The Nearshoring Boom Mexico Almost Had

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Abstract

This paper identifies nearshoring in the corporate credit market in Mexico that resulted from the US-China trade war in 2018. We estimate that firms in the industries with highest tariffs borrowed up to 9% more than firms in other industries, and enjoyed up to 0.2 percentage point lower interest rates. Yet, the aggregate economic outcomes of the nearshoring boom are elusive. To learn why, we build a quantitative general equilibrium model with heterogeneous firms and calibrate it to replicate the microeconomic estimates of the nearshoring shock. In a counterfactual experiment, we find that Mexico's growth from the trade war could have *doubled* if the economy featured a more flexible credit intermediation system.

Keywords: trade war, nearshoring, tariffs, banking

1 Introduction

Why do so many emerging countries struggle to catch up with the developed world? Figure 1, which plots the GDP per capita in Mexico relative to the US, provides an illustrative example. Up until the early 1980s, it appeared as if the two countries' living standards were converging. Since then, however, Mexico has been falling behind and its GDP per capita is currently at only 15% of the US level, down from nearly 30% at the peak. Why this is the case remains among the most pressing questions in international economics.



Figure 1: Living standards in Mexico relative to the US over time

In this paper, we investigate the frictions in Mexico's growth engine in a recent and well-identified empirical case study of *nearshoring*. In years 2018-2020, the United States and China launched a trade war that led to a significant increase in tariffs levied on Chinese goods sold in the US. Mexico, with its proximity to the US and participation in the USMCA trade agreement, stood to benefit from hosting new business activities relocating from China. Using a dataset that covers the universe of bank loans in Mexico, we show in a difference-in-differences setting that nearshoring caused a boom in lending to firms in the affected industries. At the same time, aggregate credit remained flat and nearshoring did not lift the real economy by nearly as much. To understand why, we build a quantitative general equilibrium model with heterogeneous firms, and we discipline it by replicating our microeconometric results. The main model exercise shows that GDP growth due to the trade war could have doubled if Mexico had a more elastic credit supply.

Between March 2018 and March 2020, the average US tariff applied to imports from China rose from under 5% to over 20%. This episode, known as the first trade war, was very heterogeneous across industries, with final tariff rates ranging from as low as 6% to over 50%. Using a credit registry dataset at the Bank of Mexico, which comprises a universe of bank loans to businesses in that country, we first document the resulting nearshoring process. Up until 2017, total credit grows along parallel trends within industries soon to be hit by low and high tariffs alike. Starting from 2018, the two trends diverge, with credit growing faster within the industries that faced higher tariffs. The same industries also tended to experience higher imports in the US from Mexico in the following years. Finally, we show a similar nearshoring process taking place at the level of Foreign Direct Investment in Mexico. When the trade war starts, FDI surges among the high tariff industries compared to the low tariff ones, and originating from China relative to the US or all other countries.

To estimate a direct causal effect of the US-China trade war on credit provision in Mexico, we set up a difference-in-differences specification. Our data is ideal for this purpose as it measures loan amounts at the borrower-bank level and it includes detailed information about the identities of both parties, allowing us to control for various inherently unobservable characteristics that could bias a typical regression. We focus on the 29 industries that were imposed a tariff during the trade war, and divide them into two groups: a "high-tariff" (treatment) group and a "low-tariff" (control) group. The high-tariff group consists of industries subject to US-China tariffs above the median level in 2020, while the remaining industries, subject to below-median tariff rates, are classified as the low-tariff group.[1] The dependent variable is the monthly outstanding credit balance, aggregated at the borrower-bank pair, and we measure how it is differentially impacted by the "trade war treatment" over time. The richness of our data allows us to include diverse fixed effects (e.g. borrower-bank and location-year) to control for unobserved, potentially time-varying, sources of demand and supply heterogeneity that could be specific to lending relationships, time periods or locations.

We find that, at the onset of the trade war, firms in the high-tariff group borrowed on average 3% more in bank loans compared to those in the low-tariff group. This divergence in borrowing continues to grow for the next few years, peaking in 2020 at nearly 9% and

[1]Studies find that the 2018-19 tariff changes associated with the tariff war were uncorrelated with previous price and import trends, making the event an ideal laboratory environment to understand the trade policies and global value chains (e.g., Cavallo et al. (2021), Fajgelbaum et al. (2020), Amiti, Redding and Weinstein (2020)).

plateauing afterwards through 2024, the latest year in our sample. Using the same identification strategy, we also find that the interest rate at which firms in the high tariff group borrowed *declined* by around -0.2 percentage point relative to the interest rate applied to the low tariff group, with the effect closing down later in the sample period. This implies that the trade war had a positive effect on the most affected firms by allowing them to borrow more at a lower cost. We conduct a host of robustness checks to confirm the validity of these findings.

What does the estimated effect on the credit market imply for the overall growth of Mexico's economy? To answer this question, and to analyze some interesting counterfactual scenarios, we develop a quantitative general equilibrium model of the production sector of Mexico's economy. The model features a continuum of heterogeneous firms who produce with a decreasing returns to scale technology driven by a stochastic productivity process. Each firm invests in the stock of physical capital using a combination of debt and equity, its own or externally raised. Debt features limited collateralizability and can be defaulted on when the firm exits. In turn, banks must be compensated for this risk by a higher interest rate. The model is closed by aggregating loan demand across all firms and setting it equal to an exogenous credit supply curve with a constant elasticity parameter. The market is cleared by a risk-free real interest rate.

We bring the model to the data in two steps. First, we solve for a steady-state stationary distribution of firms and calibrate it to mimic the behavior of Mexico's economy prior to the US-China trade war. In particular, the model features a realistic amount of firm leverage and matches several moments from the distribution of corporate interest rate spreads. In the second step, we introduce the trade war as a temporary sequence of exogenous shocks that lift demand for the output of about half of the firms in the economy (the treated group). These firms respond to the shocks by borrowing more to increase their productive capacity. The other half (the control group) is affected indirectly, through a general equilibrium effect on the risk-free interest rate that clears the credit market. We parameterize and calibrate the sequence of these trade war shocks to replicate the empirical difference-in-differences results in a panel of simulated firms over the transition. We find that the trade war is equivalent to higher productivity of the treated firms by about 2.5% at its peak and has a trajectory that extends into mid-2030s when its effects dissipate and the economy starts converging back to its original steady state. In addition to the micro-level results, we also target the macro-dynamics of aggregate borrowing for the two groups of firms to inform the elasticity parameter of the credit supply curve. We

find this parameter to be quite low, i.e. an inelastic credit supply, which is necessary to match an overall flat profile to aggregate credit over the entire episode.

In the main exercise, we compare the economic outcomes of Mexico's economy over the trade war in the baseline scenario (low elasticity), against a counterfactual of a highly elastic credit supply that would be typical for developed countries such as the United States. We find that while the GDP grows under the baseline by nearly 2%, a result of good productivity shocks from to the nearshoring, it is accompanied by higher interest rates that negatively affect firms in the treated and control group alike. Under the counterfactual, the expansion in output *doubles* because the control group is virtually unaffected by the transition, but also because the financially constrained treated firms find it easier to finance their capital investments. This result underscores the importance of flexible capital markets for the ability of less developed economies such as Mexico to convert good shocks into realistic growth opportunities.

The paper is organized as follows. Section 1.1 reviews the literature. Section 2 provides background information regarding the trade war and nearshoring in Mexico, describes the data, and presents some aggregate descriptive statistics. Section 3 presents our empirical strategy and the estimates of the effect of the trade war on firm credit in Mexico. Section 4 develops and calibrates a model of heterogeneous firms and frictional credit, which backs out the empirical results in Section 3 and conducts counterfactual experiments to understand their drivers. Finally, Section 5 concludes.

1.1 Literature Review

Our study contributes to multiple areas within the existing literature. First, we contribute to the literature on the US reallocation in the supply chain activity, sourcing away from China (Nicita 2019; Bown and Wang 2022; Fajgelbaum et al. 2024; and Freund et al. 2023). Among this literature, our paper is related to studies that examine how the 2018-2020 US-China trade war affected the import share of China, which lost ground in the US market, and other emerging economies which gained in import share. In particular, Rotunno et al. (2024) and Jiao et al. (2024) demonstrate the impact of the 2018-2020 US-China trade war on Southeast Asian countries, and on the European Union, respectively. Overall, our conclusions are in line with these studies, since the 2018-2020 US-China trade war brought positive spillover effects on Vietnamese exports to the US, and positive spillover effects on Chinese exports to the EU, which increased moderately.

Our study is particularly associated with articles that examine the effects of the 2018-2020 US-China trade war on the Mexican economy, using Mexican confidential longitudinal firm-level trade data. For instance, Alfaro and Chor (2023) show evidence that US sourcing directly from China has decreased since its peak in 2017, with low-wage locations (Vietnam) and nearshoring or friendshoring alternatives (Mexico) gaining in import share since then. Moreover, Utar, Cebreros and Torres (2025) show that the 2018-2020 US-China trade war triggered and adjustment of global value chains and nearshoring towards Mexico, and this positive impact is entirely driven by global value chain firms, especially those in skill-intensive manufacturing industries. Our study contributes to the existing literature by documenting how Mexican firms belonging to the industries most affected by a tariff change during the 2018-2020 US-China trade war received more credit from Mexican banks, potentially signaling an increase in their respective industrial activities as a consequence of the reallocation of global value chains from China to Mexico.

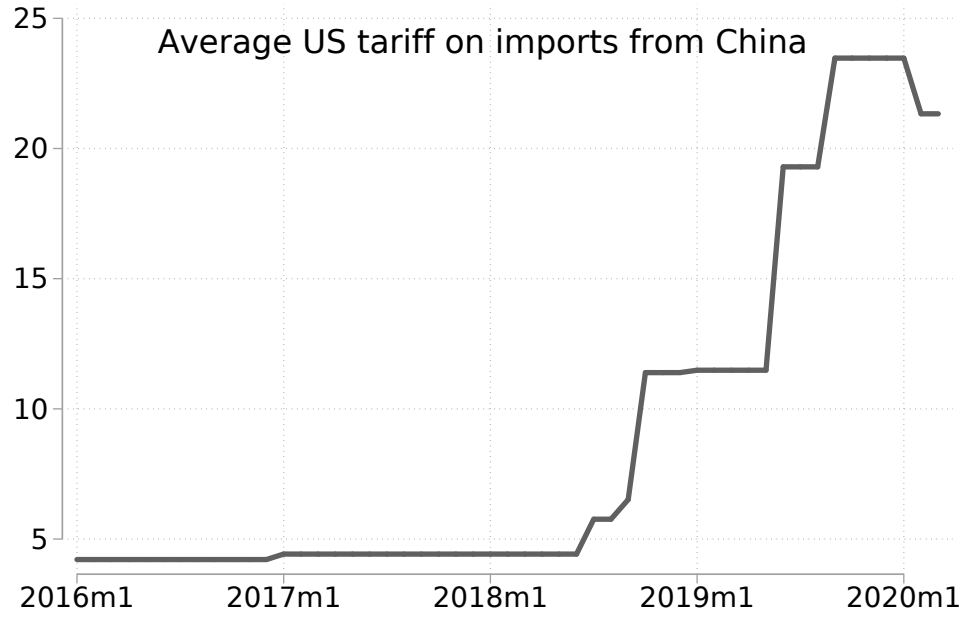
Our paper is also connected to the literature providing evidence that the US policies which have set these global value chain reallocations may ultimately not achieve their goal of reducing the US dependence on supply chains linked to China. For instance, Alfaro and Chor (2023), and Utar, Cebreros and Torres (2025) demonstrate that while China's share in US imports has fallen, China has stepped up its trade and FDI in Mexico. Thus, the US could well remain indirectly connected to China through its global value chain links with third-party countries.

Lastly, our study is also part of (and extends) the literature that analyzes potential retrenchments in global trade as a result of the 2018-2020 US-China trade war and other government policies that foster geoeconomic fragmentations (see, for example, Antràs 2020; Aiyar et al. 2023; Goldberg and Reed 2023). In particular, these articles show that the aggregate value of the main trade flows, such as US goods imports, rebounded strongly after the Covid-19 pandemic to all-time highs in 2022. Our paper contributes to this literature by analyzing the impact of 2018-2020 US-China trade war on the lending activity by banks to firms in Mexico, which could be a signal of greater economic activity due to increased trade between Mexico and the US.

2 Background

2.1 US-China Trade War and Nearshoring

US-China Trade War Before March 2018, the average U.S. tariff rate on imports from China was 4.42%. By March 2020, it had increased to 21.33% and then stayed at that level until 2025. Figure 2 illustrates the increase in the average tariff during that episode. Table 1 provides a breakdown of the pre- and post-trade war tariffs by industries at the 3-digit NAICS level. The industries that experienced some of the largest increases in the tariff rate include agricultural products, oil and gas, as well as transportation equipment that includes car parts, Mexico's largest export into the US. On the other hand, the industries with lower tariff increases include minerals and ore, textile mill products or computer and electronic products, the second largest export category from Mexico to the US. As can be seen hence, the tariff changes affected industries across the entire spectrum of tradable goods, with no clear pattern in terms of the size of the change.



