottom of the distribution, the gap between the wage job loss for the economy with



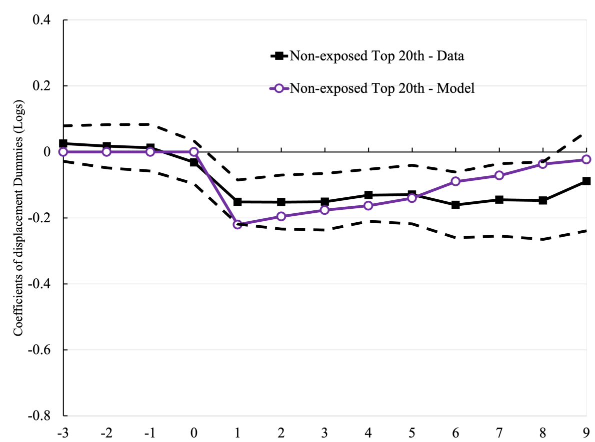
(a) Job loss in the Exposed Sector: Bottom 20th percentile.



(b) Job loss in the Exposed Sector: Top 20th percentile.



(c) Job loss in the Non-Exposed Sector: Bottom 20th percentile.



(d) Job loss in the Non-Exposed Sector: Top 20th percentile.

Figure 15: Job loss for different percentiles: Model vs Empirical

Notes: The black (red) lines represent the deviation in logs of non-exposed (exposed) displaced workers relative to non separators in year 2001. The dashed lines represent 95 percent confidence intervals. Standard errors are clustered at the level of the firm where the worker was displaced. The purple squared lines represent the log deviations of displaced workers relative to non-separators in the model. The 0 represents the displacement year.

zero minimum wage and the economy with a minimum wage of 0.32 is around 22 log points.

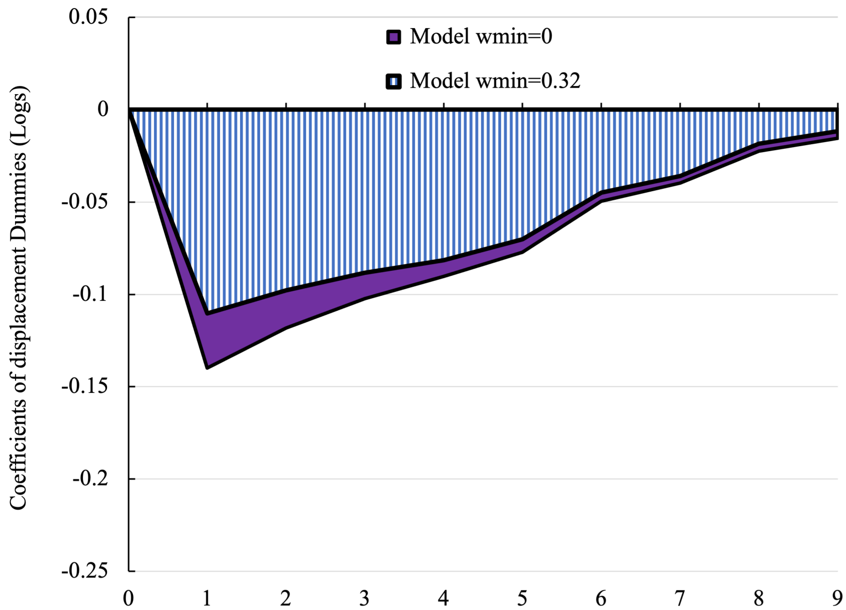
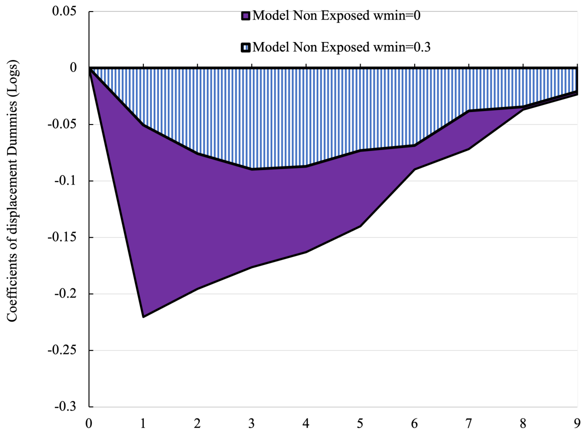


