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Early effects of nearshoring in the manufacturing labor market in Mexico

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Early effects of nearshoring in the manufacturing labor market in Mexico^{*}

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Abstract: We apply the synthetic control method to analyze the initial effects of nearshoring on labor outcomes in Mexico's manufacturing sector from July 2020 to June 2023. Our methodology compares jobs, earnings, and productivity among industry groups more likely to be affected by nearshoring, as identified through a propensity index, with a counterfactual constructed from less likely affected industries. Our results indicate that nearshoring is potentially generating early gains in manufacturing jobs but has not led to improvements in earnings. Furthermore, we do not observe a consistent impact on productivity, although some specifications suggest a modest positive effect in industries with a higher nearshoring propensity. While nearshoring effects may take longer to materialize, our findings highlight its initial implications for the Mexican manufacturing sector.

Keywords: Nearshoring, Manufacturing Sector, Jobs, Earnings, Productivity

JEL Classification: J01, J40, F61

Resumen: Aplicamos el método de control sintético para analizar los efectos iniciales de la relocalización en el mercado laboral del sector manufacturero mexicano de julio de 2020 a junio de 2023. Nuestra metodología compara empleos, ingresos y productividad entre las ramas industriales con mayor probabilidad de verse afectados por la relocalización, las cuales son identificadas mediante un índice de propensión, con un contrafactual construido a partir de ramas con menor probabilidad de verse afectadas. Nuestros resultados indican que la relocalización generó ganancias iniciales en empleos manufactureros, pero no conllevó mejoras en los ingresos. Además, no encontramos resultados concluyentes sobre la productividad, aunque algunas especificaciones sugieren un efecto positivo moderado en industrias con mayor propensión a la relocalización. Si bien los efectos completos podrían tardar en materializarse, nuestros hallazgos resaltan sus implicaciones iniciales para el sector manufacturero de México.

Palabras Clave: Relocalización Productiva, Sector Manufacturero, Empleos, Ingresos, Productividad

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I. Introduction

The reconfiguration of global supply chains and the resulting relocation of production have garnered significant attention from academics, government offices, financial and non-governmental institutions, and the media. These stakeholders seek to understand and measure the effects of this process called nearshoring on economic indicators. Nearshoring represents an opportunity for various developing countries, as it could increase investment and production levels by enhancing their participation in global value chains. However, quantifying its economic impact remains challenging due to limited data and the difficulty of constructing a counterfactual scenario that isolates its effects from other contemporaneous shocks.

Nearshoring involves relocating production activities to counter offshoring by geographically concentrating production supplies (Pietrobelli and Seri 2023). This stems as a particularly favorable opportunity for Mexico, driven by its proximity to the United States and its cost-competitive labor compared to other countries. Mexico's rise as the top U.S. trading partner and the burgeoning trend of nearshoring underscore the profound impact of evolving global supply chains. Its strategic advantages, coupled with policy shifts and trade dynamics, position it as a pivotal player in the ongoing reconfiguration of international commerce. For these reasons, we believe it is essential to quantify the effects of nearshoring on Mexican jobs, earnings and productivity, to confirm its benefits and propose policies to prepare all regions to maximize these potential gains.

During the late twentieth century, maquiladoras became a cornerstone of Mexico's economy, particularly in the northern region, driving industrial growth in sectors such as electronics, automotive, and textiles (Contreras and Munguia 2007; Carrillo and Zárate 2009). Despite their significant contribution to economic development, this model revealed critical limitations, including a decline in productivity over time (de la Garza 2007). As Mexico embraces nearshoring as a new avenue for economic advancement, it is crucial to critically examine its evolution and impacts to avoid perpetuating a low productivity scheme such as with the maquiladora model.

At the outset of 2023, Mexico became the United States' leading trading partner, moving up from second place and surpassing China, as reported by the U.S. Census Bureau.

Although the two countries already maintained a high level of economic integration, this shift was partly driven by the trade escalation between the United States and China, initiated by the trade war between the two countries in 2017 and the subsequent trade restrictions imposed (Oropeza 2024). Additionally, transformations in global supply chains due to the COVID-19 pandemic and the war between Russia and Ukraine have enhanced Mexico's image as a potential investment destination, offering greater certainty and lower systemic risk in production chains (Berasaluce 2024). These disruptions in global supply chains revealed their fragility due to their "extensive geographical reach and the difficulty of managing the issue", a situation further exacerbated by protectionist measures. This has underscored the importance of the regional dimension and, consequently, the relevance of geographical proximity inherent in nearshoring (Garrido 2022). The Bank of Mexico's Regional Economic Reports have extensively documented this process anecdotally and qualitatively: According to its April-June 2024 Report, as of July 2024, 12.9% of companies with more than 100 workers in Mexico have reported favorable impacts attributed specifically to nearshoring (Banco de México 2024).

Efforts to measure the potential impacts and benefits of nearshoring in Mexico have gained momentum. For example, a recent analysis by Chiquiar and Tobal (2024) provides evidence that the early nearshoring process improved Mexico's GDP by 1% over the past five years, with the potential for an additional increase of more than 0.8% in the coming years. Their analysis considers a counterfactual scenario examining the effects of the U.S.-China trade war on Mexico's manufacturing exports to the United States. The paper also identifies industries already benefiting from increased exports, such as computer and peripheral equipment manufacturing, beverages, semiconductors, electronic components, other electrical equipment, and communications equipment manufacturing.

In a separate analysis, Alfaro and Chor (2023) examine the decline in U.S. supply chain activity in China, identifying Vietnam and Mexico as the primary beneficiaries of increased U.S. import shares. They enhance their study by performing robustness checks, documenting firm-level decisions to shift activity away from China. By analyzing earnings call transcripts for terms like reshoring, nearshoring, and friendshoring, alongside mentions

of specific countries, their results confirm these trends. Vietnam leads in mentions, followed by Mexico, in discussions about shifting sourcing strategies.

Utar, Torres, and Cebreros (2023) underscore the reorganization of global value chains toward Mexico in response to the U.S.-China trade war. The analysis highlights Mexico's advantages, such as its economic integration with the United States, participation in the US-Mexico-Canada Agreement and competitive labor costs. Notably, Mexican firms integrated into global value chains have experienced a significant boost in exports to the U.S. during the trade war, demonstrating the tangible benefits of this shift.

In this paper, we employ a methodology to identify the early effects of nearshoring on labor outcomes in Mexico's manufacturing sector by contrasting industry groups with a higher probability of being affected by nearshoring against a counterfactual constructed from less susceptible sectors, by using an index of nearshoring propensity covering the period from July 2020 to June 2023. As a contribution to the literature that examines the effects of nearshoring on the labor market in Mexico's manufacturing sector, our findings reveal that manufacturing industry groups with a higher proclivity for nearshoring, as defined in this work, have experienced an increase in the number jobs from July 2020 to June 2023 compared to the counterfactual scenario. Interestingly, we did not find a discernible impact on earnings per employee during the same period. Productivity results suggest a small positive effect of nearshoring but are inconclusive. Our results provide valuable insights into the effects of the nearshoring process during the period under study, offering empirical evidence that complements qualitative information derived from business contacts, interviews and the media. These results emphasize the importance of closely monitoring this process to avoid replicating maquiladora challenges, which created jobs but yielded limited improvements in productivity and wages.

The remainder of this paper is organized as follows: In Section II we introduce our nearshoring propensity index. In Section III, we outline our identification strategy for quantifying the impact of nearshoring in Mexico. Section IV contains a description of the data used, while Section V presents our empirical findings. Finally, In Section VI we offer concluding remarks.

II. Index of propensity to nearshoring

To determine which industry groups in Mexico's manufacturing sector are more likely to be affected by the process of relocating plants and production lines closer to the final market (the United States), we constructed a nearshoring propensity index. This index was developed by sampling the number of results (news articles, documents, reports, etc.) returned by Google's search engine when entering the term "nearshoring" together with the name of the industry group and the word "Mexico." Subsequently, this number was divided by the total results obtained from a joint search for the name of the industrial activity and the word "Mexico." This index represents the relative frequency of nearshoring mentions in relation to the total results found for each industry group. We propose that it be interpreted as a measure of the likelihood of an industry group being affected by nearshoring. However, it does not necessarily indicate it is actually affected nor the magnitude of such impact from the relocation of plants and production lines (nearshoring).

Our searches were conducted in both Spanish and English, using the names of the industry groups from the North American Industry Classification System (NAICS) at the 4-digit level. This exercise considered the number of search results for the period between January 1, 2015, and May 9, 2023. We used quotation marks in the search terms to ensure exact matches and to enforce the inclusion of those terms in the retrieved content. Commonly used words, such as function words and lexical fillers, were removed from the names before performing the searches. In cases where the term "except" appeared in the industry group name, the words following it were excluded from the results by prefixing them with a minus sign. For example, for the industry group named Fiber, Yarn, and Thread Mills, the search was conducted as "fiber" "yarn" "thread" "mills" "nearshoring" "Mexico". Meanwhile, for Nonferrous Metal (except Aluminum) Production and Processing, the search was conducted as "nonferrous" "metal" -aluminum "production" "processing" "nearshoring", "Mexico". It is important to note that this approach does not rely on browser search dynamics, such as those provided by Google Trends. Instead, it focuses on the volume of news articles, reports, documents, and other content containing the specified terms.

