The U.S-China Trade War Creates Jobs (Elsewhere)

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Abstract

This study examines the indirect effects of the U.S.-China trade war on the Brazilian labor market. We exploit the tariff increases across industries and the sectoral employment distribution across local labor markets to measure the degree of exposure of a Brazilian region to the trade war. Our findings reveal that while American discriminatory tariffs did not significantly impact Brazilian local labor markets, regions more exposed to Chinese retaliatory tariffs experienced a relative increase in formal workers and wage bills. Moreover, we investigate the impact of the conflict on total investments made by firms using bank loans as a proxy for investments, revealing that bank loans were not affected by the tariff hikes. These insights contribute to a better understanding of the intricate implications of the U.S.-China trade war on the Brazilian labor market.

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1 Introduction

The trade war between China and the United States represents an unprecedented setback for world trade liberalization since World War II. The process of increasing U.S. protection started at the beginning of 2017 when President Trump set the stage to conduct its trade policy and raise import tariffs on China (Bown, 2021). During 2018 and 2019, the Trump Administration significantly increased import tariffs on various Chinese products, targeting over $250 billion worth of Chinese exports.[1] In response, China retaliated by imposing import tariffs on more than $100 billion worth of American exports. What makes these trade war tariff changes even more noteworthy is their magnitude: from 2018 to 2019, average U.S. tariffs on Chinese products surged from 2.94% to 24.94%, while China's average tariffs on American products rose from 9.79% to 28.24%.[2] Moreover, despite the phase one deal at the beginning of 2020, import tariffs between the two countries remained at high levels (Bown, 2021).

The trade barriers imposed during the trade war have a discriminatory nature, with both the U.S. and China applying extra tariffs exclusively to each other's exports while keeping import tariffs on goods from other countries unchanged. Consequently, one can expect these tariffs to increase the demand for the affected products from the rest of the world. Given the magnitudes of the trade barriers imposed and the size of the economies involved, these shifts in demand are likely to drive up international prices, resulting in distributional consequences not only for the U.S. and China but also for other countries.[3] While several studies have explored the impacts of the trade war on the U.S. and China, little is known about the indirect effects this shock may have caused on the rest of the world. This paper sheds light on this topic by investigating how Trump's trade war impacted Brazilian local labor markets.

Using the variation in the initial employment structure across Brazilian local la-

[1] The value of exports affected by the trade war tariffs is calculated based on the 2017 export values.

[2] These values are derived from simple averages of tariffs on the 6-digit HS product codes.

[3] Previous literature, such as Feenstra (1989) and Irwin (2019), has suggested the possibility of incomplete pass-through for U.S. tariff increases to other countries in similar situations (i.e., reduction of tariff-exclusive import prices). However, contrary evidence from Amiti et al. (2019), Fajgelbaum et al. (2020), and Cavallo et al. (2021) reveals a complete pass-through of American tariff increases in 2018-2019. Similarly, Chang et al. (2020) and Ma et al. (2021) find evidence of complete pass-through for retaliatory Chinese tariffs. Therefore, there appears to be plenty of room for other countries to increase their export prices to both China and the U.S., thereby impacting international prices.

bor markets to construct geographic measures of exposure, we find that Brazilian regions specialized in industries targeted by China's trade policy towards the U.S. faced a relative increase in the number of formal workers and the total wage bill from 2016 to 2019. In contrast, the labor market in regions more exposed to the price changes induced by the American tariffs on China did not behave differently from other Brazilian regions. Therefore, While previous studies find that the trade conflict harmed the labor markets in the U.S and China (Goswami (2020), Waugh (2019) Benguria and Saffie (2020), and Flaaen and Pierce (2021)), our study presents a new perspective of the trade war impacts, showing that the conflict may have created jobs elsewhere. [4]

Given that the process of increasing U.S. trade protection began in 2017, with Trump initiating trade policy investigations to set the stage for the trade war against China (Bown, 2021), there is a possibility that economic agents anticipated the trade war's impacts and started changing their behavior before the tariff escalation even began.[5] Thus, to guarantee that the anticipation is not interfering with our results, we use 2016 as the baseline in our estimations. Moreover, using data from December 2017, we find evidence suggesting that individuals anticipated part of the effect. The magnitude of the impact in 2017 is about half the one in 2019, indicating that individuals anticipated the event, but the effect increased after the tariff escalation began.

Additionally, we investigate the impacts on the total regional amount of bank loans from 2016 to 2019, using it as a proxy for firms' investment. To construct this measure, we only consider loans used to finance real estate, agriculture, or other kind of business. We find no impact on loans from both American and Chinese trade policies, indicating that firms in Brazil did not increase investments due to the trade war. This result suggests that Brazilian firms hesitated to change their investment patterns and take risks during an uncertain moment.

To conduct the analysis, we first exploit the variation in tariff increases across in-

[4]Since our methodology only estimates the impacts in relative terms, we cannot conclusively state that the trade war created jobs in Brazil. Nevertheless, our findings suggest that regions more exposed to the price changes induced by the Chinese trade policy experienced an enhancement in their labor markets compared to less exposed regions.

[5]The possibility of a trade war between the two countries was already in the news in early 2017. See (1) Soumaya Keynes "The Trump Administration Starts to Turn up the Heat on Trade," The Economist, April 29, 2017; (2) Bill Ide, "China Anxious About Trade War With US," Voice of America, March 15, 2017; (3) Landler and Shear, "Trump Administration to Take Harder Tack on Trade With China," The New York Times, April 6, 2017.

dustries and the relevance of the trade flow affected to construct two proxies, one for China and another for the U.S., that capture the impact of the policies implemented by each country on international prices at the industry level.[6]. Building on Kovak (2013) and later studies on regional impacts of trade policies, we use the heterogeneity in pre-shock employment structure across Brazilian regions and the variation in the tariff-induced price changes proxies to assess how much a region is exposed to the effects of the U.S. or China trade war tariff increases. Using these exposure variables, we estimate the causal indirect impacts of the trade war on Brazil's local labor market. An important feature of our estimation method is that we separately identify the effects of the trade war coming from the retaliatory tariffs imposed by China and the tariff increases implemented by the United States.

To validate the parallel trends assumption in our context, we conduct pre-trends placebo tests for all estimations and outcomes analyzed. The absence of correlation between outcomes' pre-trends and the proposed exposure measures allows us to interpret our findings as causal impacts of the trade war on the Brazilian economy. Furthermore, we perform robustness tests using alternative methods to calculate exposure measures to Chinese and American tariff changes, confirming that our results are not driven by how we construct the main exposure variables.

This paper contributes to the growing literature investigating the distributive impacts of the US-China trade conflict. We build upon existing studies that exploit the heterogeneity in geographic exposure to the trade war tariff increases to assess the impacts on labor market outcomes. These early studies demonstrate that the American commuting zones more exposed to Chinese retaliatory tariffs faced a relative reduction in employment growth, while the U.S. tariffs did not affect employment growth in a relevant manner (Goswami, 2020), Waugh (2019), and Benguria and Saffie (2020).[7] In contrast, using a similar empirical strategy, our study provides a fresh perspective, showing that the trade war may have positive labor market effects in non-involved countries.

Additionally, this study relates to the literature that investigates the impacts of the U.S.-China trade war on investments. Prior studies use firm-level data to show that the trade conflict reduced firm investments in the U.S. and China. Especially, Amiti et al.

[6]The construction of this proxy is detailed in equation 2 in section 4

[7]Waugh (2019) also shows that the retaliatory Chinese tariffs reduced consumption growth on most exposed regions.

