CESifo WORKING PAPERS

11839
2025

April 2025

The US-China Trade War Creates Jobs (Elsewhere)

Tiago Cavalcanti, Pedro Molina Ogeda, Emanuel Ornelas

CESifo

Impressum:

CESifo Working Papers
ISSN 2364-1428 (electronic version)
Publisher and distributor: Munich Society for the Promotion of Economic Research - CESifo GmbH
The international platform of Ludwigs-Maximilians University's Center for Economic Studies and the ifo Institute
Poschingerstr. 5, 81679 Munich, Germany
Telephone +49 (0)89 2180-2740, Telefax +49 (0)89 2180-17845, email office@cesifo.de
Editor: Clemens Fuest
https://www.cesifo.org/en/wp
An electronic version of the paper may be downloaded
· from the SSRN website: www.SSRN.com
· from the RePEc website: www.RePEc.org
· from the CESifo website: https://www.cesifo.org/en/wp

The US-China Trade War Creates Jobs (Elsewhere)*

Tiago Cavalcanti † Pedro Molina Ogeda‡ Emanuel Ornelas§

April 20, 2025

Abstract

We examine the indirect effects of the US-China trade war on Brazil's labor market. Using industry-specific tariff changes and the sectoral employment distribution across local labor markets, we construct a measure of regional exposure to the trade conflict. Following higher exports to China, our findings reveal that regions more exposed to Chinese retaliatory tariffs on US exports experienced a relative increase in formal employment and wage bills. In contrast, American tariffs on Chinese exports had no significant impact on Brazilian labor markets. These results contribute to a better understanding of the intricate worldwide implications of bilateral trade wars.

Keywords: Trade War; Trade Diversion; Local Labor Markets; Brazil
JEL classification: D31, F14, F16, F66, J23

*We are grateful to Bladimir Carrillo, Caio Castro, Rafael Dix-Carneiro, João Paulo Pessoa, Joris Hoste, Alexandre Rabello, Rodrigo Soares, and seminar participants at several venues for valuable comments and discussions. Ornelas acknowledges financial support from the Brazilian Council of Science and Technology (CNPq).

†University of Cambridge, CEPR and Sao Paulo School of Economics-FGV (email: tvdvc2@cam.ac.uk).
‡Sao Paulo School of Economics-FGV (email: pedromogeda@gmail.com).
§Sao Paulo School of Economics-FGV, CEPR, CESifo and CEP-LSE (email: eaornelas@gmail.com).

1 Introduction

We study the consequences of the United States (US)-China trade war during the first Trump Administration. Between 2018 and 2019, the average US tariff on Chinese products rose from 2.9% to 24.9%, while China's average tariff on US products increased from 9.8% to 28.2%.[1] Despite the Phase One deal in early 2020, tariffs between the two countries remained elevated (Bown, 2021).

Although Trump repeatedly justified his protectionist turn during his first term as "the quickest way to bring our jobs back to our country,"[2] research finds no evidence of job gains in either the US or China. But did the trade war create jobs elsewhere? Because the trade war tariffs were discriminatory—both the US and China imposed additional tariffs exclusively on each other's exports while leaving most other countries' tariffs unchanged—demand for affected goods may have shifted to third countries. This paper examines that possibility by analyzing how Trump's 2017–2019 trade war affected local labor markets in Brazil.

Given that China and the US are Brazil's main export markets, one might expect Brazil to benefit from trade diversion caused by discriminatory tariffs. However, trade patterns reveal a notable asymmetry: before the trade war, Brazil's export composition was highly correlated with US exports to China (53.5%), but showed almost no correlation with Chinese exports to the US (1.4%).[3] This pattern suggests that Brazil is a potential substitute for US exports to China, but has limited overlap with Chinese exports to the US. Thus, Brazilian regions specialized in industries targeted by Chinese tariffs may have gained from trade diversion, while there was little scope for gains from American tariffs.

When we examine the product-level impact of the discriminatory tariffs imposed by China and the US, we find that Brazil's exports of the affected products to China increased within a few months of the tariff implementation, while exports to the US showed no significant response. These findings support the hypothesis that Brazil was affected by trade diversion resulting from China's retaliatory tariffs, but not by the tar-

[1]Simple averages of tariffs at the 6-digit HS product level.

[2]`https://time.com/4386335/donald-trump-trade-speech-transcript/`

[3]Those figures are based on 2016 trade data at the 6-digit HS product level. See Table A1, Online Appendix A.

iffs imposed by the US. These trade effects, in turn, suggest the possibility of broader economic consequences, including labor market impacts.

To investigate this possibility, we exploit variation in tariff increases across industries and the relevance of affected trade flows to construct two variables—one for China and another for the US—that capture industry-level exposure to each country's trade policies. Building on Topalova (2010) and subsequent studies on regional impacts of trade policies, we use the heterogeneity in pre-shock employment structure across Brazilian regions and the variation in industry exposure due to the tariff changes to assess how much a region is exposed to the effects of the tariff increases. Using these regional variables, we estimate the causal indirect impacts of the trade war on Brazil's local labor markets. A key feature of our empirical strategy is that we separately identify the effects of China's retaliatory tariffs and the US-imposed tariff hikes.

We find that Brazilian regions specialized in industries targeted by China's trade policy toward the US experienced a relative increase in the number of formal workers and in the total wage bill between 2016 and 2021. By contrast, regions more exposed to US tariffs on China did not exhibit differential labor market outcomes relative to other Brazilian regions. These results are noteworthy for two reasons. First, while prior studies have documented adverse labor market impacts of the trade conflict in the US and China, our findings offer a contrasting perspective, suggesting that the conflict did create jobs—albeit outside the countries directly involved. This implies that Brazilian firms expected the trade war's effects to last long enough to justify costly labor adjustments. Second, we show that the labor market effects of trade diversion were not uniform: only the retaliatory tariffs imposed by China contributed to the observed gains in Brazil's local labor markets.

We perform robustness checks to validate our identification strategy. First, we find no evidence that pre-trends in outcomes are correlated with the trade war tariffs. Second, we show that our results are robust to different specifications, including controls for changes in MFN tariffs, alternative exposure measures, and restricting the analysis to tariffs implemented through 2018.

This paper contributes to the growing literature on the distributive impacts of the US-China trade conflict. Most studies exploit geographic variation in exposure to trade war tariffs to assess labor market effects in the US. They find that American commuting zones more exposed to Chinese retaliatory tariffs experienced slower employment growth, while US-imposed tariffs reduced job opportunities and regional earnings by raising input costs (Goswami, 2022; Waugh, 2019; Benguria and Saffie, 2020; Javorcik et al., 2024; Flaaen and Pierce, 2024). Freund et al. (2024) find that the trade war reshaped global value chains, inducing nearshoring to countries close to the US. Studies on China find that US-imposed tariffs reduced per capita income in the most exposed regions (Chor and Li, 2024) and lowered job vacancies in the most affected firms (He et al., 2021).

Evidence on the trade war's effects on third countries' labor markets remains scarce. Chen et al. (2025) find positive employment and wage effects due to higher labor demand from Mexican exporters exposed to US tariffs against China. Other three contemporaneous studies focus on Vietnam. Mayr-Dorn et al. (2023) find that regions more exposed to US tariffs on Chinese goods experienced increases in employment, working hours, wages, and formality. Nguyen and Lim (2023) show that the trade war shifted workers from informal agriculture to formal industry. Rotunno et al. (2023) find that Vietnam's employment levels rose because of the trade war.

Our findings provide additional evidence that a bilateral trade war can stimulate labor demand in third countries. We also provide two key innovations. First, we separately identify the effects of discriminatory tariffs imposed by the US and China, whereas prior work focuses mainly on demand diverted from China. Second, when measuring industries' exposure to these tariffs, we account for the share of world trade flows directly affected by the tariffs, yielding a more precise estimate of the tariffs' impact on global markets.[4]

A recent strand of research explores the trade war impacts on third-country exports. Fajgelbaum et al. (2024) use a Ricardian-Armington model with heterogeneous export-tariff elasticities to study product-level export responses to the US–China trade war in 48 countries, including Brazil. They find that Brazil's exports of affected products rose by about 5%, compared to 6.5% in the average country. Benguria and Saffie (2024) finds that US export losses were offset by gains elsewhere. Using a difference-in-differences approach, Casagrande et al. (2023) find that China's trade war tariffs in-

[4]For instance, although China is a major steel and aluminum exporter, the US tariffs had limited impact because China had already redirected much of its exports before the trade war (Bown, 2021). As a result, the affected trade flows were relatively small.

creased the Brazil's exports to China by 28.4%. Beyond labor market effects, our study complements these findings by showing that exports to China rose significantly, while exports to the US remained unaffected.[5]

2 Context and Trade Diversion

2.1 Institutional Background

This section summarizes key events of the US–China trade war during Trump's first term. For details, see Bown and Kolb (2021).

The initial tension began in 2017, but the first tariff hikes took effect on March 23, 2018, when the US imposed a 25-percentage-point increase on steel tariffs and a 10-percentage-point increase on aluminum tariffs for all trading partners—except Argentina, Australia, Brazil, Canada, the European Union, Mexico, and South Korea. Although few Chinese products were affected, China responded in early April with retaliatory tariffs on selected US goods (Bown, 2021).