The results of this exercise should be interpreted with consideration, as they depend on Google's search algorithm and the policies governing its search results. Consequently, the

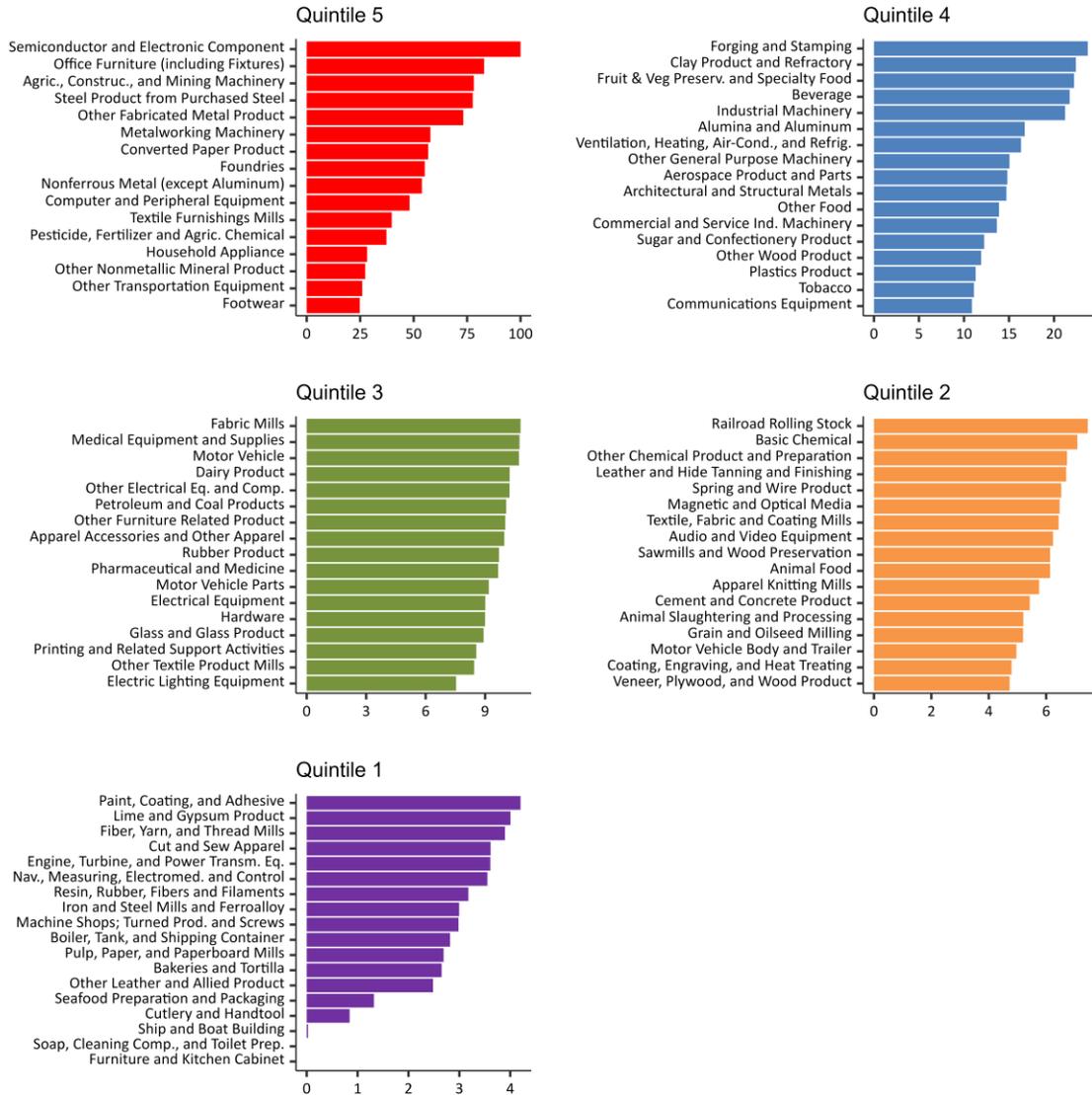
index may vary even when repeating the same procedure, thus limiting the exact reproducibility of the results. This variability arises from factors such as periodic updates to combat spam, improvements to the search algorithm, and changes in the availability of content, whether due to the removal of previously indexed pages, articles, or other materials, or the inclusion of newly discovered sites.

In Graph 1 we present the results of this exercise, ranking the industry groups by quintiles.¹ The groups highlighted in red are the most likely to be affected by nearshoring, based on this index. The industry groups with the highest propensity for nearshoring include: semiconductor and electronic components, office furniture, agricultural, construction, and mining machinery, as well as steel and metallic products.²

¹ Excluding the industry group named “Other miscellaneous manufacturing”, whose results are highly likely to be contained in those of other industries.

² When constructing the index by making the Google searches, we noticed a majority of positively oriented news. However, in order to illustrate and get a better sense of the content, we performed an additional exercise and, when searching the terms "nearshoring" "mexico" OR "m xico" in Google, we got 6 million 530 thousand results, but when we forced the exclusion of the negatively-oriented words "cancel", "cancels", "cancelled", "cancellation", "delay", "delayed", "postponed" and "shutdown" from this same search, there were 5 million 590 thousand results left, which represent 86% from the total. This suggests that the proportion of this published content tends to be more positively reported.

Graph 1. Nearshoring propensity index of manufacturing industry groups, by quintile
 Maximum propensity = 100



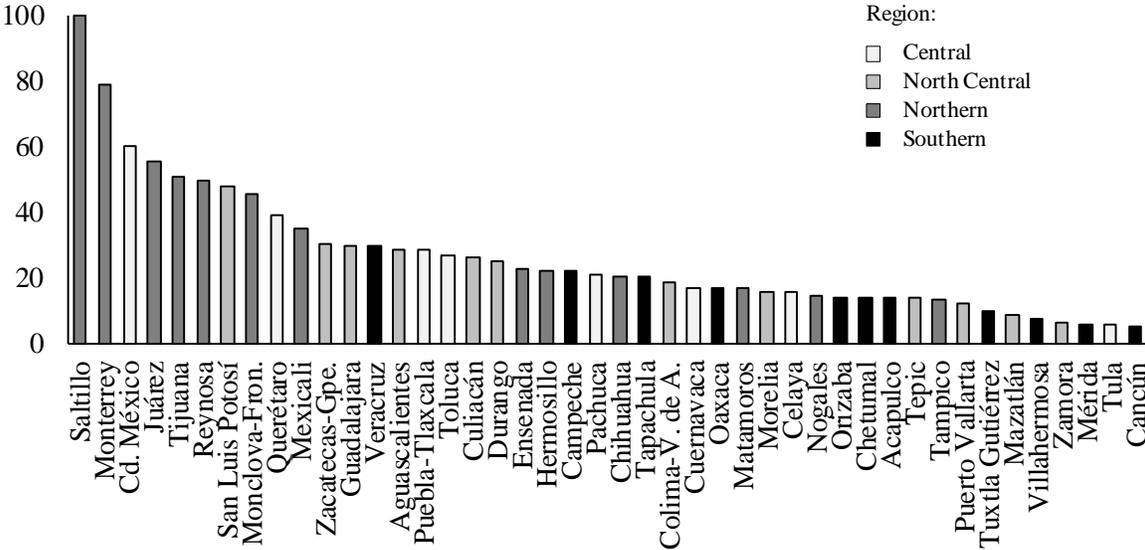
Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023. Note: The index is normalized in such a way that the industry group with the highest propensity takes the value of 100 and the rest is presented in terms relative to this base.

Notes: This index shows relative mentions of nearshoring in relation to all the results found in each industry group and could be interpreted as the probability of each one of being affected by nearshoring, not necessarily implying that it actually is, nor reflecting the magnitude of its potential impact.

To further analyze the behavior and reliability of our methodology, we also applied this procedure to construct an index for the main metropolitan areas of Mexico. The results

are shown in Graph 2, where the cities are grouped by region.³ The findings indicate that the cities with the highest propensity for nearshoring are predominantly located in the northern region, including Saltillo, Monterrey, Juárez, and Tijuana. Additionally, some large cities in the central region also exhibit high index values, such as Mexico City, San Luis Potosí, and Querétaro. This outcome bolsters confidence in the index, as it aligns with general knowledge—albeit qualitative—on nearshoring trends.⁴

Graph 2. Nearshoring propensity index by metropolitan area of Mexico
Maximum propensity = 100



Source: Prepared by the authors with data from the Secretariat of Agrarian, Territorial, and Urban Development and Google Search Engine, January 2015 to May 9, 2023.

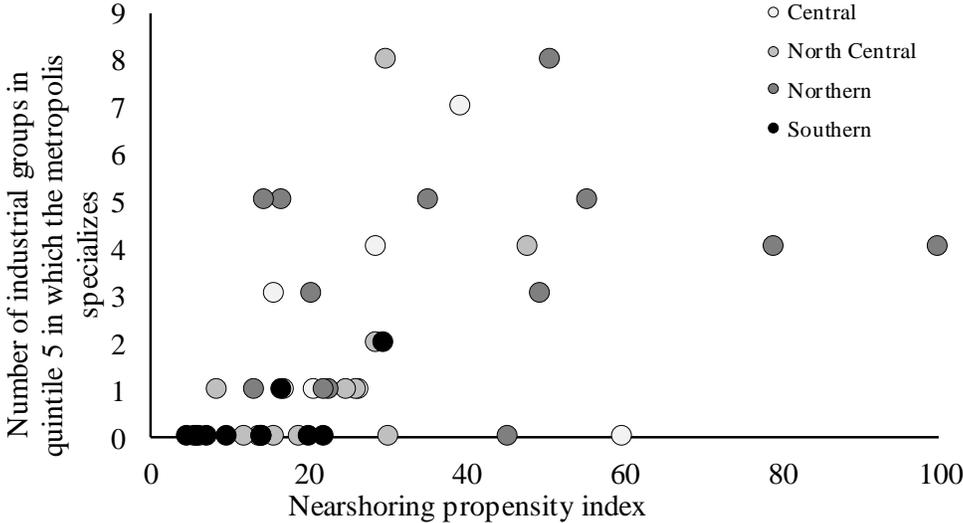
Notes: Values are normalized relative to the metropolis with the highest percentage of their Google search results that contain the term 'nearshoring'. Fill colors represent the regions into which Mexico is divided according to Banco de México's classification.

³ Our analysis is performed for four regions: Northern, North-Central, Central and Southern. This regionalization corresponds to the one used by Banco de México in its Regional Economic Reports. Specifically, the Northern region includes the states of Baja California, Chihuahua, Coahuila, Nuevo León, Sonora and Tamaulipas; the North-Central region comprises Aguascalientes, Baja California Sur, Colima, Durango, Jalisco, Michoacán, Nayarit, San Luis Potosí, Sinaloa and Zacatecas; the Central is made up of Mexico City, State of Mexico, Guanajuato, Hidalgo, Morelos, Puebla, Querétaro and Tlaxcala; and the Southern region covers Campeche, Chiapas, Guerrero, Oaxaca, Quintana Roo, Tabasco, Veracruz and Yucatan.

⁴ Our index uses data from January 2015 to May 9, 2023, and considers metropolitan areas defined by the National Urban System 2018. However, the cities of Delicias, La Laguna, La Paz, La Piedad, and León were excluded because their search results included information unrelated to those cities. Similarly, we omitted terms related to newspapers that share names with any of the sampled cities to avoid overestimating the volume of news referencing these metropolitan areas.

Furthermore, we analyzed the association between the nearshoring propensity of each metropolitan area and the number of Quintile 5 manufacturing industry groups in which these metropolitan areas specialize.⁵ Graph 3 illustrates the linear relationship between these variables. The observed association suggests that cities with a higher propensity for nearshoring also tend to specialize in a greater number of industry groups with a high nearshoring propensity index. Specialization was determined using data from the 2019 Economic Censuses.

