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Import Competition and Educational Attainment

EVIDENCE FROM THE CHINA SHOCK IN MEXICO

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Abstract

This paper examines the impact of import competition on educational attainment in Mexico, emphasizing its effects through labor market dynamics. Using China´s entry into global trade markets as a source of exogenous variation, we implement a shift-share approach to measure regional exposure to Chinese imports and employ a staggered difference-in-differences estimation strategy–marking a novel contribution to the China Shock literature. Our analysis reveals that import competition negatively affected educational outcomes, increasing dropout rates and the proportion of students falling behind their normative grade. These outcomes were accompanied by sustained wage declines, particularly in the secondary and tertiary sectors. We identify a significant decline in the returns to schooling as the primary mechanism explaining the adverse educational effects. Our findings offer novel empirical evidence linking import competition to reduced returns to schooling.

Keywords: China shock, import competition, educational attainment, returns to schooling.

JEL Codes: F14, F16, I25, I26, J24.

Resumen

Este artículo examina el impacto de la competencia de las importaciones en los logros educativos en México, haciendo hincapié en sus efectos a través de la dinámica del mercado laboral. Utilizando la entrada de China a los mercados comerciales globales como una fuente de variación exógena, implementamos un enfoque de cambio de participación para medir la exposición regional a las importaciones chinas y empleamos una estrategia de estimación de diferencias en diferencias escalonadas, lo que marca una contribución novedosa a la literatura sobre el shock de China. Nuestro análisis revela que la competencia de las importaciones afectó negativamente los resultados educativos, aumentando las tasas de deserción y la proporción de estudiantes que se quedan atrás de su grado normativo. Estos resultados fueron acompañados por caídas salariales sostenidas, particularmente en los sectores secundario y terciario. Identificamos una disminución significativa en los retornos a la educación como el mecanismo principal que explica los efectos educativos adversos. Nuestros hallazgos ofrecen evidencia empírica novedosa que vincula la competencia de las importaciones con la reducción de los retornos a la educación.

Palabras claves: choque de China, competencia de las importaciones, logros educativos, retornos a la educación.

Código JEL: F14, F16, I25, I26, J24.

Import Competition and Educational Attainment: Evidence from the China Shock in Mexico*

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Abstract

This paper examines the impact of import competition on educational attainment in Mexico, emphasizing its effects through labor market dynamics. Using China's entry into global trade markets as a source of exogenous variation, we implement a shift-share approach to measure regional exposure to Chinese imports and employ a staggered difference-in-differences estimation strategy—marking a novel contribution to the China Shock literature. Our analysis reveals that import competition negatively affected educational outcomes, increasing dropout rates and the proportion of students falling behind their normative grade. These outcomes were accompanied by sustained wage declines, particularly in the secondary and tertiary sectors. We identify a significant decline in the returns to schooling as the primary mechanism explaining the adverse educational effects. Our findings offer novel empirical evidence linking import competition to reduced returns to schooling.

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1 Introduction

Educational attainment remains a critical challenge in developing economies. Mexico exemplifies this as a middle-income developing country, ranking lowest in overall educational completion among OECD countries. Despite notable progress in expanding access to education over the past decade, dropout rates in Mexico remain high, particularly at the upper secondary level (high school). Only about 57% of Mexicans aged 25 to 34 have completed this level—well below the OECD average of 86% (OECD, 2023). This gap is significant and has implications for understanding development status. Development accounting literature suggests that cross-country income disparities are primarily driven by differences in human capital, which accounts for approximately 60% of income variation, with the remaining 40% attributed to variations in technology or fixed capital (Hendricks and Schoellman, 2018). Although some studies propose a lower share for human capital—around 30% according to Jones (2016)—the conclusion is consistent: educational attainment plays a critical role in understanding why countries like Mexico have yet to achieve higher income levels.

Labor outcomes are a key determinant of educational attainment (Hanushek and Woessmann, 2011; Blanden et al., 2023). Recent evidence has shown that labor outcomes are, in turn, closely influenced by trade, particularly at the local level (Topalova, 2010; Autor et al., 2013; Dix-Carneiro and Kovak, 2017). Trade-induced shifts in labor markets can influence educational decisions through three potential channels: the income channel, the opportunity cost channel, and the returns-to-schooling channel. The income channel operates as wage changes affect household income, influencing families' ability to cover the direct and indirect costs of schooling. The opportunity cost channel reflects how wage changes, particularly for younger workers, alter the relative cost of staying in school versus entering the workforce (Soares et al., 2012; Atkin, 2016). On the other hand, the returns-to-schooling channel relates to how trade-induced wage shifts, especially in skill-intensive sectors, affect the perceived economic value of additional education. The relative importance of these channels depends on context and labor market conditions, making it an empirical question.

We analyze the impact of trade on education, mediated through its effects on the labor market, using Mexico as a case study and leveraging China's entry into global trade markets –henceforth, the China Shock– as a natural experiment providing exogenous variation. In particular, we leverage year-to-year exposure to Chinese import competition at the commuting zone level and exploit the staggered exposure of local industries across time using a shift-share measure in a differences-in-differences setting. This strategy allows us to provide event-study-type estimates, a novel approach in the context of the China Shock literature. We find that the China Shock substantially affected educational attainment in Mexico, particularly in high school dropout rates and student progression. Regions more exposed to imports from China experienced an average 2-percentage-point increase in dropout rates, with effects intensifying to nearly five percentage points between 10 and 14 years after exposure. Additionally, exposure to the China Shock increased the share of students lagging behind their normative grade level by approximately three percentage points. Thus, the trade shock adversely impacted both retention and timely progression.

Our analysis reveals that these educational impacts coincide with significant shifts in labor market conditions. Regions more exposed to the China Shock experienced a temporary decline in formal employment of around 5%, with some recovery over time—a trend consistent with findings by Blyde et al. (2023). However, this recovery did not extend to the manufacturing sector, where employment fell permanently and significantly, reflecting the severe impact of import competition on industrial jobs. In contrast, employment in the service sector shows some evidence of recovery, potentially absorbing lost industrial jobs. Wages in highly exposed regions fell by an average of 7.5%, with the decline exceeding 10% thirteen years after exposure. Notably, these wage reductions were concentrated in the secondary (manufacturing) and tertiary (service) sectors, with no significant impact observed in the primary sector.

We identify the returns-to-schooling channel as the primary mechanism driving the adverse educational effects of the China Shock for two main reasons. First, the trade shock disproportionately reduced wages in skill-intensive sectors—specifically, the secondary and tertiary sectors—while largely sparing the primary sector. This shift lowered the economic returns to additional education. Second, based on a Mincer-type regression that accounts for variation in returns to schooling by exposure to import competition, we estimate that in highly exposed regions, returns to schooling were about 1.9% lower than in less exposed regions by 2009, with this gap increasing slightly to 2.3% by 2017. While returns to schooling remained positive across all regions, the persistent negative effects in treated areas suggest that prolonged exposure to Chinese import competition likely prompted students to adjust their educational decisions, reducing the perceived value of continuing their education.

Our heterogeneous analysis indicates that the effects of the China Shock are more fully concentrated in non-poor areas of Mexico. These areas experience the complete negative educational and labor impacts we see in the full sample. In contrast, poorer areas experienced employment declines but no effect on wages and education outcomes. These findings align with the theory by Basu and Van (1998), suggesting that marginal income changes have limited effects on schooling decisions in regions below a certain income threshold. Moreover, the heterogeneous analysis reinforces the returns-to-schooling channel as the primary mechanism driving the adverse educational impacts of the China Shock, as wage decline, and not employment change, coincided with worsened educational outcomes.

Our work makes three novel contributions. First, the literature on the impact of the China Shock on educational outcomes is scarce; we provide new evidence by analyzing this relationship in the context of a developing economy. More specifically, to our knowledge this is the first paper to empirically demonstrate that the returns-to-schooling channel can play a central role in shaping educational impacts of import competition, showing how trade shocks can undermine the perceived value of education in developing economies.

Second, we provide event-study-type estimates, capturing both short- and long-term impacts with greater precision than previous studies that relied on less frequent survey or census data. To do so, we leverage detailed administrative data to track dynamic educational and labor market responses at an annual frequency. These data include the "Statistics 911" administrative dataset from the Ministry of Education, a census-like source providing annual school-level data on enrollment, dropout rates, and grade-level progression. For labor market outcomes, we use administrative records from the Social Security Institute, covering the universe of formal private-sector employees.[1]

Third, we advance the methods used in the China Shock literature by exploiting both sectoral and timing variation in import exposure. Our strategy leverages a shift-share variable that measures regional exposure to Chinese imports, constructed from pre-existing industrial employment patterns. A key distinction of our approach from previous literature is that we exploit not only cross-industry differences in import competition but also variation in timing, implementing a staggered difference-in-differences analysis. Specifically, we take advantage of the fact that some industries faced increased import competition earlier than others. By defining the treatment at an annual frequency rather than as a 10-year shock, as exemplified by Autor et al. (2013), we can more precisely capture the staggered nature of exposure and better approximate dynamic effects.

1.1 Related literature

Our paper contributes to two key strands of literature. First, it extends research on the relationship between trade shocks and human capital by examining how import competition affects educational outcomes.[2] The study most closely related to ours is Greenland and Lopresti (2016), which finds that U.S. regions more exposed to the China Shock experienced improved educational outcomes due to declining opportunity costs. In contrast, our analysis focuses on a developing economy, finding that the China Shock led to a deterioration in educational attainment, particularly in high school dropout rates and grade-level progression.[3] Our findings of negative educational outcomes are consistent with studies examining other import competition shocks in developing countries. For example, Edmonds et al. (2010) and Nakaguma and Viaro (2024) document poorer educational outcomes in regions more exposed to trade liberalization in India and Brazil, respectively, during the 1990s. Similarly, Li et al. (2019) finds that trade liberalization in China during the 2000s adversely affected educational

[1] We validate our findings using labor survey data from ENOE, which includes both formal and informal workers. We also use ENOE data to explore the mechanisms.

[2] A related body of research has explored the educational impacts of trade shocks resulting from expanded export opportunities (Atkin, 2016; Blanchard and Olney, 2017; Leight and Pan, 2024).