The conflict escalated after a formal US investigation under Section 301 of the Trade Act of 1974, which examined whether Chinese policies harmed US technological development or violated intellectual property rights. On April 3, the US announced a list of over 1,000 Chinese products—worth $50 billion—targeted for a 25-percentage-point tariff increase. The next day, China released a reciprocal list of US products, also valued at $50 billion and subject to the same tariff hike. On July 6, both countries imposed tariffs on $34 billion of their respective lists, with the remaining $16 billion set to take effect on August 23.

In early September 2018, the US announced a new round of tariff increases—ranging from 5 to 10 percentage points—on $200 billion worth of 2017 imports from China. Shortly after, China issued a retaliatory list covering $60 billion in US goods. Both sets of tariffs took effect on September 24, 2018. In December 2018, both coun-

[5]Complementary research finds that the trade war reduced welfare in the countries involved (Amiti et al., 2019; Fajgelbaum et al., 2020; Chang et al., 2024), lowered the market value of exposed firms (Amiti et al., 2020; Huang et al., 2023), slowed firm entry in China (Cui and Li, 2021), and contributed to increased support for Republican candidates in the 2018 US elections (Blanchard et al., 2024).

tries signaled their intention to further increase tariffs on the products targeted in the September round.

In 2019, the US carried out three additional rounds of tariff increases on Chinese products, each met with retaliatory measures from China. In early May, the US raised tariffs by 15 percentage points on the $200 billion list announced in September 2018. China responded by increasing tariffs on its $60 billion list of US goods from the same period. In August, the US announced a new round targeting $300 billion in Chinese imports, prompting Chinese tariffs on $75 billion in US exports. The final tariff hike of 2019 came in December, with the US targeting phones, laptops, and video game consoles, while China imposed higher tariffs on cars and car parts. By January 2020, average US tariffs on Chinese goods were six times higher than in 2017.

In January 2020, China and the US signed the Phase One deal, which included provisions on purchase commitments, financial market access, and intellectual property protection. As part of the agreement, China committed to buy an additional $200 billion worth of US exports, but tariffs remained at similarly high levels through 2024.

2.2 Brazil's Trade with China and the US

China and the US are Brazil's main export destinations, accounting for 22% and 12% of total Brazilian exports in 2017, respectively. Following the onset of the trade war, China's share increased significantly, reaching 31% by 2021, while the US share declined slightly to 11%. As shown in Online Appendix Figure B1, while Brazilian export values to the US, other major partners, and the rest of the world remained relatively stable during the trade war, exports to China rose substantially by 85% over the same period.[6] This pattern suggests that Brazil deepened its commercial ties with China in the aftermath of the trade conflict.

To assess how Brazilian exports were affected by the trade war, we analyze the impact of the discriminatory tariffs imposed by China on US imports and by the US on Chinese imports on Brazil's export flows to both countries. We exploit the variation in the timing of tariff impositions to implement a staggered difference-in-differences

[6] Data on Brazilian exports are from the COMEX STAT portal of the Brazilian Foreign Trade Secretariat, available at `https://comexstat.mdic.gov.br/pt/home`.

approach, following the methodology developed by Callaway and Sant'Anna (2021). We use monthly data on the value and weight of Brazilian exports to China and the US, disaggregated by product at the 6-digit HS level, covering the period from January 2017 to December 2021. Specifically, we estimate:

$$Y_{pmt} = \alpha_p + \alpha_{mt} + \sum_{k=-34}^{-1} \theta_k T_{kpmt} + \sum_{j=0}^{45} \theta_j T_{jpmt} + \varepsilon_{pmt}, \tag{1}$$

where Y_{pmt} denotes the log of one plus the trade outcome of interest—either the value or quantity of product p exported by Brazil to China or the US in month m of year t. The term α_p denotes product fixed effects, α_{mt} are month-year fixed effects, and T_{jpmt} (T_{kpmt}) are indicator variables equal to 1 if j (k) periods have passed since the first discriminatory tariff was imposed on product p. These indicator variables are always zero for products not affected by any discriminatory tariff. Standard errors are clustered at the HS 4-digit level.

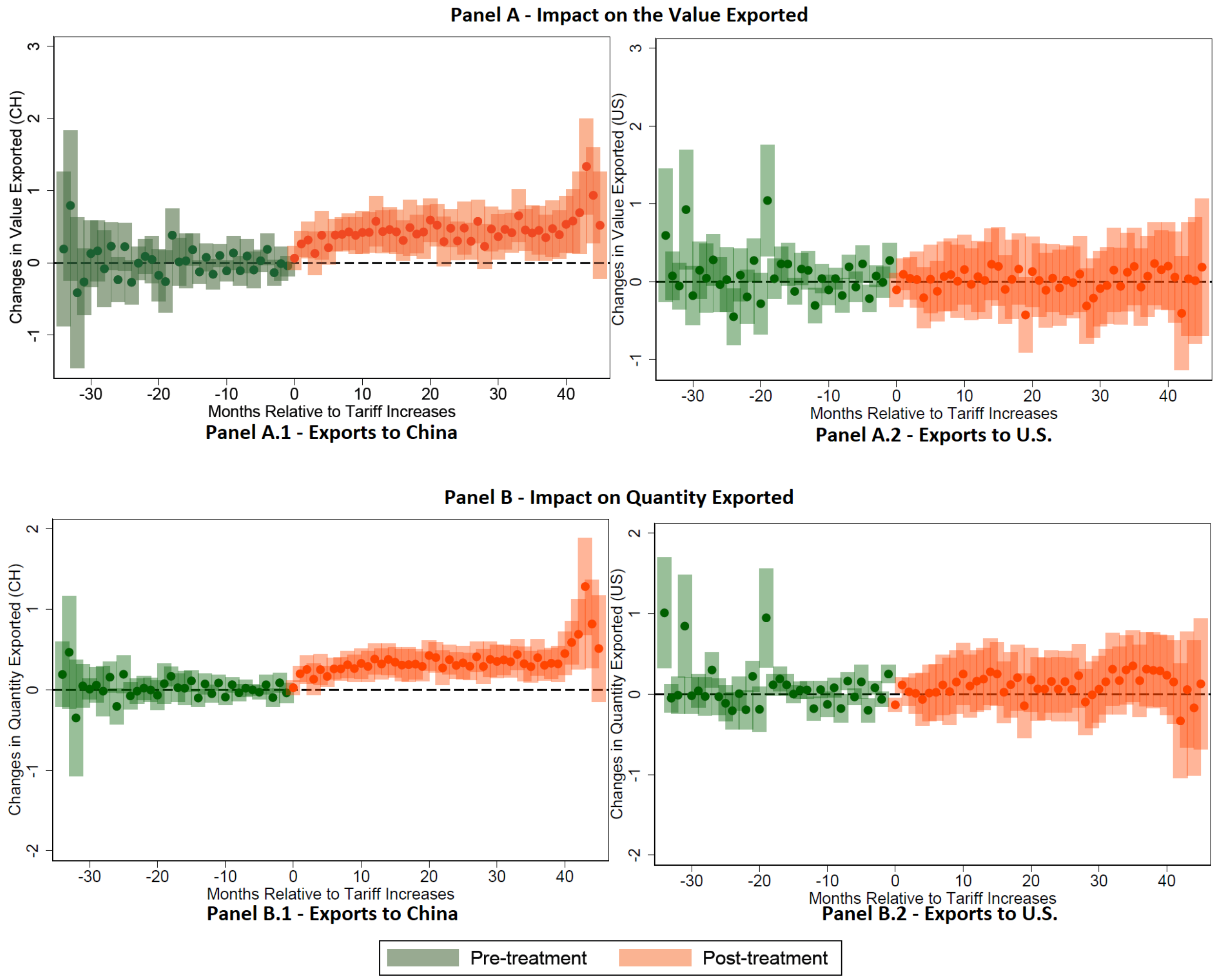
Panel A of Figure 1 presents the θ_k estimates for the 34 months preceding and 45 months following the month of tariff implementation, showing the impact on the value of exports from Brazil to China (Panel A.1) and to the US (Panel A.2). The bars around the point estimates represent 95% confidence intervals.

There is no evidence of anticipation effects in the value exported to either China or the US before the implementation of the discriminatory tariffs. However, immediately after the tariffs were imposed, the value of affected products exported to China significantly increases. The estimates indicate that Brazil's exports of those products to China rose by an average of 44% in the 45 months following the tariffs.[7] In contrast, the estimates suggest that the discriminatory tariffs had no significant effect on the value of exports to the US.

To assess whether this effect is driven solely by higher prices for Brazilian goods, Panel B of Figure 1 plots the θ_k estimates for the impact of the tariffs on the quantity exported to China and the US. The results follow a similar pattern to those for export value. The estimates indicate that the trade war tariffs led to a 36% increase in the quantity exported by Brazil to China, while exports to the US remained unaffected.

[7] The aggregate estimate is calculated as the average of the post-tariff impacts, weighted by group size in each period.

Figure 1: Impact of Trade War Tariffs on Brazilian Exports



Each dot represents the estimated coefficient θ_k from equation 1. In Panel A, the dependent variable is the logarithm of one plus the value exported (in billions of dollars) to China (Panel A.1) or the US (Panel A.2). In Panel B, the dependent variable is the logarithm of the quantity exported (in kilograms) to China (Panel B.1) or the US (Panel B.2). Bars represent 95% confidence intervals. Standard errors are clustered at the HS 4-digit level.

Overall, the results show that Brazil's exports to China were positively affected by the trade conflict between China and the US, while exports to the US were not significantly impacted. These findings suggest that, to the extent Brazilian local labor markets were affected by the trade war, the impact likely stemmed from Chinese imports diverted from the US to Brazil, rather than from US-imposed barriers on Chinese goods. Accordingly, our main analysis focuses on the effects of the discriminatory tariffs imposed by China on US products, although we also include results for US tariffs to ensure the robustness of our conclusions.