Figure 16: Job loss for different Minimum Wage

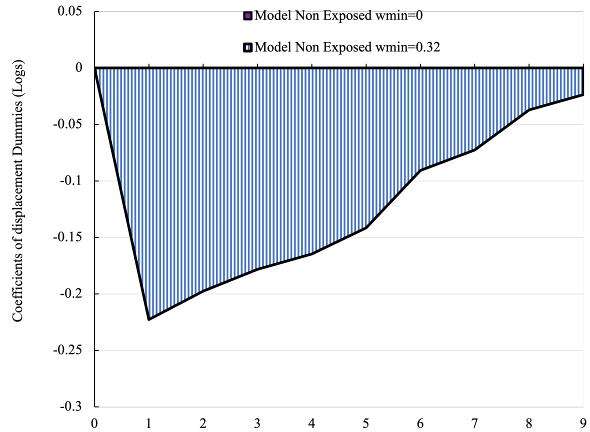
Notes: The dark purple area represents the log deviation of displaced workers relative to non-separators in the model with zero minimum wage. The light blue area represent the log deviation of displaced workers relative to non-separators in the model with minimum wage equal to 0.32. The 0 represents the displacement year.

4.3 The "China Shock" in Mexico

In this section, I perform a quantitative exercise to model the "China Shock." To capture the effect of the shock, I calibrate the sector-specific productivity after the shock to match the change in value added of the exposed sector relative to the non-exposed sector from 2000 to 2008. The data shows a 24 percent decline in the value added in the exposed industries. The value of the calibrated productivity after the shock is $\eta_M^{CS} = 0.61$. I assume workers have rational expectations and expect the shock to be permanent. I solve the model and store the policies under the steady state of the new economy. Given that the model is Block Recursive, the distribution of agents across states does not alter the market tightness functions. It is only through the path of productivities η_M^{CS}, individuals' policy functions and market tightness depend on the distribution of agents across states. Given the permanent shock, I simulate the transition path for 40,000 workers. As in the empirical analysis, I run regression 2 taking as the displacement year when the change in η_M^{CS} takes



(a) Job loss for the bottom 20th percentile of the income distribution.



(b) Job loss for the top 20th percentile of the income distribution.

Figure 17: Job loss for different percentiles and different Minimum Wage schedules
Notes: The dark purple area represents the log deviation of displaced workers relative to non-separators in the model with zero minimum wage. The light blue area represent the log deviation of displaced workers relative to non-separators in the model with minimum wage equal to 0.32. The 0 represents the displacement year.

place. Figure 18 displays the regression coefficients for displaced workers in the exposed sector. In the model, there is a sudden drop in the year of the shock, and workers recover at a relatively constant rate. Given the calibrated productivity, the model overpredicts the initial wage losses of workers in the exposed sector. Part of this effect is explained by the parameter ζ, which captures the comparative advantage of workers in a particular sector. In the data, the exposed and non-exposed workers in the middle of the distribution have similar losses after displacement. Given the parametric assumption for ζ, the workers in the middle of the distribution would also experience loses from reallocation.

In Figure 19, I plot the regression coefficients of workers at the top 20th percentile of the income distribution in the model and the data. Notice that we targeted the parameter ζ to match the initial wage loss for these workers. Although the initial drop is close to the data, the model misses explaining the wage recovery for these workers.

In figure 20 , I show that the model can endogenously generate the reallocation of workers across sectors. In the model, the reason there is not a sudden decline in the share of workers is that workers are not allowed to quit or do on-the-job search. This means that workers need to wait to be separated from the match to decide if they reallocate to