Graph 3. Industries’ specialization and nearshoring propensity index by metro area
Each point represents a metropolitan area



Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.

Notes: Specialization was determined with data from the 2019 Economic Censuses, in such a way that a city specializes in an industry group if the percentage that it represented in the gross added value of the industry is higher than that represented by it in the corresponding value at the national level. The colors represent the regions into which Mexico is divided according to Banco de México's classification.

III. Identification Strategy

Quantifying the impact of nearshoring in Mexico on economic indicators poses significant challenges, particularly in constructing a counterfactual scenario that disentangles

⁵ For the purpose of our work, a city specializes in an industry group if the percentage that represents the industry group of its total gross value added is higher than that corresponding value at the national level.

the effects of nearshoring from other contemporaneous shocks affecting the Mexican economy. In other words, it is difficult to distinguish changes in outcome variables caused by nearshoring from those driven by other factors, or to separate the changes in variables such as jobs, earnings, and productivity that are attributable to nearshoring from those that result from their prior trends. A simple comparison of these response variables' performance between manufacturing industry groups with varying propensities to nearshoring could capture not only the impact of nearshoring on them, but also the effects of other contemporaneous shocks.

To identify the initial effects of nearshoring on labor outcomes in Mexico's manufacturing industry, we employed the synthetic control method (SCM). The SCM offers several advantages over other inference algorithms, including its ability to address issues of unobserved heterogeneity (Abadie, Diamond and Hainmueller, 2010), its effectiveness in handling small sample sizes where traditional matching methods might face limitations (Abadie, Diamond and Hainmueller, 2015), its capacity to combine multiple control units to create a synthetic control group that provides a more robust counterfactual for the treated unit (Abadie, Diamond and Hainmueller 2010), and its ability to handle time-varying covariates, allowing the incorporation of dynamic changes in both treatment and control units (Abadie and Gardeazabal 2003).

According to Abadie (2021), the core idea of the SCM is to construct a counterfactual scenario for a variable that represents the outcomes of the treated unit in the post-treatment period under a hypothetical situation in which the treatment never occurred. By comparing the actual outcomes with those of the synthetic control, the treatment effect can be estimated. This is achieved by constructing a synthetic control unit from a pool of donor units (which did not receive the treatment) and comparing the outcomes of the treated unit to those of the synthetic control after the treatment begins. Using a minimum distance approach, SCM selects weights for the donor units to form the synthetic control that best resembles the treatment unit's outcome and through a set of predictor variables measured prior to the treatment's start. Weights for control units are restricted to non-negative values and must sum to one, ensuring no extrapolation beyond the support of the data.

In our study, we compare industry groups with a higher probability of being affected by nearshoring to a counterfactual constructed using the behavior and characteristics of other industries less likely to be influenced by nearshoring. It is important to emphasize that, for our work, the treatment refers to having a high propensity for nearshoring, as measured by the index previously detailed, rather than the actual process of nearshoring itself, so our results correspond to intentions-to-treat, since we estimate the effect of being assigned to treatment (nearshoring), regardless of whether the industry group actually received it.

In general terms, our objective is to estimate Equation 1:

$$\tau_{1t} = Y_{1t}^{High\ propensity} - Y_{1t}^{Low\ propensity} \quad (1)$$

Where τ_{1t} represents the intention-to-treat effect on the outcome variable of interest Y at time t for unit 1. Without loss of generality, we assume that unit 1 is the one receiving the treatment. To estimate this effect, we compared the trajectory of the fifth quintile ($Y_{1t}^{High\ propensity}$) of the propensity-to-nearshoring index (treatment industries group) with a counterfactual constructed using a weighted combination of industry groups that exhibit similar behavior and are subject to the same shocks over time but are less likely to be affected by nearshoring (synthetic control). Specifically:

$$\hat{\tau}_{1t} = Y_{1t}^{High\ propensity} - \hat{Y}_{1t}^{Low\ propensity} \quad (2)$$

where:

$$\hat{Y}_{1t}^{Low\ propensity} = \sum_{j=2}^{J+1} w_j Y_{jt} \quad (3)$$

In this case unit 1 is the treated group and units $j = (2, \dots, J + 1)$ are the J industry groups in the donor pool (quintiles 1-3).

The weights w_j are selected to replicate the behavior and characteristics of the treatment group prior to nearshoring, both on the outcome variable of interest and its relevant predictors, in order to achieve a proper counterfactual scenario where the unique difference between this synthetic control and the observed treated unit is the treatment. Thus, for the SCM to be valid, it is assumed that no nearshoring occurs in any industry group other than

the treatment group. To ensure this assumption holds, we excluded industry groups in quintile 4 from the donor pool, as their inclusion could potentially bias the estimate.

The treatment period is marked by the COVID-19 pandemic and by a strong growth in external demand, which could bias the results if industries with higher propensity-to-nearshoring also experienced heterogeneous effects for reasons distinct to nearshoring. The possibility of new shocks affecting units differently after treatment remains a concern, as is common in any inference study, since these could influence and bias the estimates. One such factor is the increase in minimum wages in border regions, which may alter employment dynamics independently of nearshoring. Given that the northern region is more likely to host industries in the top quintile of the nearshoring propensity index, it is crucial to consider whether part of the observed employment effect is driven by this policy rather than nearshoring itself. Additionally, broader policy changes, such as the U.S. Chips Act and the Inflation Reduction Act, may have influenced investment patterns in certain manufacturing activities during the post-treatment period, further complicating the attribution of effects.

First, to address some of these potential difficulties, we analyzed the correlation at the industry group level between the propensity-to-nearshoring index and the growth rate of total U.S. imports from 2019 to 2022 (used as a proxy for demand). While the correlation is positive, it is not statistically significant, as many industry groups with high import growth are classified as having lower propensity in the index (not only those in quintile 5, as shown in Graph 1). Regardless, to further minimize potential bias, we excluded from the analysis the five industries with the largest increases in U.S. demand during the treatment period.⁶ Secondly, we chose the pre-treatment period to span from January 2013 to June 2020, and the treatment period to extend from July 2020 to June 2023. We picked the extended pre-treatment period up to June 2020 to identify a combination of industry groups that experienced similar effects to the treatment group units during the pandemic. This approach improves the similarity between the synthetic control and the treatment group in terms of composition and dynamics. While unobserved covariates may introduce heterogeneity in the

⁶ The annual growth rate in US imports is estimated using data from the US Census Bureau. US import data were deflated using the Bureau of Labor Statistics' Beta Lab producer price indexes by industry. Among the excluded industry groups of activity are three that belong to quintile 5, which correspond to the non-ferrous metals industry, except aluminum; manufacture of electronic components; and manufacture of other transportation equipment. The results are also robust when removing those industry groups from the 90th percentile upwards, or those that are more than one standard deviation away from the mean.

post-treatment period, incorporating lags of the outcome variable into the algorithm to estimate the weights, as we did, helps account for most unobservable factors that could influence the response variables during this phase.

Even with these considerations, there is no guarantee that donor pool industries remain unaffected by nearshoring. Additionally, some selected industry groups in the synthetic control may compete with the treatment group for workers, potentially leading to an overestimation of the intention-to-treat effect. Moreover, there could be spillover effects unaccounted for, which could violate the assumptions for the SCM to work properly. However, we consider that grouping industries into quintiles based on their propensity for nearshoring index helps mitigate these biases by capturing more aggregated industry behaviors. Furthermore, we analyzed the manufacturing sectors using the input-output matrix published by INEGI and found that only 13.8% of the intermediate demand of the treatment group sectors corresponds to the donor pool output. Moreover, when considering the weights assigned to these sectors to construct the synthetic control for jobs, as presented below, the percentage decreases to 9.1%. This result bolsters the confidence in the donor pool and in the weights assigned by the algorithm. Nevertheless, the results should be interpreted with care.

During the analysis, we conducted sensitivity assessments and placebo tests to evaluate the robustness of the results. As commonly done in the literature, after obtaining the synthetic control for each outcome variable, we re-estimated each model under the assumption that the treatment occurred twelve months earlier, to evaluate the extent to which the pre-treatment period makes sense. Additionally, to further ensure that the observed differences between the treated series and their counterfactuals were not due to chance or poor model fit, we employed the nonparametric permutation test proposed by Abadie (2021). Intuitively, this test assesses how likely it is to observe a result of the magnitude found between the treated group and the counterfactual. This is achieved by applying the SCM to each industry group in the donor pool as if they were treated, known for this reason as placebo tests. If this exercise yields differences similar in magnitude to those observed for the industry groups in quintile 5 of the nearshoring propensity index, it would suggest that there is no significant evidence of a nearshoring effect on jobs, wages, or productivity in the treated industry groups. Conversely, if these permutation tests—where the SCM is iteratively

applied to untreated industry groups—show that the estimated difference for the industry groups in quintile 5 is significantly higher in relative terms than those for industry groups in quintiles 1 to 3 (Figure 1), it would provide statistical evidence of distinct behavior in the treated manufacturing industry groups. We present these in-time and permutation placebo tests after the main results are shown.

IV. Data

For the construction of the synthetic control through the weighted average described above, we used lags of the response-variables, as well as covariates that help explain their evolution. All outcome and explanatory variables were sourced from the Monthly Survey of the Manufacturing Industry (Encuesta Mensual de la Industria Manufacturera), a representative survey of Mexico’s manufacturing sector. This survey provides monthly statistics on the economic behavior of key variables in the manufacturing industry and allows for disaggregation up to the 6-digit NAICS level. To ensure comparability, we adjusted all monetary variables to constant 2019 Mexican pesos for the analysis.

We evaluated the differential behavior between the treatment group and its synthetic control for three labor market indicators at the industry group (4-digit NAICS) level:

1. The average number of jobs per industry group
2. Total earnings per employee
3. The production value per hour worked (productivity)

The intention-to-treat estimated effects aim to reflect the impact of nearshoring on these key indicators, capturing the differences between the treatment group and its synthetic counterpart.⁷

We used as covariates in the analysis the percentage of installed capacity utilization and the percentage of subcontracted personnel (to account for potential effects of changes in

⁷ The average number of jobs of the fifth-quintile industry groups was calculated as the arithmetic mean of the total employed personnel per industry group within the treated group. Meanwhile, the total number of jobs in industry groups from quintiles 1 to 3 was used to construct the counterfactual. Remuneration per employee in the treated group was determined by dividing total remunerations by the total number of employed personnel. Productivity was calculated by dividing the sum of the production value added in the fifth quintile industries by the sum of the hours worked. The synthetic control was then constructed using a weighted average, where the weights minimized the difference between the treated group’s indicator and the corresponding ratio for industry groups in quintiles 1 to 3. These variables were chosen to ensure that the treated group series remained within the convex hull of the donor pool, as required by the Synthetic Control Method.

