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

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Abstract

China's integration into world trade generated a raw-biased demand shock, as its imports grew much more in raw commodities than in their processed counterparts. I study how such a shock reshapes the exports of resource-rich developing economies, and whether the resulting shift toward raw materials is costly. I develop a model in which this demand raises the prices of the commodities that dominate the export baskets of the regions endowed with them, while processing industries gain little. Guided by the model, I identify the causal effects of this shock on Brazilian micro-regions with a shift-share instrument that combines China's demand growth for each product, recovered from gravity equations that exclude Brazil, with their *ex-ante* export baskets. More exposed micro-regions exported more, and their baskets became more concentrated and shifted from processed goods toward raw commodities, a primarization accompanied by a decline in sophistication. Wages rose in the primary and service sectors and GDP per capita increased, while manufacturing's share of employment fell. Fed with the measured shocks, the model reproduces the effects on export value and concentration and most of the income gain, which comes mainly from higher commodity prices. These gains arrive early, but a break-even analysis shows that the long-run cost of a less sophisticated export basket could offset them only if learning from exports is at the upper end of published estimates. Similar trade-offs may arise in other commodity exporters exposed to raw-biased demand.

Keywords: China's demand; Resource boom; Primarization; Export concentration; Export sophistication; Dutch disease.
JEL codes: F14; F16; F43; O13; O14.

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1 Introduction

World demand for natural resources rose sharply in the first two decades of this century, as China became a major importer of land- and resource-intensive commodities (Costa et al., 2016). The growth of China's demand, however, was concentrated in raw materials rather than in the goods processed from them. Between 2000 and 2019, China's share of world imports of iron ore rose from about 14 percent to about two-thirds and its share of bauxite imports from about 1 percent to nearly 70 percent, while its shares of world imports of steel and aluminum remained below 10 percent. For soybeans, its share rose from about 20 percent to nearly 60 percent, but stayed below 10 percent for soybean oil and meal. In 10 of the 13 main commodity chains of South American exporters, China's share rose more in the raw stage than in the processed stage, consistent with the expansion of its own steel, aluminum, and soybean crushing industries. China's integration into world trade thus generated a raw-biased demand shock. For commodity exporters, it brought a resource boom that raised the prices of the raw materials they sell, while the industries that process these materials gained little and faced more expensive inputs.

Such booms have long raised concerns about the Dutch disease, in which a surge in resource revenues undermines other economic sectors, particularly manufacturing, by drawing labor and capital into the resource sector and raising the prices of non-traded goods (Corden & Neary, 1982; Corden, 1984; Matsuyama, 1992; Van Wijnbergen, 1984a). Whether manufacturing actually shrinks, however, depends on how the boom reaches the local economy. Because resource production also buys local inputs and services, studies of local economies often find gains in local income (Aragón & Rud, 2013) and even in manufacturing (Allcott & Keniston, 2018), especially when extraction is capital-intensive and does not compete for local workers (Pelzl & Poelhekke, 2021). A raw-biased boom points to a different margin, one that can operate even when labor and capital are not pulled from more dynamic sectors of the economy. Since it raises the prices of raw materials but adds little to the demand for the goods processed from them, it shifts exports, and production more broadly, within the resource sector itself, concentrating them in a few raw materials at the expense of processed goods.

This paper asks how such a shock reshapes the export baskets of commodity-exporting economies, and whether the resulting shift toward raw materials is costly. The second part of this question is a long-standing one in development economics. Policy concerns regarding export concentration in primary products — and its potential negative effects on terms of trade, income volatility, and long-term economic growth — go back to the foundational works of Prebisch (1949) and Singer (1950), and a more recent literature argues that what a country exports shapes its growth and development trajectory (Hausmann et al., 2007; Hidalgo & Hausmann, 2009). Resource-rich countries have also tried to resist this specialization by promoting the domestic processing of their raw materials, often

through export taxes (Ruta & Venables, 2012) and with limited success (Venables, 2016). Yet whether this specialization pattern is costly is not straightforward, since the same boom that produces it also raises the income of the economies that export these raw materials.

Brazil, a resource-rich developing country and major global exporter, presents a particularly relevant case for these questions. China, which bought only a small share of Brazilian exports in 2000, had become the country's largest trading partner by the late 2000s and the destination of more than a quarter of its exports by 2019. Over the same period, the share of resource products in Brazil's exports rose from under 50 percent to three-quarters, while the share of manufactures fell by half, the export basket became more concentrated, and its sophistication declined. These national patterns, however, cannot be read as the effect of China's demand alone, since they also reflect forces that affected all Brazilian regions at the same time, such as the appreciation of the Brazilian real. Brazil's vast size and diverse geography give rise to regional economies with varied comparative advantages, which exported very different products before the shock, so their exposure to China's demand for raw materials varied widely. Comparing more and less exposed regions therefore separates the effects of China's demand from these common forces. I develop a theoretical framework of raw-biased demand to guide these comparisons, and I then use it to quantify the effects and to assess whether they carry a long-run cost. I find that China's demand brought both the gains that a commodity boom promises and the shift that the development literature warns against. Since each region takes world prices as given and exports what its endowments allow, much like a small open economy, understanding how these regions adjusted also helps identify the structural changes that resource booms bring to other commodity-exporting countries with similar economic structures.

This framework builds on the specific-factors model of Kovak (2013), which I extend with differentiated exports sold under gravity demand and a non-traded sector that captures the spending effect of Corden and Neary (1982), similar to the wealth channel in Benguria et al. (2024). Commodities are traded at world prices, so China's demand reaches Brazilian regions whether or not they ship to China. They are also produced with land and mineral deposits tied to specific locations, so the shock raises the prices of the products that already dominate the export baskets of the regions endowed with them, while resource-based manufactures, such as soybean oil, do not share in this price boom. The exports of more exposed regions therefore grow, become more concentrated in a few booming commodities, and shift toward primary products at the expense of the goods processed from them, a "primarization" that lowers the sophistication and complexity of the export basket, since raw commodities rank among the least sophisticated and complex products. Regional income rises, mainly through the terms-of-trade gain on commodity exports, while manufacturing's share of employment falls as the regional wage rises. As in Kovak (2013), the model delivers the appropriate measure of regional exposure to such

demand shocks, which I take to the data.

I test these theoretical predictions with a quasi-natural experiment that generated varied export demand across Brazilian regions: the growth of China's demand in the two decades that followed its accession to the World Trade Organization (WTO) in 2001. Following the model, I construct a shift-share instrument that combines the growth of China's demand for each product, recovered from gravity equations estimated on the trade of all countries except Brazil, with the *ex-ante* composition of the export baskets of micro-regions, groups of neighboring municipalities that I treat as local economies. Identification comes from these product-level shocks, which do not reflect supply conditions in Brazil (Borusyak et al., 2022). Comparing more and less exposed micro-regions within the same state, I estimate the effects of China's demand on export baskets, local labor markets, and income, addressing reverse causality and omitted variable bias, two common challenges in identifying the effects of resource booms. The approach aligns with recent studies of such booms in US regional economies (Allcott & Keniston, 2018; Feyrer et al., 2017; James & Smith, 2020).

The results show a large increase in total export value and heightened concentration in the most exposed regions. A one-standard-deviation increase in exposure raises export value by about $929 million, or 35 percent of the average in 2000, an effect that builds up during the 2000s with no differential trends before 2001. It also raises the Herfindahl-Hirschman Index (HHI) of the export basket by about 10 percent. Both effects come from resource exports, while the value and concentration of non-resource exports do not change significantly. The rise in concentration is driven by a focus on already-exported products, with minimal changes in export variety, as China's demand amplified the pre-existing advantages of resource-exporting regions rather than creating new ones. Unlike in Brazil as a whole, the share of manufactures in exports does not decline in the most exposed regions relative to less exposed ones. Within the resource basket, however, the share of resource-based manufactures falls by about 3.2 percentage points and that of primary products rises by about 2.7 points, a move toward less complex products within the same production chains. Building on the extensive literature on export basket sophistication (Hausmann et al., 2007; Hidalgo & Hausmann, 2009; Hidalgo et al., 2007; Jarreau & Poncet, 2012), I find that this primarization comes with a decline of about 2.8 percent in the sophistication of exposed export baskets, while their complexity moves in the same direction but imprecisely.

To further analyze patterns of structural transformation, I examine local labor markets and find that the adjustment comes through sectoral wages more than through employment. Despite the shift toward more primary exports, the primary sector's share of employment does not rise significantly, which may reflect 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). Instead, I find wage increases

of about 8 percent in the primary sector and 1 percent in services per standard deviation of exposure, which the model attributes to higher returns to land and mineral deposits and to the local spending of higher income. The average wage does not change significantly, as the model predicts, since exports are a small share of income in most micro-regions. Manufacturing's share of employment still declines in the most affected regions, in line with the Dutch disease and with the model, in which even a small wage increase lowers employment in tradables that gain little from China's demand. I find suggestive evidence that this contraction is accompanied by a rise in likely informal activities. Consistent with Cícero and Heras-Recuero (2026), GDP per capita also increased in more exposed regions, rising sharply after 2009 and remaining 6 percent higher in 2019.

In a quantification exercise using the measured shocks, each region's 2000 export basket, and parameters taken from the literature or set to simple benchmarks, the model reproduces the effects of China's demand on export value and concentration and accounts for two-thirds of the increase in GDP per capita, a gain that comes mainly from higher world prices for commodity exports. It generates only between a fifth and a third of the declines in complexity and sophistication, which suggests that other forces also lowered the sophistication of exposed baskets. The model also helps reconcile the regional evidence with the national decline in manufactures, from half of Brazil's exports in 2000 to a quarter in 2019. Most of this decline came from export weight shifting toward the regions whose exports grew, which a comparison across regions does not capture, and China's demand alone accounts for about a third of it in the main calibration.

The shift toward raw materials nonetheless raises concerns about the long-term development of these local economies, particularly in terms of technological progress and upgrading. In the static model, however, this shift carries no cost, and the gains from the shock arrive in the short run. Whether it is costly depends on how strongly the export basket feeds into the capabilities of exposed regions over time. I build on Atkin et al. (2026), letting capabilities accumulate with the complexity of the export basket, and ask how strong this learning effect would need to be for China's demand to lower the present value of income in exposed regions. With a common rate of catch-up, this threshold, the break-even elasticity, sits at the upper edge of published estimates (Hausmann et al., 2007; Jarreau & Poncet, 2012), and under the largest of them, the net effect on GDP per capita turns negative by 2032. Under the smaller ones, it turns negative only in 2050 and 2088, too late to offset the gains of the boom years. Once each estimate is paired with the rate of catch-up estimated alongside it, the threshold lies above all of them. The evidence does not show that China's demand made exposed regions poorer in the long run, but it cannot rule this out if learning is stronger in Brazilian regions than these estimates imply. The case for policies that resist primarization, such as the export taxes mentioned above, therefore rests on evidence of such learning rather than on the shift itself.

This paper makes three contributions. First, it identifies a margin of adjustment to

resource booms that operates within the booming sector itself. Extensive literature documents how natural resource booms harm non-resource tradable sectors through the resource movement and spending effects (Alberola & Benigno, 2017; Corden & Neary, 1982; Corden, 1984; Matsuyama, 1992; van der Ploeg & Venables, 2011; Van Wijnbergen, 1984a, 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). Evidence from local economies comes mostly from extraction booms and discoveries (Allcott & Keniston, 2018; Aragón & Rud, 2013; Feyrer et al., 2017; Pelzl & Poelhekke, 2021), including in Brazil, where oil discoveries raised local output and moved workers from informal agriculture into formal services (Cavalcanti et al., 2019). Yet, little attention has been paid to how such booms reshape the composition and concentration of export baskets, which reflect the productive structure of local economies, especially their most dynamic firms (Bernard & Jensen, 2004). Bahar and Santos (2018) provide an 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 leaves aside both the shifts within the resource basket and the regional dynamics, which often diverge from national trends following resource booms (Cust & Poelhekke, 2015; Marchand & Weber, 2018). I show that a demand shock acting through world prices, rather than the discovery of new reserves, concentrates regional export baskets along the intensive margin and shifts them from processed goods toward raw materials, while leaving the relative share of manufactures unchanged. The national decline in manufactures came mostly from a reallocation of exports between regions, a margin that national data cannot reveal.

Second, it provides evidence on how China's demand reached the export baskets of a developing economy, with a measure of exposure derived from a theoretical framework. Most research on China's rise as a dominant force in international trade 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), while fewer studies have examined the demand-side effects of China's economic expansion (Dauth et al., 2014). In Brazil, Costa et al. (2016) find that regions exposed to Chinese import competition experienced slower growth in manufacturing wages between 2000 and 2010, while regions benefiting from heightened Chinese export demand saw faster wage growth. Carreira et al. (2024) and Cícero and Heras-Recuero (2026) employ a similar empirical strategy to study deforestation and consumption patterns, and Benguria et al. (2024) study how the commodity price super-cycle was transmitted to Brazilian local labor markets. The effects of such external shocks on regional export dynamics and productive structures, however, remain underexplored. Unlike these studies, I recover China's demand shocks from gravity equations, adapting the approach that Autor et al. (2013) use for China's supply shocks. The model that yields the measure of exposure then quantifies the channels

behind the reduced-form effects.

Third, it offers a way to assess the long-run cost of primarization without assuming how strongly the export basket feeds into growth. In theory, such a cost arises when the activities a boom displaces generate learning by doing (Matsuyama, 1992; Van Wijnbergen, 1984a). Research on the "natural resource curse" explores how resource dependence negatively impacts economic growth (Barbier, 2019; Isham et al., 2005; Sachs & Warner, 1995, 2001; van der Ploeg & Venables, 2011, 2013), and export diversification and sophistication are closely tied to development (Cadot et al., 2011; Hausmann et al., 2007; Hidalgo et al., 2007; Imbs & Wacziarg, 2003; Klinger & Lederman, 2006). Branstetter and Laverde-Cubillos (2024) find that Colombia's recent resource boom, while associated with income growth, came with persistent declines in R&D spending and technological upgrading in manufacturing. In the United States, by contrast, specialization in oil raised long-run income (Michaels, 2011), and resource booms shrank tradable manufacturing without lowering its productivity (Allcott & Keniston, 2018). Whether booms carry such a cost is therefore not settled, and estimates of how strongly export sophistication feeds into growth vary, each with its own rate of catch-up (Hausmann et al., 2007; Jarreau & Poncet, 2012). Under the capability law of Atkin et al. (2026), the loss of capabilities depends only on the observed path of export complexity and on the rate of catch-up, so the break-even elasticity can be computed from the reduced-form estimates. This approach turns what the theory leaves open, how strong learning must be for a boom to become costly, into a threshold that can be compared with published elasticities, and shows that the comparison depends on the catch-up behind each of them.

The remainder of the paper is organized as follows. Section 2 documents the raw-biased pattern of China's import growth and the changes in Brazil's export basket that motivate the paper. Section 3 develops the model and derives the measure of exposure, and Section 4 describes the data and builds this measure from the gravity equations. Section 5 lays out the empirical strategy, and Section 6 presents the effects on export baskets and local labor markets. Section 7 traces the response of GDP per capita, asks how much of these effects the model explains, and shows how they add up to the national decline in manufactures. Section 8 computes the break-even elasticity, and Section 9 concludes.

2 Background: Transformative Trade Dynamics

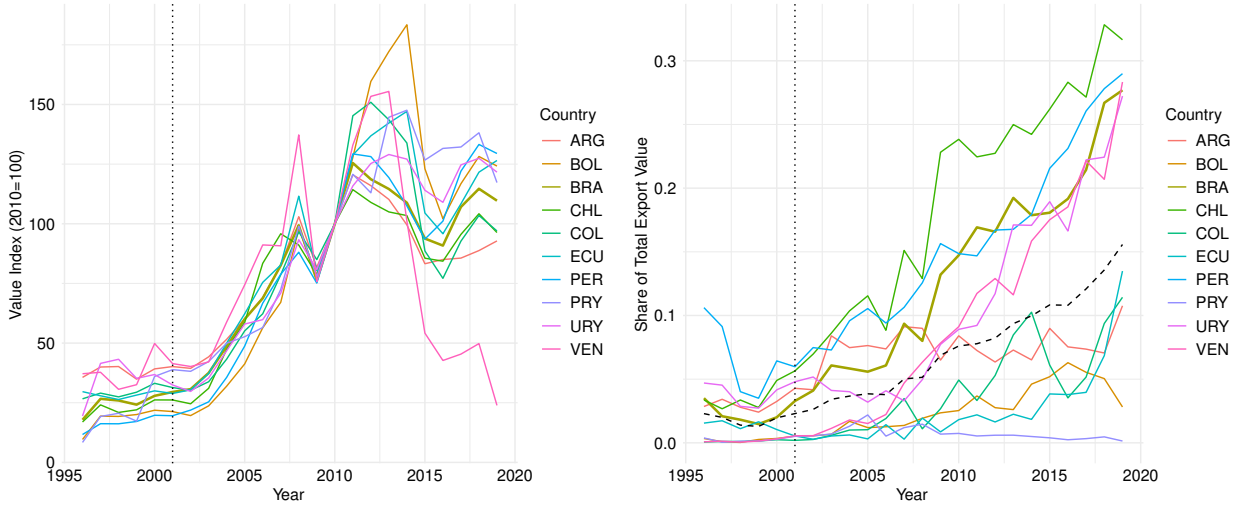
2.1 China's ascent to the WTO: transformation in trade patterns

China's rapid emergence as a global economic powerhouse has profoundly altered the demand for primary goods over recent decades. Its remarkable economic growth has been supported by abundant labor and capital, while its endowments of arable land and high-grade mineral deposits, despite the country's vast territory, are modest relative to the

size of its economy. China's accession to the WTO in 2001 marked a pivotal moment in international trade, deepening its integration into the global economy and 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 land- and resource-intensive commodities (Costa et al., 2016).