[3] Unlike in the U.S., where trade shocks have been shown to reduce local education funding due to reliance on property and sales tax revenues (Feler and Senses, 2017), public education in Mexico is federally funded, which insulates local budgets from such fiscal shocks.

attainment. By identifying the returns-to-schooling channel as the primary mechanism, we add a novel dimension to this body of research, contrasting with prior studies that emphasize opportunity costs or income effects.[4]

Second, our work contributes to the extensive literature examining the impact of trade shocks on local labor markets. Since Topalova (2010) first used quasi-experimental tariff variation in India, research has consistently demonstrated that trade shocks significantly affect local labor market conditions. Autor et al. (2013) later popularized the shift-share design with their study of the China Shock's impact on U.S. labor markets, inspiring subsequent applications in Brazil (Kovak, 2013; Dix-Carneiro and Kovak, 2017), Germany (Dauth et al., 2014), and South Africa (Erten et al., 2019). In the context of Mexico, Blyde et al. (2023) analyze the China Shock's local labor market effects, finding negative medium-term impacts on formal employment that dissipate over time.[5] Similarly, Heckl (2024) explore gender-based differences in labor market responses to the China Shock. Unlike much of this shift-share literature, our approach incorporates variation in the timing of exposure, allowing us to define treatment at an annual frequency and better capture the dynamic short- and long-term effects of trade shocks on labor market outcomes.

The rest of the paper proceeds as follows: Section 2 presents Mexico's educational context and institutions and details the natural experiment we study. Section 3 describes the data and methodology we use. Section 4 presents our results. Finally, Section 5 concludes.

2 Context and institutional setting

2.1 Education in Mexico

Approximately 92% of schools in Mexico are publicly financed. The country's elementary and "mandatory" –with varying compliance levels– education system starts at pre-school (ages 3-5 years), transitioning to primary (grades 1-6), secondary school (grades 7-9), and high school

[4]Edmonds et al. (2010) provides evidence supporting the family income channel while finding no significant role for the returns-to-schooling channel.

[5]We also document negative medium-term effects on formal employment, which dissipate in the long term.

(grades 10-12, normative age of 15 to 17). Primary school enrollment has been practically universal since the 2000-2001 academic year. Secondary education enrollment experienced a rapid increase following a major reform in 1993 at the national level, establishing secondary education as compulsory. By then, secondary enrollment was around 68%, and by 2018-2019, secondary enrollment reached 95%. Net enrollment rates have been increasing sharply over the last two decades for higher levels of education as well. High school net education enrollment went through a remarkable increasing trend at the national level; it grew from 34% in 2000-2001 to 62% in 2020-2021. Yet, the biggest challenge remains in retaining students in high school, as the largest dropout rates are observed at this education level. High-school dropout rates stood at 24% in 2000-2001 without significant changes across time, stabilizing at around 20% from the academic year 2015-2016. Moreover, half of the students abandoning high school do it during the first academic year. Consequently, by 2023, only 56% of the population aged 25-34 in Mexico had completed high school (vs. 86% in the OECD countries), from which less than a half, or approximately 25% aged 25-34, have obtained a bachelor's degree (OECD, 2023).

High school education in Mexico gathers three systems/types of schools: a) general high schools aiming to prepare students to continue tertiary education (typically in a university), representing approximately 86% of all high schools in the period 2000-2001 and 80% in 2016-2017; b) vocational or technical schools, aiming to offer education for the labor market, typically for the manufacturing industry, representing 14% of the total in 2000-2001 and 16% in 2016-2017; and 3) professional high schools aiming to offer technical training for a broader set of industries and services, during four academic years (one more than in the other systems), representing approximately 4% of the total in 2016-2017.[6]

2.2 The China Shock

We exploit as a natural experiment the so-called China Shock, a global import competition episode first exploited by Autor et al. (2013). The China Shock refers to China's rapid rise

[6]This type of high school started to be notable in the academic year 2005-2006 when they represented 2% of the total.

as a global manufacturing power, especially after it joined the World Trade Organization (WTO) in 2001. This phenomenon impacted developed and developing countries alike, as China's impressive manufacturing productive expansion altered the landscape in global international trade: China's share of global manufacturing exports rose significantly, increasing from 2.3% in 1991 to 18.8% by 2013 (Autor et al., 2016).

The China Shock is a global phenomenon, but it appears to be driven by factors specific to China's local economy. The fundamental factor explaining China's rise in the global economy relates to the rapid productivity growth of the Chinese economy, which is, in turn, related to extensive domestic reforms. Brandt et al. (2012) document that between 1998 and 2007, annual total factor productivity (TFP) growth in Chinese manufacturing was 8% on average, while that of the U.S. was less than 4% (Autor et al., 2013). In the same period, Mexican TPF growth was negative (Cepeda and Ramos, 2015). According to the detailed account by Storesletten and Zilibotti (2014) on China's recent exploding growth trajectory, China's surge in the global economy was driven ultimately by substantial policy reforms that had been underway for decades. As just one example of such reforms, Alder et al. (2016) finds that industrial policies are related to faster productivity growth and human capital accumulation, leading to enormous GDP increases, even reaching a whopping 20% at some localities.

Given that Chinese internal factors mainly drove the shock, Chinese import competition in Mexico in the 2000s was not driven by Mexico's domestic conditions. Thus, the shock can be considered exogenous to Mexico. Figure 1, Panel (a), shows that the China Shock effectively increased the share of Chinese manufacturing imports, both in Mexico and worldwide. The share is higher for the world than for Mexico, but the trends for both shares are remarkably similar. The pattern of Chinese import competition faced by Mexico was, therefore, very similar to what all countries were facing. The correlation between the two shares is 0.98, almost deterministic, supporting that the China Shock was a global phenomenon driven by factors exogenous to Mexican domestic conditions. Additionally, the graph confirms that the growth of Chinese exports, both globally and in Mexico, accelerated significantly only after 2000.

Another essential feature of the China Shock for Mexico was that it was not connected to expanded export opportunities. The import competition from China did not happen hand-in-hand with export expansion as in other countries. For example, Costa et al. (2016) show that the China Shock for Brazil had two fronts, one associated with increased manufacturing import competition and another with an export boom of commodities. Figure 1, Panel (b), shows that this was not the case for Mexico. Total imports grew substantially during this period, while exports (including manufacturing and primary goods) did not. This is another advantage of studying the China Shock for Mexico: it allows the identification of import competition effects without potential confounding factors from expanded export opportunities. This condition is essential for educational outcomes, given the existing evidence on expanded export opportunities affecting educational outcomes negatively (Atkin, 2016).

Finally, Panel (c) of Figure 1 shows the growth in imports from China to Mexico and other Latin American economies in 2000-2017 by industry. The figure shows that the industries that experienced growth in imports from China are quite similar in Mexico and other countries in Latin America. This gives further evidence that China's entry into the global markets affected certain industries across the whole region more heavily for reasons that were determined by China's own competitive advantages and not by factors internal to the Mexican economy. Thus, the China Shock can be considered exogenous to Mexico, even at the sectoral level, providing quasi-experimental variation in import competition across Mexican regions. We leverage this exogenous variation using a dynamic difference-in-differences design.[7]

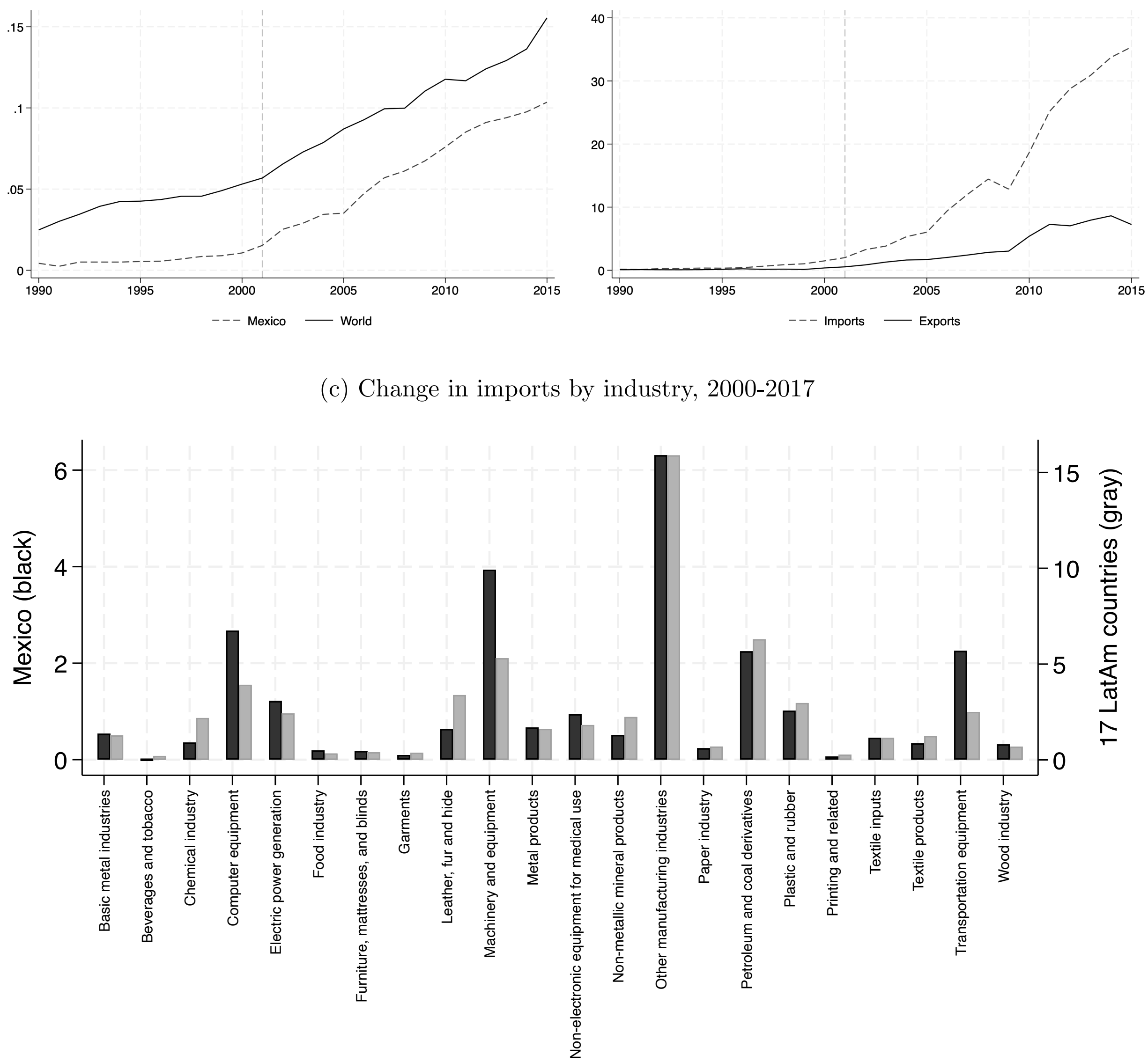
[7]Nonetheless, to avoid remaining endogeneity concerns, following the literature on the China Shock, we also include instrumental variable estimates in one of our robustness exercises in Section A in the Appendix confirming our main results.