Mexico's outsourcing laws). Additionally, all models included three lagged averages of the response variables: one for the first half of the months in the pre-treatment period, one for the second half (excluding the last two months), and one for the two-month period immediately prior to the treatment to account for the effects of the pandemic. Among the reasons for using the SCM for our analysis is that, at the industry group level, there are not a large number of variables that could be used as controls for inference. However, the ability of this methodology to take advantage of the information contained in the lags of the outcome variables gives us greater confidence that unobserved heterogeneity is being mitigated. Likewise, the choice of the installed capacity used, as a measure of industry dynamics, and that of the percentage of subcontracted personnel seems to us to be consistent in explaining the evolution of the variables we seek to analyze, in addition to the fact that they improve the synthetic control adjustment and are effectively balanced with the selected weights.

V. Results

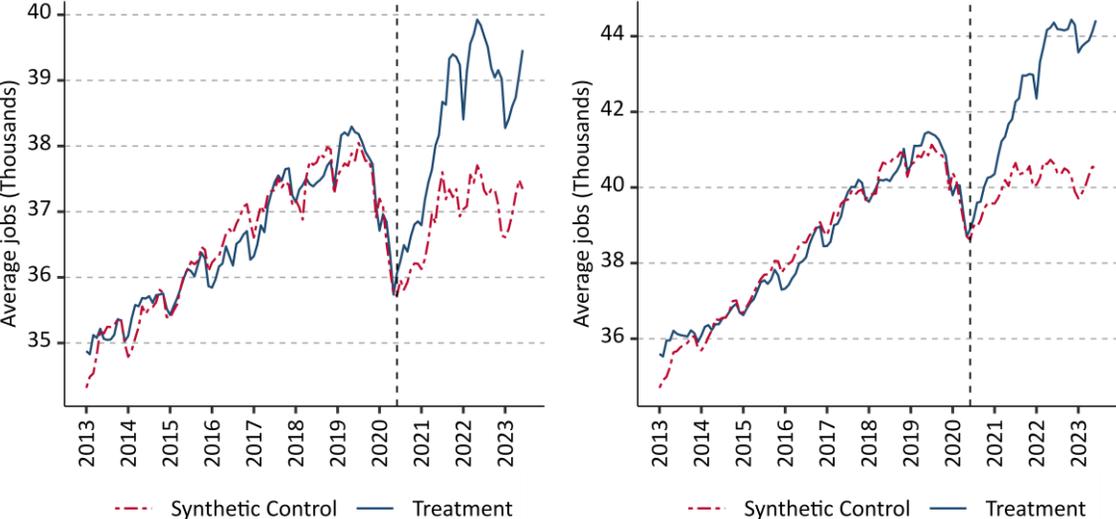
In Graph 4 we show the monthly time series of average jobs for the fifth quintile industries (treatment group) and its synthetic counterpart, both excluding (left) and including (right) industries with strong growth in external demand. The evolution of this variable for the treatment group and its counterfactual appears very similar in the pre-treatment period, suggesting a good fit for the model. During the treatment period, the average monthly jobs in industry groups identified as most prone to nearshoring was 4.1% higher than their synthetic control, representing approximately 0.6% of the total jobs in the manufacturing sector during this period.⁸ When industries with strong growth in external demand are included in the analysis (in both the treatment group and the donor pool), the average effect on jobs rises to 6.2% during the treatment period, as shown in the right-hand graph.

In Table 1 we show a comparison of the monthly averages of covariates for the treatment group industries, their synthetic control, and the donor pool. Our results indicate that the synthetic control is a better candidate for comparison than simply using the rest of the industries in the donor pool. Further details, including the economic activities and their

⁸ This percentage results from dividing the monthly average of estimated jobs by the difference of the industry groups treated and its counterfactual between the total number of jobs observed in the sector. It is assumed that there are no effects of nearshoring in any industry group other than those of the treatment group.

respective weights used to estimate the synthetic control, are provided in Tables A1–A3 in the Annex.

Graph 4. Average jobs (treatment group and synthetic control), not including (left) and including (right) industries with strong growth in external demand



Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.
 Notes: The left plot does not include the top five industries in growth rate of total U.S. imports from 2019 to 2022.

Table 1. Covariates pre-treatment means for the average jobs model

Covariates	Quintile 5 industries		Donor pool average
	Treatment	Control	
Capacity use	78.5%	78.5%	79.3%
Outsourcing	17.2%	17.2%	20.4%

Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the 2019 Monthly Survey of the Manufacturing Industry by INEGI.
 Notes: Capacity use refers to the percentage of installed capacity utilization and Outsourcing to the percentage of subcontracted personnel.

To verify that this observed difference is not due to chance or poor model fit, we applied the non-parametric permutation test proposed by Abadie (2021). Graph 5a illustrates the trajectories of the differences between the treated group series and their synthetic version (darker line), as well as the placebo series. Graph 5b shows the distribution of the test statistics for the placebos and the treated group, arranged in descending order. This visualization provides an indication of how rare the observed statistic is. As previously

mentioned, the objective of this test is to determine whether the post-treatment differences between the treated series and its control are sufficiently large compared to the pre-treatment differences to rule out that this divergence is due to randomness or poor adjustment for the pre-treatment series. This is measured by the ratio between the post and pre mean squared errors. A distribution for this measure is obtained by constructing a synthetic control to the untreated industry groups, as a kind of placebo, and calculating the ratio of each, to obtain an empirical distribution against which the ratio of the treated unit is compared. The pseudo p-value obtained for this analysis was zero, indicating that the likelihood of the observed effect being due to chance is negligible. Therefore, the effect of the treatment can be regarded as statistically significant.⁹

Another common robustness check in the literature is the in-time placebo test, or backdating, which involves replicating the SCM for the treated series while shifting the treatment period to an earlier date. The rationale is that the real and synthetic control series should exhibit similar behavior in this scenario, as the impact of the treatment should only be reflected after its actual occurrence and not beforehand as an anticipation effect. However, our analysis faces certain limitations with this approach, as the treatment may have been occurring before the selected date, albeit at a lower intensity, since the starting point for the treatment period was chosen by considering both the increasing popularity of the term nearshoring over time and the deepest impact of the COVID-19 pandemic, but not necessarily when the actual nearshoring process began. This choice was also intended to better capture the pandemic's effects on the treated industry groups.¹⁰ We estimated the synthetic control and plotted the series assuming the treatment period began one year earlier, as shown in Graph 6. The results indicate that the difference between actual average number of jobs and its synthetic control begins around the proposed start date, and almost capture the most significant negative impacts of the COVID-19 pandemic. This shows that the synthetic control obtained closely lines up with the trajectory of the treated group up to the onset of

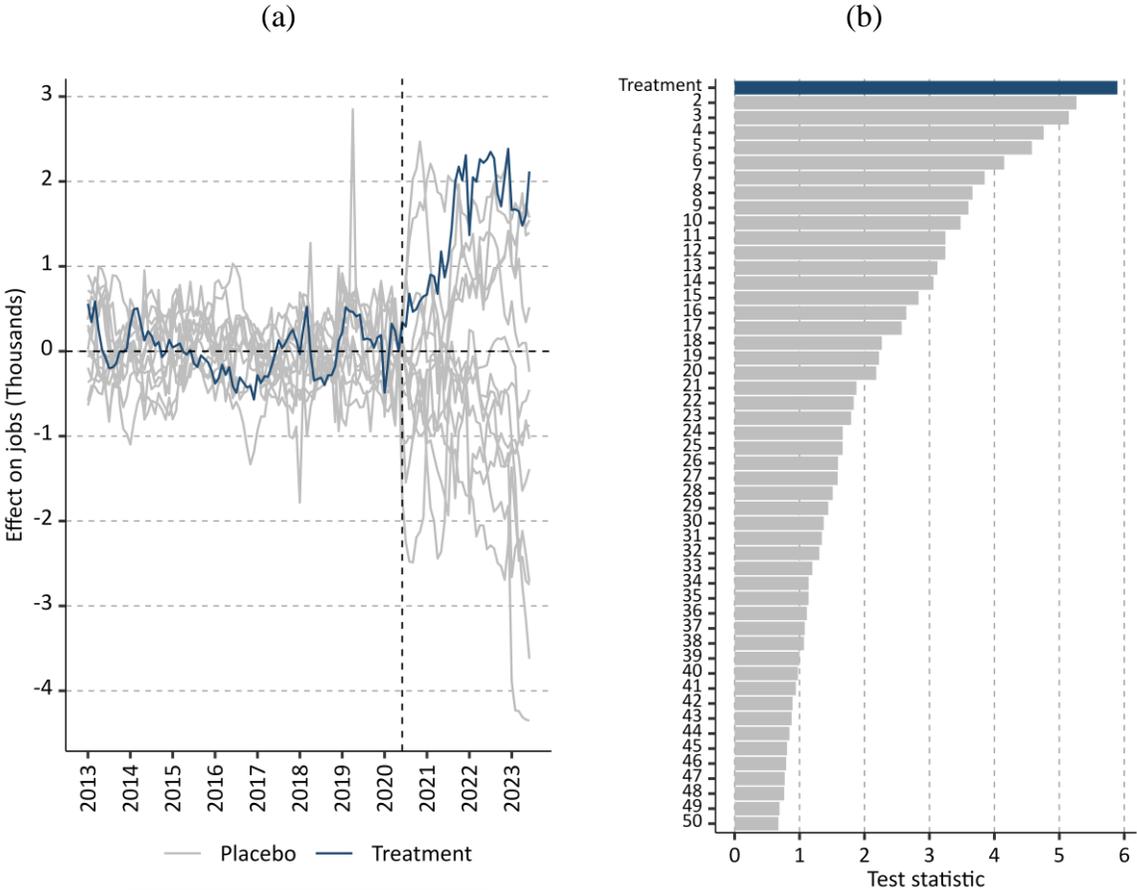
⁹As a robustness check, we conducted two additional estimations: one using only the industrial groups from the first quintile of the nearshoring propensity index as the donor pool, and another using those from the first and second quintiles. The results largely retained their sign and magnitude despite changes in the donor pool specification. However, the only substantial difference observed in this exercise pertained to wages: when using the bottom three quintiles as the donor pool, no significant treatment effect was found, whereas using only the first quintile yielded a negative effect.