The effects of China's demand for primary goods have been particularly pronounced in countries historically reliant on such exports, especially across South America. Figure 1 shows the evolution of exports from South American countries over the past three decades. Panel (a) illustrates a clear upward trajectory in total export values for each country in the years following 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 export value — South American countries



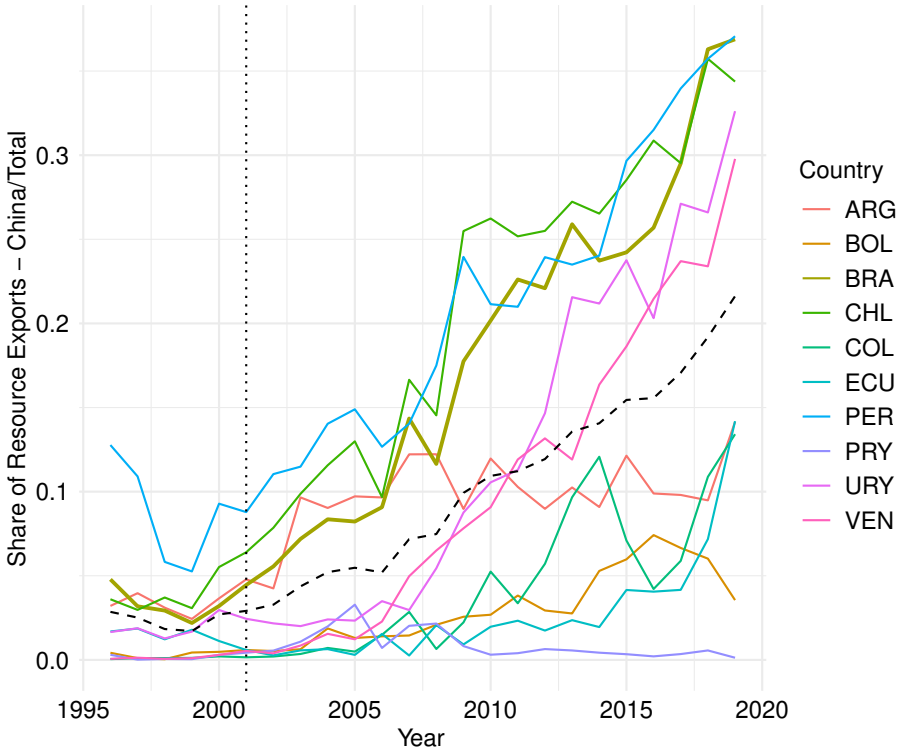
(a) Total Value — Index (2010 = 100)

(b) Share of Total Export 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. The thicker line highlights Brazil.

Resource exports, including primary products and resource-based manufactures, show an even sharper rise in the share destined for China, as illustrated in Figure 2. For the largest South American economies, this share rose from around 3% in 2001 to over 20% by 2019, and in Chile, Peru, and Brazil it exceeded 35%.

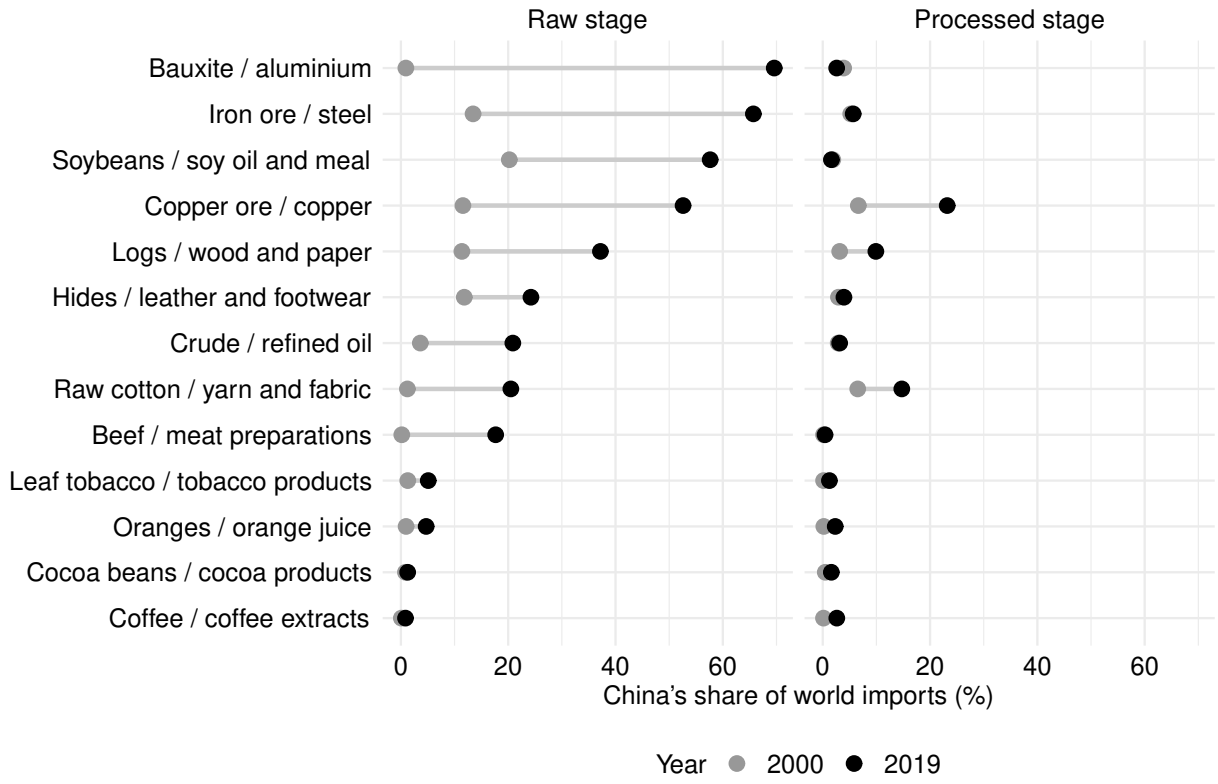
Figure 2: Share of resource exports — China/Total



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. The thicker line highlights Brazil.

The resource shares in Figure 2, however, hide large differences across stages of production. Figure 3 compares China's share of world imports in the raw and processed stages of the main commodity chains of these South American exporters, in 2000 and 2019. China's share rose more in the raw stage in 10 of the 13 chains, and in several of them the gap is large. Its share of world imports of iron ore increased from about 14% in 2000 to about two-thirds in 2019, and its share of soybean imports rose from about 20% to nearly 60%. Over the same period, its share of world imports of steel and of soybean oil and meal remained below 10%. Bauxite, beef, logs, and crude oil follow a similar pattern. Even in the chains where China's imports of processed goods also grew, such as copper and cotton, its share of world imports of the raw stage grew considerably faster. The exceptions are chains in which China remained a minor buyer at both stages, such as coffee and cocoa. China's import growth was thus concentrated in raw materials, consistent with the expansion of its own steel, aluminum, and soybean crushing industries over the period. For large commodity exporters such as Brazil, China's demand therefore favored raw materials over their processed counterparts.

Figure 3: China's share of world imports by production stage, 2000 and 2019



Source: Bilateral trade flow data from the BACI database, developed by the *Centre d'Études Prospectives et d'Informations Internationales* (CEPII). Each row is a commodity chain, labeled by its raw stage and its processed stage, both defined at the HS4 level. The thirteen chains are the main commodity chains of South American exporters for which the trade classification separates a raw stage from processed stages. Together, they account for about two-thirds of these countries' primary and resource-based exports in 2000. Gray dots mark 2000 and black dots 2019.

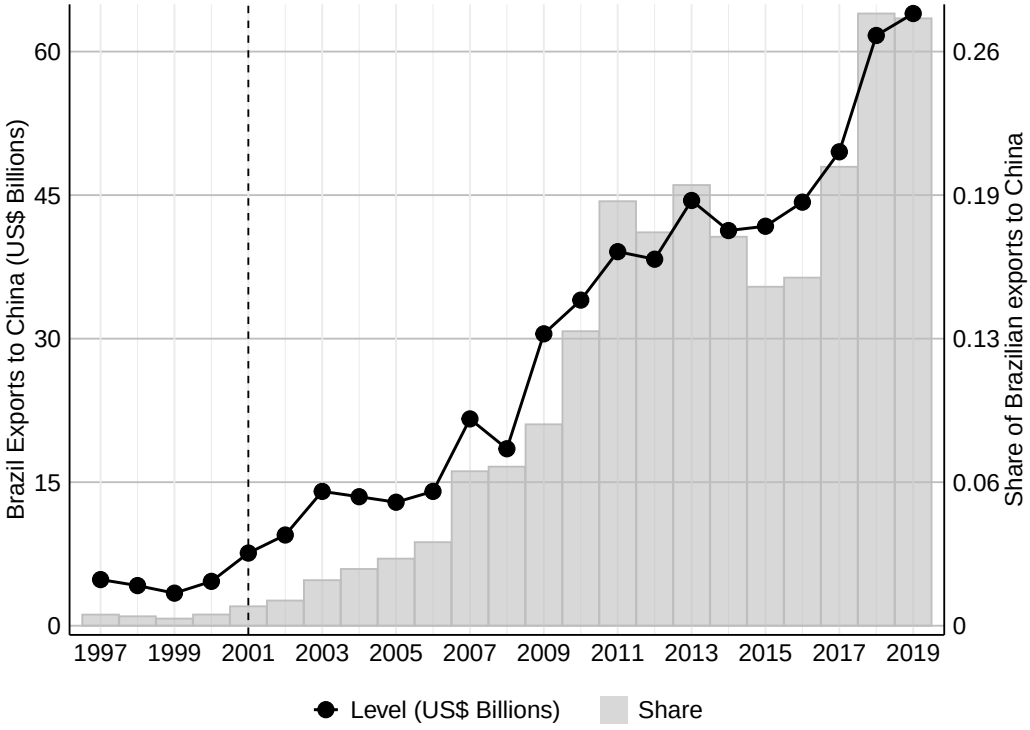
2.2 The China-driven resource boom in Brazil

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 two reasons.

First, China's significance as an export destination for Brazil surged over the past two decades, placing Brazil among the South American economies most oriented toward China, as shown in Figure 1. Figure 4 shows that Brazil's exports to China grew rapidly after 2001, both in value and as a share of Brazil's total exports. By the late 2000s, China had already

become Brazil's largest trading partner.

Figure 4: Brazil's exports to China — total value and share



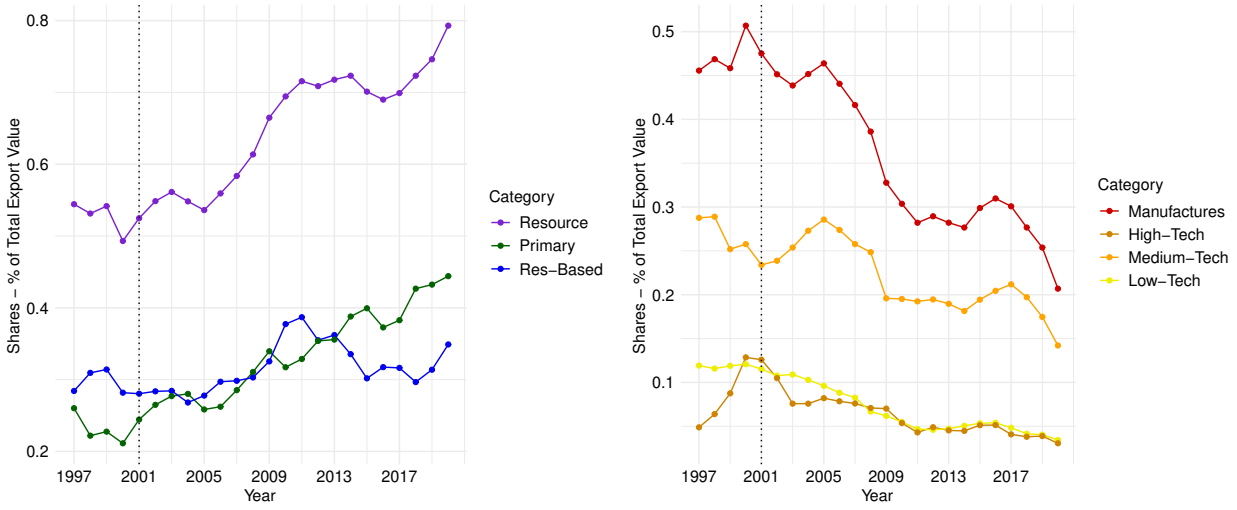
Source: Export value data are based on declarations by exporters in Brazil (SISCOMEX, Ministry of Industry, Foreign Trade, and Services). Dashed line indicates 2001.

Second, 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 effects of China's demand on the export baskets of local economies that resemble typical small open economies.

Over the past two decades, Brazil's export basket also changed in ways that mirror broader South American trends, as exports shifted increasingly toward agricultural and extractive products. Figure 5 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. Panel (b) shows the counterpart of this shift, with the share of manufacturing exports falling by about half and decreases across all subcategories.

Beyond changes in composition, Brazil's export basket also became more concentrated. Figure 6 provides high-level evidence of stability in the number of products exported by

Figure 5: 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.

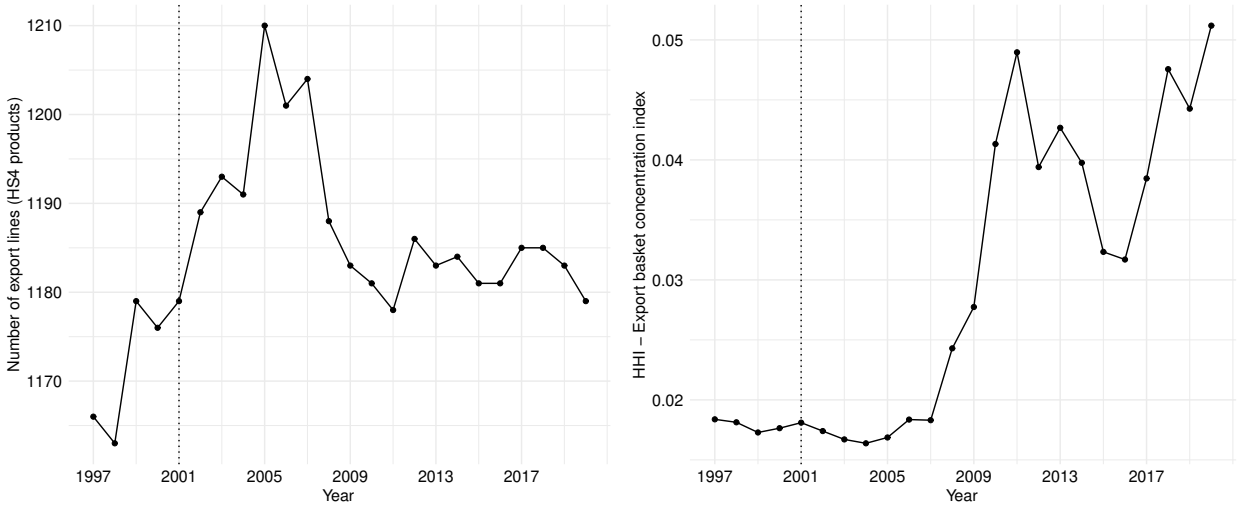
Brazil from 2000 to 2019, while also revealing a clear increase in the Herfindahl-Hirschman Index (HHI), indicating growing concentration in Brazil's export basket over time along the intensive margin.[1] This rise in export basket concentration coincides with the growth of China's demand for raw materials.

The shift toward primary products and the rise in concentration were also accompanied by a decline in the average sophistication and complexity of Brazil's export basket. Figure 7 presents two measures commonly used in the literature.[2] Panel (a) shows the log of the export sophistication index of Hausmann et al. (2007), which captures the income level associated with the products Brazil exports, while panel (b) shows the average complexity of Brazil's exports, following Hidalgo and Hausmann (2009). Both indices peaked in 2000 and remained relatively stable until the mid-2000s. They then fell sharply until 2011, as commodity prices reached their peak, and neither returned to its pre-boom level when commodity prices declined in the 2010s. Since both measures hold the sophistication and complexity of each product fixed at their 1997–2000 levels, these declines reflect only changes in the composition of Brazil's exports, namely the growing weight of less sophisticated and less complex products.

[1] Section 4 describes the exact computation of the HHI, which is normalized by the number of exported lines.

[2] The construction of these measures is discussed in detail in Section 4.

Figure 6: Export basket concentration: Brazil, 1997–2019



(a) Number of export lines (b) HHI

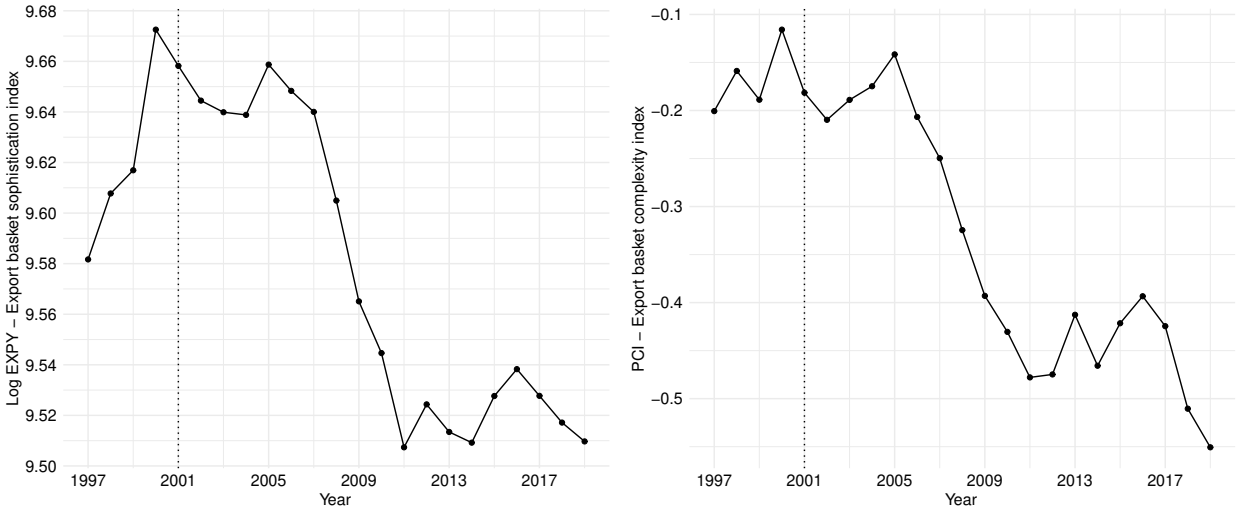
Source: Export value and composition data are based on declarations by exporters in Brazil (SISCOMEX, Ministry of Industry, Foreign Trade, and Services). Dotted lines indicate 2001.

These national patterns, however, cannot be read as the effect of China's demand alone, since they also reflect forces that affected all Brazilian regions at the same time, such as the appreciation of the real. This is why the regional diversity of Brazil discussed above matters. Local economies exported very different products before the shock, so their exposure to China's demand for raw materials varied widely, and comparing them separates the effects of China's demand from forces that affected all regions alike. The next section develops a model that links the changes in export baskets to the composition of China's demand and predicts how they should differ across Brazilian local economies, depending on the products each region exported before the shock.