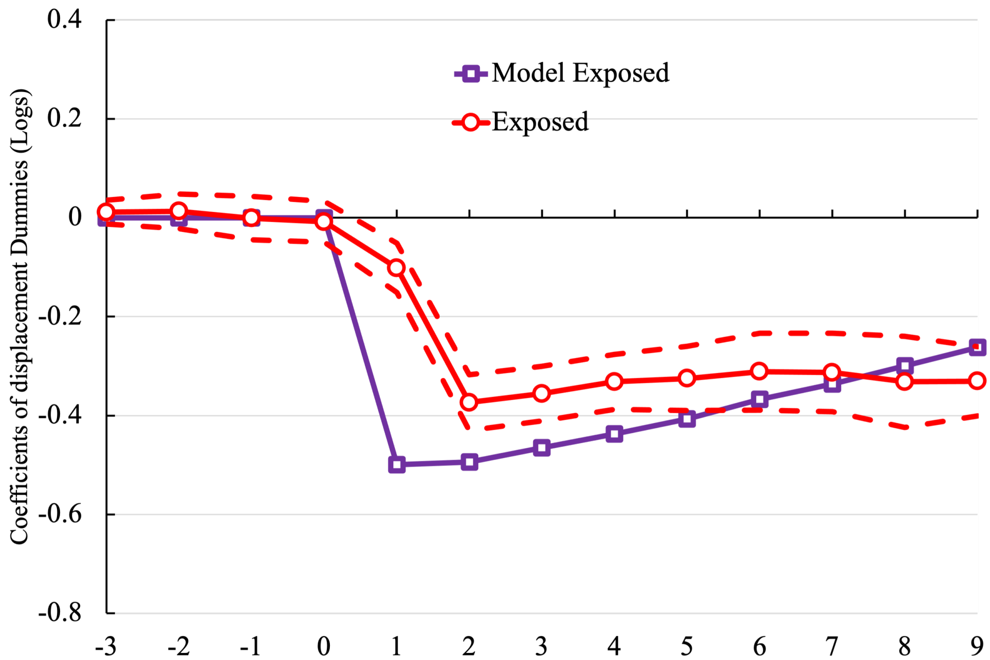


Figure 18: Job loss for the Exposed sector: Model vs Data.
Notes: The graph displays the relative deviation in logs of displaced workers in each sector relative to non-separators in year 2001. The dashed lines represent 95 percent confidence intervals. Standard errors are clustered at the level of the firm where the worker was displaced. The 0 represents the displacement year. The purple squared line represents the log deviations of displaced workers in the exposed sector relative to non-separators in the model.

a different sector. As a result, the share of workers in the exposed sector stabilizes in the model after six years.

Distributional effects of the China Shock

To calculate the welfare criterion, I add the lifetime discounted income of individuals for two versions of the economy: the economy with the sector-specific shock and the economy without the shock. I decompose the analysis for different deciles of the income distribution. As in the previous sections, I rank workers according to their three-year average income previous to the shock. 3 shows the results of the welfare calculations for the exposed workers in the model. As we can see from the table, workers' welfare decrease with their permanent. This result is explained by the fact that the comparative advantage is amplified when workers accumulate human capital in each sector. Hence, the switching costs experienced

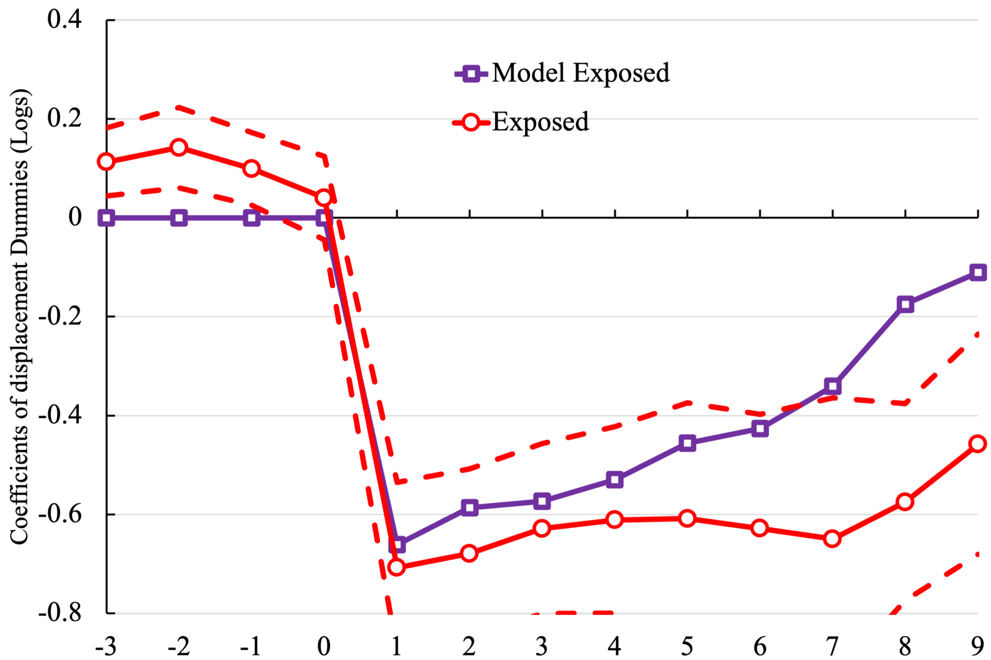


Figure 19: Job loss for the Exposed sector, top 20th percentile: Model vs Data.
Notes: The graph displays the relative deviation in logs of displaced workers in the exposed sector of workers at the top 20th percentile of the income distribution relative to non separators in year 2001. The dashed lines represent 95 percent confidence intervals. Standard errors are clustered at the level of the firm where the worker was displaced. The 0 represents the displacement year. The purple squared line represents the log deviations of displaced workers in the exposed sector relative to non-separators in the model.

by workers with low levels of human capital are not as significant as the switching costs of workers at the top of the income distribution.