Figure 1: China Shock Exogeneity

(a) Share of Chinese manufacturing imports (%)

(b) Mexican trade with China (bill. of dollars)

(c) Change in imports by industry, 2000-2017



Notes: Panel (a) shows the share of Chinese manufacturing imports as a percentage of total manufacturing imports. Panel (b) shows Mexican imports from China and Mexican exports to China. Data is taken from BACI. The year 2001 marks the year of China's entrance to the World Trade Organization (WTO). Panel (c) displays changes in imports by industry in Mexico and other Latin American countries. Changes in imports are normalized by the number of Mexican workers in each industry (i.e., thousands of USD per worker). While our analysis exploits variation across 286 manufacturing industries, we summarize the shift variation across 22 aggregated industries.

3 Data and methodology

3.1 Data

To construct our shift-share exposure measures to import competition at the commuting zone level, we use employment data from the 1999 Mexican Economic Census and import flow data from the BACI dataset by CEPII (Gaulier and Zignago, 2010). The 1999 Economic Census provides detailed information on manufacturing employment at the municipal level for 1998, covering 286 manufacturing industries at the 6-digit level of the 1997 NAICS classification. We also collect trade flow data from China to Mexico from 1995–2017 from BACI. These trade flows, classified under the 1992 Harmonized System (H.S.) at a 6-digit level, encompass approximately 5,000 products.

To harmonize the imports and employment data, we perform several intermediate steps. First, we translate the 1997 NAICS classification to the 2018 NAICS classification.[8] To do so, we use correspondence tables from Mexico's Statistics Institute (INEGI).[9] Next, we convert the 2017 H.S. codes to 1992 H.S. codes using a correspondence table from the United Nations Statistical Commission.[10] Finally, we align the 1992 H.S. codes with the 2018 NAICS codes by using a correspondence table that converts 2017 H.S. to 2018 NAICS codes.[11] This enables us to express import flows in 2018 NAICS codes, making them consistent with our manufacturing employment data.

Our education data comes from educational census information at the high school level, known as "Statistics 911". The Ministry of Education provides these data ranging from 1997 to 2017. Each school reports on several variables (at least 911) at the beginning and end of each academic year. The dataset contains information on infrastructure and the type of education provided (technical/vocational or general). Schools report the total number of students enrolled and those remaining at the end of the academic year, and how many of

[8] From 1997 to 2018, the classifications for manufacturing industries became more aggregated. In 1997, there were 286 6-digit manufacturing industries, while in 2018, there were 284. As a result, we use the 2018 classification.

[9] The translation process involves four correspondence tables: 1997 to 2002, 2002 to 2007, 2007 to 2013, and 2013 to 2018. These tables were obtained from https://www.inegi.org.mx/scian/.

[10] The correspondence table is available at https://tinyurl.com/HS2017toHS1992.

[11] This correspondence table is available at https://www.inegi.org.mx/app/tigie/.

these continue in the school over the next cycle, allowing us to compute total dropout rates.[12] The data also details statistics on the number of students by age and gender, allowing us to compute the share of students lagging behind from the total in school s in academic year t (i.e., those who are at least two years older for the normative age-by-grade). Each academic year, dropout and lagging behind measures at the school level are matched to a calendar year; for example, education statistics in the academic year 2001-2002 are matched to the 2002 calendar year, and we merge them to the corresponding shift-share measures at the commuting zone level.

Data on labor outcomes comes from the *Asegurados* datasets collected by the Social Security Institute (IMSS). This dataset contains monthly information on the universe of employees in formal private firms at the municipality level. We use two variables in the dataset: mean daily labor earnings and employment level. Daily earnings are obtained from the definition of *salario base de cotización* (SBC) in the datasets.[13] The IMSS datasets do not include the informal workforce in Mexico, which was around 57% of the total workforce in the 2000-2020 period. To address the missing informal sector in the IMSS data, in Section A in the Appendix, we perform robustness tests with data from INEGI's *Encuesta Nacional de Ocupación y Empleo* (ENOE), the largest labor survey in Mexico. We also use ENOE data to test the mechanisms driving our results. ENOE is not representative at the municipality level. However, it is representative for 39 cities, covering 45 percent of Mexico's population (47 percent of the workforce). We use data from these cities to replicate our main results for the formal and informal sectors.

3.2 Methodology

We exploit the quasi-experimental nature of the China Shock to study the impact of import competition on cross-regional educational and labor outcomes in Mexico. The varying shares of directly competing industries –i.e., producing similar products to those imported from

[12] I.e., the total students enrolled in academic year t in school s minus the total of students in $t+1$ in school s, over the total of students in t, s, times a hundred.

[13] While *salario* is directly translated to English as "wage," SBC is not precisely the usual price of labor per hour in the English-speaking world because, in Mexico, the shortest period of wage setting is on a daily basis. SBC does not include compensation from overtime work, bonuses, or other type of compensation.

China– across Mexican commuting zones allow comparing areas of Mexico more exposed to the China Shock to less affected areas across time. To examine this, we use the following shift-share exposure measure:

$$Exposure_{c,t} = \sum_i \underbrace{\frac{Workers_{i,c,t=1999}}{Workers_{e,c,t=1999}}}_{\text{share}} \underbrace{\frac{Imports_{i,t=2001-2017}}{Workers_{i,t=1999}}}_{\text{shift}} \tag{1}$$

The $shift$ part in Equation 1 captures the value of industry i imports (in thousands of dollars) from China to Mexico at time t, weighted by the total number of workers in industry i in the base year $t = 1999$. We only use industries i within manufacturing, given that the China Shock essentially altered import competition in this sector. The *share* reports the share of industry i workers of total non-agricultural employment e in commuting zone c for the base year $t = 1999$.[14] Therefore, our $shift - share$ variable $Exposure_{c,t}$ considers differences in commuting zone exposure to imports from China across time. Our exposure definition varies annually, allowing us to leverage industry and timing variation for identification. Specifically, we exploit differences in regional exposure to import competition based on industry composition and the temporal variation in exposure, where some industries experienced import competition earlier (e.g., starting in 2001 or 2002) while others faced it later (e.g., in 2007 or 2008). This approach departs from previous contributions in the shift-share literature,[15] enabling us to estimate the dynamic effects of import competition through the following event study design equation:

$$y_{c,t} = \alpha + \sum_{t=-7,t\neq 0}^{t=14} \delta_t ChinaShock_{c,t} + \zeta_c + \nu_t + \varepsilon_{c,t} \tag{2}$$

where $y_{c,t}$ is the average education or labor market outcome measure in commuting zone c at time t.[16] The specification includes commuting zone fixed-effects ζ_c and time fixed-effects

[14] We take the commuting zones defined by Blyde et al. (2023). To create the commuting zones, they aggregate municipalities with a high degree of interaction based on workers' commuting between residence and workplace.

[15] The shift-share literature on trade shocks typically relies on defining the shock within a fixed medium-term time window, thereby overlooking potential timing variation in exposure. For example, the seminal work by Autor et al. (2013) on the China Shock in the U.S. models the shock as a one-time change over 10 years, implicitly assuming that all industries experienced the same timing in import competition variation.

[16] The main dependent variables of interest are dropout rates in high school, the share of students lagging

ν_t. Additionally, we demean our dependent variable from their cohort-by-time average for our school outcomes, essentially introducing cohort-by-time fixed effects. Our treatment variable $ChinaShock_{c,t}$ is equal to 1 if $Exposure_{c,t}$ in commuting zone c at time t exceeds the median country-level exposure to imports from China, averaged over 2001-2021. δ_t measures the average effect on y across commuting zones exposed for $k + 1$ years to the China Shock. Thus, equation (2) uses the within-commuting-zone variation in exposure to the increase in imports from China across time to calculate the dynamic effects of import competition. Using within-commuting zone variation eliminates the need to control for the sum of exposure shares, as emphasized by Borusyak et al. (2022), since commuting zone fixed effects account for this and any other time-invariant characteristics of each unit. The coefficients δ_t are identified under the standard common trends assumption.

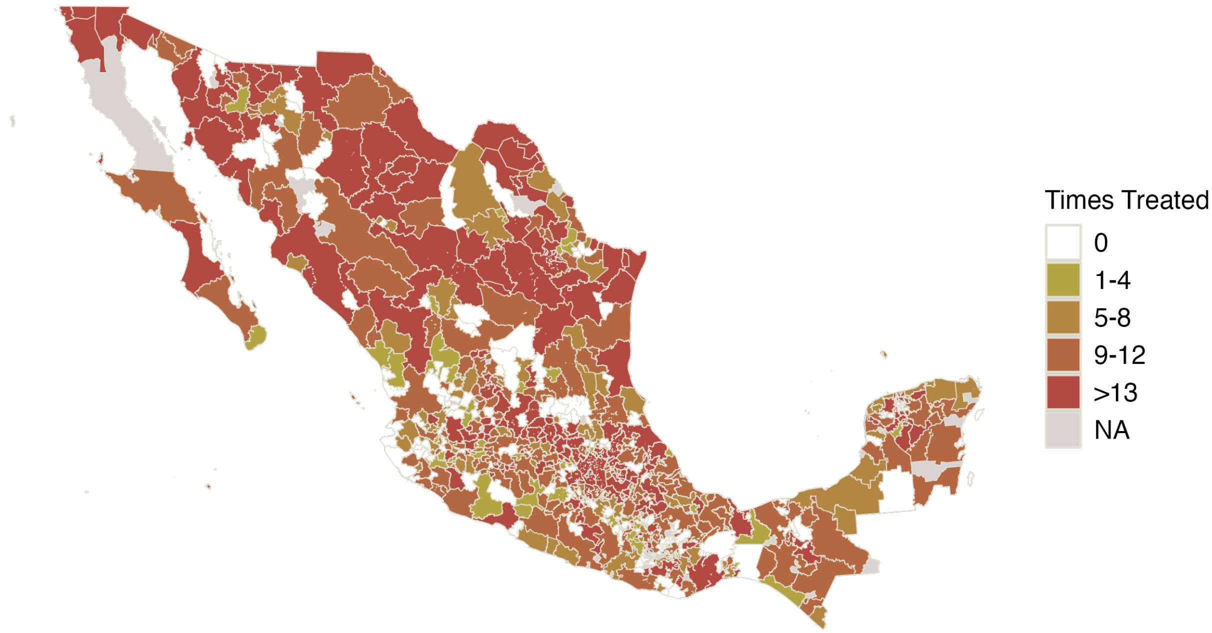
Figure 2 shows the number of times each commuting zone is treated in the 2001-2017 period. Our data comprises an average of 740 year-zones, of which 209 are never treated at any given time.[17] The figure indicates that the most intensely treated commuting zones are located in the northern and central parts of the country. This is expected due to the predominantly manufacturing profile of these regions. Figure B.1 in the Appendix shows the evolution of the treated commuting zones in different years. The figure shows that the number of treated zones increases throughout the period, with an initial cohort of 157 regions receiving treatment in 2001 and 568 zones being treated by 2017, the last year for which educational data is available. As we measure treatment as exposure to the average profile of imports from China over the 2001-2017 period, it is straightforward that we get an increasing number of treated zones over time: different Mexican regions were exposed to a wider variety of products imported from China.