3 A Model of Raw-Biased Demand

Section 2 documented four stylized facts. First, China's import growth between 2000 and 2019 was concentrated in the raw stage of commodity chains (Figure 3). Second, over the same period, Brazil's export basket shifted toward primary products (Figure 5). Third, the basket became more concentrated along the intensive margin, while the number of exported products remained stable (Figure 6). Fourth, the average sophistication and complexity of the basket declined (Figure 7). In this section, I develop a simple framework that rationalizes this motivating evidence. The model connects the first fact to the other

Figure 7: Export basket sophistication and complexity: Brazil, 1997–2019



(a) Sophistication (EXPY)

(b) Complexity (PCI)

Source: Export value and composition data are based on declarations by exporters in Brazil (SISCOMEX, Ministry of Industry, Foreign Trade, and Services). Both panels are export-weighted averages over Brazil's HS4 exports: (a) of each product's income level, the RCA-weighted GDP per capita of its exporters (1997–2000), following Hausmann et al. (2007); (b) of product complexity, following Hidalgo and Hausmann (2009) (1997–2000). Dotted lines indicate 2001.

three and yields testable implications for how these changes should differ across Brazilian local economies, which I take to the data in Section 6 and quantify in Section 7.

The model builds on two features of China's demand shock and of Brazilian local economies. Most of China's import growth was in homogeneous commodities, such as iron ore and soybeans, which are traded at world prices. China's demand therefore reached Brazilian exporters through world prices, regardless of whether they shipped directly to China. Moreover, commodities are produced with land and mineral deposits that are tied to specific locations, so the commodities each region exports are determined by its endowments and tend to be concentrated in a few products. In this setting, a raw-biased demand shock raises the prices of the products that already dominate the export baskets of the regions endowed with them. Resource-based manufactures, such as soybean oil, do not share in this price boom, and more expensive commodity inputs can further reduce their sales. As a result, the export baskets of the most exposed regions become more concentrated in a few booming commodities and shift toward primary products, a process the Latin American literature calls primarization. Since raw commodities are among the least complex products, the average complexity of these baskets also declines.

The regional economy builds on the specific-factors framework of Kovak (2013), which

has been used to study the effects of Brazil's trade liberalization on local labor markets. I extend it by adding differentiated exports sold under gravity demand, through which China's demand also reaches manufactured exports, and a non-traded sector that captures the spending effect of Corden and Neary (1982), similar to the wealth channel in Benguria et al. (2024). As in Kovak (2013), the model indicates how to measure each region's exposure to the shock, which guides the empirical design. It yields two sets of testable predictions, one for regional export baskets and one for the regional economy, along with a characterization of the static gains from the shock.

3.1 Environment

The economy consists of regions r, foreign destinations j, and tradable products k. Regions correspond to the micro-regions used in the empirical analysis, and each operates *as if* it were a small open economy, taking as given world commodity prices, foreign demand, and the prices of imported goods and traded intermediates. Henceforth, a hat denotes a log change relative to a counterfactual without China's demand shock, $\widehat{z} \equiv d \ln z$, and I focus on first-order changes around the 2000 equilibrium.

Tradable products fall into three groups. Commodities ($\mathcal{R}$) are the raw products of agriculture, mining, and forestry. Resource-based manufactures ($\mathcal{P}$) process a commodity input $c(k) \in \mathcal{R}$, such as soybeans in the case of soybean oil. All remaining products are other manufactures ($\mathcal{M}$), and I refer to $\mathcal{D} \equiv \mathcal{P} \cup \mathcal{M}$ as differentiated goods. Each product also has a complexity level κ_k, which plays no role in the static responses but determines the average complexity of the export basket and, in Section 8, how productivity responds to capability.

Commodities. Region r produces commodity k, a homogeneous good traded at the world price p_k^*, by combining labor with a region-specific factor $F_{rk} \geq 0$, such as land suitable for a given crop or a mineral deposit:

$$Q_{rk} = A_{rk} F_{rk}^{1-\alpha} \ell_{rk}^{\alpha}, \qquad 0 < \alpha < 1. \tag{1}$$

Producers are price takers, and endowments are held fixed over the period. The fixed factor makes commodity supply upward sloping, with elasticity $\alpha/(1-\alpha) \equiv 1/\nu$, so higher world prices raise both output and the returns to land and deposits. It also ties each region's commodity exports to its endowments, since a region can export commodity k only if $F_{rk} > 0$.

Differentiated goods. In each differentiated product it makes, a region supplies a distinct variety under monopolistic competition, with markup $\sigma_k/(\sigma_k - 1)$. Destination j's

spending on region r's variety of product k is

$$X_{rjk} = \left(p_{rk}\tau_{rjk}\right)^{1-\sigma_k} D_{jk}, \tag{2}$$

where $\tau_{rjk} \geq 1$ is an iceberg trade cost and $D_{jk} \equiv E_{jk}P_{jk}^{\sigma_k - 1}$ is the destination's demand shifter, which combines its total spending on the product, E_{jk}, with its price index, P_{jk}. Summing over destinations, region r's exports of product k are $X_{rk} = p_{rk}^{1-\sigma_k}\Phi_{rk}$, where $\Phi_{rk} \equiv \sum_j \tau_{rjk}^{1-\sigma_k} D_{jk}$ measures the region's market access in that product. Across products, destinations substitute with elasticity $\eta_k \geq 1$, so that E_{jk} is proportional to $P_{jk}^{1-\eta_k}$ times an exogenous term through which China's demand shock enters. The world-trade counterpart of Equation (2) is the gravity equation I estimate in Section 4 to measure this shock. On the supply side, the unit cost of production is

$$u_{rk} = \frac{1}{A_{rk}}\left(p^*_{c(k)}\right)^{\gamma_k}\left(w_r^{c_L}\, q_k^{1-c_L}\right)^{1-\gamma_k}, \tag{3}$$

where $\gamma_k = \gamma$ is the commodity input share of resource-based manufactures and $\gamma_k = 0$ for other manufactures, c_L is the share of local inputs, whose price moves with the regional wage w_r, and q_k is the given price of traded intermediates. Finally, exporting a differentiated product requires a fixed cost of $w_r f_k$ per period.

The rest of the regional economy. Since most employment in Brazilian local economies is outside exporting sectors, each region also produces domestic tradables T, sold to the rest of Brazil at national prices, and non-traded goods N, such as local services and commerce, sold only within the region. Both sectors combine labor with a sector-specific factor in a Cobb–Douglas technology, with labor shares α_T and α_N. Residents spend a share $\beta_N \in [0, 1)$ of their income on non-traded goods and the remainder on traded goods at given prices, so the consumer price index changes by $\widehat{P}_r = \beta_N \widehat{p}_{rN}$. Regional income Y_r is the sum of factor incomes,

$$Y_r = w_r L_r + \sum_{k \in \mathcal{R}} \Pi_{rk} + \Pi_{rT} + \Pi_{rN}, \tag{4}$$

where the Π terms denote the returns to the specific factors.[3] Labor moves freely across sectors within a region, while regional labor supply is $L_r = \bar{L}_r\, w_r^{\varepsilon}$, with $\varepsilon \geq 0$ capturing migration across regions.

Raw-biased demand. Let ψ_k denote the growth of China's demand for product k relative to other markets, which I recover from the gravity equation above. Figure 3 shows that

[3] Value added in differentiated exports is attributed to labor, and markup income is ignored.

China's import growth was concentrated in the raw stage of commodity chains. As a result, the world prices of the commodities that Brazilian regions export and that processors use as inputs rose, while the market access of differentiated goods improved comparatively little, since China imported few of them. I refer to this pattern as raw-biased demand and, in what follows, take it to mean that the changes in the market access of differentiated goods are small relative to the changes in world commodity prices. In most regions, the export basket as a whole also gained from the shock.

3.2 Demand shocks and regional responses

The shock reaches a region through world prices and market access, which determine how each of its exports responds, and the regional wage then adjusts to clear the local labor market.

For a commodity, faster growth of China's demand shifts world import demand by the factor $1 + \mu_k(e^{\psi_k} - 1)$, where μ_k is China's share of world imports of k in 2000, so the same growth in China's demand has a larger effect when China is a larger buyer. If world import demand has price elasticity η_D and world export supply has elasticity η_S, market clearing implies that the world price changes by

$$\widehat{p}_k^{\,*} = \frac{\ln\big(1 + \mu_k(e^{\psi_k} - 1)\big)}{\eta_W}, \tag{5}$$

where $\eta_W \equiv \eta_D + \eta_S$. For a differentiated good, the shock operates through market access instead. The change in Φ_{rk} is a weighted average of the changes in each destination's demand shifter, with weights equal to the share of the region's exports of k sold to that destination, so that

$$\varphi_{rk} = \ln\big(1 + \pi_{r,\mathrm{CHN},k}(e^{\psi_k} - 1)\big), \tag{6}$$

where $\pi_{r,\mathrm{CHN},k}$ is the share of region r's exports of k sold to China in 2000. The two channels differ in what determines a region's exposure. For commodities, what matters is China's weight in world demand rather than whether the region ships to China, so iron ore exported to Europe also benefits from China's demand through the world price. Differentiated goods, in contrast, gain only to the extent that they are sold to China.

Holding productivity fixed, region r's exports of product k then change by

$$\widehat{x}_{rk} = \xi_{rk} - b_k\,\widehat{w}_r, \tag{7}$$

where the demand term ξ_{rk} is the change in exports at a constant regional wage, and the wage pass-through b_k is the percentage decline in exports when the regional wage rises by one percent. Table 1 reports both components for each product group.

For commodities, a higher world price raises revenue one-for-one and output along the supply curve with elasticity $1/\nu$, while a higher wage lowers output with the same

Table 1: Export responses to China's demand shock, by product group

Product group	*Demand term,* ξ_{rk}	*Wage pass-through,* b_k
Commodities, $k \in \mathcal{R}$	$(1+1/\nu)\,\widehat{p}^*_k$	$1/\nu$
Resource-based manufactures, $k \in \mathcal{P}$	$\varphi_{rk} - (\eta_k - 1)\gamma\,\widehat{p}^*_{c(k)}$	$(\sigma_k - 1)(1-\gamma)c_L$
Other manufactures, $k \in \mathcal{M}$	φ_{rk}	$(\sigma_k - 1)c_L$

Notes: Components of $\widehat{x}_{rk} = \xi_{rk} - b_k\widehat{w}_r$ in Equation (7), with $\widehat{p}^*_k$ and φ_{rk} from equations (5) and (6). $c(k)$ is the commodity processed into product k.

elasticity. For differentiated goods, the export price is a constant markup over the unit cost in Equation (3), so a higher wage raises it by $(1-\gamma_k)c_L\,\widehat{w}_r$, and export revenue falls by $\sigma_k - 1$ times this increase. Both groups of differentiated goods also gain from the change in market access. A more expensive commodity input raises the prices of all producers of a resource-based manufacture alike, so it leaves the region's share of each destination's spending on the product unchanged, but it shifts destinations' spending toward other products when $\eta_k > 1$, which gives the term $-(\eta_k - 1)\gamma\,\widehat{p}^*_{c(k)}$. Wage pass-throughs are ordered as $b_{\mathcal{R}} \leq b_{\mathcal{P}} \leq b_{\mathcal{M}}$ as long as $(\sigma_k - 1)(1-\gamma)c_L \geq 1/\nu$ and the elasticity of substitution is no larger for resource-based manufactures than for other manufactures, so commodities are the most shielded from higher local costs.

The regional wage clears the local labor market. In each exporting sector, labor costs are a fixed share λ_k of revenue, equal to α for commodities, $(1-\gamma)c_L$ for resource-based manufactures, and c_L for other manufactures, so employment changes by $\widehat{x}_{rk} - \widehat{w}_r$. Employment changes by $-\widehat{w}_r/(1-\alpha_T)$ in domestic tradables, sold at given national prices, and by $\widehat{Y}_r - \widehat{w}_r$ in non-traded goods, whose revenue is a fixed share of regional income. The specific factors earn the rest of revenue, so commodity rents change by $\widehat{\Pi}_{rk} = \widehat{x}_{rk}$, the returns to the domestic tradables factor by $\widehat{\Pi}_{rT} = -\alpha_T\widehat{w}_r/(1-\alpha_T)$, and the returns to the non-traded factor by $\widehat{\Pi}_{rN} = \widehat{Y}_r$. Substituting these returns into Equation (4), regional income changes by $\widehat{Y}_r = \mathcal{Y}_A + \mathcal{Y}_w\,\widehat{w}_r$, where

$$\mathcal{Y}_A \equiv \frac{1}{D_Y}\sum_{k\in\mathcal{R}}\theta_{\Pi k}\xi_{rk}, \qquad \mathcal{Y}_w \equiv \frac{1}{D_Y}\left[(1+\varepsilon)\theta_W - \sum_{k\in\mathcal{R}}\theta_{\Pi k}b_k - \frac{\alpha_T\theta_{\Pi T}}{1-\alpha_T}\right],$$

θ_W, $\theta_{\Pi k}$, and $\theta_{\Pi T}$ are the shares of labor income, commodity rents, and the returns to the domestic tradables factor in regional income, and $1/D_Y$, with $D_Y \equiv 1 - (1-\alpha_N)\beta_N$, is a local spending multiplier. Weighting the employment changes by each sector's share in the regional wage bill, ϖ_{rk}, ϖ_{rT}, and ϖ_{rN}, which sum to one, and equating the change in labor demand to the change in labor supply, $\varepsilon\widehat{w}_r$, gives the regional wage

$$\widehat{w}_r = \frac{\sum_k \varpi_{rk}\xi_{rk} + \varpi_{rN}\mathcal{Y}_A}{\varepsilon + \sum_k \varpi_{rk}(1+b_k) + \varpi_{rT}/(1-\alpha_T) + \varpi_{rN}(1-\mathcal{Y}_w)}. \tag{8}$$

The denominator of Equation (8) is at least $(1+\varepsilon)(1-\beta_N)/D_Y > 0$, since $b_k \geq 0$, $1/(1-\alpha_T) \geq 1$, and $\varpi_{rN}\mathcal{Y}_w \leq (1+\varepsilon)\alpha_N\beta_N/D_Y$, because $\varpi_{rN} = \alpha_N\beta_N/\theta_W$. The weights ϖ_{rk} and $\theta_{\Pi k}$ in the numerator are proportional to X_{rk}/Y_r, so the wage response is of order X_r/Y_r. Exports account for about 1% of GDP in the median micro-region, so in most regions the export basket responds mainly to world prices and market access, while the wage plays a second-order role.

3.3 Testable predictions

I now derive the model's testable predictions, first for regional export baskets and then for the regional economy. For region r, let $s_{rk} \equiv X_{rk}/X_r$ denote the initial export share of product k, S_g the export share of product group g, and $\bar{x}_g$ the share-weighted mean growth of the products in group g. The complexity of the export basket is the share-weighted average complexity of its products, $\Theta_r \equiv \sum_k s_{rk}\kappa_k$, and Cov_s denotes a covariance across products weighted by s_{rk}.

Proposition 1 (The export basket)**.** *Suppose China's demand is raw-biased, the basket gains at constant wages, $\sum_k s_{rk}\xi_{rk} > 0$, and wage pass-throughs are ordered as $b_{\mathcal{R}} \leq b_{\mathcal{P}} \leq b_{\mathcal{M}}$. To first order, in regions where exports are a small share of regional income:*

(i) Value. *Export value rises.*

(ii) Primarization. *The commodity share rises and, when commodities are a meaningful part of the basket, the share of resource-based manufactures falls.*

(iii) Complexity. *When commodities are less complex than differentiated goods on average, the rise in the commodity share lowers the complexity of the basket. Complexity falls unless reallocation toward more complex products, between resource-based and other manufactures or within groups, more than offsets this effect.*

(iv) Concentration. *The Herfindahl index rises when product growth is positively correlated with initial shares. No new commodity lines enter, and differentiated lines with little demand from China do not enter and may exit.*

Proof. Because the shares sum to one, $ds_{rk} = s_{rk}(\widehat{x}_{rk} - \widehat{X}_r)$, where $\widehat{X}_r = \sum_k s_{rk}\widehat{x}_{rk}$, and each part follows from applying this rule to the responses in Table 1.

(i) Summing Equation (7) over products gives $\widehat{X}_r = \sum_k s_{rk}\xi_{rk} - \left(\sum_k s_{rk}b_k\right)\widehat{w}_r$. The first term is positive by assumption[4] and first order in the shock, while the second is of order X_r/Y_r by Equation (8), so export value rises where exports are a small share of regional income.

[4]With the calibration in Section 7, this assumption fails in 37 of the 424 micro-regions, which account for 2.4 percent of Brazil's exports in 2000.

(ii) Summing the share rule within each group gives $dS_g = S_g(\bar{x}_g - \widehat{X}_r)$, and since $\widehat{X}_r = \sum_g S_g \bar{x}_g$,

$$dS_{\mathcal{R}} = S_{\mathcal{R}} S_{\mathcal{D}} \big(\bar{x}_{\mathcal{R}} - \bar{x}_{\mathcal{D}}\big), \qquad dS_{\mathcal{P}} = S_{\mathcal{P}} \big[S_{\mathcal{R}}(\bar{x}_{\mathcal{P}} - \bar{x}_{\mathcal{R}}) + S_{\mathcal{M}}(\bar{x}_{\mathcal{P}} - \bar{x}_{\mathcal{M}})\big].$$

From Table 1, the growth gaps between groups are

$$\bar{x}_{\mathcal{R}} - \bar{x}_{\mathcal{P}} = (1 + 1/\nu)\, \widehat{p}^{\,*}_{\mathcal{R}} + (\eta - 1)\gamma\, \widehat{p}^{\,*}_{\mathcal{P}} - \bar{\varphi}_{\mathcal{P}} + (b_{\mathcal{P}} - b_{\mathcal{R}})\, \widehat{w}_r,$$

$$\bar{x}_{\mathcal{P}} - \bar{x}_{\mathcal{M}} = (\bar{\varphi}_{\mathcal{P}} - \bar{\varphi}_{\mathcal{M}}) - (\eta - 1)\gamma\, \widehat{p}^{\,*}_{\mathcal{P}} + (b_{\mathcal{M}} - b_{\mathcal{P}})\, \widehat{w}_r,$$

where $\widehat{p}^{\,*}_{\mathcal{R}}$ is the share-weighted world price change of the region's commodities, $\widehat{p}^{\,*}_{\mathcal{P}}$ is the average price change of the commodities processed by its resource-based manufactures, and, for simplicity, η is common across these manufactures. Under raw-biased demand, the market-access terms are small relative to the world price changes, and the wage terms are of order X_r/Y_r. Since the basket gains at constant wages and the demand terms of differentiated goods are at most of the order of their market-access terms, $\widehat{p}^{\,*}_{\mathcal{R}} > 0$. The first gap is therefore positive and first order in the world price increase, and so is $\bar{x}_{\mathcal{R}} - \bar{x}_{\mathcal{M}}$, which implies $\bar{x}_{\mathcal{R}} > \bar{x}_{\mathcal{D}}$ and $dS_{\mathcal{R}} > 0$. The second gap is small when $\eta = 1$ and negative when $\eta > 1$, since more expensive inputs then depress resource-based manufactures. Hence $S_{\mathcal{R}}(\bar{x}_{\mathcal{R}} - \bar{x}_{\mathcal{P}}) > S_{\mathcal{M}}(\bar{x}_{\mathcal{P}} - \bar{x}_{\mathcal{M}})$ whenever commodities are a meaningful part of the basket, and $dS_{\mathcal{P}} < 0$.

