Resource boom, export composition, concentration, and sophistication: evidence from Brazilian local economies*

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This version: March, 2025
Latest version

Abstract

This paper investigates the impact of resource booms on export value, concentration, composition, and sophistication in resource-rich developing economies. Using a shift-share instrument that leverages heterogeneous exposure to Chinese demand after China's 2001 WTO accession and the *ex-ante* composition of export baskets, I examine the causal effects on export baskets and sectoral employment of Brazilian local economies. The findings reveal increased export values and concentration in more exposed regions, with a shift from resource-based manufactures to primary products and declining export sophistication. Despite wage growth in primary and service sectors, primary employment remained stable while manufacturing jobs contracted, resembling a Dutch disease pattern. These results underscore the trade-offs of resource booms, where short-term gains in export value and sectoral wages may be offset by long-term development challenges. Given Brazil's similarities to other commodity exporters, these findings may indicate similar trends emerging across developing economies.

Keywords: Resource boom; Resource curse; Export composition; Export concentration; Export sophistication; China's export demand; Dutch disease.
JEL codes: F14; F16; O13; O14; O19; O54.

*I am grateful for insightful discussions, comments, and suggestions from Edward Barbier, Elissa Braunstein, Firat Demir, Rafael Dix-Carneiro, Iasmin Goes, Timothy Komarek, Ray Miller, Fernando Rugitsky, Gilberto Tadeu Lima, Daniele Tavani, and Ramaa Vasudevan. I also appreciate the feedback from seminar participants at City College of New York, Colorado State University, Denison University, Governors State University, New Mexico State University, Smith College, Universidad de Los Andes, University of Massachusetts Amherst, University of Utah, the 50th Eastern Economic Association Annual Conference, and the 5th International Growth Workshop in Rio de Janeiro. Any remaining errors are my own.

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1 Introduction

The economic phenomenon known as Dutch disease continues to pose a persistent challenge for resource-abundant countries, especially amid rising global commodity prices in recent decades. It occurs when a surge in revenue from booming natural resources undermines other economic sectors, particularly manufacturing. This raises key questions about how these booms impact export structures and broader economic development.

Extensive literature highlights the negative effects of natural resource booms on non-resource tradable sectors (Corden, 1984; van der Ploeg & Venables, 2011; Van Wijnbergen, 1984a). These booms often redirect labor and capital from manufacturing to resource industries, leading to deindustrialization (Corden & Neary, 1982; Matsuyama, 1992). Simultaneously, resource windfalls frequently boost demand for non-tradable goods and services, intensifying manufacturing contraction (Alberola & Benigno, 2017; Corden, 1984; Van Wijnbergen, 1984b; Venables, 2016). Beyond intersectoral adjustments, recent evidence suggests that within manufacturing, commodity booms reallocate market share away from exporters and capital-intensive firms, potentially reducing average productivity (Heresi, 2023). Yet, little attention has been paid to how export baskets evolve after such booms, leaving a gap in understanding the broader economic consequences of resource dependence. This is particularly important as export baskets reflect the productive structure of local economies, especially their most dynamic firms (Bernard & Jensen, 2004).

This study focuses on Brazil, a resource-rich developing country and major global exporter. Leveraging a novel shift-share instrument, I examine how exogenous trade shocks — specifically those linked to commodity production — reshape the composition, concentration, and sophistication of regional export baskets over time. Understanding these shifts is key to identifying localized structural changes caused by resource booms. Moreover, these findings could have broader relevance for other commodity-exporting countries with similar economic structures.

Policy concerns regarding export concentration in primary products — and its potential negative effects on terms of trade, income volatility, and long-term economic growth — have long been recognized. Foundational works by Prebisch (1949) and Singer (1950) underscore the developmental challenges tied to dependence on commodity production. Research on the "natural resource curse" further explores how resource dependence negatively impacts economic growth (Barbier, 2019; Isham et al., 2005; Sachs & Warner, 1995, 2001; van der Ploeg & Venables, 2011, 2013). Although these macroeconomic effects are well-documented, less attention has been given to how resource booms and external demand shocks reshape the composition and concentration of both resource and non-resource sectors. Bahar and Santos (2018) provide a notable exception, finding that countries with larger shares of natural resource exports tend to have more concentrated non-resource export baskets. However, their national-level analysis overlooks regional dynamics and also does not fully consider shifts in export structures. Addressing this gap is critical since export diversification and sophistication are widely recognized as key drivers of growth (Cadot et al., 2011; Hausmann et al., 2007; Hidalgo et al., 2007; Imbs & Wacziarg, 2003; Klinger & Lederman, 2006). Furthermore, regional dynamics often diverge from national trends following resource booms (Allcott & Keniston, 2018; Cust & Poelhekke, 2015; Marchand & Weber, 2018; Pelzl & Poelhekke, 2021), underscoring the importance of accounting for these variations to comprehend their long-term developmental consequences fully.

This paper addresses these gaps by leveraging a quasi-natural experiment that generated varied export demand across Brazilian regions. The analysis focuses on the surge in Chinese export demand following China's accession to the World Trade Organization (WTO) in 2001. Using a novel identification strategy, I examine the causal effects of resource booms on export performance and sectoral employment in Brazil from 2000 to 2019. Brazil presents a particularly relevant and timely case, as its share of resource exports rose from under 50% in 2000 to nearly 80% by 2019. This approach allows for precise identification of the causal effects of resource booms, overcoming challenges such as reverse causality and omitted variable bias. It also aligns with recent studies exploring the impact of resource booms on US regional economies (Allcott & Keniston, 2018; Feyrer et al., 2017; James & Smith, 2020).

Although some studies have explored the effects of China's rise as a dominant global trade player on Brazil, this literature remains relatively limited. Costa et al. (2016) use a quasi-experimental approach to examine how China's ascent impacted Brazilian local labor markets. They find that regions exposed to Chinese import competition experienced slower growth in manufacturing wages between 2000 and 2010. Conversely, regions benefiting from heightened Chinese export demand saw faster wage growth. Carreira et al. (2024) employ a similar empirical strategy to assess the impacts of trade shocks on deforestation in Brazil, observing significant impacts on land use but no direct link between exposure to Chinese demand and deforestation. While these studies offer valuable insights into labor markets and land use, the effects of such external shocks on regional export dynamics and productive structures remain underexplored.

In this paper, I construct a shift-share instrument that leverages the heterogeneous exposure of regions to China's export demand shock, based on the *ex-ante* composition of regional export baskets. The results show a notable increase in total export value and heightened concentration in the most exposed regions. For example, moving a region from the 25th to the 75th percentile of exposure leads to a $270 million increase in export value (14% growth) and a 0.008 rise in the Herfindahl-Hirschman Index (HHI). This concentration is driven by a focus on already-exported products, with minimal changes in export variety. Interestingly, the share of non-resource (i.e., manufacturing) exports remains stable, showing no relative decline in the most affected regions compared to less exposed areas. However, I find suggestive evidence of adjustment within the resource basket, indicating a shift toward primary products at the expense of resource-based manufactures.

Building on the extensive literature on export basket sophistication (Hausmann et al., 2007; Hidalgo & Hausmann, 2009; Hidalgo et al., 2007; Jarreau & Poncet, 2012), I investigate the "primarization" effect — where regions shift toward exporting lower value-added resource goods — triggered by the surge in Chinese demand. The analysis reveals a decline in the average complexity of export baskets in more exposed regions relative to less exposed ones. This shift toward raw materials and basic commodities, rather than processed, higher-value-added goods, may indicate a decline in average value added and productivity *within* the resource or booming sector, highlighting an additional channel through which resource booms can contribute to overall productivity reductions. This dynamic raises concerns about the long-term development of these local economies, particularly in terms of technological progress and upgrading.

I also explore how these structural changes affect labor market dynamics. Despite a shift toward more primary exports, this change does not increase employment in the primary sector. Instead, I find wage increases in both the primary and service sectors. Concurrently, there is a notable decline in manufacturing employment in the most affected regions, consistent with the Dutch disease phenomenon. I also find suggestive evidence that this contraction in manufacturing employment is accompanied by a rise in likely informal activities.

These findings carry important policy implications for Brazil and other resource-rich developing economies. While the resource boom driven by Chinese demand has significantly boosted regional export values and sector-specific wages, it has also led to a shift toward simpler, lower-value-added exports, with consequences for sectoral employment, particularly in manufacturing and potentially the informal sector. These results challenge the predominantly positive view of the China-led export demand shock in Brazilian labor markets presented by Costa et al. (2016), revealing structural changes that could undermine long-term economic development, in part by reducing total factor productivity in the most exposed regions. Furthermore, they align with recent evidence from Branstetter and Laverde-Cubillos (2024), who find that Colombia's recent resource boom, while associated with income growth, negatively impacted technological development through persistent declines in R&D spending and investment in technological upgrading within the manufacturing sector. These dynamics may be unfolding in other resource-dependent economies, highlighting the importance of policies that not only capture short-term benefits from resource booms but also promote sustained economic diversification to support long-term development.

This study also contributes to the growing literature on the global repercussions of

China's rise as a dominant force in international trade. Most prior research has focused on the effects of Chinese import competition on manufacturing employment and wages (Autor et al., 2013, 2014; Dix-Carneiro et al., 2023; Pierce & Schott, 2016). However, fewer studies have examined the demand-side effects of China's economic expansion. For example, Dauth et al. (2014) use a reduced-form approach to explore how rising imports from and exports to China and Eastern Europe affect labor markets in Germany. Yet, research specifically addressing the demand-side effects of China's expansion in developing economies remains limited.

The remainder of the paper is organized as follows. Section 2 provides background on the effects of China's WTO accession on resource-rich economies, with a focus on South America, and outlines recent trends in Brazil's resource boom. Section 3 describes the data used in the empirical analysis, while Section 4 details the empirical strategy and identification approach. Section 5 presents the main results, and Section 6 concludes with a discussion of broader implications.

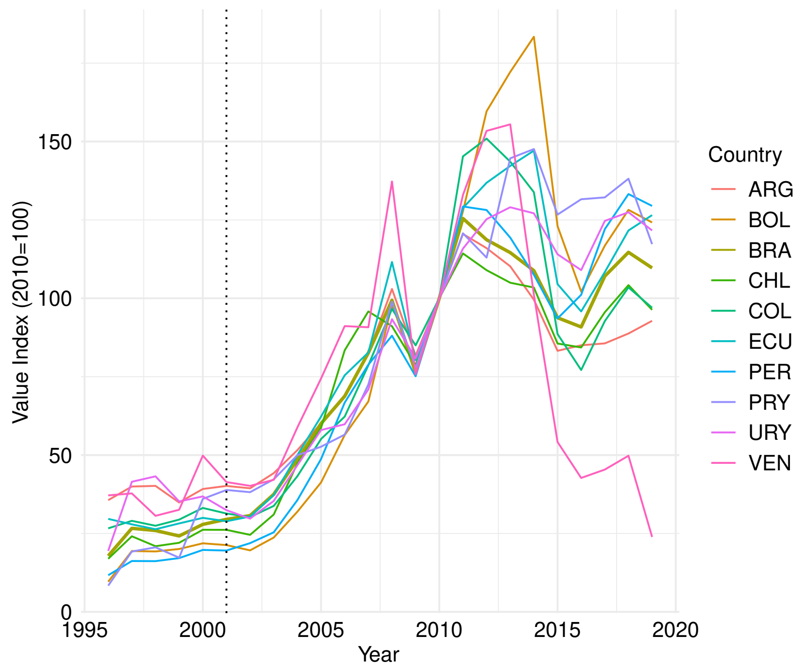
2 Background: Transformative Trade Dynamics

2.1 China's ascent to the WTO: transformation in trade patterns

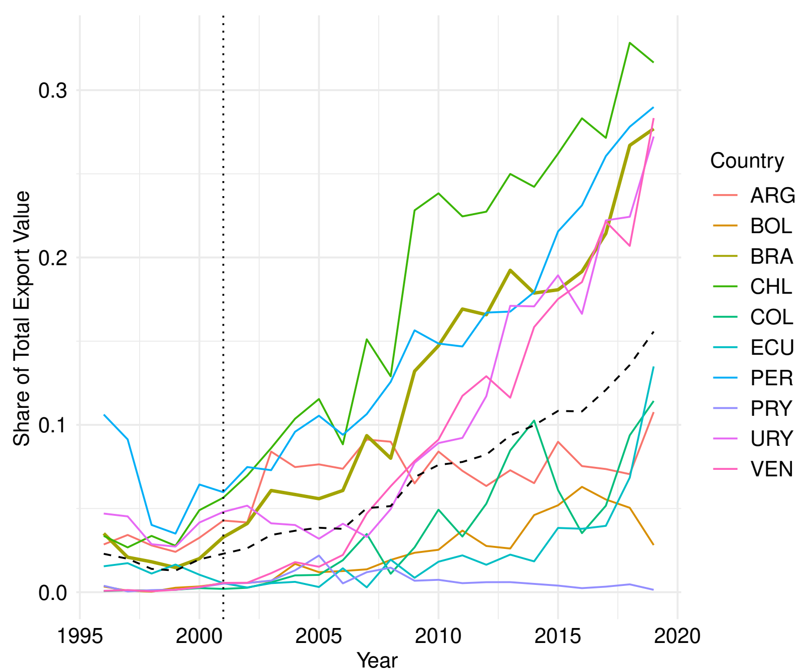
China's rapid emergence as a global economic powerhouse has profoundly altered the demand for primary goods over recent decades. Its remarkable economic growth, abundant reserves of labor, land, and capital, and deepening integration into the global economy have driven substantial shifts in global economic dynamics. China's accession to the WTO in 2001 marked a pivotal moment in international trade, transforming trade patterns worldwide (Autor et al., 2013). For developing countries, China quickly became a dominant exporter of manufactured goods and a major importer of raw materials (Costa et al., 2016).

The surge in demand for primary goods has been particularly pronounced in countries historically reliant on such exports, particularly across South America. Figure 1 shows that the total value of exports from South American countries has significantly increased over the past three decades, with a large portion of this growth attributable to trade with China. Panel (a) illustrates a clear upward trajectory in total export values for each country since 2001, coinciding with China's WTO accession. Panel (b) highlights the sharp rise in the share of total exports destined for China, with the average share across the sample increasing from approximately 3% in 2001 to over 15% by 2019. Resource-dependent economies such as Chile, Peru, and Brazil saw shares exceeding 25% in 2019.

Figure 1: Total exports value — South American countries



(a) Total Value — Index

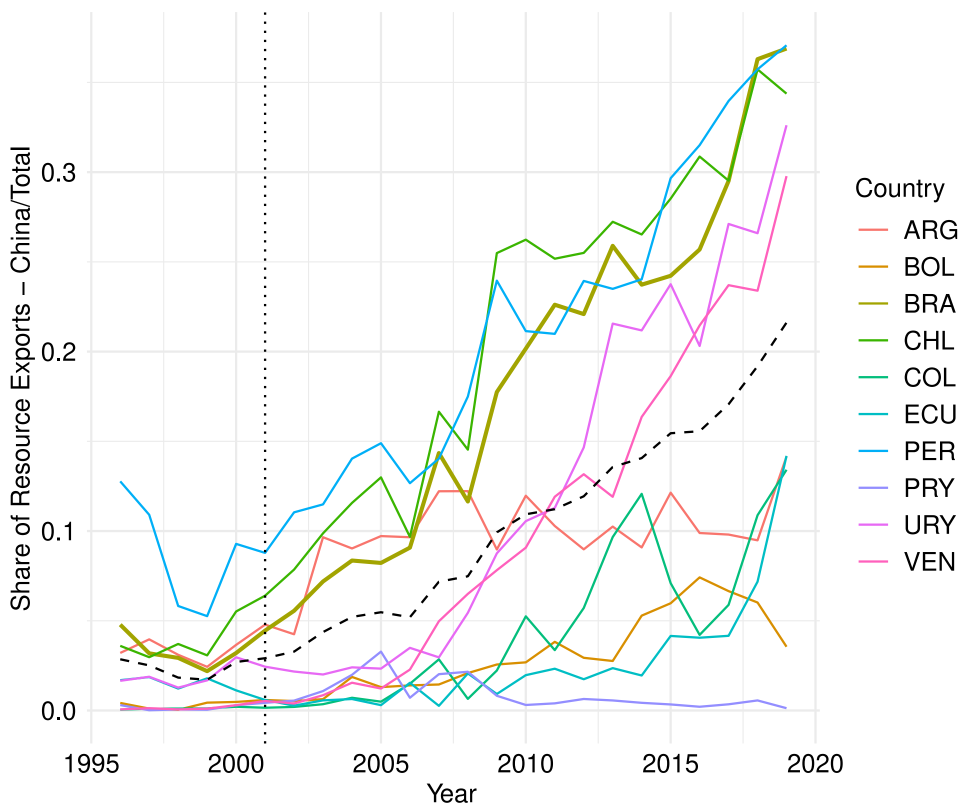


(b) Share of Total Exports Value — China/Total

Source: Bilateral trade flow data from the BACI database, developed by the *Centre d'Études Prospectives et d'Informations Internationales* (CEPII). Dotted lines indicate 2001, and the dashed line in panel (b) represents the yearly average. Thicker line highlights Brazil.

This trend is even more pronounced when we focus on the share of total export value represented by resource goods, including primary products and resource-based manufactures, as shown in Figure 2. The largest South American economies experienced a significant increase in these shares, rising from around 3% in 2001 to over 20% by 2019. This pattern underscores China's growing role as a major importer of resource-based products from these countries. Notably, Chile, Peru, and Brazil saw shares exceed 35%. Among these, Brazil stands out not only for its significant export share but also for its broader economic implications, making it a compelling case study for understanding the full impact of China's ascent.

Figure 2: Share of resource exports — China/Total



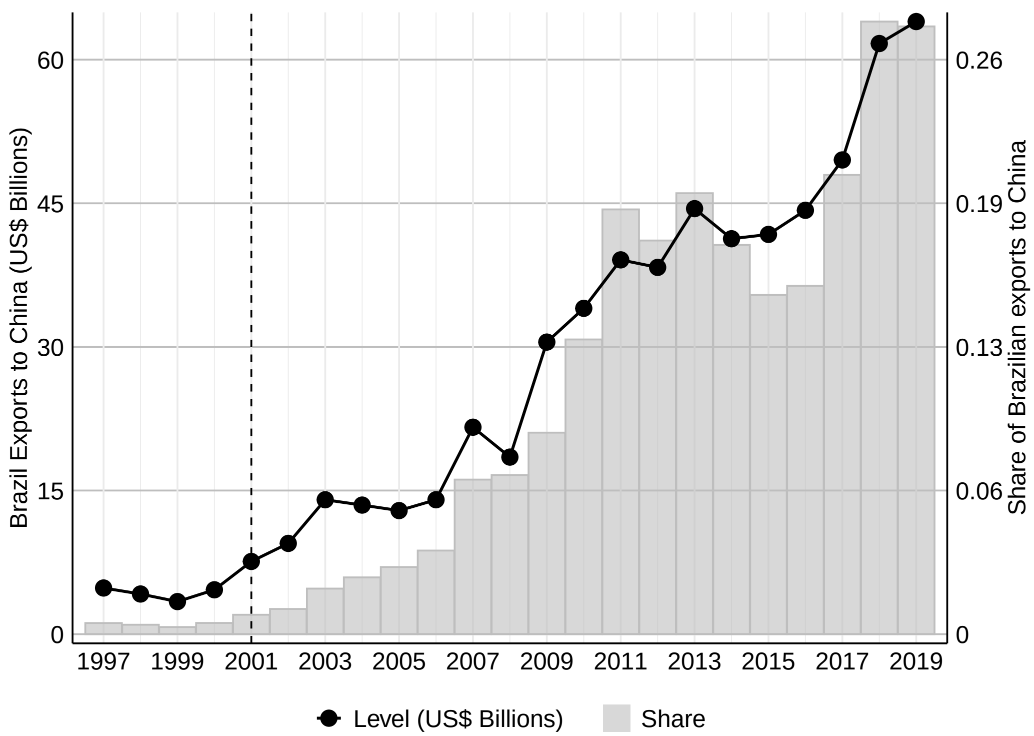
Source: Bilateral trade flow data from the BACI database, developed by the *Centre d'Études Prospectives et d'Informations Internationales* (CEPII). Product classification follows Lall (2000). Dotted line indicates 2001, and the dashed line represents the yearly average. Thicker line highlights Brazil.

2.2 The China-driven resource boom in Brazil

Building on broader South American trends and given its economic significance for the region, Brazil's experience offers a detailed case study of how China's rise in international trade has fueled a commodities boom, particularly in soybeans and iron ore (Carreira et al., 2024). Brazil provides a compelling context for examining China's impact on the export composition of developing countries for several reasons.

First, China's significance as an export destination for Brazil surged in recent years, surpassing its importance to other major South American economies, as shown in Figure 1. Figure 3 illustrates China's growing relevance as a key export market for Brazilian products over the past decades, both in terms of total export value and the share of exports destined for China. By the late 2000s, China had already become Brazil's largest trade partner.

Figure 3: Brazil's exports to China - total value and share

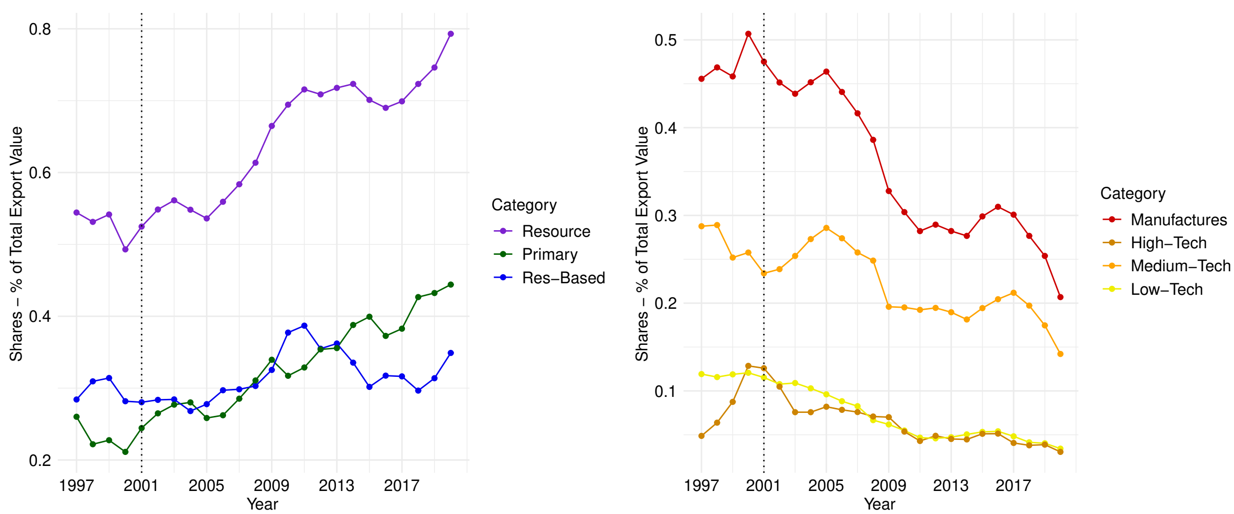


Source: Export value data is based on declarations by exporters in Brazil (SISCOMEX, Ministry of Industry, Foreign Trade, and Services). Dashed line indicates 2001.