(2020) uses a q-theory of investments to show that the declines in stock prices led by the trade war reduced U.S. firms' returns to capital and investment rates. Moreover, Benguria et al. (2020) use firm-level data to show that the trade policy uncertainty generated by the trade conflict reduces firms' investment and R&D expenditure in China. Our study departs from the previous ones by investigating the impacts on investment at the regional level instead of at the firm level. Furthermore, to the best of our knowledge, we are the first to study the impacts of the trade conflict on business financing.

More generally, our paper enhances the broader understanding of the economic consequences of the U.S.-China trade war. Earlier investigations have shown that the trade conflict negatively affects the welfare of the involved countries (Amiti et al. (2019), Fajgelbaum et al. (2020), and Chang et al. (2020)), is responsible for reducing the market values of the most exposed firms (Huang et al. (2020) and Amiti et al. (2020)) and explain a shift in voting to republican candidates in the 2018 American elections (Blanchard et al. (2019)). By delving into the spillover effects of the conflict in non-involved countries, our research significantly contributes to this field, offering valuable insights into the multifaceted consequences of the escalating protectionism arising from the trade war between China and the United States.

Finally, our study adds to the literature on the impacts of trade shocks on the Brazilian regional economy. Previous studies in this literature show that increasing Chinese import competition has slowed manufacturing wage growth in more exposed Brazilian labor markets between 2000 and 2010, at the same time that the boost in Chinese commodity demand accelerated wage growth in benefited regions Costa et al. (2016). Kovak (2013) and Dix-Carneiro and Kovak (2017) show that the tariff reduction of Brazil's main unilateral liberalization process harmed the labor market in regions specialized in producing goods from the most affected industries. Ogeda et al. (2021) also exploit the Brazilian trade liberalization episode to investigate the impacts of tariff reductions on elections and labor union strength. The authors find that the weakening of unions is responsible for a relative reduction of left-wing votes in all presidential elections after the reform. Our paper expands this literature by investigating the impacts of the conflict between Brazil's two main trade partners on its economy.

This paper is structured as follows. In section 2, we present the main events of the ongoing trade war. Section 3 describes data sources and presents some descriptive statistics. In Section 4, we discuss how we construct the exposure measures and how we estimate the causal impacts of the trade war on the Brazilian economy. Section 5 presents the main results, and section 6 shows the robustness tests. The last section concludes the paper.

2 Institutional Background

This section details the events of the trade war between China and the United States. We begin by exposing the 2017 investigations that led to the first tariff increases by the United States. We then describe the chronology of the tariff increases imposed by the Trump Administration in 2018 and 2019 and the corresponding Chinese retaliations. Here, we only discuss the major trade war events that culminated in tariff increases by the U.S. and China, but see Bown and Kolb (2021) for additional details about the trade war events.

In April 2017, the United States began an investigation under Section 232 of the Trade Expansion Act of 1962 into whether steel and aluminum imports threatened American national security.[8] This investigation led to an increase of 25 percentage points in steel tariffs and 10 percentage points in aluminum tariffs to all American trading partners except Argentina, Australia, Brazil, Canada, the European Union, México, and South Korea on March 23, 2018. Although these tariffs were not discriminated by origin, it was clear that the U.S. was trying to affect Chinese imports. In response to the Section 232 tariffs, China imposed retaliatory tariffs on selected American products at the beginning of April. The American tariff increases and the Chinese retaliation were similar regarding the value of trade flow impacted: \$2.8 billion and \$2.4 billion of Chinese and American 2017 exports, respectively.

In August 2017, Trump's administration started another investigation, but this one was based on Section 301 of the Trade Act of 1974. This investigation aimed to verify whether there were Chinese laws, policies, or actions that could harm technology development in the United States or infringe on American intellectual property rights.

[8]Section 232 of the Trade Expansion Act of 1962 authorizes the Secretary of Commerce to conduct investigations to determine whether a product is being imported in quantities or circumstances that may threaten American national security. See `https://www.commerce.gov/news/fact-sheets/2017/04/fact-sheet-section-232-investigations-effect-imports-national-security` for more information.

On April 3, 2018, the U.S. announced a $50 billion list of more than one thousand Chinese products under consideration for an increase of 25 percentage points in their import tariffs. The next day, China also released a $50 billion worth list of American products subject to a 25 percentage points increase in their tariffs. On July 6, both countries imposed tariffs on the first $34 billion of their $50 billion lists of products subject to tariff increases. The tariffs on the remaining $16 billion went into effect on August 23.

At the beginning of September 2018, the United States announced a new list of tariff increases ranging from 5 to 10 percentage points worth $200 billion of American 2017 imports. Shortly after the American announcement, China released a $60 billion list of retaliatory tariff increases. Both lists went into effect on September 24. In December, both countries announced their intentions to increase tariffs on the products from the September list even more.

In 2019 there were three new events where the United States raised its tariffs on Chinese products, and China retaliated. First, at the beginning of May 2019, Trump increased tariffs on the products in the $200 billion list of September 2018 by 15 percentage points. In response, China also raised tariffs on products from the $60 billion list of September. After that, in August, the United States announced a new increase in tariffs, targeting $300 billion of imports from China. Again China retaliated with $75 billion. The last tariff increase event of 2019 occurred in December, with another tariff hike on phones, laptop computers, and video game consoles by the United States and on cars and car parts by China.

At the beginning of January 2020, China and the United States signed the phase one deal, which implemented provisions covering purchase commitments, financial market access, and intellectual property protection. Together with the agreement, China also committed to buying an additional $200 billion worth of U.S. exports. Despite the agreement, the import tariffs remained in effect at higher levels. In terms of comparison, U.S. tariffs on Chinese products in January 2020 were 6 times higher than before 2018.

3 Data

To investigate how the trade war between China and the United States impacted Brazilian local labor markets, we combine data from different sources and construct a yearly frequency dataset spanning 2012 to 2019.[9] For all years, we use data for December. Following the literature that studies the impact of trade shocks and tariff changes on the Brazilian labor market, we conduct our analysis at the microregion level, defined as a group of economically integrated contiguous municipalities with similar geographic and productive characteristics (IBGE, Instituto Brasileiro de Geografia e Estatistica, 2002). During the period covered by our analysis, Brazil had 558 microregions, yielding a total of 4,464 observations in our sample.

In the following subsections, we detail the data used in our analysis, explaining all the manipulations to get to the final dataset. We also comment on the descriptive statistics in Table 1.

Table 1: Descriptive Statistics

Outcome:	t = 2012	t = 2013	t = 2014	t = 2015	t = 2016	t = 2017	t = 2018	t = 2019
Panel A. Employment								
Total (Millions)	37.56	38.59	38.25	36.77	35.27	35.19	35.67	34.54
Mean	67,309.26	69,162.29	68,543.05	65,893.83	63,216.23	63,066.01	63,918.16	61,903.52
Std.Dev	271,541.15	274,673.22	271,564.41	258,904.64	247,000.95	244,026.82	246,573.27	237,137.35
Panel B. Wage bill (R$ Millions)								
Total	65,210.14	69,027.97	74,605.01	70,137.94	67,860.37	68,292.85	68,347.56	65,044.32
Mean	116.86	123.71	133.70	125.70	121.61	122.39	122.49	116.57
Std.Dev	609.27	633.90	679.70	639.30	609.84	607.18	608.02	584.64
Panel C. Loans (R$ Millions)								
Total	833,929.54	1,000,820.42	1,118,534.53	1,092,345.45	1,015,514.67	972,321.70	959,108.23	935,341.22
Mean	1,494.50	1,793.59	2,004.54	1,957.61	1,819.92	1,742.51	1,718.83	1,676.24
Std.Dev	12,846.18	14,643.10	15,535.79	15,022.31	13,316.32	12,312.29	12,013.11	11,594.62
Observations	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 wage bill, and Panel C shows the values for Loans.