We estimate Equation (2) using the estimator by de Chaisemartin and D'Haultfœuille (2020) for two reasons. First, commuting zones are exposed to imports from China in a staggered manner, as not all commuting zones exceed the median country-level exposure

behind the normative grade for their age, the log of employment and log of daily wages per worker.

[17]The number of commuting zones in each treatment category of Figure 2 are: 0 times - 209; 1 to 4 times - 47; 5 to 8 times - 103; 9 to 12 times - 173; 13 or more - 208.

Figure 2: Treated Commuting Zones



Notes: This figure shows the number of times each commuting zone was treated in the 2001-2017 period. A commuting zone is treated if its measure of exposure to the China Shock as defined in Equation (1) exceeds the median country-level exposure to imports from China, averaged over 2001-2021. Regions exposed 0 times - 209; 1 to 4 times - 47; 5 to 8 times - 103; 9 to 12 times - 173; 13 or more - 208.

simultaneously.[18] Second, there may be heterogeneous treatment effects across commuting zones and over time.[19] The estimators δ_t show the $k+1$ years-long China Shock effect for the commuting zones treated at time t. In this setup, the control group is the commuting zones not yet treated at time t.

It could be argued that our difference-in-differences strategy is prone to endogeneity concerns, as the treated regions may have unobserved characteristics that affect both exposure to imports from China and labor and education outcomes. For instance, regions that

[18]Goodman-Bacon (2021) and de Chaisemartin and D'Haultfœuille (2020) show that, in a staggered setting, estimating eq. (2) using the regular two-way fixed effects estimator leads to biased estimates.

[19]The estimates proposed by de Chaisemartin and D'Haultfœuille (2020) are robust to dynamic effects and heterogeneous treatments across treated groups.

manufacture similar products as those imported from China may have a greater propensity to adopt labor-replacing technologies, which affects the labor and education outcomes we include in $y_{c,t}$. We argue that these endogeneity concerns do not bias our difference-in-differences estimator because, as indicated in Section 2.2, the China Shock was driven by domestic factors, and these affected imports across the globe. Consequently, Mexican commuting zones did not self-select into treatment. Instead, their varying initial production profiles determined their relative exposure to import competition when China entered global trade markets, leading to differential treatment intensity beyond their control. Nevertheless, to address any remaining concerns about endogeneity, we implement two alternative estimation strategies that use exposure to Chinese import competition in other countries as an external instrument—a common approach in the China Shock literature. These exercises, detailed in Appendix A, confirm the validity of our baseline strategy.

4 Results

We present our results in three steps. First, we demonstrate that the China Shock negatively impacted both educational attainment and labor market outcomes in Mexico. Next, we examine two theoretically relevant mechanisms to explain the negative educational effects: the family income and the returns-to-schooling channels. Our results indicate that lower returns to education are the primary driver of educational effects. Finally, we conduct a heterogeneity analysis by poverty levels, which reveals that the negative impacts on employment are concentrated in poorer areas. In contrast, the negative effects on wages and education are concentrated in non-poor areas, further reinforcing the importance of the returns-to-schooling channel in explaining our findings.

4.1 Educational and labor market outcomes

We first show the main effects of the China Shock on education outcomes in Mexico. Figure 3 shows the δ_t estimates from Equation (2) for dropout rates (Panel a), students lagging behind (Panel b), and high school enrollment (Panel c). The figure indicates that above-the-median exposure to imports from China increases dropout and student lag, key education performance indicators. Dropout increased by two percentage points on average from 2001-2017. The effect is null in the first five years after treatment, then becomes positive and statistically significant in the rest of the years after exposure. The size of the impact represents 8.4% of our dropout measure in the base year (23.7%). Moreover, the China Shock leads students lagging behind to increase by 2.95 percentage points in more exposed commuting zones –with the effect zero in the first four years and positive over the rest of the period. This effect represents an increase of 14.5% from the base year (with 20% of enrolled students being two years above their normative grade-for-age in the year 2000). On the other hand, there is no evidence of an effect on high school enrollment. The δ_t estimators are not different from zero in any after-treatment period, suggesting that students remain enrolling at the same rate but start to be less attached to school in more exposed areas. Note that the δ_t coefficients are not statistically significant in all three outcomes and are close to zero in the pre-treatment periods, supporting the common trends assumption of the difference-in-differences method.[20]

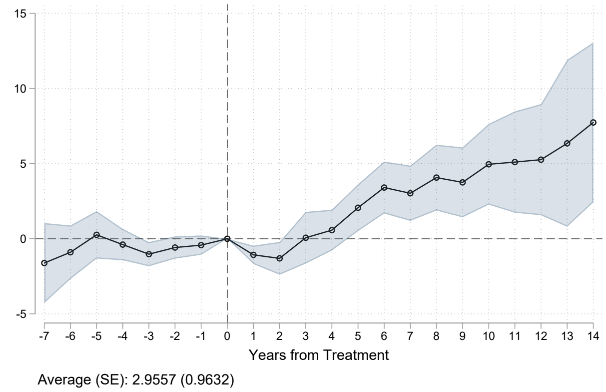
To better understand the adverse effects on educational outcomes, we now focus on labor market outcomes. Figure 4 shows the δ_t estimates from Equation (2) on our main labor outcomes: employment (Panel a) and average wages (Panel b) in the universe of the formal private sector. The figure indicates that the China Shock led to a deterioration of the Mexican labor market. There is an immediate negative effect on employment, lasting 10 years after first exposure. The effect dissipates in the later years, resulting in an average effect over the 2001-2017 period of 5% lower employment in above-the-median exposed commuting zones. These effects align with those documented by Blyde et al. (2023), using a different methodology (instrumental variables): a negative impact on employment in the short term

[20]We introduce cohort-by-time fixed effects in our preferred estimation regarding education outcomes because, during this period, several education policies were gradually introduced, with varying effects across cohorts in Mexico. For example, in 2001, the Schools Quality Program started in some schools, gradually expanding across Mexico up to 2016. Similarly, the Full-Time Schools program was gradually implemented in primary and secondary schools from 2007 to 2018, influencing school outcomes. Finally, in 2012, high school studies became mandatory, with varying levels of compliance across time and regions (Garcez et al., 2024). In Figure B.2 in the Appendix, we also present our results on school outcomes without cohort-by-time fixed effects. Although the estimates in Figure B.2 are noisier, the direction of the effect is similar in direction and size and still statistically significant.

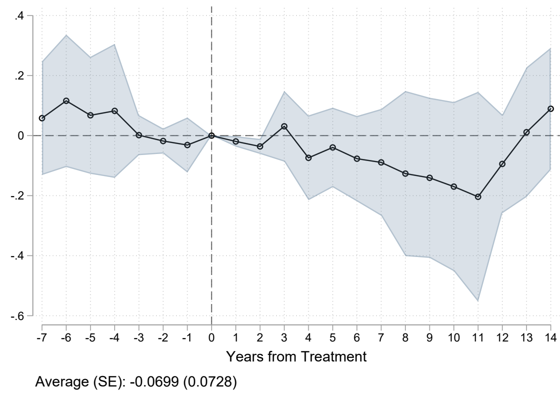
Figure 3: Effects on High School Outcomes

(a) Dropout Rates (p.p.)

(b) Students Lagging Behind (p.p.)



(c) Overall High School Enrollment (in logs)



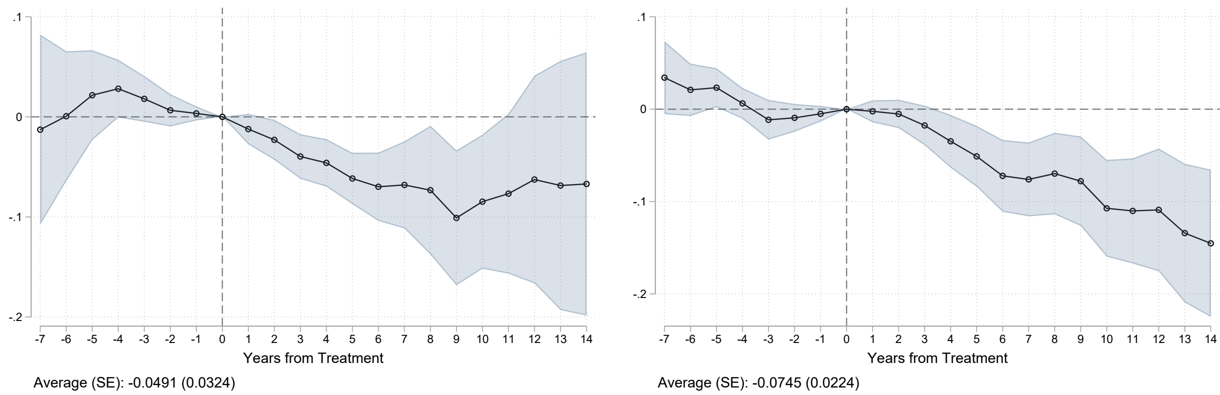
Notes: This figure shows the δ_t estimates from Equation (2) on high school dropout rates (Panel a), the percentage of students lagging behind their normative grade-for-age (Panel b), and the logarithm on students enrolled every academic year (Panel c). Estimated coefficients include their 95% confidence intervals. All estimates come from a single regression using de Chaisemartin and D'Haultfœuille (2020) method weighted by total non-agricultural employment. Standard errors are clustered at the commuting zone level. The number of average switching commuting zones is 5176 from of 10401 observations.

that goes towards zero in the longer term.

Furthermore, we contribute to the previous findings by showing that the effect on wages in the formal labor market is larger and sustained across time. Over the 2011-2017 period, the negative average impact on wages is 7.5 percent and statistically significant, indicating that those employed in more exposed areas received lower wages due to the China Shock. Moreover, wages do not recover during the whole period we study. Overall, our results suggest that the local labor markets adjust to higher competition from China by increasing layoffs (temporarily) and lowering wages (permanently).

Figure 4: Effects on Formal Labor Outcomes

(a) Employment (in logs) (b) Average Wage (in logs)



Notes: This figure shows the δ_t estimates from Equation (2) on the logarithm of formal employees plus one in Mexico (Panel a), and the logarithm of average wages (Panel b). Estimated coefficients include their 95% confidence intervals. All estimates come from a single regression using de Chaisemartin and D'Haultfœuille (2020) method weighted by total non-agricultural employment. Standard errors are clustered at the commuting zone level. The number of average switching commuting zones is 5176 from 10401 observations.

