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, focusing on the effects of the China Shock in the early 2000s. Using a shift-share approach that combines import flows with commuting zone employment structure, we measure regional exposure to Chinese imports and employ a staggered difference-in-differences strategy, a novel approach within the China Shock literature. Our findings reveal significant negative effects on high school educational outcomes: dropout rates rose by an average of 2 percentage points in highly exposed regions, intensifying to nearly 5 percentage points over a decade, and the share of students lagging behind grade level increased by 3 percentage points. These adverse impacts coincide with falling wages, which declined by 7.5% in highly exposed regions with no recovery, particularly in manufacturing and services. Formal employment initially declined by 5% before partially recovering, while formal manufacturing employment experienced a persistent decline, compounding wage pressures. Impacts are concentrated in non-poor areas where wage declines likely heightened income constraints. In contrast to findings from developed economies, our results suggest that in developing economies, income effects play a more prominent role than opportunity costs in shaping educational responses to import competition shocks.

Keywords: China Shock, import competition, educational attainment, wage effects, labor market impacts, developing economies.

JEL Codes: F14, F16, I25.

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1 Introduction

Educational attainment remains a critical challenge in developing economies. Mexico exemplifies this issue 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; 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.

One of the main determinants of low educational attainment is labor market outcomes (Hanushek and Woessmann, 2011; Blanden et al., 2023), which recent research shows are influenced by trade. A large body of literature highlights the substantial effects that trade has had on labor markets, 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 both income and opportunity cost channels: as wages in certain sectors rise or fall, household income fluctuates, affecting families' capacity to invest in education; simultaneously, changing employment opportunities alter the opportunity cost of schooling, influencing young people's likelihood of continuing their education or entering the workforce (Soares et al., 2012; Atkin, 2016). Which of these effects dominates depends largely on specific contexts and income constraints, making it an empirical question.

The China Shock, a major trade shock in recent decades, has been shown to impact educational outcomes, though studies have focused only on developed economies. This shock transformed global trade, substantially increasing China's share in global manufacturing exports (Autor et al., 2016). Greenland and Lopresti (2016) examine the educational effects in the U.S., finding that regions most affected by import competition saw increases in high school completion. Their findings suggest this effect operates through opportunity costs: trade-induced declines in wages and employment made staying in school more attractive compared to limited job opportunities. In developing economies, however, these dynamics could operate differently, with the effects of import competition likely acting more through income channels than opportunity costs[1]. However, the impact of the China Shock on educational outcomes in developing economies remains unexplored in the literature.

We address this gap in the literature by analyzing the impact of the China Shock on educational and labor market outcomes in Mexico. We leverage the China Shock as a source of quasi-experimental variation, allowing us to employ a difference-in-differences approach directly[2]. To measure regional exposure to Chinese import competition, we construct a shift-share variable based on pre-existing industrial employment patterns. Using this measure, we define a binary treatment variable that annually classifies each commuting zone (CZ) as either above or below the median exposure level observed between 2001 and 2021, following the commuting zone classifications provided by Blyde et al. (2023). This binary treatment variable allows us to analyze the China Shock's effects in a staggered setting, with regions "treated" at different times and incorporating timing variation. This staggered setting, leveraging timing variation, is novel in cross-regional analyses of the China Shock and allows for accurate estimation of dynamic effects using the robust difference-in-differences estimator by de Chaisemartin and D'Haultfœuille (2020).

Our findings show that the China Shock had substantial effects on educational attainment in Mexico, particularly on high school dropout rates and student progression. We draw on detailed data from Statistics 911, a comprehensive database akin to a census of Mexican high schools, which provides annual, school-level reports on enrollment, dropout rates, and grade-level progression across the country. This information, reported directly by each high

[1]Empirical evidence supporting this exists, as demonstrated by Edmonds et al. (2010) in their study of India's trade liberalization in the 1990s.

[2]We additionally implement an instrumental variable approach in the Appendix to confirm the robustness of our findings, with qualitatively identical results

school, allows us to analyze the impacts of import competition with precise regional and temporal detail. Using this dataset, we find that regions more exposed to Chinese imports experienced an average 2-percentage-point increase in dropout rates, with effects intensifying over time to nearly 5 percentage points between 10 and 14 years after exposure. Additionally, exposure to the China Shock led to a rise of approximately 3 percentage points in the share of students significantly behind their expected grade level, underscoring adverse impacts on both retention and timely progression.

Our findings reveal that these educational impacts are closely tied to shifts in labor market conditions, suggesting that trade-induced changes in employment and wages drive the increases in dropout rates and lagging progression. Specifically, we find that regions more exposed to the China Shock experienced an average 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 persistently. Wage reductions were similarly enduring, with an average decline of 7.5% in highly exposed regions, affecting both the secondary (manufacturing) and tertiary (service) sectors. The prolonged wage declines, coupled with persistent manufacturing job losses, likely intensified income constraints for households, shaping adverse educational outcomes. This evidence suggests that income effects, rather than opportunity costs, play a key role in educational responses to import competition in Mexico, contrasting with findings in the U.S. by Greenland and Lopresti (2016).

To further understand the mechanisms driving the observed educational impacts, we conduct a heterogeneous analysis between poor and non-poor regions. Our findings show that the average adverse educational effects of the China Shock—such as increased dropout rates and students lagging behind—are primarily driven by non-poor areas. In these regions, substantial wage declines without corresponding employment losses likely intensified household income constraints, which may have influenced schooling decisions, especially where credit constraints are binding. In poorer areas, by contrast, where employment declines but wages remain stable, educational responses to labor market changes are limited. This may align with the theory proposed by Basu and Van (1998), which suggests that below a certain threshold income level, households are less likely to send children to school, meaning that marginal changes in income may have limited effects on educational decisions. Together, these results suggest that income effects are the predominant mechanism linking trade shocks to educational outcomes in Mexico, particularly in regions where initial economic conditions allow for some responsiveness to income fluctuations.

1.1 Related literature

Our paper contributes to the literature on the relationship between trade shocks and human capital outcomes. Specifically, it adds to empirical research examining the effects of increased import competition on educational outcomes[3]. The study most closely related to ours is, as mentioned before, Greenland and Lopresti (2016), which found that U.S. local labor markets more exposed to import competition from the China Shock experienced improved educational outcomes compared to less exposed markets. In contrast, our analysis focuses on the impact of import competition from the China Shock in a large developing economy, Mexico, and finds the opposite: the China Shock led to worse educational outcomes. Our negative results align qualitatively with those of Edmonds et al. (2010) and Nakaguma and Viaro (2024), who analyzed the effects of 1990s trade liberalization in India and Brazil, respectively, and found that regions more exposed to liberalization had poorer educational outcomes than less exposed regions[4]. Consistent with our findings of negative wage effects, import competition in developing economies seems to operate primarily through income effects, amplifying negative labor market impacts, unlike its mechanism through opportunity costs in developed economies[5]. Compared to previous studies, a distinctive advantage of our approach is that our detailed administrative data on educational outcomes allows us to provide event study-type estimates, capturing dynamic annual effects on educational outcomes rather than focusing solely on medium-term impacts.