[9] We do not use data from 2020 and 2021 as the COVID-19 pandemic considerably affected trade flows worldwide and may contaminate the estimates in our analysis.

3.1 Labor Market Data

Brazilian labor market data comes from the *Registro Anual de Informações Sociais* (RAIS), a matched employer-employee administrative dataset covering all formally registered firms and workers in Brazil. We compute the number of workers per microregion in each year of the sample period as the number of workers between 15 and 64 years old, employed, with positive earnings on the last day of the year, valid information on gender, sector, and age. We omit individuals working in the public sector because the labor laws and regulations are very different for public sector workers.[10]

Using the RAIS data, we also sum the wages paid to these workers to get the total wage bill in each microregion. To compare wage bill over time, we deflate the wages to December 2012 values using the *Índica de Preços as Consumidor Amplo* (IPCA) from the *Instituto Brasileiro de Geografia e Estatística* (IBGE), which is one of the main inflation indexes used in Brazil.

To construct the variable that measures a region's level of exposure to the trade war, detailed in section 4, we collect information on the number of microregions' workers in each tradable sector from the 2016 RAIS data. Again, we only count the individuals between 15 and 64 years old, not employed in the public sector, and formally registered on the last day of 2016. The 2016 RAIS data aggregate workers in 662 industries following revision 2.0 of the CNAE code (Brazilian Industries classification system), where 318 are considered tradable, and the others are non-tradable.

In Panel A of Table 1, we display the total number of formal workers in Brazil in millions, the mean across microregions, and the standard deviations for every year of the analysis. The number of employees between 2012 and 2014 increased slightly but fell abruptly in 2015, reflecting the Brazilian economic and political crises that started at the end of 2014. The number of formal employees fell by 2 million more from 2015 to 2019, and the average number of workers per microregion fell by almost 4 thousand. However, as depicted in Panel B of Table 1, the total real wage bill in 2019 was almost the same as in 2012. Hence, it is possible to conclude that the average wage per worker increased during this period.

[10]Labor legislation in Brazil makes it virtually impossible to fire career public servants, although a small minority of the workforce in the public sector can be hired (and therefore fired) on a temporary basis. There are no such rules for private-sector workers.

3.2 Bank Loan

If the tariff increases imposed by China and the U.S. on one another stimulate the Brazilian economy, one would imagine that firms would increase investments, which would also lead to an increase in the volume of bank financing. Therefore, to investigate whether the trade war between China and the United States indirectly influences firms' investment in Brazil, we look at the effects of conflict on the total amount of bank loans to finance companies.

To do so, we collect data on bank loans from the *Estatística Bancária Mensal por município* (ESTBAN) dataset from the Brazilian Central Bank (BCB).[11] The ESTBAN reports data on the main commercial banks' balance sheet accounts by municipalities at a monthly frequency for the period spanning 1998 to 2022. During the sample period, there were 11 microregions without bank data, which are excluded from our analysis when estimating the impact of the conflict on loans. To adjust the values for the same currency, we also deflate all accounts to December 2012 values using the IPCA index.

The bank loans variable is constructed as the sum of the balance sheet accounts related to the stock of commercial banks' loans in December of each year. It is essential to mention that this variable does not include personal credit and credit card accounts. Hence, the bank loans variable only includes the money to finance real estate, agriculture, and other business. For robustness check, we also make an effort to measure bank loans by adding individuals' loans and credit card accounts, but the results are unchanged using this alternative measure.

In Panel C of Table 1, we show the total value of loans in Brazil and the mean and standard deviations across microregions. The total loans increased from 2012 to 2014 but decreased just after, which may also indicate that the economic crises affected investments in Brazil. The decrease in loans is even more relevant when we consider that the interest rates at the end of 2014 were more than double the ones from 2019.[12]

[11] The ESTBAN dataset is available at `https://www4.bcb.gov.br/fis/cosif/estban.asp?frame=1`.

[12] The interest rate in the end of 2014 was 11.75%, in the end of 2015 it raised to 14.25%. After 2015, interest rates decreased to 13.75% in 2016, 7% in 2017, 6.5% in 2018, reaching 4.5% in 2019.

3.3 Trade Data

As further commented in the following subsection, we use 2016 data on the value imported by China and the United States on each product to aggregate tariffs at the industry level. We also use 2016 industry-level data on the value imported by the U.S. from China, the value imported by China from the U.S., and the total value traded worldwide to construct the primary exposure measure used in this paper. Data on imports comes from the UN Comtrade Database, which reports data on imports and exports for all countries in the world at the 6-digit Harmonized System (HS) products code level.[13]

3.4 Tariff Data

To conduct the analysis, we use yearly data on American and Chinese Most-Favored-Countries (MFN) tariffs, the tariff increases imposed by the United States on Chinese products in 2018 and 2019, and the retaliation tariffs imposed by China on American goods. As previously mentioned, we used data related to tariff levels in December of each year.

We collect Chinese and American MFN tariffs for 2012 to 2019 from the Tariff Analysis Online at the World Trade Organization (WTO) website.[14] We only consider ad valorem MFN tariffs. Hence, products with only non-ad valorem duties (e.g., specific tariffs based on quantity or weight.) are interpreted as having no import tariffs. The MFN tariffs are reported at the 8-digit HS level, which we aggregate to the 6-digit level using simple averages.[15]

The import tariff changes due to the trade war come from the database reported by Li (2021), which provides American and Chinese aggregated tariff increases at the 6-digit HS level from the beginning of 2018 to the end of 2019. We consider cumulative tariff increases; for example, if in March 2018, China increased in five percentage points the import tariff on an American good and in December it increased by five more percentage points, then we consider the increase in the Chinese tariff in December 2018 to be ten percentage points. Given that some tariff changes occur in the middle of months,

[13]see https://comtrade.un.org/data/

[14]The tariff data is available at `http://tao.wto.org/`.

[15]Listar alguns papers que fazem isso! (Tanto Ad valorem e simple average)

we construct the average tariff increases in December of each year by scaling tariffs by the number of days in the month they are in effect.

Tariff and Trade data from 2012 to 2016 are reported using the 2012 revision of the HS product code, while the data from 2017 until 2019 was reported using the 2017 revision. To make data comparable over the years, we transform tariffs and trade data at the 2017 revision HS code to the 2012 revision using the correspondence from UNSTATS.[16]

To link tariff data with employment data from the RAIS, we construct a correspondence that links product codes at the 2012 revision of the 6-digit HS level to revision 2.0 of the CNAE activity codes. The correspondence was constructed 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 correspondence between HS4 to CPC 2.1 and CPC 2.1 to ISIC 4.0 from the World Integrated Trade Solution (WITS) website. Then we use the correspondence from ISIC 4.0 to CNAE 2.0 available at Brazil's *Comissão Nacional de Classificação* (CONCLA) website. [17] In our proposed classification, some products are linked to more than one industry. In those cases, we include these products in all industries that they are linked. The proposed correspondence can be provided upon request.[18]

Using the correspondence detailed in the last paragraph, we aggregate cumulative trade war tariff increases and MFN tariffs to CNAE 2.0 industry level. We do this by calculating the weighted average of the industry's product tariffs, using the product's share of industry imports in 2016 as weights. As commented before, some products are linked to more than one industry. In those cases, we considered the products' tariffs in calculating aggregated tariffs of all industries linked to it. Thus, MFN tariffs and Trade war tariff changes at the industry level imposed by country $C1$ in year t are constructed as follows:

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

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

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

[17]The WITS website can be accessed at `https://wits.worldbank.org/product_concordance.html` and the CONCLA website is available at `https://concla.ibge.gov.br/classificacoes/correspondencias/atividades-economicas.html`.