(iii) Since $\Theta_r = \sum_k s_{rk}\kappa_k$, the share rule gives $d\Theta_r = \sum_k \kappa_k\, ds_{rk} = \mathrm{Cov}_s(\kappa_k, \widehat{x}_{rk})$. Decomposing this covariance between and within groups, and splitting the between-group term into the contrast between commodities and differentiated goods and the contrast between resource-based and other manufactures, gives

$$\begin{aligned} d\Theta_r = {} & (\bar{\kappa}_{\mathcal{R}} - \bar{\kappa}_{\mathcal{D}})\, dS_{\mathcal{R}} + \frac{S_{\mathcal{P}} S_{\mathcal{M}}}{S_{\mathcal{D}}} (\bar{\kappa}_{\mathcal{P}} - \bar{\kappa}_{\mathcal{M}})(\bar{x}_{\mathcal{P}} - \bar{x}_{\mathcal{M}}) \\ & + \sum_{g \in \{\mathcal{R}, \mathcal{P}, \mathcal{M}\}} S_g\, \mathrm{Cov}_{s|g}(\kappa_k, \widehat{x}_{rk}), \end{aligned}$$

where $\bar{\kappa}_g$ is the share-weighted complexity of group g. By part (ii), the first term is negative and first order in the world price increase when $\bar{\kappa}_{\mathcal{R}} < \bar{\kappa}_{\mathcal{D}}$. The second term captures the reallocation between resource-based and other manufactures, and the last captures shifts within groups, so complexity falls unless these two terms favor more complex products by more than the rise in the commodity share lowers it.

(iv) Since $\mathrm{HHI}_r = \sum_k s_{rk}^2$, the share rule gives

$$d\,\mathrm{HHI}_r = 2 \sum_k s_{rk}\, ds_{rk} = 2 \sum_k s_{rk}^2 (\widehat{x}_{rk} - \widehat{X}_r) = 2\, \mathrm{Cov}_s(s_{rk}, \widehat{x}_{rk}),$$

where the last step uses $\sum_k s_{rk}(\widehat{x}_{rk} - \widehat{X}_r) = 0$. The index therefore rises when products with larger initial shares grow faster.[5] For the extensive margin, a region can export commodity k only if $F_{rk} > 0$, and it already does so in that case, since price-taking producers supply a positive amount at any positive price. A differentiated line is exported only if its operating profit, X_{rk}/σ_k, covers the fixed cost $w_r f_k$. For lines with little demand from China, the ratio of the two changes by $\xi_{rk} - (1 + b_k)\widehat{w}_r \leq 0$, so these lines do not enter, and those close to the threshold may exit. □

The proof makes clear what the model contributes. The expressions for complexity and concentration hold as accounting identities for any pattern of product growth. The model pins down that pattern, in which growth rises with initial shares and falls with complexity, because both are tied to endowments and world prices. The signs then rest on two conditions that are natural in this setting. Raw commodities are among the least complex products, and the regions most exposed to China's demand are those whose 2000 baskets were dominated by the commodities China bought.

I now turn to the regional economy and the static gains from the shock.

Proposition 2 (Regional economy and static gains)**.** *Suppose China's demand is raw-biased and the regional wage rises. To first order:*

(i) Factor returns. *Commodity rents change by $\widehat{\Pi}_{rk} = \widehat{p}^*_k + (\widehat{p}^*_k - \widehat{w}_r)/\nu$, which exceeds the price increase whenever $\widehat{w}_r < \widehat{p}^*_k$. Returns to the non-traded factor rise with regional income, and returns to the domestic tradables factor fall.*

(ii) Employment. *Employment falls in domestic tradables and in manufactured exports with little demand from China. Manufacturing's share of employment therefore falls when manufacturing consists mainly of these producers.*

(iii) Wage and real income. *The regional wage rises by an amount of order X_r/Y_r, and regional real income rises by*

$$\widehat{Y}_r - \widehat{P}_r = \sum_{k \in \mathcal{R}} \frac{X_{rk}}{Y_r}\, \widehat{p}^*_k + \theta_{W\mathcal{D}}\, \widehat{w}_r + \varepsilon\, \theta_W\, \widehat{w}_r, \tag{9}$$

where $\theta_{W\mathcal{D}} \equiv \sum_{k \in \mathcal{D}} \lambda_k X_{rk}/Y_r$ is the wage bill of differentiated exporters relative to regional income.

Proof. (i) Commodity rents are a share $1 - \alpha$ of revenue, so $\widehat{\Pi}_{rk} = \widehat{x}_{rk} = (1 + 1/\nu)\widehat{p}^*_k - \widehat{w}_r/\nu$, which rearranges to the expression above. The returns to the non-traded factor

[5] The empirical analysis uses the Herfindahl index normalized by the number of exported lines. For a given value of $\sum_k s_{rk}^2$, the normalized index falls when lines exit, so the exit of marginal lines works against finding the predicted increase.

change by $\widehat{Y}_r$, which is positive, as shown in part (iii), and those of the domestic tradables factor by $-\alpha_T \widehat{w}_r/(1-\alpha_T) < 0$.

(ii) Employment changes by $-\widehat{w}_r/(1-\alpha_T) < 0$ in domestic tradables. For a manufactured export with little demand from China, $\varphi_{rk} \approx 0$, so its demand term is zero or negative, and employment changes by $\xi_{rk} - (1+b_k)\widehat{w}_r < 0$. Total employment changes by $\varepsilon \widehat{w}_r \geq 0$, so manufacturing's share of employment falls when it consists mainly of these producers.

(iii) The order of the wage response follows from Equation (8). For real income, non-traded prices change by $\widehat{p}_{rN} = (1-\alpha_N)\widehat{Y}_r + \alpha_N \widehat{w}_r$, since non-traded revenue moves with regional income and output moves with employment. Differentiating Equation (4) and subtracting $\widehat{P}_r = \beta_N \widehat{p}_{rN}$, the returns to the non-traded factor cancel against part of the price increase, and

$$\widehat{Y}_r - \widehat{P}_r = (1+\varepsilon)\theta_W \widehat{w}_r + \sum_{k \in \mathcal{R}} \theta_{\Pi k} \widehat{\Pi}_{rk} + \theta_{\Pi T} \widehat{\Pi}_{rT} - \alpha_N \beta_N \widehat{w}_r.$$

Using part (i) and $\theta_{\Pi k} = (1-\alpha) X_{rk}/Y_r$, each commodity contributes $(X_{rk}/Y_r)\widehat{p}_k^* - \alpha(X_{rk}/Y_r)\widehat{w}_r$. The negative wage terms are the wage bills of commodities, domestic tradables, and non-traded goods relative to regional income, times $\widehat{w}_r$. They cancel against the corresponding part of $(1+\varepsilon)\theta_W \widehat{w}_r$, which leaves the wage bill of differentiated exporters and the income of migrants and gives Equation (9). Real income rises because world prices and the wage rise. Since $D_Y \widehat{Y}_r = (\widehat{Y}_r - \widehat{P}_r) + \alpha_N \beta_N \widehat{w}_r$, nominal income rises as well. □

The terms of Equation (9) have a simple interpretation. The first is the terms-of-trade gain on commodity exports, the standard envelope result for a small open economy that sells at higher prices. The second arises because differentiated exporters price at a markup over local costs, so foreign buyers pay part of the higher wage. The third is the income of workers who move into the region. Since this term reflects a larger population rather than higher income for existing residents, real income per worker, which excludes it, is the relevant welfare measure. In Section 6, I test part (i) with sectoral wages, which approximate the factor returns in the model, part (ii) with manufacturing's share of employment, and part (iii) with the average wage. Section 7 compares the prediction for real income with the response of GDP per capita.

3.4 Measuring exposure

Both propositions describe how a region responds to China's shock relative to a counterfactual without it, while the empirical analysis compares regions that differ in their exposure to the shock. To first order, and with the wage response second order in most regions, the outcomes in both propositions depend on the shock through the product-level demand

terms ξ_{rk}, weighted by the region's initial exports. The model's measure of a region's exposure is therefore the share-weighted demand term

$$\mathcal{E}_r \equiv \sum_k s_{rk}\, \xi_{rk}, \tag{10}$$

in the same way that the model of Kovak (2013) delivers the appropriate measure of regional exposure to trade liberalization. Exposure has two components that mirror the two channels. The commodity component depends on the shocks through China's share of world imports, μ_k, and on η_W and ν only through a common scale, while the component for differentiated goods depends mainly on the share-weighted change in market access.

In the empirical analysis, I measure exposure with

$$G_r \equiv \sum_k s_{rk}\, \chi_k\, (e^{\psi_k} - 1), \tag{11}$$

where χ_k is the share of Brazil's exports of product k sold to China in 2000. This measure approximates the model's exposure under a simple assumption: ex ante, Brazil is a representative supplier, so that $\chi_k = \mu_k$ and the share of its exports of each product sold to China equals China's share of world imports of that product. To first order, the commodity terms of G_r then match the commodity component of exposure up to its common scale, and the remaining terms match the changes in market access, with Brazil's share in place of each region's. Since raw-biased demand keeps the second component small relative to the first, G_r is approximately proportional to $\mathcal{E}_r$, and the reduced-form coefficients on G_r carry the signs that the two propositions predict.

In the static framework, then, China's demand raises regional real income, and the shift in the export basket carries no static cost. Whether the shift matters in the long run depends on what the export basket does to the region's capabilities over time, which Section 8 examines.

4 Data Description and Measurement

4.1 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. For the analysis, I aggregate these data to the municipal and yearly levels from 1997 to 2019, covering the years before and after China's accession to the WTO in 2001 and excluding the period affected by COVID-19. Although the accession marks the beginning of China's rapid integration into world trade,

the variation I use comes from the growth of China's demand for each product over the following two decades, rather than from the timing of the accession itself.

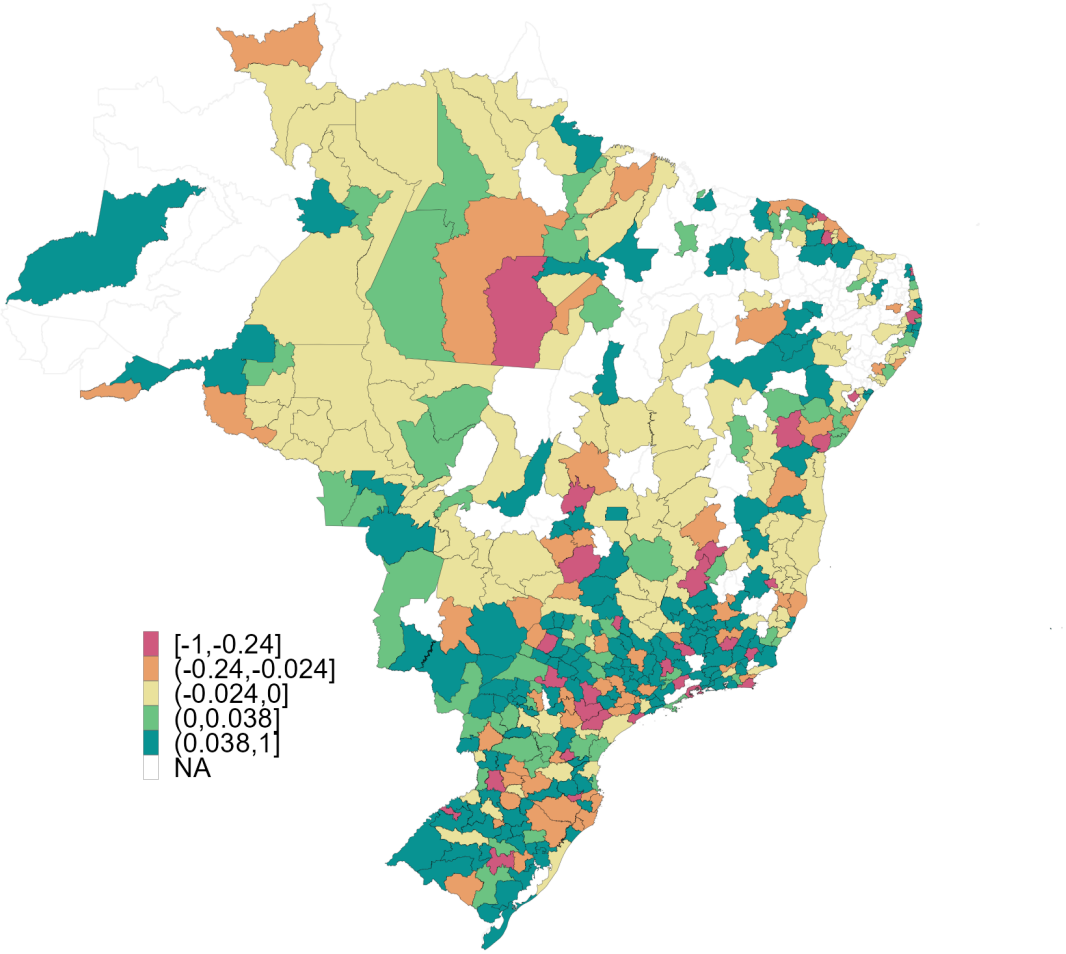
Given the data structure and the relatively low share of exports in Brazil's GDP during the 1990s, I focus on municipalities with consistent export activity, excluding those that did not export in 2000 or in 2019. This results in a smaller sample than the total number of municipalities recorded during the same period. To reduce potential distortions and gain clearer insights into the impact of China's demand 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 & Kovak, 2017; Dix-Carneiro et al., 2018; Hirata & Soares, 2020; Ogeda et al., 2024; Ponczek & 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, each containing only the municipalities that exported in both years.

The export data at the municipal level disaggregate 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 International 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. Lall's primary products, resource-based manufactures, and low-, medium-, and high-tech manufactures correspond to the commodities, resource-based manufactures, and other manufactures of the model in Section 3. Throughout, resource products refer to primary products and resource-based manufactures together, and manufactures refer to the other three categories.

Figure 8 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. When this change is broken down by product category, regions in the North, Central-West, Southeast, and South — particularly those historically focused on agrarian production — expanded their primary product exports from 2000 to 2019, while reducing the share of resource-based manufactures in their export baskets, with some exceptions. The evolution of manufactured exports, in contrast, was more heterogeneous, with metropolitan areas in the Southeast increasing their exports of medium-tech manu-

factures.[6]

Figure 8: Change in the share of resource exports, 2000–2019



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).

[6]The Online Appendix maps the change in the share of each product category across Brazilian local economies from 2000 to 2019, except high-tech manufactures, whose change varies too little across micro-regions to map, as well as the shares of all categories in 2000 and 2019.

4.2 Export basket concentration

To analyze the relationship between China's demand shock 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 (exports evenly spread across lines) and 1 (exports concentrated in a single line). It is calculated using the following formula:

$$\text{HHI}_r = \frac{\sum_k s_{rk}^2 - \frac{1}{N_r}}{1 - \frac{1}{N_r}}, \tag{12}$$

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

4.3 Export basket sophistication and complexity

In addition to examining total value and concentration, I explore the impacts of China's demand shock on the sophistication and complexity of export baskets across local economies. I use two measures. The first follows the methodology established by Hausmann et al. (2007), which evaluates the sophistication of a region's exports by comparing them to the income levels of countries with similar export structures. The second follows the economic complexity approach of Hidalgo and Hausmann (2009), which infers the complexity of each product from how many countries export it and how diversified those countries are. For both, I construct an annual measure for each Brazilian micro-region's export basket.

Both measures begin 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 $RCA_{j,k}$ is defined as

$$RCA_{j,k} = \frac{x_{j,k} / X_j}{\sum_{j'} x_{j',k} / \sum_{j'} X_{j'}}, \tag{13}$$

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 a 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 given by each country's RCA normalized to sum to one across countries:

$$P_k = \sum_j \left(\frac{RCA_{j,k}}{\sum_{j'} RCA_{j',k}} \right) Y_j, \tag{14}$$

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 & Hausmann, 2009; 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 second measure, the product complexity index (PCI), uses the RCA in Equation (13) to define a binary matrix of export specialization, with $M_{j,k} = 1$ if $RCA_{j,k} \geq 1$ and $M_{j,k} = 0$ otherwise. The diversity of country j, $d_j = \sum_k M_{j,k}$, counts the products it exports with comparative advantage, and the ubiquity of product k, $u_k = \sum_j M_{j,k}$, counts the countries that export it with comparative advantage. Following Hidalgo and Hausmann (2009), the complexity of a product combines these two pieces of information, since complex products are exported by few countries, and those countries tend to be highly diversified. In practice, the PCI is the eigenvector associated with the second largest eigenvalue of the matrix

$$\widetilde{M}_{k,k'} = \sum_j \frac{M_{j,k} M_{j,k'}}{d_j \, u_k}, \tag{15}$$

standardized to have mean zero and unit standard deviation across products. Unlike PRODY, the PCI does not use income data, so the two measures provide complementary rankings of products.

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, which I use for both measures. Additionally, I use data from the Penn World Table (PWT) to compute the average real per capita income for each country during the same period. Both PRODY and PCI are therefore fixed at their pre-shock levels, so that changes in regional sophistication and complexity reflect only changes in the composition of export baskets.

Following the construction of the product-level indices, I compute two regional measures for each local economy's export basket, following Jarreau and Poncet (2012). Each is the weighted sum of the product-level index of each exported good k, with weights representing the share of each good in the micro-region's total exports:

$$S_r = \sum_k s_{rk} \, P_k, \tag{16}$$

$$C_r = \sum_k s_{rk} \, \text{PCI}_k, \tag{17}$$

where s_{rk} is defined as in Equation (12), so that S_r is the regional counterpart of the EXPY index of Hausmann et al. (2007). The complexity index C_r is the empirical counterpart of the basket complexity Θ_r in Section 3, with PCI_k measuring κ_k, and the sophistication index S_r provides an alternative ranking of the same products. Since the leading term of the complexity prediction in Proposition 1 requires only that raw commodities rank below differentiated goods on average, the prediction applies to both measures. Although the time subscript is omitted for simplicity, both measures are constructed annually, based on the export data discussed earlier.