[3] 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).

[4] Another study by Li et al. (2019) similarly shows that trade liberalization led to adverse educational outcomes, focusing on China during the 2000s.

[5] A theoretical framework is provided by Soares et al. (2012), who develop a model capturing both income and substitution effects.

Our work also contributes to the extensive literature examining the impact of trade shocks on local labor markets. Since the pioneering work of Topalova (2010), a large body of research has used shift-share exposure measures to analyze national trade shocks across regions. Topalova (2010) combined quasi-experimental tariff variation with regional industrial structures in India to measure differential exposure to liberalization, finding that liberalization was associated with increased poverty rates in more exposed regions. Subsequently, the influential work by Autor et al. (2013) analyzing Chinese import competition in U.S. commuting zones popularized this approach, along with the use of the China Shock as a quasi-experimental shock of import competition. More closely related to our study, Blyde et al. (2023) analyze the local labor market effects of the China Shock in Mexico using the shift-share approach[6]. Another recent study by Heckl (2024) further investigates the labor market effects of the China Shock in Mexico, highlighting gender-based differences in responses. A key distinction of our approach from all this shift-share literature is that we leverage not only cross-industry differences in import competition but also variation in timing—specifically, 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 better approximate dynamic, both short- and long-term labor market effects.

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 (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

[6]Consistent with their findings, we observe negative medium-term effects on formal employment, which largely dissipate in the long term.

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 2000/01 to 62% in 2020-2021. Yet, the biggest challenge remains in retaining students in high school; the largest dropout rates are observed in this education level; we compute this at 24% in 2000-2001 without major 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. This meant that by 2023, only 56% of the population aged 25-34 in Mexico completed high school (vs. 86% in the OECD countries), from which less than a half, or approximately 25% of the total, obtain 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 representing 14% of the total in 2000-2001 and 16% in 2016-2017, and aiming to offer education for the labor market, typically for the manufacturing industry; 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[7].

2.2 The China Shock

We focus on the so-called China Shock, a global import competition episode (Autor et al., 2016). The China Shock is the name given in the literature to the phenomenon of China's rapid rise as a global manufacturing power, especially after it entered into 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

[7] These types of high schools only appeared considerably in the academic year 2005-2006 when they represented 2% of the total.

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).

As a global phenomenon, the China Shock appears to be driven by factors specific to China. More specifically, the fundamental factor explaining China's rise in the global economy seems to be the extremely 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 TFP growth in Chinese manufacturing was of 8% on average, while that in the U.S. was less than 4%, for example, (Autor et al., 2013)[8]. 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 led to GDP increases of even 20% at the local level, in turn related to faster productivity growth and human capital accumulation.

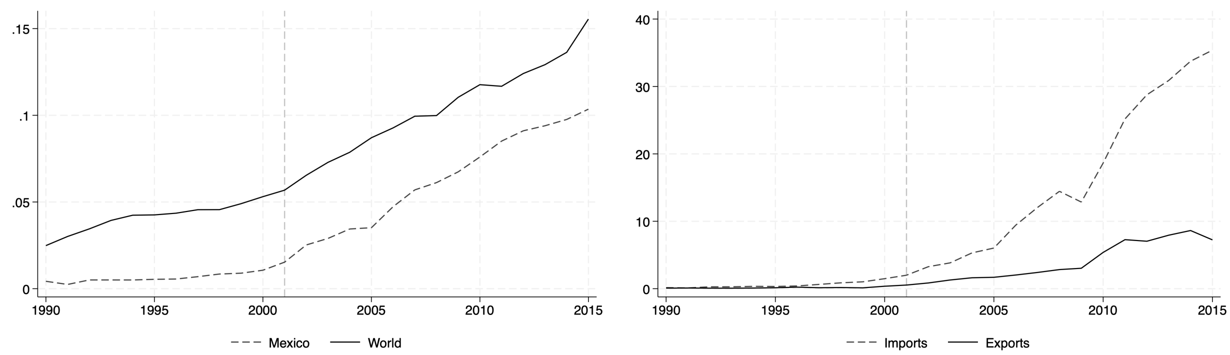
Given that Chinese internal factors mainly drove the shock, Chinese import competition in Mexico in the 2000s was not driven by Mexico's domestic conditions. Figure 1, panel (a), shows that the China Shock essentially increased the share of Chinese manufacturing imports, both in Mexico and worldwide. 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, confirming that the China Shock was a global phenomenon and suggesting it was driven by factors other than related to Mexican domestic conditions. Additionally, the graph confirms that the growth of Chinese exports, both globally and in Mexico, accelerated significantly only after 2000. We argue this feature allows us to understand the China Shock as providing quasi-experimental variation in import competition[9].

[8]As another example, the growth of TFP in Mexican manufacturing between 1991 and 2011 was even negative (Cepeda and Ramos, 2015).

[9]Nonetheless, to avoid remaining endogeneity concerns associated with Mexican domestic conditions, we use an instrumental variable approach in one of our robustness exercises. Table A.1 shows the results of this check, confirming the validity of our baseline estimates.

Figure 1: Import competition from China

(a) Share of Chinese manufacturing imports (%)　　(b) Mexican trade with China (bill. of dollars)



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).

Another important feature of the China Shock for Mexico was that it was not connected to expanded export opportunities. In other words, the import competition from China did not happen hand-in-hand with export expansion as it did in other countries. Costa et al. (2016), for instance, show that the China Shock for Brazil had two faces, one associated with increased manufacturing import competition and another associated 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 focusing on the China Shock in Mexico: it allows the identification of import competition effects, without potential confounding factors from expanded export opportunities[10].

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

[10] This is essential for educational outcomes, given that expanded export opportunities have been shown to affect educational outcomes negatively (Atkin, 2016).

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 for 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[11] using correspondence tables from INEGI (National Institute of Statistics and Geography) in Mexico[12]. Next, we convert the 2017 H.S. codes to 1992 H.S. codes using a correspondence table from the United Nations Statistical Commission[13]. 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[14]. This enables us to express import flows in 2018 NAICS codes, making them consistent with our manufacturing employment data.

Our education data comes from census information at the high school level, known as the "Statistics 911". The Ministry of Education provides these data and range from 1997 to 2017. Each school reports on several variables (at least 911) at the beginning and end of each academic year. It 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 these continue in the school over the next cycle, allowing us to compute total dropout rates[15]. The data also details statistics on the number of students by age and gender, allowing us to compute total dropout rates and 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

[11] 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.