3 Data

We combine data from multiple sources to construct an annual dataset spanning 2012 to 2021, using data from each December. Following the literature on trade shocks and tariff impacts on the Brazilian labor market (Kovak, 2013; Dix-Carneiro and Kovak, 2017), our analysis is conducted at the microregion level, defined as a group of contiguous, economically integrated municipalities with similar geographic and productive characteristics (IBGE, 2002)—totaling 558 microregions during the study period.

3.1 Labor Market Data

Labor market data are drawn from the *Registro Anual de Informações Sociais* (RAIS),[8] a matched employer–employee administrative dataset that covers all formally registered firms and workers in Brazil. We compute the number of workers per microregion and sector for each year in the sample as the count of employed individuals aged 15 to 64 who had positive earnings on the last day of the year and valid information on gender, sector, and age. We exclude public-sector employees, as labor laws and regulations differ substantially from those governing the private sector.[9]

We also calculate the total formal wage bill for each microregion based on RAIS data. To ensure comparability over time, wages are deflated to December 2016 values with the consumer price index from IBGE. Table A2 in Online Appendix A presents descriptive statistics for the number of employees and the total wage bill across regions.

[8] Online Appendix C contains more information on RAIS.

[9] In Brazil, it is virtually impossible to dismiss career public servants, who are typically hired through competitive public examinations. In contrast, no such rules apply to private-sector workers.

3.2 Tariff Data

We use annual data on US and Chinese Most-Favored-Nation (MFN) tariffs, the tariff increases imposed by the US on Chinese products in 2018 and 2019, and the retaliatory tariffs imposed by China on US goods. Ad valorem MFN tariffs are obtained from the World Trade Organization's Tariff Analysis Online database[10] The MFN tariffs are reported at the 8-digit HS level, which we aggregate to the 6-digit level using simple averages.[11] The import tariff changes resulting from the trade war come from Li (2021), who provides aggregated US and Chinese tariff increases at the 6-digit HS level from early 2018 through the end of 2019. We consider cumulative tariff increases; for example, if China raised the import tariff on a US good by five percentage points in March 2018 and by another five percentage points in December, we treat the total increase by December 2018 as ten percentage points.

Tariff and trade data from 2012 to 2016 are reported using the 2012 revision of the HS product codes, while data from 2017 to 2021 follow the 2017 revision. To ensure comparability over time, we convert data classified under the 2017 HS revision to the 2012 revision based on the correspondence provided by UNSTATS.[12]

To link tariff data with employment data from RAIS, we construct a correspondence that maps product codes at the 6-digit HS level (2012 revision) to revision 2.0 of the CNAE activity codes. This correspondence is built in two steps. First, we map 6-digit 2012 HS product codes to revision 4.0 of the International Standard Industrial Classification (ISIC), using the concordances between HS4 and CPC 2.1, and between CPC 2.1 and ISIC 4.0, as provided by the World Integrated Trade Solution (WITS) website. Then, we apply the correspondence from ISIC 4.0 to CNAE 2.0, available on the website of Brazil's *Comissão Nacional de Classificação* (CONCLA).[13] In the proposed classification, some products are linked to multiple industries. To address this, we first aggregate industries that share an identical set of products. Additionally, 16 industries are grouped

[10] The tariff data are available at `http://tao.wto.org/`.

[11] Less than 0.5% of Chinese products and approximately 6.5% of US products are subject exclusively to non–ad valorem duties. We treat these as lacking MFN tariff information. As a robustness check, we exclude MFN tariffs when constructing exposure measures and find similar results.

[12] The correspondence between the 2017 and 2012 HS codes is available at `https://unstats.un.org/unsd/trade/classifications/correspondence-tables.asp` (accessed July 1, 2021).

[13] WITS: `https://wits.worldbank.org/product_concordance.html`. CONCLA: `https://concla.ibge.gov.br/classificacoes/correspondencias/atividades-economicas.html`.

into three broader categories due to their high similarity—each group shares more than 65 products in common.[14] For the remaining cases, when a product is associated with multiple industries, it is included in all relevant ones. The final classification comprises 174 CNAE codes, with over 85% of tradable products assigned to a single industry. Online Appendix D provides further details on the construction of this correspondence.

We then aggregate cumulative trade war tariff increases and MFN tariffs to the CNAE 2.0 industry level. This is calculated as a weighted average of product-level tariffs within each industry, using each product's share of industry imports in 2016 as weights. When a product is linked to multiple industries, its tariff is included in the aggregated tariff calculation for each associated industry. Accordingly, industry-level trade war and MFN tariff changes imposed by country $C1$ in year t are defined as:

$$\tau^{TW}_{C1,t,i} = \sum_{p\in i} \frac{M^{C1}_{p,2016}}{\sum_{p\in i} M^{C1}_{p,2016}} \tau^{TW}_{C1,t,p},$$

$$\tau^{MFN}_{C1,t,i} = \sum_{p\in i} \frac{M^{C1}_{p,2016}}{\sum_{p\in i} M^{C1}_{p,2016}} \tau^{MFN}_{C1,t,p},$$

where $\tau^{TW}_{C1,t,i}$ represents the trade war tariff imposed by country $C1$ in industry i in year t, while $\tau^{MFN}_{C1,t,i}$ denotes its corresponding MFN tariff for the same industry and year. These industry-specific tariffs are calculated as the weighted average of tariffs on all products p belonging to industry i, with weights based on each product's share of the industry's total imports. Additionally, $\tau^{TW}_{C1,t,p}$ denotes the discriminatory tariff applied by country $C1$ on product p from country $C2$ in year t (e.g., if $C1$ is China, then $C2$ is the US). $\tau^{MFN}_{C1,t,p}$ is the MFN tariff of country $C1$ on product p in year t, and $M^{C1}_{p,2016}$ is the total value of product p imported by $C1$ in 2016.

3.3 Trade Data

We rely on 2016 data on the value of each product imported by China and the US to aggregate tariffs at the industry level. Additionally, 2016 industry-level data on US imports from China, Chinese imports from the US, and global trade are used to construct our primary exposure measure. All data are sourced from the UN Comtrade Database

[14]Results are robust when industries with similar compositions are not aggregated.

at the 6-digit Harmonized System (HS) product code level (`https://comtrade.un.org/data/`).

4 Empirical Strategy

To investigate the impacts of the trade war on Brazil's local labor markets, we construct two industry-specific variables: one reflecting the effect of US tariff increases on Chinese products, and the other measuring the impact of China's retaliatory tariffs. For each, we calculate a microregion's exposure to the trade war shock as a weighted average of the corresponding industry-specific measure, using the microregion's employment shares across industries as weights.

Although tariff hikes began only in 2018, the initial American investigations that triggered the escalation process started in April 2017 (Bown, 2021). Consequently, individuals and firms may have anticipated the trade war's effects and adjusted their behavior before 2018. To address this concern, we use 2016 as the baseline year.[15] Our results suggest that anticipation is not a concern.

4.1 Global Market Impacts of Trade War Tariffs

The US-China trade war could affect the Brazilian economy only indirectly, as Brazilian products were not subject to the tariffs. These indirect effects depend on whether the tariffs significantly disrupted global markets in the affected industries. To see that, suppose Chinese imports from the US of a given product account for only a small fraction of global trade in that product. Then, a Chinese retaliatory tariff on it is unlikely to affect international markets or third countries, including Brazil. In contrast, if the trade flows are substantial, the resulting distortions are more likely to impact other economies.

We construct a proxy for the effect of trade war tariff changes on the global market of each industry i, denoted as the Global Market Impact (GMI_i^{C1}), which captures the intuition described above. This proxy weights the trade war tariffs imposed on industry

[15] Mayr-Dorn et al. (2023) also use 2016 as the baseline to estimate the US-China trade war effects on Vietnam's labor market.

i through the end of 2019 by the baseline share of global trade flows directly affected by the tariff increase.[16] We measure the trade flows directly affected by tariff increases as the 2016 value of industry i imported by China from the US (for Chinese tariffs) or by the US from China (for American tariffs), divided by the global trade flows of the corresponding products in the same year. Formally, we define the global market impact proxy as:

$$GMI_i^{C1} = \frac{M_{i,2016}^{C1 \leftarrow C2}}{M_{i,2016}^{W}} log(1 + \tau_{C1,i,2019}^{TW}), \tag{2}$$

where GMI_i^{C1} is a proxy for the global market impact on industry i of the discriminatory tariff imposed by country C_1; $M_{i,2016}^{C1 \leftarrow C2}$ is the total value of products from industry i imported by C_1 from C_2 in 2016; $M_{i,2016}^{W}$ is the total value of global trade in industry i in 2016; and $\tau_{C1,t,i}^{TW}$ is the trade war tariff imposed by country C_1 on products from industry i originating in C_2 by the end of 2019.[17]

To illustrate the relevance of this approach, consider the toys and recreational games industry. During the trade war, the US imposed a 15 p.p. tariff increase on Chinese imports, while China raised tariffs on US goods by 24 p.p. Yet in 2016, US imports from China accounted for nearly a quarter of global trade in this industry, whereas China's imports from the US made up just 0.36%. This asymmetry suggests that US tariffs are likely to have a much greater global market impact than China's retaliation, despite the latter being steeper.