[18]Send an e-mail to `pedro.ogeda@fgv.br`, and I will gladly send you the proposed classification.

where I is the set of products in industry i, $\tau_{C1,t,p}^{TW}$ are product p's import tariffs increases due to the trade war imposed by country C1 on country C2 in year t (In this case, if C1 is China, then C2 is the United States), $\tau_{C1,t,p}^{MFN}$ are product p's MFN tariff imposed by C1 in year t, $M_{p,2016}^{C1}$ is the total value imported of product p by country $C1$ in 2016.

4 Empirical Strategy

To investigate the impacts of the trade war between China and the United States on Brazilian regional economic activity, we first construct two variables that measure microregions' degree of exposure to the tariff war shock. One variable captures the region's degree of exposure to the tariff increases imposed by the United States on Chinese products, and the other variable captures the exposure to the retaliatory Chinese tariff changes. We then estimate a regression model relating exposure measures to the labor market and bank outcomes. In this section, we detail how we construct these exposure measures and explain how we estimate the impact of the trade war on Brazilian economic outcomes.

Even though the tariff raises started only in 2018, the first American investigations that started the process of the tariff escalation started in April 2017, Bown (2021). Hence, it is possible that individuals and firms already anticipated the impacts of the trade war and changed their behavior and decisions before 2018. Therefore, we consider 2016 as the baseline year to avoid any possibility of anticipation and avoid empirical problems that would compromise our analysis. The concern about anticipation is especially relevant in our case, as we use data for the last month of the year to estimate the impact of the trade war. Considering 2016 as the baseline, we can also gather evidence that the anticipation hypothesis is true when estimating the impacts in December 2017.

4.1 Exposure Measures

To capture the indirect effect of the US-China trade war on the Brazilian economy, we must first identify how the trade war impacts the global market of the affected industries. To do this, we first construct trade war tariff changes imposed by country $C1$ on products of industry i's from country $C2$ ($\Delta\tau_{t,i}^{C1\leftarrow C2}$) as follows:

$$\Delta\tau_{t,i}^{C1\leftarrow C2} = ln(1+\tau_{C1,t,i}^{TW}+\tau_{C1,2016,i)}^{MFN}) - ln(1+\tau_{C1,2016,i}^{TW}+\tau_{C1,2016,i)}^{MFN}) \tag{1}$$

where $\tau_{C1,t,i}^{TW}$ is the trade war cumulative tariff increases imposed by country $C1$ to products of industry i from country $C2$ until year t, and $\tau_{C1,2017,i}^{TW}$ is industry i's 2016 MFN tariff level imposed by country $C1$. Observe that we sum import duties changes due to the trade war with the 2016 MFN tariff to capture the tariff increases relative to its initial level.[19] We use the relative increase in tariffs relative to its initial level since it is expected that the impact on increases in tariffs of products that already had larger MFN tariffs before the war to be smaller than increases of products with no tariffs prior to the conflict.[20]

Suppose Chinese imports from the United States of a particular good represent only a tiny fraction of the global trade flows of this product. In that case, the Chinese retaliatory tariffs on this product are expected to have a negligible impact on global prices. Accordingly, it will have a correspondingly small impact on the Brazilian economy. Analogously, if the trade flow affected is large, the same tariff increase is expected to have a correspondingly large impact on global prices and, consequently, on Brazil.

Thus, we construct a proxy variable for the effect of trade war tariff changes on global prices, which captures the intuition described in the previous paragraph. This proxy is constructed by weighing industry $i's$ trade war tariff changes by the baseline share of global trade flow directly affected by the tariff increase. We measure the trade flow affected by an increase in Chinese import tariffs on American goods as the 2016 value of industry i imported by China from the United States, divided by the global trade flow of this product in the same year. Similarly, the trade flow directly affected by an increase in the American tariffs on Chinese products is computed as the 2016 value of industry i imported by the U.S. from China, divided by the global trade flow of this product. Formally, we can write these proxies as follow:

$$\Delta P_{i,t}^{C1\leftarrow C2} = \frac{M_{i,2016}^{C1\leftarrow C2}}{M_{i,2016}^{W}}\Delta\tau_{i,t}^{C1\leftarrow C2} \tag{2}$$

[19] We use 2016 MFN tariffs, to avoid any endogenous changes due to the announcements of the U.S. investigations that started in 2017.

[20] As robustness, we also construct our main exposure measures using alternative measures for the trade war tariff changes. See section 6 for more details about these alternative measures.

where, $\Delta P_{i,t}^{C1 \leftarrow C2}$ is the proxy for global price changes on industry $i's$ products in period t relative to 2016, $M_{i,2016}^{C1 \leftarrow C2}$ is the total value imported of products from industry i from country $C2$ to $C1$ in 2016, $M_{i,2016}^{W}$ is industry $i's$ products total value traded in the world in 2016.

Following the methodology proposed by Kovak (2013), we exploit the variation of the proxy for global price changes across sectors and the heterogeneity in industry mix across regions to construct a measure that captures the extent to which Brazilian microregion r is impacted by the tariff increases imposed by country C1 on products from country C2.[21] These variables are called regional trade war tariff changes ($RTW_{r,t}^{C1}$). They are calculated as the weighted average of $\Delta P_{i,t}^{C1 \leftarrow C2}$ across industries, weighted by the share of formal workers in region r allocated in industry i in 2016.

$$RTW_{r,t}^{C1} = \sum^{I} \lambda_{r,i} \Delta P_{i,t}^{C1 \leftarrow C2} \tag{3}$$

where λ_r is the 2016 share of formal workers in region r employed in industry i.

Figure 1 displays the 2019 Regional Trade War Tariffs Changes distribution. Darker regions are the ones most exposed to trade war tariff increases imposed by China in Panel A and imposed by the United States in Panel B, while the lighter regions are the less impacted regions. In Panel A, we notice that the most exposed regions to Chinese tariff increases on American goods are located in the North, Centre-West, and South. In those regions, the primary industries are related to agriculture and commodities. The most affected regions in Panel B are concentrated in the southeast, Brazil's most industrialized region. One important feature of the data that can be seen in the figure is that the exposure to China tariff increases and American tariff increases are distributed differently across Brazilian regions and are not strongly correlated (correlation = -0.3495). This feature allows us to disentangle better the impact on the Brazilian economy between these two mechanisms.

[21] The idea of using the heterogeneity in the industry mix to calculate region's exposure to a trade shock at the industry-level was first proposed by Topalova (2010) but formalized by Kovak (2013).