[12] 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/.

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

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

[15] This is, the total of 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

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.[16] 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. 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 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:

[16]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.

$$Exposure_{c,t} = \underbrace{\sum_i \frac{Workers_{i,c}}{Workers_{i,c,t=2000}}}_{\text{share}} \left(\underbrace{\sum_i \frac{Imports_{i,t=2001-2017}}{Workers_{i,t=2000}}}_{\text{shift}} \right) \tag{1}$$

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 $t = 2000$. We only use industries i within manufacturing, given that the China Shock essentially altered import competition in this sector. The $share$ part reports the share of industry i workers of total non-agricultural employment $-i$ in commuting zone c for the base year $t = 2000$.[17] Therefore, our $shift - share$ variable $Exposure_{c,t}$ considers differences in commuting zone exposure to imports from China across time. Our definition of exposure varies annually, allowing us to leverage both 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[18], 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.[19] The specification includes commuting zone fixed-effects ζ_c and time fixed-effects 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

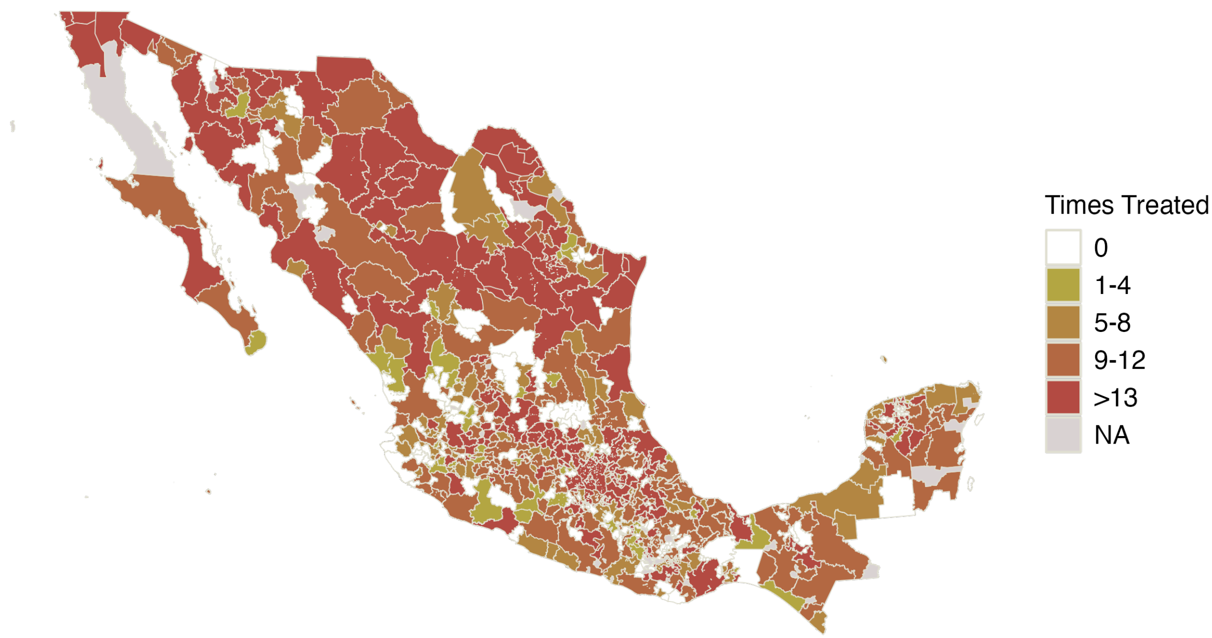
[17] We take the commuting zones defined by Blyde et al. (2023). To create the commuting zones, they aggregate municipalities with a high degree of interaction based on workers' commuting between residence and workplace.

[18] 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.

[19] The main dependent variables of interest are dropout rates in high school, the share of students lagging behind the normative grade for their age, the log of employment and log of daily wages per worker.

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: 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.

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.[20] 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 A.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 proposed 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 simultaneously.[21] Second, there may be heterogeneous treatment effects across commuting zones and over time.The estimates proposed by de Chaisemartin and D'Haultfœuille (2020) are robust to dynamic effects and heterogeneous treatments across treated groups. 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 that are not yet treated at time t.

4 Results

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-

[20] 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.

[21] 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.

median exposure to imports from China leads to a positive effect on 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 —being 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 of the after-treatment periods, suggesting that higher dropouts do not come from the expansion observed in high school enrollment in Mexico during these years. Note that in all three outcomes, the δ_t coefficients are not statistically significant and are close to zero in the pre-treatment periods, supporting the common trends assumption of the difference-in-differences method.[22]

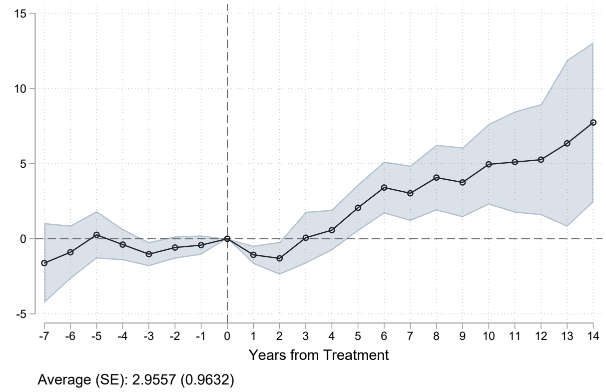
To explore what could be a potential mechanism behind the effects of the China Shock on education outcomes, we complement our analysis by linking the effects of this shock on labor outcomes. The intuition behind this is supported by literature documenting negative effects on employment, as in Blyde et al. (2023) and the effects on education documented in Greenland and Lopresti (2016). We argue that such impacts may change the direct and opportunity costs of education; however, such costs are relative to base income constraints. To elaborate on this, Figure 4 shows the δ_t estimates from Equation (2) on the employment (Panel a) and average wages (Panel b) in the universe of the formal private sector, our main labor outcomes. 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

[22]During our analysis 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 (Cabrera et al., 2018). Similarly, the Full-Time Schools program was gradually implemented from 2007 to 2018, influencing school outcomes (Cabrera-Hernández, 2020). Finally, in 2012, high school studies became mandatory, with varying levels of compliance across time and regions (Garcez et al., 2024). In Figure A.2 in the Appendix, we also present our results on school outcomes without cohort-by-time fixed effects.