5 Conclusion

In this paper, I document a heterogeneous scarring effect for workers who were employed in industries affected by the entrance of China to the WTO. Workers at the bottom of the income distribution suffered lower losses relative to workers at the top. To rationalize my empirical findings, I developed a directed search model that can account for the scarring effect after a displacement episode. The minimum wage can explain part of the shape of the job loss for workers at the bottom of the income distribution. However, it cannot account

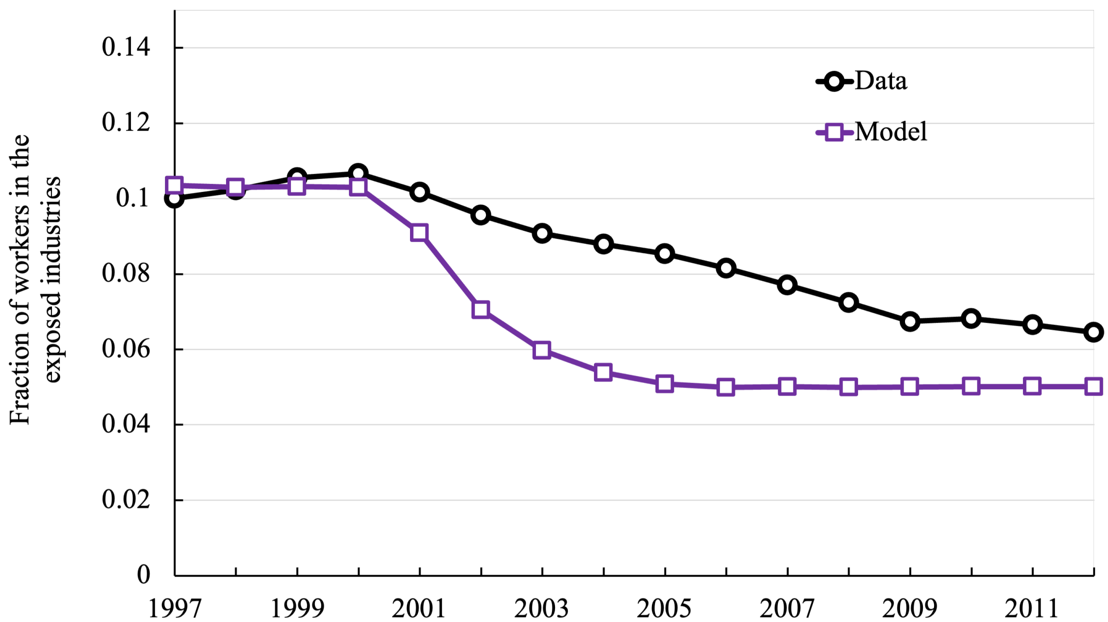


Figure 20: Share of Exposed workers relative to total workers.
Notes: The graph displays the share of workers in the exposed sector relative to the total workers. The circled black line represents the share of exposed workers in the data. The purple squared line represents the share of exposed workers in the model.

Table 3: Welfare effects in Exposed workers for different deciles

Decile	Welfare % Change
I	-1.3%
II	-3.4%
III	-8.4%
IV	-19.0%
V	-23.1%
VI	-25.1%
VII	-30.3%
$VIII$	-32.3%
IX	-33.3%
X	-34.7%

Notes: The reported numbers are welfare averages within each decile.

for all of it. I performed a quantitative analysis that can reproduce the reallocation of workers from the exposed sector to the non-exposed sector after the China shock. The welfare analysis shows that workers at the top of the income distribution are the ones that experienced the largest losses. This phenomenon is partly explained by the evolution of the comparative advantage of workers in the exposed sector. Workers that spent more time accumulating human capital in the exposed sector suffered higher losses from switching to the non-exposed sector.

References

Artuç, Erhan, Shubham Chaudhuri, and John McLaren, "Trade Shocks and Labor Adjustment: A Structural Empirical Approach Author(s):," *The American Economic Review*, 2010, *100* (3), 1008–1045.

Autor, David H., David Dorn, and Gordon H. Hanson, "The China syndrome: Local labor market effects of import competition in the United States," *American Economic Review*, 2013, *103* (6), 2121–2168.

_ , _ , _ , and Jae Song, "Trade adjustment: Worker-level evidence," *Quarterly Journal of Economics*, nov 2014, *129* (4), 1799–1860.

Balassa, Bela, "Trade Liberalisation and Revealed Comparative Advantage," *The Manchester Shool*, 1965, *33*, 99–123.

Bergin, Paul R., Robert C. Feenstra, and Gordon H. Hanson, "Offshoring and Volatility: Evidence from Mexico's Maquiladora Industry," *American Economic Review*, 2009, *99* (4), 1664–1671.