We disaggregate the China Shock impact on labor by economic sector in Figure 5. The figure shows no effect on employment in the primary and tertiary sectors (Panels a and e). However, there is a negative, permanent, and statistically significant employment effect on the secondary sector. This is intuitive and straightforward, as the sector most likely to be impacted by a trade shock is the tradable-producing manufacturing sector. This supports our main findings. Our results regarding wages indicate that the China Shock does not affect the primary sector (Panel b). However, the secondary and tertiary sectors (Panels d and f) display a negative, permanent, and statistically significant effect. Thus, the labor market deterioration caused by the shock pulls wages downward not only in the sector most exposed to trade but also in the tertiary sector.

Placing both sets of results together, the China Shock creates, on the one hand, a deterioration of the labor market in Mexico, which, on the other hand, coincides with a worsening of key educational measures, affecting overall human capital accumulation. As earnings in the economy worsen, people still enroll in high school at the same rate in more and less exposed commuting areas, but the propensity to stay in school over the academic year (dropouts) decreases in the former areas. Moreover, students in these areas have worse performance (lagging behind).

Our findings stand in contrast to those of Greenland and Lopresti (2016), who show that the China Shock worsens labor market conditions in the United States while improving educational attainment. They argue that this outcome arises because the shock depresses low-skill wages, leading individuals to increase their education levels. In the U.S. context, the authors posit that the primary mechanism connecting deteriorating labor market conditions to higher educational attainment is the opportunity cost of staying in school. In other words, their findings suggest that teenagers, facing diminished labor market prospects, chose to remain in school longer. Our findings, together with the findings by Greenland and Lopresti (2016), suggest that the effect of trade on education may vary significantly depending on the type of economy experiencing the trade shock. Moreover, as the effects we find are inconsistent with the opportunity cost mechanism, the relevant channels explaining our main findings differ from those of the U.S. economy. We explore this in the following subsection.

4.2 Mechanisms: Returns to schooling vs. family income

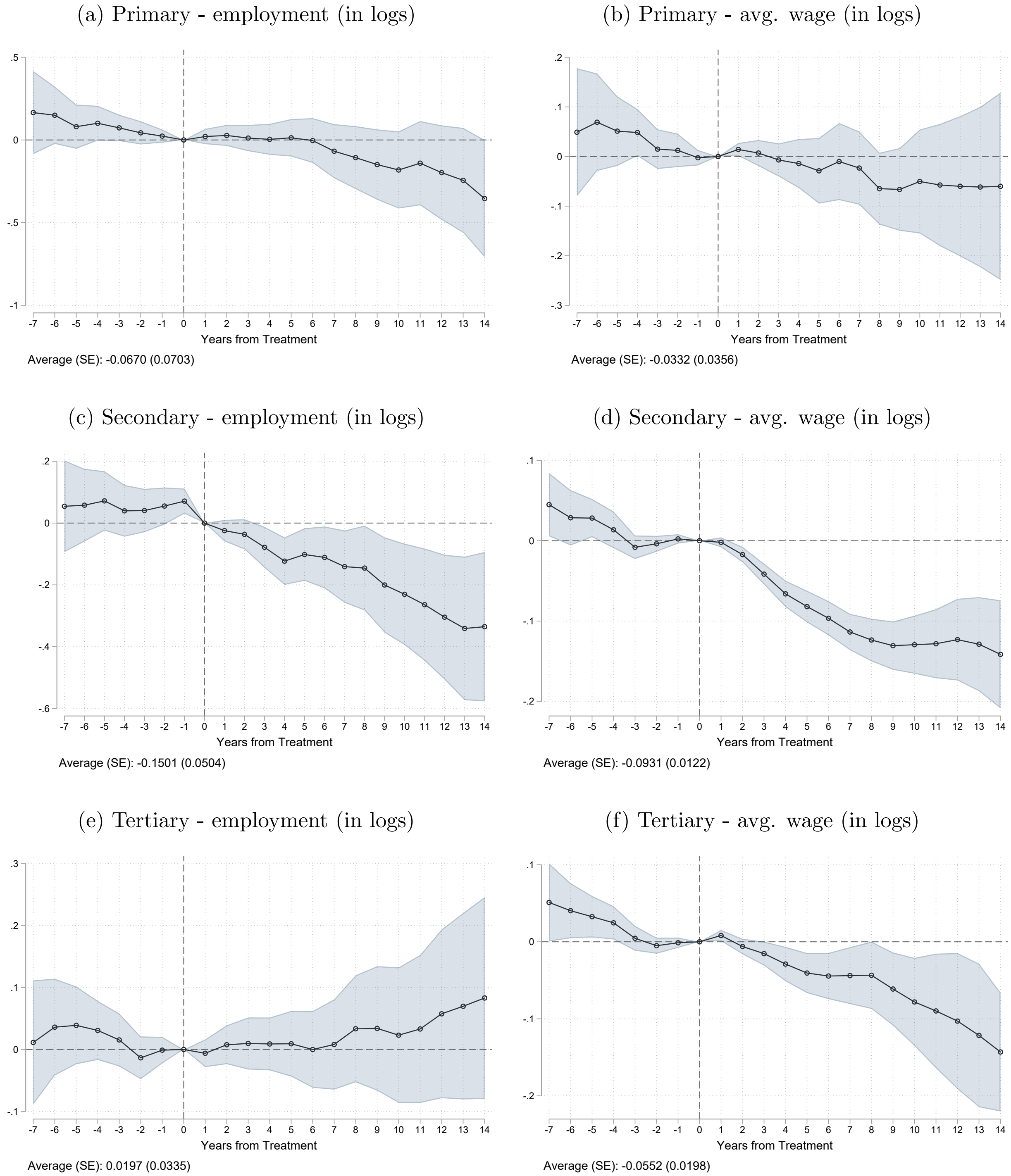
Two theoretical mechanisms might explain the education and labor results we find. First, deteriorating labor market outcomes might reduce the returns to schooling, making education a less attractive investment for teenagers. We call this the *returns to schooling mechanism*.[21] Second, changes in labor market conditions may directly affect family incomes, influencing teenagers' ability to pursue further schooling. This is the *family income mechanism*.[22] While our sectoral evidence indicates that wages decline primarily in relatively skill-intensive sectors (secondary and tertiary), suggesting the empirical relevance of the returns-to-schooling channel, we formally test both potential channels below.

We begin by examining the relevance of the family income channel. The argument is as follows: negative labor market outcomes resulting from import competition lead to declines in family incomes. These reduced incomes may prompt teenagers to leave school in favor of

[21] Greenland and Lopresti (2016) suggest that in the U.S., deteriorating labor market conditions may have increased the relative returns to skilled work compared to low-skilled work, indicating that the returns-to-schooling channel could also complement the opportunity cost channel in their case.

[22] Evidence for this channel is provided by Edmonds et al. (2010) in the context of India's trade liberalization during the 1990s.

Figure 5: Effects on Formal Labor by Sector



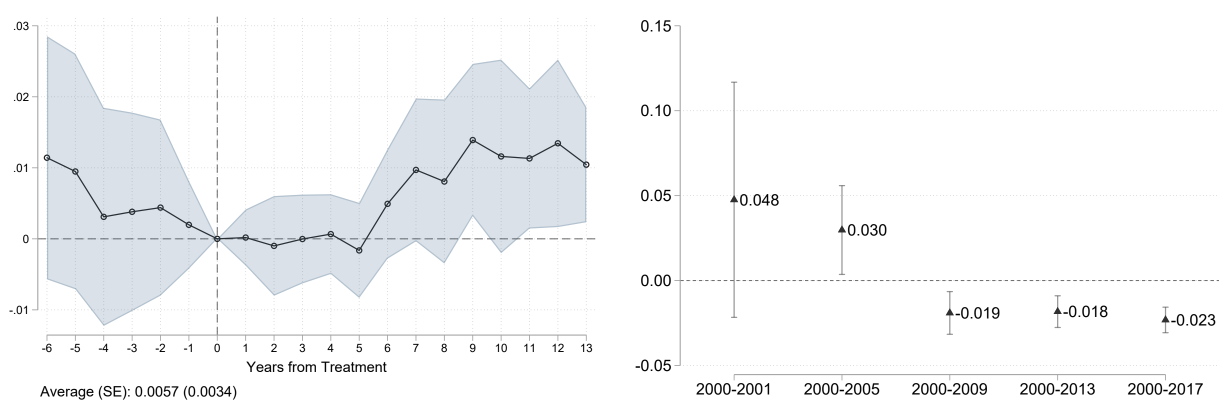
Notes: This figure shows the δ_t estimates from Equation (2) on the logarithm of formal employees plus one and the logarithm of average wages for the primary sector (Panels a and b), the secondary sector (Panels b and d) and the tertiary sector (Panels e and f). Estimated coefficients include their 95% confidence intervals. All estimates come from a single regression using de Chaisemartin and D'Haultfœuille (2020) method weighted by total non-agricultural employment. Standard errors are clustered at the commuting zone level. The number of average switching commuting zones is 5176 from 10401 observations.

seeking work opportunities to supplement household earnings. While seeking work may not always result in employment—particularly given the documented negative impact of import competition on the secondary and tertiary sectors—it could lead to increased labor force participation. To test this channel, we estimate Equation (2) using labor force participation rates from 39 cities for which ENOE, Mexico's largest labor survey, provides representative data. These cities account for 45% of Mexico's population.[23]

Panel (a) of Figure 6 shows the effect of the China Shock on the labor force participation rate. The effect is null on average. After 10 years of exposure to Chinese import competition, a significant positive effect emerges. However, the size of the estimator is pretty tiny. We follow a cautious stance and take this as empirical evidence that the China Shock did not impact labor force participation in Mexico. This indicates that the family income mechanism does not drive the main education and labor results described in the previous subsection.

Figure 6: Mechanisms

(a) Labor force participation (b) Returns to education



Notes: Panel (a) shows the shows the δ_t estimates from Equation (2) on labor force participation using de Chaisemartin and D'Haultfœuille (2020) method. Panel (b) shows the two-way-fixed effects β_t estimates from Equation (3) on returns to education. Estimated coefficients include their 95% confidence intervals. Standard errors are clustered at the city level.