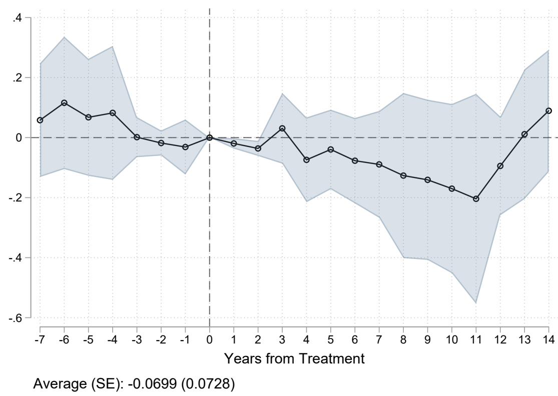
Figure 3: Effects on High School Outcomes

(a) Dropout Rates (p.p.)

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



(c) Overall High School Enrollment (in logs)

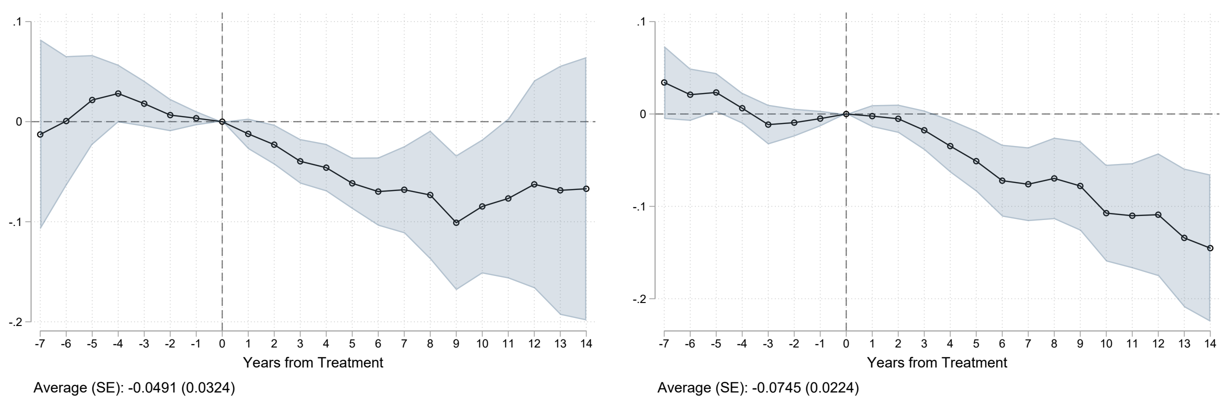


Notes: This figure shows the δ_t estimates from Equation (2) on high school dropout rates (Panel a), the percentage of students lagging behind their normative grade-for-age (Panel b), and the logarithm on students enrolled every academic year (Panel c). Estimated coefficients include their 95% confidence 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.

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. The effect is not statistically significant over the whole period. These effects align with those documented by (Blyde et al., 2023), using a different methodology (instrumental variables), suggesting a negative impact on employment in the short term 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 effect on wages is 7.5 percent and statistically significant, suggesting that those who remained 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.

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). Note that the educational effects we describe concern high school students, those soon to join the labor market, and their decisions regarding high school completion and general motivation may be closely related to employment and wage dynamics in their immediate context.[23]

[23]Note that 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

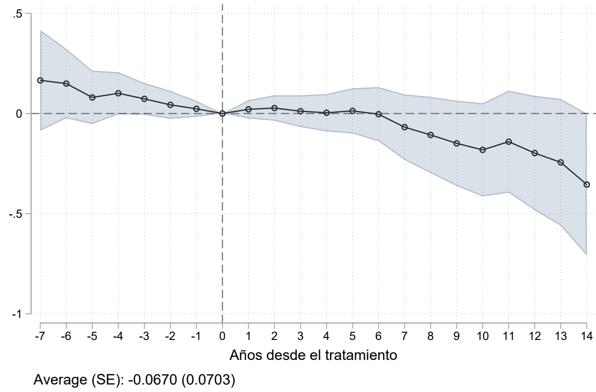
Our labor market results suggest two effects that may affect educational decisions differently. Worsening labor market opportunities and wages may influence students to stay in school, given the lower opportunity cost of studying. In contrast, negative income effects due to lower employment and wages could increase the relative costs of staying, pushing students to abandon their studies or imposing constraints that could affect their performance. Given our education market results, we argue that, on average, income effects are dominant. This is sensible in the Mexican context, where high school is considered the minimum educational level to be successfully integrated into the labor market, and yet a large proportion of 25 to 34-year-old Mexicans only have a secondary diploma (43%), and 30% complete only high school as their highest attained educational level OECD (2023). Therefore, high school achievement may still be strongly subjected to income constraints.

The education effects we find differ from those shown by Greenland and Lopresti (2016). They find that the China Shock improves educational effects in the United States. The authors argue that the shock leads people to increase their education level because low-skill wages go down. Thus, in the U.S. context, the opportunity cost of studying is dominant. Our results, together with those by Greenland and Lopresti (2016), indicate that the effect of trade on education may go in opposite directions, depending on the type of country receiving the trade shock.

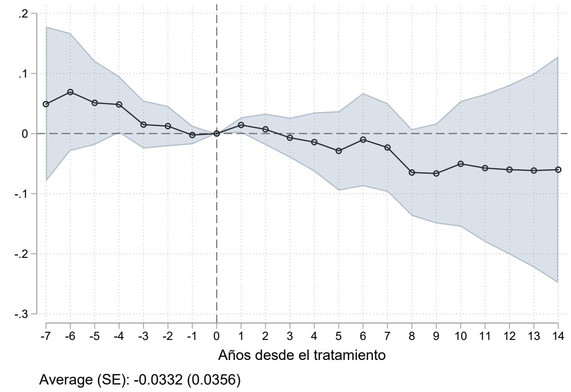
vocational high schools, typically specialized in educating for jobs in the manufacturing industry. We provide evidence of this response in Figure A.3 indicating that the number of vocational and technical high schools increases up to 30% in commuting zones more exposed to the China Shock, while other high schools offering general skills, typically oriented to prepare students for tertiary education (e.g., university or professional degrees) remain similar in treated and control commuting zones.