Birinci, Serdar, "Spousal Labor Supply Response to Job Displacement and Implications for Optimal Transfers," *Working Paper*, 2019, (September).

Braxton, Carter, Kyle Herkenhoff, and Gordon Phillips, "Can the Unemployed Borrow? Implications for Public Insurance," *National Bureau of Economic Research*, 2019.

Caliendo, Lorenzo and Fernando Parro, "Estimates of the Trade and Welfare Effects of NAFTA," *The Review of Economic Studies*, 2014, *2.*

Castellanos, Sara G., Rodrigo García-Verdú, and David S. Kaplan, "Nominal wage rigidities in Mexico: Evidence from social security records," *Journal of Development Economics*, 2004, *75* (2 SPEC. ISS.), 507–533.

Cosar, A. Kerem, Nezih Guner, and James Tybout, "Firm dynamics, job turnover, and wage distributions in an open economy," *American Economic Review*, 2016, *106* (3), 625–663.

Davis, Steven J. and Till von Wachter, "Recessions and the costs of job loss," *Brookings Papers on Economic Activity*, 2011, (2), 1–72.

den Haan, Wouter J ., Garey Ramey, and Joel Watson, "Job Destruction and Propagation of Shocks," *The American Economic Review*, 2000, *90* (3), 482–498.

Dix-Carneiro, Rafael, "Trade Liberalization and Labor Market Dynamics," *Econometrica*, may 2014, *82* (3), 825–885.

Frias, Judith A., David S. Kaplan, Eric Verhoogen, and David Alfaro-Serrano, "Exports and Wage Premia: Evidence from Mexican Employer-Employee Data," *Working Paper*, 2018.

Goldberg, Pinelopi Koujianou and Nina Pavcnik, "Distributional Effects of Globalization in Developing Countries," *Journal of Economic Literature*, 3 2007, *45*, 39–82.

Hanson, Gordon H., "Why isn't Mexico rich?," *Journal of Economic Literature*, 2010, *48* (4), 987–1004.

Jacobson, Louis S., Robert J. LaLonde, and Daniel G. Sullivan, "Earnings Losses of Displaced Workers," *The American Economic Review*, 1993, *83* (4), 685–709.

Jarosch, Gregor, "Searching for Job Security and the Consequences of Job Loss," *Working Paper*, 2015, (Fall), 1–26.

Kambourov, Gueorgui, "Labour market regulations and the sectoral reallocation of workers: The case of trade reforms," *Review of Economic Studies*, 2009, *76* (4), 1321–1358.

Lucas, Robert E. and Edward C. Prescott, "Equilibrium search and unemployment," *Journal of Economic Theory*, 1974, *7* (2), 188–209.

Menzio, Guido and Shouyong Shi, "Efficient search on the job and the business cycle," *Journal of Political Economy*, 2011, *119* (3), 468–510.

_ , **Irina A. Telyukova, and Ludo Visschers**, "Directed search over the life cycle," *Review of Economic Dynamics*, 2016, *19* (Montreal 2010), 38–62.

Schaal, Edouard, "Uncertainty and Unemployment," *Econometrica*, 2017, *85* (6), 1675–1721.

Shimer, Robert, "The Cyclical Behavior of Equilibrium Unemployment and Vacancies," *The American Economic Review*, 2005, *95* (1), 25–49.

Song, Jae, David J. Price, Fatih Guvenen, Nicholas Bloom, and Till Von Wachter, "Firming up inequality," *Quarterly Journal of Economics*, 2 2019, *134*, 1–50.

Verhoogen, Eric A., "Trade , Quality Upgrading , and Wage Inequality in the Mexican Manufacturing Sector," *Quarterly Journal of Economics*, may 2008, *123*, 489–530.

A Appendix I

A.1 Share of workers in the Manufacturing Sector

To extend the series, I use data from CUBOS (IMSS). This is a bank of data that collects information from social security records and reports aggregate statistics that comes from confidential data. The data is reported from 1997 to 2022. In figure 21, I plot the time series I use by accessing confidential microdata and the public records published in CUBOS. One reason that the two-time series do not overlap perfectly is that in the microdata, I condition workers to be between 25 and 60 years old as opposed to the public records that do not make any restrictions. A particular thing to highlight is that the share of workers stabilized after 2008 and started increasing at a low pace from 2008 to 2019. This is consistent with the correlation between the mild increase in U.S. imports coming from Mexico over this period and the share of workers in this sector.