4.4 Local exposure to China's demand

To quantify the impact of increased export demand from China at the local level, I begin by calculating a simple measure of local exposure. 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 Brazil's exports of each product to China between 2000 and 2019 by the relative significance of that product in the export basket of each region:

$$\Delta X_r = \frac{1}{X_{r,00}} \sum_k \frac{X_{r,k,00}}{X_{B,k,00}} \, \Delta X_{BC,k,00/19}, \tag{18}$$

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 $\Delta X_{BC,k,00/19}$ is the change in Brazil's exports of product k to China between 2000 and 2019. However, this measure may be endogenous, as Brazil's sales to China also respond to local supply conditions that 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), Carreira et al. (2024), and Cícero and Heras-Recuero (2026), isolates China-specific demand shocks using the trade of countries other than Brazil. It parallels the methodology used to identify the "China shock" in the US economy (e.g., Autor et al., 2013, 2014, 2019, 2020). Unlike these studies of Brazil, I estimate China's

demand shocks from product-level gravity equations, adapting the gravity approach that Autor et al. (2013) use to measure China's supply shocks. The shift-share instrument addresses the endogeneity problem by leveraging variation in China's demand that is independent of local conditions in Brazil.

The first step isolates China-specific demand shocks from a gravity equation estimated on the trade of all countries except Brazil. For each product k, I estimate by Poisson pseudo-maximum likelihood (Silva & Tenreyro, 2006):

$$x_{ijk,t} = \exp\left(a_{ik,t} + m_{jk,t} + d_{ijk}\right) u_{ijk,t}, \tag{19}$$

where $x_{ijk,t}$ is the value of exports of product k from country i to country j in year $t \in \{2000, 2019\}$, $a_{ik,t}$ and $m_{jk,t}$ are exporter-year and importer-year fixed effects, and d_{ijk} is a pair fixed effect. The sample excludes Brazil as both exporter and importer and includes every pair that trades in either year, with zeros in the other. The importer-year effect $m_{jk,t}$ measures country j's demand for product k, net of supply conditions in exporting countries and of bilateral trade costs. China's demand shock is the growth of its demand relative to the rest of the world:

$$\psi_k = \Delta m_{CHN,k} - \ln \sum_{j \neq CHN} \omega_{jk} \exp\left(\Delta m_{jk}\right), \tag{20}$$

where $\Delta m_{jk} = m_{jk,19} - m_{jk,00}$ and ω_{jk} is country j's share of 2000 imports of product k by countries other than China. The estimated $e^{\hat{\psi}_k} - 1$ therefore represents the growth of China's demand for product k in excess of the import-weighted average growth in the rest of the world between 2000 and 2019.

Using the estimated $\hat{\psi}_k$ 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:

$$G_r = \sum_k \frac{X_{r,k,00}}{X_{r,00}} \times \frac{X_{BC,k,00}}{X_{B,k,00}} \times \left(e^{\hat{\psi}_k} - 1\right) = \sum_k s_{rk}\, \chi_k \left(e^{\hat{\psi}_k} - 1\right), \tag{21}$$

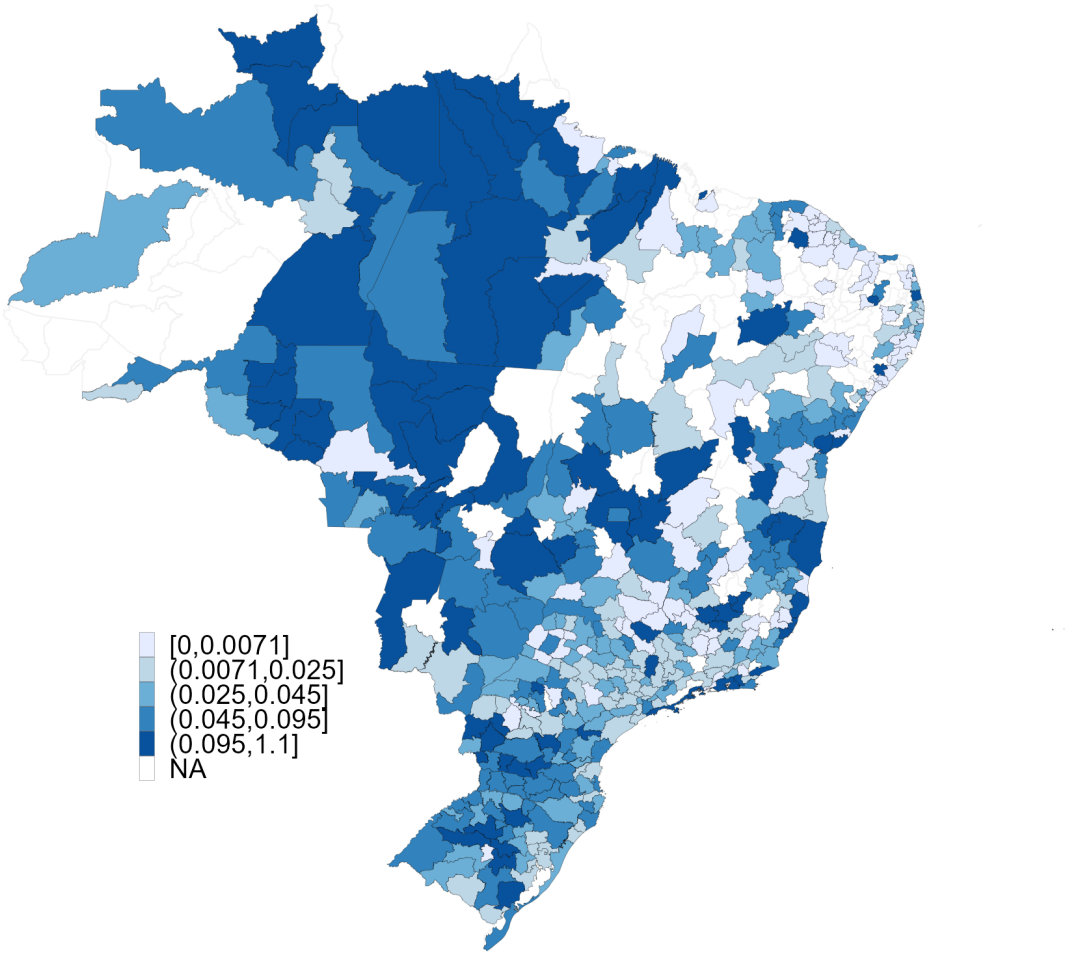
where $X_{BC,k,00}$ is Brazil's exports of product k to China in 2000.[7] This is the exposure measure in Equation (11), with $s_{rk} = X_{r,k,00}/X_{r,00}$ and $\chi_k = X_{BC,k,00}/X_{B,k,00}$. The measure G_r is the growth in a micro-region's exports implied by China's demand shock when Brazil's sales of each product to China grow with China's demand, that is, when China's demand affects Brazil as it affects any other supplier of the product. The regional shares sum to one, and χ_k scales each shock by how much of Brazil's exports of the product went

[7] I use HS2 products to compute the shift-share, resulting in 96 categories. The reduced-form results are virtually identical when using the HS4 classification, with approximately 1,200 categories, although the first stage is weaker (see the Online Appendix).

to China in 2000. Identification therefore comes from the product-level shocks $\chi_k(e^{\hat{\psi}_k} - 1)$, in which China's demand growth is estimated without Brazil's trade (Borusyak et al., 2022). To ensure that the results are not skewed by outliers, I winsorize G_r at the 1st and 99th percentiles.

Finally, Figure 9 maps the local exposure to China's demand, G_r, calculated from Equation (21). Local economies in the Central-West, much of the North, the South, and the mining regions of Minas Gerais are the most exposed.

Figure 9: Exposure to China's demand — G_r



Source: Regional exposures to China's demand, G_r, are computed according to Equation (21). Data from CEPII-BACI and SISCOMEX are used to compute the shift-share instrument. Micro-regions are grouped by quintiles of exposure.

4.5 Additional variables

In addition to trade data, I incorporate local labor market and income variables to examine the predictions of Proposition 2 for the regional economy.

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 the private sector employment rate, sectoral employment shares, and average hourly wages for all employed individuals. Wages are adjusted for inflation using the Brazilian Consumer Price Index (IPCA) and are expressed in 2010 Brazilian reais.

To measure local income, I follow Cícero and Heras-Recuero (2026) and compute annual GDP per capita for each micro-region using municipal GDP and population data from IBGE.

5 Empirical Strategy and Identification

My empirical objective is to analyze the effects of the surge in China's demand that followed its accession to the WTO in 2001 on the export baskets of regional economies across Brazil. Guided by the predictions in Section 3, this analysis focuses on changes in export value, concentration, composition, and sophistication over time, as well as on the responses of local labor markets and income.

Recent research has established a formal framework for the identifying assumptions in shift-share regression designs (Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020). Following Borusyak et al. (2022), my identification assumption is that the product-level demand shocks that make up G_r are orthogonal to unobserved local conditions that also affect the outcomes, such as local political and institutional dynamics across micro-regions in Brazil. Estimating the growth of China's demand relative to all other countries from gravity equations that exclude Brazil ensures that the shocks do not reflect supply conditions in Brazil. Under this assumption, G_r provides quasi-exogenous variation in local exposure to China's demand.

I estimate a long-difference specification, similar to those in Autor et al. (2013), Costa et al. (2016), and Carreira et al. (2024), with the micro-region as the unit of analysis:

$$\Delta y_{r,t} = y_{r,t} - y_{r,2000} = \beta\, G_r + \delta_s + u_{r,t}, \tag{22}$$

where $\Delta y_{r,t}$ represents the change in the outcome variable in region r from 2000 to t (2019 for the export outcomes and 2010 for the Census outcomes), G_r denotes the measure of local exposure for region r to China's demand shock (as detailed in Equation (21)), and

δ_s are state fixed effects. The coefficient β therefore compares more and less exposed micro-regions within the same state. I weight micro-regions by their exports in 2000 for the export outcomes and by their population for the Census outcomes. 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.[8]

Equation (22) is the baseline for all results. For the main results on export value and concentration, I also present estimates from a dynamic difference-in-differences (DiD) model, in which exposure to China's demand shock is interacted with year indicators and the outcomes are in levels rather than in changes. Following recent work on event-study designs (Borusyak et al., 2024; De Chaisemartin & d'Haultfoeuille, 2020; Roth et al., 2023), this specification shows whether more and less exposed micro-regions followed similar trends before 2001. The dynamic counterpart of Equation (22) is

$$y_{r,t} = \sum_{\tau \neq 2001}^{t} \beta_\tau \mathbb{1}\{t = \tau\} G_r + \zeta_r + \delta_{s,t} + u_{r,t}. \tag{23}$$

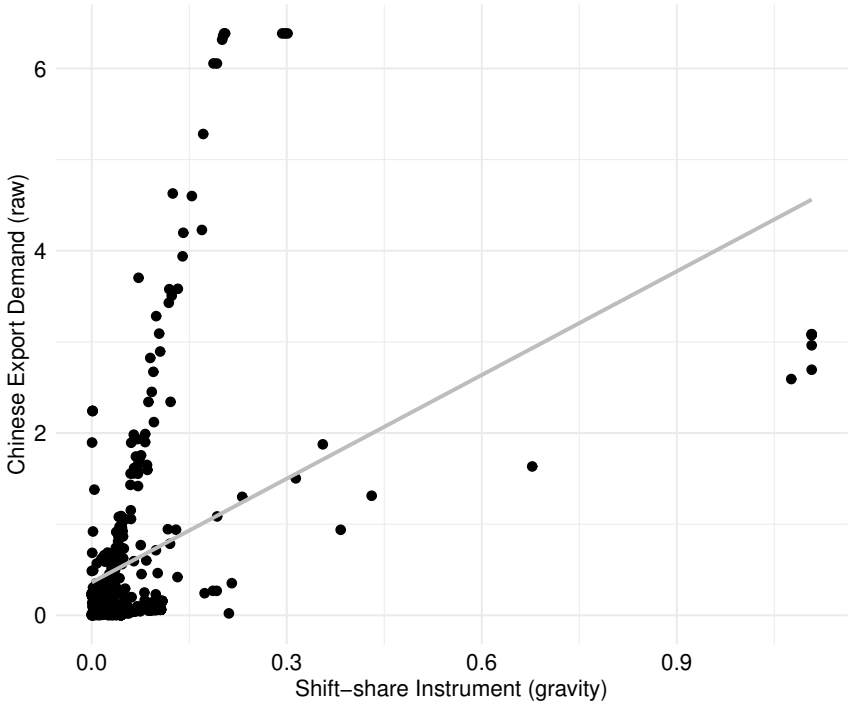
In Equation (23), 2001 is the reference year and G_r is the treatment intensity, while ζ_r are micro-region fixed effects, $\delta_{s,t}$ state-year fixed effects, and $\mathbb{1}\{t = \tau\}$ year indicators. Because micro-regions differ in the intensity of their exposure rather than in its timing, the design does not involve staggered treatment adoption, which is the setting of the recent methodological criticisms of the DiD literature (Callaway & Sant'Anna, 2021; De Chaisemartin & d'Haultfoeuille, 2022; Goodman-Bacon, 2021). Under parallel trends, the coefficients β_τ for the years before 2001 should not differ significantly from zero, individually or jointly. The coefficients after 2001, in turn, show how the effects build up as China's demand grows over the following two decades.

Lastly, although the main text reports reduced-form estimates, the strength of the shift-share instrument matters for the 2SLS estimates in the Online Appendix, which measure the regional effects of the increase in Brazil's exports to China after 2001. Figure 10 shows that the endogenous measure of exposure, ΔX_r in Equation (18), and the instrument, G_r, are strongly and positively correlated.

Table 2 reports the first-stage regressions of ΔX_r on G_r, weighting micro-regions by their exports in 2000, as in the export outcomes, or by their population, as in the Census outcomes. The coefficient on G_r is positive and significant at the 1% level in all specifications, and the Kleibergen–Paap F-statistics are above the conventional threshold. The Online Appendix reports the same regressions with exposure built from HS4 products.

[8] In the Online Appendix, I show 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.

Figure 10: Correlation: Chinese export demand and shift-share instrumental variable



Notes: Each dot is a micro-region. ΔX_r is defined in Equation (18) and G_r in Equation (21), both built with HS2 products. The line is the linear fit.

6 Impacts of China's Demand Shock

6.1 Export value and concentration

I begin by estimating Equation (22), using changes in the total export value per micro-region as the dependent variable, analyzed both in levels and growth rates. Part (i) of Proposition 1 predicts that local economies more exposed to China's demand shock see a larger increase in their total export value than less exposed regions, since the rise in world prices is first order while the response of the regional wage is second order in most regions. The results in Table 3 confirm this prediction: both the value of exports and their growth rate increased more in the micro-regions most exposed to China's demand.

The analysis starts with a simple specification without controls, reported in column 1 of Table 3, where observations are weighted by the total export value of each micro-region in 2000, the base year. This weighting accounts for the correlation between the variance of export values and the economic size of the regions. Column 2 adds state fixed effects, which in the long-difference specification account for state-specific changes that may influence export dynamics. The results are similar across the two columns. The effect on

Table 2: First stage: Chinese export demand and exposure to China's demand

Dependent variable:	**Chinese export demand (ΔX_r)**			
	(1)	(2)	(3)	(4)
Exposure to China's demand (G_r)	2.630***	2.995***	3.990***	4.262***
	(0.394)	(0.422)	(0.811)	(0.876)
Observations	424	424	424	424
R^2	0.257	0.420	0.237	0.416
KP F-stat	44.7	50.3	24.2	23.7
Weighted by exports in 2000	X	X		
Weighted by population in 2000			X	X
State-year fixed effects		X		X

Notes: Unit of analysis r is a micro-region. The dependent variable is ΔX_r in Equation (18), the growth of the micro-region's exports to China between 2000 and 2019, and the regressor is exposure G_r in Equation (21), built with HS2 products. Columns 1–2 weight micro-regions by their exports in 2000, as in the export outcomes, and columns 3–4 by their population in 2000, as in the Census outcomes. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. KP F-stat is the Kleibergen–Paap first-stage F-statistic. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

export value is significant in both, while the effect on the growth rate becomes significant, at the 10% level, once state fixed effects are included. The corresponding 2SLS estimates, which use G_r as an instrument for ΔX_r, are reported in the Online Appendix.

From the preferred specification in column 2, a micro-region at the 75th percentile of exposure to Chinese demand ($G_r = 0.083$) experienced, on average, an increase of approximately $465 million in total export value compared to a micro-region at the 25th percentile ($G_r = 0.013$), about 17% of the weighted average export value of micro-regions in 2000. A one-standard-deviation increase in exposure (0.14) raises total export value by approximately $929 million, or 35% of that average. In terms of growth rates, these differences in exposure correspond to export growth about 25 and 50 percentage points higher between 2000 and 2019, respectively. In what follows, I report the effects of a one-standard-deviation increase in exposure.

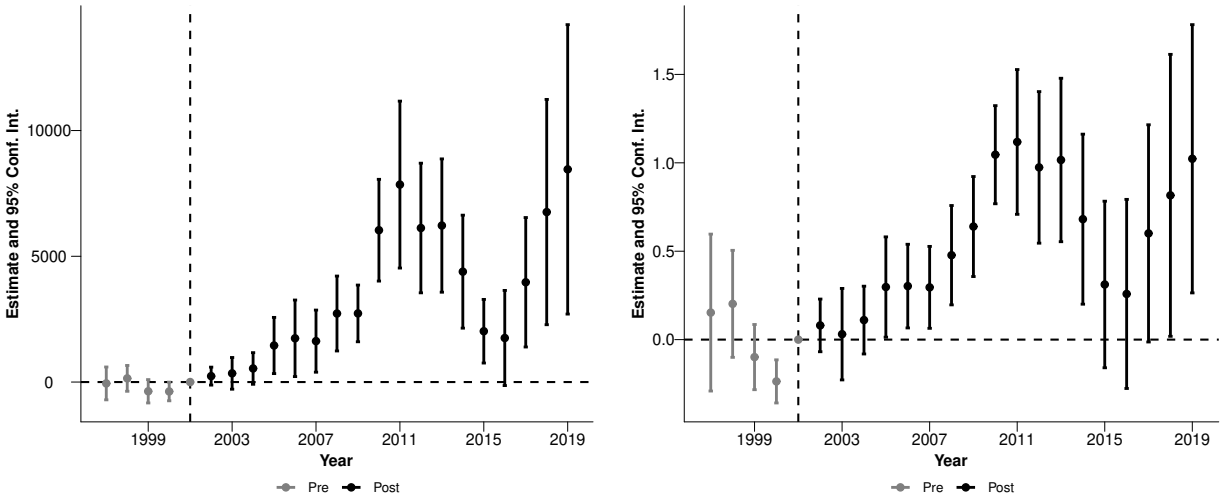
To assess the causal effects of China's demand shock on regional export values, I test the parallel trends assumption underlying the identification strategy. This assumption posits that, prior to 2001, regions with *ex-post* varying levels of exposure to the shock would exhibit *ex-ante* similar trends in their export values. To evaluate this, I employ the event-study specification outlined in Equation (23), focusing on the coefficients on the interaction of the exposure measure, G_r, with year indicators. Figure 11 illustrates the dynamic effects of China's demand shock on regional export values, along with 95% confidence intervals.