Figure 5: Effects on Formal Labor by Sector

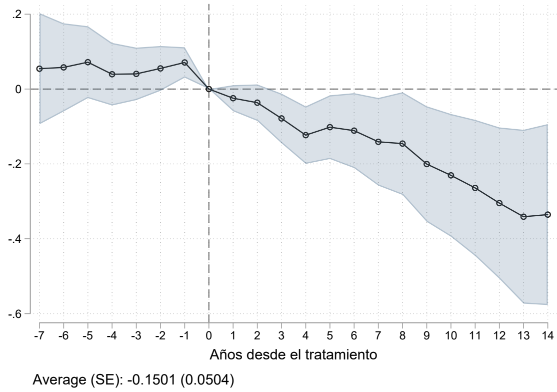
(a) Primary - employment (in logs)



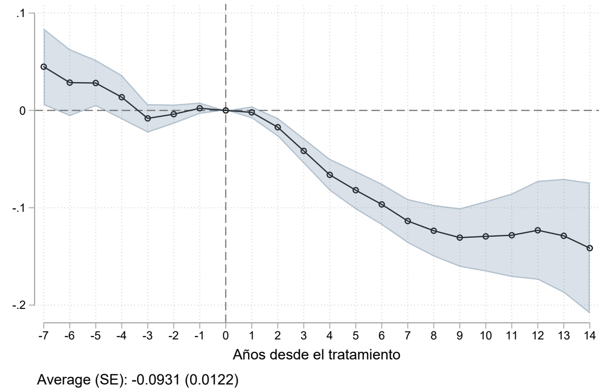
(b) Primary - avg. wage (in logs)



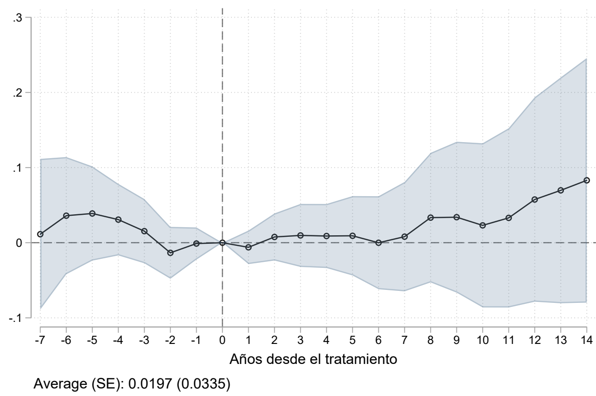
(c) Secondary - employment (in logs)



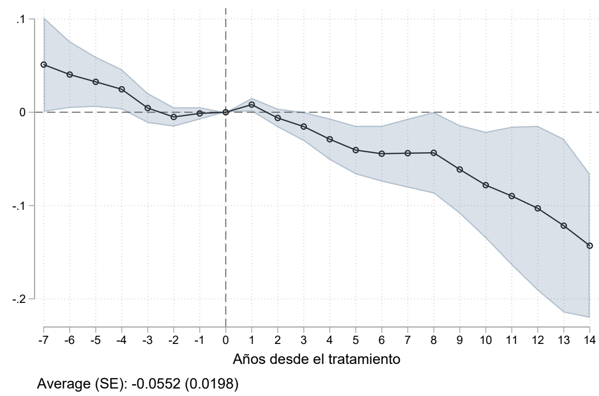
(d) Secondary - avg. wage (in logs)



(e) Tertiary - employment (in logs)



(f) Tertiary - avg. wage (in logs)



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.

To complement our discussion of the education and labor effects, we disaggregate the China Shock impact 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.

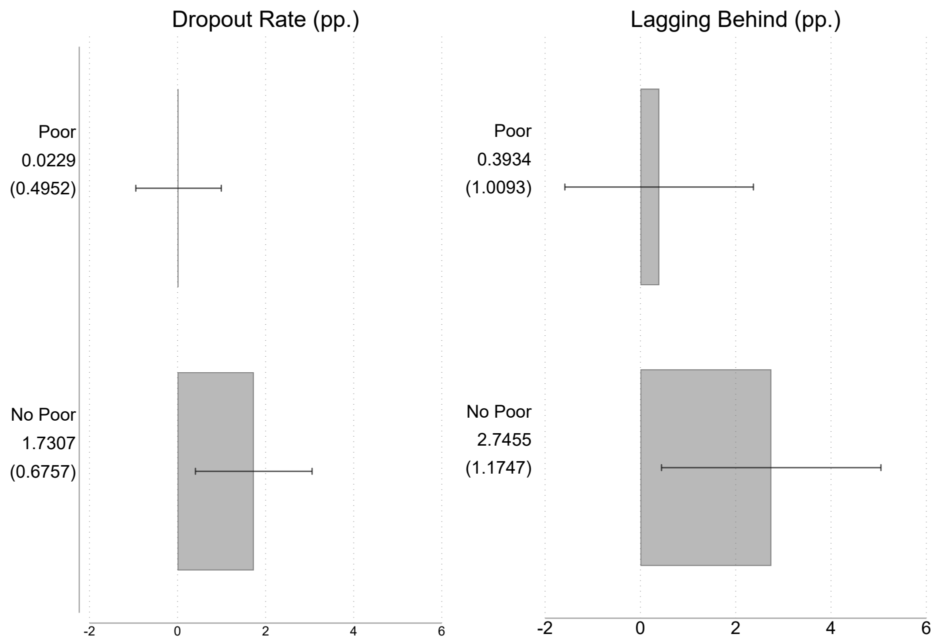
Our results regarding wages indicate that the China Shock does not affect the primary sector (Panel b). However, the secondary and tertiary sectors (Panels d and f) display a negative, permanent, and statistically significant effect. Thus, the labor market deterioration caused by the shock pulls wages downward not only in the sector most exposed to trade but also in the tertiary sector. As the tertiary sector tends to employ relatively more educated employees, people may not find it attractive to improve their education performance, leading to the education effects we see in Figure 3.

4.1 Heterogeneity by poverty conditions

To offer more evidence on how the China shock effects on the labor market interact with students' socioeconomic context, we separate our sample between poorer and richer commuting zones and explore the effects on our education and labor outcomes.[24] The results are presented in Figures 6 and 7. The results suggest the effects on dropout rates and students lagging behind concentrate in non-poor zones. The labor market effects, on the contrary, are split. Employment effects are strong and significant in poorer areas, whereas non-poor commuting zones fully explain average negative wage effects. In sum, these findings suggest that while the China Shock strongly affected employment in poorer areas, this did not translate into education outcomes. On the other hand, negative effects on wages due to the China shock are observed along with higher dropout rates and lower performance for high school students.

[24] We define poorer commuting zones as those where more than 50% of the municipalities integrating them are considered poor according to the marginality index provided by the National Council of Population. This index comprises eight measures at the municipality level reflecting general health, education, and recreational infrastructure (for example, public parks).