¹⁰ We implemented an exercise using the popularity of the terms “nearshoring” and “Mexico” over time, showing a sudden increase near the starting point of the treatment period.

the actual treatment period. This alignment indicates robustness in the results, even when the starting point of the treatment period is adjusted.

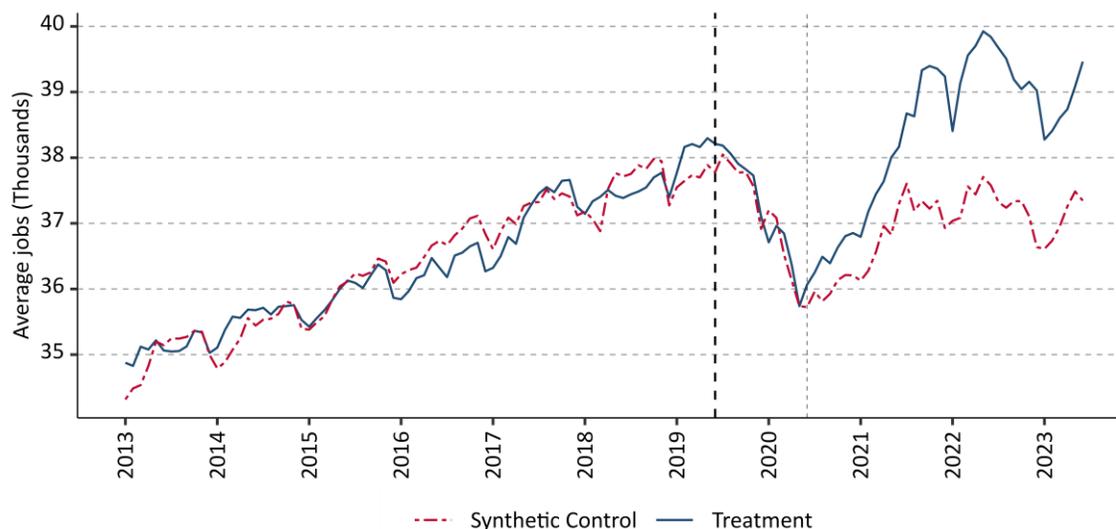
Even with the measures taken, robustness checks and statistical significance tests, we emphasize that the results may still be subject to bias if the assumption of no spillover effects is violated or if any of the donor pool groups actually received the treatment. Additionally, potential general equilibrium issues between the industries in quintile 5 and those selected for their synthetic control could further impact the findings.

Graph 5. (a) Monthly differences between the treatment group series and their synthetic control (darker line) and the placebos'. (b) Values of the test statistics for the placebos and the treated group, in decreasing order



Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.
 Notes: Each gray line represents the difference between a supposedly treated industry group in the donor pool and its estimated synthetic control. All series with a root mean squared error higher than 2 times that of the pre-treatment series for the treatment group were excluded from the plot.

Graph 6. Average jobs (treatment group and synthetic control), assuming the start of the treatment period one year earlier.



Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.

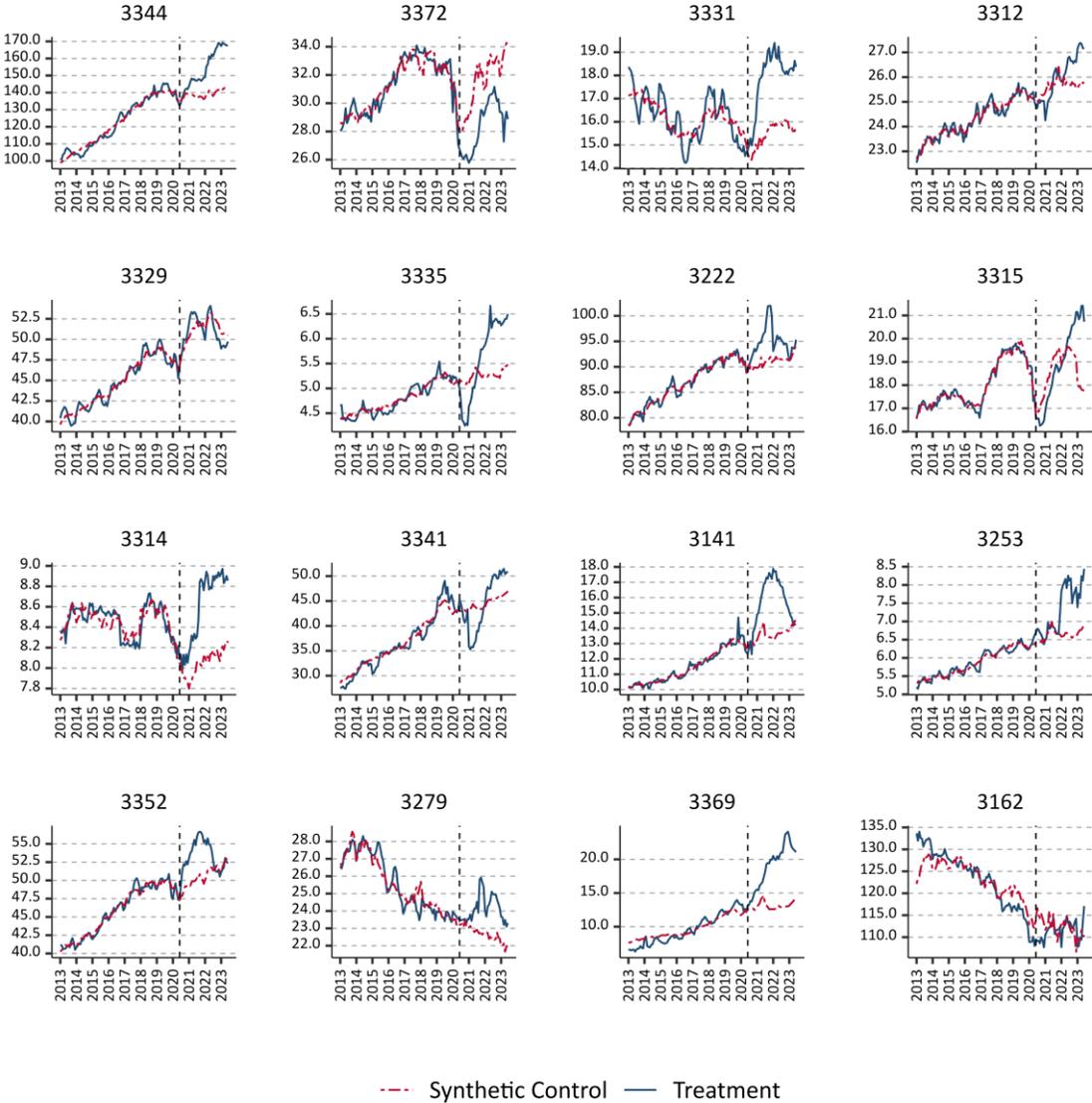
Notes: this plot represents the in-time placebo test commonly carried out in the synthetic control method.

To further confirm the robustness of the results, we also approached the estimation problem by applying the synthetic control methodology to each of the treatment industry groups individually. We estimated counterfactual scenarios for each of the 16 industries in the fifth quintile by using the same donor pool, as shown in Graph 7. Due to the time-intensive nature of including covariates for every treatment group industry, for this analysis we used only lags of the outcome variable, following the approach of Funke, Schularick and Trebesch (2023). The fit varies across industries, with some exhibiting better alignment between their pre-treatment trajectories and their synthetic controls. As a result, we excluded from the analysis of aggregate effects those industries for which the synthetic control did not adequately approximate the pre-treatment trajectory.

To estimate the average effect on the treatment units, we employed the methodology of Abadie and L’Hour (2021). Additionally, we conducted the permutation test for inference on aggregate effects proposed by the same authors, performing 100,000 random permutations on the units in the treatment group and the donor pool. Our results indicate that, on average, the well-fitted treatment industry groups had an average number of jobs 4.6% higher than

their synthetic control, a result significant at the 97% level. This average effect on jobs during the treatment period is presented in Graph 8.

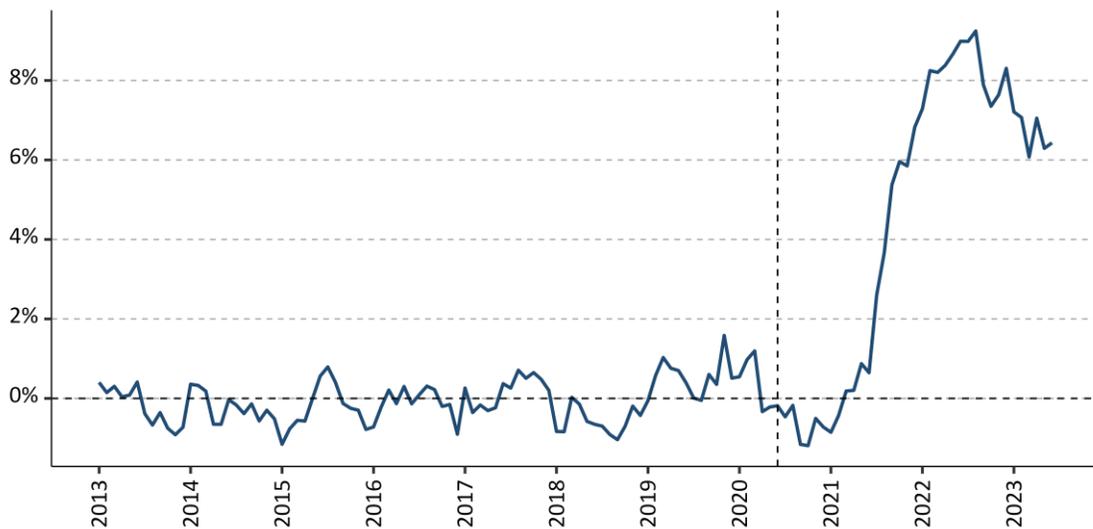
Graph 7. Average jobs (thousands) by NAICS: treatment group and synthetic control



Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.

Notes: values in thousands of jobs. NAICS codes equivalence: 3141: Textile Furnishings Mills, 3162: Footwear Manufacturing, 3222: Converted Paper Product Manufacturing, 3253: Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing, 3279: Other Nonmetallic Mineral Product Manufacturing, 3312: Steel Product Manufacturing from Purchased Steel, 3314: Nonferrous Metal (except Aluminum) Production and Processing, 3315: Foundries, 3329: Other Fabricated Metal Product Manufacturing, 3331: Agriculture, Construction, and Mining Machinery Manufacturing, 3335: Metalworking Machinery Manufacturing, 3341: Computer and Peripheral Equipment Manufacturing, 3344: Semiconductor and Other Electronic Component Manufacturing, 3352: Household Appliance Manufacturing, 3369: Other Transportation Equipment Manufacturing, 3372: Office Furniture (including Fixtures) Manufacturing.