Second, the trade pattern between Brazil and China aligns with broader South American trends, as Brazilian exports increasingly shift towards agricultural and extractive products.

Figure 4 tracks the evolution of export shares across different product classifications, based on the definitions by Lall (2000), which categorize goods by their technological content. Panel (a) reveals a substantial increase in resource exports relative to total exports from 2001 onward, with a shift from resource-based manufactures to primary products. In panel (b), a significant decline appears in the share of manufacturing exports at the aggregate level, with decreases observed across all subcategories.

Figure 4: Brazil's export shares, 1997-2019



(a) Resource

(b) Manufactures

Source: Export value and composition data are based on declarations by exporters in Brazil (SISCOMEX, Ministry of Industry, Foreign Trade, and Services). Product classification follows Lall (2000). Dotted lines indicate 2001.

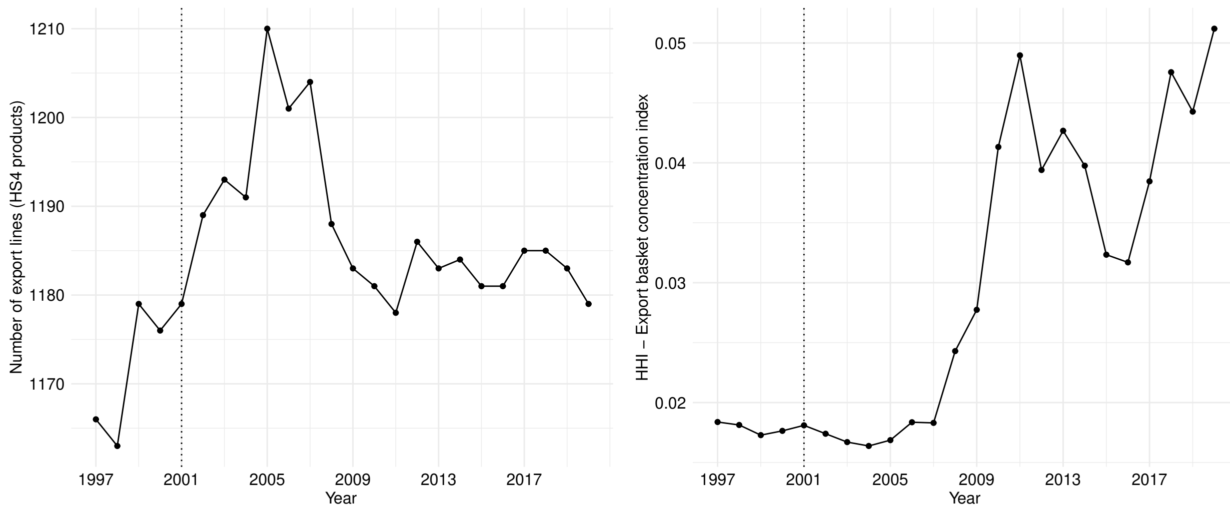
Third, Brazil's vast size and diverse geography give rise to regional economies with varied comparative advantages, enabling the identification of heterogeneous trade effects without relying on cross-country regressions. This approach allows a closer examination of the causal impacts of a resource boom on the export baskets of local economies that resemble typical small open economies.

Beyond assessing the impacts on the value and composition of the export basket, this paper focuses on its concentration following the resource boom. Figure 5 provides high-level evidence of stability in the number of products exported by Brazil from 2000 to 2019, while also revealing a clear increase in the Herfindahl-Hirschman Index (HHI), indicating growing concentration in Brazil's export basket over time along the intensive margin.[1]

[1]The construction of this concentration measure is discussed in detail in Section 3.

This rise in export basket concentration temporally coincides with China's growing global influence.

Figure 5: Export basket concentration: Brazil, 1997-2019



(a) Number of export lines (b) HHI

Source: Export value and composition data are based on declarations by exporters in Brazil (SISCOMEX, Ministry of Industry, Foreign Trade, and Services). Dotted lines indicate 2001.

3 Data Description

3.1 Regional export data

To investigate regional export dynamics in Brazil, I use the SISCOMEX dataset, an administrative source maintained by Brazil's Ministry of Industry, Foreign Trade, and Services. This dataset captures monthly export data from 1997 to 2024, documenting the tax jurisdiction or fiscal location of the exporting firm.[2] For the analysis, I aggregate this data to the municipal and yearly levels from 1997 to 2019, focusing on periods before and after the quasi-natural experiment triggered by the Chinese export demand shock, excluding the period affected by COVID-19.

Given the data structure and the relatively low share of net exports as a percentage of GDP in Brazil during the 1990s, I focus on municipalities with consistent export activ-

[2]While the primary analysis uses municipal-level data, the Online Appendix presents state-level results, measured at the locality of production, confirming that findings are consistent across different levels of aggregation.

ity during the years studied. This results in a smaller sample than the total number of municipalities recorded during the same period. To reduce potential distortions and gain clearer insights into the resource boom's impact on Brazil's local economies, I aggregate municipalities into micro-regions. These micro-regions, encompassing groupings of economically integrated municipalities with similar geographic and productive characteristics, are delineated by the Brazilian Institute of Geography and Statistics (IBGE) and are widely recognized in economic literature for characterizing regional economies in Brazil (e.g. Costa et al. (2016), Dix-Carneiro and Kovak (2017), Dix-Carneiro et al. (2018), Hirata and Soares (2020), Ogeda et al. (2024), and Ponczek and Ulyssea (2022)). As noted earlier, these local economies closely approximate the conditions of small open economies. The aggregation results in a dataset of 424 consistently observed exporting micro-regions.

The export data at the municipal level disaggregates products based on the Harmonized System (HS) classification at the four-digit level, corresponding to headings rather than subcategories. This classification encompasses over 1,200 product lines. To classify products as resource-based or non-resource-based, I use the technological definitions provided by Lall (2000), which categorize goods based on their technological content using the Standard Industry Trade Classification (SITC 3-digit, revision 2). I then cross-reference this classification with the HS to categorize the products exported by Brazilian local economies.

Figure 6 contextualizes the observed expansion of resource product exports in Brazil over recent decades and their geographic distribution across the country. It presents the change in the share of resource exports, which includes both primary products and resource-based manufactures, relative to the total export value across local economies in Brazil.

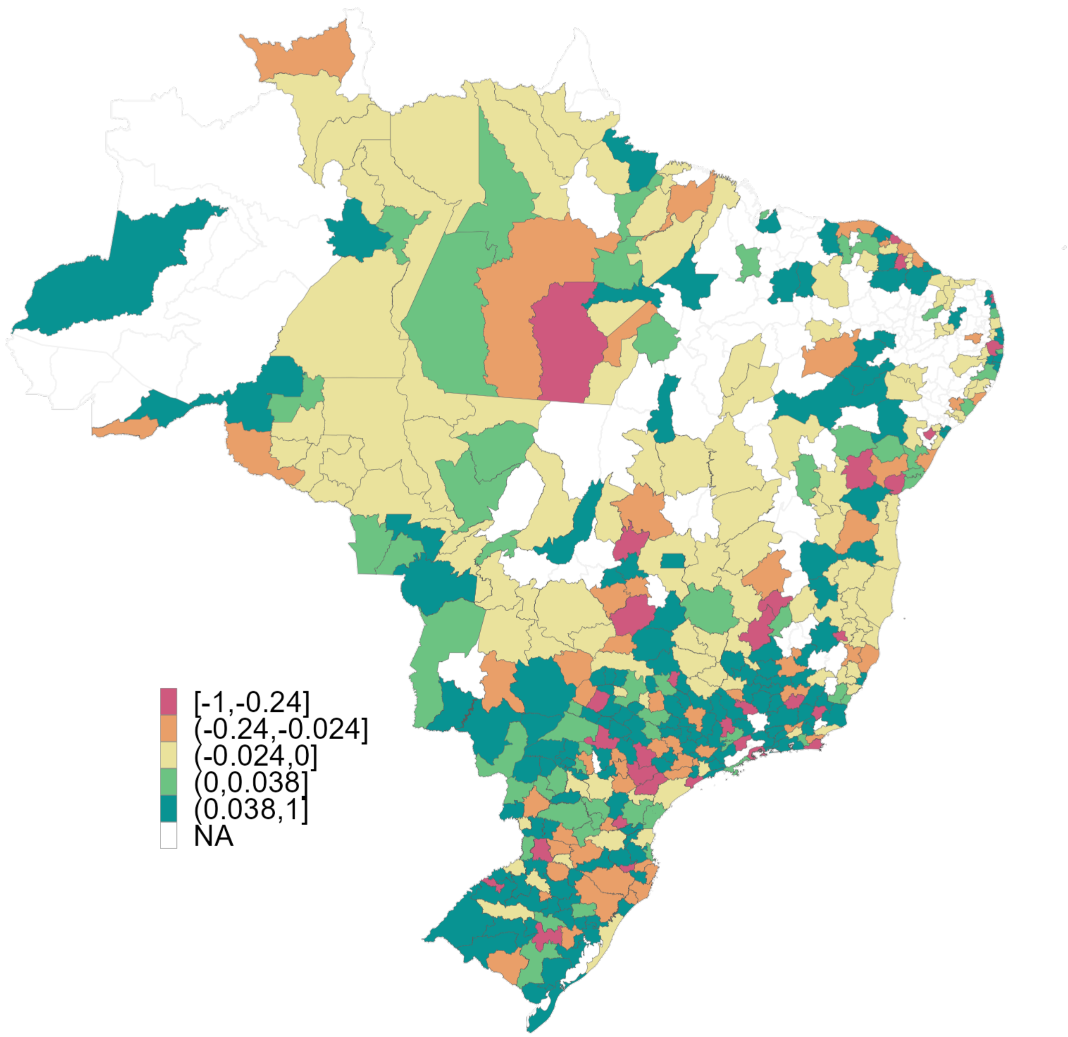
Further disaggregation in Figure 7 shows the variations in export shares of each product classification across Brazilian local economies from 2000 to 2019, excluding high-tech manufactures due to their limited relevance during this period.[3]

Comparing panels (a) and (b), regions in the North, Central-West, Southeast, and South — particularly those historically focused on agrarian production — show an expansion in primary product exports from 2000 to 2019. Concurrently, these regions have reduced the share of resource-based manufactures in their export baskets, with some exceptions. Regarding manufacturing, as depicted in panels (c) and (d), significant heterogeneity exists in the evolution of export patterns across Brazilian regions during this period. Notably, the Southeast region, particularly its metropolitan areas, which are historically more economically developed and possess a more diversified productive structure, appears to have increased its exports of medium-tech manufactures. Many locations experiencing

[3] The Online Appendix presents the spatial distribution of the share of total export value for each category across Brazilian local economies in 2000 and 2019.

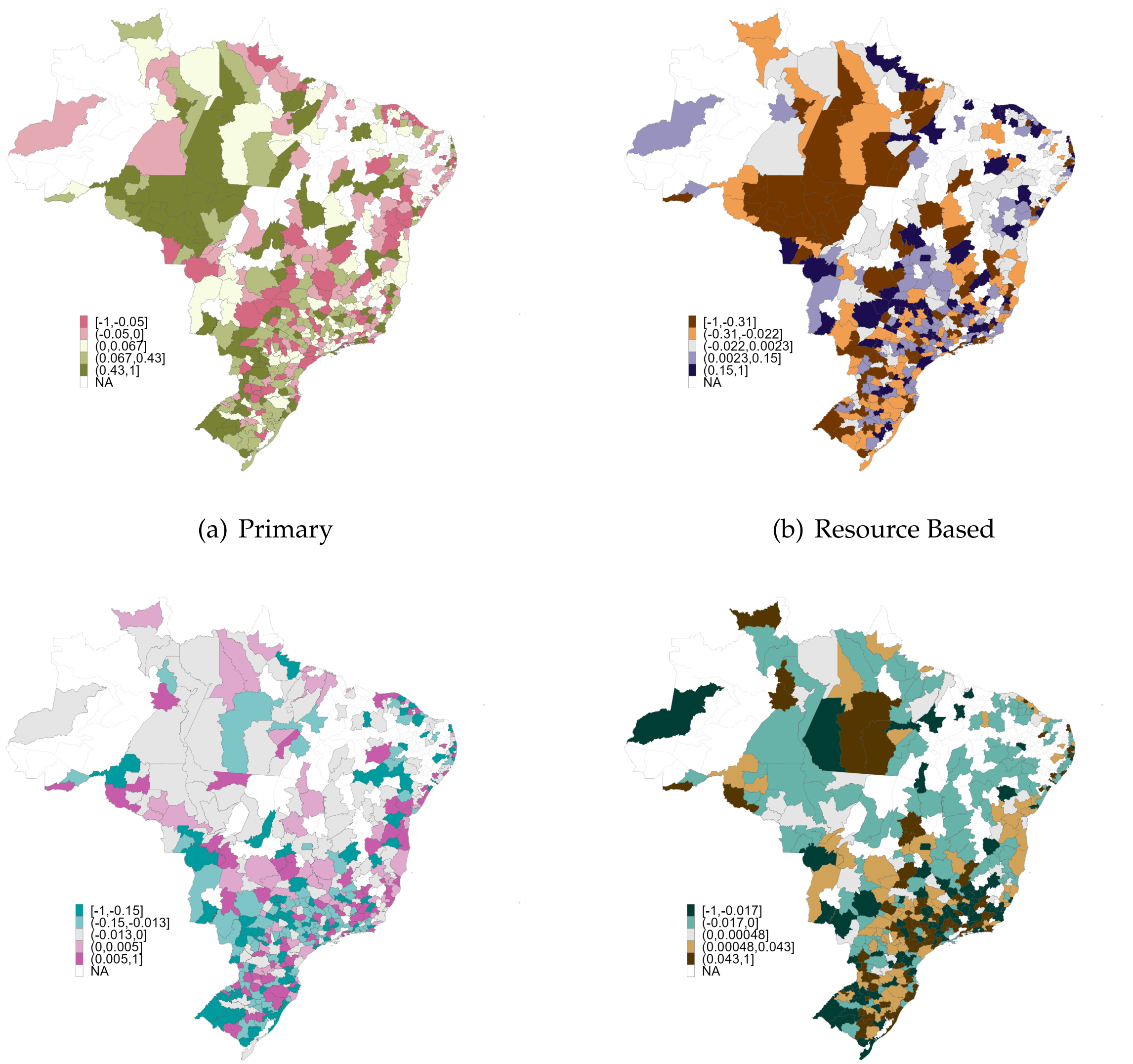
such shifts also witnessed relative reductions in exports of low-tech manufactures.

Figure 6: Difference in the share of resource exports: 2019 - 2000



Source: Export value and composition data are based on declarations by exporters in Brazil (SIS-COMEX, Ministry of Industry, Foreign Trade, and Services). Product classification follows Lall (2000).

Figure 7: Difference in share of exports per category: 2019 - 2000



(a) Primary

(b) Resource Based

(c) Low Tech

(d) Medium Tech

Source: Export value and composition data are based on declarations by exporters in Brazil (SISCOMEX, Ministry of Industry, Foreign Trade, and Services). Product classification follows Lall (2000).

3.2 Export basket concentration

To analyze the relationship between the resource boom and export concentration, I employ two widely recognized measures of concentration for each local economy and year: the number of export lines (products exported with a value above zero) and the Herfindahl-

Hirschman Index (HHI) (as used in Bahar and Santos (2018), Cadot et al. (2011), Imbs and Wacziarg (2003), and Koren and Tenreyro (2007)).

The HHI quantifies the concentration of export activity within a region, normalized to range between 0 (indicating no concentration) and 1 (indicating maximum concentration). It is calculated using the following formula:

$$HHI_r = \frac{\sum_k s_{r,k}^2 - \frac{1}{N_r}}{1 - \frac{1}{N_r}} \tag{1}$$

where $s_{r,k} = \frac{X_{r,k}}{\sum_{k=1}^{N} X_{r,k}}$ represents the share of export line k (with an export value of $X_{r,k}$) in the total exports of micro-region r, and N_r is the number of export lines in that region.

3.3 Export basket sophistication

In addition to examining total value and concentration, I explore the impacts of the resource boom on export sophistication across local economies. To measure export basket sophistication, I adopt the methodology established by Hausmann et al. (2007), which evaluates the complexity of a region's exports by comparing them to the income levels of countries with similar export structures. Specifically, I construct an annual measure of sophistication for each Brazilian micro-region's export basket.

The process begins with the calculation of a country's revealed comparative advantage (RCA) in exporting a specific good, following the approach of Balassa (1965). The RCA index $RCA_{k,j}$ is defined as:

$$RCA_{j,k} = \frac{\frac{x_{j,k}}{X_j}}{\sum_j \frac{x_{j,k}}{X_j}} \tag{2}$$

where $x_{j,k}$ is the value of exports of good k by country j and $X_j = \sum_k x_{j,k}$ is the total value of country j's exports.

Next, I calculate an intrinsic sophistication level P_k for each good k. This level is determined as the weighted average of the income levels of countries exporting good k, with weights corresponding to the RCA of each country:

$$P_k = \sum_j RCA_{j,k} \times Y_j \tag{3}$$

where Y_j is the per capita income of country j, measured as the real GDP per capita in PPP.

This measure, commonly referred to as "PRODY" in the literature (e.g., Hausmann et al. (2007), Hidalgo and Hausmann (2009), and Hidalgo et al. (2007)), reflects the average income level associated with the production and export of good k, weighted by each exporter's comparative advantage. Essentially, this measure infers from observed trade patterns which products require higher levels of economic development for their export, rather than directly determining intrinsic product features such as embedded technology (Jarreau & Poncet, 2012).

The data for these calculations come from the CEPII-BACI database, which consolidates information from the United Nations Statistical Division's COMTRADE database. This dataset contains annual bilateral trade values at the 6-digit level of the HS classification for over 200 countries, starting from 1995. For this analysis, I aggregate products to the 4-digit level and use data from 1997 to 2000 to establish average RCA measures for each product and country prior to China's accession to the WTO. Additionally, I use data from the World Development Indicators (WDI) and the Penn World Table (PWT) to compute the average real per capita income for each country during the same period.

Following the construction of the product-level sophistication index, I compute a regional export sophistication level, denoted S_r, for each local economy's export basket following Jarreau and Poncet (2012). This index is calculated as the weighted sum of the sophistication levels P_k of each exported good k, with weights representing the share of each good in the micro-region's total exports:

$$S_r = \sum_k s_{r,k} P_k \tag{4}$$

where $s_{r,k}$ is defined as in Equation (1). Although the time subscript is omitted for simplicity, this measure of regional export basket sophistication is constructed annually, based on the export data discussed earlier.

3.4 Local exposure to the resource boom

To quantify the impact of increased export demand from China at the local level, I begin by calculating a simple measure of local exposure. This measure is constructed by classifying exports by product category for each region in 2000 and 2019. Using data from SISCOMEX, I compile export values for each product at the micro-region level for the year 2000. The export share of each product in each locality is then calculated by dividing the export value for each product by the total export value in the micro-region. Additionally, I incorporate international trade data from the CEPII-BACI database, focusing on the years 2000 and 2019. The values for 2000 are adjusted to 2019 US dollars using the US GDP deflator provided by the US Bureau of Economic Analysis, ensuring consistent comparison and enabling the construction of measures of increased Chinese demand for products.

This initial measure provides a raw estimate of local exposure to heightened export demand from China by multiplying the increase in demand for each product exported by

Brazil to China between 2000 and 2019 by the relative significance of that product in the export basket of each region. However, this measure may still be endogenous, as local factors influencing export performance could affect the outcomes.

To address this potential endogeneity, I construct an exogenous measure of local exposure using a shift-share, or "Bartik", instrument. This method, drawing on the approaches of Costa et al. (2016) and Carreira et al. (2024), isolates the effect of global and Brazil-specific shocks on trade patterns It parallels the methodology used to identify the "China shock" in the US economy (e.g., Autor et al. (2013, 2014, 2019, 2020)). The shift-share instrument addresses the endogeneity problem by leveraging variations in global demand shifts that are independent of local conditions in Brazil.

The first step in constructing the instrument involves conducting auxiliary regressions for all countries except Brazil, weighted by initial import values, to isolate China-specific demand shocks:

$$\frac{\Delta \tilde{I}_{j,k,00/19}}{\tilde{I}_{j,k,00}} = \beta_k + \psi_{China,k} + v_{j,k} \tag{5}$$

where $\frac{\Delta \tilde{I}_{j,k,00/19}}{\tilde{I}_{j,k,00}}$ is the growth rate in imports of product k by country j from all countries other than Brazil between 2000 and 2019; β_k is the product fixed effect that captures the world average growth of net-of-Brazil imports of product k; $\psi_{China,k}$ is a China-product specific dummy that measures the deviation of the China import growth rate of product k in comparison to the one from the rest of the world. The estimated $\hat{\psi}_{China,k}$ represents the predicted change in global exports to China (excluding Brazil) induced by China-specific factors between 2000 and 2019.

Using the estimated $\hat{\psi}_{China,k}$ and the share of product exports per micro-region in Brazil, I then construct the "Bartik" instrument that quantifies local exposure to China-induced export demand:

$$\Delta \tilde{X}_r = \frac{1}{X_{r,00}} \sum_k \frac{X_{r,k,00}}{X_{B,k,00}} \times X_{BC,k,00} \hat{\psi}_{China,k} \tag{6}$$

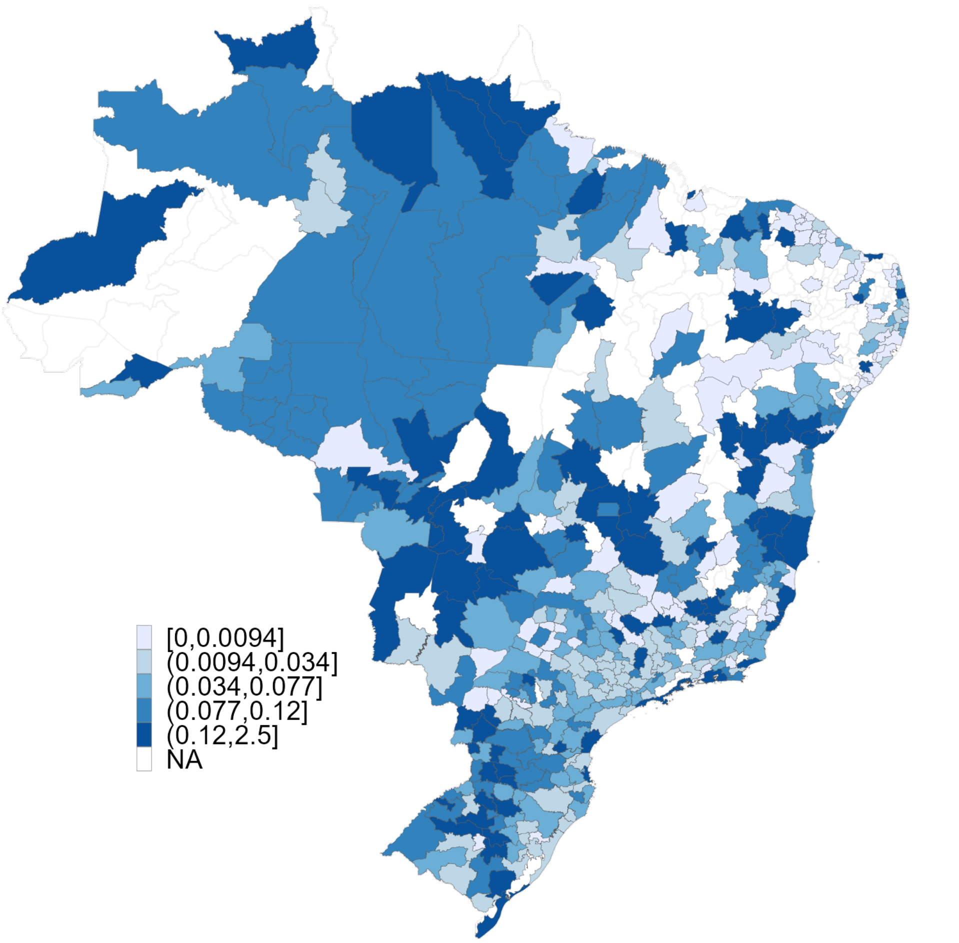
where $X_{r,00}$ is the total value of exports in region r in 2000; $X_{r,k,00}$ is the total value of exports of product k within region r in 2000; $X_{B,k,00}$ is the Brazil-wide total export value for product k in 2000 and, $X_{BC,k,00}$ is the Brazilian exports of product k to China in 2000.[4] To ensure that the results are not skewed by outliers, I winsorize $\Delta \tilde{X} r$ at the 1st and 99th percentiles.