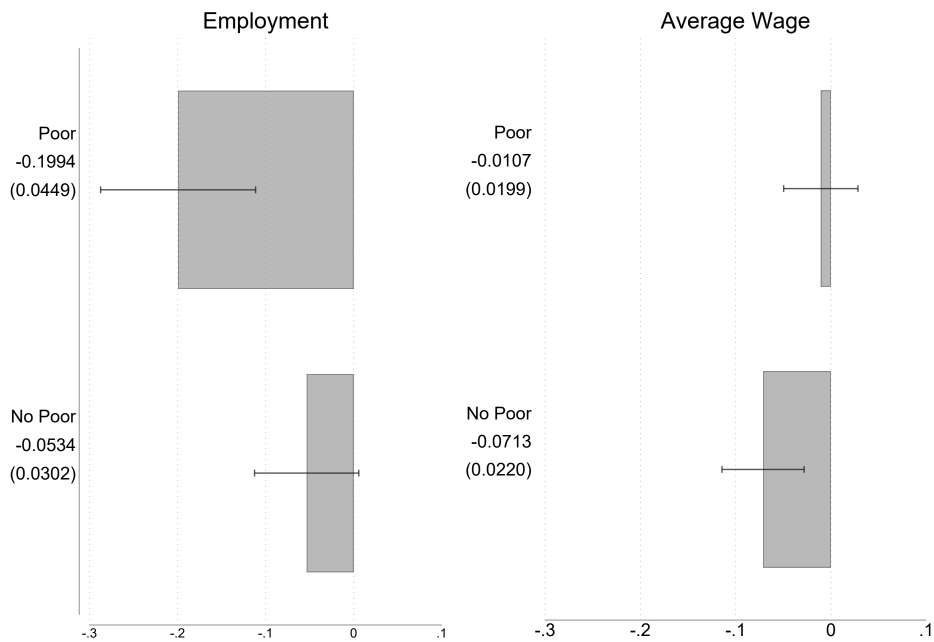
Figure 6: Education Outcomes by Commuting Zone Poverty



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.

To contextualize these results, let us discuss the education literature, which has largely suggested that results in poorer contexts are subjected to long-term income and the common restrictions that less advantaged students face along their life cycle. At the same time, more advantaged students may still face credit constraints; moreover, when reaching higher educational levels, and hence income and credit constraints could still affect their education results in the margin (Carneiro and Heckman, 2002; Alfonso, 2009; Heckman et al., 2013; Hai and Heckman, 2017). In this context, education decisions in poorer areas may be ex-ante determined, given their context limitations, regardless of the further income constraints generated by the Chinese import competition and employment losses. In this regard, our data shows that in non-poor commuting zones, 27% of the 15 to 24-year-old population was enrolled in high school in the base year, while only 5% was enrolled in poorer zones. These large differences in the base year may suggest that the sum of people reaching high school before the China Shock in poorer commuting zones was already low. The average wage, on the other hand, may have imposed income constraints in less disadvantaged areas.[25]

Figure 7: 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.

5 Conclusion

This study finds that the China Shock has had significant adverse effects on educational outcomes in Mexico, particularly through increased dropout rates and lagging student progression at the high school level. These negative impacts on educational attainment appear quickly and intensify over time, with dropout rates rising to nearly 5 percentage points higher in highly exposed regions after a decade. Our analysis also reveals that the China Shock substantially weakened local labor markets, especially within manufacturing: while total formal employment initially declines in exposed regions and partially recovers over time, manufacturing employment falls and does not recover, with persistent wage reductions observed in

[25]Furthermore, the public response by building more vocational and technical schools concentrated in non-poor areas, as depicted in Figure A.4

the manufacturing and service sectors, but not in the primary sector. These enduring wage declines, alongside lasting job losses in manufacturing, likely intensified income constraints for affected households, resulting in poorer educational outcomes. A heterogeneous analysis shows that these adverse educational effects are concentrated in non-poor areas.

This study makes two key contributions to the trade-education literature. First, we analyze the impact of the China Shock on educational outcomes in a developing economy, revealing distinct mechanisms compared to those observed in developed economies. Unlike the study by Greenland and Lopresti (2016) on the U.S., which links import competition to improved educational attainment through reduced opportunity costs, we find that in Mexico, constrained household incomes due to import competition lead to worsened educational outcomes. This contrast highlights the significance of local economic conditions in shaping how import competition impacts education in developing contexts. Second, we introduce a novel approach for analyzing the China Shock by exploiting both sectoral and timing variation in import exposure, allowing for a staggered difference-in-differences design. This design is implemented using the robust estimator developed by de Chaisemartin and D'Haultfœuille (2020), which accounts for dynamic effects and heterogeneous treatment timing across regions, enabling precise estimation of both short- and long-term impacts as they develop over time.

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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. 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]

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

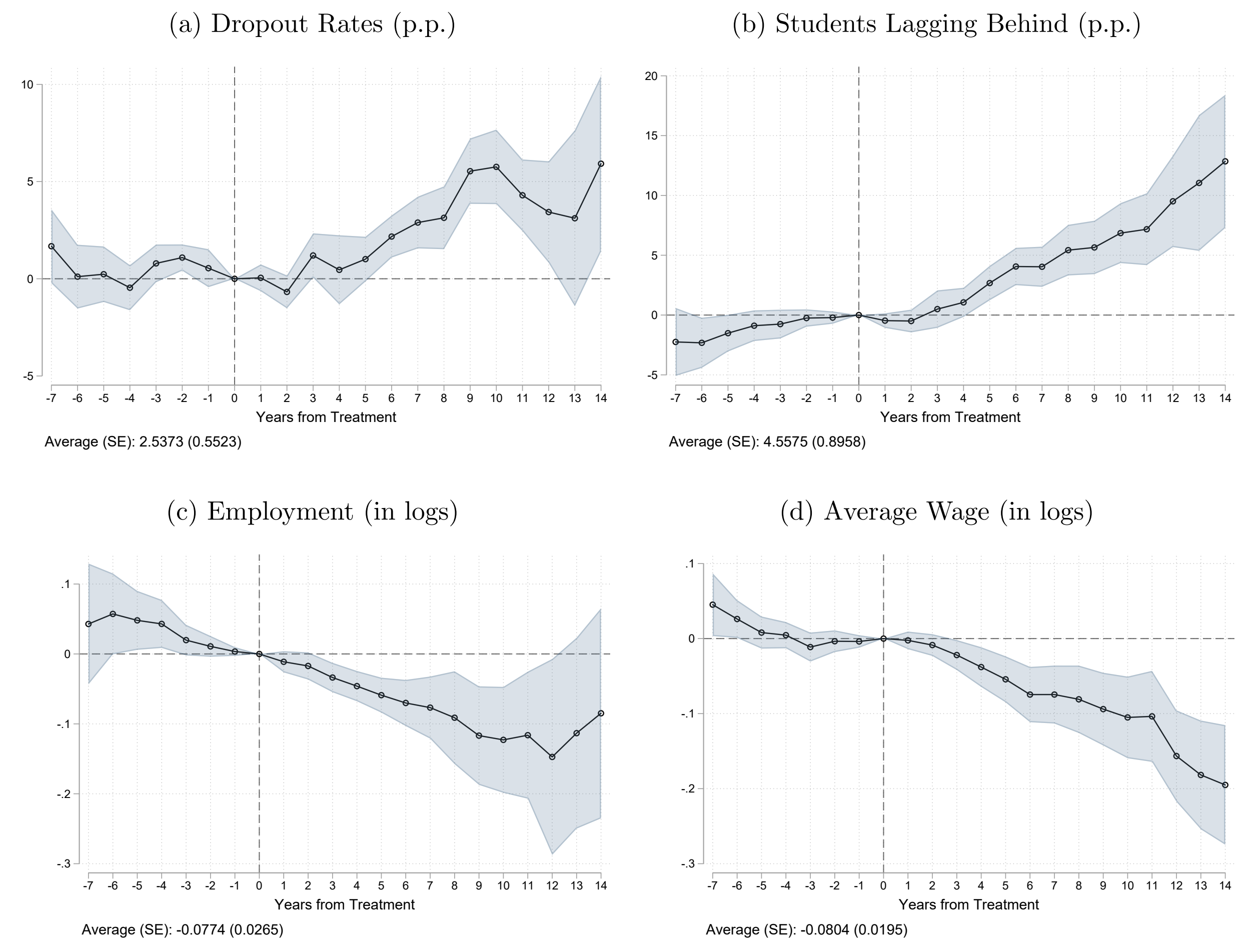
Notes: Each column comes from a regression estimating the effect of the China shock measured as a shift-share, representing the weighted average of Mexican imports (in thousands of dollars) per industry worker. This is instrumented with the import data from 11 Latin American Countries, weighted by the 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 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