Graph 8. Average percentage intention-to-treat effect on jobs



Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.

Notes: The series show each months' average of the percentage difference between the industry groups and their synthetic controls.

In recent years, the Synthetic Difference-in-Differences (SDiD) methodology developed by Arkhangelsky, Athey, Hirshberg, Imbens, and Wager (2021) has been proposed as an alternative for estimating causal effects in panel data. This method extends the standard difference-in-differences approach by incorporating the synthetic control methodology. Intuitively, SDiD re-weights and matches pre-exposure trends to reduce reliance on parallel trends assumptions, similar to SCM. Like DiD, it is invariant to additive unit-level shifts and allows for valid inference in large panels. We leveraged this advancement in the literature to strengthen the validity of our results, applying the SDiD methodology using the same outcome variables and covariates and the same treatment period. However, due to the nature of this estimator, we implemented it without aggregating the treated industries and instead included all outcome and covariate lags.

When estimating the average intention-to-treat effect on the fifth-quintile industries using the SDiD method, we observe a 3.3% increase, compared to the 4.1% estimated using the SCM (see Table 2). This effect is statistically significant at the 97% level, based on standard errors derived from 1,000 bootstrap permutations, as recommended by Arkhangelsky et al. (2021). Although smaller than the estimate obtained with the SCM, this

result reinforces our confidence that a positive intention-to-treat effect on employment exists for these industries. Furthermore, it must be considered that the SDiD approach estimates the effect by taking the difference-in-differences between the treated groups and their SDiD estimators, whereas the SCM relies on the difference between the treated series and its synthetic control.

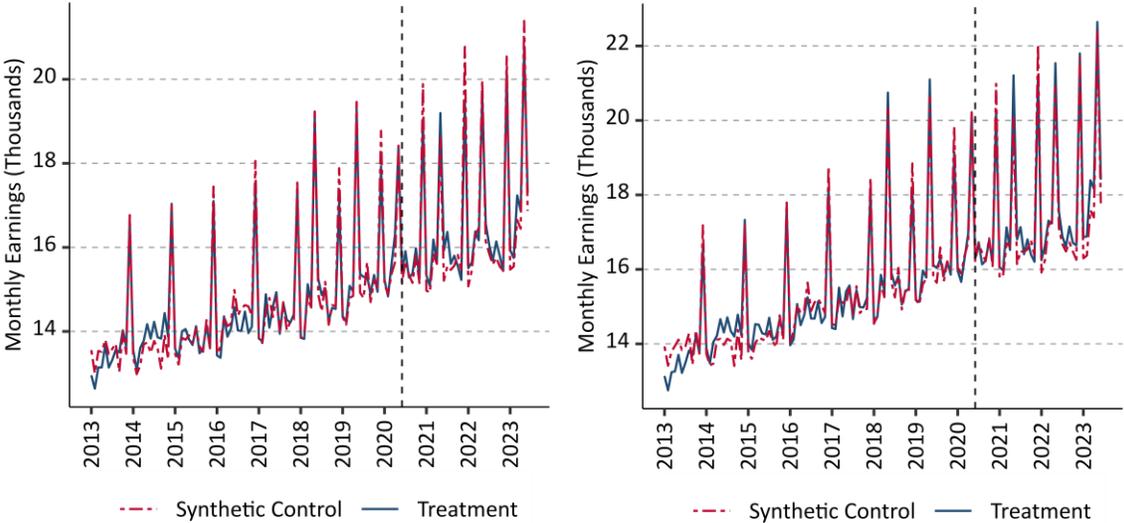
Table 2. Estimated effect on jobs: Synthetic Control and Synthetic Differences in Differences

Method	Estimated Effect
SCM aggregated	4.1% (***)
SCM not aggregated	4.6% (***)
SDiD	3.3% (***)

Source: Prepared by the authors with data from the INEGI 2019 Monthly Survey of the Manufacturing Industry
 Notes: Statistical significance: (***) all estimated effects are significant at the 95% level or more.

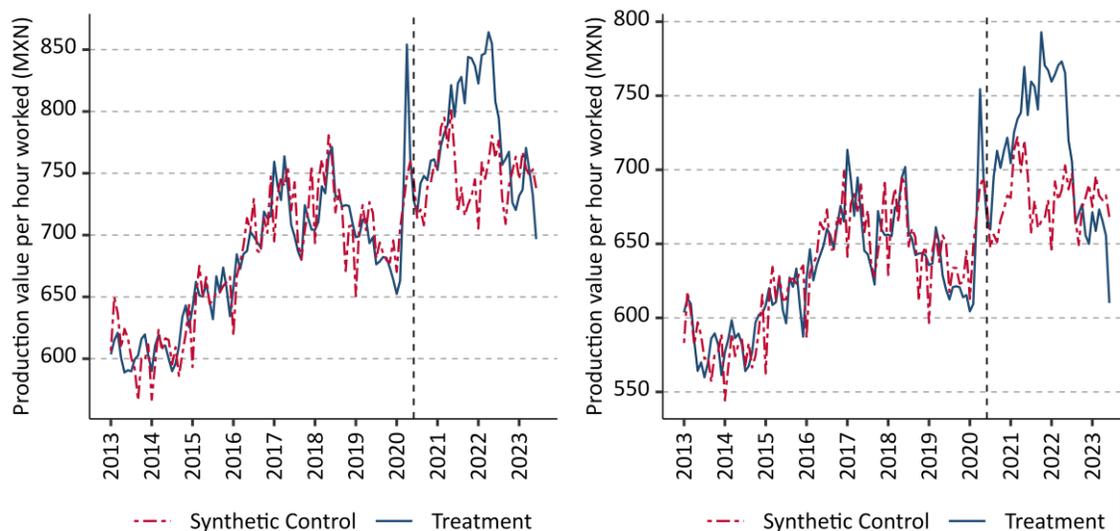
The previous analysis for jobs was also conducted for earnings and productivity (measured as production value per hour worked) in Mexico’s manufacturing sector. Our results from the aggregated SCM are shown in Graphs 9 and 10, both including and excluding industries with strong growth in external demand from the analysis.

Graph 9. Earnings (treatment group and synthetic control), not including (left) and including (right) industries with strong growth in external demand



Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.
 Notes: Values in thousands of MXN. The left plot does not include the top five industries in growth rate of total U.S. imports from 2019 to 2022.

Graph 10. Productivity (treatment group and synthetic control), not including (left) and including (right) industries with strong growth in external demand



Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.

Notes: Productivity is defined as the production value per hour worked. The left plot does not include the top five industries in growth rate of total U.S. imports from 2019 to 2022.

The weights selected by the algorithm for this response variables achieve a great covariate balance (as shown in Tables A4 and A5 in the Annex) and successfully fit the pretreatment period outcomes for both earnings and productivity. However, in the case of earnings, the similarity between the treatment group industries and their synthetic control persisted during the treatment period, and no statistically significant effect was found in either scenario. For productivity, the treatment period exhibited a different trajectory. However, when we performed the placebo test, the effect was not statistically significant when industries with strong external demand were excluded. Conversely, when no industries were excluded from the analysis, the average effect on productivity during the treatment period was 5.1% higher for industries more prone to nearshoring, with the result nearing statistical significance (p -value = 0.11). We present the results of these statistical tests in Graphs A1 and A2 in the Annex.

When applying the methodology separately by industry groups and estimating the average intention-to-treat impact for these variables, our results indicate that the effect of higher propensity to nearshoring on earnings was not statistically significant for units with well-approximated synthetic controls. For productivity, however, an average increase of 1% was estimated for the treated industries, and this effect is statistically significant at the 96% level. These findings are presented in Graphs A3 and A4 of the Annex, respectively. Finally, when we applied the SDiD for these variables, we did not find effects statistically different from zero, as shown in Tables A6 and A7 of the Annex, which gives further support to the SCM results.

VI. Final remarks

Measuring the effects of nearshoring on economic outcomes is a complex task. Our paper presents an econometric estimation that, though not without challenges, aims to distinguish these effects from those caused by other contemporaneous shocks. Our results suggest that the nearshoring process may have generated initial benefits for manufacturing jobs in Mexico for the period between July 2020 to June 2023. However, no significant impact is observed on the earnings of industries most prone to nearshoring. Similarly, it is not possible to identify a robust effect of nearshoring on productivity in manufacturing, although some specifications indicate a small positive effect in industries with higher propensities for nearshoring.

While the methodology we used aims to separate the potential effects of nearshoring from other simultaneous shocks, certain factors not accounted for in the models could influence the estimates during the analysis period. For instance, it is uncertain whether the industry groups in quintile 5 have been affected directly by nearshoring. Moreover, some industries in the donor pool may also have been influenced by nearshoring, either directly or indirectly, or may compete in the labor market with the treatment industries. These circumstances would likely bias the estimated effects downward, implying that our results may be conservative and that the true impact of nearshoring could be somewhat larger than what is captured by our estimates.

Some of the effects of nearshoring may take time to materialize. While production lines are being relocated from Asia and other regions to Mexico to leverage proximity to the

large U.S. consumer market, the construction of new plants often requires several years. Once completed, these plants are expected to increase capital per worker, and with the adoption of new technologies, productivity in industries tied to nearshoring is likely to improve. It will be critical to monitor the nearshoring process to ensure that it produces better outcomes than the maquiladora model, which generated jobs but with limited gains in productivity and wages. More broadly, nearshoring should be leveraged not only to foster job creation but also to enhance productivity and compensation, thereby generating sustainable and equitable economic benefits for Mexico.

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VIII. ANNEX

Table A1. Weights assigned to industry groups for the average jobs model.