A.2 Effects on Annual Earnings

In this section, I compute earnings by dividing workers' total compensation during a year by twelve. In this case, earnings also capture the unemployment spell of workers in a given year. We can observe that unemployment increases the displacement effects on workers' earnings. Figure 22 plots the effects on annual earnings comparing displaced workers in exposed against non-exposed industries. As in the paper, the effects on displaced workers

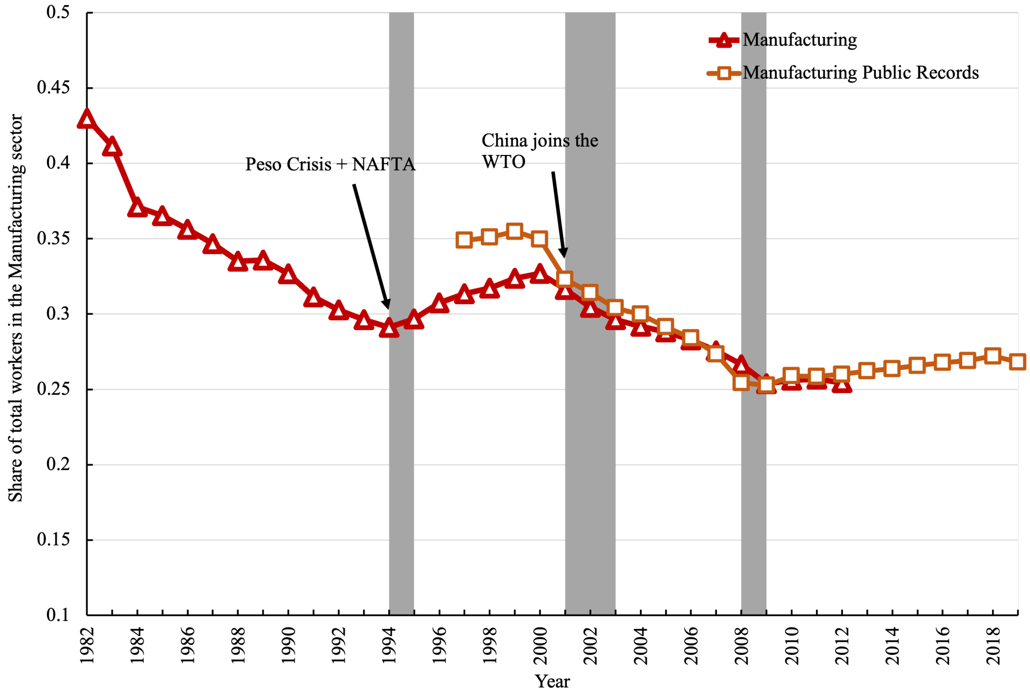


Figure 21: Share of workers in the manufacturing sector 1982-2019.
Notes: The shaded area reflects recessions in Mexico. Only employed workers aged 25 to 60 are included in the statistics. The data used in this graph are administrative records from IMSS.

from exposed industries are substantially larger compared to the job loss of those in non-exposed industries. A similar conclusion happens with Figures 23a, 23b, and 23c. Workers at the top of the earnings distribution lose more compared to workers at the bottom of the distribution.

A.3 Separation year $u = 1994$

In this section, I report the displacement effects of workers laid-off in 1994 and compare the effects on workers from exposed and non-exposed industries. We can observe that, in this case, the effects of displacement are similar for both groups. Furthermore, the patterns show that being displaced seven years before the entrance of China to the WTO did not have effects on the difference in wage trajectories of displaced workers.