Finally, Figure 8 maps the local exposure to Chinese export demand using the shift-share instrument calculated from Equation (6). Notably, local economies in the Central-West, parts of the North, and the South of Brazil exhibit significant exposure to China-induced

[4]In the main results, I use HS2 products to compute the shift-share, resulting in 92 categories. However, the results are virtually identical when using the HS4 classification with approximately 1,200 categories.

growth in export demand, highlighting the heterogeneous regional impacts of the resource boom.

Figure 8: Exposure to China's Export Demand - $\Delta\tilde{X}_r$



Source: Regional exposures to China's export demand, $\Delta\tilde{X}_r$, are computed according to Equation (6). Data from CEPII-BACI and SISCOMEX are used to compute the shift-share instrument.

3.5 Additional variables

In addition to trade data, I incorporate local labor market variables to further investigate the channels through which the resource boom may influence regional patterns of structural change.

For this analysis, I use individual-level labor market and socioeconomic data from the Brazilian Demographic Census for the years 2000 and 2010, provided by the Brazilian

Institute of Geography and Statistics (IBGE). Following Costa et al. (2016), I restrict the sample to individuals aged 18 to 60, who are most likely to be active in the labor market. Within this cohort, I calculate sectoral employment shares and average hourly wages for employed individuals. Wages are adjusted for inflation using the Brazilian Consumer Price Index (IPCA) and are expressed in 2010 Brazilian reais.

4 Empirical Strategy and Identification

My empirical objective is to analyze the effects of the surge in demand for resource exports, driven by China's accession to the WTO in 2001, on the export baskets of regional economies across Brazil. As outlined in Section 1, this analysis focuses specifically on changes in export value, composition, concentration, and sophistication over time.

Concerning the empirical strategy, recent research has established a formal framework for identifying assumptions in shift-share regression designs (Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020). Building on the work of Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2022), my identification assumption relies on the notion that the trade shock induced by China, denoted as $\Delta\tilde{X}_r$, is orthogonal to local political and institutional dynamics across micro-regions in Brazil. This independence is largely assured by focusing on the relative effects of increased demand from China compared to all other countries worldwide, excluding Brazil. Therefore, the "Bartik" instrument can be considered a quasi-exogenous shock to local political and institutional dynamics in Brazil.

To achieve this empirical objective, I employ a long-difference or first-difference specification, similar to the methodologies used by Autor et al. (2013), Costa et al. (2016), and Carreira et al. (2024). Specifically, I analyze changes over time in the variables of interest with the following specification, using the micro-region as the unit of analysis:

$$\Delta y_{r,t} = y_{r,t} - y_{r,2000} = c + \beta\Delta\tilde{X}_r + \alpha_{s,t} + \varepsilon_{r,t} \tag{7}$$

where $\Delta y_{r,t}$ represents the change in the outcome variable in region r from 2000 to t (2019 in the primary results), $\Delta\tilde{X}r$ denotes the measure of local exposure for region r to the China-induced export demand shock (as detailed in Equation (6)), and $\alpha_{s,t}$ are state-time fixed effects. This long-difference specification captures variation in $\Delta\tilde{X}_r$ across micro-regions within states, allowing for clear treatment-control comparisons. In all estimations, I cluster the standard errors at the meso-region level — a larger grouping of micro-regions defined by IBGE — to account for potential spatial correlation in outcomes.[5]

[5]In the Online Appendix, I demonstrate the robustness of the main results to the inference procedures recommended by Borusyak et al. (2022) to address cross-region residual correlation in shift-share designs.

The model specified in Equation (7) serves as the baseline for the main results, utilizing a first-difference specification. Alternatively, I implement a dynamic difference-in-differences (DiD) model. In this approach, the measure of exposure to the China-induced regional export demand shock is interacted with year indicators, and I analyze the variables of interest in levels rather than relative changes. This event-study design aligns with recent advancements in the literature (Borusyak et al., 2024; De Chaisemartin & d'Haultfoeuille, 2020; Roth et al., 2023), allowing the assessment of whether treatment and control micro-regions exhibited similar trends in export basket dynamics before the exogenous resource boom. The equivalent dynamic DiD specification to Equation (7) is expressed as follows:

$$y_{r,t} = c + \sum_{t=1997}^{2019} \beta_t \mathbb{1}\left\{\tau = t\right\} \Delta\tilde{X}_r + \mu_r + \alpha_{s,t} + \varepsilon_{r,t} \tag{8}$$

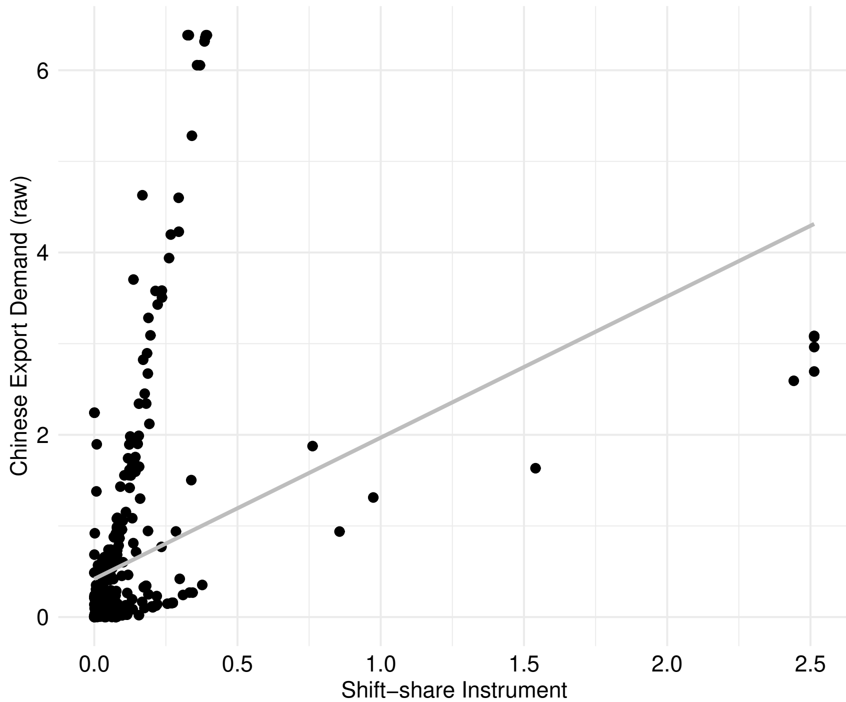
In Equation (8), the year 2001 is set as the baseline treatment year, with $\Delta\tilde{X}r$ serving as the treatment variable. Additionally, μr represents micro-region fixed effects, and $\mathbb{1}$ denotes year indicators. Since all micro-regions were affected simultaneously by China's accession to the WTO in 2001, this empirical approach is not subject to the recent methodological criticisms of the DiD literature (Callaway & Sant'Anna, 2021; De Chaisemartin & d'Haultfoeuille, 2022; Goodman-Bacon, 2021).

As outlined, the dynamic difference-in-differences specification offers a more flexible version of the baseline model, enabling a rigorous empirical evaluation of the parallel trends assumption. Under this assumption, the coefficients β_t for years preceding 2001 should not exhibit significant deviations from zero, either individually or collectively, across all outcome variables of interest. This assessment is crucial for validating that before the treatment — China's accession to the WTO in 2001 — the treatment and control groups experienced similar trends in the variables under study, thus supporting the credibility of the causal inferences.

Lastly, evaluating the validity of the shift-share instrument is crucial for accurately measuring the regional impacts of the significant increase in Brazilian exports to China following 2001. The credibility of this instrument is central to the identification strategy. Figure 9 illustrates the relationship between the endogenous measure of exposure and the instrument, revealing a significant correlation. This correlation underscores that the measure of the impact of increased Chinese export demand on Brazilian micro-regions and the instrumental variable ($\Delta\tilde{X}_r$), which captures estimated changes in Chinese demand, are closely aligned.

To further validate the shift-share instrument, I conduct first-stage regression analyses, detailed in the Online Appendix, incorporating state-year fixed effects to control for

Figure 9: Correlation: Chinese export demand and shift-share instrumental variable



potential unobserved heterogeneity. These analyses support the instrument's validity, reinforcing the robustness of the empirical findings.

5 Impacts of China-Induced Resource Boom

5.1 Export value and concentration

I begin by estimating Equation (7), using changes in the total export value per micro-region as the dependent variable, analyzed both in levels and growth rates. The expectation is that local economies most affected by the resource boom would see a significant increase in their total export value compared to less impacted regions. The results, presented in Table 1, confirm this hypothesis, showing a notable relative increase in both export value and growth rate in micro-regions most influenced by the surge in Chinese demand.

The analysis starts with a simple specification without controls, where observations are weighted by the total export value of each micro-region in 2000, the base year. This approach is crucial for addressing the correlation between the variance in export basket values and the economic size of the regions, as shown in column 1 of Table 1. To refine the model and control for potential confounding factors, I introduce state-year fixed effects in column 2, accounting for time-varying regional characteristics that may influence export dynamics. The inclusion of these fixed effects not only maintains the qualitative nature of the initial results but also enhances their statistical robustness. Finally, in column 3, I employ a 2SLS regression model using the shift-share as an instrumental variable for the observed local export growth to China. This specification further reinforces the findings, demonstrating a strong correlation between increased exposure to Chinese demand and export growth.

From the preferred specification in column 2, a micro-region at the 75th percentile of exposure to Chinese demand ($\Delta\tilde{X}r$ = 0.108) experienced, on average, an increase of approximately \$270 million in total export value, compared to a micro-region at the 25th percentile ($\Delta\tilde{X}r$ = 0.015). This relative change corresponds to a growth of about 14% in export value. These results highlight the substantial economic impact of Chinese demand on the most affected Brazilian micro-regions.

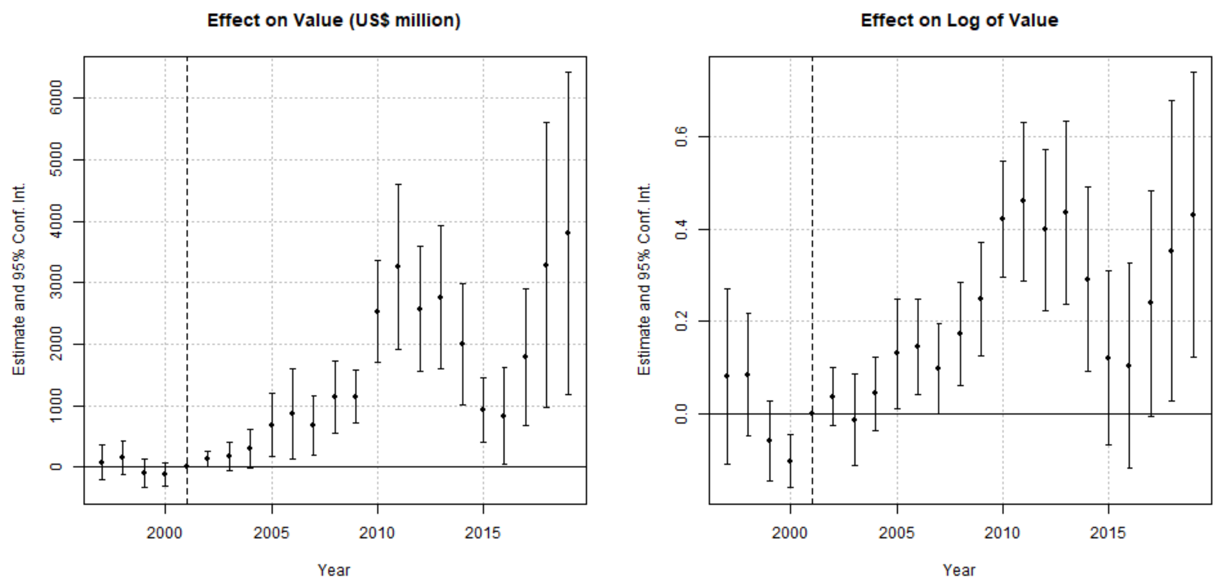
Table 1: Commodity boom and export value

Dependent variable:	**Δ Value of exports (US\$ millions)**			**%Δ Value of exports**		
	OLS	OLS	2SLS	OLS	OLS	2SLS
	(1)	(2)	(3)	(1)	(2)	(3)
$\Delta\tilde{X}_r$	3,312.141**	2,902.794***		1.730	1.486*	
	(1,628.508)	(1,081.950)		(1.169)	(0.795)	
ΔX_r			2,537.285***			1.299*
			(886.315)			(0.669)
Weighted	X	X	X	X	X	X
State-year fixed effects		X	X		X	X
Observations	424	424	424	424	424	424
Adjusted R^2	0.182	0.625	0.296	0.002	0.066	0.066
KP F-stat			99.7			99.7

Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the total exports in 2000; column 2 adds state-year fixed effects to column 1; column 3 presents the 2SLS using $\Delta\tilde{X}_r$ as the IV for ΔX_r. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To assess the causal effects of the China-induced export demand shock on regional export values, I test the parallel trends assumption underlying the identification strategy. This assumption posits that, prior to China's WTO accession, regions with *ex-post* varying levels of exposure to the trade shock would exhibit *ex-ante* similar trends in their export values. To evaluate this, I employ the event-study specification outlined in Equation (8), focusing on the coefficients resulting from the interaction of the treatment indicator, $\Delta\tilde{X}_r$, with year dummies. Figure 10 illustrates the dynamic effects of the China-induced demand shock on regional export values, along with 95% confidence intervals.

Figure 10: Dynamic effects of the resource boom on export value and growth



(a) Dynamic effects on export value (b) Dynamic effects on growth of export value

Notes: Each point reflects an individual regression coefficient $\hat{\beta}$ following Equation (8), where the dependent variables are the regional export value in level (US$ millions) and log, respectively, in year $t = 1997, ..., 2019$. The regressions include micro-regions fixed effects and state-year fixed effects. Standard errors are adjusted for 129 meso-region clusters and the observations are weighted by total exports in 2000.

The results in Figure 10 visually corroborate the findings in Table 1. The overall insignificance of pre-treatment coefficients supports the assumption of parallel trends, thereby reinforcing the robustness of the research design.

Next, I examine the implications of the resource boom on the concentration of regional export baskets. While the increase in export value for regions most affected by the shock is evident, its effect on export concentration — measured by the number of exported products and the HHI — is more complex. One might expect that the resource windfall could lead to a heightened concentration of exports in products experiencing surging demand following China's WTO accession. Alternatively, increased demand for certain products could drive greater diversification of the export basket, potentially facilitated by backward linkages in the production structure.

Table 2 presents the results from the estimation of Equation (7), focusing on changes in the number of export lines and the HHI between 2000 and 2019 as dependent variables. Across the two main specifications, the relationship between exposure to the resource boom and the number of export lines is negative but does not reach statistical significance. This suggests that the regions most affected by the export demand shock did not alter the number of products they exported between 2000 and 2019 compared to less impacted regions.

However, the analysis of the regional export basket concentration index reveals significant effects of the resource boom. Regions most impacted by the shock experienced an increase in the HHI of their export baskets relative to less affected regions. The estimates in column 2 indicate that a micro-region at the 75th percentile of exposure to Chinese demand ($\Delta\tilde{X}r = 0.108$) saw, on average, an increase of 0.008 in the HHI associated with its export basket compared to a micro-region at the 25th percentile ($\Delta\tilde{X}r = 0.015$).

These findings suggest that the concentration of the export basket in regions most affected by the resource boom occurred primarily on the intensive margin rather than the extensive margin. In other words, while the number of products exported by these regions remained relatively stable, the export basket itself became more concentrated. Consequently, the increase in total export value in these regions was concentrated in a few products that were already part of the export repertoire, significantly increasing their share in the total export basket.

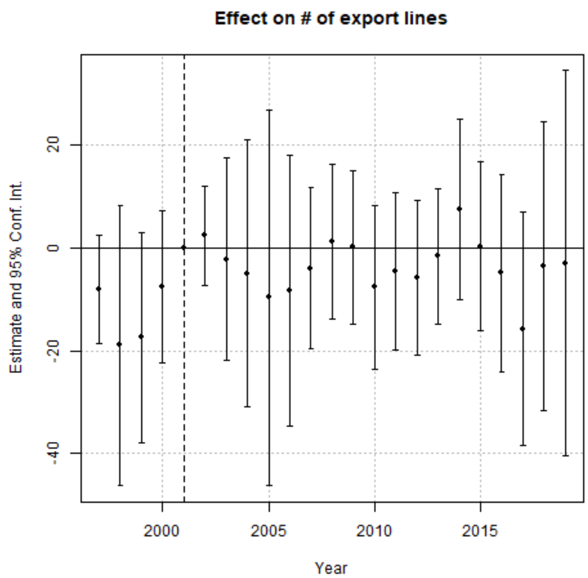
Table 2: Commodity boom and export concentration: number of lines and HHI

Dependent variable:	**Δ Lines**			**Δ HHI**		
	OLS	OLS	2SLS	OLS	OLS	2SLS
	(1)	(2)	(3)	(1)	(2)	(3)
$\Delta\tilde{X}_r$	3.658	-16.494		0.085	0.083***	
	(30.516)	(29.669)		(0.052)	(0.029)	
ΔX_r			-14.417			0.073***
			(25.858)			(0.026)
Weighted	X	X	X	X	X	X
State-year fixed effects		X	X		X	X
Observations	424	424	424	424	424	424
Adjusted R^2	-0.002	0.191	0.117	0.053	0.324	0.249
KP F-stat			99.7			99.7

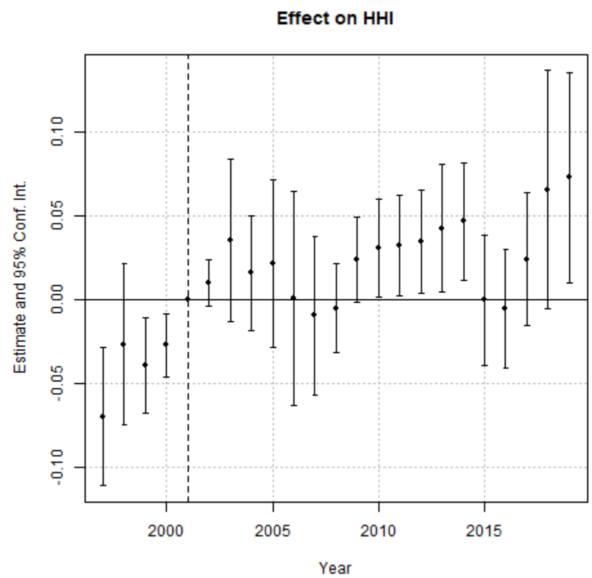
Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the total exports in 2000; column 2 adds state-year fixed effects to column 1; column 3 presents the 2SLS using $\Delta\tilde{X}_r$ as the IV for ΔX_r. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To further validate the causal interpretation of these results, I re-estimate the event-study specification provided by Equation (8) for the measures of export concentration. Figure 11 illustrates the dynamic effects of the China-induced demand shock on export basket concentration, complete with 95% confidence intervals.

Figure 11: Dynamic effects of the resource boom on export concentration



(a) Dynamic effects on export lines



(b) Dynamic effects on HHI

Notes: Each point reflects an individual regression coefficient $\hat{\beta}$ following Equation (8), where the dependent variables are the number of exported lines and the HHI associated with regional export baskets, respectively, in year $t = 1997, ..., 2019$. The regressions include micro-regions fixed effects and state-year fixed effects. Standard errors are adjusted for 129 meso-region clusters and the observations are weighted by total exports in 2000.

Similar to the findings on export value, the results depicted in Figure 11 are consistent with those presented in Table 2. The overall insignificance of pre-treatment coefficients for the years leading up to the trade shock further supports the validity of the parallel trends assumption.

5.2 Heterogeneity analysis

To address this, I conduct a heterogeneity analysis by categorizing local export baskets into resource-based and non-resource-based segments, following the classifications by Lall (2000). I then re-estimate the previous models for each category to discern the differential impacts on both the relative value of total exports and the concentration of regional export baskets. This approach allows me to determine whether the surge in export values and changes in export basket concentration are predominantly associated with resource-intensive products or a broader array of goods.

Table 3 presents the disaggregated results by broad type of export basket, focusing on variations in the total value of exports and the growth rate of these values from 2000 to 2019. The findings indicate that the increases documented in Table 1 are predominantly driven by the expansion of resource exports. Notably, there is no significant impact on the non-resource export basket in the regions most affected by the trade shock compared to less affected regions.

Table 3: Commodity boom and export value - Resource and non-resource baskets

Dependent variable:	**Δ Value of exports (US$ millions)**			**%Δ Value of exports**		
	OLS	OLS	2SLS	OLS	OLS	2SLS
	(1)	(2)	(3)	(1)	(2)	(3)
Panel A: Resource basket						
$\Delta\tilde{X}_r$	2,747.192**	2,366.870**		1.405	1.449*	
	(1,302.870)	(940.415)		(1.219)	(0.819)	
ΔX_r			2,228.851**			1.365*
			(870.496)			(0.750)
Observations	406	406	406	406	406	406
Adjusted R^2	0.1883	0.710294	0.290033	-0.000	0.071	0.071
KP F-stat			94.1			94.1
Panel B: Non-resource basket						
$\Delta\tilde{X}_r$	504.032	70.895		0.203	-0.730	
	(437.353)	(364.996)		(0.364)	(1.122)	
ΔX_r			55.404			-0.570
			(277.034)			(0.852)
Observations	314	314	314	314	314	314
Adjusted R^2	0.034	0.265	0.264	-0.001	0.071	0.075
KP F-stat			82.5			82.5
Weighted	X	X	X	X	X	X
State-year fixed effects		X	X		X	X

Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the total exports in 2000; column 2 adds state-year fixed effects to column 1; column 3 presents the 2SLS using $\Delta\tilde{X}_r$ as the IV for ΔX_r. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4 presents results for export basket concentration. The impact on the HHI occurs primarily within the resource basket of the most affected regions, though with some variability compared to Table 2.