Industry group	Weight	Industry group	Weight
Motor Vehicle Body and Trailer	6.2%	Lime and Gypsum Product	2.0%
Apparel Accessories and Other Apparel	5.0%	Cement and Concrete Product	1.9%
Petroleum and Coal Products	4.0%	Veneer, Plywood and Wood Product	1.9%
Sawmills and Wood Preservation	2.8%	Household Furniture and Kitchen Cabinet	1.9%
Apparel Knitting Mills	2.8%	Nav., Measuring, Electromed. and Control	1.8%
Other Textile Product Mills	2.8%	Fiber, Yarn, and Thread Mills	1.8%
Printing and Related Support Activities	2.7%	Iron and Steel Mills and Ferroalloy	1.8%
Other Leather and Allied Product	2.7%	Glass and Glass Product	1.7%
Other Chemical Product and Preparation	2.6%	Pulp, Paper, and Paperboard Mills	1.5%
Magnetic and Optical Media	2.5%	Soap, Cleaning Comp., and Toilet Prep.	1.5%
Fabric Mills	2.4%	Pharmaceutical and Medicine	1.4%
Hardware	2.4%	Rubber Product	1.4%
Textile and Fabric Coating Mills	2.4%	Resin, Rubber, Fibers and Filaments	1.4%
Railroad Rolling Stock	2.4%	Animal Food	1.4%
Electric Lighting Equipment	2.3%	Dairy Product	1.4%
Cut and Sew Apparel	2.2%	Electrical Equipment	1.2%
Paint, Coating, and Adhesive	2.2%	Seafood Product Preparation and Pckging	1.2%
Spring and Wire Product	2.2%	Grain and Oilseed Milling	1.2%
Other Furniture Related Product	2.2%	Motor Vehicle	1.0%
Basic Chemical	2.1%	Cutlery and Handtool	0.9%
Boiler, Tank, and Shipping Container	2.1%	Animal Slaughtering and Processing	0.9%
Engine, Turbine, and Power Transm.	2.1%	Medical Equipment and Supplies	0.7%
Machine Shops; Turned Prod.; and Screws	2.1%	Bakeries and Tortilla	0.3%
Leather and Hide Tanning and Finishing	2.0%	Motor Vehicle Parts	0.2%
Coating, Engraving, Heat Treating	2.0%		

Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.

Table A2. Weights assigned to industry groups for the earnings model.

Industry group	Weight	Industry group	Weight
Apparel Knitting Mills	6.4%	Lime and Gypsum Product	1.5%
Other Textile Product Mills	5.5%	Animal Slaughtering and Processing	1.4%
Glass and Glass Product	5.4%	Fiber, Yarn, and Thread Mills	1.3%
Household Furniture and Kitchen Cabinet	4.8%	Leather and Hide Tanning and Finishing	1.3%
Seafood Product Preparation and Pckging	4.6%	Boiler, Tank, and Shipping Container	1.2%
Railroad Rolling Stock	3.9%	Electrical Equipment	1.2%
Sawmills and Wood Preservation	3.8%	Magnetic and Optical Media	1.2%
Other Leather and Allied Product	3.7%	Motor Vehicle Body and Trailer	1.2%
Cut and Sew Apparel	3.6%	Spring and Wire Product	1.0%
Paint, Coating, and Adhesive	3.5%	Veneer, Plywoo, and Wood Product	0.9%
Animal Food	3.3%	Motor Vehicle	0.8%
Textile and Fabric Coating Mills	3.1%	Apparel Accessories and Other Apparel	0.8%
Medical Equipment and Supplies	3.0%	Soap, Cleaning Comp., and Toilet Prep.	0.7%
Coating, Engraving, Heat Treating	3.0%	Grain and Oilseed Milling	0.7%
Printing and Related Support Activities	2.9%	Nav., Measuring, Electromed. and Control	0.6%
Hardware	2.5%	Iron and Steel Mills and Ferroalloy	0.6%
Motor Vehicle Parts	2.4%	Engine, Turbine, and Power Transmission	0.5%
Dairy Product	2.2%	Cement and Concrete Product	0.5%
Bakeries and Tortilla	2.1%	Resin, Rubber, Fibers and Filaments	0.5%
Pharmaceutical and Medicine	2.0%	Cutlery and Handtool	0.4%
Other Chemical Product and Preparation	1.9%	Rubber Product	0.4%
Electric Lighting Equipment	1.8%	Pulp, Paper, and Paperboard Mills	0.4%
Other Furniture Related Product	1.7%	Basic Chemical	0.3%
Machine Shops; Turned Product; and Screws	1.6%	Petroleum and Coal Products	0.2%
Fabric Mills	1.5%		

Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.

Table A3. Weights assigned to industry groups for the productivity model.

Industry group	Weight	Industry group	Weight
Cement and Concrete Product	37.1%	Medical Equipment and Supplies	0.6%
Household Furniture and Kitchen Cabinet	10.2%	Animal Slaughtering and Processing	0.4%
Sawmills and Wood Preservation	9.4%	Grain and Oilseed Milling	0.4%
Seafood Product Preparation and Packaging	7.1%	Dairy Product	0.4%
Machine Shops; Turned Product; and Screws	7.0%	Cutlery and Handtool	0.3%
Other Leather and Allied Product	5.9%	Other Chemical Product and Preparation	0.2%
Printing and Related Support Activities	3.6%	Magnetic and Optical Media	0.2%
Apparel Accessories and Other Apparel	2.6%	Textile and Fabric Coating Mills	0.2%
Animal Food	2.5%	Electric Lighting Equipment	0.2%
Electrical Equipment	2.1%	Fabric Mills	0.2%
Railroad Rolling Stock	1.5%	Fiber, Yarn, and Thread Mills	0.2%
Boiler, Tank, and Shipping Container	1.4%	Leather and Hide Tanning and Finishing	0.1%
Cut and Sew Apparel	1.4%	Soap, Cleaning Comp., and Toilet Prep.	0.1%
Other Textile Product Mills	1.0%	Coating, Engraving, Heat Treating	0.1%
Apparel Knitting Mills	0.9%	Engine, Turbine, and Power Transmission	0.1%
Bakeries and Tortilla	0.7%	Lime and Gypsum Product	0.1%
Veneer, Plywood and Wood Product	0.6%	Pulp, Paper, and Paperboard Mills	0.1%

Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.

Table A4. Covariates pre-treatment means for the earnings model

Covariates	Quintile 5 industries		Donor pool average
	Treatment	Control	
Capacity use	78.5%	78.5%	79.3%
Outsourcing	17.2%	17.2%	20.4%

Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the 2019 Monthly Survey of the Manufacturing Industry by INEGI.

Notes: Capacity use refers to the percentage of installed capacity utilization and Outsourcing to the percentage of subcontracted personnel.

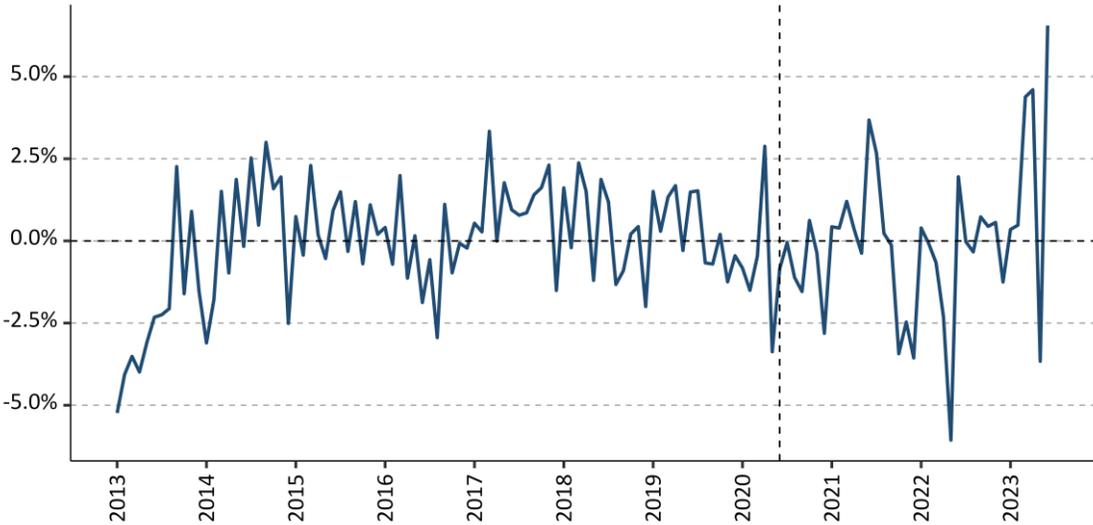
Table A5. Covariates pre-treatment means for the productivity model

Covariates	Quintile 5 industries		Donor pool average
	Treatment	Control	
Capacity use	78.5%	78.5%	79.3%
Outsourcing	17.2%	17.2%	20.4%

Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the 2019 Monthly Survey of the Manufacturing Industry by INEGI.

Notes: Capacity use refers to the percentage of installed capacity utilization and Outsourcing to the percentage of subcontracted personnel.

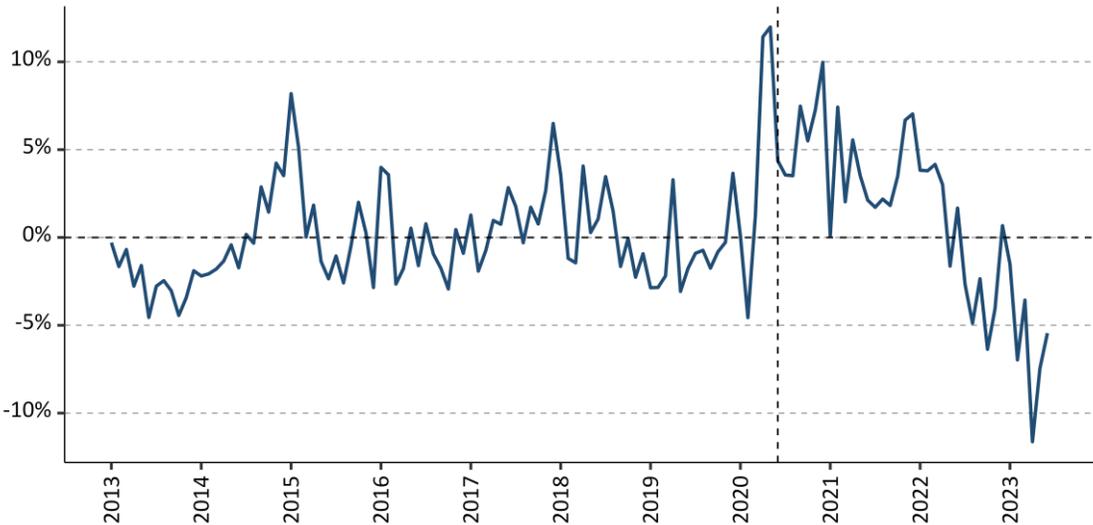
Graph A1. Average percentage intention-to-treat effect on earnings



Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.

Notes: The series show each months' average of the percentage difference between the industry groups and their synthetic controls.