Source: Trade War Tracker by Michael Waugh (2024)

Figure 2: Average tariff on imports from China to the US

Nearshoring in Mexico The trade war between the US and China spurred reports of business activity moving to locations geographically or politically closer to the US. In the ensuing process, commonly referred to as nearshoring, Mexico stood to benefit the most,

Table 1: List of industries by pre- and post-trade war tariffs

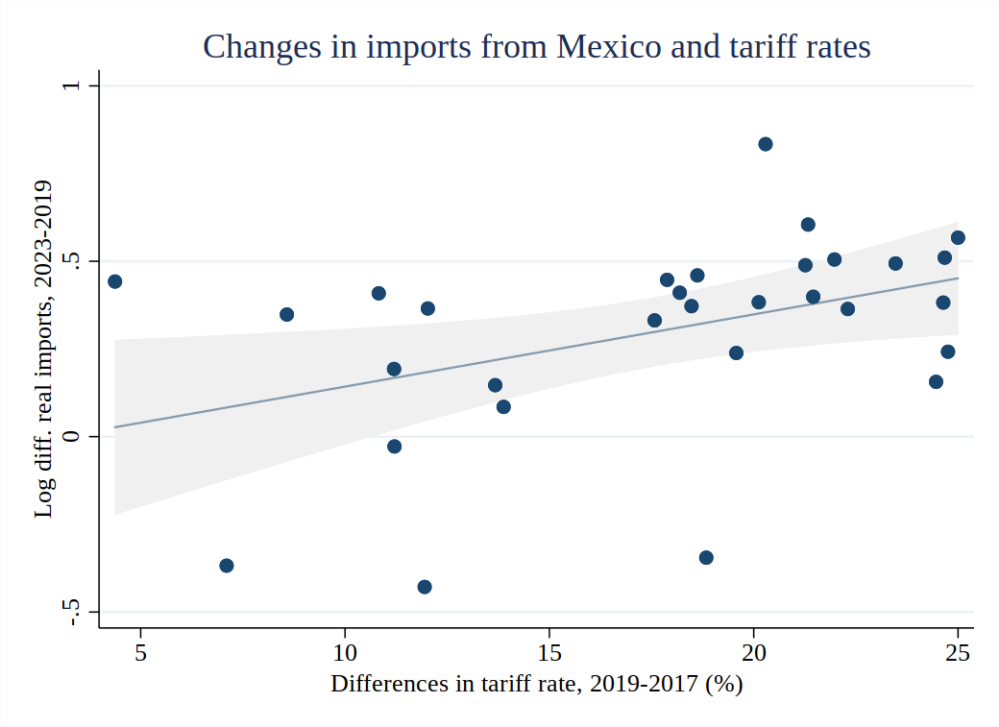
NAICS	Industry Name	Post-Tariff	Pre-Tariff	Tariff Difference	Tariff Group	GDP share	Export share
111	Agricultural Products	26.16	2.69	23.47	high	2.41	3.57
211	Oil & Gas	25.00	0.00	25.00	high	2.05	3.96
311	Food & Kindred Products	30.36	9.09	21.26	high	4.18	3.06
312	Beverages & Tobacco Products	26.63	5.30	21.33	high	1.05	1.82
313	Textiles & Fabrics	27.74	9.26	18.48	high	0.10	0.18
315	Apparel & Accessories	28.74	17.52	11.21	high	0.25	0.67
316	Leather & Allied Products	51.36	31.79	19.57	high	0.11	0.18
321	Wood Products	26.90	4.92	21.98	high	0.17	0.10
324	Petroleum & Coal Products	24.61	4.32	20.29	high	0.63	0.32
327	Nonmetallic Mineral Products	27.11	8.92	18.19	high	0.67	0.88
332	Fabricated Metal Products	24.56	4.43	20.12	high	0.69	2.41
335	Electrical Equipment, Appliances & Components	28.02	3.38	24.64	high	0.78	6.10
336	Transportation Equipment	27.34	2.58	24.75	high	4.42	37.43
337	Furniture & Fixtures	24.81	0.14	24.67	high	0.24	0.61
112	Livestock & Livestock Products	10.84	0.02	10.83	low	1.12	0.32
113	Forestry Products	12.22	1.02	11.20	low	—	—
114	Fish, Fresh/chilled/frozen & Other Marine Products	20.22	1.38	18.84	low	0.04	0.05
212	Minerals & Ores	7.22	0.12	7.10	low	1.33	2.33
314	Textile Mill Products	18.06	9.48	8.58	low	0.07	0.18
322	Paper	23.14	0.84	22.30	low	0.44	0.47
323	Printed Matter And Related Products	12.04	0.02	12.03	low	0.10	0.22
325	Chemicals	20.94	3.36	17.58	low	1.47	2.74
326	Plastics & Rubber Products	23.23	4.61	18.62	low	0.62	2.73
331	Primary Metal Mfg	16.95	3.28	13.68	low	1.12	2.62
333	Machinery, Except Electrical	22.95	1.49	21.46	low	0.79	4.04
334	Computer & Electronic Products	14.35	0.47	13.88	low	1.75	18.80
339	Miscellaneous Manufactured Commodities	6.29	1.91	4.37	low	0.57	4.22
910	Waste And Scrap	17.88	0.00	17.88	—	—	—
930	Used Or Second-hand Merchandise	12.28	0.33	11.95	—	—	—

Note: Tariff group = "high" corresponds to industries with a high tariff increase (above the median in 2020): NAICS 111, 211, 311, 312, 313, 315, 316, 321, 324, 327, 332, 335, 336, 337. Tariff group = "low" corresponds to industries with a lower but positive tariff increase: NAICS 112, 113, 114, 212, 314, 322, 323, 325, 326, 331, 333, 334, 339. *Source: Trade War Tracker by Michael Waugh (2024) and authors' calculations.*

as it shares both a border and a trade deal with the United States (USMCA). To investigate the potential spillover effect on the Mexican economy during the trade war, in Figure 3 we plot the changes in log real imports of the US from Mexico between 2019 and 2023. The graph shows that industries which were subjected to higher tariff increases in the course of the U.S.-China trade war also ended up importing more from Mexico. While such evidence is suggestive, in the following Section 3 we use formal econometric tool to show much stronger evidence behind nearshoring, coming from the credit market in Mexico.

2.2 Credit Registry Data

Our main dataset is the credit registry, which comprises the universe of bank loans, available to us at the Bank of Mexico. Every month regulated financial institutions in Mexico report granular information on all existing loans to the banking supervisor (CNBV). For each individual loan, the dataset identifies the lender, the borrower, the outstanding balance (from inception to maturity), the loan status (current or delinquent), the annualized



Source: US Census and Trade War Tracker by Michael Waugh (2024).

Figure 3: Tariffs on China and changes US imports from Mexico

interest rate and the loan maturity. For the borrower, the dataset also reports details such as industry, location at the municipality level, age, and the intended use of the loan (e.g., working capital, acquisition of fixed assets, payment of liabilities).

The baseline sample period in our dataset ranges from June 2016 until December 2024. We focus on loans granted by commercial banks to private non-financial firms established in Mexico. All loans are reported, regardless of their size. While we observe loan-level information in the raw dataset, for the main empirical analysis we aggregate the data at firm-industry-bank-month level, henceforth referred to as "business unit"-bank-month level. In our dataset, a firm's industry code is identified at loan-level information — often, a firm borrows in multiple loans and industry codes for the same firm may be different across loans. While around 90% of firms in our dataset report a single industry, the remaining 10% of firms are associated with more than 2 industries.[2] This may be due to the existence of multiproduct firms, and the fact that multi-industry firms tend to borrow larger amounts support this conjecture along with the existing literature. Therefore, we define our borrower unit as the firm-industry pair, which we name as a *business unit*, or

[2]More specifically, around 5% of firms report 2 industries, and 4% of firms report 3 or 4 industries. The remaining 1% reports 5 or more.

b.unit for short.

Specifically, we aggregate observations at the business unit-bank-month level by summing up the outstanding balance in a given month across all loans within a b.unit-bank pair, while interest rates are averaged monthly, weighted by the outstanding balance.[3] We end up with more than 70,000 business units and over 3 million observations at the business unit-bank-month level.

Aggregate credit by sectors We first investigate the aggregate trends of corporate credit in the affected sectors. In Figure 4 we define the high and low tariff tradable industry groups (corresponding to above- and below-median tariff in 2020) and plot the total real amounts of credit.[4] The high and low tariff groups mostly display parallel trends in terms of their aggregate credit up until the onset of the trade war. Importantly, the high tariff sector's credit amount significantly diverges from the low tariff group after the trade war

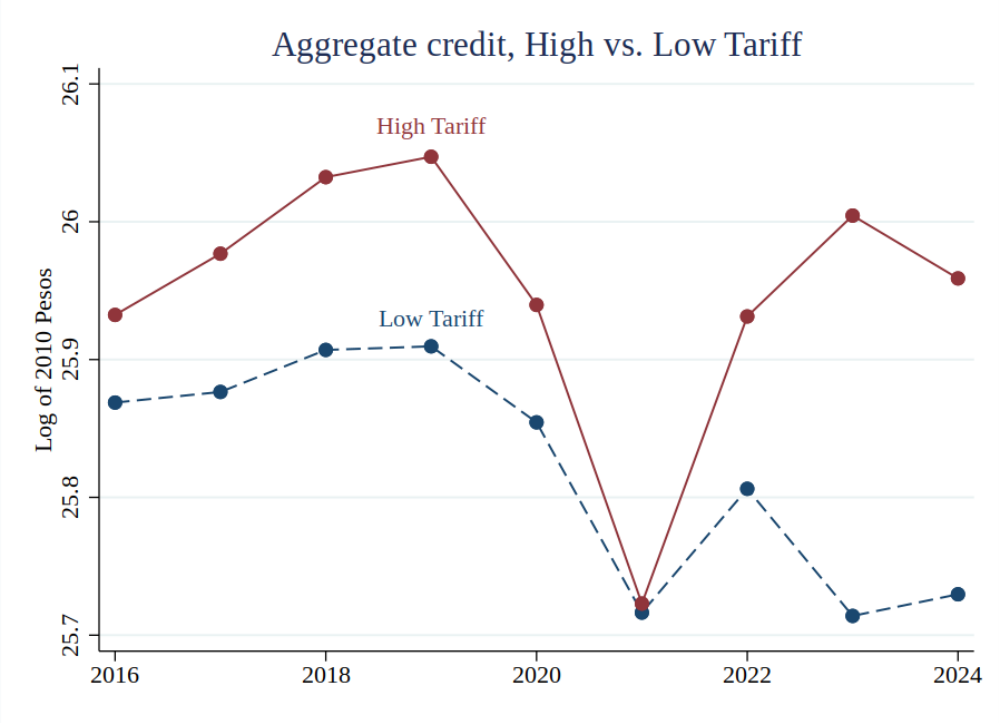


Figure 4: Aggregate credit by High vs. Low Tariff sectors

[3] In some observations, interest rates are either less than 1% or larger than 100%. We assume that these are potentially data entry errors, and we drop them in our analysis.

[4] We use monthly balance of aggregate credit within our sample and calculate a simple average within each calendar year to obtain annual series. The numbers are deflated using the Mexican *unidad de inversión (UDI)*, a commonly used inflation index for financial products.

begins, and such divergence persists through the end of our sample period in 2024. In our subsequent econometric analysis (Section 3), we tease out the causal effect of the trade war on the apparent divergence between the credit provision to high and low tariff groups leveraging the detailed micro data. It is also noteworthy that the total credit provided to tradable industries (the sum of the two lines) is mostly flat over the entire time period.