Table 4: Commodity boom and export concentration - Resource and non-resource baskets

Dependent variable:	Δ **Lines**			Δ **HHI**		
	OLS	OLS	2SLS	OLS	OLS	2SLS
	(1)	(2)	(3)	(1)	(2)	(3)
Panel A: Resource basket						
$\Delta\tilde{X}_r$	-10.209	-15.654		0.065	0.058***	
	(10.562)	(15.032)		(0.045)	(0.022)	
ΔX_r			-14.741			0.054**
			(13.923)			(0.023)
Observations	406	406	406	402	402	402
Adjusted R^2	0.004	0.165	0.060	0.030	0.429	0.353
KP F-stat			94.1			93.1
Panel B: Non-resource basket						
$\Delta\tilde{X}_r$	44.253	-11.653		-0.029	0.103	
	(50.747)	(21.497)		(0.093)	(0.085)	
ΔX_r			-9.107			0.081
			(14.816)			(0.080)
Observations	314	314	314	292	292	292
Adjusted R^2	0.035	0.348	0.346	-0.000	0.301	0.238
KP F-stat			82.5			76.2
Weighted	X	X	X	X	X	X
State-year fixed effects		X	X		X	X

Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the total exports in 2000; column 2 adds state-year fixed effects to column 1; column 3 presents the 2SLS using $\Delta\tilde{X}_r$ as the IV for ΔX_r. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Next, I explore how the composition of the export basket in the regions most affected by the China-induced trade shock evolved between 2000 and 2019. To this end, I estimate Equation (7) using the share of total export value for each product sub-category, as defined by Lall (2000), as the dependent variable. The outcomes, summarized in Table 5, suggest that there was no substantial aggregate structural change in the relative composition of the export basket between the regions most and least affected by the shock. This stability in export composition is expected, considering that at the highly disaggregated level of analysis, regions with a comparative advantage *ex-ante* generally continued to focus on exporting similar products. This is a distinctive aspect of the quasi-natural experiment used here: unlike previous studies evaluating resource windfalls characterized by the discovery of substantial natural reserves, this shock amplified the pre-existing advantages of historically resource-exporting regions rather than altering their comparative advantages.

Table 5: Commodity boom and export shares

Classification	Share of export value	Estimated coefficients	
	Average 2000-2019	OLS 2000-2019	2SLS 2000-2019
Resource	**0.639**	**-0.005**	**-0.004**
		(0.018)	**(0.016)**
Primary	0.326	0.070	0.061
		(0.048)	(0.039)
Resource-based	0.313	-0.075*	-0.066*
		(0.043)	(0.035)
Manufactures	**0.361**	**0.005**	**0.004**
		(0.018)	**(0.016)**
Low-Tech	0.072	0.011	0.009
		(0.013)	(0.011)
Medium-Tech	0.227	-0.005	-0.004
		(0.024)	(0.021)
High-Tech	0.067	-0.001	-0.001
		(0.003)	(0.002)
Observations		424	424
KP F-stat			99.7

Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In all regressions, observations are weighted and state-year fixed effects are added. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

While the overall share of resource exports remained stable, the composition within these categories appears to have shifted relatively in the most impacted regions. Despite modest statistical significance, there is a relative reduction in the share of resource-based manufactures, coupled with an increase in the share of primary product exports in the localities more affected by the shock compared to less impacted economies. Essentially, while the overall balance between resources and manufactures stayed largely stable in the regions most affected by the shock, there is evidence of a "primarization" within the resource basket. This trend reflects a shift from exporting more complex, resource-based manufactures to simpler, primary products. For instance, regions that exported soybean oil in the early 2000s may have transitioned to exporting raw soybeans, indicating a move toward less complex items within the same production chain.

This shift towards "primarization" suggests a potential decline in the sophistication or complexity of the products exported by these regions over the past two decades. This trend could significantly impact long-term economic diversification and value addition in the affected regions. I explore these implications further in the following subsection.

5.3 Export sophistication

To examine whether the export demand shock led to changes in the complexity of export baskets, I use the established export sophistication measure outlined in Equation (4) (Hausmann et al., 2007; Jarreau & Poncet, 2012). This measure helps determine if shifts in the concentration and composition of local Brazilian export baskets, induced by the export demand shock, are associated with a decline in the average complexity of exported goods.

I estimate Equation (7), with the change in the export sophistication index, $\Delta S_{r,t}$, for each micro-region as the dependent variable. The analysis is conducted using two distinct real income per capita measures from the World Development Indicators (WDI) and the Penn World Table (PWT). The findings, presented in Table 6, reveal a relative decrease in the sophistication index of the export baskets in micro-regions most affected by the increased Chinese demand compared to less impacted areas.

The estimates in column 2 indicate that a micro-region at the 75th percentile of exposure to Chinese demand experienced, on average, a decline of just over 30 points in the sophistication index of its export basket compared to a micro-region at the 25th percentile of the shock distribution. This decline reflects a shift toward less complex, lower-value-added activities. Similar to Heresi (2023), this shift can be linked to a reduction in average value added and productivity within the sector following a resource boom. However, in this case, the effect is observed within the resource or booming sector itself, highlighting an additional channel through which resource booms can contribute to overall productivity declines. Figure A.1 illustrates the combined direct and indirect effects of the resource boom, showing how these dynamics may lead to reductions in total factor productivity in the most exposed localities. Given the central role of average productivity in sustaining long-run growth, this additional mechanism suggests that the commodity boom may, in fact, hinder long-term economic development in these regions.

As with the analyses of export value and concentration, I further evaluate the causal implications of these findings on export sophistication using the event-study approach specified in Equation (8). Figure 12 illustrates these dynamic effects, reinforcing the findings in Table 6. The figures show a clear post-treatment decline in export sophistication for the most affected regions, with pre-treatment coefficients remaining largely insignificant. This pattern supports the validity of the parallel trends assumption and strengthens the

Table 6: Commodity boom and export sophistication

Dependent variable:	Δ **Export sophistication (WDI)**			Δ **Export sophistication (PWT)**		
	OLS	OLS	2SLS	OLS	OLS	2SLS
	(1)	(2)	(3)	(1)	(2)	(3)
$\Delta\tilde{X}_r$	35.522	-327.907*		6.714	-371.524*	
	(89.544)	(179.980)		(83.741)	(190.815)	
ΔX_r			-286.619*			-324.743**
			(156.630)			(164.629)
Weighted	X	X	X	X	X	X
State-year fixed effects		X	X		X	X
Observations	424	424	424	424	424	424
Adjusted R^2	-0.001	0.248	0.238	-0.002	0.146	0.165
KP F-stat			99.7			99.7

Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the total exports in 2000; column 2 adds state-year fixed effects to column 1; column 3 presents the 2SLS using $\Delta\tilde{X}_r$ as the IV for ΔX_r. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

causal link between the export demand shock and reduced export complexity.

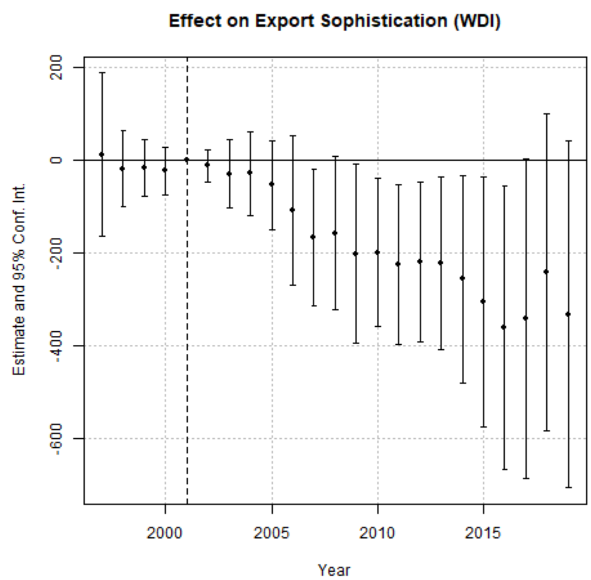
5.4 Employment variables

The findings presented thus far suggest a degree of structural change, particularly in the export baskets of regions most affected by the resource boom compared to those less impacted. This subsection extends the analysis to examine whether these changes in export dynamics are mirrored in local labor markets, with a focus on sectoral employment composition and wage variations.

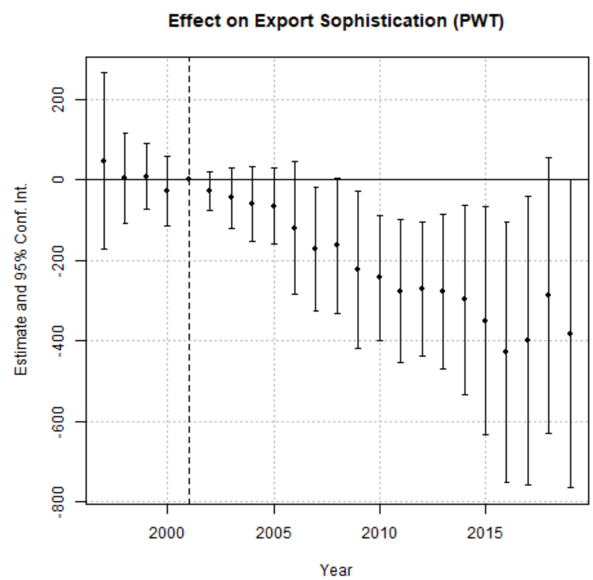
To explore these labor market effects, I adapt the shift-share instrument from Equation (6) to capture export demand growth from 2000 to 2010. This period represents the most recent year for which comprehensive micro-data from the Brazilian Demographic Census are available. This adaptation allows for an evaluation of whether the China-induced export demand shocks, as captured by $\Delta\tilde{X}_r$, led to sectoral employment shifts or wage adjustments, as economic theory would predict.

Building on Costa et al. (2016), I use the modified shift-share instrument to investigate the impacts of Chinese demand shocks on local labor market outcomes in Brazil. Table 7 presents regression results at the micro-region level, focusing on changes in log average hourly wages and private sector employment rates between 2000 and 2010. Notably, regions most affected by the resource boom show no significant variation in log average

Figure 12: Dynamic effects of the resource boom on export sophistication



(a) Dynamic effects on sophistication (WDI)



(b) Dynamic effects on sophistication (PWT)

Notes: Each point reflects an individual regression coefficient $\hat{\beta}$ following Equation (8), where the dependent variables are the sophistication indexes associated with regional export baskets as described in Equation (4) in year $t = 1997, ..., 2019$. The regressions include micro-regions fixed effects and state-year fixed effects. Standard errors are adjusted for 129 meso-region clusters and the observations are weighted by total exports in 2000.

hourly wages compared to less impacted localities. The effect of the Chinese demand shock on the aggregate employment rate is positive but statistically significant only at the 10% level in specifications that include state-year fixed effects.

Next, I assess changes in local employment composition across sectors by estimating the specification from Equation (7), using sectoral employment shares as the dependent variables. The literature on the resource curse, particularly studies on the Dutch disease, suggests that trade shocks, such as this commodity boom, might lead to a labor shift toward booming sectors at the expense of manufacturing employment. Table 8 presents the results for changes in sectoral employment shares between 2000 and 2010 across Brazilian micro-regions.

In Panels A and C of Table 8, no statistically significant impact is observed on the share of workers in the primary and services sectors, respectively, in regions experiencing relatively larger increases in Chinese demand. Although the estimated coefficients point in the expected direction, the absence of significant changes in the employment share of the

Table 7: Commodity boom, employment and remuneration - aggregate results

Dependent variable:	Δ Log average hourly wages			Δ Employment share		
	OLS	OLS	2SLS	OLS	OLS	2SLS
	(1)	(2)	(3)	(1)	(2)	(3)
$\Delta \tilde{X}_r$	0.058*	0.024		0.023	0.026*	
	(0.034)	(0.019)		(0.016)	(0.013)	
ΔX_r			0.011			0.012*
			(0.009)			(0.006)
Weighted	X	X	X	X	X	X
State-year fixed effects		X	X		X	X
Observations	424	424	424	424	424	424
Adjusted R^2	0.008	0.625	0.623	0.007	0.335	0.342
KP F-stat			751.2			751.2

Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the total exports in 2000; column 2 adds state-year fixed effects to column 1; column 3 presents the 2SLS using $\Delta \tilde{X}_r$ as the IV for ΔX_r. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

booming sector could be attributed to the labor-saving technologies increasingly adopted in commodity production, such as in the soybean industry (Bustos et al., 2016, 2020; Farrokhi & Pellegrina, 2023; Pellegrina, 2022). In contrast, Panel B reveals a statistically significant decline in the share of manufacturing employment in regions more affected by the trade shock compared to less impacted counterparts.

These results partially align with the Dutch disease literature. While there is no significant increase in the share of workers in the booming sector in regions most affected by the export demand shock, there is a notable decline in manufacturing employment. Importantly, Panel D indicates that the adjustment appears to have occurred within the residual category of our sector classification — individuals reporting income from employment but without specifying occupations. These positions are likely more closely linked to the informal labor market than those in other sectors. Thus, the reduction in manufacturing employment is accompanied by a modest increase in the share of individuals in these unspecified positions in the regions most impacted by the shock.

Table 9 further investigates changes in average wages across various sectors by applying long differences to log average wages in the primary, manufacturing, service , and the residual sectors. The results reveal a significant wage impact of the Chinese demand shock, particularly in the primary and service sectors. This suggests that while the resource boom predominantly raises wages in directly affected sectors, such as agriculture and extractive

Table 8: Commodity boom and sectoral employment patterns

Dependent variable: Δ **Employment share**	OLS (1)	OLS (2)	2SLS (3)
Panel A: Primary sector			
$\Delta\tilde{X}_r$	0.048	0.032	
	(0.029)	(0.020)	
ΔX_r			0.014
			(0.009)
Adjusted R^2	0.0208	0.283	0.287
F Statistic			751.2
Panel B: Manufacturing sector			
$\Delta\tilde{X}_r$	-0.014	-0.020**	
	(0.013)	(0.008)	
ΔX_r			-0.009**
			(0.004)
Adjusted R^2	0.005	0.172	0.152
F Statistic			751.2
Panel C: Services (nontraded) sector			
$\Delta\tilde{X}_r$	-0.038*	-0.022	
	(0.020)	(0.018)	
ΔX_r			-0.010
			(0.008)
Adjusted R^2	0.013	0.326	0.335
F Statistic			751.2
Panel D: Residual sector			
$\Delta\tilde{X}_r$	0.005	0.010**	
	(0.007)	(0.004)	
ΔX_r			0.005**
			(0.002)
Adjusted R^2	0.001	0.353	0.353
F Statistic			751.2
Observations	424	424	424
Weighted	X	X	X
State-year fixed effects		X	X

Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the total exports in 2000; column 2 adds state-year fixed effects to column 1; column 3 presents the 2SLS using $\Delta\tilde{X}_r$ as the IV for ΔX_r. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

industries, it also has positive spillover effects on wages in indirectly linked sectors.

Overall, the findings on employment dynamics following the China-induced export demand shock suggest that the significant increase in the value and concentration of primary product exports in the most affected regions does not correspond with a proportional rise in employment shares. Instead, the primary impact manifests in wage dynamics. Notably, there is a marked increase in average hourly wages within the primary sector, reflecting wage pressures driven by heightened demand. Additionally, consistent with Corden and Neary (1982) and Corden (1984), there is a significant rise in service sector wages in regions most impacted by the export demand surge, indicating positive income spillovers from the primary to non-traded sectors.

6 Concluding remarks

This paper examines the impact of resource booms on local export baskets in Brazil, a key example of a resource-rich developing country, focusing on export value, concentration, and composition. By leveraging a shift-share instrument that captures heterogeneous exposure to Chinese export demand following China's WTO accession in 2001, I analyze how this resource boom affected regional export dynamics across Brazilian local economies. The findings reveal significant increases in total export value and heightened concentration in export baskets within the most impacted regions. Contrary to initial expectations, the share of manufacturing exports in these regions did not significantly decline; instead, the increased concentration is driven by a focus on a narrower range of previously exported products, with minimal changes in the overall variety of goods.

The heterogeneity analysis indicates that these aggregate changes are primarily driven by shifts within the resource basket rather than the non-resource basket, highlighting a nuanced pattern of specialization across regions. Specifically, there is a shift toward exporting primary products at the expense of resource-based manufactures in the regions most affected by the surge in Chinese demand.

To further explore this "primarization" effect, I constructed an index of export basket sophistication, drawing upon the methodologies of Hausmann et al. (2007) and Jarreau and Poncet (2012). The analysis shows a decline in the average complexity of export baskets in regions more impacted by the shock compared to less affected areas. The shift toward simpler, lower-value-added goods — favoring raw materials over processed products — reveals another channel through which commodity booms reshape local productive structures. Similar to Heresi (2023), I document a within-sector adjustment, where a decline in value-added production within the resource or booming sector may be linked to a reduction in average productivity. This mechanism, if it indeed affects total factor

Table 9: Commodity boom and sectoral remuneration patterns

Dependent variable: Δ **Log average hourly wages**	OLS (1)	OLS (2)	2SLS (3)
Panel A: Primary sector			
$\Delta \tilde{X}_r$	0.489*	0.322***	
	(0.259)	(0.079)	
ΔX_r			0.146***
			(0.037)
Adjusted R^2	0.021	0.283	0.287
F Statistic			751.2
Panel B: Manufacturing sector			
$\Delta \tilde{X}_r$	0.036	-0.018	
	(0.036)	(0.030)	
ΔX_r			-0.008
			(0.013)
Adjusted R^2	0.000	0.354	0.355
F Statistic			751.2
Panel C: Services (nontraded) sector			
$\Delta \tilde{X}_r$	0.085***	0.052***	
	(0.030)	(0.016)	
ΔX_r			0.023***
			(0.007)
Adjusted R^2	0.023	0.682	0.718
F Statistic			751.2
Panel D: Residual sector			
$\Delta \tilde{X}_r$	0.021	-0.020	
	(0.086)	(0.054)	
ΔX_r			-0.009
			(0.024)
Adjusted R^2	-0.001	0.176	0.176
F Statistic			751.2
Observations	424	424	424
Weighted	X	X	X
State-year fixed effects		X	X

Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the total exports in 2000; column 2 adds state-year fixed effects to column 1; column 3 presents the 2SLS using $\Delta \tilde{X}_r$ as the IV for ΔX_r. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

productivity, could have lasting developmental consequences for these local economies and the broader Brazilian economy. Future research could focus on developing a theoretical framework to more comprehensively analyze the implications of such specialization patterns on regional growth trajectories.

Beyond export dynamics, this study also examines the broader implications of this trade shock for structural change, particularly in local labor markets. Despite the shift to a more "primary" export orientation, there was no corresponding increase in employment within the primary sector. Instead, this sector experienced substantial wage increases, suggesting that labor market adjustments occurred primarily along the intensive margin rather than through large-scale reallocation of workers. Additionally, relatively higher wage growth was observed in the service sector in regions more exposed to the China-induced trade shock. Meanwhile, manufacturing employment contracted significantly in the most affected regions, consistent with the Dutch disease phenomenon discussed in the resource curse literature. This contraction in manufacturing employment was partially offset by an increase in employment within a residual category — likely linked to the informal labor market — suggesting that resource booms may not only induce structural shifts in formal employment but also contribute to the expansion of less stable, informal economic activities.

In sum, the resource boom driven by Chinese demand has considerably reshaped regional economic dynamics in Brazil. While it substantially increased export values and boosted wages in certain sectors, it also led to a structural shift toward simpler, lower-value-added exports, with adverse effects on manufacturing employment. These findings offer a more nuanced perspective on the impacts of the China-led export demand shock in Brazilian labor markets, expanding on the evidence provided by Costa et al. (2016) and uncovering deeper structural changes that may hinder long-term economic diversification. These insights are crucial for policymakers in resource-rich developing countries, underscoring the need for strategies that not only capitalize on the immediate benefits of resource booms but also address the sustained pressures of maintaining diversified productive structures at the regional level.

Furthermore, the implications of this study extend beyond Brazil, offering broader lessons for other resource-rich developing economies facing similar external shocks. As recent evidence from Colombia suggests (Branstetter & Laverde-Cubillos, 2024), resource booms often come with a decline in technological development and long-term competitiveness. The patterns observed in Brazil may be part of a larger global trend, underscoring the urgent need for policies that foster economic diversification and technological upgrading.

By way of conclusion, while this study provides new causal evidence on resource booms and regional export dynamics, further research is needed to fully understand their long-term growth and development implications. Although this analysis captures additional partial equilibrium effects of China's WTO accession on the Brazilian economy — extending the limited literature, including works by Costa et al. (2016) and Carreira et al. (2024) — the findings presented here broaden the scope of existing research on developing economies and suggest new avenues for future investigation.