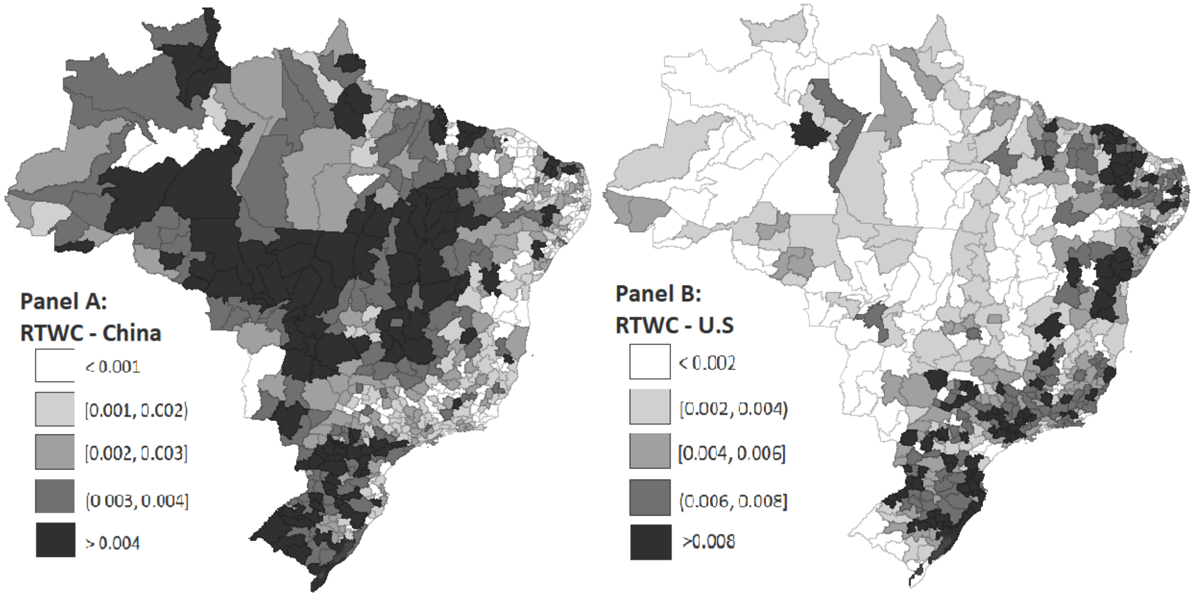

Figure 1: Regional Trade War Tariff Changes

4.2 Empirical Analysis

To compare the 2016 to 2019 evolution of labor market outcomes and bank loans in Brazilian microregions with larger and smaller regional trade war tariff changes, we estimate the following regression:

$$y_{r,2019} - y_{r,2016} = \alpha_s + \beta^{US} RTW^{US}_{r,2019} + \beta^{CH} RTW^{CH}_{r,2019} + \varepsilon_{r,2019} \tag{4}$$

where $y_{r,2019}$ is the log of the economic outcome, α_s are state fixed effects, and $\varepsilon_{r,2019}$ is an statistical error. We cluster standard errors at the mesoregion level to account for potential spatial correlation in outcomes across neighboring regions.[22]

We are interested in the trade war's effect on the Brazilian economy outcomes, which is captured by coefficients β_t^{CH} and β_t^{US}. If β_t^{CH} is positive, then we can conclude that regions with greater exposure to tariff increases imposed by China on American imports experienced an improvement in their outcomes relative to less exposed regions. We have the opposite relationship if the coefficients associated with the regional tariff are negative. An analogous interpretation applies to β_t^{US}.

[22]Mesoregions are groupings of microregions defined by the Brazilian Statistical Agency (IBGE).

To check the evolution of the impact over time and the possibility of anticipation in 2017, we also run regressions 4 using outcome data from 2018 and 2017. However, to simplify the comparison between the estimates over the years, and since there were no tariff changes in 2017, we use the variation in the trade war tariffs until 2019 to construct the exposure measure and estimate the effects in these two years. Hence, for years $t \in 2017, 2018$ we estimate the following regression:

$$y_{r,t} - y_{r,2016} = \alpha_s + \beta_t^{US} RTW_{r,2019}^{US} + \beta_t^{CH} RTW_{r,2019}^{CH} + \varepsilon_{r,t} \tag{5}$$

Since we are using the 2019 regional trade war tariff changes ($RTW_{r,2019}^{US}$ and $RTW_{r,2019}^{CH}$) to measure the impacts of the trade war on the economic outcomes in 2017 and 2018, the estimates from this specification must be interpreted with care. For completeness, in table **??** in Appendix A, we also estimate equation 5 using outcome data and regional trade war tariff changes from 2018.

We follow Goldsmith-Pinkham et al. (2020) and define our identification strategy based on the exogeneity of the formal employment structure across Brazilian regions. Hence, we must guarantee that the difference in exposure in one region only affects the changes in the outcomes through the indirect impacts of the trade war tariff changes and not through other potential confounding channels. To provide evidence that this assumption is satisfied, we use data on economic outcomes before 2016 and conduct a test to verify the presence of preexisting trends. The parallel trend hypothesis is the main identification assumption of the difference-in-difference approach and is also used as evidence that the pre-shock share of employment is exogenous. Therefore, testing for preexisting trends is crucial for our identification strategy. To conduct this identification hypothesis test, we estimate equation 5 using the difference in the outcome from 2016 to years $t \in [2012, 2015]$.

As recommended by Goldsmith-Pinkham et al. (2020), we also calculate the Rotemberg weights, which tell us which industry tariff change is more relevant to identify the impact of the trade war on the outcomes analyzed. These weights are industry-specific and inform the estimates' sensitivity to misspecification for the case in which the share of formal employment, represented by λ_{ri} in equation 3, is endogenous.[23] The

[23]Observe that in this case, the share is only the $\lambda_{r,i}$ since it is the only information that varies by both industry and region.

top 10 industries with the largest Rotemberg weights for the 2019 Chinese and American regional trade war tariff changes and their respective weights and weights among positive weights are reported in Appendix B.[24] The estimated weights indicate that the variation we are exploring in our results from the American tariffs comes mainly from the footwear, furniture, and textile industries. Hence, it can be concluded that the variation from the U.S. tariffs comes from more industrialized sectors. When looking at the Rotemberg weights associated with the Chinese tariffs, the largest are related to the agricultural sector, such as the sawmill industry and the cultivation of soy, cereal, cotton, seeds, and temporary crops.

5 Results

In this section, we analyze the causal effects of the U.S.-China trade war on the number of formal workers, the region's wage bill, and bank loans. The results are displayed in Table 2. The estimates from equation 4, which is the main specification, are depicted in column (1). In Columns (2) and (3), we show the estimates for the impacts of the trade war in 2018 and 2017, respectively. Columns (4) to (7) present a placebo test to verify the existence of a correlation between the exposure measures and the difference in outcomes before Trump took charge and before the U.S. started the investigations that led to the trade conflict. The correlation between the exposure measures and pre-trends is estimated by regressing equation 5 using $t \in [2012, 2015]$. Moreover, in column (8), we show the pooled estimates using data from all years after 2016, and column (9) displays the estimates of pooled regression using data before 2016.[25]

As commented before, in all years and all panels, we construct the exposure measures considering the whole tariff changes from 2016 to 2019 ($RTW^{US}_{r,2019}$ and $RTW^{CH}_{r,2019}$). Moreover, in all columns and panels, we standardize the RTW variables to reflect the variation in standard deviations from the mean. We cluster standard errors at the mesoregion level.

[24]Some Rotemberg weights can be negative, hence Goldsmith-Pinkham et al. (2020) suggest showing the Rotemberg Weights among the industries with Positive Weights adjusted to sum one.

[25]The pooled regressions includes state-year fixed effects.