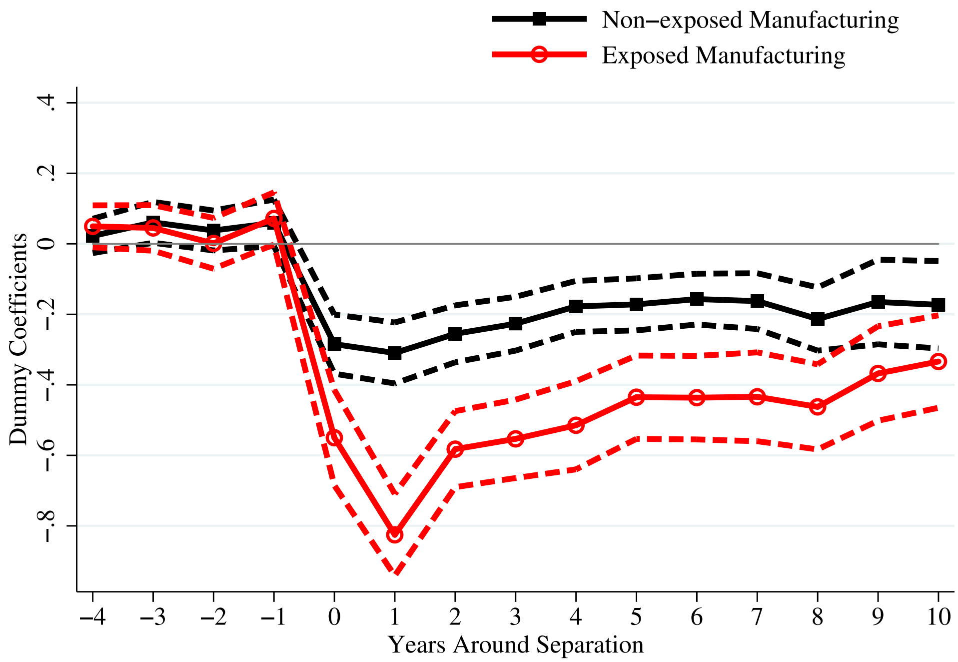
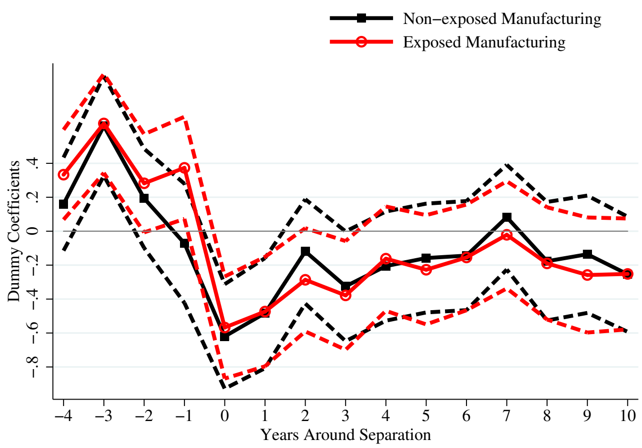


Figure 22: Earnings job loss for the exposed and non-exposed sector.
Notes: The graph displays the relative deviation in logs of displaced workers in each sector relative to non separators in year 2001. The dashed lines represent 95 percent confidence intervals. Standard errors are clustered at the level of the firm where the worker was displaced. The 0 represent the displacement year.

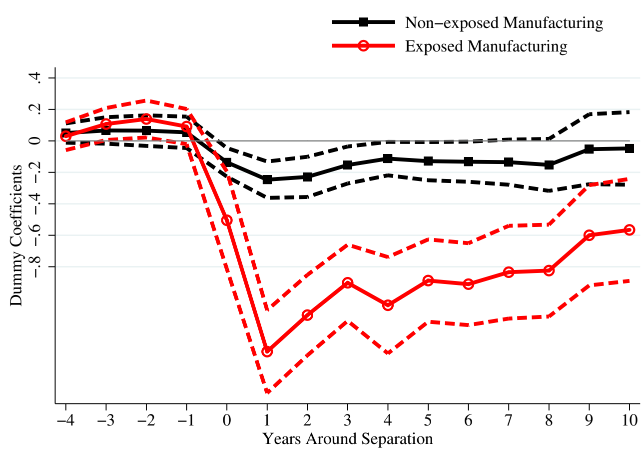
A.4 Job Loss – other years

In this section I provide robustness checks of regressions for other separation years ($u = 2003, 2004$ and 2005)



(a) 10th to 20th percentile.

(b) 50th to 60th percentile.



(c) 90th to 100th percentile.

Figure 23: Job loss for different percentiles

Notes: The graph displays the relative deviation in logs of displaced workers in each sector relative to non separators in year 2001. The dashed lines represent 95 percent confidence intervals. Standard errors are clustered at the level of the firm where the worker was displaced. The 0 represent the displacement year.