Table 3: China's demand shock and export value

Dependent variable:	Δ **Value of exports (US$ millions)**		%Δ **Value of exports**	
	(1)	(2)	(1)	(2)
Exposure to China's demand (G_r)	7,540.774**	6,600.281**	4.065	3.584*
	(3,684.386)	(2,540.742)	(2.638)	(1.918)
Control mean (2000)	2,678.8	2,678.8	–	–
Weighted	X	X	X	X
State-year fixed effects		X		X
Observations	424	424	424	424

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r. 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. The control mean is the export-weighted average of the outcome in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 11: Dynamic effects of China's demand shock 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 $\hat{\beta}_\tau$ following Equation (23), 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-region fixed effects and state-year fixed effects. Standard errors are adjusted for 129 meso-region clusters and the observations are weighted by total exports.

The coefficients before 2001 are not statistically significant, consistent with parallel trends. After 2001, they rise during the 2000s, as China's demand grew, and remain at similar levels from the early 2010s through 2019, in line with the estimates in Table 3.

Next, I examine the effects of China's demand shock on the concentration of regional

export baskets. While the increase in export value for regions most exposed to the shock is evident, its effect on export concentration — measured by the number of exported products and the HHI — is less obvious *a priori*. Part (iv) of Proposition 1 predicts that the export baskets of more exposed regions become more concentrated along the intensive margin. The commodities whose prices China raised are precisely those that already dominate the baskets of the regions endowed with them, while new commodity lines would require endowments these regions lack, and new differentiated lines face a higher wage and little new demand. Alternatively, increased demand for certain products could drive greater diversification of the export basket, potentially facilitated by backward linkages in the production structure, a channel the model abstracts from.

Table 4 presents the results from the estimation of Equation (22), 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 China's demand and the number of export lines is small and statistically insignificant, positive in column 1 and negative in column 2. This suggests that the regions most exposed to the export demand shock did not alter the number of products they exported between 2000 and 2019 compared to less exposed regions, in line with the model's prediction that no new lines enter.

However, the analysis of the regional export basket concentration index reveals significant effects of China's demand shock. Regions most exposed to the shock experienced an increase in the HHI of their export baskets relative to less exposed regions. The estimates in column 2 indicate that a one-standard-deviation increase in exposure raises the HHI of the export basket by 0.026, about 10% of the weighted average index in 2000. The estimate in column 1 is similar in magnitude but less precise.

These findings suggest that the concentration of the export basket in regions most exposed to China's demand occurred primarily on the intensive margin rather than the extensive margin, as part (iv) of Proposition 1 predicts. 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, substantially increasing their share in the total export basket.

Figure 12 reports the event-study estimates for the number of export lines and the HHI, with 95% confidence intervals.

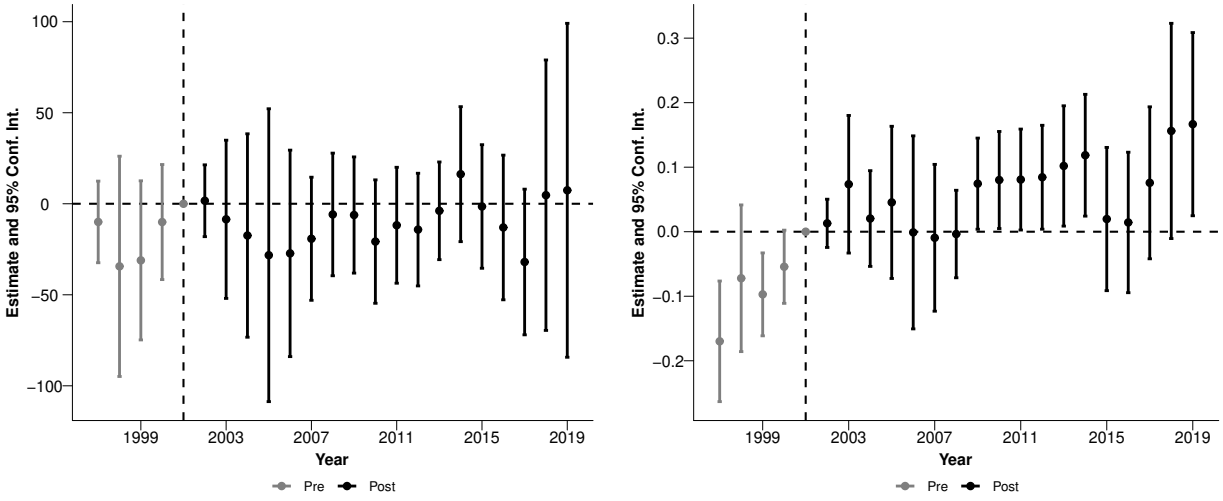
Similar to the findings on export value, the results depicted in Figure 12 are broadly consistent with those presented in Table 4. The coefficients for the number of export lines remain close to zero throughout the period, while those for the HHI increase over the boom years. The pre-treatment coefficients for the number of export lines are not statistically significant, which supports the parallel trends assumption for this outcome. For the HHI, however, two of the coefficients before 2001 are negative and deviate from zero, suggesting

Table 4: China's demand shock and export concentration: number of lines and HHI

Dependent variable:	**Δ Lines**		**Δ HHI**	
	(1)	(2)	(1)	(2)
Exposure to China's demand (G_r)	5.206	-51.007	0.190	0.187***
	(69.979)	(65.571)	(0.118)	(0.072)
Control mean (2000)	363.2	363.2	0.271	0.271
Weighted	X	X	X	X
State-year fixed effects		X		X
Observations	424	424	424	424

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r. 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. The control mean is the export-weighted average of the outcome in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 12: Dynamic effects of China's demand shock on export concentration



(a) Dynamic effects on export lines

(b) Dynamic effects on HHI

Notes: Each point reflects an individual regression coefficient $\hat{\beta}_\tau$ following Equation (23), 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-region fixed effects and state-year fixed effects. Standard errors are adjusted for 129 meso-region clusters and the observations are weighted by total exports.

that concentration was already rising in more exposed micro-regions in the years leading up to 2001. Part of the increase in the HHI may therefore reflect trends that were already under way before 2001, and the estimates for this outcome should be interpreted with some caution.

6.2 Heterogeneity analysis

The model attributes the increase in export value and concentration to the commodities whose world prices China raised, while manufactures gain little from China's demand and face a higher regional wage (Proposition 1). To examine this, I conduct a heterogeneity analysis by categorizing local export baskets into resource segments, which include primary products and resource-based manufactures, and non-resource 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 value of 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 5 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 3 are predominantly driven by the expansion of resource exports. In the preferred specification, a one-standard-deviation increase in exposure raises resource exports by about $749 million, or 79% of their weighted average value in 2000.[9] Notably, there is no significant impact on either the value or the growth rate of the non-resource export basket in the regions most exposed to the shock compared to less exposed regions. This is in line with the model, in which manufactures gain from China's demand only to the extent that they are sold to China, which raw-biased demand keeps small, while facing higher local costs.

Table 6 presents results for export basket concentration. The number of export lines does not change significantly in either basket, and neither does the HHI of the non-resource basket. The HHI rises within the resource basket of the most exposed regions, significantly so in the preferred specification, where a one-standard-deviation increase in exposure raises the index by 0.016, about 4% of its weighted average in 2000. This is where the model locates the increase in concentration, since commodity exports are tied to endowments, and the commodities whose prices rose already dominate the resource baskets of exposed regions.

Next, I explore how the composition of the export basket in the regions most exposed to China's demand shock evolved between 2000 and 2019. To this end, I estimate Equation

[9] The estimates for the two baskets need not add up to those in Table 3, since the samples differ across baskets (406 micro-regions for the resource basket and 314 for the non-resource basket).

Table 5: China's demand shock and export value - Resource and non-resource baskets

Dependent variable:	**Δ Value of exports (US$ millions)**		**%Δ Value of exports**	
	(1)	(2)	(1)	(2)
Panel A: Resource basket				
Exposure to China's demand (G_r)	6,260.470**	5,320.623**	3.235	3.381*
	(2,946.616)	(2,212.388)	(2.755)	(1.981)
Control mean (2000)	952.6	952.6	–	–
Observations	406	406	406	406
Panel B: Non-resource basket				
Exposure to China's demand (G_r)	1,090.718	-33.401	0.398	-1.921
	(986.482)	(893.907)	(0.832)	(2.677)
Control mean (2000)	2,596.2	2,596.2	–	–
Observations	314	314	314	314
Weighted	X	X	X	X
State-year fixed effects		X		X

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r. 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. The control mean is the export-weighted average of the outcome in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

(22) 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 7, suggest that there was no substantial change in the overall balance between resource products and manufactures between the regions most and least exposed to the shock. In the preferred specification, none of the manufacturing subcategories changes significantly either, and the shift from medium- to low-technology manufactures in column 1 disappears once state fixed effects are included. 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 shock studied here: unlike previous studies evaluating resource windfalls characterized by the discovery of substantial natural reserves, China's demand amplified the pre-existing advantages of historically resource-exporting regions rather than altering their comparative advantages, as the fixed endowments in the model imply. Section 7.4 shows how this result is consistent with the fall in the share of manufactures in Brazil's exports documented in Section 2.

While the overall share of resource exports remained stable, the composition within this category shifted in the most exposed regions. There is a relative reduction in the share of resource-based manufactures of about 3.2 percentage points per standard deviation of exposure, significant at the 5% level, coupled with an increase of about 2.7 percentage

Table 6: China's demand shock and export concentration - Resource and non-resource baskets

Dependent variable:	**Δ Lines**		**Δ HHI**	
	(1)	(2)	(1)	(2)
Panel A: Resource basket				
Exposure to China's demand (G_r)	-26.160	-42.571	0.139	0.115**
	(24.824)	(34.026)	(0.101)	(0.054)
Control mean (2000)	92.8	92.8	0.431	0.431
Observations	406	406	406	406
Panel B: Non-resource basket				
Exposure to China's demand (G_r)	98.415	-35.853	-0.034	0.286
	(114.043)	(53.926)	(0.218)	(0.179)
Control mean (2000)	313.4	313.4	0.257	0.257
Observations	314	314	314	314
Weighted	X	X	X	X
State-year fixed effects		X		X

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r. 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. The control mean is the export-weighted average of the outcome in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

points in the share of primary product exports, significant at the 10% level, which correspond to about 11% and 13% of their weighted average shares in 2000. This is evidence of a "primarization" within the resource basket, as predicted by part (ii) of Proposition 1, reflecting 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. In the model, this happens because the commodities whose prices China raised gain share, while resource-based manufactures, which do not share in the price boom, lose it.

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, which part (iii) of Proposition 1 predicts, since raw commodities are among the least complex products. I test this prediction in the following subsection.

Table 7: China's demand shock and export shares

Classification	Control mean	Estimated coefficients	
	2000	(1)	(2)
Resource	**0.493**	**0.004**	**-0.035**
		(0.056)	**(0.039)**
Primary	0.211	0.123	0.190*
		(0.125)	(0.113)
Resource-based	0.282	-0.119	-0.225**
		(0.101)	(0.102)
Manufactures	**0.507**	**-0.004**	**0.035**
		(0.056)	**(0.039)**
Low-Tech	0.121	0.080*	0.038
		(0.044)	(0.036)
Medium-Tech	0.258	-0.119**	-0.004
		(0.049)	(0.054)
High-Tech	0.129	0.036	0.002
		(0.031)	(0.008)
Weighted		X	X
State-year fixed effects			X
Observations		424	424

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r. 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. The control mean is the export-weighted average share in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.3 Export sophistication and complexity

To examine whether China's demand shock led to changes in the complexity of export baskets, I use the two measures described in Section 4: the export sophistication index in Equation (16) (Hausmann et al., 2007; Jarreau & Poncet, 2012) and the complexity index in Equation (17) (Hidalgo & Hausmann, 2009). Part (iii) of Proposition 1 predicts that the complexity of the export basket declines in more exposed regions, mainly because primarization shifts the basket toward raw commodities, which are among the least

complex products. These measures help determine whether the shifts in the concentration and composition of local Brazilian export baskets documented above are associated with a decline in the average sophistication and complexity of exported goods.

I estimate Equation (22) with the change in each index between 2000 and 2019 as the dependent variable, using the log of the sophistication index, $\Delta \ln S_r$, as is standard in this literature (Hausmann et al., 2007; Jarreau & Poncet, 2012), and the level of the complexity index, ΔC_r. The findings, presented in Table 8, reveal a relative decrease in the sophistication of the export baskets of micro-regions most exposed to the increased Chinese demand compared to less exposed areas. The effect emerges once state fixed effects are included, so it comes from comparisons between micro-regions within the same state. In column 2, a one-standard-deviation increase in exposure lowers export sophistication by about 2.8 percent. Since the sophistication of each product is held fixed, this decline reflects a shift in the composition of export baskets toward less sophisticated products, consistent with the primarization documented above. The complexity index also declines in more exposed regions, by about 0.05 product-level standard deviations per standard deviation of exposure in column 2, but this estimate is imprecise and not statistically significant. Both indices therefore move in the direction predicted by the model, although only the decline in sophistication is statistically significant.

Heresi (2023) finds that resource booms can lower average productivity by reallocating market share within manufacturing, and the shift documented here raises a similar concern within the booming sector itself. In the static model, however, the shift carries no cost, since regional income rises with the shock (Proposition 2). Whether it hinders long-term development depends on how the complexity of the export basket affects the accumulation of capabilities in these regions, which I examine in Section 8.

Table 8: China's demand shock, export sophistication and complexity

Dependent variable:	**Δ Log export sophistication (PWT)**		**Δ Export complexity (PCI)**	
	(1)	(2)	(1)	(2)
Exposure to China's demand (G_r)	-0.020	-0.198**	-0.493	-0.332
	(0.052)	(0.083)	(0.325)	(0.227)
Control mean (2000)	–	–	-0.115	-0.115
Weighted	X	X	X	X
State-year fixed effects		X		X
Observations	424	424	424	424

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1 of each outcome, observations are weighted by total exports in 2000, and column 2 adds state fixed effects. The control mean is the export-weighted average of the complexity index in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

6.4 Employment variables

The findings presented thus far show changes in the export baskets of regions most exposed to China's demand shock compared to those less exposed. 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, which allows me to test the predictions of Proposition 2 for the regional economy.

To explore these labor market effects, I estimate Equation (22) for changes between 2000 and 2010, the most recent year for which comprehensive micro-data from the Brazilian Demographic Census are available. I use the same measure of exposure, G_r, as in the previous subsections, so that the labor market results are directly comparable with those for export baskets. This allows for an evaluation of whether China's demand shock led to structural change in local labor markets, through sectoral employment shifts or wage adjustments, as the model predicts.

Following Costa et al. (2016), I first examine aggregate labor market outcomes. Table 9 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. In the preferred specification, regions most exposed to China's demand show no significant variation in log average hourly wages compared to less exposed localities. This is what part (iii) of Proposition 2 predicts, since the regional wage responds in proportion to the share of exports in local income, which is small in most micro-regions. The effect of China's demand shock on the aggregate employment rate is positive, about 0.5 percentage points per standard deviation of exposure, but statistically significant only at the 10% level in the specification that includes state fixed effects.

Table 9: Commodity boom, employment and remuneration — aggregate results

Dependent variable:	**Δ Log average hourly wages**		**Δ Employment share**	
	(1)	(2)	(1)	(2)
Exposure to China's demand (G_r)	0.090*	0.032	0.024	0.039*
	(0.051)	(0.029)	(0.024)	(0.021)
Control mean (2000)	1.754	1.754	0.585	0.585
Weighted	X	X	X	X
State-year fixed effects		X		X
Observations	424	424	424	424

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the population in 2000. Column 2 adds state-year fixed effects to column 1. The control mean is the population-weighted average of the outcome in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Next, I assess changes in local employment composition across sectors by estimating

the specification from Equation (22), 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. Part (ii) of Proposition 2 makes a similar prediction: as the regional wage rises, employment falls in domestic tradables and in manufactured exports that face little additional demand from China, so manufacturing's share of employment should decline. Table 10 presents the results for changes in sectoral employment shares between 2000 and 2010 across Brazilian micro-regions.

Table 10: Commodity boom, sectoral employment and remuneration

Dependent variable:	**Δ Employment share**		**Δ Log average hourly wages**	
	(1)	(2)	(1)	(2)
Panel A: Primary sector				
Exposure to China's demand (G_r)	0.070	0.049	0.809**	0.548***
	(0.044)	(0.032)	(0.390)	(0.127)
Control mean (2000)	0.150	0.150	1.340	1.340
Panel B: Manufacturing sector				
Exposure to China's demand (G_r)	-0.030	-0.038***	0.061	-0.021
	(0.019)	(0.012)	(0.054)	(0.046)
Control mean (2000)	0.148	0.148	1.698	1.698
Panel C: Services (nontraded) sector				
Exposure to China's demand (G_r)	-0.047	-0.028	0.122***	0.066**
	(0.031)	(0.029)	(0.045)	(0.026)
Control mean (2000)	0.688	0.688	1.856	1.856
Panel D: Residual sector				
Exposure to China's demand (G_r)	0.007	0.017**	0.010	-0.040
	(0.011)	(0.007)	(0.132)	(0.087)
Control mean (2000)	0.013	0.013	1.743	1.743
Observations	424	424	424	424
Weighted	X	X	X	X
State-year fixed effects		X		X

Notes: Unit of analysis r is a micro-region. Changes between the 2000 and 2010 Censuses. Reduced-form estimates on exposure G_r. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. In column 1, observations are weighted by the population in 2000. Column 2 adds state-year fixed effects to column 1. The control mean is the population-weighted average of the outcome in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

In Panels A and C of Table 10, 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 coefficient for the primary sec-

tor points in the expected direction, the absence of significant changes in the employment share of the 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). For services, the model does not predict a clear sign, since non-traded employment rises only when regional income grows faster than the wage. In contrast, Panel B reveals a statistically significant decline in the share of manufacturing employment in regions more exposed to the shock compared to less exposed counterparts, as Proposition 2 predicts. A one-standard-deviation increase in exposure lowers manufacturing's share of employment by about 0.5 percentage points, or 4% of its weighted average in 2000.

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 exposed to the export demand shock, there is a significant decline in manufacturing's share of employment. Panel D indicates that part of the adjustment appears to have occurred within the residual category of the 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 the share of manufacturing employment is accompanied by a modest increase in the share of individuals in these unspecified positions in the regions most exposed to the shock.