Median credit by lenders and sectors Before we proceed to the econometric analysis, we confirm that the diverging trends of credit provision between the high and low tariff groups are observed not only at the aggregate level but also at a more granular level. To do so, we first calculate the total amount of credit extended to the high and low tariff groups at each Bank×State level for the sample period of 2016 to 2024. We then normalize the time series of each lender by normalizing the log credit level to be 0 in 2017, so that the changes before and after the onset of the trade war are easily comparable across lenders. Finally, we calculate the median of (normalized) log credit across lenders within a year for the high and low tariff groups, and compare their evolution over time. In Figure 5, we plot the resulting median values for the high tariff (solid line) and low tariff (dashed line) groups. In 2016, prior to the onset of the trade war, both sectors display nearly identical trends. However, starting from 2018, the median amount of credit extended to the high

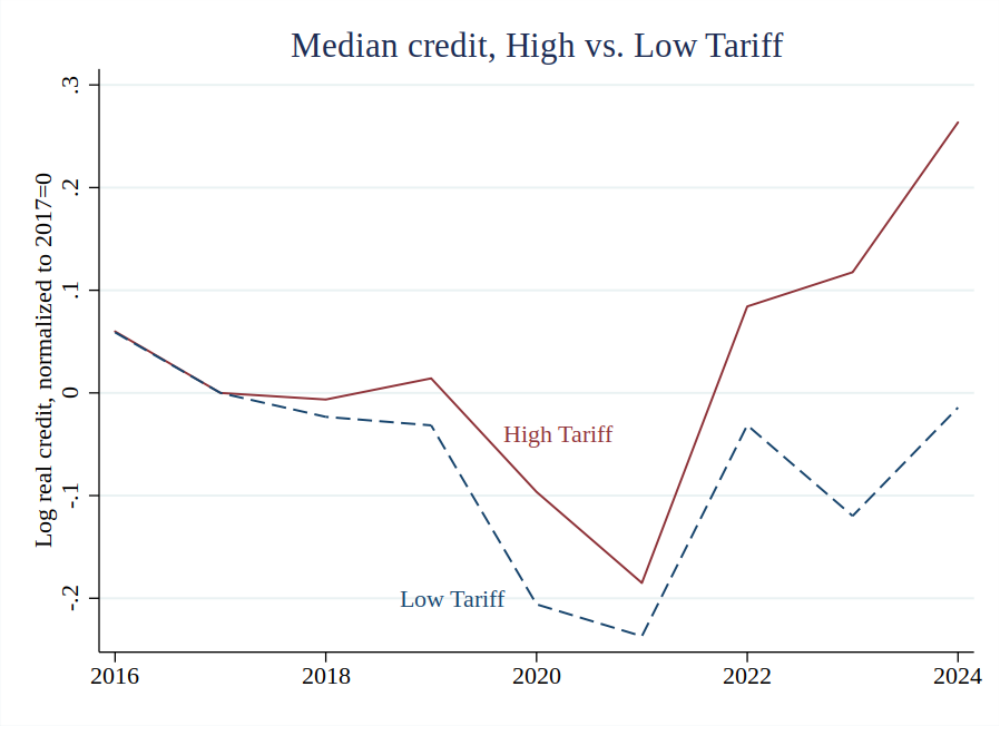


Figure 5: Median credit by High vs. Low Tariff sectors

tariff group is considerably higher than that of the low tariff group. In 2020, this difference amounts to nearly 10% for a median lender. In Section 3, we formally estimate the gap in log credit amounts between these two groups using the micro data.

3 Econometric Analysis

3.1 Spillover Effect of Trade War on Domestic Bank Credit

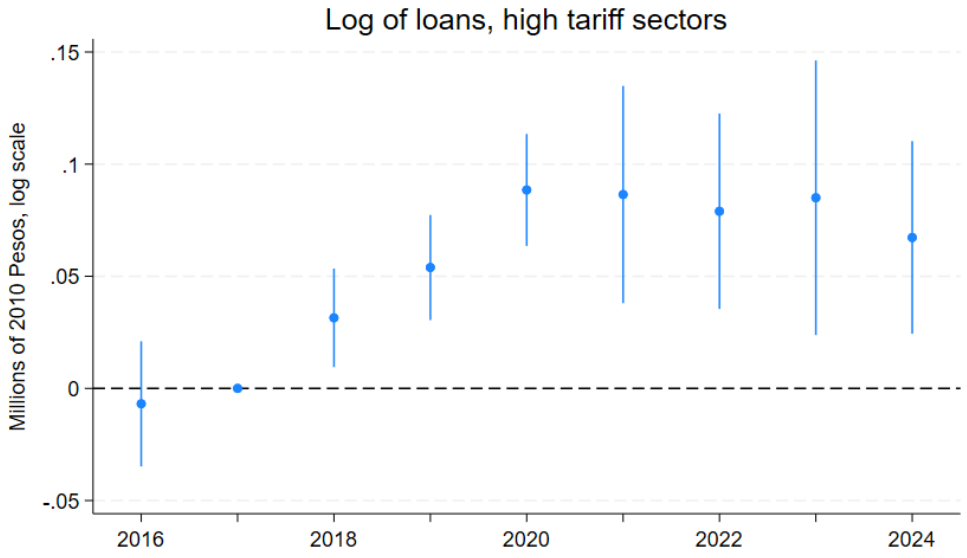
Credit amounts We first estimate the dynamic effects of the US-China trade war on the corporate credit market in Mexico. The primary goal of this analysis is to identify the causal effect of the trade war on the local credit market, focusing on commercial bank loans extended to all tradable sectors. We apply the difference-in-differences (diff-in-diff) method, treating the trade war as a natural experiment. The tradable sectors are divided into two groups: a "high-tariff" group and a "low-tariff" group. The high-tariff group consists of industries subject to US-China tariffs above the median level in 2020, while the industries subject to below-median tariff levels, are classified as the low-tariff group. We consider the high-tariff group as *treated* by the trade war and the low-tariff group as *non-treated* in the diff-in-diff framework. The specification thus includes a series of time-relative-to-treatment dummies (event-time dummies) to measure the effect of the treatment; that is, US tariffs imposed on Chinese industries. Our empirical specification features the following panel regression:

$$ln.Loan_{ijt} = f_{ij} + f_{sk} + \sum_{k=2016}^{2024} \gamma_k D_i^k + \epsilon_{ijt} \tag{1}$$

where $ln.Loan_{ijt}$ is the dependent variable, which is the log of loan quantity granted by bank i to business unit j during month t. Loan volume is expressed in real terms. The coefficients of interest, γ_k, measure the effect of the treatment on the outcome at year k relative to one year before the treatment. The treatment variables D_i^k are dummies that equal to 1 for industries that are above the median of tariff changes in 2020, and equal to 0 for industries below the median. We use the same values for the treatment variables in all years so that the composition of the high tariff group does not change over time. The regression also includes bank-business unit (f_{ij}) and state-year (f_{sk}) fixed-effects. Finally, standard errors ϵ_{ijt} are clustered at the bank level.

Figure 6 presents our main result, the estimated differences in bank loan amounts of the high-tariff sector compared to the low-tariff sector (γ_k from equation (1)). We set 2017 as

the base year, with the US-China trade war tariffs beginning to rise in 2018. Prior to the trade war, there are no statistically significant differences in bank loan amounts between the high- and low-tariff groups. However, starting from 2018, firms in the high-tariff group, on average, borrow approximately 2.5% more in bank loans compared to those in the low-tariff group. This divergence in borrowing continues to grow for the next 2 years, reaching close to 9% in years 2020-2023.

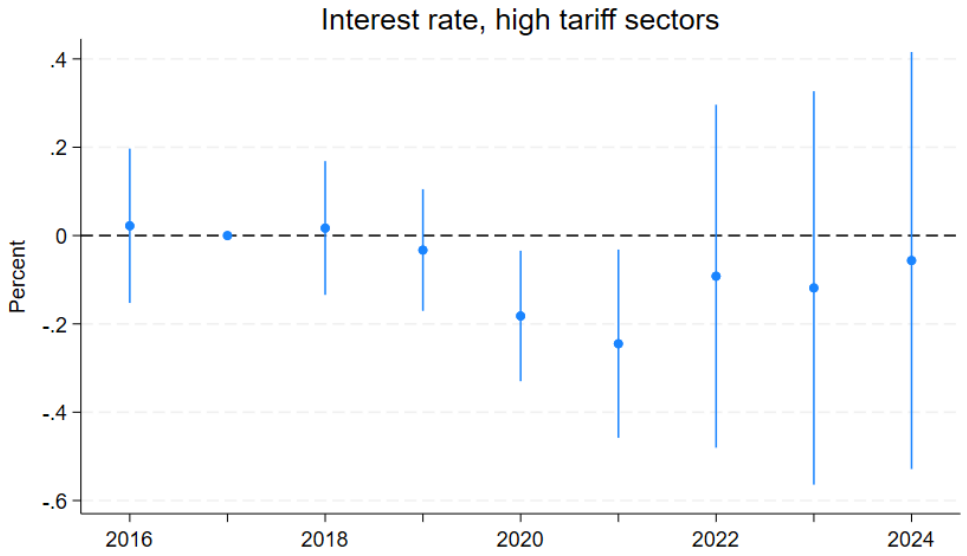


Note: $N_{obs} = 3.28m$, R^2. adj.$= 0.76$

Figure 6: Dynamic effect of US-China trade war on Mexican bank loans

Our econometric specification addresses important endogeneity issues. First, the size of the Mexican economy relative to that of the US or China makes it unlikely that the corporate credit granted by banks in Mexico affected the US and Chinese economies, or the tariffs they imposed on each other during the trade war. Second, our comprehensive and detailed loan-level dataset allows us to saturate the regression equation with fixed effects to control for unobserved characteristics. In principle, business units borrowing from different types of banks may bias identification, so the inclusion of b.unit-bank fixed effects controls for the unobserved, time-invariant, business unit (i.e., demand) and bank (i.e., supply) heterogeneity as well as for potential sticky borrower-lender relationships. In this sense, we exploit the variation within each b.unit-bank pair over time. Moreover, the inclusion of state-year fixed effects controls for unobserved, time-varying characteristics of the regional trends that may affect credit demand or supply across Mexican states.

Interest rates We now turn to another important loan characteristic which is its price or the interest rate. We run an analogous regression as in equation (1), but substituting interest rates as the dependent variable at the b.unit-bank-month level.[5] Figure 7 depicts the main result of the regression, the effects of the trade war on interest rates over time. While the estimates are more noisy compared to the effects on loan quantity, we observe that the interest rates for the High-Tariff group decline from the onset of the trade war, with the difference peaking at about -0.2 percentage point in year 2021. This implies that the industries subject to the nearshoring windfall experienced not only an increase in quantity but also a decrease in price of loans extended by banks. While intuitive, this result is theoretically not obvious because the firms in these industries borrow more, which potentially raises their default risk. Ultimately, such positive effect of additional borrowing on the interest rate is evidently dominated by the negative effect stemming from higher demand or firm productivity yielded by the nearshoring phenomenon.



Note: $N_{obs} = 3.28m$, R^2. adj.$= 0.57$

Figure 7: Dynamic effect of US-China trade war on Mexican bank loan interest rates

To summarize our main results, in the course of the US-China trade war, the loan quantity granted by banks in Mexico to the firms operating in the high-tariff industries increased by almost 10% relative to the firms operating in low-tariff industries. At the same time, the interest rates on these loans declined by up to -0.2 percentage point for the high-tariff

[5]Interest rates are calculated as a weighted average across different loans within a b.unit-bank-month level.

firms relative to the low-tariff ones. This result will the key to identifying the nearshoring effect in our quantitative model in Section 4.

3.2 Robustness checks

Bank-year fixed effects In this section we conduct several additional tests to ensure the robustness of our main results. First and foremost, we run analogous regressions with a finer set of fixed effects controlling for the bank-state-year and bank-firm fixed effects. Such fixed effects allow us to adjust the estimated effects for various unobserved bank and location characteristics that are also time-varying. Figure 18 in Appendix A reports the result of this estimation for loan quantities, while Figure 22 shows the result for interest rates. Both are quite similar to the results from our baseline specification. Compared to the low tariff industries, firms in the high tariff industries experienced about 7% higher credit provision, and about -0.2 percentage point lower interest rate in the course of the trade war.

All industries and new loans only Next, we run the same set of regressions as in the baseline, except that we change the control group. We broaden the non-treated sector by including non-tradable sectors such as services in addition to the low-tariff industries. Figure 19 in Appendix A summarizes the results for the loan quantity regression and Figure 23 shows it for the interest rates. While the average loan size is smaller for the non-tradable sectors compared to either high- or low-tariff tradable sectors, the parallel trend assumption still holds with the inclusion of non-tradable sectors. Figures 19(b) and 23(b) additionally plot the results of running our regressions on the subsample of new loans only. In this case, we find a similar pattern of higher credit quantity of the high tariff group relative to the low tariff group. However, the pattern is opposite for the interest rate regression towards the end of our sample period.

Types of credit There are two main categories of credit in our dataset: non-revolving and revolving loans.[6] Broadly speaking, non-revolving loans are term loans, whereas revolving loans mostly consist of corporate credit cards. We divide the samples into these two categories and inspect the effect of the trade war on the quantity of loans and interest rate as in the main estimation (equation (1)). We find that the increase in loan quantity for the High-Tariff group dominant in the main result is mostly driven by the non-revolving

[6]We also have the third category, syndicated loans, but the number of observations is very small so we abstract from them.

loans. As Figure 20 in Appendix A shows, only the non-revolving loans display a similar effect of trade war on loan quantity compared to the baseline. Among revolving loans, the loan quantity within a business unit-bank pair stays statistically unchanged over our sample period. It is worth emphasizing that this contrast in estimation results between the two groups is not due to sample sizes — the number of observations for revolving loans is in fact higher (1.12 million) compared to that of non-revolving loans (0.96 million). Figure 24 shows that this conclusion also broadly holds for the interest rate, although by separating the two credit types we lose statistical significance of the results.