Table 2: Regional Trade War Tariff Changes and Economic Outcomes

Dep. Var: Δ_t Log(y_t)	(1) t = 2019	(2) t = 2018	(3) t = 2017	(4) t = 2015	(5) t = 2014	(6) t = 2013	(7) t = 2012	(8) $t > 2016$	(9) $t < 2016$
Panel A. Formal Employment									
$RTW^{CH}_{r,2019}$	0.020***	0.016*	0.011**	0.002	-0.007	-0.016	-0.012	0.016***	-0.008
	(0.006)	(0.008)	(0.004)	(0.009)	(0.008)	(0.010)	(0.014)	(0.005)	(0.008)
$RTW^{US}_{r,2019}$	0.003	-0.002	0.001	-0.004	0.002	-0.001	0.013	0.001	0.003
	(0.006)	(0.005)	(0.004)	(0.005)	(0.008)	(0.009)	(0.010)	(0.004)	(0.007)
Panel B. Formal Wages									
$RTW^{CH}_{r,2019}$	0.028***	0.018**	0.014**	0.002	-0.014	-0.021**	-0.013	0.020***	-0.011
	(0.009)	(0.009)	(0.006)	(0.010)	(0.010)	(0.011)	(0.016)	(0.007)	(0.009)
$RTW^{US}_{r,2019}$	0.011	0.005	0.004	-0.006	-0.002	-0.012	0.003	0.007	-0.004
	(0.010)	(0.006)	(0.005)	(0.005)	(0.008)	(0.009)	(0.012)	(0.006)	(0.007)
Observations	558	558	558	558	558	558	558	1,674	2,232
Panel C. Bank Loans									
$RTW^{CH}_{r,2019}$	0.002	0.004	-0.003	0.002	0.007	-0.000	-0.006	0.001	0.001
	(0.019)	(0.014)	(0.011)	(0.005)	(0.008)	(0.014)	(0.018)	(0.014)	(0.010)
$RTW^{US}_{r,2019}$	0.007	-0.002	-0.004	0.003	0.000	0.007	0.000	0.000	0.003
	(0.020)	(0.014)	(0.009)	(0.007)	(0.011)	(0.015)	(0.020)	(0.014)	(0.012)
Observations	547	547	547	547	547	547	547	1,641	2,188

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, (Panel B) the region's Wage bill, and (Panel C) the total value of bank loans. Columns (1) to (3) display the estimates for the years 2019 to 2017 (after investigations), and columns (4) to (7) show the estimates for the years 2015 to 2012 (before investigation). Column (8) estimates a pooled OLS regression using data from 2017 to 2019, including state-year fixed effects. Column (9) also estimates a pooled OLS regression but using data from 2012 to 2015. All regressions include state-fixed effects. Standard errors in parentheses clustered at the mesoregion level (137 clusters).
Significance at the *10%, **5%, *** 1% levels.

5.1 Formal Employees

In Panel A, we present the estimates for β^{US} and β^{CH} using the number of formal workers in the microregion to construct the regressand. The coefficients in column (1), which are estimated by regression 4, indicate that both American and Chinese Regional Trade War Tariff Changes impact positively on the changes in the number of Brazilian formal workers from 2016 to 2019, though only the coefficient associated with RWT^{CH}_{2019} is statistically significant. Thus, the results reveal that Brazilian regions most exposed to the price changes induced by the Chinese retaliatory tariffs experienced an increase in formal workers from 2016 to 2019 compared to less exposed regions. However, the evolution of the number of workers in regions most exposed to U.S. tariffs was not significantly different from the evolution in less affected regions.

The magnitudes of the coefficient associated with the Chinese tariff in column (1) of Panel A indicate that an increase in one standard deviation on RTW^{CH}_{2019} is related to an increase of 2% in the employment of formal workers from 2016 to 2019. Considering a municipality on the average of the number of formal employees distribution, an increase in one standard deviation on $RTW^{CH}_{r,2019}$ is associated with the creation of 1,356 jobs.[26]

Columns (2) and (3) of Panel A show the estimates for the coefficient related to $RTW^{CH}_{r,2019}$ and $RTW^{US}_{r,2019}$ when using the difference in the log number of formal employees from 2016 to 2018 and from 2016 to 2017, respectively. Again, we find a positive and statistically significant coefficient for the $RTW^{CH}_{r,2019}$ and a small and non-statistically significant coefficient for the $RTW^{US}_{r,2019}$. As the coefficient increases over time, the results indicate that regions with larger $RTW^{CH}_{r,2019}$ experienced a continuous increase in formal employees compared to less exposed regions from 2017 until 2019.[27] Furthermore, the significant coefficient for 2017 suggests that even before China and the U.S. started to increase tariffs, individuals already anticipated part of the trade war effect and changed their behavior in terms of labor allocation.

[26] It is important to mention that our specification does not allow us to infer anything about the general effects of the trade war. Therefore, all interpretations are in relative terms, and we can only interpret the effect by looking at how the outcome in a given microregion would change by increasing or decreasing the degree of exposure in that specific region.

[27] In the appendix, we re-estimate the results in column (2) but using the variation in tariffs only until 2018 to construct the RTW variables. By doing so, we show that the patterns are unchanged by this variation in the specification.

In columns (4) to (7) of Panel A, we observe that there does not exist any statically significant correlation between both regional trade war tariff change variables and the pre-investigation trends on the number of formal employees in each microregion. This exercise brings evidence that the parallel trends hypothesis holds in our context and that the estimates in the first three columns reflect the trade war's causal impacts.

Finally, the estimates in columns (8) and (9) display the estimates when running a pooled OLS specification, including state-year fixed effects. These specifications bring us the average effect of the trade war over the years. Column (8) estimates the pooled specification using outcomes from 2017 to 2019, while column (9) uses data before 2016. The conclusions taken from these two columns also indicate that there do not exist statistically significant pre-trends on formal employment and that the Chinese tariff on American goods raises formal employment in most exposed Brazilian regions after 2016 compared to the average across regions.

5.2 Wage Bill

In Panel B, we display the results using the log difference from 2016 to year "t" on the total wage paid by firms in each region as the dependent variable. The coefficients in column (1) indicate a positive and statistically significant causal impact of the Chinese regional trade war tariff changes on the changes in regions' wage bills from 2016 to 2019. As in the results in Panel A, the $RTW^{US}_{r,2019}$ has no significant impact on the change in wages paid to formal employees. From the estimates in columns (2) and (3), we also observe that the total spent on formal workers' wages increased since 2017 in most exposed regions relative to the less exposed ones. Hence, there are signs that firms and individuals anticipate the impacts of the trade war.

The value of coefficients in column (1) of Panel B indicates that by increasing the $RTW^{CH}_{r,2019}$ in one standard deviation, the total wage bill increases, on average, by 2.8%. Considering a microregion located in the average of the distribution of formal wage paid, the magnitude of the coefficients indicates that by increasing the $RTW^{CH}_{r,2019}$ in one standard deviation, the total wage bill increases in R$ 3.40 million.

The coefficients in columns (4) to (7) present the placebo tests using the total wage bill to construct the dependent variable. Except for the coefficient from 2013, the coefficients from the placebo tests are not statistically significant. Hence, this exercise brings evidence that there exist no pre-trends on formal wage paid in each microregion.

Therefore, from the results presented in Panel A and Panel B of Table 2, we can conclude that the Trade War between China and the U.S. enhanced the labor market in Brazilian microregions specialized in industries targeted by China's retaliation against the U.S. Furthermore, the results indicate that firms anticipated the impacts of the trade war after the 2017 announcements made by Trump and changed their production plans by hiring more workers.

5.3 Bank Loans

To better understand how the trade war impacted firms in Brazilian local labor markets, we also investigate whether the firm's investments increased in regions more exposed to the price changes generated by the tariff escalation between U.S. and China. Given the causal impact of the tariff exposure on employment growth, it is possible that the firms also decided to invest more in capital to increase their production or even that new firms started to operate in the regions. If this is the case, one would also expect an increase in bank loans to finance firms' investments or new businesses. Therefore, to verify the trade war's impact on investments in Brazilian regions, we use the total bank loan value as a proxy for business investment.