To measure industries' global market impact, we use discriminatory tariffs imposed through the end of 2019. This ensures our baseline specification reflects the full set of trade barriers enacted during the trade war, even when analyzing earlier years such as 2018 and 2017. As a robustness check, Section 6 presents results using an alternative exposure measure based only on tariffs implemented by the end of 2018, confirming the consistency of our findings for Brazilian labor market outcomes.

[16] Using an alternative GMI based on tariffs through end-2018 yields similar results.

[17] We obtain similar results using a global market impact proxy that excludes Brazil's imports and exports from total global trade.

4.2 Regional Exposure to Trade War Tariffs

Building on the literature that investigates the impacts of tariff changes on local labor markets, we exploit the variation of the GMI across sectors and the heterogeneity in industry mix across regions to construct a measure that captures the extent to which microregion r is affected by the tariff increases imposed by country $C1$ on products from country $C2$. These variables are denoted as regional trade war tariff changes (RTW_r^{C1}). They are calculated as the average of GMI_i^{C1} across industries, weighted by the share of formal workers in region r allocated in tradable industry i in 2016:

$$RTW_r^{C1} = \sum^{I} \lambda_{r,i} GMI_i^{C1}, \tag{3}$$

where λ_r is the 2016 share of formal workers in tradable sectors in region r employed in industry i.[18]

In short, the regional trade war tariff change (RTW_r^{C1}) is constructed in two steps. First, we define the global market impact proxy for industry i due to the tariffs imposed by country $C1$ (GMI_i^{C1}) as the product between industry i's trade war tariff imposed until the end of 2019 and the trade flows impacted by the discriminatory tariffs in this industry. Second, the regional trade war tariff changes (RWC_r^{C1}) from tariffs imposed by country $C1$ in industry i is defined as the average of GMI_i^{C1}, weighted by the relevance of each industry i in region r's labor market. To simplify the visualization of each step, we plug Equation (2) into Equation (3) to obtain:

$$RTW_r^{C1} = \sum^{I} \lambda_{r,t} \overbrace{\frac{M_{i,2016}^{C1 \leftarrow C2}}{M_{i,2016}^{W}} ln(1 + \tau_{C1,i,2019}^{TW})}^{GMI_i^{C1}}.$$

Therefore, RTW_r^{C1} is the average of the log of one plus trade war tariffs, multiplied by the trade flows affected by this discriminatory tariff, weighted by the relevance of each industry for region r's labor market.

[18]As in Kovak (2013), we exclude the nontradable sector and the sum of the shares (λ_r) equals one in all regions. Table A3 in Online Appendix A shows that our results remain similar when we include the nontradable sector—that is, when the sum of shares is not constrained to one. In this alternative specification, we follow Borusyak et al. (2022) and control for the sum of shares.

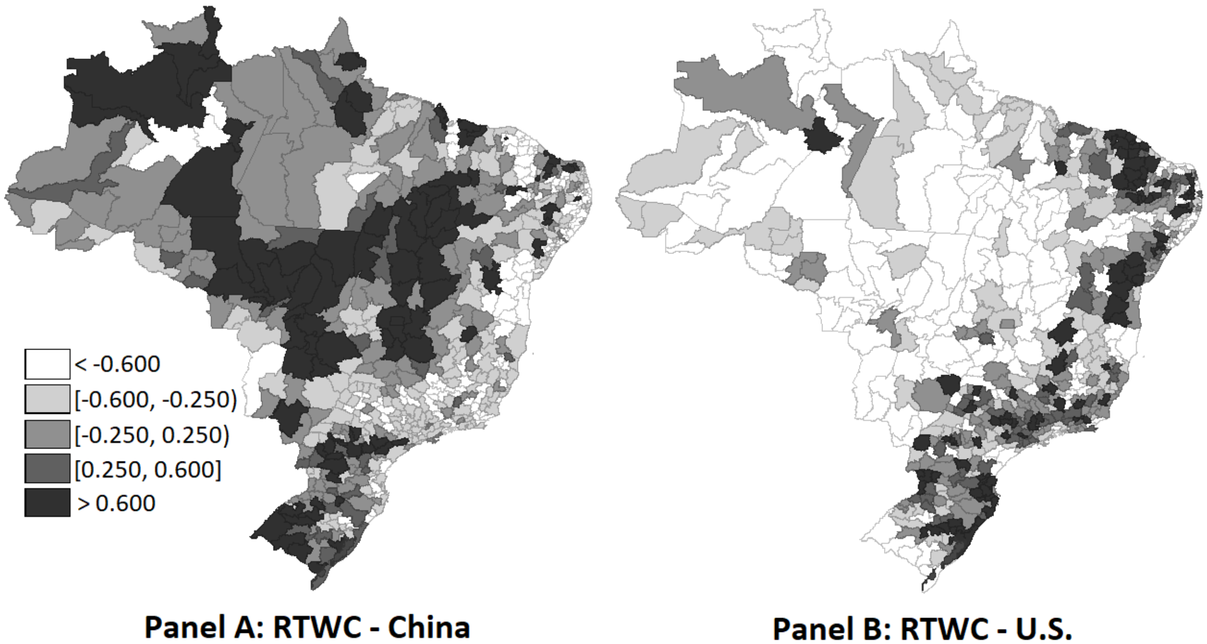


Figure 2: Regional Trade War Tariff Changes (Standardized)

Figure 2 displays the spatial distribution of RTW_r^{C1}. We standardize the Chinese and American regional trade war tariff change variables to reflect variation in standard deviations from the mean. Darker regions are the ones most exposed to trade war tariff increases imposed by China (Panel A) and by the US (Panel B). The regions most exposed to Chinese tariff increases on American goods are located in the North, Center-West, and South, where primary industries are largely agricultural or commodity-based. In contrast, the most affected regions in Panel B are concentrated in the Southeast, Brazil's most industrialized area. Exposure to Chinese and American tariff increases is distributed differently across Brazilian regions and is negatively correlated (correlation=–0.3495). This feature allows us to disentangle the impact on the Brazilian local labor markets of these two shocks.

4.3 Empirical Analysis

To estimate the effect of regional trade war tariff changes on the evolution of labor market outcomes across Brazil's microregions, we estimate the following regression:

$$y_{r,t} - y_{r,2016} = \alpha_s + \beta^{CH} RTW_r^{CH} + \gamma X_r + \varepsilon_{r,t}, \tag{4}$$

where $y_{r,t}$ is the log of the labor market outcome in region r in period t, α_s are state fixed effects, and X_r is a set of regional-level control variables at the baseline.[19] We cluster standard errors at the mesoregion level to account for potential spatial correlation across neighboring microregions.[20]

Coefficient β_t^{CH} captures the impact of China's trade war tariffs. A positive β_t^{CH} indicates that regions more exposed to Chinese tariff increases on American imports experienced improved outcomes relative to less exposed regions. Our main specification uses the 2019 regional trade war tariff changes.

We use data on economic outcomes prior to 2016 to test for the presence of preexisting trends, as the parallel trends assumption is central to the difference-in-differences approach. Specifically, we estimate Equation (4) using the difference in outcomes between each year $t \in [2012, 2015]$ and 2016.

We follow Borusyak et al. (2022) and base our identification strategy on the exogeneity of shock assignment. Specifically, two key conditions must be satisfied: (i) shocks must be assigned quasi-randomly, and (ii) there must be a sufficiently large number of uncorrelated shocks. The first condition is likely met, as it is unlikely that the discriminatory tariffs were systematically related to the performance of Brazil's local labor markets. The main concern, therefore, is whether the 174 industries in our sample provide enough independent variation to yield consistent estimates.

To assess whether the second condition holds, we compute the inverse of the Herfindahl-Hirschman Index (HHI), as recommended by Borusyak et al. (2022). In our case, the HHI is 82.16, which is relatively high. Borusyak et al. (2022) demonstrate that when the HHI surpasses 20, the effective sample size is sufficiently large to ensure a broad distribution of uncorrelated shocks. This finding indicates that production was not overly concentrated in a few industries.

[19]Our baseline controls include the share of female workers, the share of workers with a high school diploma, the share of workers under the age of 30, the microregion's GDP, and the share of workers employed in the agricultural sector.

[20]Mesoregions are groupings of microregions defined by the IBGE.

5 Results

Table 1 presents the estimated causal effects of the US–China trade war on formal employment and regional wage bills. Panels A.1 and B.1 report results using only Chinese discriminatory tariffs as the shock variable, while Panels A.2 and B.2 include both Chinese and American discriminatory tariffs. Columns (1)–(3) show estimates for changes in outcomes between 2016 and 2021, 2020, and 2019, respectively. Columns (4) and (5) present results for 2018 and 2017, capturing pre-implementation effects. Columns (6)–(9) report placebo estimates for 2012–2015, testing for pre-trends using Equation (4). In all cases, exposure measures are constructed using the full set of tariff changes from 2016 to 2019. The trade war tariff change variables are standardized to represent standard deviations from the mean.

Panels A.1 and A.2 present the estimated impact of the US–China trade war on the number of formal workers in Brazilian regions. In both panels, the coefficients in Columns (1)-(3) indicate that Chinese discriminatory tariffs led to an increase in formal employment in the regions most exposed to these tariffs, relative to less exposed regions. The estimated effect remains stable from 2019 to 2021. Additionally, accounting for regional exposure to American discriminatory tariffs on Chinese products (Panel A.2) has little effect on the estimates. As expected, the coefficients associated with the American tariffs are small and statistically insignificant, suggesting that these tariffs did not meaningfully affect formal employment in Brazil.