Borrowers by size We also study potential heterogeneity across borrowers in terms of trade war effects. While we do not observe the size of the business units directly, we characterize them based on loan sizes and firm attributes such as the number of business units or the number of banking relationships.[7] First, a business unit is 'large' if the maximum amount of its outstanding loans (either individually or combined over a month) is above the median over the sample period. Second, a large business unit (as previously defined) is 'too large' if its parent has both multiple business units and multiple banking relationships. Third, a business unit is 'micro' if it is not large and its parent has both a single business unit and a single banking relationship. We run the same benchmark regression as in equation (1) separately for each group. The increase in loans to firms in the high-tariff industries relative to firms in the low-tariff industries is widespread, although short-lived for micro business units. While we find similar point estimates for both groups, as Figure 21 in Appendix A shows, the effects are more significant for large business units. Moreover, the differences in loan quantity for the High-Tariff group persists among large business units, whereas the differences taper off in 2021 among small business units. Admittedly, large business units have more observations (1.31 million) than small business units (0.79 million), partly due to the fact that large borrowers tend to borrow from multiple lenders. Tighter confidence intervals among the large borrowers could be related with uneven sample sizes between the two groups. In terms of the effect on the interest rate, we find that both groups exhibit a similar pattern as in our baseline results, as depicted in Figure 25, although the point estimates are again noisier due to diluting the sample size.

Tariff groups As a final exercise, we vary the composition of the tariff groups, so far defined as the median of the tariff levels in 2020. We first change the base year to the

[7] We do not use income nor the number of employees reported in the credit registry because these size variables are self-reported and therefore not consistent.

median of the tariff levels in 2019. Instead of the median, we also define the cutoff at the 60th percentile of the tariff levels in 2019 and 2020. Finally, we define the tariff groups as the median and the 40th percentile of the tariff *changes* in 2019 and 2020 relative to the year with the first tariff changes (2017). Our main result is not sensitive to these changes in the composition of the tariff groups. In all cases, loans to firms in the high-tariff industries increase relative to firms in the low-tariff industries, while interest rates exhibit a similar pattern as in our baseline results. Appendix A shows the results for loans using the median levels in 2019 and the other variations for 2020.

3.3 Foreign Direct Investment

To provide further evidence of nearshoring in Mexico, we analyze the evolution of inward FDI to Mexico across Mexican states, industries affected by changes in tariff levels between the U.S. and China, and countries of origin. FDI data, disaggregated by state, industry, and country of origin, is sourced from the Mexican Secretariat of Economy (2024) and measured according to BPM5 and BD4 standards. FDI refers to a category of cross-border investment made by a foreign resident (direct investor) in a Mexican company or assets located within Mexico (direct investment enterprise), with the goal of establishing a lasting interest. This investment allows the direct investor to exert a significant degree of influence over the direct investment enterprise.

We convert the current values from millions of USD into millions of pesos at 2010 constant prices, using the UDI as a deflator. Exchange rates were obtained from the Bank of Mexico's FIX series. The dataset spans from 2002 to 2023. Using the FDI flows, we computed cumulative FDI as the cumulative sum of real FDI flows from 2002 to 2023 by each state and 3-digit NAICS levels. The cumulative FDI by country of origin was calculated using the same procedure, but accumulating by country of origin.

We define the high-tariff group as industries that were subject to U.S.-China tariffs above the median level in 2020, while industries with tariffs below the median level are classified as the low-tariff group. In the difference-in-differences framework, the high-tariff group is considered treated by the trade war. Figure 8 shows the evolution of cumulative FDI for northern states vs. southern states for high tariff industries and low tariff industries.[8] As is evident from the figure, the FDI within high and low tariff industries

[8]Northern states are Baja California, Chihuahua, Coahuila, Nuevo León, Sonora, and Tamaulipas. Southern states are Chiapas, Colima, Guerrero, Michoacán, Morelos, and Oaxaca. NAIC-3 digit high tariff sectors are 111, 211, 311, 312, 313, 315, 316, 321, 324, 327, 332, 335, 336, and 337. Low tariff sectors are 112,

exhibit mostly parallel trends until around 2017, among the northern and southern states alike. Then, the high tariff industries receive substantially more FDI compared to low tariff ones, but only in the northern states, where most of the tradable goods industries are located.

To analyze the changes in inward FDI to Mexico during the trade war more systematically, we use the following difference-in-differences specification:

$$FDI_{sjt} = \mu_s + \lambda_t + \delta_j + \sum_{k \neq -1} \theta_k \mathrm{D}^k_{sjt} + \epsilon_{sjt} \tag{2}$$

where FDI_{sjt} refers to FDI stock (cumulative inward FDI flows to Mexico over the sample period) in state s for industry j in year t. The specification includes state (μ_s), year (λ_t), and industry (δ_j) fixed-effects. The coefficients of interest, θ_k measure the effect of treatment (tariff from the US to China in industry j in state s in Mexico) on FDI at time k relative to the baseline period, in this case one period before the US-China trade war initiated. The treatment variable, D^k_{ijt}, takes the value of 1 for industries with above median tariff changes in 2020 and 0 for all other industries.

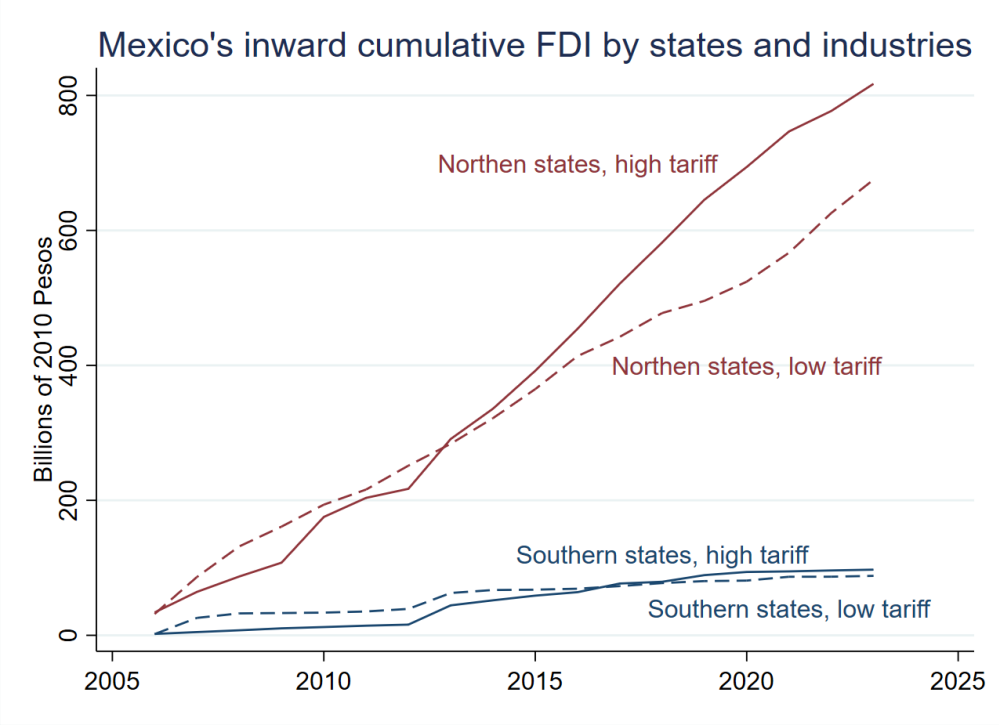
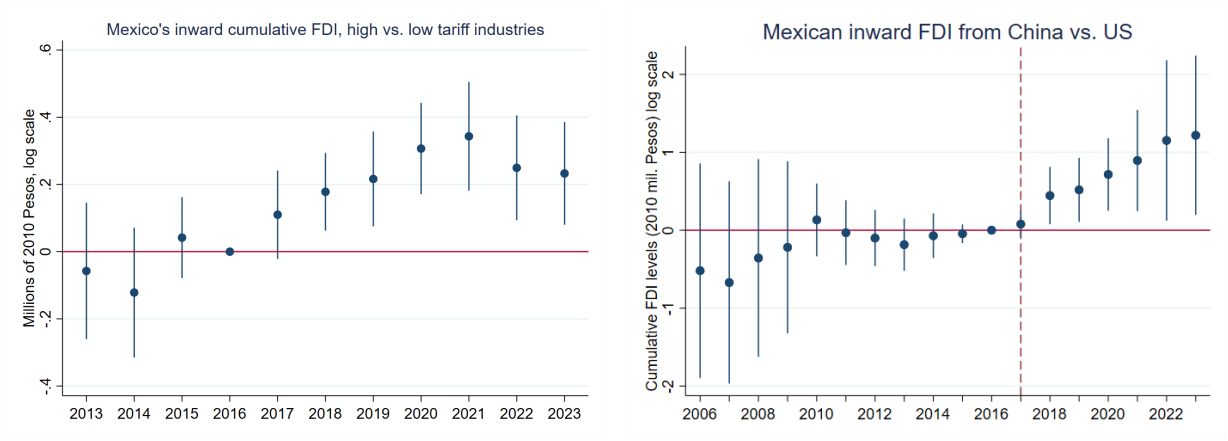


Figure 8: FDI in Mexico: industries and states

113, 114, 212, 314, 322, 323, 325, 326, 331, 333, 334, and 339.

Figure 9(a) presents the results from Equation 2. The base year is set to 2016, prior to any tariff changes between the U.S. and China. During the pre-trade war period (2013–2015), there are no statistically significant differences in inward FDI between high- and low-tariff industries. However, starting from 2018 onward, Mexico's inward FDI directed towards industries with the highest tariffs became significantly larger compared to industries with lower or no tariffs. Specifically, inward FDI to high-tariff industries in 2018 was approximately 20% higher relative to low-tariff industries. This difference peaked in 2021, reaching an approximate difference of 30%.



(a) High vs low tariffs

(b) China vs US

Figure 9: Robustness of interest rate regression: by business unit sizes

To explore the nearshoring narrative, we also analyze Mexico's inward FDI by country of origin. The U.S.-China trade war may have prompted Chinese exporting firms and investors to relocate some of their production to countries with more favorable trade conditions with the U.S., such as Mexico. If this is true, we would expect an increase in Chinese FDI to Mexico compared to that from the U.S. or other countries in the aftermath of the trade war. Conversely, the U.S. FDI to Mexico is not expected to change significantly as a result of the U.S.-China trade war.

Figure 9(b) displays the regression results of the event study for Mexico's state-level FDI by country of origin based on Equation 2. In this analysis, the treatment variable is set to 1 for all FDI originating from China and 0 for FDI originating from the U.S. Note that these FDI figures include all industries from each country, as industry-by-country-of-origin level data is unavailable. The regressions account for year and state–FDI country-of-

origin pair fixed effects, with standard errors clustered at the state–FDI country-of-origin level. The results show that during the pre-U.S.-China trade war period, there were no significant differences in FDI by country of origin between China and the U.S. However, these differences become positive and significant from 2018 onward, with FDI from China being over 10% higher compared to the pre-trade war period, and this trend persists into the post-trade war period.

As a robustness check, Figures 26 and 27 in Appendix A compare FDI from China with that from all other countries and FDI to Mexico from the U.S. with that from all other countries. In Figure 26, we observe that the results remain robust even when changing the comparison groups. As expected, Figure 27 highlights threats to parallel trends, with positive and significant coefficients in 2006 and 2007. There is a small but negative effect on FDI to Mexico from the U.S. in the post-U.S.-China trade war period; however, a negative trend appears to have started as early as 2006. Overall, FDI from the U.S. does not seem to have significantly changed during the post-trade war period.

4 Model

In this section we develop a general equilibrium model of heterogeneous firms with endogenous default on bank credit. The goal of the model is to translate the empirical results from the credit market to broader real outcomes for the economy in Mexico. The model also allows us to run interesting counterfactuals regarding the US-China trade war. We first design and calibrate the model to match the steady state distribution of Mexican firms' bank loan quantities and interest rate spreads before the trade war. Then, we use it to back out the model-implied increase in productivity within the High Tariff sector by matching the micro empirical results in Section 3, as well as the aggregate dynamics. Finally, equipped with the micro-consistent macro model, we run counterfactual exercises to shed light on the potential growth of Mexican economy under a more elastic bank loan supply.

4.1 Environment

There is a continuum of heterogeneous firms with a unit mass. Firms differ by the stock of physical capital k, amount of debt b, transitory productivity z, and permanent productivity type s.

Production function We assume a decreasing returns to scale production function, with the capital share parameter α. The only input for production is physical capital, with one unit of labor assumed to be supplied inelastically. Permanent productivity types s that are heterogeneous across firms multiply the transitory productivity z. Finally, the *treatment* parameter ξ represents the trade war impact, taking a value of $\xi = 1$ for the Low Tariff group (no treatment) and $\xi > 1$ for the High Tariff group (treated). The trade war treatment can be interpreted as increased demand for the output of the treated firms, which in our model is isomorphic to elevated productivity. In the steady state, $\xi = 1$ for all firms. Formally, the production of a firm is:

$$f(k, z; s, \xi) = \xi(z \cdot s)k^{\alpha}. \tag{3}$$

Transitory productivity The transitory productivity follows a log-normal first-order autoregressive (AR1) process, with a persistence ρ and shocks following a Normal distribution with mean 0 and standard deviation σ.

$$\log z' = \rho \log z + \sigma\epsilon,\ \epsilon \sim N(0, 1) \tag{4}$$

Objective and controls Firms maximize the expected stream of dividend payouts d, discounting future value with a discount factor β. Every period, each firm chooses the next period's stock of physical capital k' and debt amount b', subject to the budget constraint. Firms are allowed to issue external equity incurring a quadratic penalty $(\gamma_0 d + \gamma_1 d^2)$ that represents the costs associated with attracting investors. They must pay a fixed cost of f_o each period to maintain their operations. The stock of physical capital depreciates at rate δ and is subject to a quadratic adjustment cost with parameter ϕ. If a firm's value becomes negative or a firm is randomly selected with a probability χ in the next period, the firm exits and defaults on its loan.