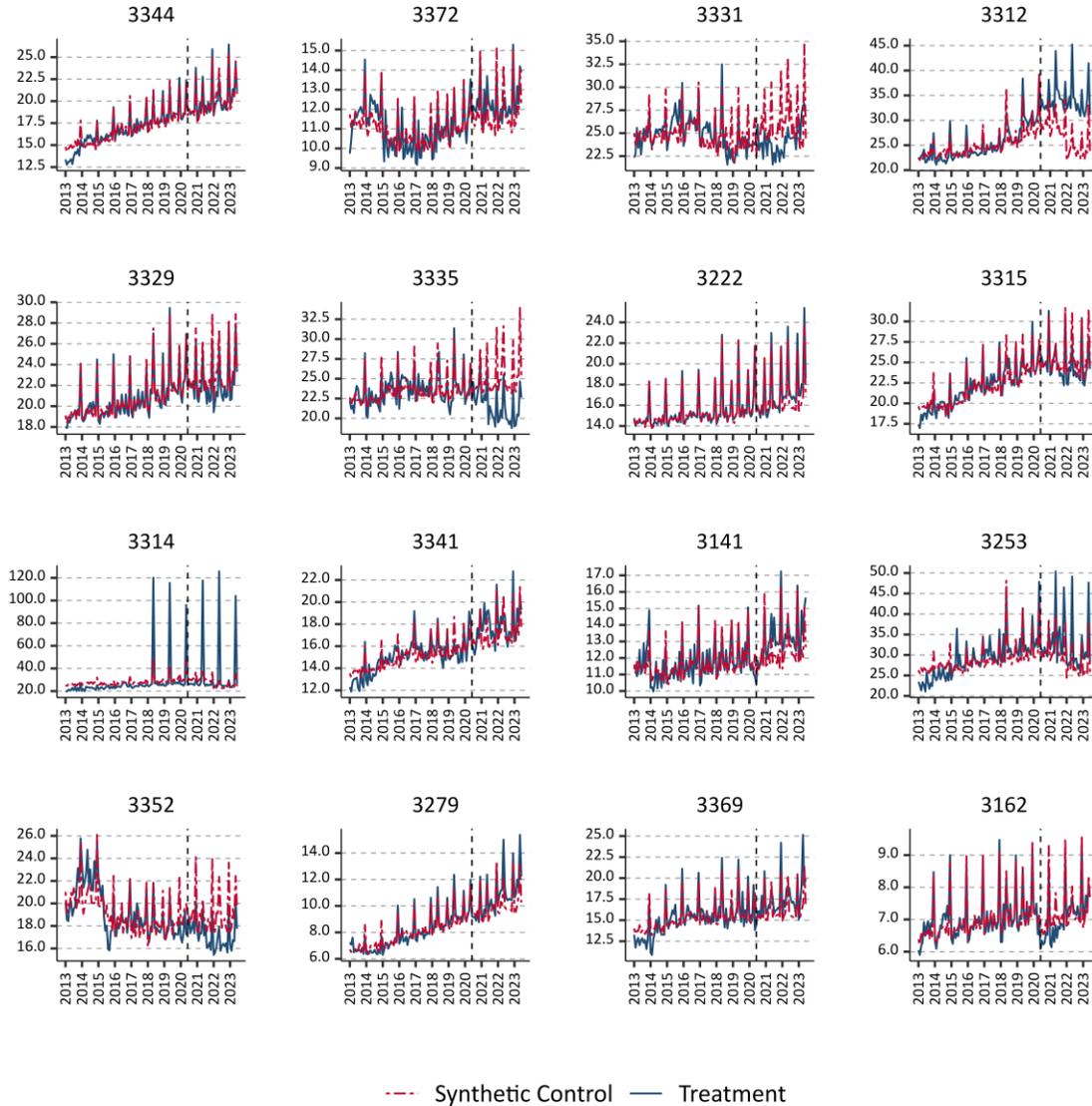
Graph A2. Average percentage intention-to-treat effect on productivity



Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.

Notes: The series show each months' average of the percentage difference between the industry groups and their synthetic controls.

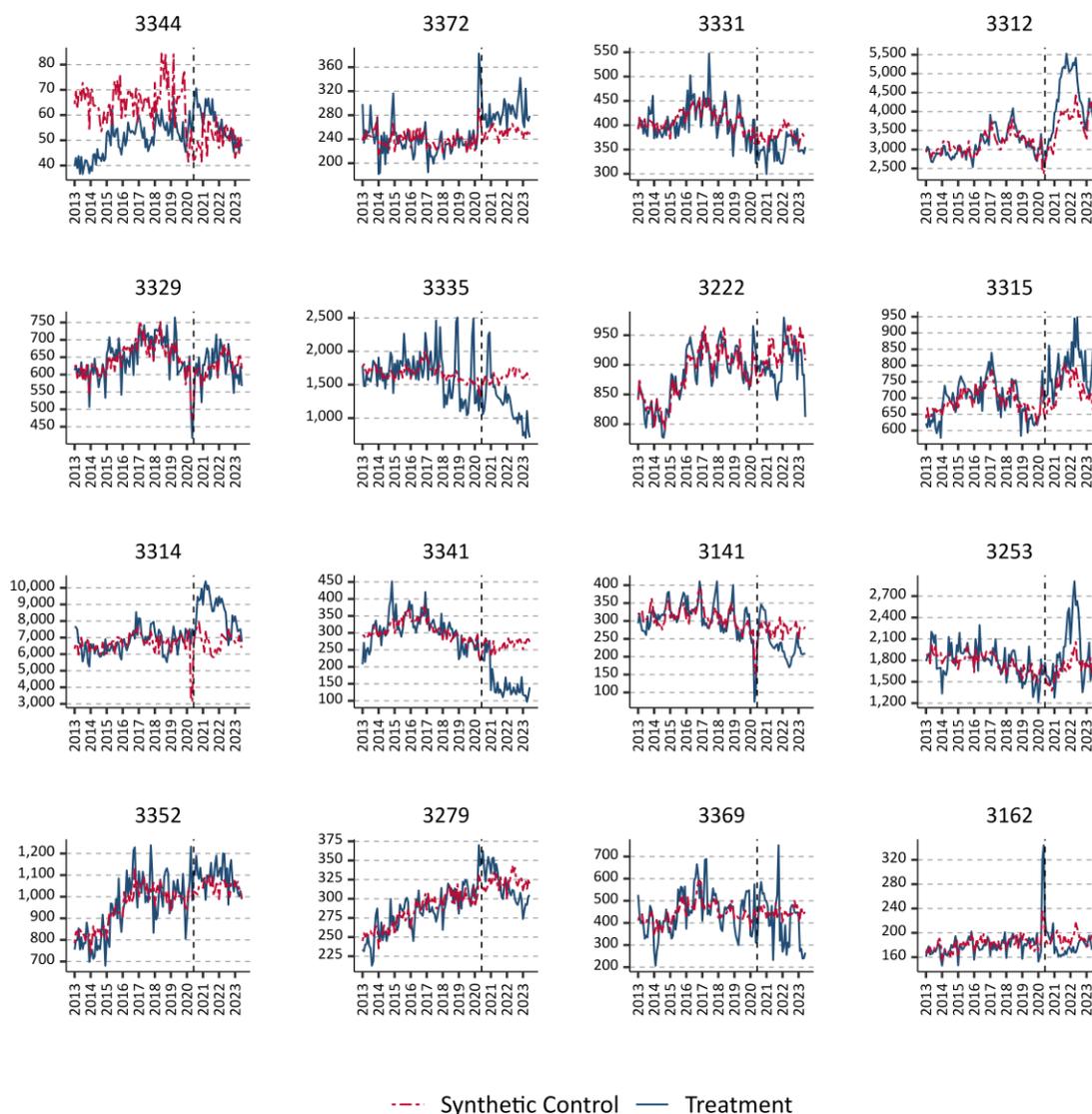
Graph A3. Earnings by NAICS: treatment group (red) and synthetic control



Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.

Notes: values in thousand MXN. NAICS codes equivalence: 3141: Textile Furnishings Mills, 3162: Footwear Manufacturing, 3222: Converted Paper Product Manufacturing, 3253: Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing, 3279: Other Nonmetallic Mineral Product Manufacturing, 3312: Steel Product Manufacturing from Purchased Steel, 3314: Nonferrous Metal (except Aluminum) Production and Processing, 3315: Foundries, 3329: Other Fabricated Metal Product Manufacturing, 3331: Agriculture, Construction, and Mining Machinery Manufacturing, 3335: Metalworking Machinery Manufacturing, 3341: Computer and Peripheral Equipment Manufacturing, 3344: Semiconductor and Other Electronic Component Manufacturing, 3352: Household Appliance Manufacturing, 3369: Other Transportation Equipment Manufacturing, 3372: Office Furniture (including Fixtures) Manufacturing.

Graph A4. Productivity by NAICS sector: treatment group (red) and synthetic control



Source: Prepared by the authors with data from Google Search Engine from January 2015 to May 9, 2023, and the Monthly Survey of the Manufacturing Industry by INEGI.

Notes: production value per hour worked in MXN. NAICS codes equivalence: 3141: Textile Furnishings Mills, 3162: Footwear Manufacturing, 3222: Converted Paper Product Manufacturing, 3253: Pesticide, Fertilizer, and Other Agricultural Chemical Manufacturing, 3279: Other Nonmetallic Mineral Product Manufacturing, 3312: Steel Product Manufacturing from Purchased Steel, 3314: Nonferrous Metal (except Aluminum) Production and Processing, 3315: Foundries, 3329: Other Fabricated Metal Product Manufacturing, 3331: Agriculture, Construction, and Mining Machinery Manufacturing, 3335: Metalworking Machinery Manufacturing, 3341: Computer and Peripheral Equipment Manufacturing, 3344: Semiconductor and Other Electronic Component Manufacturing, 3352: Household Appliance Manufacturing, 3369: Other Transportation Equipment Manufacturing, 3372: Office Furniture (including Fixtures) Manufacturing.

Table A6. Estimated effect on earnings: Synthetic Control and Synthetic Differences in Differences

Method	Estimated Effect
SCM aggregated	0.69%
SCM not aggregated	-0.005%
SDiD	-3.17%

Source: Prepared by the authors with data from the INEGI 2019 Monthly Survey of the Manufacturing Industry
 Notes: All effects estimated were not statistically different from zero.

Table A7. Estimated effect on productivity: Synthetic Control and Synthetic Differences in Differences

Method	Estimated Effect
SCM aggregated	4.6%
SCM not aggregated	1.1% (***)
SDiD	4.01%

Source: Prepared by the authors with data from the INEGI 2019 Monthly Survey of the Manufacturing Industry
 Notes: Statistical significance: (***) only the SCM not aggregated estimated effect is significant (at the 95% level or more).