Table 10 further investigates changes in average wages across various sectors by applying long differences to log average wages in the primary, manufacturing, service, and residual sectors. The results reveal a significant wage impact of China's demand shock, particularly in the primary and service sectors, where a one-standard-deviation increase in exposure raises average hourly wages by about 8% and 1%, respectively, while wages in manufacturing do not change significantly. This suggests that while China's demand shock predominantly raises wages in directly affected sectors, such as agriculture and extractive industries, it also has positive spillover effects on wages in indirectly linked sectors. The pattern is consistent with part (i) of Proposition 2. Since the model has a single regional wage, it attributes differences across sectors to factor returns, which sectoral wages in the Census can only approximate. In the model, commodity rents rise with world prices, and the returns to local businesses in the non-traded sector rise with local income, while the returns to the factor specific to domestic tradables fall.

Overall, the findings on employment dynamics following China's demand shock suggest that the significant increase in the value and concentration of primary product exports in the most exposed regions does not correspond with a proportional rise in employment shares. Instead, the main impact manifests in wages. There is a marked increase in average hourly wages within the primary sector, which the model attributes to higher returns to land and deposits, given that the aggregate average wage barely

moves. Additionally, consistent with Corden and Neary (1982) and Corden (1984), there is a significant rise in service sector wages in regions most exposed to the export demand surge, indicating positive income spillovers from the primary to non-traded sectors.

7 Matching the Model to the Evidence

Section 6 showed that the signs predicted by the model hold in the data. This section asks how much of these effects the model generates when it is fed with the shocks measured in Section 4 and with each region's 2000 export basket. Apart from the elasticity of world commodity markets, which I report over a range, no parameter is chosen to fit the regional effects.

7.1 Procedure and calibration

For each micro-region, I start from its 2000 export basket at the HS4 level. The gravity shocks ψ_k, estimated at the HS4 level with the gravity equation of Section 4, China's 2000 share of world imports, and Brazil's 2000 share of exports sold to China give each product's world price change and change in market access (equations (5) and (6)). Each region's accounts come from IBGE's 2002 municipal value added, with services and public administration as non-traded goods and agriculture and industry, net of exports, as domestic tradables. Solving for regional income and the wage (equations (4) and (8)) gives the growth of every product in the basket (Table 1), and therefore each region's 2019 basket and income. As in Section 3, the regional equilibrium is solved to first order. Since the product-level responses in Table 1 are log-linear, the approximation affects only the regional wage and income, which respond little in most regions. I then regress these model-implied changes on G_r exactly as in the data.

Table 11 lists the parameters, taken from the literature or set to simple benchmarks. The parameter that matters most is the elasticity of world commodity markets, η_W, which governs how much China's demand raises world prices and scales every outcome, so I report results for $\eta_W = 0.5$, 1 and 2.[10] With $\eta_W = 1$, the implied world price changes track observed unit values for the commodity that matters most: the model implies an increase of 109 log points for iron ore between 2000 and 2019, and the data show 100. I also set $\eta_k = 1$, which shuts down the input-cost channel for resource-based manufactures. This simplifies the computation and, if anything, understates the primarization the model generates.

[10] I present a sensitivity analysis of each outcome to every parameter in the Online Appendix.

Table 11: Calibration

Parameter	*Description*	*Value*	*Source*
α	Labor share in commodity production	0.25	Filippi et al. (2026)
γ	Commodity input share, resource-based manufactures	0.5	Benchmark
c_L	Local input share, differentiated goods	0.4	Bustos et al. (2022)
σ_k	Elasticity of substitution across varieties	5	Simonovska & Waugh (2014)
η_k	Elasticity of substitution across products	1	Benchmark
ε	Elasticity of regional labor supply	1	Benchmark
α_T, α_N	Labor shares, domestic tradables and non-traded goods	0.5, 0.6	Benchmark
β_N	Spending share on non-traded goods	By region	IBGE value added, 2002
η_W	Elasticity of world commodity markets	0.5, 1, 2	Range

Notes: The shocks ψ_k come from the gravity equations in Section 4. China's share of world imports, μ_k, and Brazil's share of exports sold to China, χ_k, are measured in 2000 from CEPII-BACI and SISCOMEX, and the export shares s_{rk} come from SISCOMEX in 2000.

7.2 Export baskets

Table 12 compares the reduced forms generated by the model with those in the data. The model brackets the effects on export value and concentration around $\eta_W = 1$: the value estimate implies a world elasticity somewhat below 1 and the concentration estimate one somewhat above it. The model holds the set of exported lines fixed, consistent with the absence of an effect on the number of lines in the data, so exposed regions concentrate because the products tied to their endowments are those whose prices China raised. The model also generates the declines in sophistication and complexity that Proposition 1(iii) predicts. At $\eta_W = 1$, it accounts for about a third of the decline in sophistication, 1.0 percent against 2.8 percent per standard deviation of exposure, and for 18 percent of the point estimate for the PCI. At $\eta_W = 0.5$, these shares rise to about four-fifths and 37 percent. That world prices acting on fixed endowments generate only part of the decline in sophistication suggests that other forces also lowered the sophistication of exposed baskets, one reason to look beyond the static framework in Section 8.

7.3 Regional income

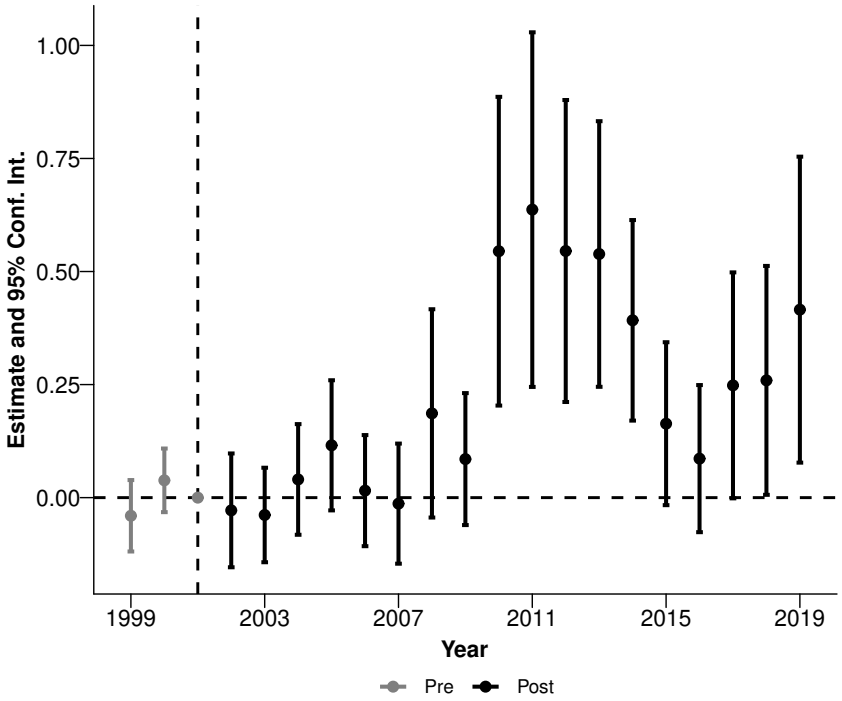
Proposition 2(iii) also predicts that regional income rises with exposure. I test this prediction with GDP per capita, which, unlike the Census variables, is available every year, so its response can be traced over the whole period and compared with the model's prediction. Figure 13 reports the event study of Equation (23) for log GDP per capita, with micro-regions weighted by their 2000 exports, as in the export outcomes. The coefficients are close to zero before 2001 and remain so until 2009. Income in more exposed regions then rises sharply, peaks in 2011, at 9.4 percent per standard deviation of exposure, and remains 6.0 percent higher in 2019.

Table 12: Regional effects of China's demand shock on export baskets: data and model

	Data	Model		
		$\eta_W = 0.5$	$\eta_W = 1$	$\eta_W = 2$
%Δ Value of exports	0.504*	1.705	0.323	0.096
Δ HHI	0.026***	0.055	0.031	0.015
Δ Log sophistication	-0.028**	-0.022	-0.010	-0.004
Δ PCI	-0.047	-0.017	-0.009	-0.002

Notes: Effects of a one-standard-deviation increase in exposure G_r between 2000 and 2019. The data column reports the column 2 estimates for the corresponding outcomes in Tables 3, 4, and 8. The model columns apply the same regression to the changes the model generates from each region's 2000 export basket. All regressions include state-year fixed effects and are weighted by the total exports in 2000, with standard errors adjusted for 129 meso-region clusters. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 13: Dynamic effects of China's demand shock on GDP per capita



Notes: Each point is a coefficient $\hat{\beta}_\tau$ from Equation (23), with log GDP per capita as the dependent variable, 1999–2019, and 2001 as the reference year. The regressions include micro-region and state-year fixed effects, observations are weighted by total exports in 2000, and standard errors are adjusted for 129 meso-region clusters.

The model generates most of this gain, although income is not targeted. Since GDP per capita is deflated with national prices, its counterpart in the model is nominal income per worker, which rises by 3.8 percent at $\eta_W = 1$, about two-thirds of the effect in the data in 2019, and by 1.9 to 7.6 percent as η_W ranges from 2 to 0.5. Most of the welfare gain comes from world prices. At $\eta_W = 1$, regional real income rises by 4.6 percent, of which 3.4 percentage points are the terms-of-trade gain on commodity exports and 1.1 points the income of workers who move into the region. Per worker, real income rises by 2.1 percent.

The model is also consistent with the Census results. With micro-regions weighted by population, as in Table 9, the model's regional wage rises by 1.2 percent and the wage in the data by an insignificant 0.45 percent, both small because exports are a small share of income in most regions. Employment in domestic tradables, which include agriculture and industry, falls by 2.4 percent, consistent in direction with the decline in manufacturing's share of employment.

7.4 The national basket

Section 2 showed that manufactures fell from half of Brazil's exports in 2000 to a quarter in 2019, while Section 6 found no change in the manufacturing share of exposed regions relative to less exposed ones. Summing the model-implied 2019 exports of all regions helps reconcile the two (Table 13). With only the channels in the model and endowments held at their 2000 levels, China's demand accounts for a third of the national decline at $\eta_W = 1$ and for all of it at $\eta_W = 0.5$. Most of this decline comes from export weight shifting toward the regions whose exports grew, rather than from changes within regions, which a comparison across regions does not capture. In the data, about 60 percent of the decline comes from shifts between regions and about 30 percent from changes within them, and the model also attributes more of the decline to shifts between regions.

Table 13: Brazil's export basket by Lall category, 2000–2019: actual and China-driven change

	Actual			**Model, change**		
	2000	2019	Change	$\eta_W = 0.5$	$\eta_W = 1$	$\eta_W = 2$
Manufactures (low, medium, high tech)	0.507	0.254	-0.253	-0.253	-0.088	-0.035
Resource goods (primary, resource-based)	0.493	0.746	0.253	0.253	0.088	0.035

Notes: Shares of Brazil's exports by Lall (2000) category. The model columns apply the model to each micro-region's 2000 HS4 export basket and sum the implied 2019 exports over micro-regions. No parameter is chosen to match these changes.

In sum, fed with the measured shocks and with parameters from the literature or simple benchmarks, the model reproduces the effects of China's demand on export value and concentration, generates between a fifth and a third of the declines in complexity and sophistication, accounts for two-thirds of the income gain, and explains a third of the

national decline in manufactures. Since the model attaches no static cost to the shift in the basket, whether the shift matters depends on what the export basket does to capabilities over time, which Section 8 examines, taking the income path in Figure 13 as the static gain.

8 The Long Run: A Break-Even Elasticity

The evidence so far shows static gains for Brazil's exposed regions: their exports grew, wages rose in the primary and service sectors, and GDP per capita increased. The concern that runs from Prebisch (1949) and Singer (1950) to the modern literature on export sophistication is about something else, namely what a region learns from what it sells. If exporting complex goods builds the capabilities that sustain growth, a basket that loses complexity may leave exposed regions less capable in the future, even as their income rises today (Hausmann et al., 2007; Hidalgo & Hausmann, 2009; Matsuyama, 1992). How strongly export complexity feeds into growth is not pinned down in the literature. Rather than choosing a value, I ask how strong this learning effect would need to be for China's demand to lower the present value of income in exposed regions, and compare that threshold, the break-even elasticity β^*, with published estimates.

8.1 Capability and income

I let productivity in product k depend on a region's capabilities, Z_r, with $\widehat{A}_{rk} = \kappa_k \widehat{Z}_r$, where κ_k is the complexity level of product k introduced in Section 3, so that a shortfall in capabilities hurts complex products the most. Following Atkin et al. (2026), capabilities accumulate relative to a frontier Z_t^* according to the complexity of the export basket:

$$\ln Z_{r,t+1} - \ln Z_{t+1}^* = \rho\big(\ln Z_{r,t} - \ln Z_t^*\big) + \beta\big(\Theta_{r,t} - \bar{\Theta}\big), \qquad 0 < \rho \leq 1,\ \beta > 0. \tag{24}$$

With $\rho < 1$, lagging regions catch up with the frontier (Alberola & Benigno, 2017), and because firms take Z_r as given, the market allocation can be dynamically inefficient, as in Matsuyama (1992). If the effect of the shock on complexity is $\delta_t\, G_r$, Equation (24) implies a capability loss per unit of exposure of $\beta\, l_t$, with

$$l_t = \sum_{s<t} \rho^{\,t-1-s}\,(-\delta_s). \tag{25}$$

Given ρ, the loss therefore depends only on the observed path of export complexity. Since a region that falls behind also loses ground in complex goods, which lowers its complexity further, holding δ_t fixed beyond the sample understates the loss.

I take β from growth regressions of GDP per capita on export sophistication, so that the loss is in the same units as the static gain. Read this way, Equation (24) is the conditional

convergence regression from which the published estimates are obtained, with capabilities measured by GDP per capita. When the dependent variable is average annual growth over T years, the coefficient on initial income in that regression is $(\rho^T - 1)/T$, so each estimate of β comes with its own rate of catch-up. The effect of exposure on GDP per capita, g_t, is observed through 2019 and already reflects any capability lost along the way. After 2019, I hold this observed gain at its 2015–2019 average, $\bar{g}$, which nets out the loss accumulated by then, and subtract only the further loss. Per unit of exposure, the net effect is

$$n_t = \begin{cases} g_t, & t \leq 2019, \\ \bar{g} - \beta\,(l_t - \bar{l}), & t > 2019, \end{cases} \tag{26}$$

where $\bar{l}$ is the average of l_t over 2015–2019. Since n_t is linear in β, its present value is zero at

$$\beta^* = \frac{\sum_{t \leq H} d_t\, a_t}{\sum_{2019 < t \leq H} d_t\,(l_t - \bar{l})}, \qquad a_t = \begin{cases} g_t, & t \leq 2019, \\ \bar{g}, & t > 2019, \end{cases} \tag{27}$$

where d_t is the discount factor and H the horizon. If learning is weaker than β^*, the static gains dominate in present value. If it is stronger, the long-run cost does.

8.2 Results

The complexity path δ_t comes from regressing, for each year from 2001 to 2019, the change in a region's complexity index C_r relative to 2000 on G_r, with state-year fixed effects and export weights. Over 2015–2019, a one-standard-deviation increase in exposure lowers complexity by 0.044, in line with the estimate in Table 8, and I hold this gap after 2019. The static gain g_t is the GDP per capita path in Figure 13, held after 2019 at its 2015–2019 average of 3.4 percent per standard deviation. For the learning elasticity, I use three published estimates of the effect of log export sophistication on growth: 0.05 from Hausmann et al. (2007), and 0.079 and 0.15 from the cross-section and fixed-effects estimates of Jarreau and Poncet (2012). I convert them to complexity units with the slope of log export sophistication on the complexity index across Brazilian micro-regions before the shock. One unit of the index corresponds to about 0.5 log points of sophistication, so the three estimates become 0.025, 0.039, and 0.075. Because these regressions condition on initial income, I pair them with catch-up at 2 percent per year ($\rho = 0.98$), within the range of roughly 1 to 6 percent implied by the coefficients on initial income in the cross-section regressions of Hausmann et al. (2007) and Jarreau and Poncet (2012). Present values use a 3 percent discount rate and run to 2100.

With this common rate of catch-up, the break-even elasticity is 0.082 with complexity and 0.143 with sophistication (Table 14), in both cases at the upper edge of the published range. With complexity, the largest published estimate, the fixed-effects estimate of Jarreau

and Poncet (2012), falls just below β^*, so the long-run cost roughly offsets the static gain in present value, and the net effect on the level of GDP per capita turns negative by 2032. With the smaller elasticities, it turns negative only in 2050 and 2088, too late to offset the gains of the boom years.[11] With sophistication, I apply the published elasticities directly to its log. Over 2015–2019, a one-standard-deviation increase in exposure lowers sophistication by 2.3 percent, in line with the estimate in Table 8. In this case, β^* lies just below the fixed-effects estimate of Jarreau and Poncet (2012), 0.15, so under that estimate the long-run cost slightly exceeds the static gain. The two measures therefore place the break-even elasticity on either side of the largest published estimate.

That estimate, however, comes from a regression with much faster catch-up. In the fixed-effects regression of Jarreau and Poncet (2012), the coefficient on initial income, -0.139 for growth over four-year periods, implies catch-up of about 18 percent per year ($\rho \approx 0.82$). The long-run effect of sophistication on income in that regression, $0.150/0.139 \approx 1.1$, is about a seventh of the $0.15/0.02 = 7.5$ that $\rho = 0.98$ attributes to it, while for their cross-section estimate the two are close, 3.8 and 4.0. With catch-up this fast, most of the capability loss occurs within a few years and is already part of the observed gain, so β^* rises to 1.035 with complexity and 1.342 with sophistication. Paired with the rate of catch-up estimated alongside it, none of the published elasticities reaches the break-even value.

Without catch-up, β^* falls to 0.046 with complexity and 0.086 with sophistication, inside the published range in both cases, although all the regressions behind these estimates find catch-up. A shorter horizon or a higher discount rate raises β^*, because the gains arrived early and the cost arrives late. Using 2019 levels instead of 2015–2019 averages also raises it, to 0.122 and 0.187, since the gain in 2019, 6.0 percent, was well above the 3.4 percent average.

In sum, the short-run gains from China's demand could be offset in the long run if learning from the export basket is strong. With a common rate of catch-up, the break-even elasticity sits at the upper edge of the range the growth literature has estimated, and once each estimate is paired with the rate of catch-up estimated alongside it, the threshold lies above all of them. The evidence therefore does not show that China's demand made Brazil's exposed regions poorer in the long run, but it cannot rule this out.