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A Appendix

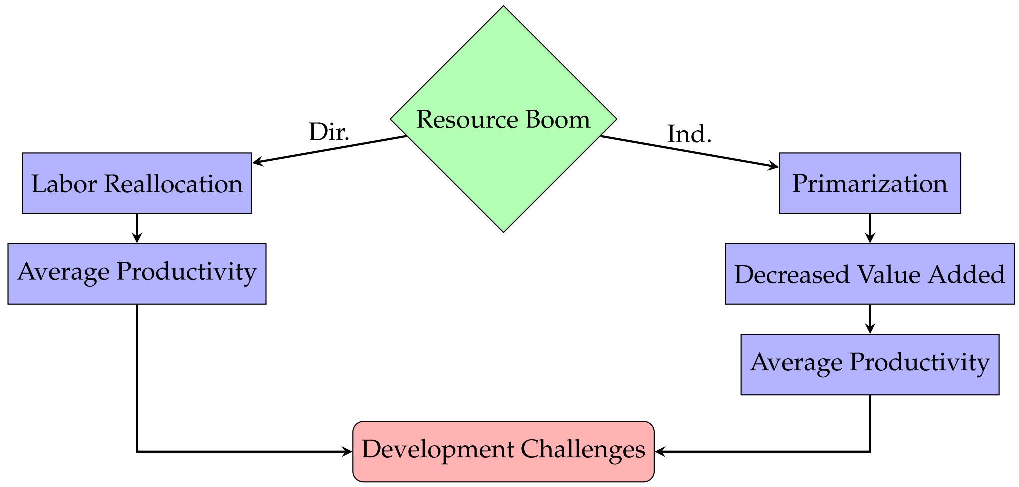
Table A.1: Descriptive statistics at the micro-region level - Long-differences (2000-2019)

Variables	*Source*	*Mean*	*Standard Deviation*	*Min*	*Max*	*Observations*
Chinese Demand Shock						
ΔX_r	COMEXSTAT	0.62	1.21	0.00	6.38	424
$\Delta \tilde{X}_r$ (instrument)	COMEXSTAT and BACI-CEPII	0.12	0.31	0.00	2.51	424
Regional Export Basket Value						
Δ Export Value	COMEXSTAT	333401105.96	1247641603.99	-1383672724.60	20543485713.80	424
Δ Log Export Value	COMEXSTAT	1.59	2.27	-6.16	12.53	424
Regional Export Basket Concentration						
Δ Lines	COMEXSTAT	47.77	83.84	-178.00	558.00	424
Δ HHI	COMEXSTAT	-0.04	0.33	-1.00	0.98	424
Regional Export Basket Sophistication						
Δ $S_{r,t}$ (WDI)	WDI, BACI-CEPII, and COMEXSTAT	225.36	1757.51	-4735.18	24695.02	424
Δ $S_{r,t}$ (PWT)	PWT, BACI-CEPII, and COMEXSTAT	287.96	2924.96	-8998.35	44524.66	424
Regional Export Basket Composition						
Δ Share of Resources (Prim. + RB)	COMEXSTAT and Lall (2000)	0.07	0.32	-1.00	1.00	424
Δ Share of Primary Products	COMEXSTAT and Lall (2000)	0.13	0.39	-1.00	1.00	424
Δ Share of Resource-Based Man.	COMEXSTAT and Lall (2000)	-0.06	0.40	-1.00	1.00	424
Δ Share of Low-Tech Man.	COMEXSTAT and Lall (2000)	-0.08	0.25	-1.00	1.00	424
Δ Share of Medium-Tech Man.	COMEXSTAT and Lall (2000)	0.01	0.24	-1.00	1.00	424
Δ Share of High-Tech Man.	COMEXSTAT and Lall (2000)	-0.01	0.11	-1.00	0.54	424

Table A.2: Descriptive statistics - Yearly dataset

Variables		*Mean*	*Standard Deviation*	*Min*	*Max*	*Observations*
Regional Export Basket Value						
Export Value	overall	392564333.77	1221829523.673	1.017	22706823321	N = 9752
	between		1055119999.552	1026.443	13700143738.131	n = 424
	within		577278271.726	-6180431422.417	16072092164.325	T = 23
Log Export Value	overall	17.383	2.794	0.016	23.846	N = 9752
	between		2.714	6.093	23.294	n = 424
	within		1.305	2.676	22.666	T = 23
Regional Export Basket Concentration						
Number of Export Lines	overall	69.482	136.295	1	1079	N = 9752
	between		129.705	1	1011.565	n = 424
	within		34.059	-293.736	502.308	T = 23
HHI	overall	0.457	0.299	0	1	N = 9752
	between		0.237	0.04	1	n = 424
	within		0.194	-0.437	1.22	T = 23
Regional Export Basket Sophistication						
$S_{r,t}$ (WDI)	overall	2551.369	1856.562	444.085	49477.073	N = 9752
	between		1551.084	719.364	21413.945	n = 424
	within		1060.919	-15435.716	30614.497	T = 23
$S_{r,t}$ (PWT)	overall	3564.521	3073.459	676.219	87262.215	N = 9752
	between		2448.242	1080.277	37069.303	n = 424
	within		1875.831	-28969.087	59412.882	T = 23

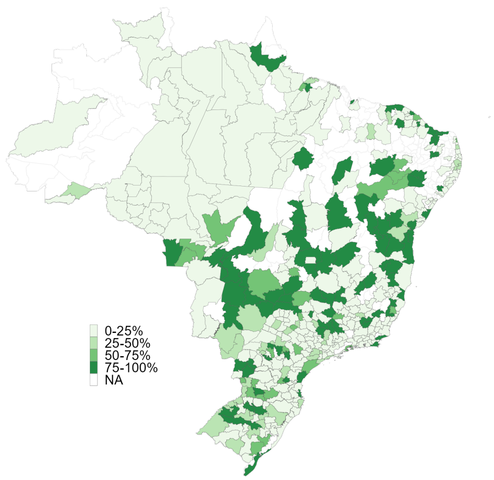
Figure A.1: Potential mechanism — Direct and indirect effects



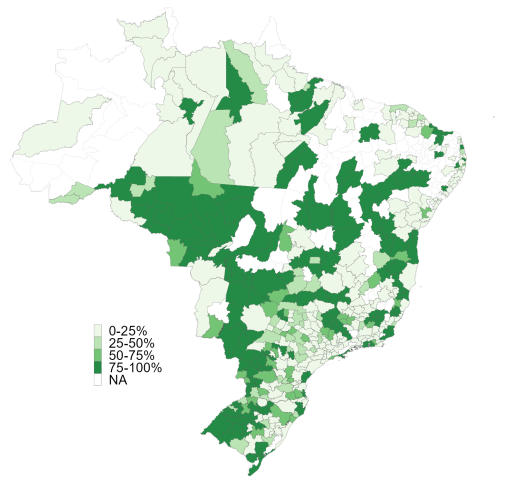
B Online Appendix

B.1 Composition of regional export baskets

Figure B.1: Share of Exports — Primary Products



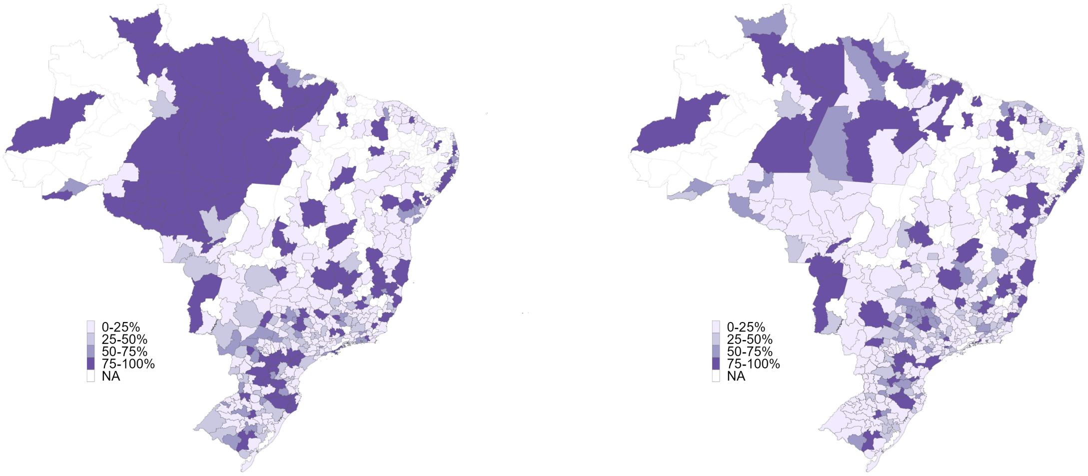
(a) 2000



(b) 2019

Source: Data on the value of exports is based on the declaration of exporters in Brazil (SISCOMEX from the Ministry of Industry, Foreign Trade and Services).

Figure B.2: Share of Exports — Resource Based Products

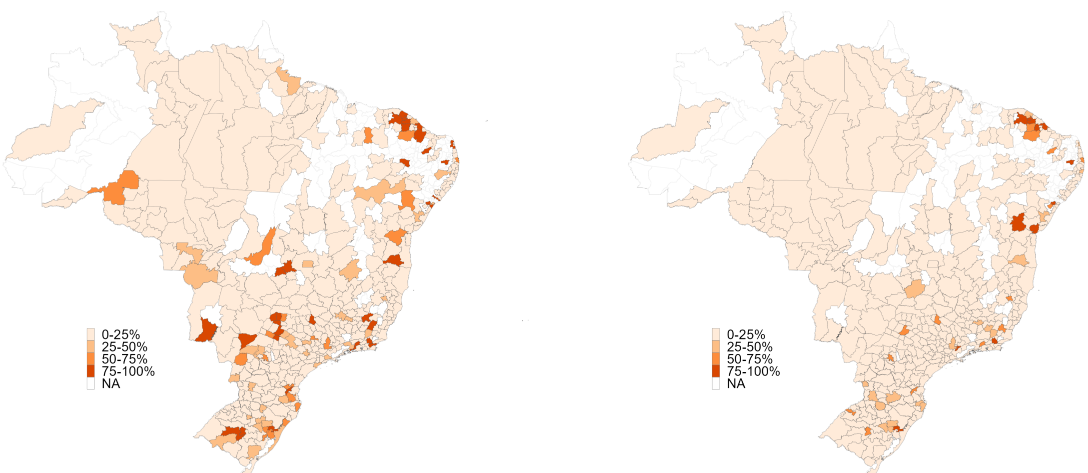


(a) 2000

(b) 2019

Source: Data on the value of exports is based on the declaration of exporters in Brazil (SISCOMEX from the Ministry of Industry, Foreign Trade and Services).

Figure B.3: Share of Exports — Low-Tech Manufactures

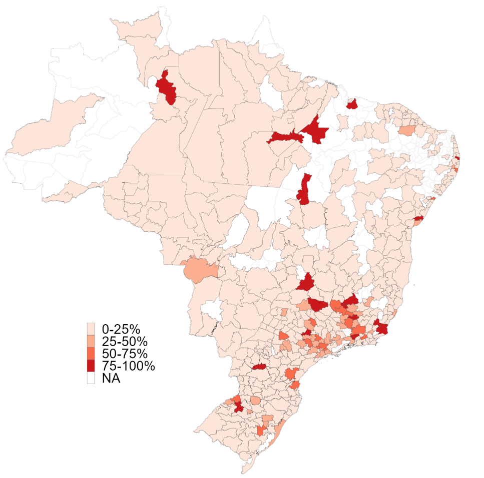


(a) 2000

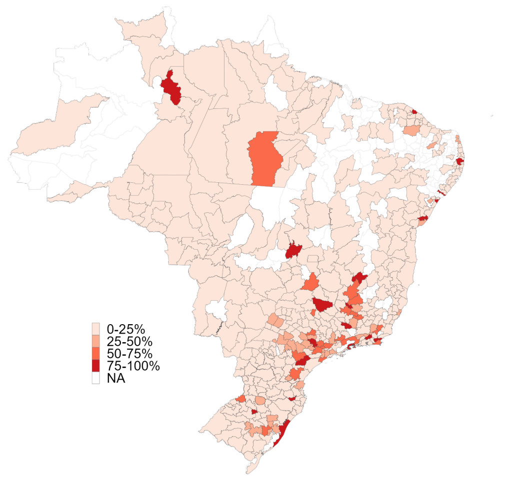
(b) 2019

Source: Data on the value of exports is based on the declaration of exporters in Brazil (SISCOMEX from the Ministry of Industry, Foreign Trade and Services).

Figure B.4: Share of Exports — Medium-Tech Manufactures



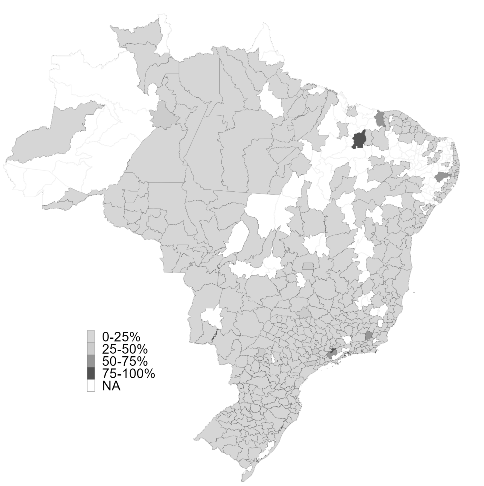
(a) 2000



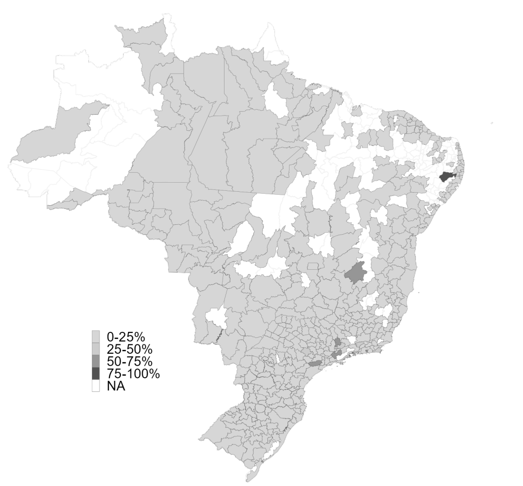
(b) 2019

Source: Data on the value of exports is based on the declaration of exporters in Brazil (SISCOMEX from the Ministry of Industry, Foreign Trade and Services).

Figure B.5: Share of Exports — High-Tech Manufactures



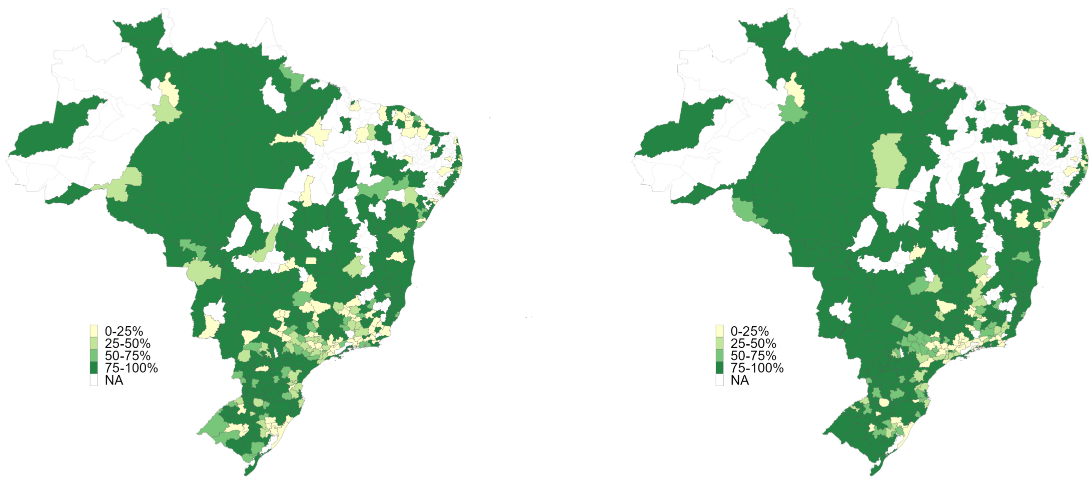
(a) 2000



(b) 2019

Source: Data on the value of exports is based on the declaration of exporters in Brazil (SISCOMEX from the Ministry of Industry, Foreign Trade and Services).

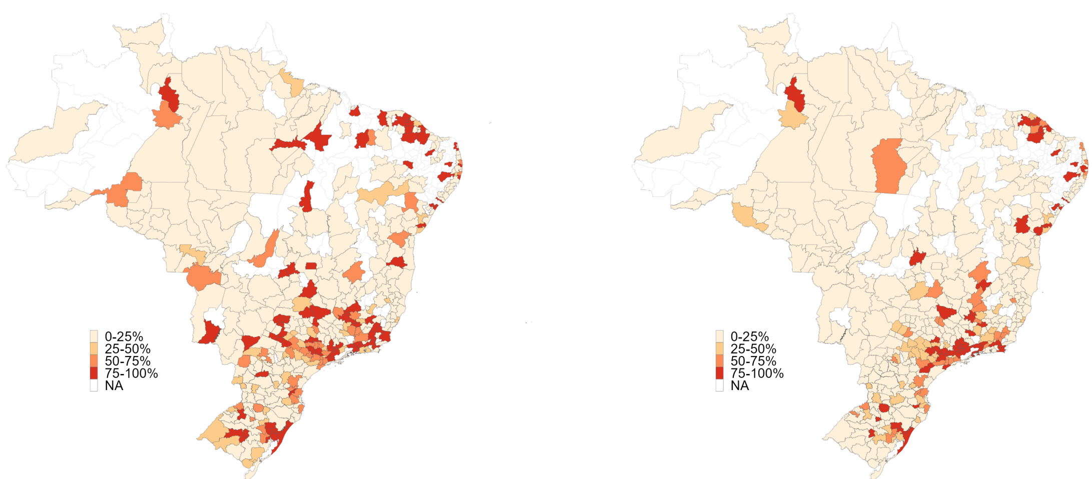
Figure B.6: Share of Exports — Resources



(a) 2000 (b) 2019

Source: Data on the value of exports is based on the declaration of exporters in Brazil (SISCOMEX from the Ministry of Industry, Foreign Trade and Services).

Figure B.7: Share of Exports — Manufactures



(a) 2000 (b) 2019

Source: Data on the value of exports is based on the declaration of exporters in Brazil (SISCOMEX from the Ministry of Industry, Foreign Trade and Services).

Figure B.8: Difference in the share of manufactures exports: 2019 - 2000

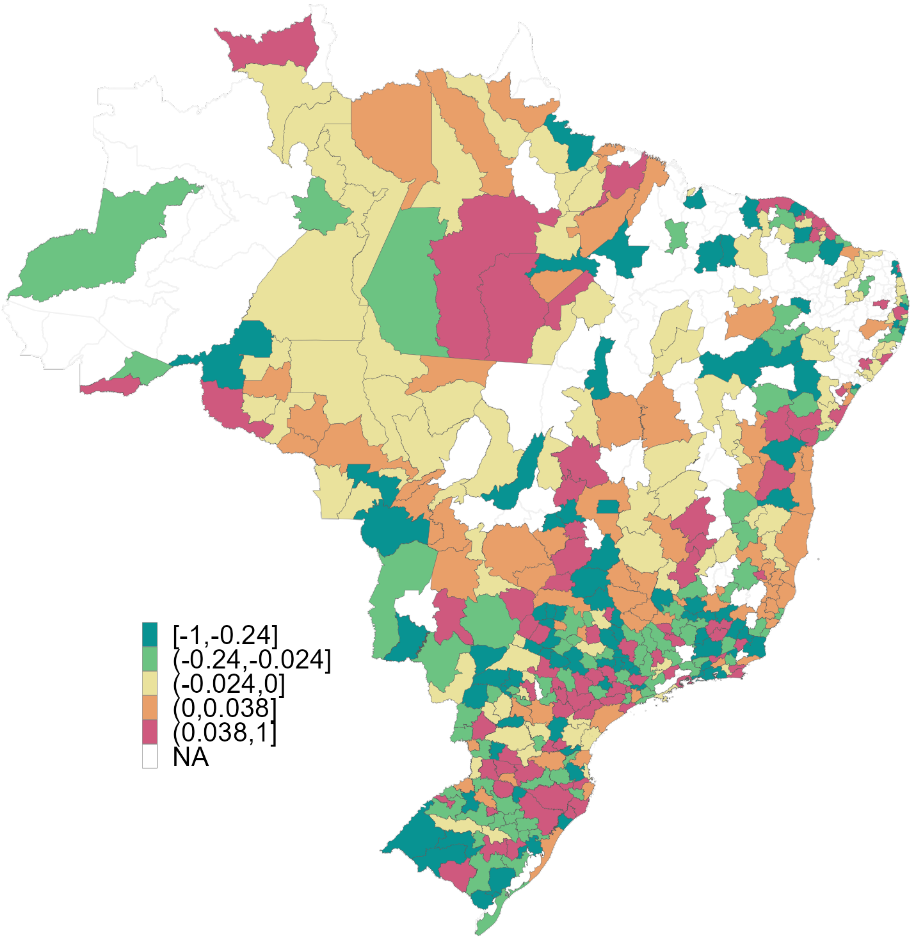


Table B.1: First Stage Regressions - Chinese Export Demand and Shift-Share Instrument

Dependent variable:	Chinese Export Demand ΔXX_r HS4 - 1217 categories 2019 - 2000	Chinese Export Demand ΔXX_r HS2 - 92 categories 2019 - 2000	Chinese Export Demand ΔXX_r HS2 - 92 categories 2010 - 2000
$\Delta\tilde{X}X_r$	1.763***	1.550***	2.282***
	(0.299)	(0.170)	(0.077)
Constant	0.570***	0.419***	0.085***
	(0.120)	(0.056)	(0.017)
Observations	439	439	439
Adjusted R^2	0.074	0.160	0.666
KP F-Stat	34.873	83.185	874.300

Notes: Robust standard errors in parentheses. Unit of analysis is a micro-region r. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

B.2 First-stage regression and additional visual evidence

Figure B.9: Correlation: Chinese export demand and shift-share instrumental variable - HS4

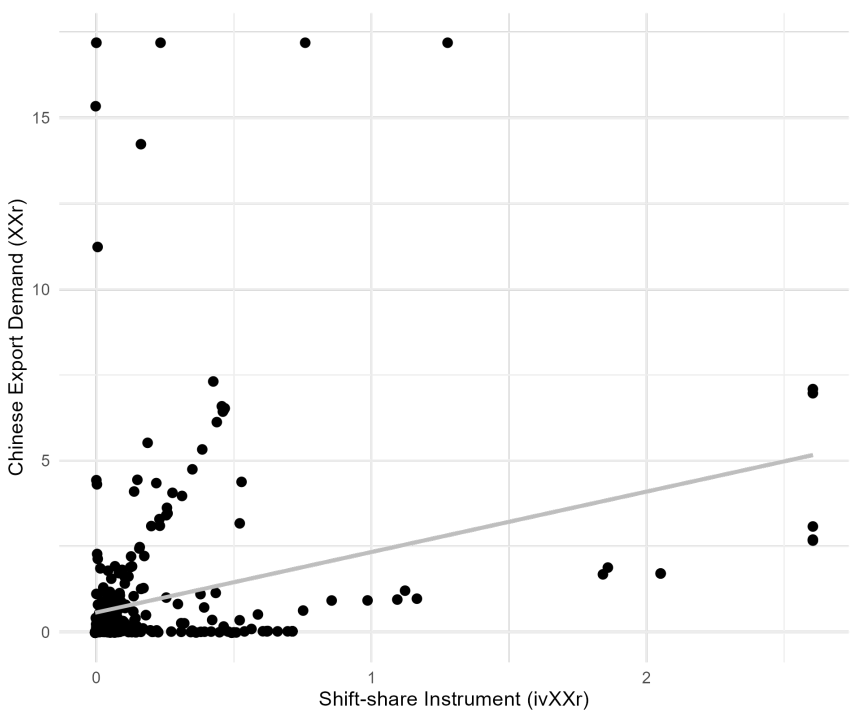
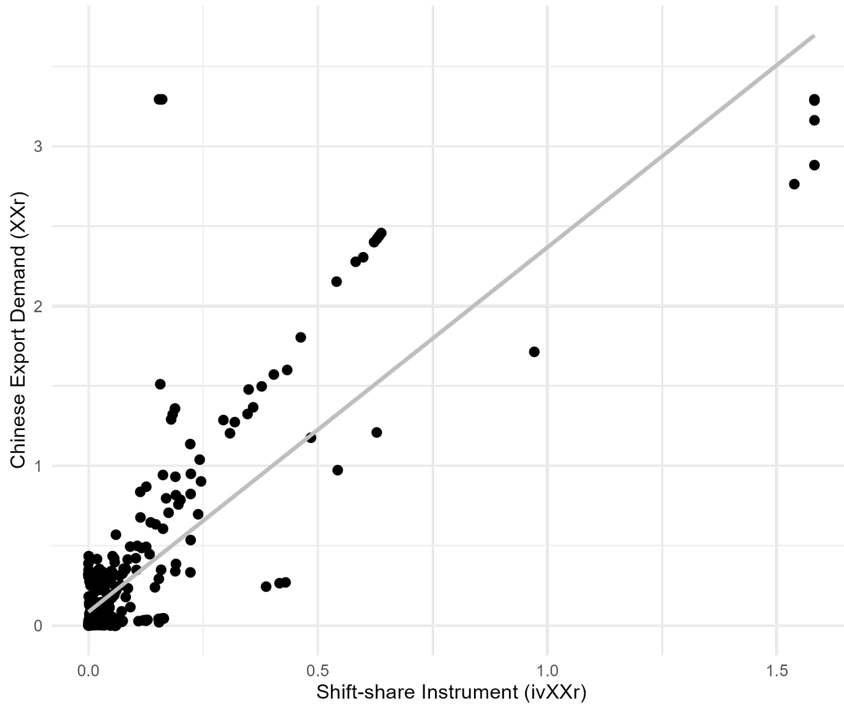


Figure B.10: Correlation: Chinese export demand and shift-share instrumental variable - HS2 and 2010-2000 (Census variables)



B.3 Robustness to alternative inference procedures

In this section, I show that the baseline results are very similar using the inference procedures proposed by Borusyak et al. (2022), which address cross-region correlation in residuals in shift-share designs. Tables B.2, B.3, and B.4 indicates that the baseline results for export basket value, concentration and sophistication, presented in Tables 1,2, and 6 of the manuscript, are not qualitatively altered when following alternative inference procedures.