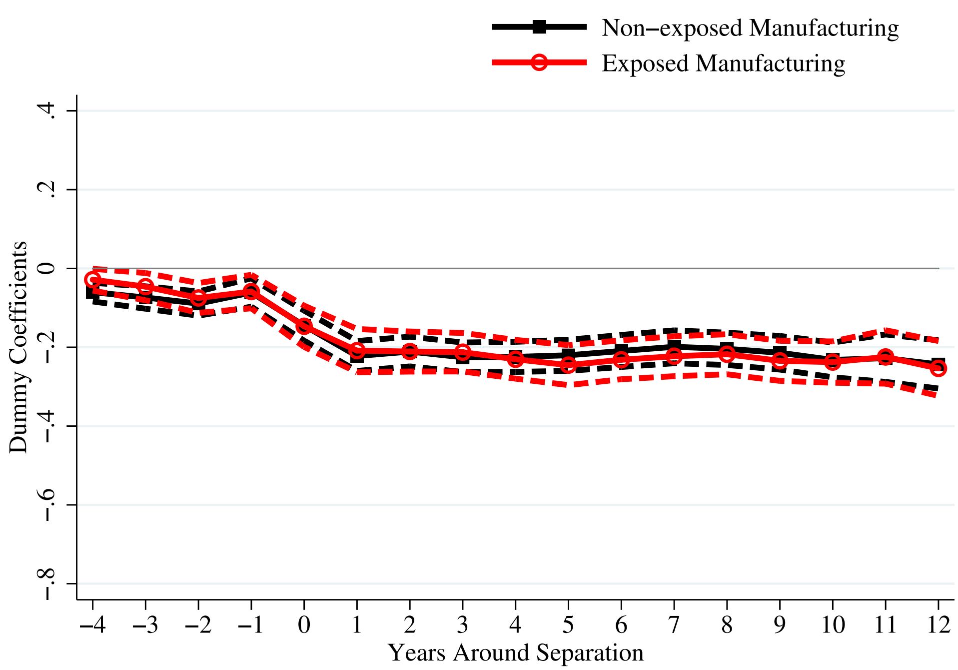
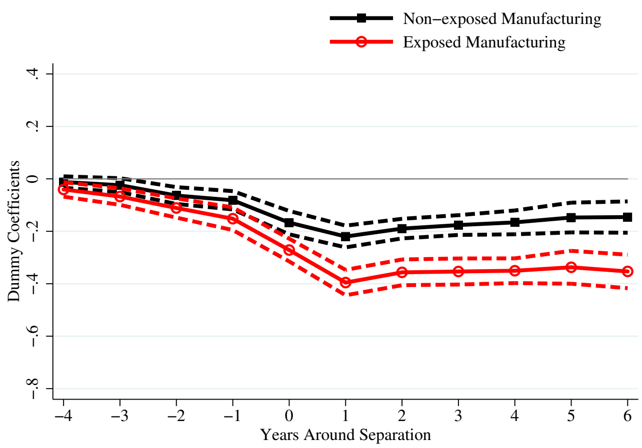
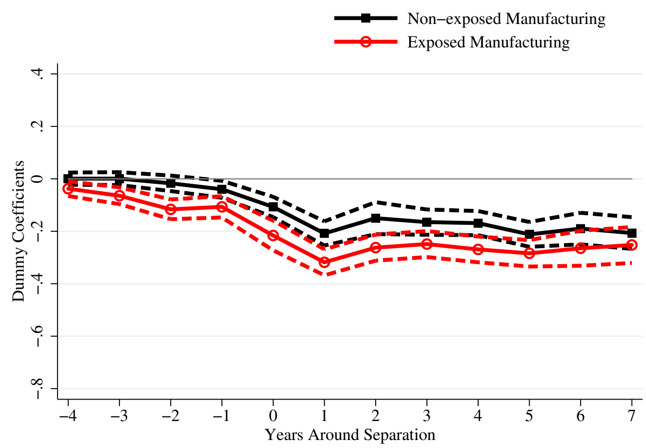


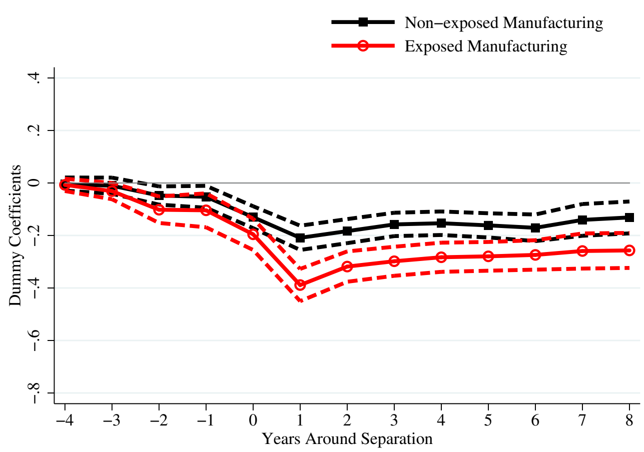
Figure 24: Job loss for the exposed and non-exposed sector.
Notes: The graph displays the relative deviation in logs of displaced workers in each sector relative to non separators in year 1994. The dashed lines represent 95 percent confidence intervals. Standard errors are clustered at the level of the firm where the worker was displaced. The 0 represent the displacement year.



(a) Overall wage loss $u = 2005$.



(b) Overall wage loss $u = 2004$



(c) Overall wage loss $u = 2003$

Figure 25: Job loss for different separation years

Notes: The graph displays the relative deviation in logs of displaced workers in each sector relative to non separators in year u. The dashed lines represent 95 percent confidence intervals. Standard errors are clustered at the level of the firm where the worker was displaced. The 0 represent the displacement year.