Recursive formulation A firm's problem presented in a recursive form is

$$V(k, a, z, s) = \max_{k', a'}\ d\Big(1 + (\gamma_0 + \gamma_1 d) I_{\{d<0\}}\Big) + \beta(1-\chi) E_{z'|z} \max\Big\{V(k', a', z', s), 0\Big\} \tag{5}$$

$$s.t.\ d = \xi\, z\, s\, k^{\alpha} + (1-\delta)k + a - q(k', a', z, s)a' - k' - \frac{\phi}{2}\frac{(k'-k)^2}{k} - f_o \tag{6}$$

$$\log z' = \rho \log z + \sigma\epsilon \tag{7}$$

Debt pricing We assume that lenders are perfectly competitive and risk-neutral. As a result, they make zero profit in expectation and can incur potentially large losses. The price of bonds issued by a firm is

$$q(k', a', z, s) = \frac{1 - D(k', a', z, s)\Big[1 - \min\Big\{\frac{(1-\lambda)k'}{-a'}, 1\Big\}\Big]}{1 + r} \tag{8}$$

$$D(k', a', z) = 1 - \Big(1 - \mathbb{E}_{z'|z}(V < 0)\Big)(1 - \chi) \tag{9}$$

Default, represented by a binary policy function $D(\cdot)$, occurs for two reasons. The first is when the firm's value turns negative, and the second is due to randomness with probability χ. When the firm defaults, its creditor can still recover a part of their claims by seizing the firm's physical capital k and splitting it among the firm's liabilities a. A fraction λ of this collateral gets destroyed in the process which represents transaction and enforcement frictions, and it is potentially high in an emerging market economy such as Mexico. We will calibrate the value of λ to match the distribution of bond spreads in equilibrium. Finally, lenders discount future cash flow with the general equilibrium interest rate r.

New entrant's problem We assume that firms who default exit the economy permanently, and each one of them is replaced with a new entrant. New entrants inherit the defaulters' permanent productivity type s but they do not produce anything in the first period. Instead they invest in their initial stock of capital using a combination of debt, external equity, and a seed wealth amount ω_e. They subsequently draw a temporary productivity level from the ergodic distribution of z.

$$V_e(s) = \max_{k', a'} \; d\Big(1 + (\gamma_0 + \gamma_1 d) I_{\{d<0\}}\Big) + \beta(1 - \chi) E_{z'} \max\Big\{V(k', a', z', s), 0\Big\} \tag{10}$$

$$s.t. \;\; d = -q(k', a', z, s)a' - k' + \omega_e(s) \tag{11}$$

$$q(k', a', z, s) = \frac{1 - D(k', a', z)\Big[1 - \min\Big\{\frac{(1-\lambda)k'}{-a'}, 1\Big\}\Big]}{1 + r} \tag{12}$$

$$D(k', a', z, s) = 1 - \Big(1 - \mathbb{E}_{z'|z}(V < 0)\Big)(1 - \chi) \tag{13}$$

$$\log z' = \frac{\sigma}{\sqrt{1 - \rho^2}}\epsilon \tag{14}$$

We set the value of the new entrants' initial wealth $\omega_e(s)$ such that the entrants value is zero for each permanent productivity type. This assumption can be interpreted as a free-entry condition. In equilibrium, the mass of new entrants is identical as the mass of firms

who exit.

Debt market clearing We aggregate the economy-wide demand for credit and close the model with an exogenous credit supply curve that depends on the risk-free interest rate r.

$$B = \theta (1 + r)^{\varepsilon} = \int a'(k, a, z, s) \, dF(k, a, z, s), \; \varepsilon > 0 \tag{15}$$

The credit supply curve has two additional parameters, elasticity ε and shifter θ. We are unable to separate these two parameters in the steady state. On the transition path induced by the trade war, we will identify the elasticity ε, and back out a fixed value of θ to ensure market clearing.

4.2 Calibration

As is standard in quantitative macroeconomics, we calibrate our model by fixing some parameters values from external data or literature, and by setting others in an internal moment-matching exercise. We split our quantification into two stages. In the first stage, we calibrate the steady state of our model so that it mimics Mexico's pre-trade war economy (up until year 2017). In the second stage, we find the path of treatments, along with the elasticity of credit supply, to replicate the micro- and macro-level credit dynamics during the trade war.

Table 2: Calibrated parameter values

Parameter	Meaning	Value	Identification source
δ	Depreciation rate	0.07	Production function parameters
α	Returns to scale	0.6	
ρ	Persistence of productivity	0.6	Productivity parameters
σ	St. dev. of shocks to productivity	0.5	
β	Firm's discount factor	0.975	Internally calibrated parameters
f_o	Fixed operating cost	1.20	
λ	Deadweight loss of default	0.975	
ϕ	Capital adjustment cost parameter	1.97	
χ	Probability of exogenous exit	0.11	
γ_0	Equity issuance cost linear term	-1.00	
γ_1	Equity issuance cost quadratic term	0.55	
r	Risk-free interest rate	3.2%	MX policy rate

Steady state Table 2 summarizes the main parameter list in our model. In order to calibrate some of these parameters, we gather data from the Economic Census (CE) and the National Business Financing Survey (ENAFIN), both undertaken by the National Institute of Statistics and Geography (INEGI).[9] In particular, the CE is a nationally representative firm census, consisting of repeated cross-sectional surveys, and carried out every five years. For the purposes of this paper, we focused on the 2014 wave, just before the trade war began, and gathered data on firm capital, investments and total factor productivity inputs by industry type. On the other hand, ENAFIN is also a nationally representative and repeated cross-sectional survey, and is carried out every three years. We focused on the 2015 wave and gathered data on leverage ratio inputs by industry type. Using this data, we estimate the parameters of the firms' production function (α and δ) as well as the temporary productivity process (ρ and σ). Of particular importance is the capital share parameter α which we set to 0.6. This somewhat high value comes from the fact that most of the firms we consider (high and low tariff groups) operate in capital-intensive sectors such as manufacturing or mining.

The remaining seven parameter values are selected such that the model replicates seven salient moments in the pre-trade war data, as reported in Table 3. Of particular importance is capturing the amount of leverage and the riskiness of corporate loans in Mexico. Four parameters are chiefly responsible for such behavior, the discount factor β, the operating fixed cost f_o, the loss of capital in default λ, and the probability of exogenous exit χ. These moments are informed by matching the mean leverage ratio and mean bond spread, of 21% and 11.5%, respectively, as well as the median and 75th percentile of the bond spread distribution equal to 9.5% and 13%, respectively. It is notable that we require a very high value of λ to achieve a close fit, which means that hardly any collateral can be recovered in Mexico in the event of default. This is driven by the overall high level of corporate bonds spreads in that country. Further, the capital adjustment cost parameter is informed by targeting the coefficient of variation of the gross investment rate of about 1. This captures the relative dispersion of investment rates in the data. The two parameters of the equity issuance cost, γ_0 and γ_1, are informed by targeting the fraction of firms that issue external equity and that pay positive dividend in any given period. Finally, we also pin down the risk-free interest rate of 3.2% in the steady state using Mexico's 2017 policy rate net of the US federal funds rate.

[9] CE focus on economic variables of all firms that produce goods, merchandise marketers, and service providers, while ENAFIN provides information related to the sources and use of financing, as well as the needs of financial and banking services of firms.

Transition In the second stage of our quantification, we fit the path of demand shocks (treatment) affecting Mexican firms in the high tariff group as a result of the US-China trade war. To operationalize this exercise, we parameterize the sequence of treatments using the following functional form

$$\xi_t = 1 + c \times (t - t_0)^a \times (T - t)^b \tag{16}$$

Equation (16) can be thought of as a flexible bump, and comes with four parameters. Figure 10 illustrates an example of such a function. The total effect is a product of the time since the treatment began (t_0) raised the power a, and the time until the treatment ends (T), raised to the power b, by which time the economy will start converging to the original steady state. Parameters a and b determine how fast the effect increases and declines, while parameter T determines the treatment horizon. The total effect is ultimately scaled by the fourth parameter c. To make interpretation more intuitive, we convert parameters

Table 3: Simulated steady state behavior

Moment	**Model**	**Data**
Mean leverage ratio (book), %	23.8	20.9
Average bond spread, %	10.0	11.5
St. deviation bond spread, %	11.5	9.1
25th percentile bond spread, %	0.0	6.1
50th percentile bond spread, %	9.1	9.5
75th percentile bond spread, %	16.2	13.2
combined default and exit rate, %	13.4	1.7
Mean dividend payout (to capital), %	23.1	29.4
% of firms that pay dividend	47.8	38
Mean equity issuance (to capital), %	15.4	7.4
% of firms that issue external equity	19.9	26.5
Mean gross investment rate, %	16.3	6.0
Mean net investment rate, %	8.8	−2.2
St. deviation investment rate, %	12.4	6.1
Coeff. of var. gr. inv. rate, %	0.8	1.0

Note: Targeted moments are marked in bold font.

T and c into the "size" and "timing" of peak effect, as illustrated in Figure 10.[10]

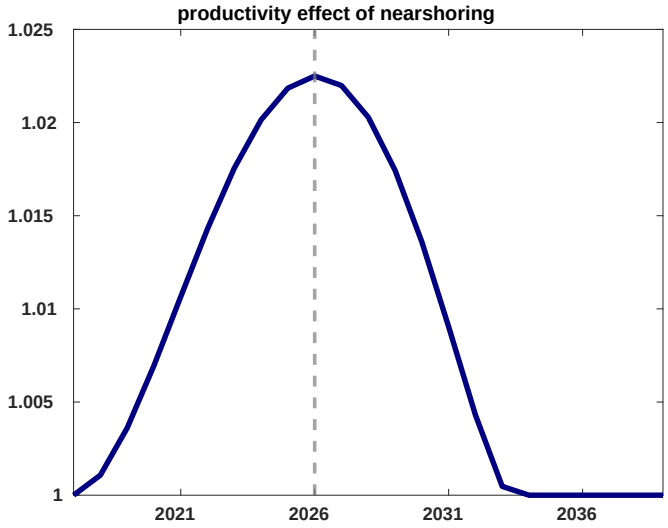


Figure 10: Parametric form of the impact of trade war

Table 4 summarizes the calibration of our parameters on the transition. We identify the parameters of the transition treatments by replicating the main empirical result visualized in Figure 6. We simulate a panel of 100,000 agents in our model and subject 52% of them (which corresponds to the share of the high tariff group by value added) to treatment. The remaining firms are unaffected directly, but they are still respond to the general equilibrium effects of the transition. We then run a regression analogous to specification (1) and seek to minimize the sum of squared deviations between the paths of point estimates, from the model and the data. The result of this matching is visualized in the left panel

Table 4: Calibrated parameter values of the transition path

Parameter	**Meaning**	**Value**	**Identification source**
ϵ	Elasticity of loan supply	0.50	Varied in analysis
θ	Supply curve scaling parameter	0.96	Picked to clear market
$P(\xi > 1)$	Fraction of treated firms	0.52	Share of VA in data
a	Pace of rise	1.89	Transition productivity parameters
b	Pace of decline	1.50	
max	Peak effect	2.25%	
t_max	Peak period	9.07	

[10]The "peak period" of the treatment is obtained as $t^* = \frac{aT}{a+b}$, while "peak size" of the treatment is then given by $peak = (t^* - t_0)^a (T - t^*)^b \times c$.

of Figure 11. We achieve a very close match between the two paths. In particular, all of the model-generated point estimates lie well within the empirical confidence intervals, and all of the empirical point estimates (with an exception of year 2020) are within the model-generated confidence intervals. The identify parameters imply a modestly nonlinear increase and decline of the treatment effect over time. The peak productivity boost the treated firms enjoy as a result of the trade war amounts to 2.25% and occurs in year 2026. The trade war effects then declines to zero by year 2034.