[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.

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

Figure A.1: Predicted Shock using Latin American Imports



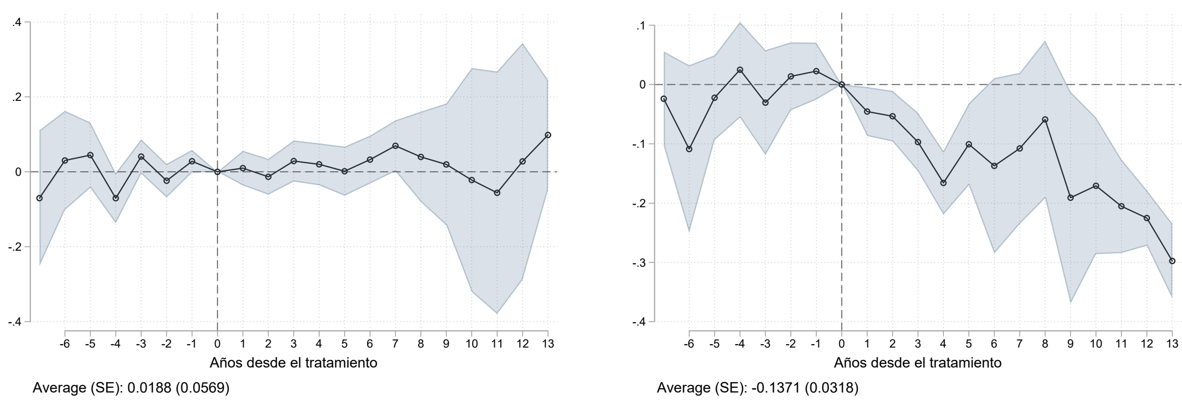
Notes: This figure shows the δ_t estimates from Equation (2) for high school dropout rates (Panel a), students lagging behind their normative education level (Panel b), the logarithm of formal employees plus one (Panel c), and the logarithm of average wages (Panel d). Estimated coefficients include their 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.

Formality vs. informality

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 4.1, the employment effects concentrate in poorer commuting zones. Therefore, the ENOE results appear consistent with our main labor results.

Figure A.2: Labor Outcomes: ENOE

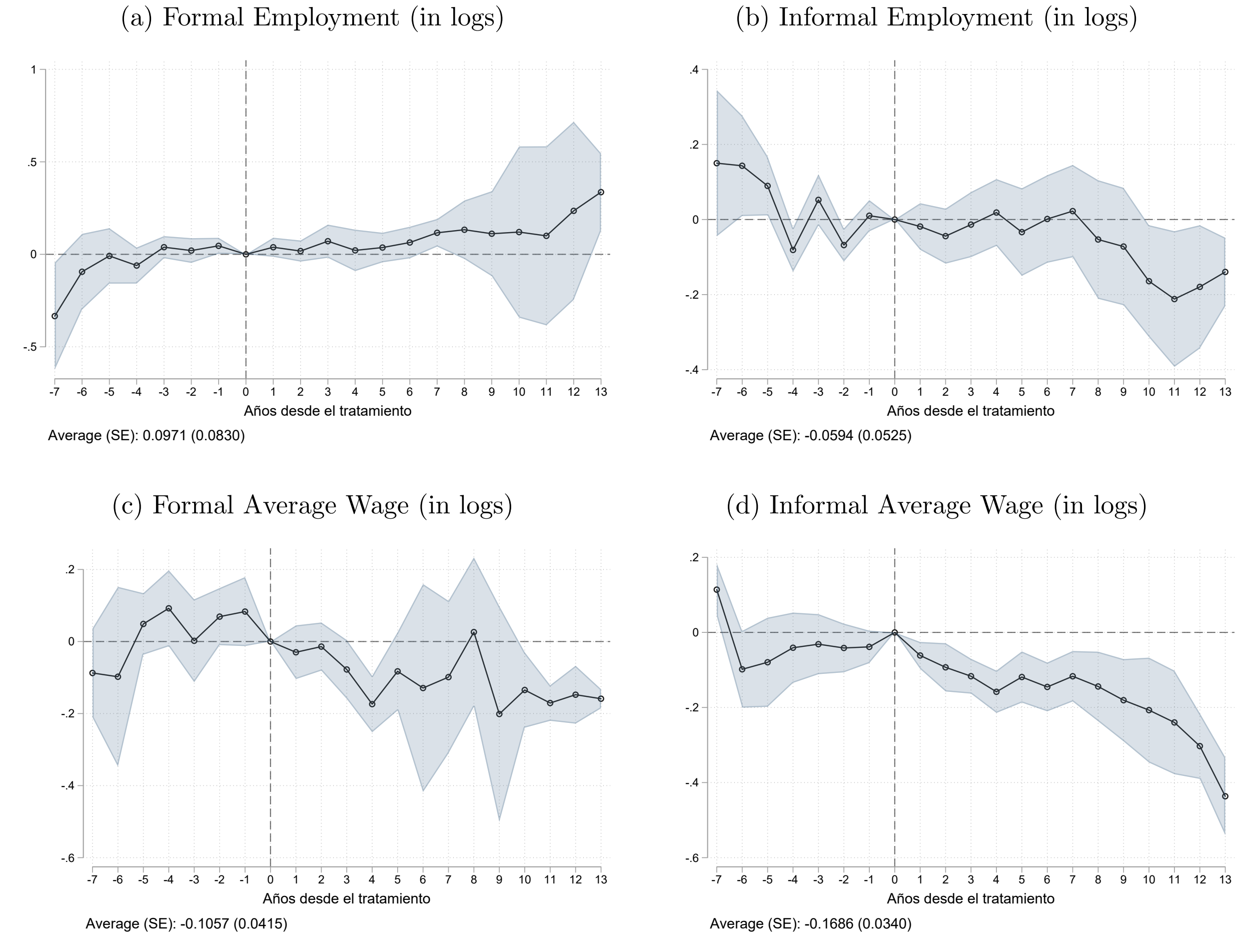
(a) Employment (in logs) (b) Average Wage (in logs)



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.