The magnitude of the coefficient associated with Chinese tariffs in Column (1) indicates that a one standard deviation increase in RTW_r^{CH} led to a 2.1% increase in formal employment from 2016 to 2021. For a microregion with the average number of formal employees, this corresponds to the creation of approximately 1,328 new formal jobs. It is important to note that our specification does not allow us to infer about the aggregate effects of the trade war; all interpretations are relative.

Columns (4) and (5) of Panel A present estimates using the change in the log number of formal employees from 2016 to 2018 and from 2016 to 2017, respectively. We find a positive but statistically insignificant coefficient for $RTW^{CH}r$; and small, negative, and also insignificant coefficients for $RTW^{US}r$, suggesting that microregions may take time to fully adjust and for the effects of discriminatory tariffs to materialize. Although not

Table 1: Regional Trade War Tariff Changes and Labor Outcomes

	After Trade War					Before Trade War			
Dep.Var: Δ_{16} Log(Y$_t$)	(1) t = 2021	(2) t = 2020	(3) t = 2019	(4) t = 2018	(5) t = 2017	(6) t = 2015	(7) t = 2014	(8) t = 2013	(9) t = 2012
Panel A. Formal Employment									
A.1 Main Specification									
RTW_r^{CH}	0.021*	0.023**	0.020*	0.018	0.008	0.012	0.004	-0.000	0.004
	(0.009)	(0.008)	(0.008)	(0.012)	(0.005)	(0.009)	(0.009)	(0.010)	(0.016)
A.2 Including U.S. Tariffs									
RTW_r^{CH}	0.021*	0.022**	0.018*	0.016	0.008	0.010	0.005	0.001	0.008
	(0.009)	(0.008)	(0.008)	(0.011)	(0.006)	(0.010)	(0.009)	(0.011)	(0.016)
RTW_r^{US}	-0.001	-0.005	-0.007	-0.007	-0.004	-0.008	0.003	0.005	0.017
	(0.007)	(0.008)	(0.007)	(0.006)	(0.005)	(0.004)	(0.007)	(0.010)	(0.010)
Panel B. Formal Wages									
B.1 Main Specification									
RTW_r^{CH}	0.023*	0.025*	0.028**	0.020	0.013	0.014	0.001	-0.006	0.008
	(0.011)	(0.011)	(0.010)	(0.012)	(0.008)	(0.011)	(0.011)	(0.011)	(0.018)
B.2 Including U.S. Tariffs									
RTW_r^{CH}	0.023*	0.023*	0.025*	0.018	0.012	0.012	0.001	-0.007	0.009
	(0.011)	(0.011)	(0.011)	(0.012)	(0.008)	(0.012)	(0.012)	(0.012)	(0.019)
RTW_r^{US}	-0.004	-0.010	-0.013	-0.008	-0.006	-0.009	0.000	-0.005	0.004
	(0.009)	(0.010)	(0.009)	(0.006)	(0.006)	(0.005)	(0.008)	(0.011)	(0.012)
Obs.	558	558	558	558	558	558	558	558	558

Notes: Coefficients obtained from OLS regressions of the changes in the log of economic outcomes on 2019 Chinese and American regional trade war tariff changes. Each Panel displays the estimates using a different economic outcome. Economic outcomes used are: (Panel A) The number of formal workers, and (Panel B) the region's Wage bill. Panels A.1 and B.1 shows results considering only the Chinese discriminatory tariffs, while Panels A.2 and B.2 incorporates both Chinese and American discriminatory tariffs. Columns (1) to (4) display the estimates for the years 2021 to 2018 (after trade war), column (5) displays the results for 2017, and columns (6) to (9) show the estimates for the years 2015 to 2012 (before trade war). All regressions include state-fixed effects and a set of baseline regional-level control variables: share of female workers, share of workers with a high school degree, share of workers under 30 years old, the microregion's GDP, and the share of workers employed in the agricultural sector. Standard errors in parentheses clustered at the mesoregion level (137 clusters).
Significance at the *5%, ** 1% levels.

statistically significant, the estimate for Chinese tariffs in Column (4) is similar in magnitude to those in Columns (1) to (3), indicating that regions may have already begun to experience the effects of the trade war by 2018.

Columns (6)–(9) of Panel A show no consistent, statistically significant correlation between regional trade war tariff change variables and pre-investigation changes in the number of formal employees across microregions. This provides evidence that the parallel trends assumption holds in our context, supporting the interpretation of the estimates in Columns (1)-(3) as reflecting the causal impact of the trade war.

Panels B.1 and B.2 present results using the total wage bill of firms in each region as the dependent variable. The coefficients in Columns (1)-(3) indicate a positive and statistically significant causal effect of Chinese regional trade war tariff changes on wage bills. As in Panel A, RTW_r^{US} does not have a significant effect on changes in wages paid to formal employees. In Columns (4) and (5), the coefficients associated with Chinese tariffs remain positive but are not statistically significant. Notably, the magnitude of the coefficient increases over time, suggesting that regions may have already begun to feel the impact of Chinese discriminatory tariffs by 2018.

According to the coefficient in Column (1) of Panel B.1, a one standard deviation increase in RTW_r^{CH} led to an average increase of 2.3% in the total wage bill by 2021.[21] For a microregion at the mean of the formal wage bill distribution, this corresponds to an increase of R$3.7 million, equivalent to US$1.14 million in 2016 values. primarily driven by job creation rather than significant wage growth.

The coefficients in Columns (6)–(9) of Panel B present the results of the placebo tests using the total wage bill as the dependent variable. None of these coefficients are statistically significant, providing evidence that the observed effects are not driven by pre-existing trends in wage outcomes.

Altogether, the results indicate that Chinese discriminatory tariffs on American imports positively affected labor market outcomes in the Brazilian regions most exposed to these measures. This suggests that the trade war between the two largest trading nations generated localized benefits for some Brazilian workers.

[21] The effect on total wage bills is similar in magnitude to the increase in formal employment, suggesting that the observed gains were primarily driven by job creation rather than significant wage growth.

6 Robustness

We conduct several robustness checks to ensure that our results are not driven by specification choices and are consistent across alternative measures of regional exposure to trade war tariffs. Methodological details are provided in Online Appendix E. Table E2 reports robustness results using changes in employment levels, while Table E3 presents those for changes in wages.

First, we assess the potential confounding effects of changes in China's MFN tariffs, which were adjusted during the trade war (Panel B). The results indicate no significant correlation between MFN and trade war tariffs at the product level, and our main findings remain unchanged when explicitly controlling for MFN tariff changes.

Next, we evaluate an alternative measure of regional exposure that accounts for initial MFN tariff levels in 2016 (Panel C). The results are nearly identical to those from our main specification, suggesting that the magnitude of pre-existing tariffs does not affect the estimated impacts. We also test the robustness of our results to different functional forms of the trade exposure variable. Specifically, we redefine the global market impact measure using both squared and square root transformations of the affected trade flow (Panels D and E). The findings remain consistent, indicating that the results are not driven by the choice of functional form.

Finally, we verify whether our estimates are sensitive to the timing of the exposure definition. Instead of using the full set of tariffs imposed until the end of 2019, we construct an alternative measure based only on tariffs in place by the end of 2018 (Panel F). The estimates remain similar.

Overall, these tests confirm that our findings are not sensitive to specific modeling choices or alternative definitions of exposure. The main conclusions about the trade war's impact on regional labor markets remain robust across all specifications.

7 Conclusion

We examine the causal impact of the 2017–2019 US-China trade war on Brazil's local labor markets. By leveraging the variation in regional exposure to discriminatory tariffs imposed during the trade war, we identify how the bilateral trade conflict between the world's two largest economies can spillover to third countries.

We find that the Chinese discriminatory tariffs on American imports increased formal employment and wage bills in the Brazilian regions more exposed to these tariffs, relative to less exposed regions. Conversely, the discriminatory tariffs imposed by the US on Chinese goods did not significantly affect Brazil's labor markets. This reflects the fact that American and Brazilian exports to China are highly substitutable, but Chinese and Brazilian exports to the US are not.

While existing studies have documented the negative effects of the trade conflict on labor markets, welfare, and firm performance in the countries directly involved, our research highlights how international trade disputes can also generate unintended yet significant economic consequences for third countries. In Brazil's case, the trade war created opportunities for certain regions to benefit from trade diversion. This underscores the interconnectedness of the global economy and how bilateral trade conflicts can shape economic outcomes well beyond the countries engaged in the dispute.

References

Amiti, M., S. H. Kong, and D. Weinstein (2020). The effect of the US-China trade war on US investment. *NBER Working Paper 27114*.

Amiti, M., S. J. Redding, and D. E. Weinstein (2019). The impact of the 2018 tariffs on prices and welfare. *Journal of Economic Perspectives 33*(4), 187–210.

Benguria, F. and F. Saffie (2020). The impact of the 2018-2019 trade war on US local labor markets. *SSRN Working Paper 3542362*.

Benguria, F. and F. Saffie (2024). Escaping the trade war: Finance and relational supply chains in the adjustment to trade policy shocks. *Journal of International Economics 152*, 103987.

Blanchard, E. J., C. P. Bown, and D. Chor (2024). Did Trump's trade war impact the 2018 election? *Journal of International Economics 148*, 103891.

Borusyak, K., P. Hull, and X. Jaravel (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies 89*(1), 181–213.

Bown, C. and M. Kolb (2021). Trump's trade war timeline: An up-to-date guide. *Peterson Institute for International Economics*, 1–22.