B.4 Robustness to different temporalities and parallel trends

Finally, I present additional estimations aimed at assessing the robustness of the primary findings. Tables B.5, B.6, B.7, and B.8 delve into the stability of the coefficients associated with the variation in the total value of exports, the growth rate of such values, the number of export lines, and the HHI over different periods, respectively. Particularly, I scrutinize a shorter-term impact by estimating the disparities in the variables of interest between 2000 and 2010, juxtaposed with the coefficients already presented for the long differences between 2000 and 2019. Importantly, I use the variation of the shift-share instrument with

Table B.2: Commodity boom and export value (Borusyak et al. (2022) robust standard errors)

Dependent variable:	Δ **Value of exports**			%Δ **Value of exports**		
	OLS (1)	OLS (2)	2SLS (3)	OLS (1)	OLS (2)	2SLS (3)
$\Delta\tilde{X}_r$	3,312,141,960*	2,902,794,084***		1.730**	1.486***	
	[801,244,029]	[710,144,339]		[0.362]	[0.256]	
ΔX_r			2,537,285,580***			1.299**
			[1,018,991,070]			[0.767]
Weighted	X	X	X	X	X	X
State-year fixed effects		X	X		X	X

Notes: This table presents an alternative approach to inference on the baseline results in Table 1 of the manuscript. There are 96 industry observations in each regression (industry-level regressions). Borusyak et al. (2022) robust standard errors are reported in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.3: Commodity boom and export concentration (Borusyak et al. (2022) robust standard errors)

Dependent variable:	Δ **Lines**			Δ **HHI**		
	OLS (1)	OLS (2)	2SLS (3)	OLS (1)	OLS (2)	2SLS (3)
$\Delta\tilde{X}_r$	3.658	-16.494		0.085***	0.083***	
	[40.527]	[58.779]		[0.026]	[0.025]	
ΔX_r			-14.417			0.073**
			[80.825]			[0.031]
Weighted	X	X	X	X	X	X
State-year fixed effects		X	X		X	X

Notes: This table presents an alternative approach to inference on the baseline results in Table 2 of the manuscript. There are 96 industry observations in each regression (industry-level regressions). Borusyak et al. (2022) robust standard errors are reported in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

the final year of 2010 in the shorter period window. Across virtually all cases, the results exhibit qualitative similarity in both temporalities, underscoring the robustness of the findings to different temporal specifications.

Additionally, I incorporate placebo tests or parallel trend assessments in Column (4) of all tables. Here, I regress the shock exposure variable on a preceding difference in the

Table B.4: Commodity boom and export sophistication (Borusyak et al. (2022) robust standard errors)

Dependent variable:	$\Delta\ S_{r,t}$ **(WDI)**			$\Delta\ S_{r,t}$ **(PWT)**		
	OLS (1)	OLS (2)	2SLS (3)	OLS (1)	OLS (2)	2SLS (3)
$\Delta\tilde{X}_r$	35.52	-327.91***		6.7138	-371.52***	
	[119.723]	[109.899]		[130.047]	[131.002]	
ΔX_r			-286.62**			-324.74**
			[122.296]			[149.761]
Weighted	X	X	X	X	X	X
State-year fixed effects		X	X		X	X

Notes: This table presents an alternative approach to inference on the baseline results in Table 6 of the manuscript. There are 96 industry observations in each regression (industry-level regressions). Borusyak et al. (2022) robust standard errors are reported in brackets. $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

dependent variable (between 1997 and 2000 — before the occurrence of the resource boom), with observations weighted and state-year fixed effects considered. In Tables B.5 and B.6, the placebo test reveals a contrasting trend prior to treatment. In other words, there seems to be a reversal of the trend with the treatment - the regions most affected subsequently by the Chinese demand shock displayed, before the treatment, negative changes in the value of total exports. However, concerning HHI (Table B.8), the placebo test suggests that the hypothesis of parallel trends before treatment appears to be observed.

Table B.5: Commodity boom and change in export value: short and medium run

Dependent variable: Δ **Value of exports**	OLS (1)		OLS (2)		2SLS (3)		Placebo (4)	
	2000-2010	2000-2019	2000-2010	2000-2019	2000-2010	2000-2019	1997-2000	1997-2000
$\Delta\tilde{X}_r$	2,423,790,438***	3,312,141,960**	3,342,149,578***	2,902,794,084***			-409,607,604***	-246,990,431***
	(756,532,864)	(1,628,508,368)	(593,872,297)	(1,081,950,192)			(121,751,038)	(76,174,580)
ΔX_r					1,759,577,719***	2,537,285,580***		
					(335,237,141)	(886,315,027)		
Weighted	X	X	X	X	X	X	X	X
State-year fixed effects			X	X	X	X	X	X
Observations	417	424	417	424	417	424	406	406
Adjusted R^2	0.116	0.182	0.305	0.625	0.286	0.296	0.314	0.309
KP F-stat					952.8	99.7		

Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the total exports in 2000; column 2 adds state-year fixed effects to column 1; column 3 presents the 2SLS using $\Delta\tilde{X}_r$ as the IV for ΔX_r. Column 4 presents a placebo test, with observations weighted by population and considering state fixed effects. $^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$.

Table B.6: Commodity boom and percent change in export value: short and medium run

Dependent variable: **% Δ Value**								
	OLS		OLS		2SLS		Placebo	
	(1)		(2)		(3)		(4)	
	2000-2010	2000-2019	2000-2010	2000-2019	2000-2010	2000-2019	1997-2000	1997-2000
$\Delta\tilde{X}_r$	3.156***	1.730	2.467***	1.486*			-0.308***	-0.182***
	(0.755)	(1.169)	(0.911)	(0.795)			(0.085)	(0.054)
ΔX_r					1.299***	1.299*		
					(0.493)	(0.669)		
Weighted	X	X	X	X	X	X	X	X
State-year fixed effects			X	X	X	X	X	X
Observations	417	424	417	424	417	424	406	406
Adjusted R^2	-0.002	0.002	0.068	0.066	0.067	0.066	-0.017	-0.018
KP F-stat					952.8	99.7		

Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the total exports in 2000; column 2 adds state-year fixed effects to column 1; column 3 presents the 2SLS using $\Delta\tilde{X}_r$ as the IV for ΔX_r. Column 4 presents a placebo test, with observations weighted by population and considering state fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: Commodity boom and number of exports lines: short and medium run

Dependent variable: **Δ Lines**								
	OLS		OLS		2SLS		Placebo	
	(1)		(2)		(3)		(4)	
	2000-2010	2000-2019	2000-2010	2000-2019	2000-2010	2000-2019	1997-2000	1997-2000
$\Delta\tilde{X}_r$	2.097	3.658	-4.929	-16.494			6.901	6.198
	(21.455)	(30.516)	(21.539)	(29.669)			(10.319)	(6.902)
ΔX_r					-2.595	-14.417		
					(11.293)	(25.858)		
Weighted	X	X	X	X	X	X	X	X
State-year fixed effects			X	X	X	X	X	X
Observations	417	424	417	424	417	424	406	406
Adjusted R^2	-0.001	-0.002	0.01412	0.191	0.053	0.117	0.297	0.301
KP F-stat					952.8	99.7		

Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the total exports in 2000; column 2 adds state-year fixed effects to column 1; column 3 presents the 2SLS using $\Delta\tilde{X}_r$ as the IV for ΔX_r. Column 4 presents a placebo test, with observations weighted by population and considering state fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.5 Robustness to alternative spatial aggregations

First, Figure B.11 maps the local exposure to Chinese export demand — the shift-share instrument — computed at the state level. The similarities with the regional exposure shown in Figure 8 are quite clear.

Table B.8: Commodity boom and HHI: short and medium run

Dependent variable: Δ **HHI**								
	OLS		OLS		2SLS		Placebo	
	(1)		(2)		(3)		(4)	
	2000-2010	2000-2019	2000-2010	2000-2019	2000-2010	2000-2019	1997-2000	1997-2000
$\Delta\tilde{X}_r$	0.085***	0.085	0.079***	0.083***			-0.001	-0.003
	(0.025)	(0.052)	(0.026)	(0.029)			(0.029)	(0.018)
ΔX_r					0.042***	0.073***		
					(0.015)	(0.026)		
Weighted	X	X	X	X	X	X	X	X
State-year fixed effects			X	X	X	X	X	X
Observations	417	424	417	424	417	424	406	406
Adjusted R^2	0.041	0.053	0.165	0.324	0.147	0.249	0.057	0.057
KP F-stat					952.8	99.7		

Notes: Unit of analysis r is a micro-region. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the total exports in 2000; column 2 adds state-year fixed effects to column 1; column 3 presents the 2SLS using $\Delta\tilde{X}_r$ as the IV for ΔX_r. Column 4 presents a placebo test, with observations weighted by population and considering state fixed effects. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Additionally, I present the event-study specification outlined in Equation (8) for state-level observations. Figures B.12, B.13, and B.14 depict the dynamic effects of the China-induced demand shock on the value, concentration, and sophistication of state-level export baskets, respectively, along with 95% confidence intervals.

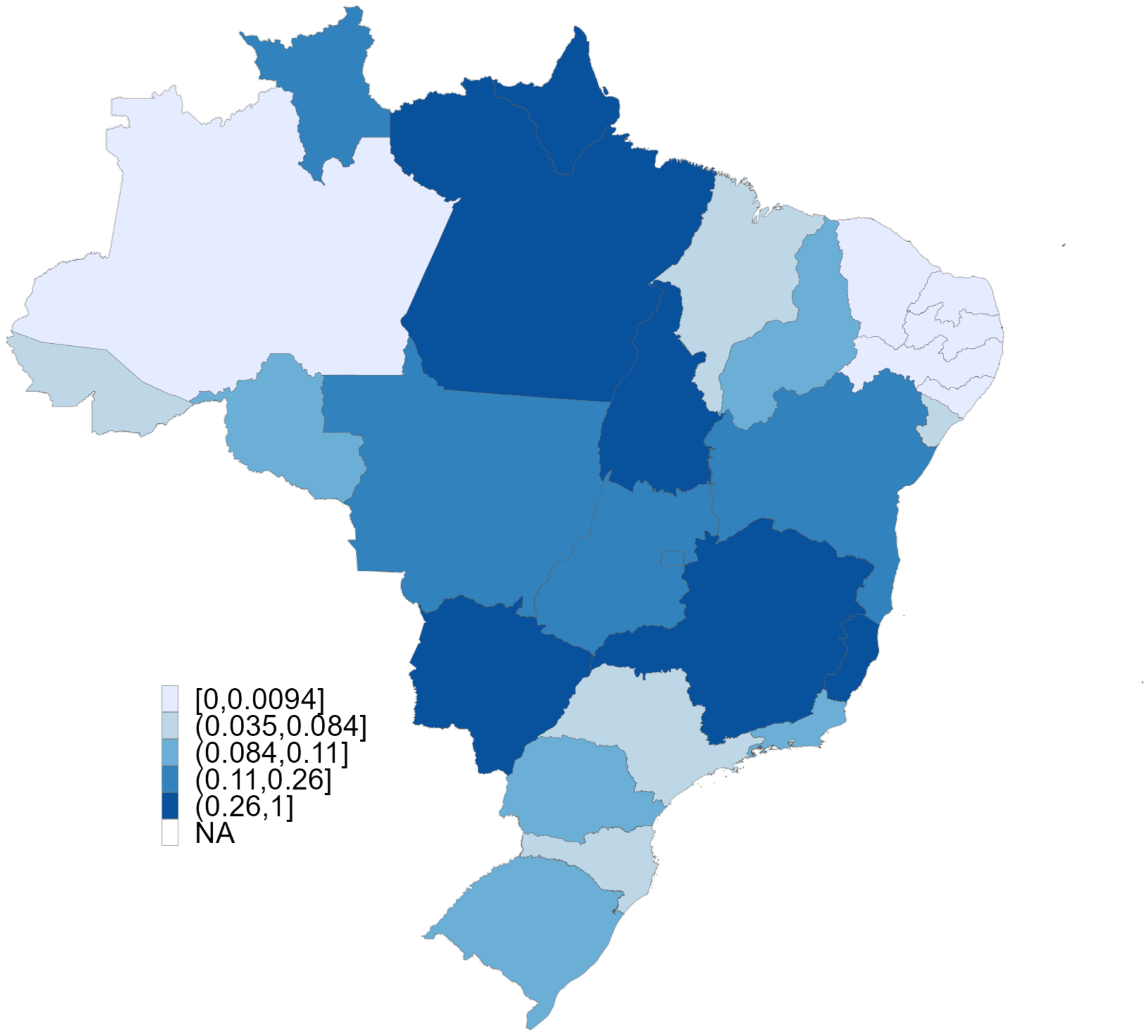
Overall, the results indicate the robustness of the causal findings to alternative spatial aggregations, which, unlike the municipality-level data, have export data computed at the production locality.

B.6 Sensitivity Analysis

To further assess the robustness of the baseline results presented in Tables 1, 2, and 6 of the manuscript, I conducted a sensitivity analysis focusing on the coefficients associated with the impacts of regional exposure to Chinese demand on key dependent variables.

For this analysis, I re-estimated the preferred specification — using weighted observations and including state-year fixed effects — by sequentially excluding one of the top or bottom 40 micro-regions based on: i) the magnitude of the China-induced export demand shock, and ii) the magnitude of the dependent variables of interest.

Figure B.11: Exposure to China's Export Demand - $\Delta\tilde{X}_r$ - State Level



Source: Regional exposures to China's export demand, $\Delta\tilde{X}_r$, are computed according to Equation (6) for the state level. Data from CEPII-BACI and SISCOMEX are used for computing the shift-share instrument.

B.6.1 Exclusion of Observations Ranked by Magnitude of Shift-Share Instrument

First, Figures B.15 and B.16 graphically present, respectively, the results of excluding the top and bottom-ranked micro-regions in terms of $\Delta\tilde{X}r$, highlighting the coefficient of interest and the 95% confidence interval for each regression where the dependent variable is either the difference in regional export value or the growth rate of export value. The analysis begins with the highest or lowest $\Delta\tilde{X}r$ on the left. The dotted black line represents the coefficient obtained in the baseline regression.

Similarly, Figures B.17 and B.18, respectively, present the results of excluding the top and bottom-ranked micro-regions based on $\Delta\tilde{X}_r$, with the difference in export lines and HHI as the dependent variables.

Lastly, I perform a similar sensitivity analysis for export sophistication measures. Figures B.19 and B.20 present the results of excluding the top and bottom-ranked micro-regions based on $\Delta\tilde{X}_r$, with the difference in export sophistication as defined in Equation (4) for both the WDI and PWT data sources.

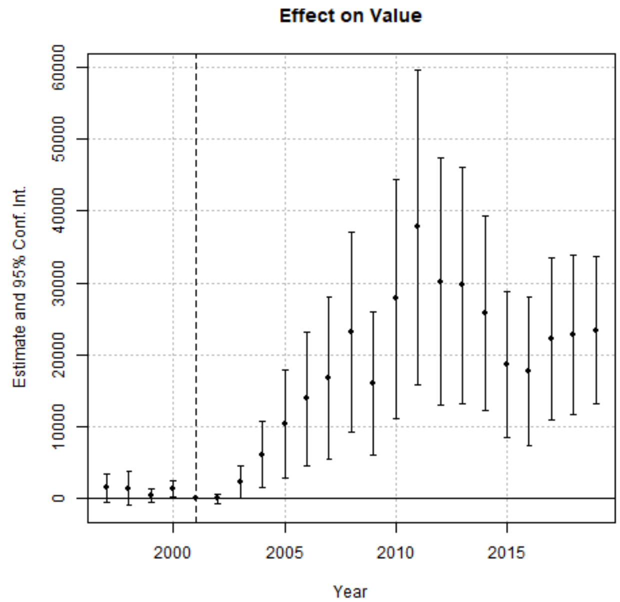
Taken together, the evidence from this subsection further support the causal relations presented in the main results of the manuscript. The results show that outliers of the shift-share instrument indeed do not drive the main results of the manuscript, in addition to the winsorizing process already described earlier.

B.6.2 Exclusion of Observations Ranked by Value of Dependent Variables

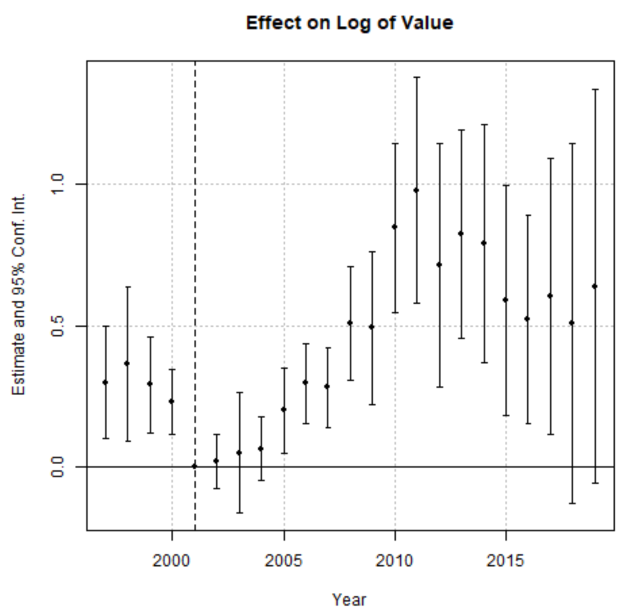
Next, I conduct a similar sensitivity analysis by excluding observations with the highest and lowest magnitudes of the dependent variables of interest. Figures B.21, B.22, B.23, B.24, B.25, and B.26 present the estimated coefficients and 95% confidence intervals for the difference in regional export basket value, growth rate of the value, number of export lines, HHI, and export sophistication using both WDI and PWT data.

Overall, the results from this subsection indicate the stability of the estimated coefficients to the exclusion of observations at the top and bottom of the distribution of the magnitude of the dependent variables of interest.

Figure B.12: Dynamic Effects of the Resource Boom on Export Value and Growth - State Level



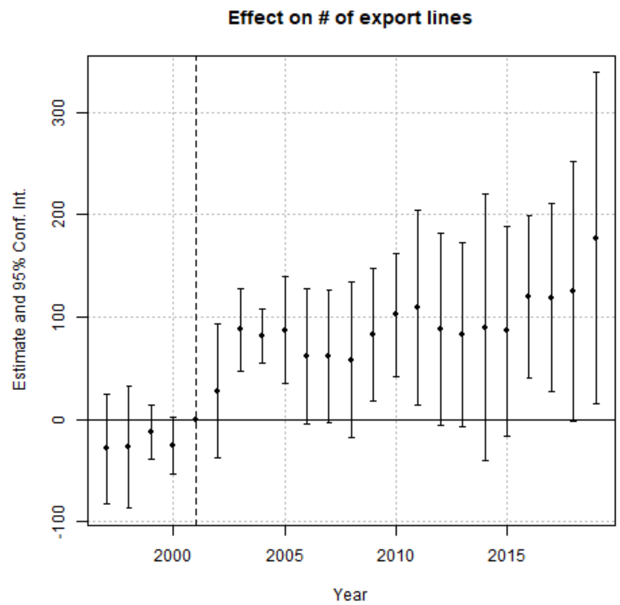
(a) Dynamic effects on export value



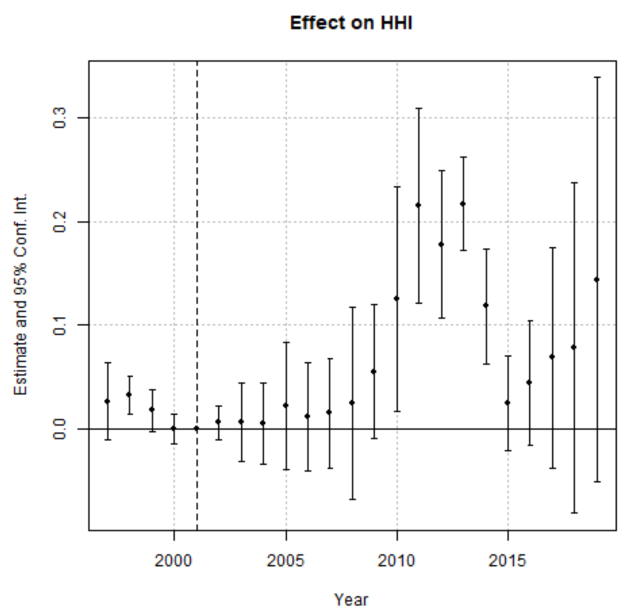
(b) Dynamic effects on log export value

Notes: Each point reflects an individual regression coefficient $\hat{\beta}$ following Equation (8), where the dependent variables are the state export value in level and log, respectively, in year $t = 1997, ..., 2019$. The regressions include state and year fixed effects. Standard errors are adjusted for 27 state clusters and the observations are weighted by total exports in 2000.

Figure B.13: Dynamic Effects of the Resource Boom on Export Concentration - State Level



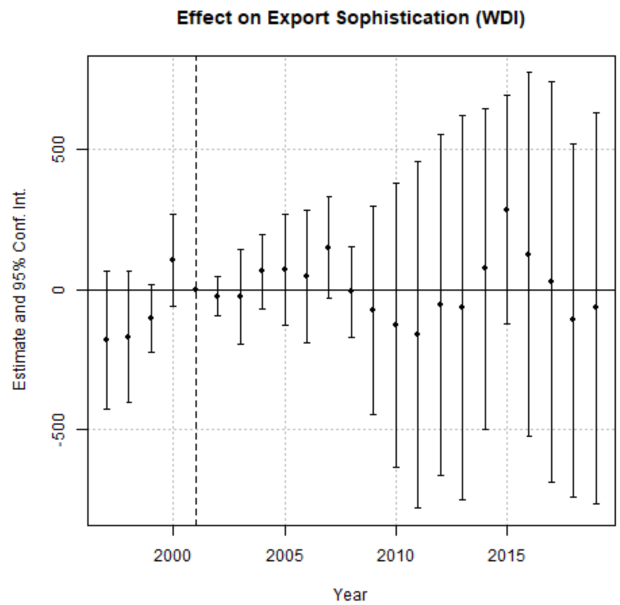
(a) Dynamic effects on export lines



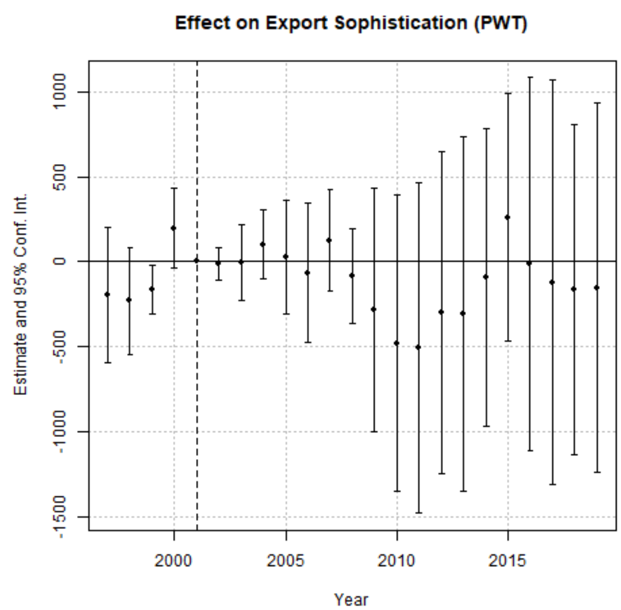
(b) Dynamic effects on HHI

Notes: Each point reflects an individual regression coefficient $\hat{\beta}$ following Equation (8), where the dependent variables are the number of export lines and the HHI associated with state export baskets, respectively, in year $t = 1997, ..., 2019$. The regressions include state and year fixed effects. Standard errors are adjusted for 27 state clusters and the observations are weighted by total exports in 2000.