Let us now test the empirical validity of the returns to schooling mechanism. This channel operates as follows: import competition adversely impacts the labor market, particularly in relatively skill-intensive sectors. As a result, the relative return to skilled labor declines,

[23]Labor force participation data for other local labor markets is unavailable because ENOE is not representative at the municipal level beyond these cities.

which should manifest as a reduction in the income gains associated with additional years of schooling. Note that the educational effects described in the previous subsection concern high school students, those soon to join the labor market, so their decisions regarding high school completion may be closely related to labor market dynamics in their immediate context.[24] We use data on workers' years of schooling from ENOE. With a Mincer-type regression, we test whether the income gains associated with an additional year of schooling are lower in cities highly exposed to the China Shock compared to those with low exposure, following the two-way fixed-effects equation:[25]

$$log(wage)_{c,k,j,t} = \sum_{t=2000}^{2017} \beta_t Schooling_{c,k,j,1999} * ChinaShock_{c,t} + \zeta_{c,k,j} + \nu_t + \varepsilon_{c,k,j,t} \qquad (3)$$

Where the $log(wage)$ is the logarithm of the average wage in time t for city c, in sector k (primary, secondary, or tertiary), and in formal or informal jobs j.[26] Our coefficient of interest β_t is the estimator of a variable interacting with our definition of $ChinaShock$ described in Section 3.2, and the average years of schooling for workers at city c in sectors j, k. We use the average years of schooling in the base year 1999 to avoid endogenous changes in schooling and include sector-by-city and time-fixed effects.

Panel (b) of Figure 6 presents the β_t estimates from Equation (3) for different time windows. In the early years of the China Shock (2000–2001 and 2000–2005), the estimates are both positive; one is barely statistically significant, while the other is not, suggesting a generally limited impact of the China Shock on returns to schooling. However, for later

[24] We observe this deterioration in high school outcomes despite the apparent government's efforts to accumulate human capital by increasing, in more exposed areas, the supply of public technical and vocational high schools, typically specialized in educating for jobs in the manufacturing industry. We provide evidence of this response in Figure B.3 indicating that this type of schools increase up to 30% in commuting zones more exposed to the China Shock, while other high schools, offering general skills typically oriented to prepare students for tertiary education, remain similar in treated and control commuting zones.

[25] We do not use the specification by de Chaisemartin and D'Haultfœuille (2020) to estimate the China Shock effects on returns to schooling because the authors' method does not allow to include interactions in their differences-in-differences estimator. We are aware that this brings the usual concerns of using the two-way fixed effects estimators in a staggered setting. Still, due to current methodological limitations, we consider this as the best approach to estimate these effects.

[26] Due to ENOE having representative data on only 39 cities, we leverage variation at the three-sector (primary, secondary and tertiary) level and formal and informal sectors. This results in six observations per city per year, increasing our statistical power.

periods, returns to schooling in more exposed regions become lower relative to less exposed areas. By 2000–2009 and later, returns to schooling are 2% lower in the treated cities. This aligns with the permanent long-term wage reduction we document in the previous subsection. Although returns to schooling remain positive in both highly and less exposed regions, the negative effect suggests that prolonged exposure to Chinese import competition disproportionately reduces the income gains associated with education in highly exposed areas. In other words, increased import competition appears to reduce the relative returns to skilled labor. We, therefore, argue that the mechanism driving our main results seems to be students adapting to deteriorating school-associated earnings prospects.

4.3 Heterogeneity by poverty conditions

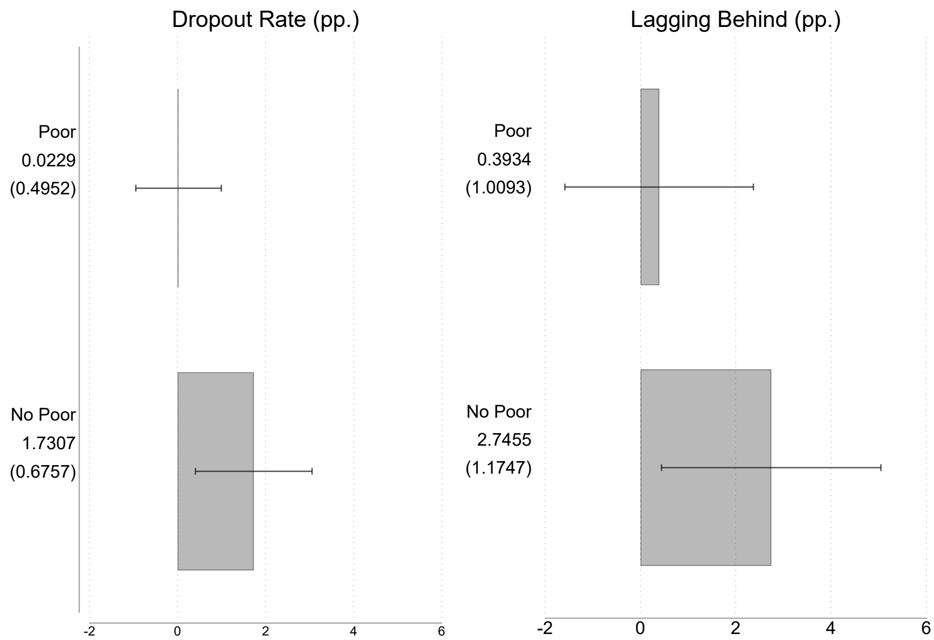
To understand for whom the China Shock matters, we present heterogeneous effects by separating commuting zones into poor and non-poor.[27] Poorer commuting zones are defined as those where more than 50% of the municipalities are classified as poor according to the marginality index provided by the National Council of Population.[28] The results, presented in Figures 7 and 8, reveal distinct patterns between these groups. The negative effects on educational outcomes, such as higher dropout rates and lagging performance, are concentrated in non-poor zones. In contrast, the labor market effects are divided: poorer areas experience significant employment losses, while non-poor zones account for the negative wage effects.

These findings suggest that the China Shock impacted the non-poor areas more thoroughly. In these areas, the wage declines coincide with increased dropout rates and poorer performance among high school students, further reinforcing the conclusion that changes in returns to schooling —-manifesting as wage effects—- are the primary mechanism driving the observed negative educational impacts of the China Shock. Wage declines in these areas may be related to a reduction in the perceived economic value of additional schooling, influencing decisions at the margin and leading to higher dropout rates and poorer performance among

[27] This also allows us to observe whether the patterns observed in our 39-city sample in the previous subsection, which likely represents relatively wealthier regions, are unique or more broadly applicable.

[28] The marginality index includes eight indicators reflecting general health, education, and recreational infrastructure, such as access to public parks.

Figure 7: Education Outcomes by Commuting Zone Poverty



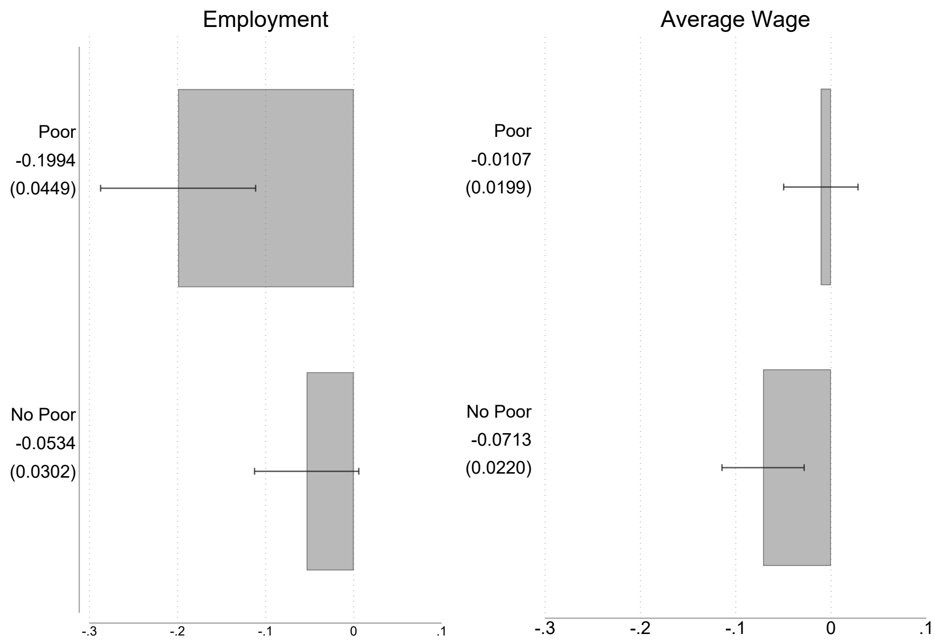
Notes: This figure shows the mean δ estimate from Equation (2) for dropout rates and students lagging behind their normative education by commuting zone poverty level. Each estimate comes from a single regression using de Chaisemartin and D'Haultfœuille (2020) method weighted by total non-agricultural employment. Standard errors are clustered at the commuting zone level. The number of switching commuting zones is 3216 from 5966 observations in non-poor areas and 1610 from 3516 observations in poorer areas.

high school students. In contrast, in poorer areas, employment losses were substantial but did not translate into adverse educational outcomes.

To understand these results, it is helpful to revisit the education literature. Students in poorer contexts often face long-term structural disadvantages and limited access to resources that shape their educational trajectories. In contrast, students in more advantaged areas are more likely to reach higher educational levels where decisions become more sensitive to economic incentives, such as the returns to additional schooling (Carneiro and Heckman, 2002; Alfonso, 2009; Heckman et al., 2013; Hai and Heckman, 2017).

Thus, education decisions in poorer areas may be largely predetermined by their limited opportunities and structural constraints, regardless of the additional labor market disruptions caused by Chinese import competition. Consistent with this narrative, our data shows that in the base year, only 5% of the 15- to 24-year-old population in poorer commuting zones was enrolled in high school, compared to 27% in non-poor zones. These large baseline

Figure 8: Labor Outcomes by Commuting Zone Poverty



Notes: This figure shows the mean δ estimate from Equation (2) for the logarithm of employment plus one and the logarithm of average wage by commuting zone poverty level. Each estimate comes from a single regression using de Chaisemartin and D'Haultfœuille (2020) method weighted by total non-agricultural employment. Standard errors are clustered at the commuting zone level. The number of switching commuting zones is 3216 from 5966 observations in non-poor areas and 1610 from 3516 observations in poorer areas.

differences suggest that fewer students in poorer zones reached high school before the China Shock, leaving less room for further educational impacts.

5 Conclusion

This paper provides evidence that the China Shock negatively affected the labor market and educational attainment in Mexico, a finding that contrasts with evidence from the United States. Our analysis identifies the returns-to-schooling channel as the primary mechanism driving the educational impacts. Non-poor regions experienced the full brunt of the adverse effects, while poorer regions were less affected; supporting the returns-to-schooling mechanism.

Education policy is not commonly addressed when discussing the impacts of trade, despite the potential reshaping of the labor markets, where the returns to schooling materialize.