Bown, C. P. (2021). The US–China trade war and Phase One agreement. *Journal of Policy Modeling 43*(4), 805–843.

Callaway, B. and P. H. Sant'Anna (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics 225*(2), 200–230.

Casagrande, D., C. Mallmann, and P. R. Feistel (2023). US-China trade war: The effects of trade conflict on Brazilian exports. *SSRN Working Paper 4577170*.

Chang, P.-L., K. Yao, and F. Zheng (2024). The response of the Chinese economy to the US-China trade war: 2018-2019. *SSRN Working Paper 4930978*.

Chen, N., D. Novy, and D. Solórzano (2025). Trade diversion and labor market outcomes. *Mimeo*.

Chor, D. and B. Li (2024). Illuminating the effects of the US-China tariff war on China's economy. *Journal of International Economics 150*, 103926.

Cui, C. and L. S.-Z. Li (2021). The effect of the US–China trade war on Chinese new firm entry. *Economics Letters 203*, 109846.

Dix-Carneiro, R. and B. K. Kovak (2017). Trade liberalization and regional dynamics. *American Economic Review 107*(10), 2908–46.

Fajgelbaum, P., P. Goldberg, P. Kennedy, A. Khandelwal, and D. Taglioni (2024). The US-China trade war and global reallocations. *American Economic Review: Insights 6*(2), 295–312.

Fajgelbaum, P. D., P. K. Goldberg, P. J. Kennedy, and A. K. Khandelwal (2020). The return to protectionism. *The Quarterly Journal of Economics 135*(1), 1–55.

Flaaen, A. and J. Pierce (2024). Disentangling the effects of the 2018-2019 tariffs on a globally connected U.S. manufacturing sector. *The Review of Economics and Statistics, forthcoming*.

Freund, C., A. Mattoo, A. Mulabdic, and M. Ruta (2024). Is US trade policy reshaping global supply chains? *Journal of International Economics 152*, 104011.

Goswami, S. (2022). Employment consequences of US trade wars. *University of California Irvine Working Paper*.

He, C., K. Mau, and M. Xu (2021). Trade shocks and firms hiring decisions: Evidence from vacancy postings of Chinese firms in the trade war. *Labour Economics 71*, 102021.

Huang, Y., C. Lin, S. Liu, and H. Tang (2023). Trade networks and firm value: Evidence from the US-China trade war. *Journal of International Economics 145*, 103811.

IBGE (2002). Censo demográfico 2000: Documentação dos microdados da amostra. *Rio de Janeiro: Instituto Brasileiro de Geografia e Estatística.*.

Javorcik, B. K. S., K. Stapleton, B. Kett, and L. O'Kane (2024). Did the 2018 trade war improve job opportunities for US workers? *Journal of International Economics, forthcoming.*

Kovak, B. K. (2013). Regional effects of trade reform: What is the correct measure of liberalization? *American Economic Review 103*(5), 1960–76.

Li, M. (2021). CARD trade war tariffs database. *Center for Agriculture and Rural Development*. `https://www.card.iastate.edu/china/trade-war-data/` (Accessed July 1, 2021).

Mayr-Dorn, K., G. Narciso, D. A. Dang, and H. Phan (2023). Trade diversion and labor market adjustment: Vietnam and the US-China trade war. *SSRN Working Paper 4444393*.

Nguyen, A. and S. Lim (2023). Structural transformation in the era of trade protectionism. *SSRN Working Paper 4426955*.

Rotunno, L., S. Roy, A. Sakakibara, and P.-L. Vezina (2023). Trade policy and jobs in Vietnam: The unintended consequences of Trump's trade war. *QPE Working Paper 2023-56*.

Topalova, P. (2010). Factor immobility and regional impacts of trade liberalization: Evidence on poverty from India. *American Economic Journal: Applied Economics 2*(4), 1–41.

Waugh, M. E. (2019). The consumption response to trade shocks: Evidence from the US-China trade war. *NBER Working Paper* (26353).

Appendix A Additional Tables

Table A1: Correlation Between Brazil's Exports, US Imports from China, and China Imports from the US

Correlation	Brazil's Exports	China Imports from the US	US Imports from China
Brazil's Exports	1		
China Imports from the U.S.	0.5350	1	
U.S. Imports from China	0.0137	0.0271	1

Notes: Correlation between the 2016 value exported by Brazil, the value imported by China from the US, and the value imported by the US from China. Analysis conducted at 6-digit HS product code level.

Table A2: Descriptive Statistics

	t = 2012	t = 2013	t = 2014	t = 2015	t = 2016	t = 2017	t = 2018	t = 2019	t = 2020	t = 2021
Panel A. Employment										
Total (Millions)	37.56	38.59	38.25	36.77	35.27	35.19	35.67	34.40	33.47	37.04
Mean	67,309.26	69,162.29	68,543.05	65,893.83	63,216.23	63,066.01	63,918.16	61,642.69	59,990.33	66,371.19
Stf.Dev	271,541.15	274,673.22	271,564.41	258,904.64	247,000.95	244,026.82	246,573.27	235,901.67	225,616.23	248,665.97
Panel B. Wage Bill (R$ Millions)										
Total (Millions)	86,447.61	91,508.83	98,902.17	92,980.29	89,960.96	90,534.30	90,606.82	85,780.40	82,082.02	88,209.40
Mean	154.92	163.99	177.24	166.63	161.22	162.25	162.38	153.73	147.10	158.08
Stf.Dev	807.70	840.34	901.06	847.51	808.45	804.92	806.04	770.47	728.85	790.30
Observations	558	558	558	558	558	558	558	558	558	558

Notes: This table displays descriptive statistics across microregions for each outcome used in the paper by year. Each Panel displays the total value, mean, and standard deviation of the outcome. In Panel A, we show the statistics for the number of employment; Panel B displays the descriptive for the wage bill. Salaries are adjusted to 2016 values.

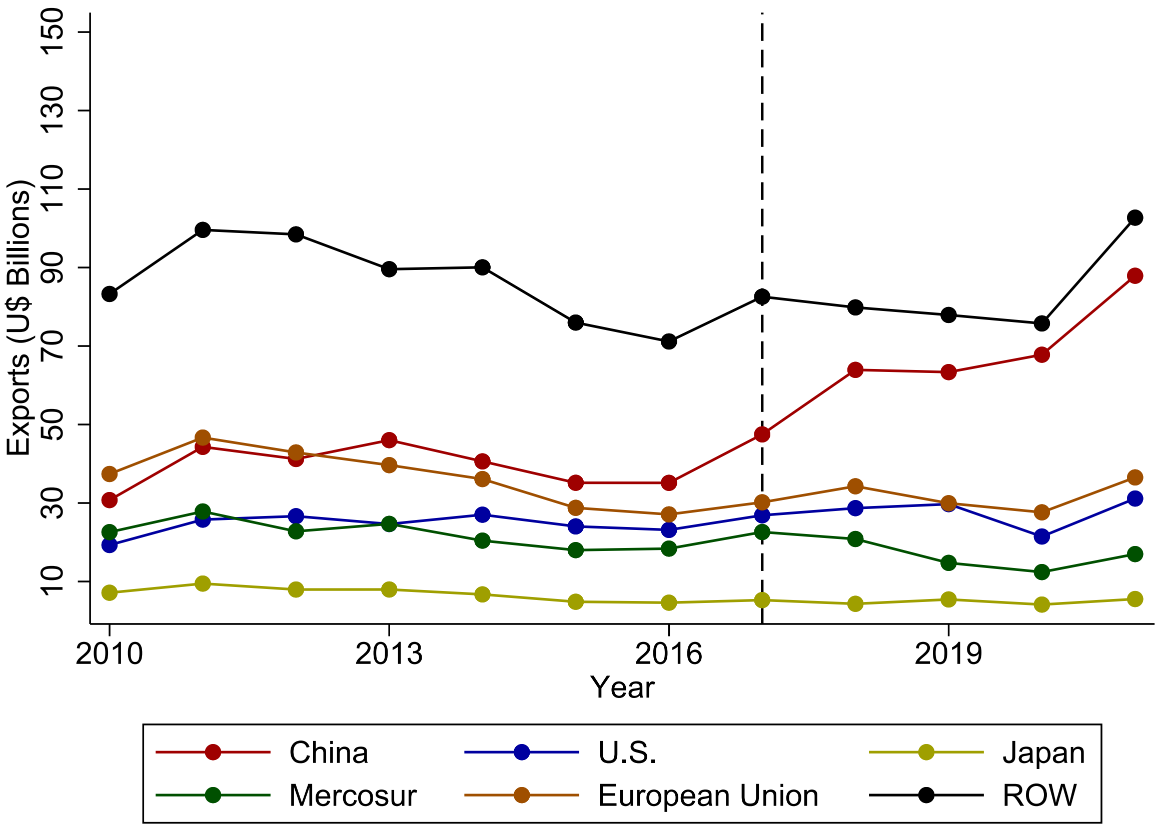
Table A3: Regional Trade War Tariff Changes and Labor Outcomes - Including Non-Tradable Industries to Calculate Shares

	After Trade War					Before Trade War			
Dep.Var: Δ_{16} Log(Y_t)	(1) t = 2021	(2) t = 2020	(3) t = 2019	(4) t = 2018	(5) t = 2017	(6) t = 2015	(7) t = 2014	(8) t = 2013	(9) t = 2012
Panel A. Formal Employment									
RTW_r^{CH}	0.029**	0.031**	0.024**	0.012	0.009	0.018	0.013	0.011	0.006
	(0.008)	(0.008)	(0.008)	(0.008)	(0.006)	(0.010)	(0.012)	(0.013)	(0.012)
Panel B. Formal Wages									
RTW_r^{CH}	0.031**	0.033**	0.034**	0.017	0.015	0.018	0.013	0.006	0.003
	(0.010)	(0.010)	(0.010)	(0.009)	(0.008)	(0.012)	(0.013)	(0.013)	(0.013)
Obs.	558	558	558	558	558	558	558	558	558

Notes: Coefficients obtained from OLS regressions of the changes in the log of economic outcomes n an alternative version of Chinese regional trade war tariff changes. This alternative RTW^{CH} is calculated by including nontradable sectors when determining regions' industry employment shares. Each Panel displays the estimates using a different economic outcome. Economic outcomes used are: (Panel A) The number of formal workers, and (Panel B) the region's Wage bill. Columns (1) to (4) display the estimates for the years 2021 to 2018 (after trade war), column (5) displays the results for 2017, and columns (6) to (9) show the estimates for the years 2015 to 2012 (before trade war). All regressions include state-fixed effects, controls for the sum of shares and a set of baseline regional-level control variables: share of female workers, share of workers with a high school degree, share of workers under 30 years old, the microregion's GDP, and the share of workers employed in the agricultural sector. Standard errors in parentheses clustered at the mesoregion level (137 clusters).
Significance at the *5%, ** 1% levels.