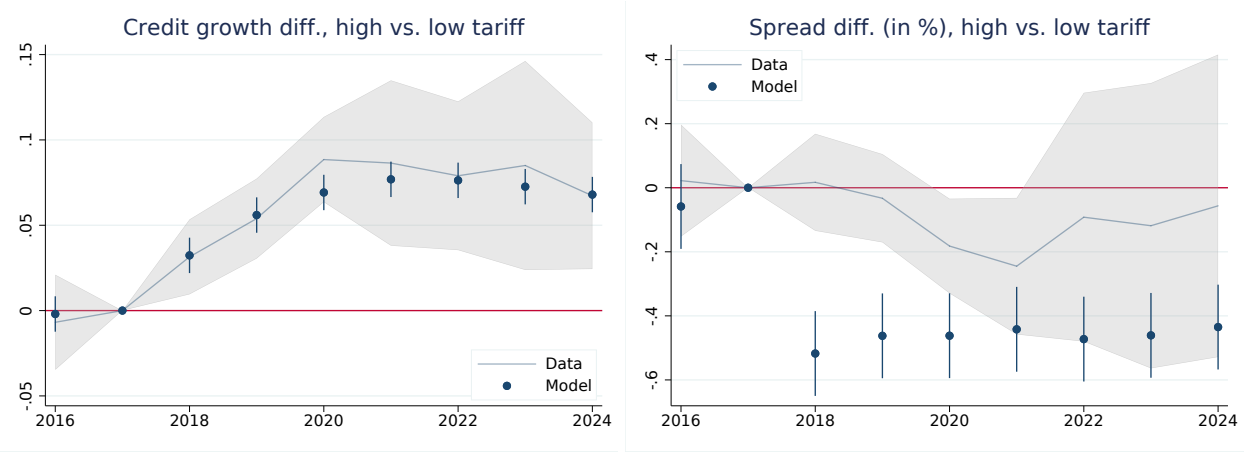


Figure 11: Loans quantity (left) and spreads (right) in the model, baseline

In addition to identifying the path of the treatment, we also need to know the baseline elasticity of credit supply ε. We identify this crucial parameter by targeting the path of the ratios of aggregate credit of the low and the high tariff groups, in addition to the aforementioned micro results. Figure 12 visualizes the result of this matching which is conducted by minimizing the sum of squared deviations. As the figure shows, we are able to capture the initial decline in the ratio closely while missing the peak decline around year 2023. The elasticity parameter that generates this behavior is 0.5, i.e. the credit supply is quite inelastic.

While non-targeted, it is also worth noting that our model captures the direction of the differential effect of the treatment on bond spreads, as illustrated in the right panel of Figure 11. Whether the spreads of treated firms rise or fall relative to the control group is theoretically ambiguous. On the one hand, treated firms increase their indebtedness and higher debt leads to higher default probabilities, all else equal. On the other hand, such firms become more productive as a result of the treatment which reduces the default risk. In the data, the latter effect dominates and we also find it to be the case in our model. In fact, our model predicts a much higher relative decline in the spreads among the treated

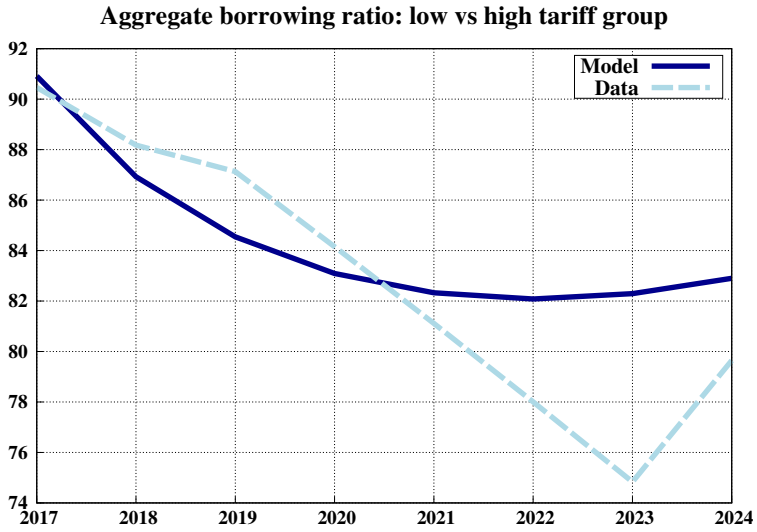


Figure 12: Ratio of total credit of the low to the high tariff groups in the model, baseline

firms on impact, and only starting from year 2021 the model-generated point estimates fall within the empirical confidence intervals.

Counterfactual In the following analysis, we present our results under the baseline calibration, as well as in a counterfactual where the elasticity of credit supply is very high, resembling that of the US.[11] For completeness, we also run our regressions on the panel of firms generated by the counterfactual exercise in the model. Figures 13 and 14 illustrate the results. At the micro level, the treatment effect is considerably stronger under an elas-

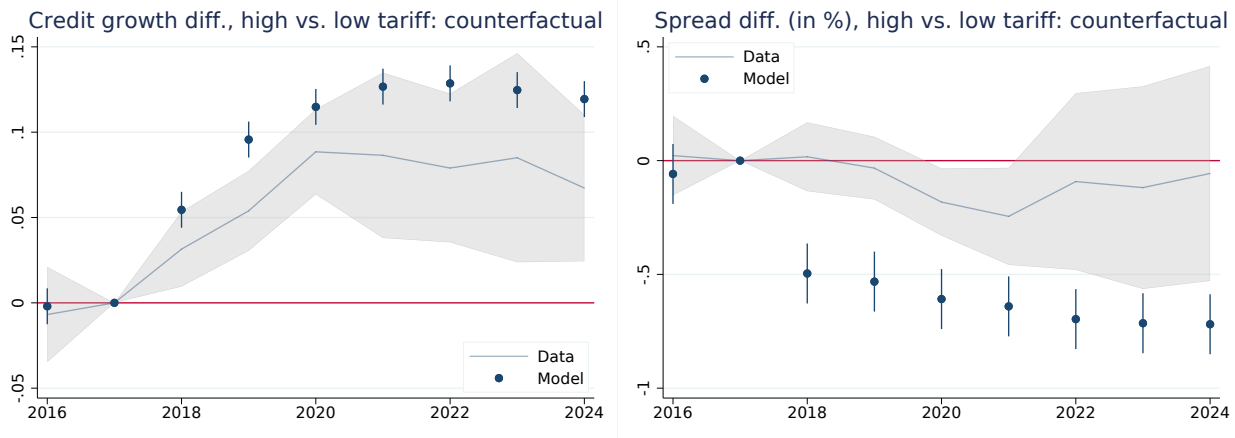


Figure 13: Loans quantity (left) and spreads (right), counterfactual

[11] We set the counterfactual elasticity to 50 which is a typical value for advanced countries' financial markets.

tic credit supply curve, with borrowing among the high tariff firms around 13% higher than the low tariff group at the peak. We similarly find a much stronger relative decline in the bond spreads. At the macro level, the ratio of the low tariff group borrowing to high tariff borrowing declines by much more than in the data or the baseline scenario. Because credit supply is so elastic, the treated firms have the capacity to expand their borrowing without affecting other firms in the economy.

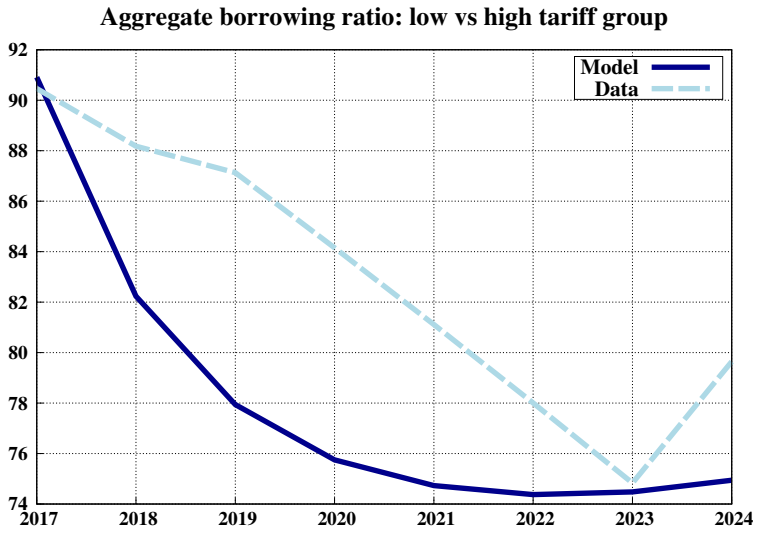


Figure 14: Ratio of total credit of the low to the high tariff groups in the model, counterfactual

4.3 Main results

Figure 15 presents the summary of the inferred transition path in our model. The left panel visualizes the strength of the productivity treatment, which peaks at 2.25% in year 2026 before declining to zero by year 2034. The right panel plots the interest rates that clear the asset market in every period. In general, interest rate must rise over the transition in response to the trade war. The good productivity shock affecting the treated firms in our model induce them to invest more in physical capital (higher k'), financed by higher borrowing (lower a'). In the aggregate, this higher demand for credit exceeds the available supply and hence the interest rate rises. How much it rises depends on the elasticity of credit supply ε. In the baseline scenario, the risk-free rate increases by 0.6 percentage point until 2022, and then declines with a dip below its original level of 3.2% in the 2030s. This amplitude is caused by the low elasticity of the credit supply curve in the baseline. In the counterfactual, where it is much more elastic, the increase is limited to 0.1 percentage point.

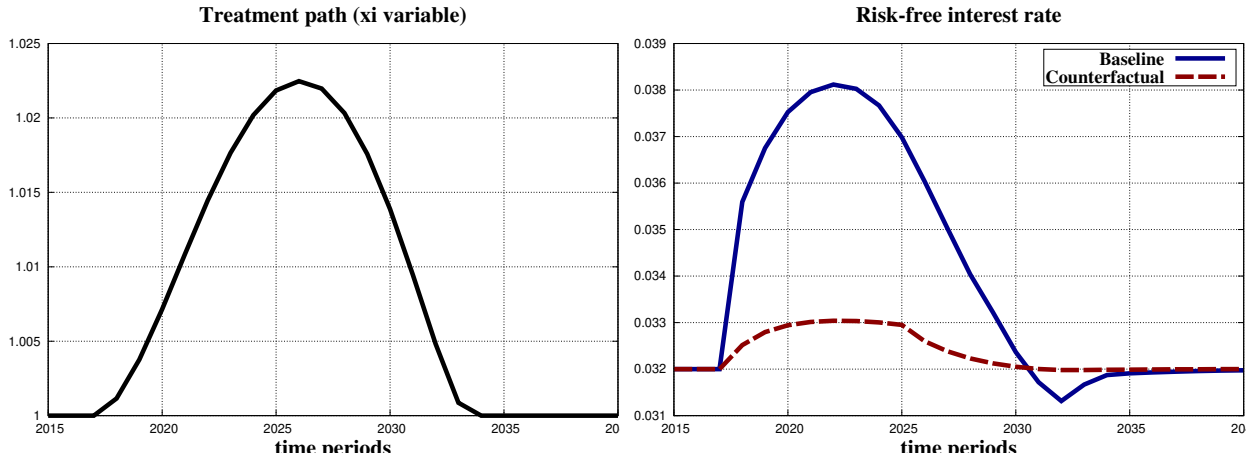


Figure 15: Treatment and the general equilibrium interest rate on transition

Figure 16 plots the aggregate series of output, capital, debt and mean spread over the transition. Because half of the firms in the economy are experiencing a productivity boom, and they accumulate more capital and output rises temporarily by up to 1.8%. This investment is financed by an overall increase in debt. Crucially, total credit is barely higher in the baseline scenario, in line with what we observe in the data. By contrast, in the counterfactual with an elastic credit supply, total debt increases by over 10% which leads the aggregate output to *i*ncrease by twice as much, 3.5%. The higher production mostly results from about three times higher increase in the aggregate capital stock. Finally, we also observe that bond spreads go down over the transition, especially so in the baseline scenario. This is because in the baseline, credit is mostly reallocated to the treated firms, who are experiencing a high productivity shocks and therefore carry a lower default risk. At the same time, the control group who are more risky lose some of their credit. In the counterfactual scenario, where this substitution is less severe, more risky firms from the control group retain their level of borrowing and as a result the spreads decline by less and with a delay.