In Panel C of Table 2, we present the estimates using the Bank loan values to construct the dependent variable. All the estimates, for both $RTW^{CH}_{r,2019}$ and $RTW^{US}_{r,2019}$, in columns (1) to (3) are small and statistically not significant, indicating that until 2019, the Trump's trade war did not impact Bank loans to firms. Moreover, the coefficients for the placebo tests in columns (4) to (7) are also small and non-significant, implying that there are no pre-trends on Bank loans as well.

Thus, although Panel A and B indicate that the trade war impacted Brazilian Labor markets, the estimates in Panel C show evidence that the trade war did not impact firms' investment differently across Brazilian regions. Though we cannot say how firm investment varies within regions, our findings suggest that firms were not expecting the trade war to last long or were unwilling to take risks during a time of uncertainty in global trade policy.

6 Robustness

This section shows that our results are robust when using an alternative specification and ways to measure regions' exposure to trade war tariff changes. We first verify whether our results are affected when including controls for MFN tariff changes. Second, we estimate the regression using an alternative measure of exposure to regional trade war tariff changes.

6.1 Including Controls for MFN Tariff Changes

During the analysis period, both the United States and China also changed their import tariffs to the rest of the world. If those MFN tariff changes are correlated with the trade war tariffs imposed by each country to another, then the interpretation of the estimates presented in Table 2 as the causal impact of the trade war would be compromised. For this reason, we estimate regressions 4 and 5 controlling for a possible confounding effect coming from the 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 for the trade flow affected is differs when considering the MFN tariff changes. Hence, the regional MFN change controls ($RTC_{r,t}^{C1}$) for country $C1$ in year t is calculated as:

$$RTC_{r,t}^{C1} = \sum^{I} \lambda_{ri} \frac{M_{i,2016}^{C1 \leftarrow W}}{M_{i,2016}^{W}} [ln(1 + \tau_{C1,i,t}^{MFN}) - ln(1 + \tau_{C1,i,2016}^{MFN})]$$

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

The estimates for β^{CH} and β^{US} coefficients in equations 4 and 5 when including MFN tariff controls are displayed in Table 3. As in Table 2, we present the estimates for the impact on the number of formal employment in Panel A, the impact on formal wages paid by firms in Panel B, and the estimates for Bank Loans in Panel C. The coefficients magnitudes and significance levels from this alternative approach are similar to the ones from the main specification. Thus, we have evidence that the MFN tariff changes are not a meaningful confounder in this context.

Table 3: Regional Trade War Tariff Changes and Economic Outcomes - Including Regional MFN Tariff Changes Controls

Dep. Var: Δ_t Log(y_t)	(1) t = 2019	(2) t = 2018	(3) t = 2017	(4) t = 2015	(5) t = 2014	(6) t = 2013	(7) t = 2012	(8) $t > 2016$	(9) $t < 2016$
Panel A. Formal Employment									
$RTW^{CH}_{r,2019}$	0.021***	0.017**	0.011**	0.002	-0.007	-0.016	-0.013	0.016***	-0.008
	(0.007)	(0.008)	(0.004)	(0.009)	(0.008)	(0.010)	(0.013)	(0.005)	(0.008)
$RTW^{US}_{r,2019}$	-0.002	-0.002	0.001	-0.004	0.004	0.002	0.017	-0.001	0.004
	(0.006)	(0.005)	(0.004)	(0.005)	(0.007)	(0.009)	(0.010)	(0.004)	(0.007)
Panel B. Formal Wages									
$RTW^{CH}_{r,2019}$	0.031***	0.019**	0.014**	0.001	-0.014	-0.021*	-0.014	0.021***	-0.012
	(0.009)	(0.008)	(0.006)	(0.010)	(0.010)	(0.011)	(0.015)	(0.007)	(0.009)
$RTW^{US}_{r,2019}$	0.001	0.004	0.004	-0.006	0.000	-0.007	0.007	0.004	-0.002
	(0.009)	(0.006)	(0.005)	(0.005)	(0.008)	(0.009)	(0.012)	(0.006)	(0.007)
Observations	558	558	558	558	558	558	558	1,674	2,232
Panel C. Bank Loans									
$RTW^{CH}_{r,2019}$	0.004	0.008	-0.003	0.001	0.006	-0.000	-0.005	0.001	0.001
	(0.020)	(0.014)	(0.011)	(0.005)	(0.008)	(0.013)	(0.018)	(0.014)	(0.010)
$RTW^{US}_{r,2019}$	0.007	-0.003	-0.004	0.003	-0.000	0.007	0.002	-0.000	0.004
	(0.030)	(0.014)	(0.009)	(0.007)	(0.011)	(0.015)	(0.020)	(0.014)	(0.013)
Observations	547	547	547	547	547	547	547	1,641	2,188

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, controlling for regional MFN tariff changes. Each Panel displays the estimates using a different economic outcome. Economic outcomes used are: (Panel A) The number of formal workers, (Panel B) the total Wage paid to formal workers, and (Panel C) the total value of bank loans. Columns (1) to (3) display the estimates for the years 2019 to 2017 (after investigations), and columns (4) to (7) show the estimates for the years 2015 to 2012 (before investigation). Column (8) estimates a pooled OLS regression using data from 2017 to 2019, including state-year fixed effects. Column (9) also estimates a pooled OLS regression but using data from 2012 to 2015. All regressions include state-fixed effects and regional MFN tariff change controls. Standard errors in parentheses clustered at the mesoregion level (137 clusters).
Significance at the *10%, **5%, *** 1% levels.

6.2 Alternative Measure for Regional Trade War tariff Changes

To construct the main version of the regional trade war tariff changes, we consider tariff changes relative to its initial level by summing the 2016 MFN tariff to the trade war tariffs, as depicted in equation 1. However, one may wonder whether the results presented in section 5 are driven by the inclusion of the 2016 MFN tariff levels to measure trade war tariff changes and construct the regional trade war tariff changes variable. In this subsection, we show that this is not the case.

To check whether the results are driven by the way we construct the exposure variables, we construct an alternative measure for RTW^{CH} and RTW^{US} considering only the absolute variation in tariffs due to the trade war instead of considering the changes relative to its initial level of tariffs. Formally, we construct the alternative exposure measures as follows:

$$RTW^{C1}_{r,2019}(Alt) = \sum^{I} \lambda_{r,i} \frac{M^{C1 \leftarrow C2}_{i,2016}}{M^{W}_{i,2016}} \Delta \tau^{C1 \leftarrow C2}_{i,2019}$$
$$\Delta \tau^{C1 \leftarrow C2}_{i,2019} = ln(1 + \tau^{TW}_{C1,2019,i}) - ln(1 + \tau^{TW}_{C1,2016,i})$$

where $\lambda_{r,i}$ is the share of formal workers in region r employed in industry i, $M^{C1 \leftarrow C2}_{i,2017}$ is country $C1$ total value imported of products from industry i from country $C2$ in 2017, $M^{W}_{i,2017}$ is the 2017 total value traded in the world of products in industry i, and $\tau^{TW}_{C1,t,i}$ is the import tariffs cumulative increase due to trade war imposed by country C1 on C2's products. It is important to note that $\tau^{TW}_{C1,2016,i} = 0$ for both countries and all industries.