Appendix B Additional Figures

Figure B1: Brazilian Exports by Destination



Notes: This figure shows the value of Brazil's exports (in billions of dollars) to its main trading partners over time. Each line corresponds to the value exported to a specific partner: China (red), the US (blue), Japan (yellow), Mercosur (green), and the European Union (orange). The value of exports to the rest of the world is depicted in grey. The vertical line indicates the year preceding the onset of the tariff escalation.

Appendix C RAIS Data

The Annual Relation of Social Information (RAIS) is an administrative data set reported by the Brazilian Ministry of Labor that provides high-quality data of Brazilian formal labor market. RAIS was instituted by the decree nº 76.900 on December 23 of 1975 to (i) Provide information regarding the formal labor market in Brazil, (ii) monitor the entry of foreign workers in the Brazilian labor market. (iii) provides statistical information for government decisions (iv) generate data for different governmental benefit programs as FGTS, unemployment insurances, PIS, PASEP, and "abono salárial".

Since report the information on every formal employee is a costly task for companies, the federal government created a mechanism to guarantee that the information reported are complete and accurate. First, companies that delay sending data or send false or incomplete information face fines until they send the complete information. Second, some governmental benefits paid to workers are conditional on having their job information correctly declared in RAIS. Hence, workers have an incentive to require the employer to send the correct information. Therefore, both workers and employers have an incentive to report accurate and complete information to the Ministry of labor, ensuring the quality of the data.

We collect the following information of RAIS:

1. The number of formal employees in each industry for the years between 2012 and 2021: To construct this variable, we considered only individuals between 15 and 64 years old, employed on the last day of December, and with a positive earning in that month. In cases in which the same worker appeared twice in the sample, we keep only the highest paying job in December.

2. We also collect data on formal employees' wages in December of each year. Based on individual wages, we calculate the total wage bill for each microregion during this month. December wages are used because data for this period is considered the most reliable.

Appendix D Correspondence Between HS and CNAE Codes

The tariff and trade data used in the analysis are reported at the 6-digit product-level HS code, whereas the employment data from RAIS are reported at the CNAE 2.0 level, an economic activity classification. To map the product-level data to CNAE 2.0, we utilized the following correspondences:

1. A correspondence between 6-digit HS codes (revision 2012) and 5-digit CPC codes (revision 2.1), obtained from the WITS website.[22]
2. A correspondence between 5-digit CPC codes (revision 2.1) and ISIC economic activity codes (version 4.0), also sourced from the WITS website.
3. A correspondence from ISIC 4.0 to CNAE 2.0 codes (the economic activity classification reported in RAIS data), obtained from the CONCLA website.[23]

During this process, 113 products (2.17% of all products at the 6-digit HS level) were excluded because they do not have a correspondent CNAE industry code.

After establishing the correspondence between 6-digit HS codes and CNAE 2.0 codes, we aggregated industry codes that were composed of the same set of products. This process resulted in 177 tradable industries. Additionally, we combined six industries into three broader categories due to high similarity (See Table D1). The final correspondence includes 174 activity codes.

For robustness, we replicated our analysis without aggregating these 11 industries. The findings remained virtually unchanged, confirming that the aggregation process does not affect the overall results or the conclusions of our analysis.

[22] https://wits.worldbank.org/product_concordance.html

[23] https://concla.ibge.gov.br/classificacoes/correspondencias/atividades-economicas.html

Table D1: Industries Aggregated due to similarity

New Group	CNAE 2.0 Codes	Group with the same products	Number of products	Observation
Group 1	14134	1	215	1) CNAE codes 14134, 14126, and 14118 consist of exactly the same set of products.
	14126		215	
	14118		215	2) All 215 prducts in these three industries are also included in industry 14142.
	14142	2	218	
Group 2	28259	1	65	1) CNAE codes 28259, 28232, and 28241 consist of exactly the same set of products.
	28232		65	
	28241		65	2) All 65 prducts in these three industries are also included in industry 28291.
	28291	2	86	
Group 3	20223	1	480	1) CNAE codes 20223,20118, 20215, 19322, 20142, 20193, 19314 consist of exactly the same set of products.
	20118		480	
	20215		480	
	19322		480	
	20142		480	
	20193		480	2) All 480 prducts in these seven industries are also included in industry 20291.
	19314		480	
	20291	2	482	

Appendix E Robustness Tests

This section demonstrates that our findings are robust to alternative model specifications and different measures of regional exposure to trade war tariff changes. Tables E2 and E3 present the robustness tests for the impacts of the trade war on employment and regions' wage bills, respectively. For reference, Panel A in each table replicates the estimates from the main specification. The subsequent panels provide the estimates for the alternative approaches, which are explained in detail in the remainder of this section.

E.1 Controls for MFN Tariff Changes

During the Trade War, China also changed their MFN import tariffs to the rest of the world. If those MFN tariff changes are correlated with the trade war tariffs imposed on the American imports, then the interpretation of the estimates presented in Table 1 as the causal impact of the trade war would be compromised. As a first check, Table E1 presents the correlation between the MFN tariff changes from 2016 to 2019 and the discriminatory tariffs imposed during the trade war until 2019 at the product level. The coefficients indicate that these tariffs are not correlated. Therefore, variations in MFN tariffs are not expected to contaminate the results presented in the previous section.

Table E1: Correlation Between Trade War Tariffs and MFN Tariff Changes

Correlation	$\tau^{TW}_{CH,2019,p}$	$\tau^{TW}_{US,2019,p}$	$\tau^{MFN}_{CH,2019,p}$	$\tau^{MFN}_{US,2019,p}$
$\tau^{TW}_{CH,2019,p}$	1			
$\tau^{TW}_{US,2019,p}$	0.0668	1		
$\tau^{MFN}_{CH,2019,p}$	-0.1306	-0.0876	1	
$\tau^{MFN}_{US,2019,p}$	-0.0259	0.0181	0.0290	1

Notes: Correlation between trade war tariffs and MFN tariff changes from 2016 to 2019.Analysis conducted at 6-digit HS product code level.

To conduct a more formal test and guarantee that the MFN tariff reductions are not influencing our findings, we estimate regressions (4) controlling for a possible confounding effect coming from MFN tariff changes. The MFN tariff change controls are constructed similarly to the regional trade war tariff changes, but using the difference in MFN tariffs instead of trade war-induced tariff increase. Also, observe that the definition of the trade flow affected differs when considering the MFN tariff changes. Hence, the MFN regional tariff change ($RTC^{C1}_{MFN,r}$) controls for country $C1$ is calculated as:

$$RTC^{C1}_{MFN,r} = \sum^{I} \lambda_{ri} \frac{M^{C1 \leftarrow W}_{i,2016}}{M^{W}_{i,2016}} [ln(1 + \tau^{MFN}_{C1,i,2019}) - ln(1 + \tau^{MFN}_{C1,i,2016})],$$

where $M^{C1 \leftarrow W}_{i,2016}$ is the total value imported by country C1 of products in industry i in 2016, $\tau^{MFN}_{C1,i,t}$ is the MFN tariff imposed by country $C1$ on in industry $i's$ products in year t.

The estimates for β^{CH} when including MFN tariff controls are displayed in Panel B of Tables E2 and E3. The coefficients magnitudes and significance levels for this alternative approach are similar to the ones from the main specification. Thus, we can conclude that the MFN tariff changes are not a meaningful confounder in this context.

E.2 Alternative Measure for Regional Trade War Tariff Changes

One might question whether the effect of tariff hikes could be less pronounced for products that were already subject to higher MFN tariffs prior to the conflict, compared to those previously untariffed. To address this, Panel C of Tables E2 and E3 presents the estimates using an alternative version of RTW^{CH}_{r} that accounts for the difference in tariffs relative to their initial levels. This alternative version of the exposure variable is constructed as follows:

$$RTW^{CH}_{r} = \sum^{I} \lambda_{r,t} \overbrace{\frac{M^{CH \leftarrow US}_{i,2016}}{M^{W}_{i,2016}} \underbrace{\left[ln(1 + \tau^{TW}_{CH,2019,i} + \tau^{MFN}_{CH,2016,i}) - ln(1 + \tau^{MFN}_{C1,2016,i})\right]}_{\Delta\tau^{C1 \leftarrow C2}_{i,t}}}^{GMI^{CH}_{i,t}}.$$

where, $\tau^{MFN}_{C1,2016,i}$ is the 2016 MFN tariff imposed by China on products from industry i.