Figure 17 presents analogous plots by tariff group. It shows that the main engine behind the increase in aggregate output in both scenarios is the high tariff (treated) group. The low tariff group generally seems less affected, with their output contracting by less than one percent. In the baseline scenario, we can see a clear pattern of credit substitution. Almost all of the increase in borrowing among the treated group comes at the expense of a reduction in borrowing among the control group. Consequently, while the treated group gets to produce much more, the control group scales down their output. The moderate size of this effect is caused by a relatively low leverage in the calibrated equilibrium of this

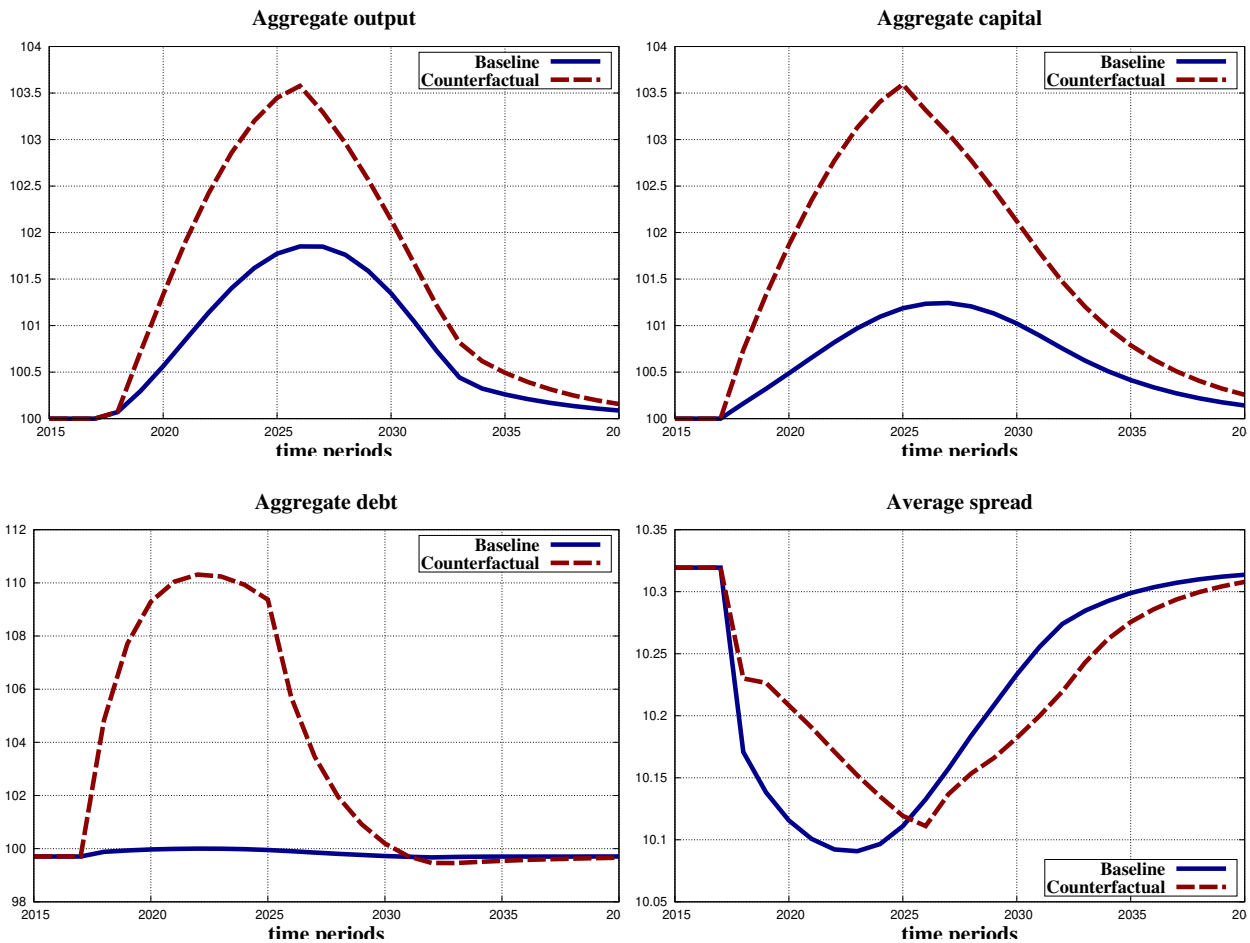


Figure 16: Main aggregates over the transition

model (24%). Even though the control group's credit contracts by about 5%, capital only falls by about 1%. On the other hand, among the treated group, debt expands by about 5% and capital increases by 3%, even though this group has the same starting leverage ratio. The additional capital investment is financed with two channels. First, the fall in interest rate spread of about 0.5% creates fiscal space to finance more investment. Second, the treated group reduces its dividend consumption by about 1.5%, before increasing it considerably over the transition as productivity and output rise.

In the counterfactual scenario, the credit reallocation effect is halved. The treated firms expand their leverage by much more than in the baseline while firms in the control group reduce their position by less. Hence, the increase in output in the counterfactual exercise relative to the baseline comes partly from the treated firms and partly from the untreated ones.

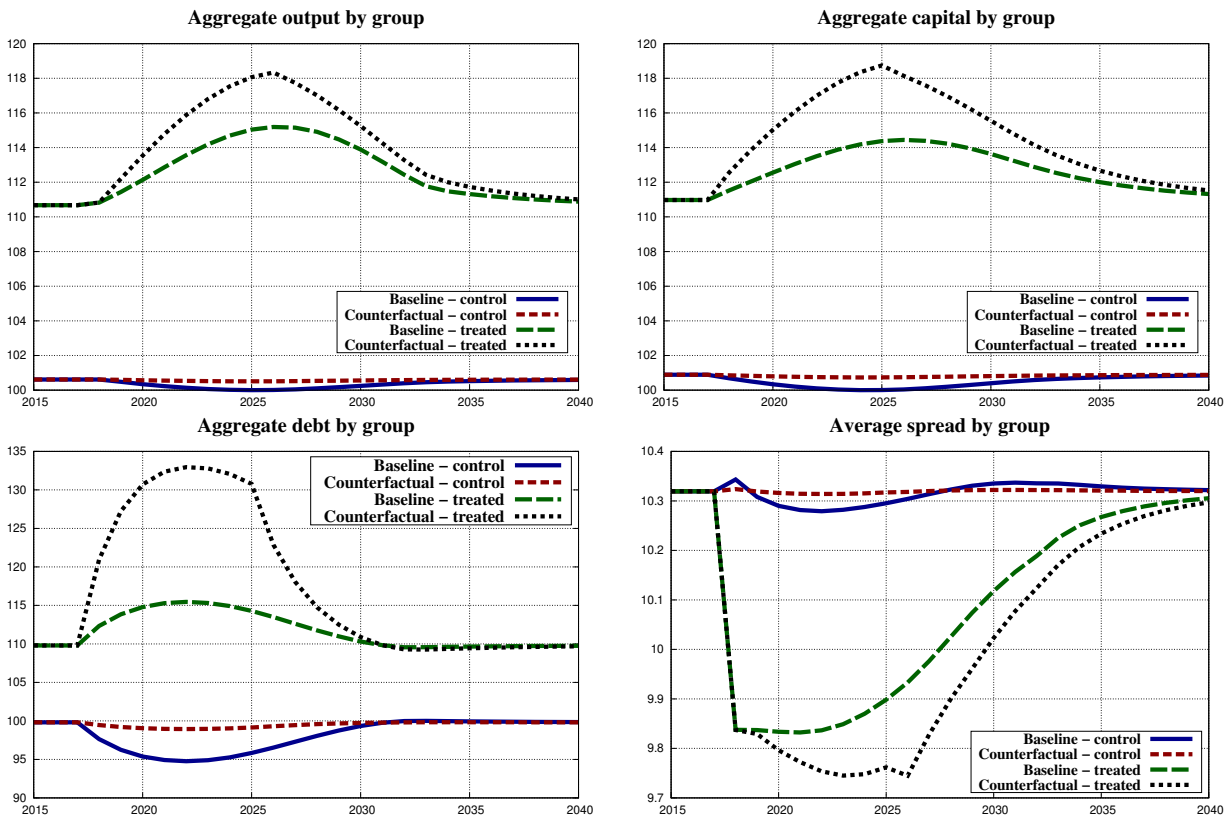


Figure 17: Main aggregates over the transition by group

5 Conclusion

We examine the effect of the 2018-2020 US-China trade war on the corporate credit market in Mexico. We cast the episode as an exogenous shock and apply difference-in-differences methodology to tease out the causal effect on firm borrowing and other lending characteristics. We leverage the rich credit registry dataset to control for typical identification issues. We find the that trade war resulted in up to 10% higher credit provision to firms in the industries affected by high tariffs relative to those in low tariff industries, and the statistically significant effect persists until today.

We use the estimates from this natural experiment to inform a quantitative general equilibrium model of the production sector of Mexico's economy. By matching the experiment in our model, we tease out demand effects the trade war had on the affected firms. We show that Mexico could have doubled its output growth from this episode if the economy featured a more elastic credit supply curve, allowing the firms who experience positive shocks to grow without negatively affecting other firms' ability to borrow.

Our results are robust and suggest a rich agenda for further research. For instance, it would be interesting to investigate the role of other types of lenders who also grant credit to private non-financial firms, such as development banks and multi-purpose financial companies (known as sofomes), in the course of the trade war. It would also be interesting to examine whether the effects of the trade policies and tariffs imposed in 2025. These and other issues are left for future research.

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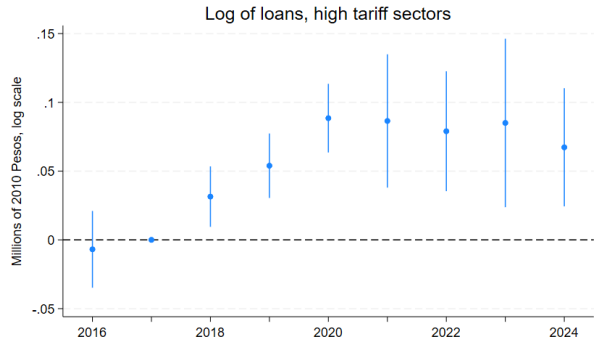
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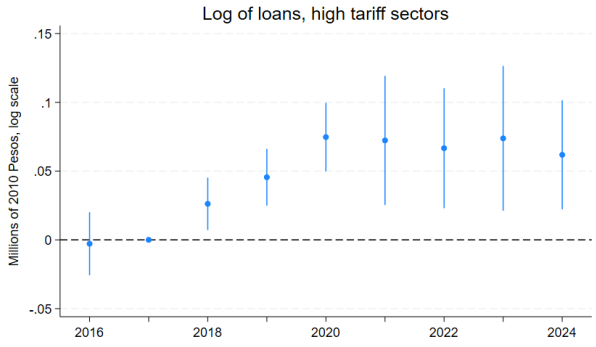
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A Additional Figures and Tables



(a) Baseline result

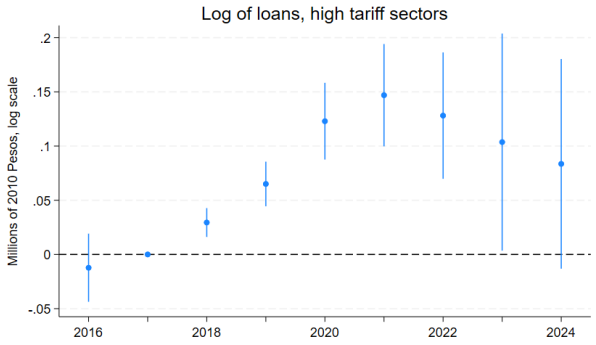
$N_{obs} = 3.28m$, R^2. adj.$= 0.76$



(b) Bank-state-year FE

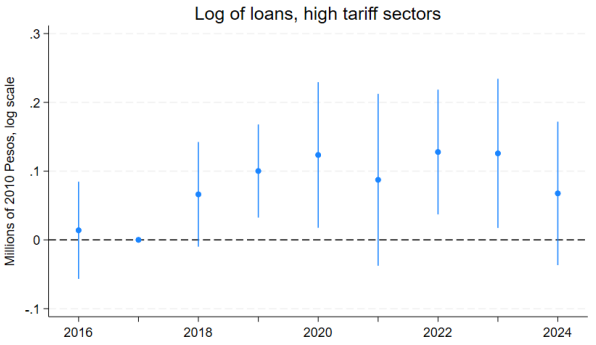
$N_{obs} = 3.33m$, R^2. adj.$= 0.77$

Figure 18: Robustness of quantity regression: bank-state-year fixed effects vs. baseline



(a) Including services and 0 tariffs

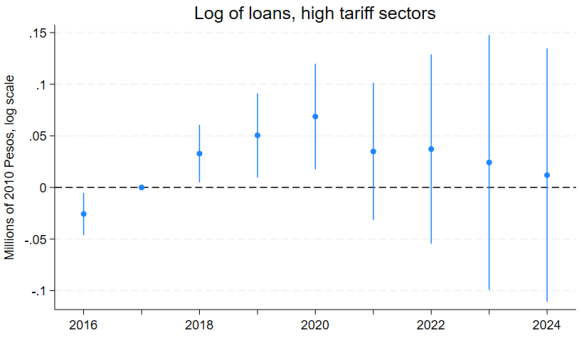
$N_{obs} = 15.62m$, R^2. adj.$= 0.76$



(b) New loans only

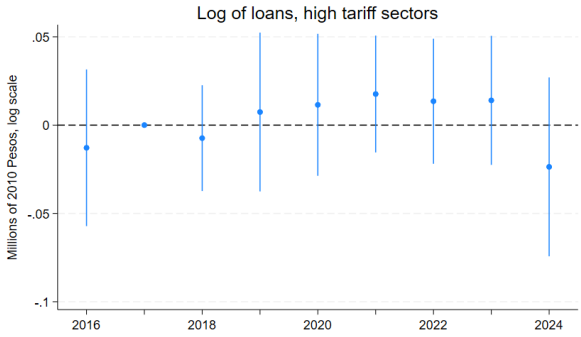
$N_{obs} = 199.57k$, R^2. adj.$= 0.71$

Figure 19: Robustness of quantity regression: including services and new loans only