Our findings highlight the critical role of returns to schooling in connecting trade shocks and educational outcomes in developing economies. Our findings support that policies to mitigate the adverse effects of import competition on education should address wage declines in skill-intensive sectors, particularly in regions more exposed to import competition. The heterogeneous impacts underscore the importance of strategies that consider region-specific conditions when aligning education policies to the challenges imposed by trade. For instance, in poorer regions, efforts to offset employment losses may be more rewarding. In contrast, wealthier regions may benefit from policies that restore the perceived value of education through workforce development or skill-building initiatives.

Future research could further explore these avenues by examining the role of income stabilization programs and direct incentives in reducing dropout rates. Investigating how trade-induced income shocks interact with existing social safety nets would also provide insights for shielding human capital development. Moreover, understanding how education systems and labor markets can adapt to global economic shifts remains a critical area for further inquiry, particularly in economies exposed to rapid trade liberalization.

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Appendix

A Robustness

Endogeneity

We follow two approaches to address endogeneity concerns of our main identification strategy presented in Section 3.2. First, we replicate our results following the instrumental variables (IV) approach as proposed by the seminal paper analyzing the effects of the China Shock Autor et al. (2013), and followed by most literature analyzing this shock (Greenland and Lopresti, 2016; Blyde et al., 2023). To do so, we instrument Mexico's imports from China in the $shift$ part of Equation (1) with the mean imports from China of eleven selected Latin American economies, and we get an IV estimator by using our instrumented exposure measure in Equation (1) as the explanatory variable for each outcome.

Table A.1: Instrumental Variable Results

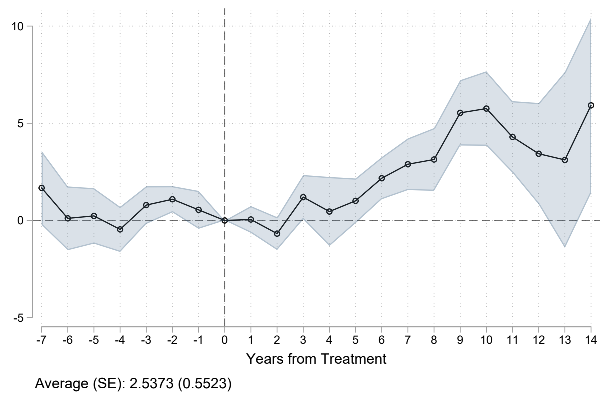
	Log-Employees (1)	Log-Wage p/w (2)	Dropout Rates (3)	Lagging (%) (4)
China Shock	-0.0020***	-0.0015***	0.0934***	0.1425***
	(0.0007)	(0.0005)	(0.0237)	(0.0405)
Two Way Fixed-Effects	yes	yes	yes	yes

Notes: Each column comes from a regression estimating the effect of the China shock measured as a shift-share, representing the weighted average of Mexican imports (in thousands of dollars) per industry worker. This is instrumented with the import data from 11 Latin American Countries, weighted by the share of industry workers on the total employment of Mexican commuting zones. Estimates are computed using two-stage least squares weighted by the total non-agricultural employment in the commuting zone. Standard errors are clustered at the commuting zone level.

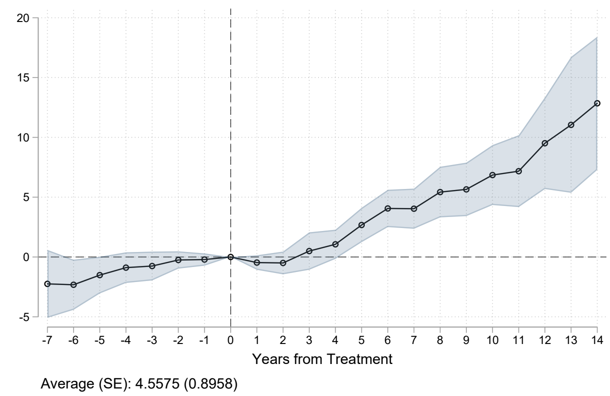
The IV estimates for the 2001-2017 period are shown in Table A.1. The IV results are in the same direction as our main results. The education effects (Columns 3 and 4) are positive and statistically significant, the same as those presented in Figure 3. The labor effects are negative and statistically significant, mostly similar to results in Figure 4. The only difference is that our main employment result is temporarily negative.[1]

Figure A.1: Predicted Shock using Latin American Imports

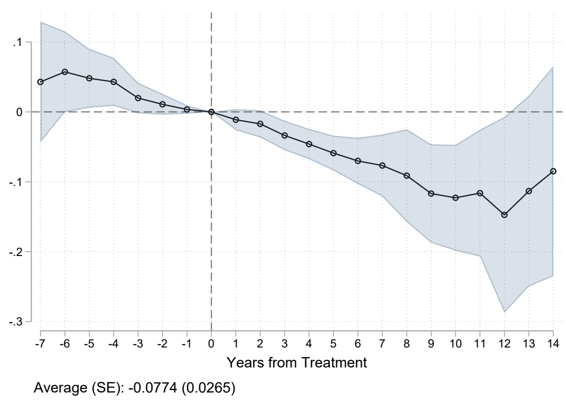
(a) Dropout Rates (p.p.)



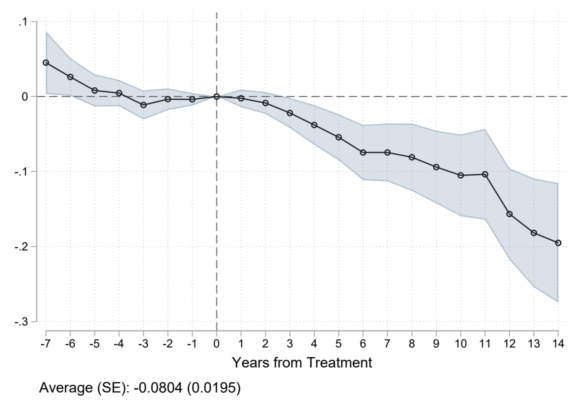
(b) Students Lagging Behind (p.p.)



(c) Employment (in logs)



(d) Average Wage (in logs)



Notes: This figure shows the δ_t estimates from Equation (2) for high school dropout rates (Panel a), students lagging behind their normative education level (Panel b), the logarithm of formal employees plus one (Panel c), and the logarithm of average wages (Panel d). Estimated coefficients include their 95% confidence intervals. All estimates come from a single regression using de Chaisemartin and D'Haultfœuille (2020) method weighted by total non-agricultural employment. Standard errors are clustered at the commuting zone level. The number of average switching commuting zones is 5176 from 10401 observations.

The second method to deal with endogeneity concerns is a mix of our main identification strategy discussed in Section 3.2 and the IV approach discussed above. Specifically, we replace Mexico's imports from China in the *shift* part of Equation (1) with the mean imports from China of eleven selected Latin American economies. Then, we use this modified exposure measure to create the treatment variable in Equation (2). The results are shown

[1]The sizes of the IV effects differ from those of our main results. However, this is expected as instrumental variables provide a biased estimator.

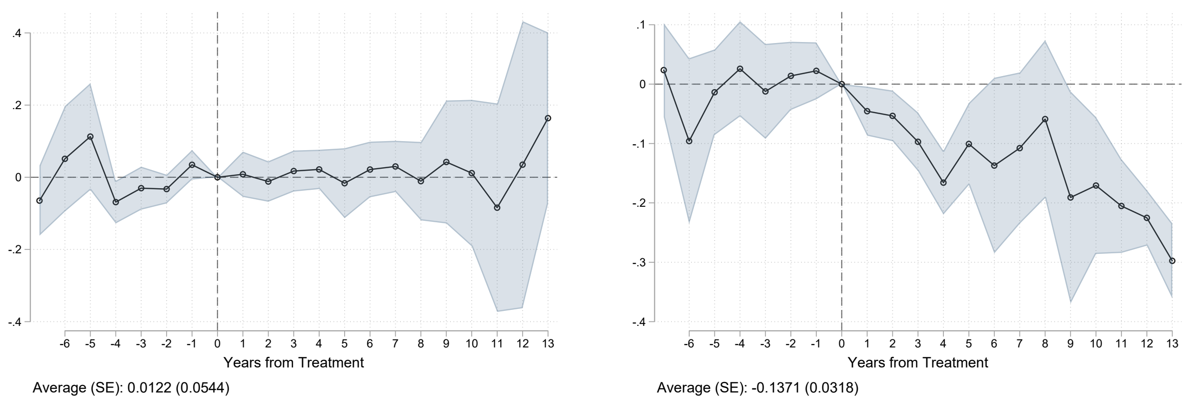
in Figure A.1 and are similar in direction and size to our main results presented in Figures 3 and 4.

Formality vs. informality

Figure A.2: Labor Outcomes: ENOE

(a) Employment (in logs)

(b) Average Wage (in logs)



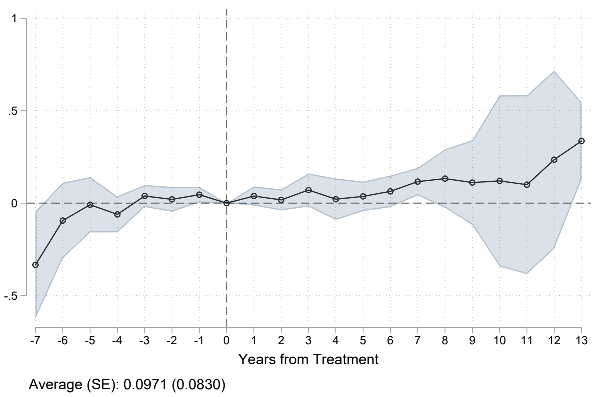
Notes: This figure shows the δ_t estimates from Equation (2) for the logarithm of formal employees plus one (Panel a), and the logarithm of average wages (Panel b). Estimated coefficients include their 95% confidence intervals. All estimates come from a single regression using de Chaisemartin and D'Haultfœuille (2020) method weighted by total non-agricultural employment. Standard errors are clustered at the commuting zone level. The number of average switching commuting zones is 259 from 489 observations.

Our main labor outcomes are measured for the formal labor market because the data covers the universe of formal employees. However, the informal sector in Mexico is large. To address this, we estimate the labor effects for the informal and formal labor markets using ENOE, the largest labor survey in Mexico. We use data from the 39 cities for which ENOE is representative, covering 45% of Mexico's population. The results are shown in Figure A.2. The wage results are pretty similar despite the much smaller number of observations in the ENOE data compared to the IMSS formal labor data. The employment results are non-significant across the whole period. This differs from our main employment effects in Figure 4, where we find a negative temporary employment effect. This may be because results from Figure A.2 come from large urban areas, which, on average, are less poor and more service-oriented. Figure 5 shows that the employment effects concentrate on the secondary sector. Moreover, as discussed in Section 4.3, the employment effects concentrate in poorer commuting zones. Therefore, the ENOE results appear consistent with our main labor results.