Figure B.14: Dynamic Effects of the Resource Boom on Export Sophistication - State Level

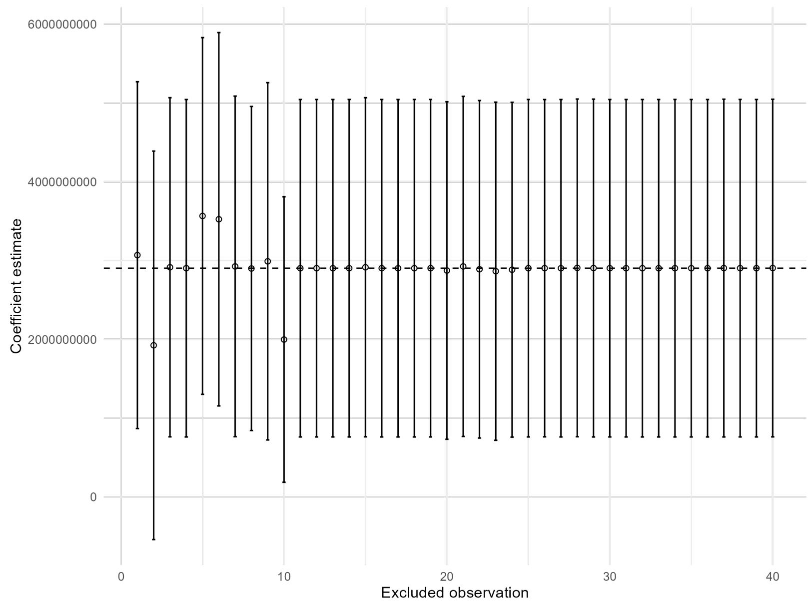


(a) Dynamic effects on sophistication (WDI)

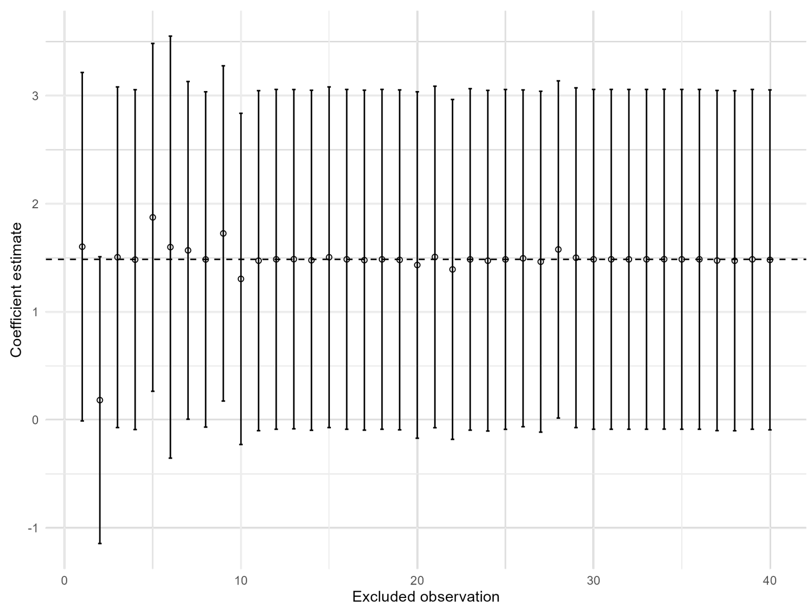


(b) Dynamic effects on sophistication (PWT)

Notes: Each point reflects an individual regression coefficient $\hat{\beta}$ following Equation (8), where the dependent variables are the sophistication indexes associated with state export baskets as described in Equation (4) in year $t = 1997, ..., 2019$. The regressions include state and year fixed effects. Standard errors are adjusted for 27 state clusters and the observations are weighted by total exports in 2000.



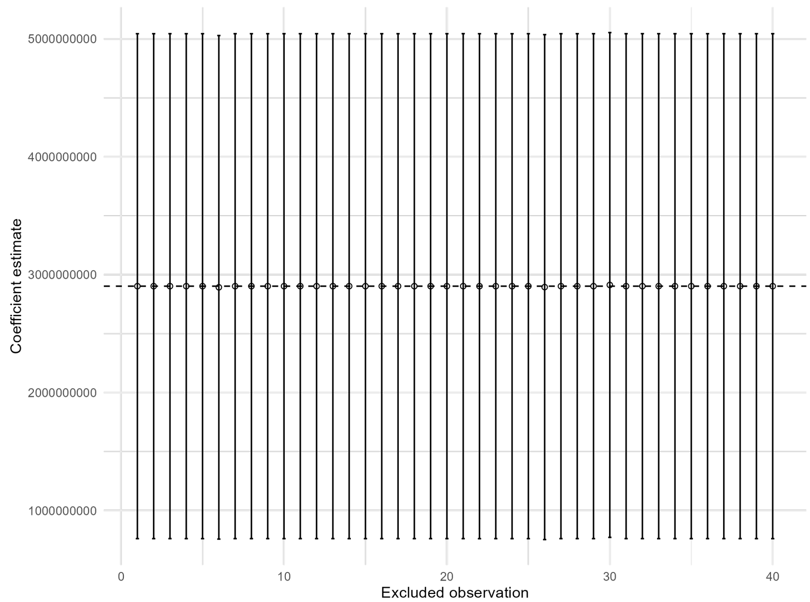
(c) Δ Value of Exports



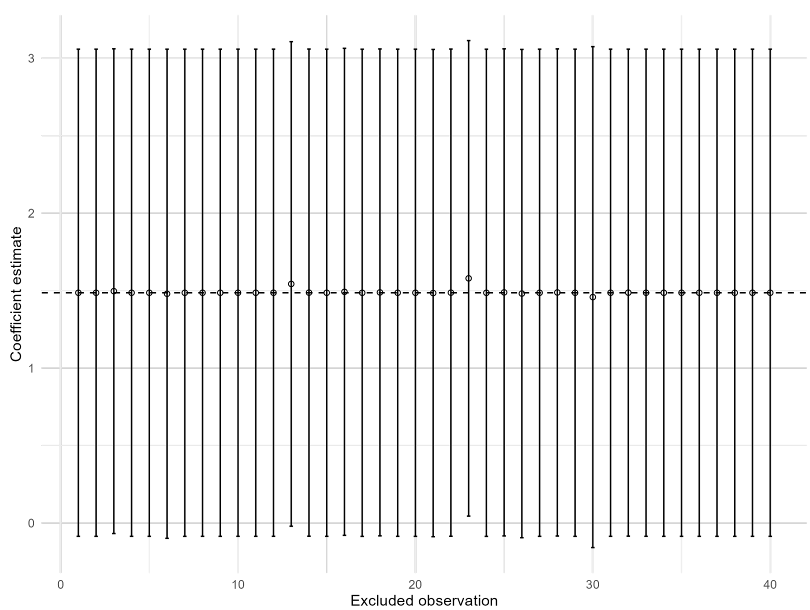
(d) $\%\Delta$ Value of Exports

Figure B.15: Commodity Boom and Export Value (Exclusion of Micro-Regions - Top 40 Based on $\Delta\tilde{X}r$ Value)

Notes: The figure shows the robustness of the results to excluding, one by one, the top 40 micro-regions with the highest $\Delta\tilde{X}r$. The estimated coefficients and confidence intervals at 95% are reported. Each coefficient and confidence interval emanate from a single estimation. Micro-regions are ranked from left to right—highest $\Delta\tilde{X}_r$ exposure is the first observation.



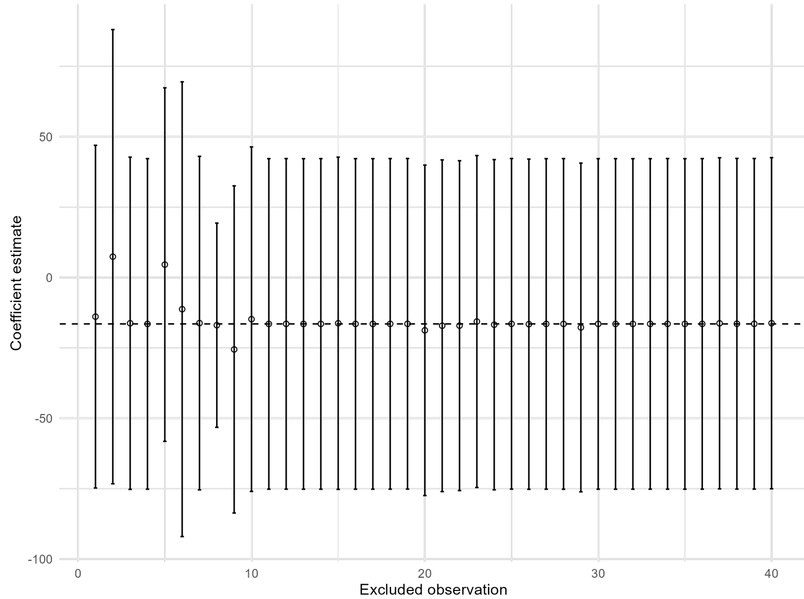
(a) Δ Value of Exports



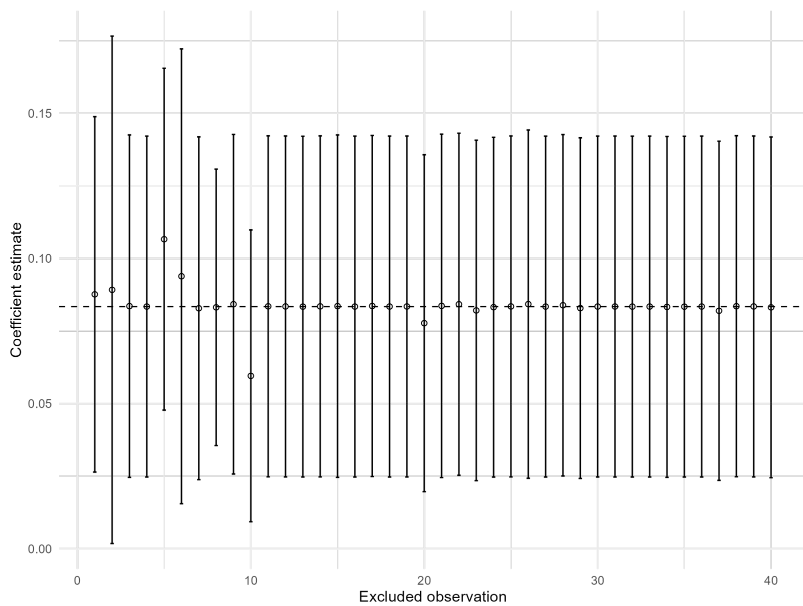
(b) $\%\Delta$ Value of Exports

Figure B.16: Commodity Boom and Export Value (Exclusion of Micro-Regions - Low 40 Based on $\Delta\tilde{X}r$ Value)

Notes: The figure shows the robustness of the results to excluding, one by one, the last 40 micro-regions with the lowest $\Delta\tilde{X}r$. The estimated coefficients and confidence intervals at 95% are reported. Each coefficient and confidence interval emanate from a single estimation. Micro-regions are ranked from left to right—lowest $\Delta\tilde{X}_r$ exposure is the first observation.



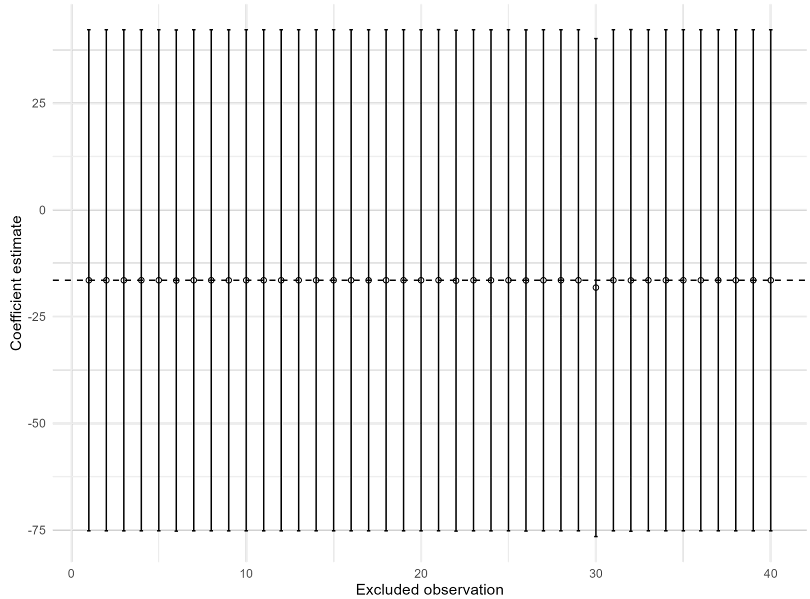
(a) Δ Lines



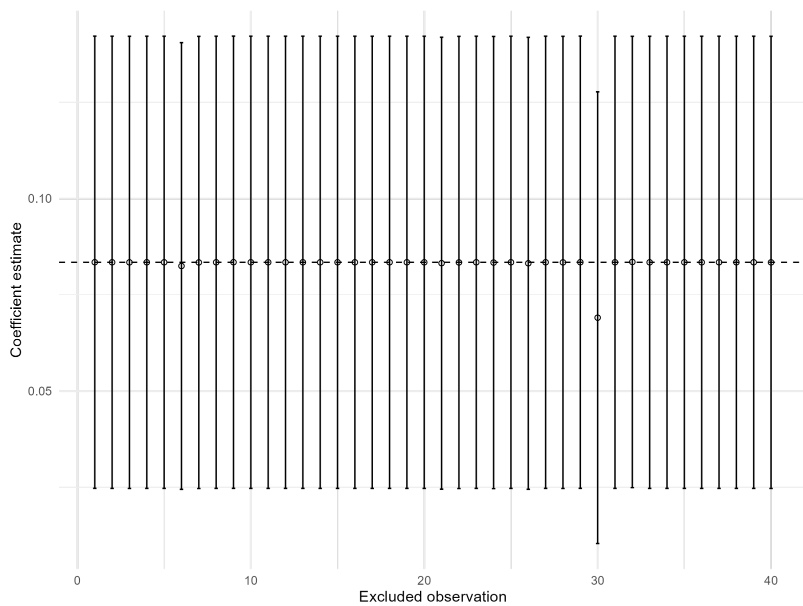
(b) Δ HHI

Figure B.17: Commodity Boom and Export Concentration (Exclusion of Micro-Regions - Top 40 Based on $\Delta\tilde{X}r$ Value)

Notes: The figure shows the robustness of the results to excluding, one by one, the top 40 micro-regions with the highest $\Delta\tilde{X}r$. The estimated coefficients and confidence intervals at 95% are reported. Each coefficient and confidence interval emanate from a single estimation. Micro-regions are ranked from left to right—highest $\Delta\tilde{X}_r$ exposure is the first observation.



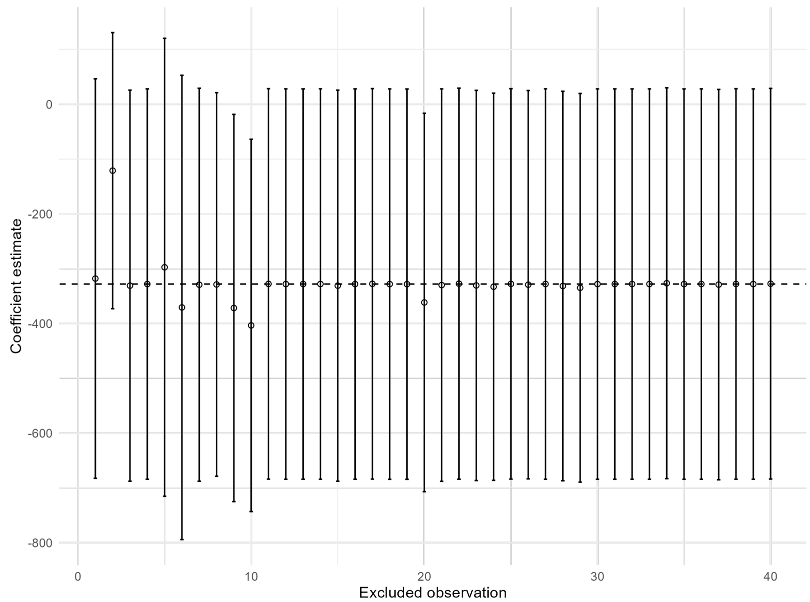
(a) Δ Lines



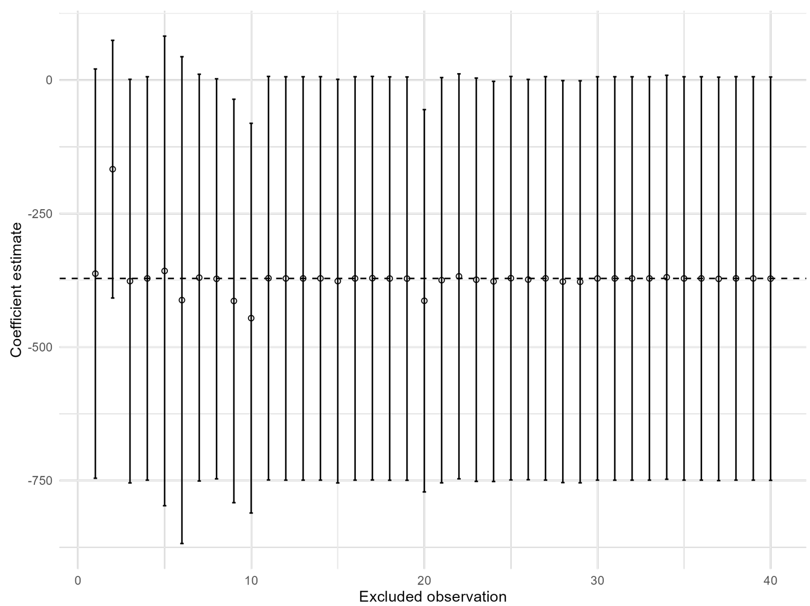
(b) Δ HHI

Figure B.18: Commodity Boom and Export Concentration (Exclusion of Micro-Regions - Low 40 Based on $\Delta\tilde{X}r$ Value)

Notes: The figure shows the robustness of the results to excluding, one by one, the last 40 micro-regions with the lowest $\Delta\tilde{X}r$. The estimated coefficients and confidence intervals at 95% are reported. Each coefficient and confidence interval emanate from a single estimation. Micro-regions are ranked from left to right—lowest $\Delta\tilde{X}_r$ exposure is the first observation.



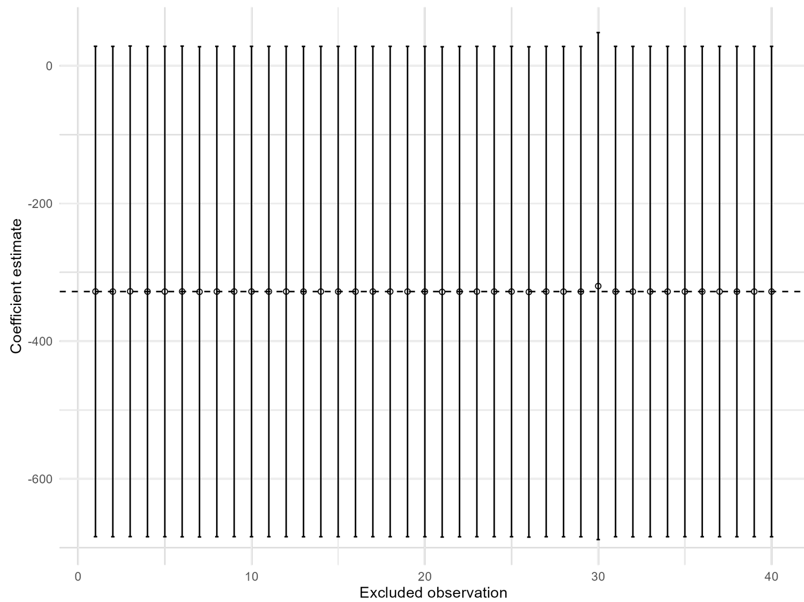
(a) $\Delta\ S_{r,t}$ (WDI)



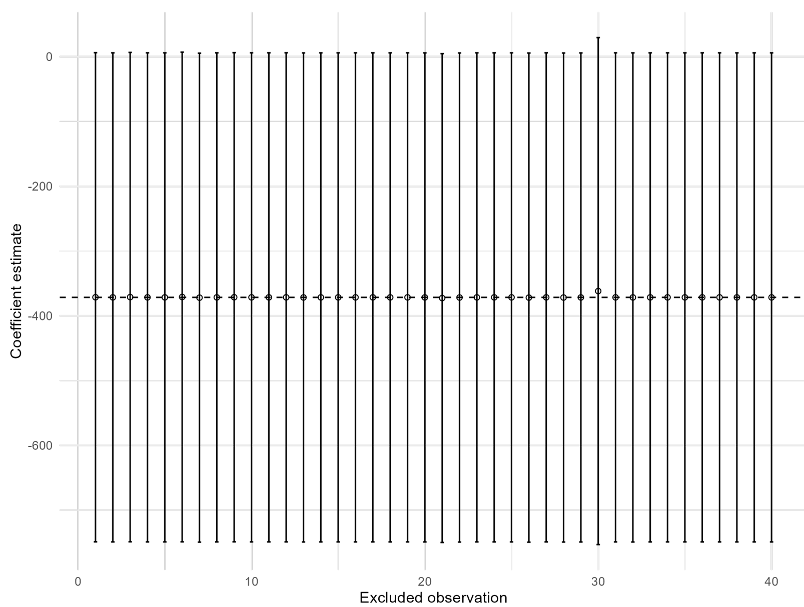
(b) $\Delta\ S_{r,t}$ (PWT)

Figure B.19: Commodity Boom and Export Sophistication (Exclusion of Micro-Regions - Top 40 Based on $\Delta\tilde{X}r$ Value)

Notes: The figure shows the robustness of the results to excluding, one by one, the top 40 micro-regions with the highest $\Delta\tilde{X}r$. The estimated coefficients and confidence intervals at 95% are reported. Each coefficient and confidence interval emanate from a single estimation. Micro-regions are ranked from left to right—highest $\Delta\tilde{X}_r$ exposure is the first observation.