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



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

A.0B.0

Figure A.1: Treated Commuting Zones in Selected Years

(a) 2002

(b) 2007

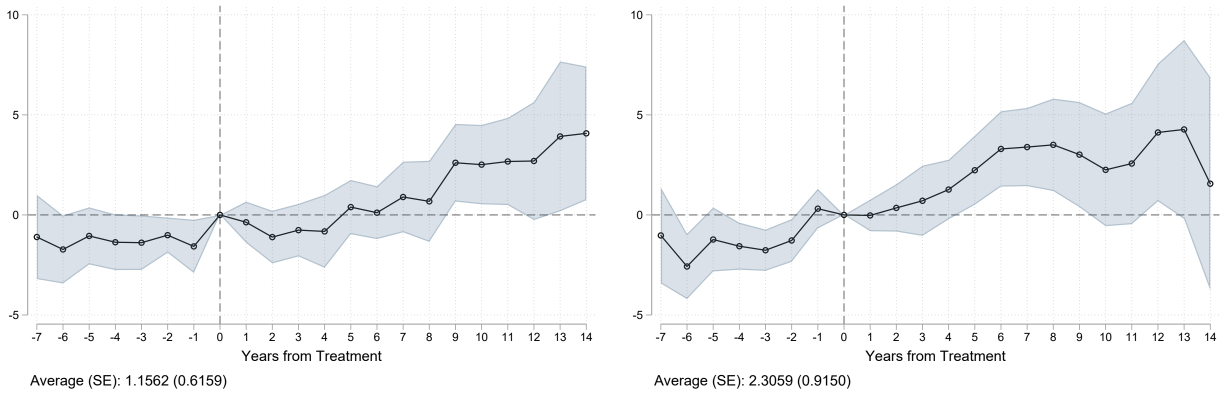
(c) 2012

(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 A.2: High School Outcomes without School-by-Time Fixed-Effects

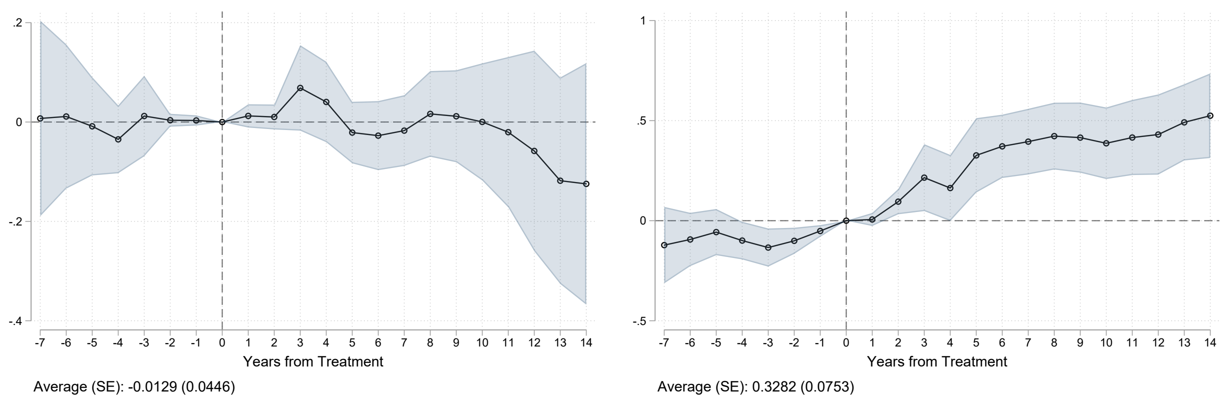
(a) Dropout Rates (p.p) (b) Students Lagging Behind (p.p.)



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.

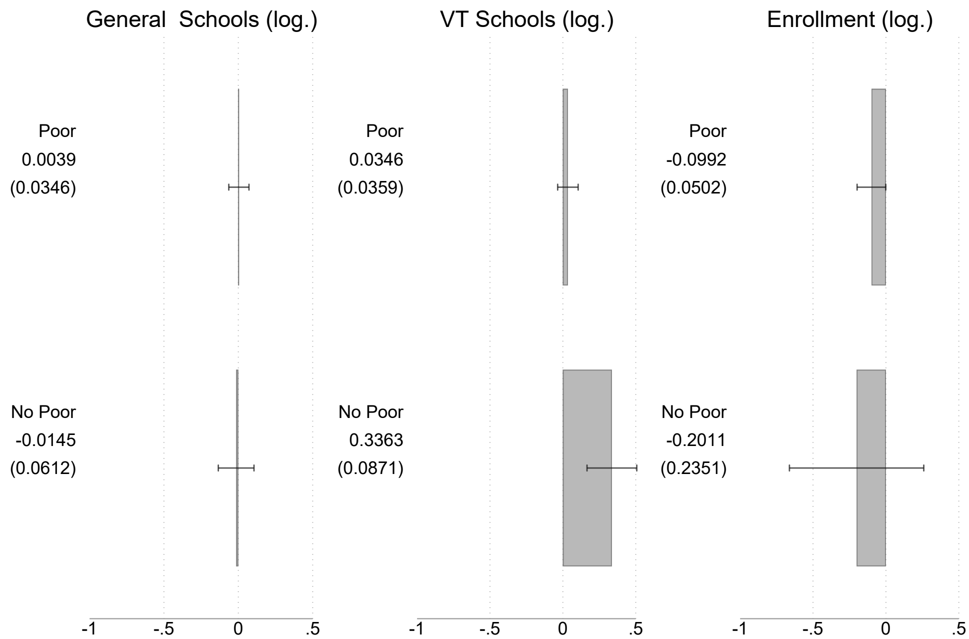
Figure A.3: Supply of Public High Schools: General and Technical/Vocational

(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 A.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.