(a) Non-revolving loans

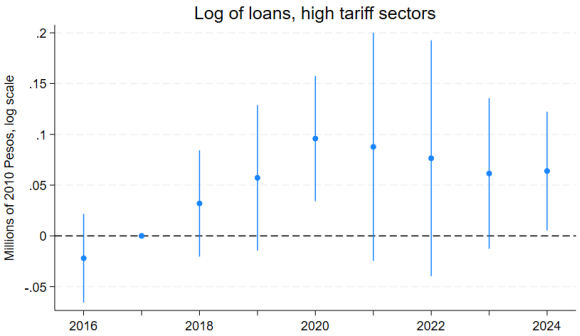
$N_{obs} = 1.56m$, R^2. adj.$= 0.83$



(b) Revolving loans

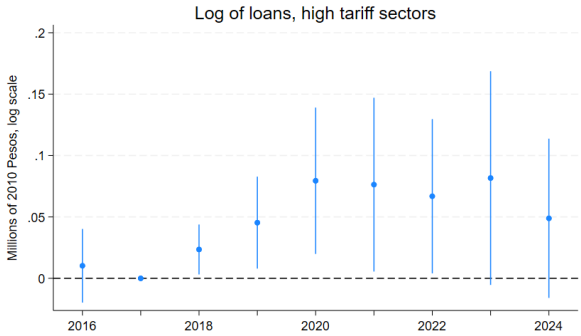
$N_{obs} = 1.69m$, R^2. adj.$= 0.75$

Figure 20: Robustness of quantity regression: non-revolving vs. revolving loans



(a) Large business units

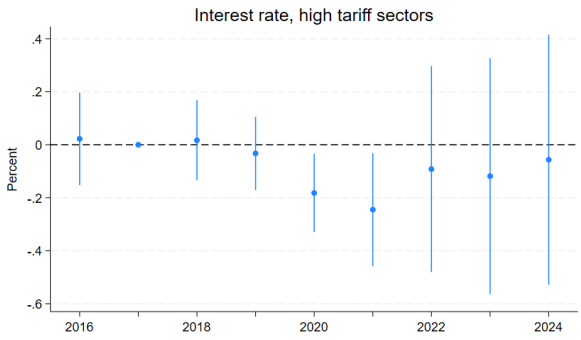
$N_{obs} = 1.13m$, R^2. adj.$= 0.64$



(b) Small business units

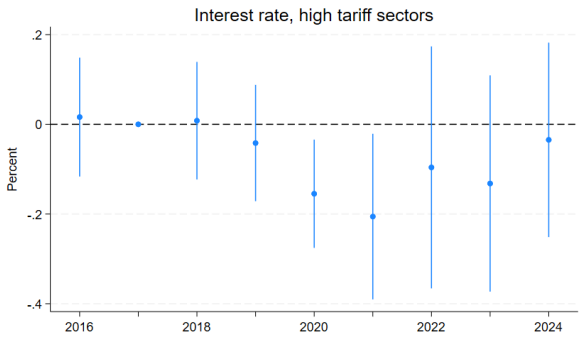
$N_{obs} = 2.15m$, R^2. adj.$= 0.67$

Figure 21: Robustness of quantity regression: by business unit sizes



(a) Baseline result

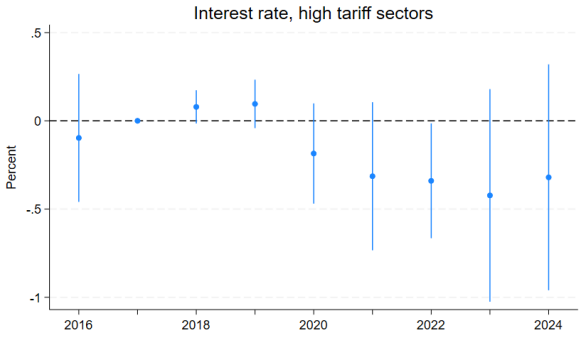
$N_{obs} = 3.28m$, R^2. adj.$= 0.57$



(b) Bank-state-year FE

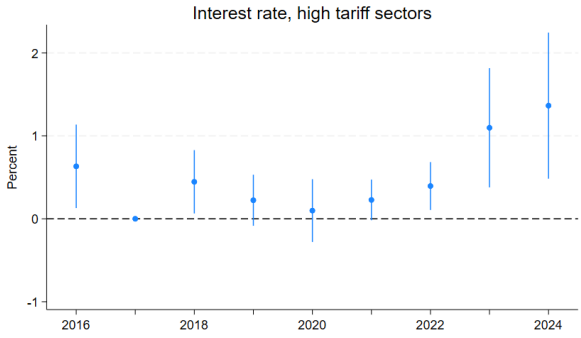
$N_{obs} = 3.33m$, R^2. adj.$= 0.59$

Figure 22: Robustness of interest rate regression: bank-state-year fixed effects vs baseline



(a) Including services and 0 tariffs

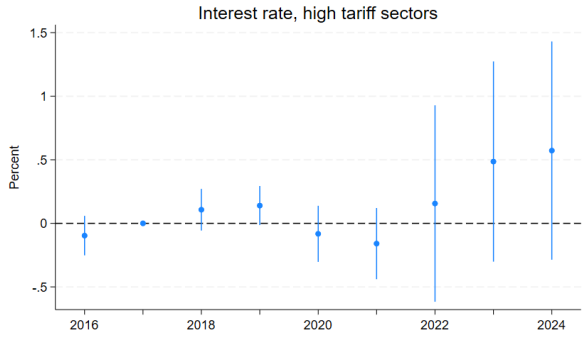
$N_{obs} = 15.62m$, R^2. adj.$= 0.59$



(b) New loans only

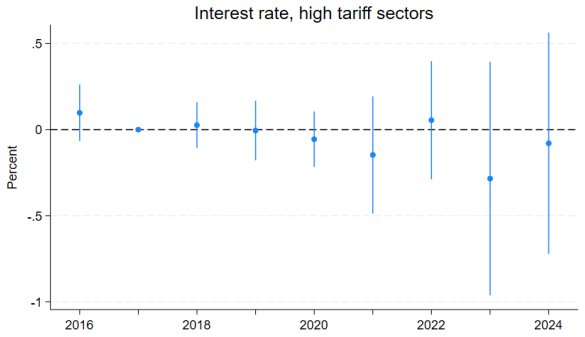
$N_{obs} = 199.57k$, R^2. adj.$= 0.41$

Figure 23: Robustness of interest rate regression: all industries vs. new loans only



(a) Non-revolving loans

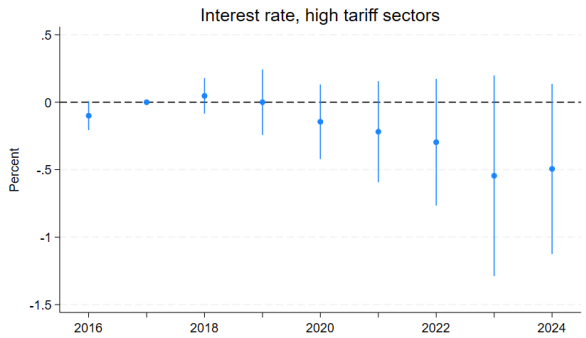
$N_{obs} = 1.56m$, R^2. adj.$= 0.56$



(b) Revolving loans

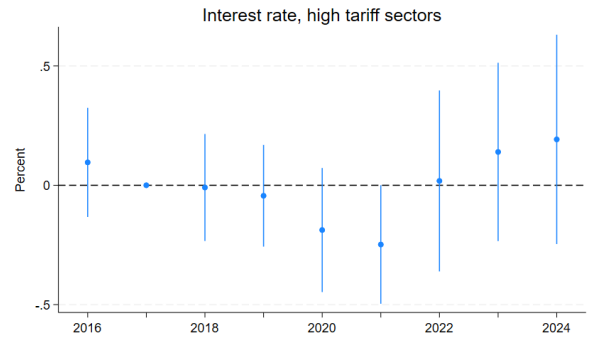
$N_{obs} = 1.69m$, R^2. adj.$= 0.64$

Figure 24: Robustness of interest rate regression: non-revolving vs. revolving loans



(a) Large business units

$N_{obs} = 1.13m$, R^2. adj.$= 0.67$



(b) Small business units

$N_{obs} = 2.15m$, R^2. adj.$= 0.50$

Figure 25: Robustness of interest rate regression: by business unit sizes

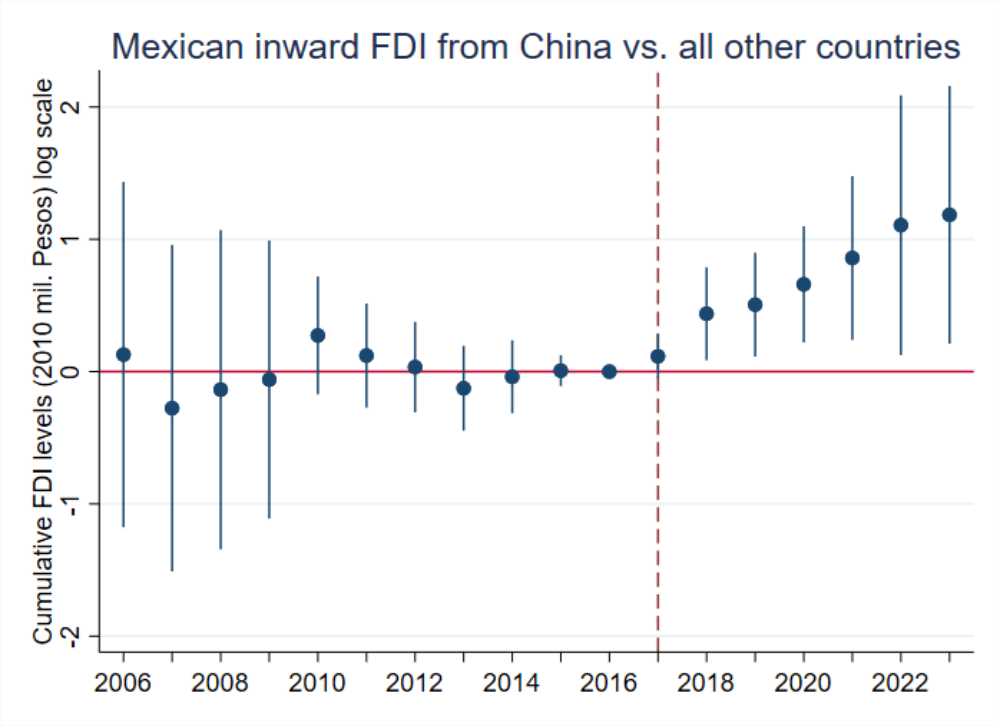


Figure 26: FDI in Mexico: China vs all other countries

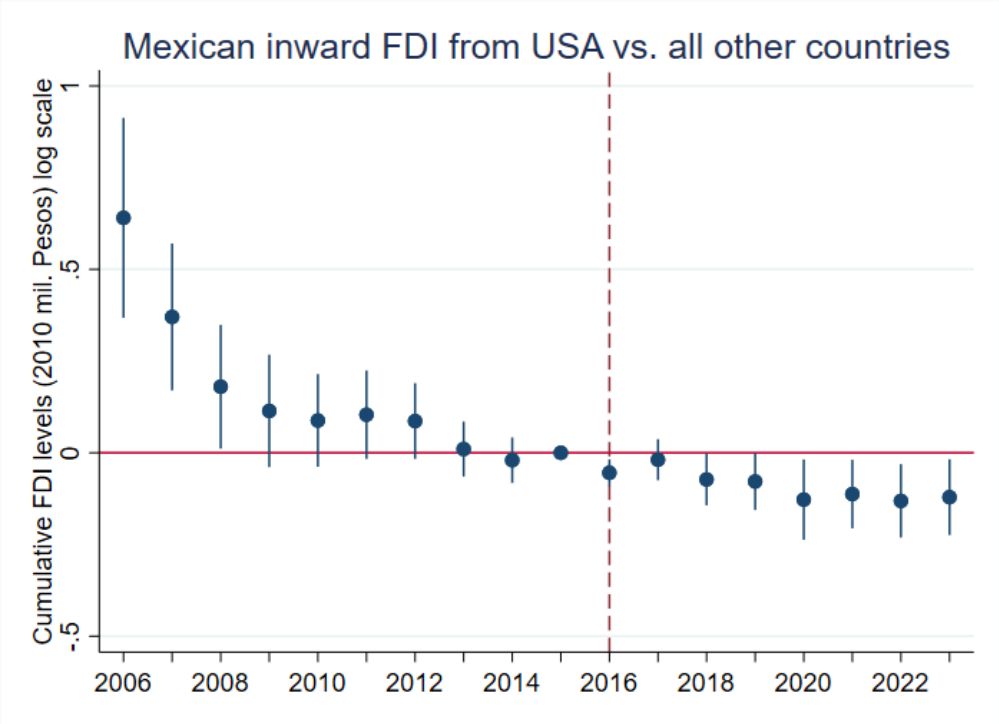


Figure 27: FDI in Mexico: US vs all other countries