The coefficients in Panel C are nearly identical to those in the main specification, suggesting that the results from this alternative approach similarly capture the impacts

Table E2: Robustness: Regional Trade War Tariff Changes and Formal Employment

Dep.Var: Δ_{16} Log(Employment$_t$)	After Trade War					Before Trade War			
	(1) t = 2021	(2) t = 2020	(3) t = 2019	(4) t = 2018	(5) t = 2017	(6) t = 2015	(7) t = 2014	(8) t = 2013	(9) t = 2012
Panel A. Main Specification									
RTW_r^{CH}	0.021*	0.023**	0.020*	0.018	0.008	0.012	0.004	-0.000	0.004
	(0.009)	(0.008)	(0.008)	(0.012)	(0.005)	(0.009)	(0.009)	(0.010)	(0.016)
Panel B. Including MFN controls									
RTW_r^{CH}	0.021*	0.023**	0.020*	0.018	0.009	0.010	0.002	-0.002	0.004
	(0.009)	(0.008)	(0.008)	(0.012)	(0.005)	(0.009)	(0.009)	(0.010)	(0.016)
Panel C. Alternative $\mathbf{RTW_r^{CH}}$ - Including 2016 MFN									
RTW_r^{CH}	0.021*	0.023**	0.020*	0.018	0.009	0.012	0.004	-0.000	0.004
	(0.009)	(0.008)	(0.008)	(0.012)	(0.006)	(0.009)	(0.009)	(0.010)	(0.016)
Panel D. Alternative $\mathbf{RTW_r^{CH}}$ - GMI_{alt-1}									
RTW_r^{CH}	0.018*	0.019**	0.018**	0.018	0.007	0.009	0.003	-0.000	0.005
	(0.008)	(0.007)	(0.006)	(0.013)	(0.004)	(0.008)	(0.009)	(0.010)	(0.018)
Panel E. Alternative $\mathbf{RTW_r^{CH}}$ - GMI_{alt-2}									
RTW_r^{CH}	0.022**	0.024**	0.020*	0.017	0.010	0.009	0.000	-0.007	-0.000
	(0.008)	(0.008)	(0.008)	(0.011)	(0.006)	(0.009)	(0.009)	(0.009)	(0.013)
Panel F. Trade War Tariffs until 2018									
$RTW_{r,2018}^{CH}$	0.020*	0.023**	0.019**	0.011	0.007	0.013	0.006	0.004	0.000
	(0.008)	(0.007)	(0.007)	(0.008)	(0.005)	(0.009)	(0.009)	(0.010)	(0.012)
Obs.	558	558	558	558	558	558	558	558	558

Notes: Coefficients obtained from OLS regressions of the changes in the log of the number of formal employment on Chinese regional trade war tariff changes. Panel A displays the estimates from the main specification. Panel B includes MFN tariff changes controls. Panel C show the estimates for the main specification but an alternative version of the RTW_r^{CH} in which we consider the log difference in trade war tariffs plus MFN tariffs in 2016. Panels D and E also test alternative exposure measures, using the squared and square root of the affected trade flows to construct the GMI, respectively. Panel F estimates the main specification but the RTW_r^{CH} is constructed using the trade war tariffs implemented until 2018. Columns (1) to (4) display the estimates for the years 2021 to 2018 (after trade war), column (5) displays the results for 2017, and columns (6) to (9) show the estimates for the years 2015 to 2012 (before trade war). All regressions include state-fixed effects and a set of baseline regional-level control variables: share of female workers, share of workers with a high school degree, share of workers under 30 years old, the microregion's GDP, and the share of workers employed in the agricultural sector. Standard errors in parentheses clustered at the mesoregion level (137 clusters).
Significance at the *5%, ** 1% levels.

of the trade war on economic outcomes. This consistency indicates that the initial MFN tariff levels of products do not significantly influence the estimated effects.

Table E3: Robustness: Regional Trade War Tariff Changes and Formal Wages

	After Trade War					Before Trade War			
Dep.Var: Δ_{16} Log(Earnings$_t$)	(1) t = 2021	(2) t = 2020	(3) t = 2019	(4) t = 2018	(5) t = 2017	(6) t = 2015	(7) t = 2014	(8) t = 2013	(9) t = 2012
Panel A. Main Specification									
RTW_r^{CH}	0.023*	0.025*	0.028**	0.020	0.013	0.014	0.001	-0.006	0.008
	(0.011)	(0.011)	(0.010)	(0.012)	(0.008)	(0.011)	(0.011)	(0.011)	(0.018)
Panel B. Including MFN controls									
RTW_r^{CH}	0.023*	0.024*	0.028**	0.020	0.013	0.012	-0.001	-0.008	0.007
	(0.011)	(0.011)	(0.010)	(0.012)	(0.008)	(0.011)	(0.011)	(0.011)	(0.018)
Panel C. Alternative RTW_r^{CH} - Including 2016 MFN									
RTW_r^{CH}	0.024*	0.025*	0.028**	0.020	0.013	0.014	0.001	-0.005	0.009
	(0.011)	(0.011)	(0.011)	(0.013)	(0.009)	(0.011)	(0.012)	(0.011)	(0.018)
Panel D. Alternative RTW_r^{CH} - GMI_{alt-1}									
RTW_r^{CH}	0.016	0.016	0.022*	0.016	0.010	0.011	0.001	-0.003	0.013
	(0.009)	(0.009)	(0.009)	(0.012)	(0.006)	(0.010)	(0.010)	(0.011)	(0.020)
Panel E. Alternative RTW_r^{CH} - GMI_{alt-2}									
RTW_r^{CH}	0.029**	0.031**	0.033**	0.023	0.016	0.012	-0.005	-0.014	0.001
	(0.011)	(0.011)	(0.012)	(0.012)	(0.010)	(0.012)	(0.012)	(0.010)	(0.016)
Panel F. Trade War Tariffs until 2018									
$RTW_{r,2018}^{CH}$	0.022*	0.026**	0.026**	0.015	0.012	0.014	0.003	-0.003	-0.002
	(0.010)	(0.009)	(0.009)	(0.009)	(0.007)	(0.011)	(0.011)	(0.011)	(0.014)
Obs.	558	558	558	558	558	558	558	558	558

Notes: Coefficients obtained from OLS regressions of the changes in the log of region's wage bill on Chinese regional trade war tariff changes. Panel A displays the estimates from the main specification. Panel B includes MFN tariff changes controls. Panel C show the estimates for the main specification but an alternative version of the RTW_r^{CH} in which we consider the log difference in trade war tariffs plus MFN tariffs in 2016. Panels D and E also test alternative exposure measures, using the squared and square root of the affected trade flows to construct the GMI, respectively. Panel F also estimates the main specification but the RTW_r^{CH} is constructed using the trade war tariffs implemented until 2018. Columns (1) to (4) display the estimates for the years 2021 to 2018 (after trade war), column (5) displays the results for 2017, and columns (6) to (9) show the estimates for the years 2015 to 2012 (before trade war). All regressions include state-fixed effects and a set of baseline regional-level control variables: share of female workers, share of workers with a high school degree, share of workers under 30 years old, the microregion's GDP, and the share of workers employed in the agricultural sector. Standard errors in parentheses clustered at the mesoregion level (137 clusters).
Significance at the *5%, ** 1% levels.

E.3 Alternative Measures for Global Market Impact

To assess the robustness of our results to different specifications of the exposure measure, we also construct the GMI using alternative transformations of the affected trade flow. Specifically, we consider two additional specifications: one using the squared value of the affected trade flow (GMI_{alt-1}^{C1}) and another using its square root (GMI_{alt-2}^{C1}). That is:

$$GMI_{alt-1}^{C1} = \left[\frac{M_{i,2016}^{C1\leftarrow C2}}{M_{i,2016}^{W}}\right]^2 log(1+\tau_{C1,i,2019}^{TW}), \tag{5}$$

$$GMI_{alt-2}^{C1} = \sqrt{\frac{M_{i,2016}^{C1\leftarrow C2}}{M_{i,2016}^{W}}} log(1+\tau_{C1,i,2019}^{TW}), \tag{6}$$

Panel D and E presents the results when constructing RTW_r^{CH} using GMI_{alt-1}^{C1} and GMI_{alt-2}^{C1}, respectively. The results obtained with these alternative measures remain consistent with those from our main specification, suggesting that our findings are not sensitive to the functional form of the trade exposure variable.

E.4 Estimating the impacts using trade war tariffs until 2018

In the main specification, we estimate the impacts of the trade war for all years using regional exposure to the discriminatory tariffs imposed by China up to the end of 2019. However, one might question whether the results, particularly the impacts in 2018, would differ if we used only the trade war tariffs imposed by the end of 2018. To address this concern, we re-estimate the main specification by constructing RTW_r^{CH} based solely on the Chinese discriminatory tariffs in place by the end of 2018.

The results of this exercise are presented in Panel F of Tables E2 and E3. The estimates in columns (1) to (4) are similar to those from the main specification, although slightly smaller, as expected, since the exposure variable does not fully capture the shock faced by the most exposed regions. Overall, the estimated coefficients in this specification closely align with those from the main specification, confirming the robustness of the results to this alternative specification.