We show the estimates using this alternative measure for the RTW variables in Table 4. In general, the estimates for this alternative specification are very similar to those in Table 2, indicating that the results from our main specification reflect only the impacts of the trade war on the economic outcomes and are not affected significantly by the products' initial MFN tariff level.

Altogether, the results in this section demonstrate that the estimates presented in Table 2 are robust to MFN tariff changes controls and by alternative measurements of the regional exposure to the trade war.

7 Conclusion

In this paper, we have delved into the indirect effects of the US-China trade war on non-involved countries, with a particular focus on the Brazilian economy and its labor market. Our findings suggest that the Brazilian regions specialized in industries targeted by Chinese retaliatory tariffs against the U.S. experienced a relative increase in the number of formal workers and the total wage bill. On the other hand, we also show

Table 4: Regional Trade War Tariff Changes and Economic Outcomes - Alternative Measure

Dep. Var: Δ_t Log(y_t)	(1) t = 2019	(2) t = 2018	(3) t = 2017	(4) t = 2015	(5) t = 2014	(6) t = 2013	(7) t = 2012	(8) $t > 2016$	(9) $t < 2016$
Panel A. Formal Employment									
$RTW^{CH}_{r,2019}$	0.020***	0.016*	0.010**	0.002	-0.007	-0.016	-0.013	0.016***	-0.008
	(0.006)	(0.008)	(0.004)	(0.009)	(0.008)	(0.010)	(0.013)	(0.005)	(0.008)
$RTW^{US}_{r,2019}$	0.003	-0.002	0.000	-0.005	0.002	-0.001	0.013	0.000	0.002
	(0.006)	(0.005)	(0.004)	(0.005)	(0.008)	(0.009)	(0.010)	(0.004)	(0.007)
Panel B. Formal Wages									
$RTW^{CH}_{r,2019}$	0.028***	0.018**	0.014**	0.002	-0.014	-0.021**	-0.013	0.020***	-0.012
	(0.009)	(0.009)	(0.006)	(0.010)	(0.010)	(0.011)	(0.016)	(0.007)	(0.009)
$RTW^{US}_{r,2019}$	0.010	0.004	0.004	-0.006	-0.002	-0.012	0.002	0.006	-0.004
	(0.009)	(0.006)	(0.005)	(0.005)	(0.008)	(0.009)	(0.012)	(0.006)	(0.007)
Observations	558	558	558	558	558	558	558	2,232	1,674
Panel C. Bank Loans									
$RTW^{CH}_{r,2019}$	0.002	0.004	-0.003	0.002	0.007	0.000	-0.005	0.001	0.001
	(0.019)	(0.014)	(0.011)	(0.005)	(0.008)	(0.014)	(0.018)	(0.014)	(0.010)
$RTW^{US}_{r,2019}$	0.007	-0.002	-0.004	0.003	0.000	0.007	0.000	0.000	0.003
	(0.021)	(0.014)	(0.009)	(0.007)	(0.011)	(0.016)	(0.020)	(0.014)	(0.013)
Observations	547	547	547	547	547	547	547	1,641	2,188

Notes: Coefficients obtained from OLS regressions of the changes in the log of economic outcomes on the alternative measures for the 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, (Panel B) the total Wage paid to formal workers, and (Panel C) the total value of bank loans. Columns (1) to (3) display the estimates for the years 2019 to 2017 (after investigations), and columns (4) to (7) show the estimates for the years 2015 to 2012 (before investigation). Column (8) estimates a pooled OLS regression using data from 2017 to 2019, including state-year fixed effects. Column (9) also estimates a pooled OLS regression but using data from 2012 to 2015. All regressions include state-fixed effects. Standard errors in parentheses clustered at the mesoregion level (137 clusters).
Significance at the *10%, **5%, *** 1% levels.

that the tariffs imposed by the U.S. on Chinese products did not significantly affect local labor markets in Brazil.

Moreover, we extended our analysis to explore the implications for business investments in Brazil. Using regions' total amount of bank loans provided to firms as a proxy for investment, we found that the trade war did not significantly alter investment patterns across regions. This finding suggests that firms in Brazil may have been cautious during this period of trade policy uncertainty, hesitating to undertake major investment decisions that could potentially compromise their financial outcomes.

In the broader context of the literature on trade shocks and their economic consequences, our paper presents a unique perspective by examining the spillover effects of the U.S.-China trade war on non-involved countries. While existing studies have demonstrated the negative impact of this conflict on labor market, welfare, and firm performance in the involved countries, our research contributes by shedding light on the potential positive labor market effects in non-involved regions. This expansion of knowledge enhances our understanding of the multifaceted consequences of the escalating protectionism generated by the US-China trade war.

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Appendix A - Results Using Tariff Changes Until 2018

Table 5: Regional Trade War Tariff Changes and Economic Outcomes - Using Tariff Changes Until 2018

Dep. Var: $\Delta_{t=2018}$ Log($y_{t=2018}$)	Formal Employment	Formal Wages	Bank Loans
$RTW^{CH}_{r,2018}$	0.012*	0.0123*	0.009
	(0.006)	(0.007)	0.010
$RTW^{US}_{r,2018}$	0.001	0.006	0.004
	(0.004)	(0.004)	0.010
Observations	558	558	547

Notes: Coefficients obtained from OLS regressions of the changes in the log of economic outcomes on 2018 Chinese and American regional trade war tariff changes. Each Column displays the estimates using a different economic outcome. Economic outcomes used are the number of formal workers, the total Wage bill to formal workers, and the total value of bank loans, respectively. All regressions include state-fixed effects. Standard errors in parentheses clustered at the mesoregion level (137 clusters). Significance at the *10%, **5%, *** 1% levels.

Appendix B - Rotemberg Weights

Table 6: Rotemberg Weights Associated with American Tariffs

Industry Code	Industry	Rotemberg Weight	Rotemberg Weight - Positive
15319	Production of leather shoes	0.3722	0.3646
31012	Furniture Made With Wood	0.1148	0.1124
15335	Production of synthetic shoes	0.0752	0.0737
15394	Production of Shoes (NES)	0.0634	0.0621
13511	Textile Manufacturing	0.0465	0.0456
10716	Sugar Production	0.0184	0.0181
1512	Cattle Raising	0.0170	0.0167
14126	Clothing Manufacturing	0.0159	0.0156
1156	Soy Farming	0.0148	0.0145
1130	Sugarcane Farming	0.0142	0.0139

Notes:This table list the 10 industries with largest Rotemberg weights related to the 2019 American regional trade war tariff changes variable ($RTWC^{US}_{r,2019}$). We list both Rotemberg Weights and the weights among the industries with positive Rotemberg weights.

Table 7: Rotemberg Weights Associated with Chinese Tariffs

Industry Code	Industry	Rotemberg Weight	Rotemberg Weight - Positive
1156	Soy Farming	0.4964	0.4888
1113	Cereal Farming	0.1880	0.1852
1199	Cultivation of temporary crop plants (NES)	0.1172	0.1154
53105	Postal Activities	0.0900	0.0886
1415	Seed Production	0.0143	0.0141
1121	Herbaceous cotton cultivation	0.0110	0.0109
16102	Sawmill	0.0097	0.0095
14126	Clothing Manufacturing	0.0077	0.0076
15319	Production of leather shoes	0.0072	0.0071
10716	Sugar Production	0.0067	0.0066

Notes:This table list the 10 industries with largest Rotemberg weights related to the 2019 Chinese regional trade war tariff changes variable ($RTWC^{CH}_{r,2019}$). We list both Rotemberg Weights and the weights among the industries with positive Rotemberg weights.