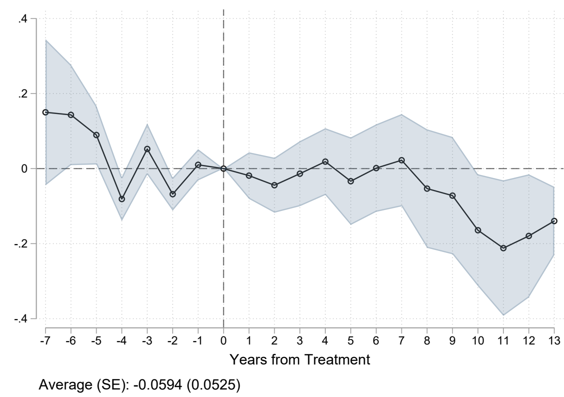
The ENOE data allows us to inspect the effect of the China Shock separately for the formal and the informal sectors. We present these separate results in Figure A.3; we get a null employment effect both for the formal and informal sectors (Panels a and b). Regarding wages, our results are negative and statistically significant for the 2001-2017 period both for the formal and informal sector, the effect being stronger for the informal sector.

Figure A.3: Labor Outcomes by Formality Status: ENOE

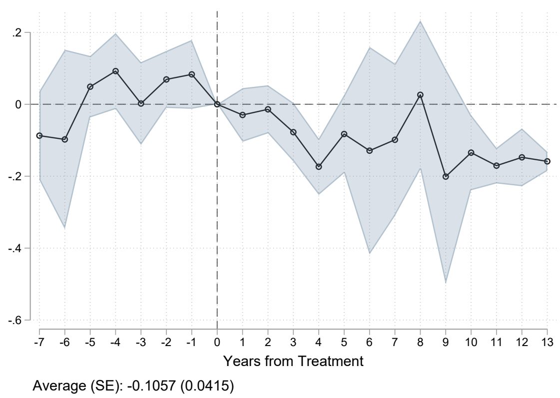
(a) Formal Employment (in logs)



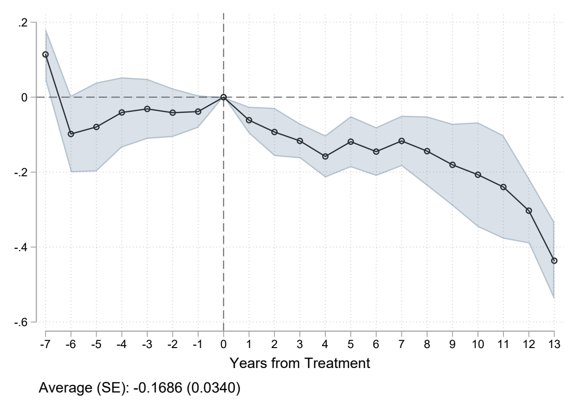
(b) Informal Employment (in logs)



(c) Formal Average Wage (in logs)



(d) Informal Average Wage (in logs)



Notes: This figure shows the δ_t estimates from Equation (2) for the logarithm of formal and informal employees plus one in Mexico (Panels a and b), and the logarithm of average wages of formal and informal employees (Panels a and d). Estimated coefficients include their 95% confidence intervals. All estimates come from a single regression using de Chaisemartin and D'Haultfœuille (2020) method weighted by total non-agricultural employment. Standard errors are clustered at the commuting zone level. The number of average switching commuting zones is 251 from 394 observations.

B Additional figures and tables

Figure B.1: Treated Commuting Zones in Selected Years

(a) 2002

(b) 2007

(c) 2012

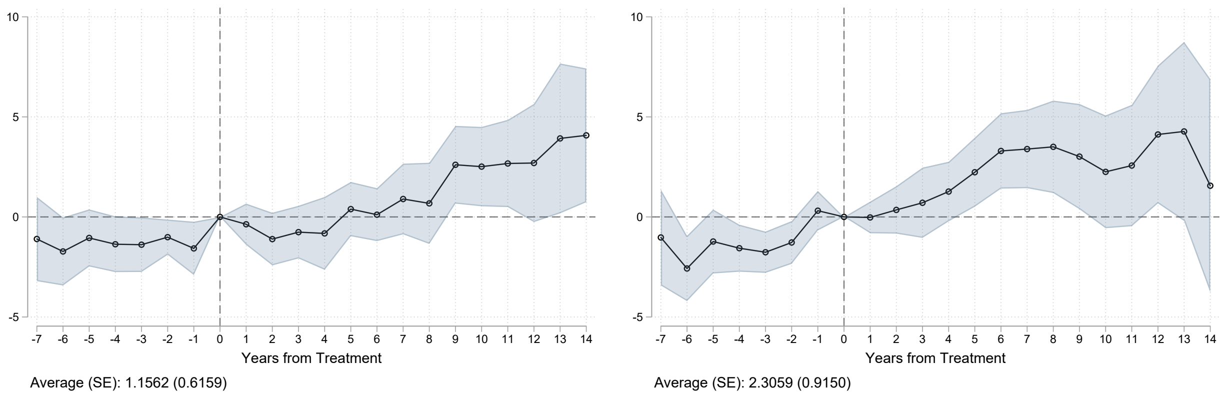
(d) 2017

Notes: This figure shows treated commuting zones in different selected years. A commuting zone is treated if its measure of exposure to the China Shock as defined in Equation (1) exceeds the median country-level exposure to imports from China, averaged over 2001-2021.

Figure B.2: High School Outcomes without School-by-Time Fixed-Effects

(a) Dropout Rates (p.p)

(b) Students Lagging Behind (p.p.)

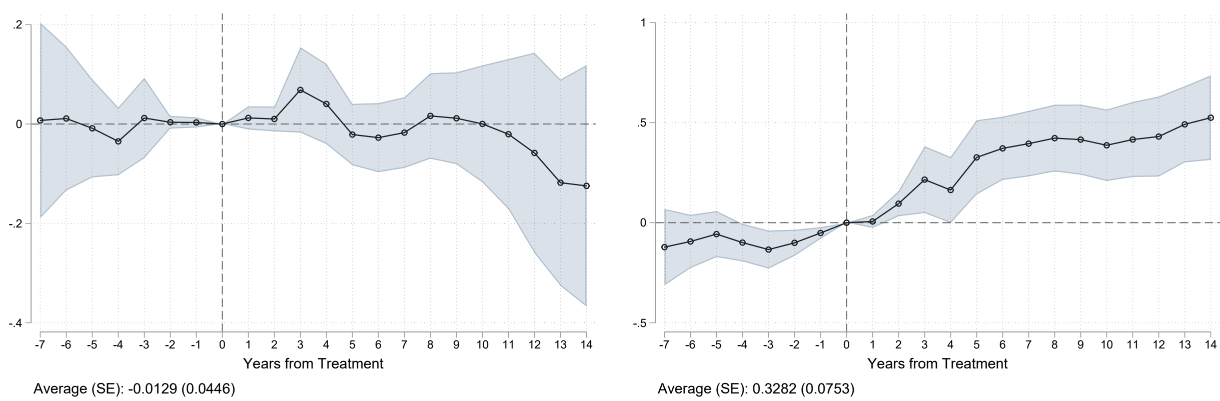


Notes: This figure shows the δ_t estimates from Equation (2) for high school dropout rates (Panel a), and the percentage of students lagging behind the normative grade-for-age (Panel b). Estimated coefficients include their 95% confidence intervals. All estimates come from a single regression using de Chaisemartin and D'Haultfœuille (2020) method weighted by total non-agricultural employment. Standard errors are clustered at the commuting zone level. The number of average switching commuting zones is 5176 from 10401 observations.

Figure B.3: Supply of Public High Schools: General and Technical/Vocational

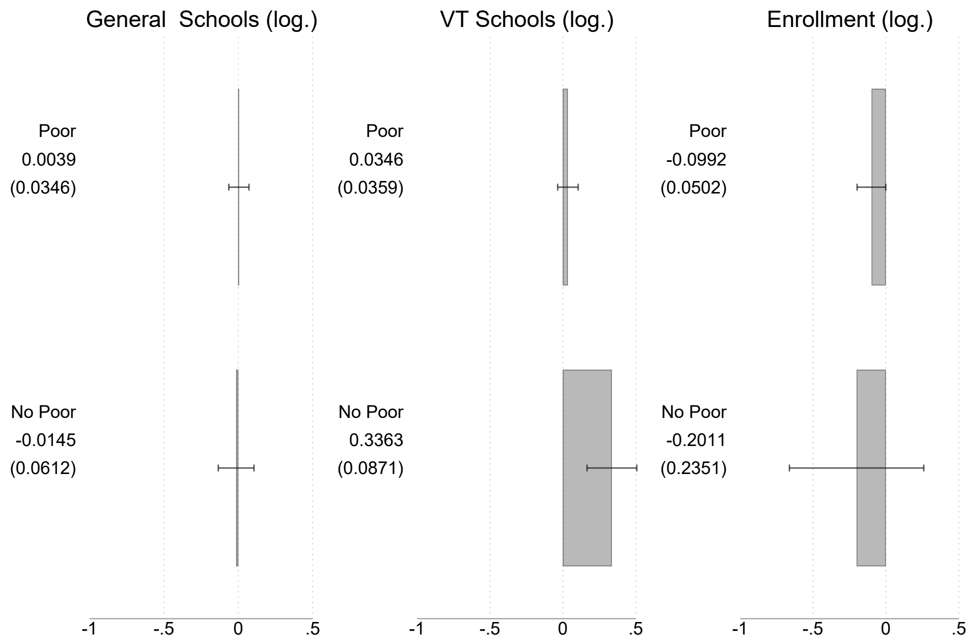
(a) General High Schools (in logs)

(b) Vocational and Technical Schools (in logs)



Notes: This figure shows the δ_t estimates from Equation (2) for the logarithm of the number of general high schools in Mexico (Panel a), and the logarithm of the number of vocational and technical high schools offering skills for industrial employment (Panel b). Estimated coefficients include their 95% confidence intervals. All estimates come from a single regression using de Chaisemartin and D'Haultfœuille (2020) method weighted by total non-agricultural employment. Standard errors are clustered at the commuting zone level. The number of average switching commuting zones is 5176 from 10401 observations.

Figure B.4: Supply of Public High Schools and Enrollment by Commuting Zone Poverty



Notes: This figure shows the mean δ estimate from Equation (2) for the logarithm of the number of general high schools in Mexico, the logarithm of the number of vocational and technical high schools offering skills for industrial employment, and high school enrollment. Estimates are separated by the poverty level of the commuting zone. Each estimate comes from a single regression using de Chaisemartin and D'Haultfœuille (2020) method weighted by total non-agricultural employment. Standard errors are clustered at the commuting zone level. The number of switching commuting zones is 3216 from 5966 observations in non-poor areas and 1610 from 3516 observations in poorer areas.