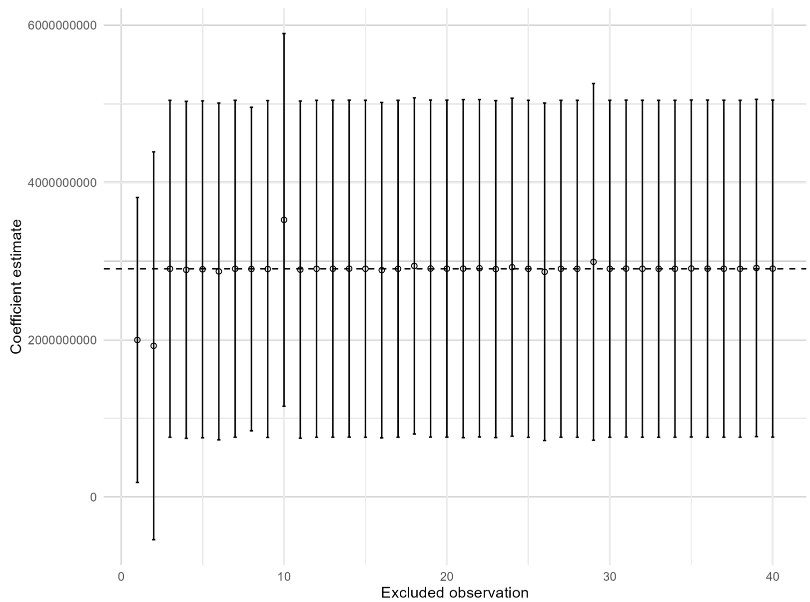
(a) $\Delta\ S_{r,t}$ (WDI)



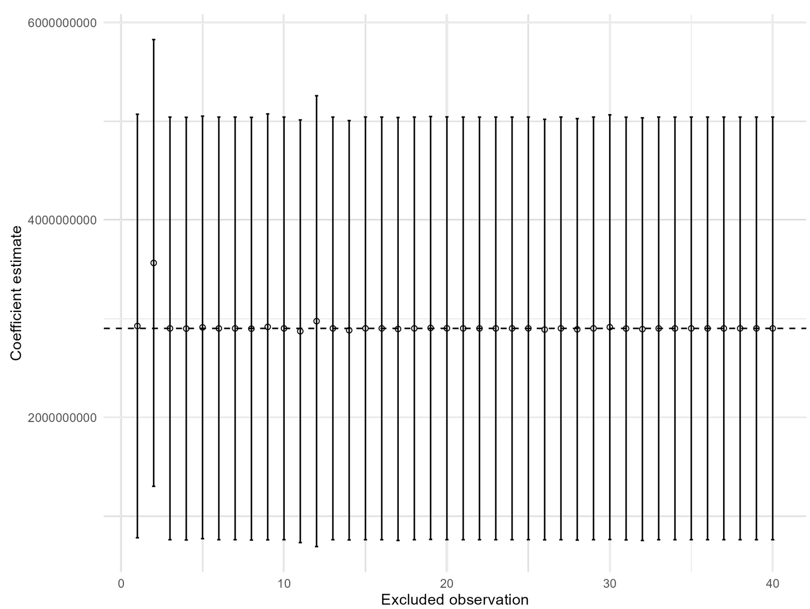
(b) $\Delta\ S_{r,t}$ (PWT)

Figure B.20: Commodity Boom and Export Sophistication (Exclusion of Micro-Regions - Low 40 Based on $\Delta\tilde{X}r$ Value)

Notes: The figure shows the robustness of the results to excluding, one by one, the last 40 micro-regions with the lowest $\Delta\tilde{X}r$. The estimated coefficients and confidence intervals at 95% are reported. Each coefficient and confidence interval emanate from a single estimation. Micro-regions are ranked from left to right—lowest $\Delta\tilde{X}_r$ exposure is the first observation.



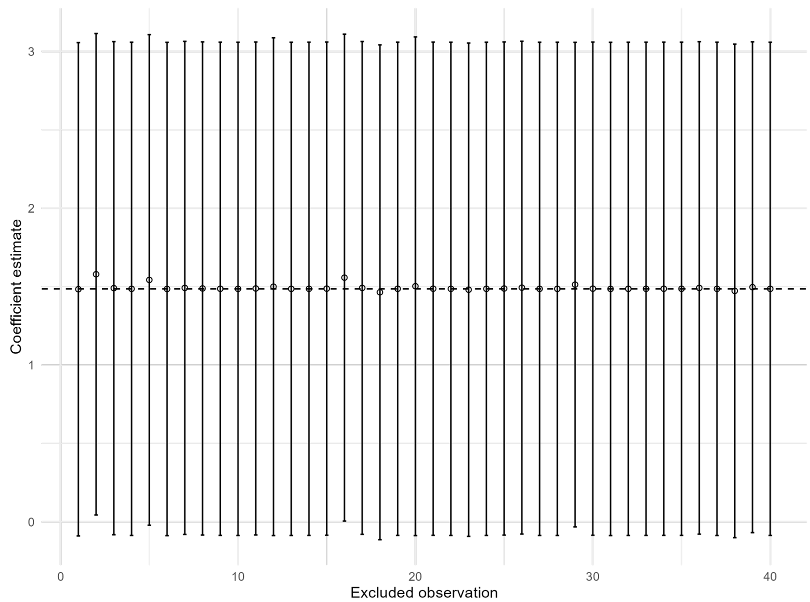
(a) Δ Value of Exports — Top



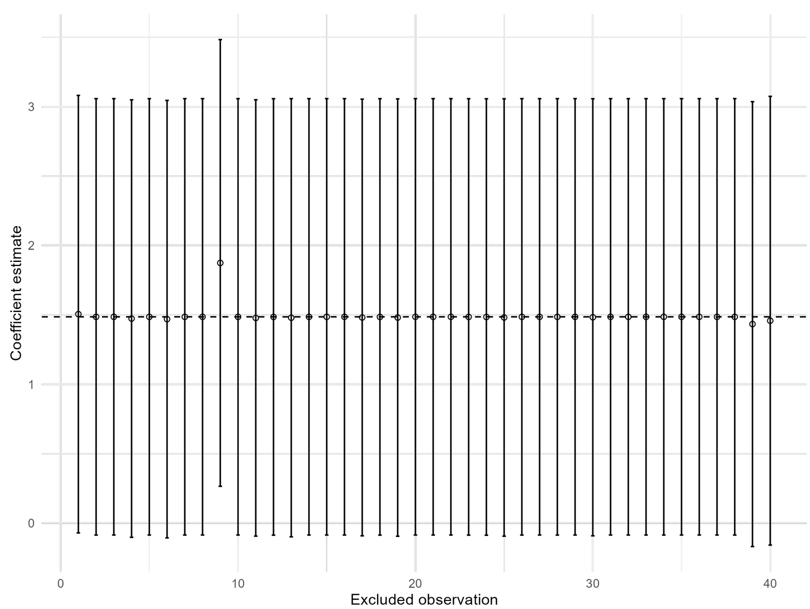
(b) Δ Value of Exports — Low

Figure B.21: Commodity Boom and Export Value (Exclusion of Micro-Regions - Top and Low 40 Based on Δ Value of Exports)

Notes: The figures show the robustness of the results to excluding, one by one, the top and bottom 40 micro-regions with the highest and lowest Δ Value of Exports. The estimated coefficients and confidence intervals at 95% are reported. Each coefficient and confidence interval emanate from a single estimation. Micro-regions are ranked from left to right—highest or lowest Δ Value of Exports is the first observation.



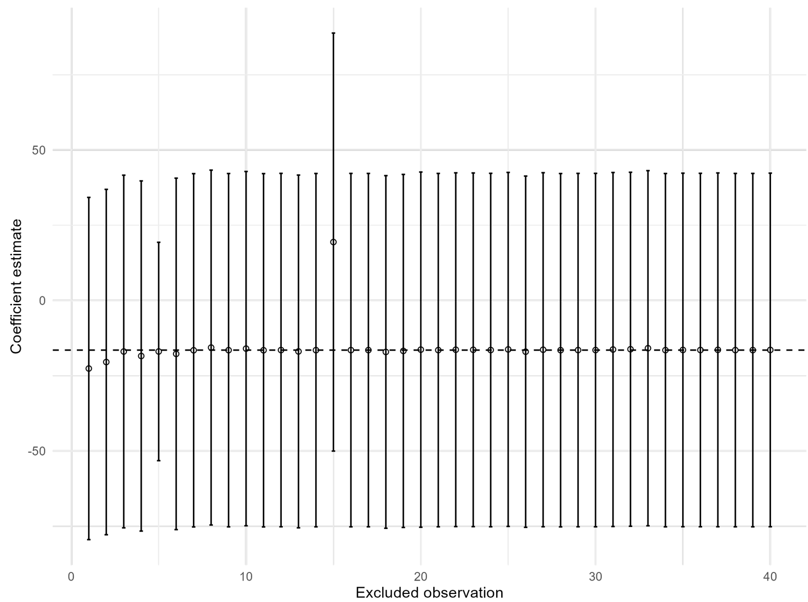
(a) %Δ Value of Exports — Top



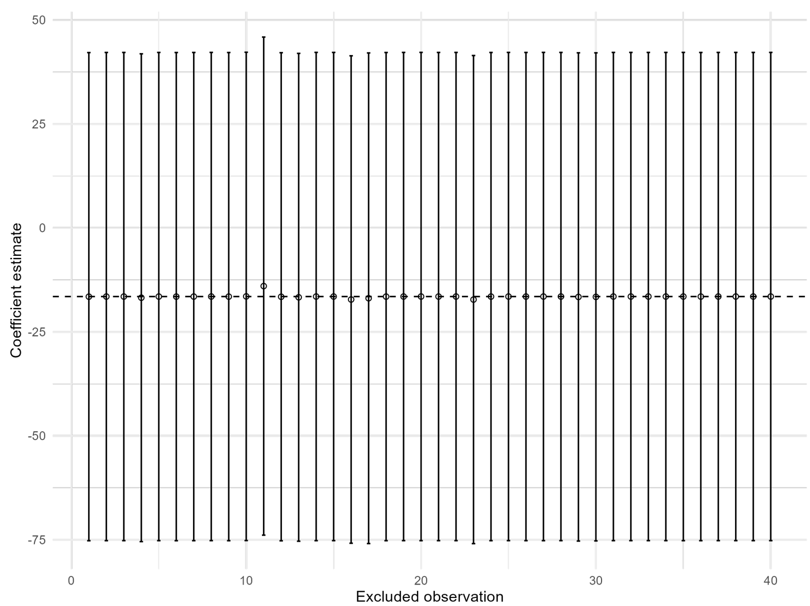
(b) %Δ Value of Exports — Low

Figure B.22: Commodity Boom and Growth Rate of Export Value (Exclusion of Micro-Regions - Top and Low 40 Based on %Δ Value of Exports)

Notes: The figures show the robustness of the results to excluding, one by one, the top and bottom 40 micro-regions with the highest and lowest %Δ Value of Exports. The estimated coefficients and confidence intervals at 95% are reported. Each coefficient and confidence interval emanate from a single estimation. Micro-regions are ranked from left to right—highest or lowest %Δ Value of Exports is the first observation.



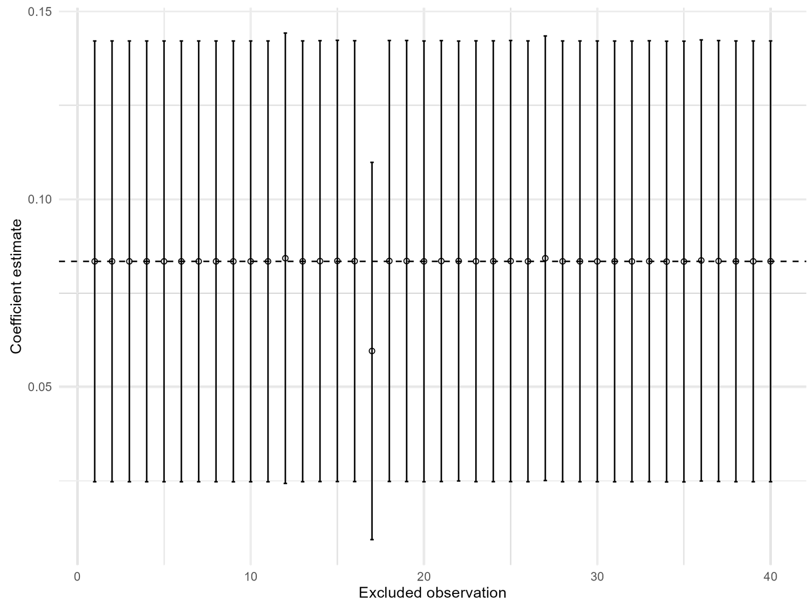
(a) Δ Lines — Top



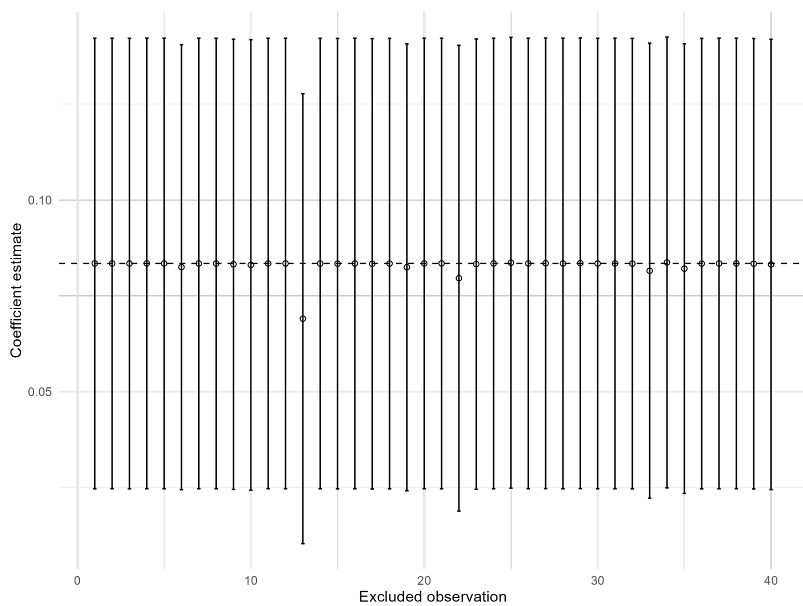
(b) Δ Lines — Low

Figure B.23: Commodity Boom and Number of Export Lines (Exclusion of Micro-Regions - Top and Low 40 Based on Δ Lines)

Notes: The figures show the robustness of the results to excluding, one by one, the top and bottom 40 micro-regions with the highest and lowest Δ Lines. The estimated coefficients and confidence intervals at 95% are reported. Each coefficient and confidence interval emanate from a single estimation. Micro-regions are ranked from left to right—highest or lowest Δ Lines is the first observation.



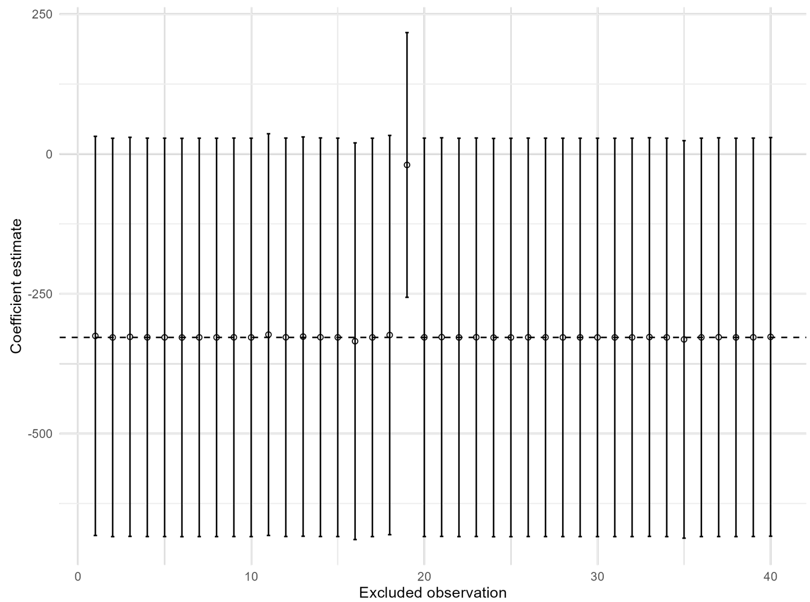
(a) Δ HHI — Top



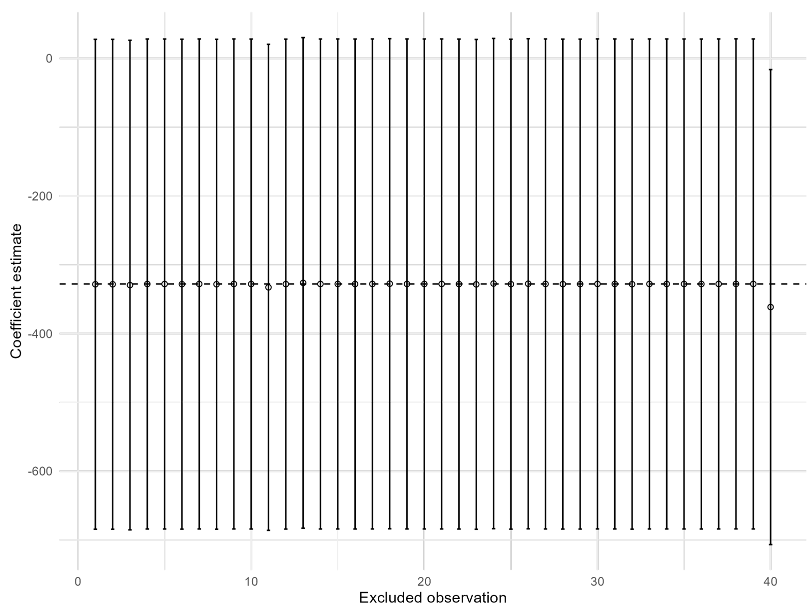
(b) Δ HHI — Low

Figure B.24: Commodity Boom and Export Concentration (HHI) (Exclusion of Micro-Regions - Top and Low 40 Based on Δ HHI)

Notes: The figures show the robustness of the results to excluding, one by one, the top and bottom 40 micro-regions with the highest and lowest Δ HHI. The estimated coefficients and confidence intervals at 95% are reported. Each coefficient and confidence interval emanate from a single estimation. Micro-regions are ranked from left to right—highest or lowest Δ HHI is the first observation.



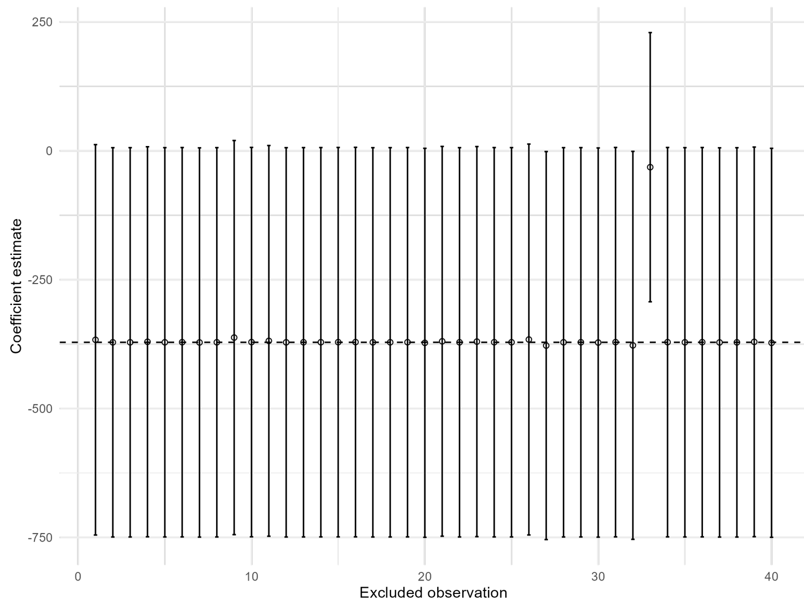
(a) $\Delta\ S_{r,t}$ (WDI) — Top



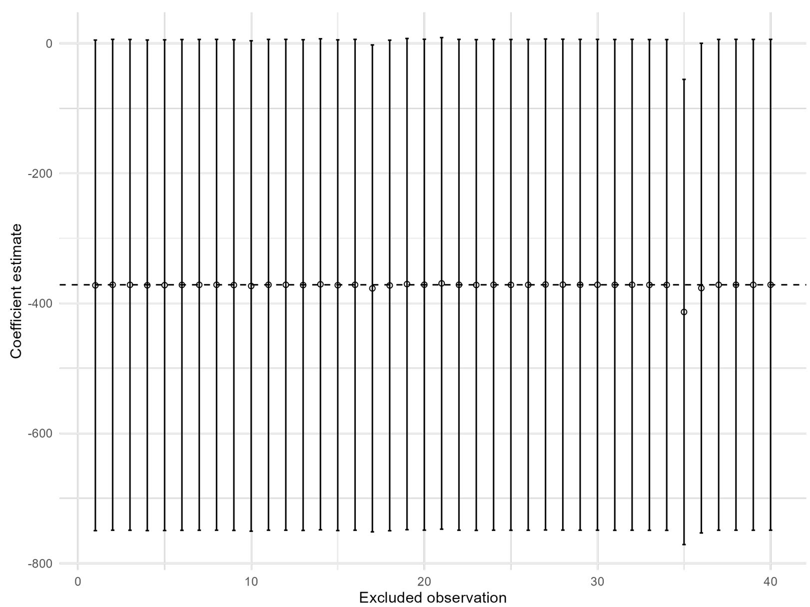
(b) $\Delta\ S_{r,t}$ (WDI) — Low

Figure B.25: Commodity Boom and Export Sophistication (WDI) (Exclusion of Micro-Regions - Top and Low 40 Based on $\Delta\ S_{r,t}$ (WDI))

Notes: The figures show the robustness of the results to excluding, one by one, the top and bottom 40 micro-regions with the highest and lowest $\Delta\ S_{r,t}$ (WDI). The estimated coefficients and confidence intervals at 95% are reported. Each coefficient and confidence interval emanate from a single estimation. Micro-regions are ranked from left to right—highest or lowest $\Delta\ S_{r,t}$ (WDI) is the first observation.



(a) $\Delta\ S_{r,t}$ (PWT) — Top



(b) $\Delta\ S_{r,t}$ (PWT) — Low

Figure B.26: Commodity Boom and Export Sophistication (PWT) (Exclusion of Micro-Regions - Low 40 Based on $\Delta\ S_{r,t}$ (PWT))

Notes: The figure shows the robustness of the results to excluding, one by one, the last 40 micro-regions with the highest and lowest $\Delta\ S_{r,t}$ (PWT). The estimated coefficients and confidence intervals at 95% are reported. Each coefficient and confidence interval emanate from a single estimation. Micro-regions are ranked from left to right—highest or lowest $\Delta\ S_{r,t}$ (PWT) is the first observation.