9 Concluding remarks

This paper examines how a raw-biased demand shock reshapes the exports of resource-rich developing economies, and whether the resulting shift toward raw materials is costly. China's integration into world trade generated such a shock, as its imports grew much more

[11] The projected paths of the net effect are shown in the Online Appendix.

Table 14: Break-even learning elasticity β^*

	To 2050, 3%	To 2100, 3%	To 2100, 5%
Panel A: Complexity (PCI)			
Baseline ($\rho = 0.98$, 2015–2019 averages)	0.148	0.082	0.132
No catch-up ($\rho = 1$)	0.100	0.046	0.079
Catch-up as in JP fixed effects ($\rho = 0.82$)	1.292	1.035	1.385
2019 levels instead of 2015–2019 averages	0.222	0.122	0.186
Published estimates: 0.025 (HHR), 0.039 (JP cross-section), 0.075 (JP fixed effects)			
Panel B: Sophistication			
Baseline ($\rho = 0.98$, 2015–2019 averages)	0.260	0.143	0.230
No catch-up ($\rho = 1$)	0.187	0.086	0.148
Catch-up as in JP fixed effects ($\rho = 0.82$)	1.696	1.342	1.813
2019 levels instead of 2015–2019 averages	0.340	0.187	0.285
Published estimates: 0.05 (HHR), 0.079 (JP cross-section), 0.15 (JP fixed effects)			

Notes: HHR refers to Hausmann et al. (2007) and JP to Jarreau & Poncet (2012). β^* is the learning elasticity per year at which the present value of the net effect on GDP per capita is zero (Equation (27)), per unit of the complexity index in Panel A and per log point of sophistication in Panel B. Column headers give the horizon and the discount rate. Published estimates are per log point of sophistication, converted to complexity units in Panel A. The coefficients on initial income imply catch-up of roughly 1 to 6 percent per year in the cross-section regressions of HHR and JP and of about 18 percent per year ($\rho = 0.82$) in the fixed-effects regression of JP.

in raw commodities than in their processed counterparts. The resource boom that followed reshaped the value, concentration, composition, and sophistication of the export baskets of local economies in Brazil, a key example of a resource-rich developing country. I develop a model in which this demand raises the world prices of the commodities that already dominate the export baskets of the regions endowed with them, while manufactures, including those that process these commodities, do not share in this price boom. Guided by the model, I identify the causal effects of China's demand with a shift-share instrument that combines the growth of its demand for each product, recovered from gravity equations that exclude Brazil, with the *ex-ante* composition of regional export baskets.

The causal estimates support the model's predictions for export baskets. A one-standard-deviation increase in exposure raised export value by about 35 percent of the average in 2000 and the Herfindahl index of the basket by about 10 percent. Concentration rose along the intensive margin, with no change in the number of exported products, as China's demand amplified the pre-existing advantages of resource-exporting regions rather than creating new ones. These changes came from the resource basket. The share of manufactures in the exports of more exposed regions did not decline relative to less exposed ones, but within the resource basket, exports shifted toward primary products and away from resource-based manufactures. This primarization was accompanied by a decline in the sophistication of export baskets, while the complexity index moved in the same direction but imprecisely.

In local labor markets, the adjustment came through sectoral wages more than through employment. Wages rose substantially in the primary sector, which the model attributes to higher returns to land and mineral deposits, and to a lesser extent in services, as part of the higher income was spent locally. The average wage did not change significantly, as the model predicts, since exports are a small share of income in most micro-regions. The primary sector's share of employment did not rise significantly either, while manufacturing's share declined, consistent with the Dutch disease and with the model's prediction that even a small increase in the regional wage reduces employment in tradables that gain little from China's demand. This decline was accompanied by a modest increase in the share of workers in unspecified occupations, which are likely linked to the informal labor market. GDP per capita also increased in more exposed regions, rising sharply after 2009 and remaining 6 percent higher per standard deviation of exposure in 2019.

Fed with the measured shocks and with parameters from the literature or simple benchmarks, the model reproduces the effects of China's demand on export value and concentration and generates between a fifth and a third of the declines in complexity and sophistication. It also accounts for two-thirds of the increase in GDP per capita in exposed regions, a gain that comes mainly from higher world prices for their commodity exports. Finally, the model helps reconcile the regional evidence with the national decline in manufactures, from half of Brazil's exports in 2000 to a quarter in 2019. Most of this decline came from export weight shifting toward the regions whose exports grew, which a comparison across regions does not capture, and China's demand alone accounts for about a third of it in the main calibration.

Heresi (2023) finds that resource booms can lower average productivity by reallocating market share within manufacturing, and the shift toward primary products raises a similar concern within the booming sector itself. In the static model, however, this shift carries no cost, since regional income rises with the shock, and these gains arrive in the short run. Whether the shift is costly depends on what the export basket does to the capabilities of exposed regions over time. Rather than assuming how strongly export complexity feeds into growth, I build on Atkin et al. (2026) and ask how strong this learning effect would need to be for China's demand to lower the present value of income in exposed regions. With a common rate of catch-up, this break-even elasticity sits at the upper edge of published estimates (Hausmann et al., 2007; Jarreau & Poncet, 2012), and under the largest of them, the long-run cost roughly offsets the short-run gains. Once each estimate is paired with the rate of catch-up estimated alongside it, the threshold lies above all of them. The evidence therefore does not show that China's demand made Brazil's exposed regions poorer in the long run, but it cannot rule this out if learning from the export basket is stronger in Brazilian regions than in the settings behind these estimates.

The implications of this study extend beyond Brazil, to other resource-rich developing economies exposed to raw-biased demand. In these economies, commodity booms bring a

trade-off over time. The gains from higher commodity prices arrive early, while the cost of a less sophisticated export basket would arrive late and could offset them if learning from exports is strong. The case for policies that resist primarization, for instance by favoring processed over raw exports, therefore rests on evidence about the strength of this learning rather than on the shift itself.

Several questions remain open. The break-even comparison relies on elasticities estimated across countries and Chinese provinces, and direct estimates of how the export basket shapes capabilities in Brazilian regions would sharpen it. More concentrated baskets also tie the income of exposed regions more closely to commodity prices, and the volatility this brings is a cost this paper does not measure. Other channels may also matter, as recent evidence from Colombia suggests that resource booms can come with a decline in technological development (Branstetter & Laverde-Cubillos, 2024). By extending the evidence on the effects of China's rise on the Brazilian economy (Carreira et al., 2024; Cícero & Heras-Recuero, 2026; Costa et al., 2016) to the composition of local export baskets, and by linking these changes to regional income through a model, this paper offers a framework that can be applied to other commodity exporters facing similar shocks.

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A Appendix

Table A.1: Descriptive statistics at the micro-region level - Long differences

Variables	*Source*	*Mean*	*Standard Deviation*	*Min*	*Max*	*Observations*
Exposure to China's Demand						
ΔX_r	COMEXSTAT and BACI-CEPII	0.62	1.21	0.00	6.38	424
G_r	COMEXSTAT and BACI-CEPII	0.07	0.14	0.00	1.11	424
Regional Export Basket Value, 2000–2019						
Δ Export Value (US$ millions)	COMEXSTAT	333.40	1,247.64	-1,383.67	20,543.49	424
Δ Log Export Value	COMEXSTAT	1.59	2.27	-6.16	12.53	424
Regional Export Basket Concentration, 2000–2019						
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 and Complexity, 2000–2019						
Δ Log S_r (PWT)	PWT, BACI-CEPII, and COMEXSTAT	0.06	0.50	-1.84	2.10	424
Δ C_r (PCI)	BACI-CEPII and COMEXSTAT	0.04	0.66	-2.76	3.37	424
Regional Export Basket Composition, 2000–2019						
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
Labor Markets, 2000–2010						
Δ Employment Share	Census (IBGE)	0.02	0.05	-0.18	0.11	424
Δ Log Average Hourly Wage	Census (IBGE)	0.21	0.13	-0.35	0.64	424
Δ Employment Share: Primary	Census (IBGE)	-0.09	0.06	-0.32	0.04	424
Δ Employment Share: Manufacturing	Census (IBGE)	0.00	0.04	-0.17	0.14	424
Δ Employment Share: Services	Census (IBGE)	0.05	0.07	-0.09	0.30	424
Δ Employment Share: Residual	Census (IBGE)	0.04	0.02	0.00	0.19	424
Δ Log Hourly Wage: Primary	Census (IBGE)	0.29	0.23	-0.68	1.19	424
Δ Log Hourly Wage: Manufacturing	Census (IBGE)	0.19	0.20	-0.50	1.10	424
Δ Log Hourly Wage: Services	Census (IBGE)	0.15	0.12	-0.38	0.57	424
Δ Log Hourly Wage: Residual	Census (IBGE)	0.30	0.40	-3.29	1.51	424

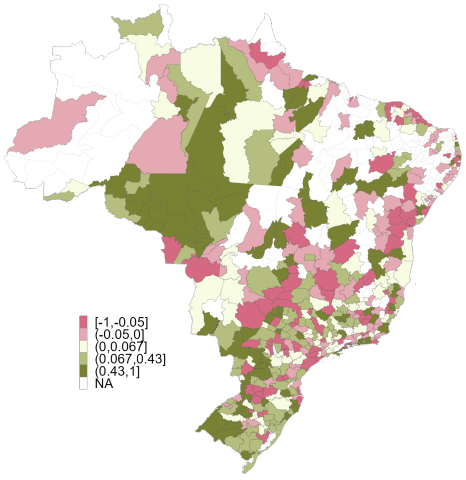
Table A.2: Descriptive statistics - Yearly dataset

Variables		*Mean*	*Standard Deviation*	*Min*	*Max*	*Observations*
Regional Export Basket Value, 1997–2019						
Export Value (US$ millions)	overall	386.822	1,214.026	0.000	22,706.823	N = 9752
	between		1,071.307	0.052	13,700.144	n = 424
	within		573.368	-6,186.174	16,066.350	T = 23
Log Export Value	overall	17.452	2.736	3.664	23.846	N = 9752
	between		2.508	9.658	23.294	n = 424
	within		1.288	6.158	22.735	T = 23
Regional Export Basket Concentration, 1997–2019						
Number of Export Lines	overall	68.454	135.589	0.000	1,079.000	N = 9752
	between		131.452	0.391	1,011.565	n = 424
	within		33.821	-294.764	501.280	T = 23
HHI	overall	0.452	0.295	0.000	1.000	N = 9752
	between		0.228	0.040	0.999	n = 424
	within		0.193	-0.427	1.214	T = 23
Regional Income, 1999–2019						
Log GDP per Capita	overall	2.468	0.830	0.061	5.528	N = 8904
	between		0.567	1.160	4.051	n = 424
	within		0.607	0.184	4.354	T = 21

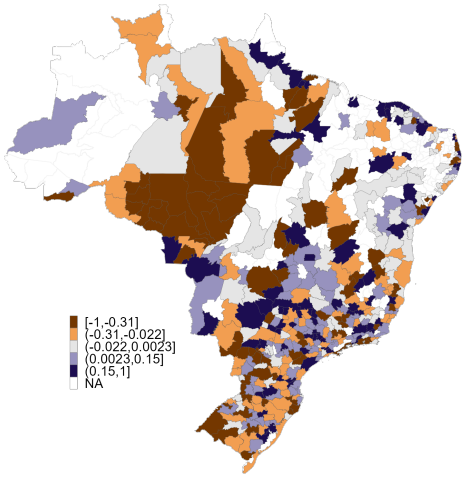
B Online Appendix

B.1 Composition of regional export baskets

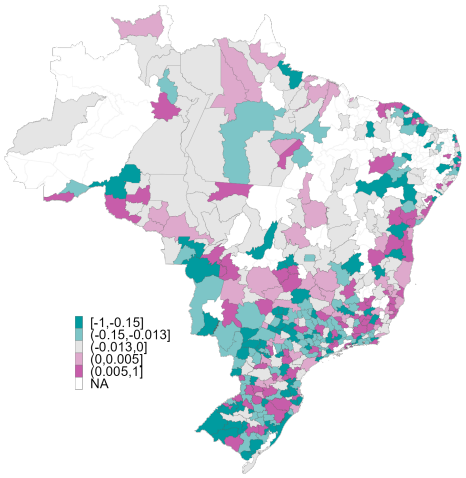
Figure B.1: Change in the share of exports by category, 2000–2019



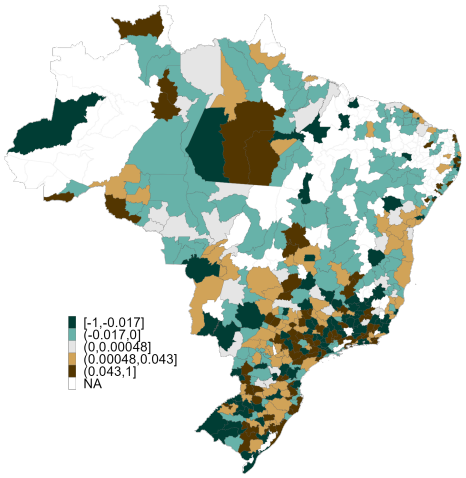
(a) Primary products



(b) Resource-based manufactures



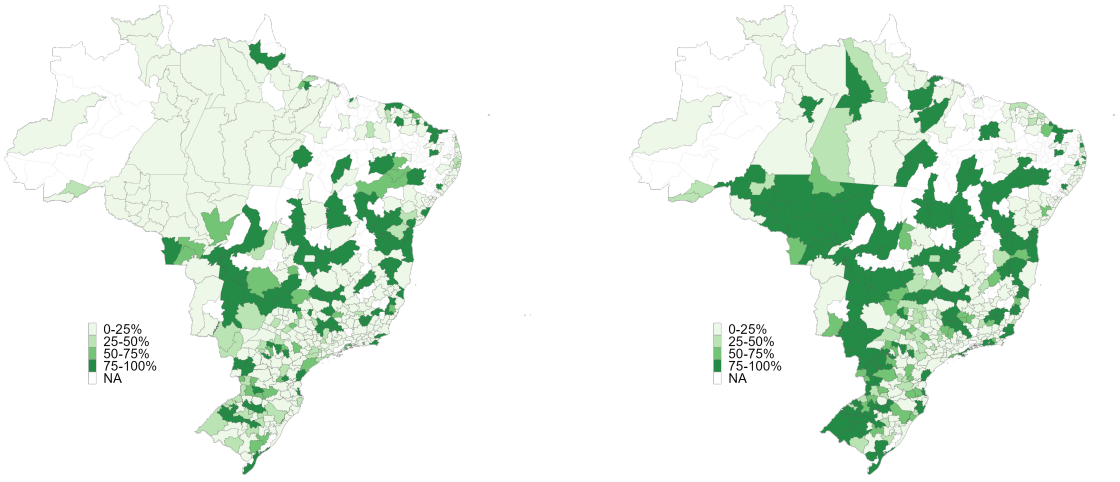
(c) Low-tech manufactures



(d) Medium-tech 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). High-tech manufactures are not shown because their change varies too little across micro-regions to map.

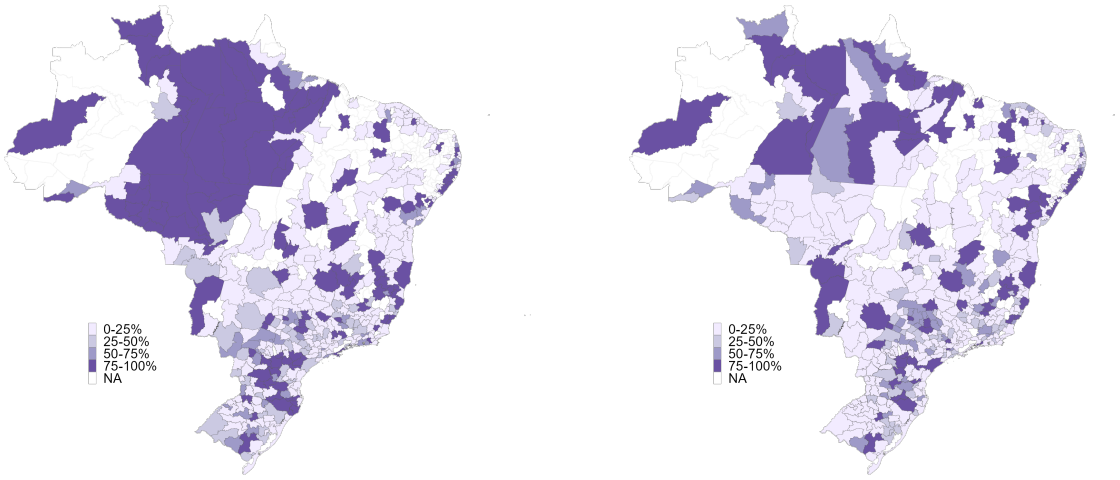
Figure B.2: Share of primary products in exports, 2000 and 2019



(a) 2000 (b) 2019

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).

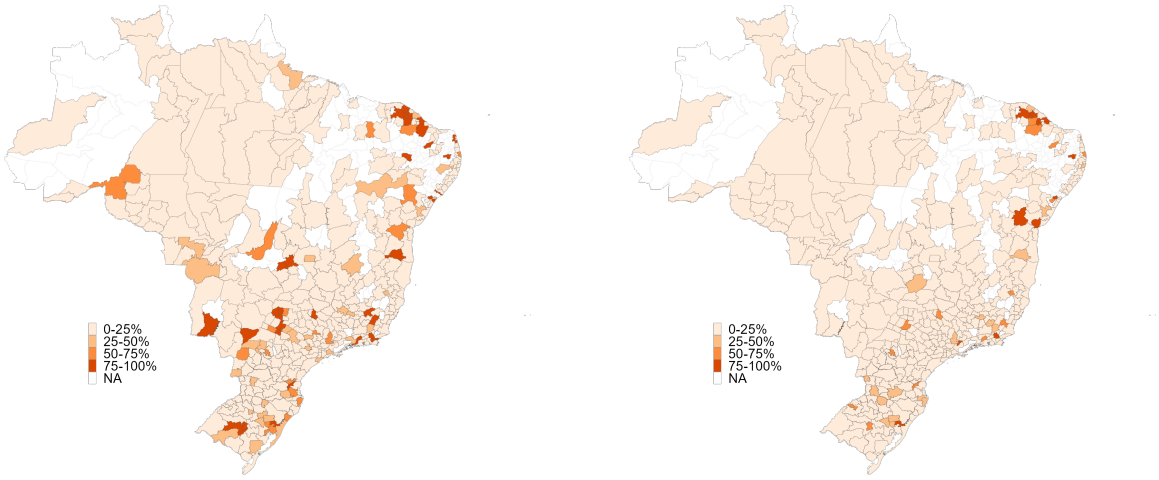
Figure B.3: Share of resource-based manufactures in exports, 2000 and 2019



(a) 2000 (b) 2019

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).

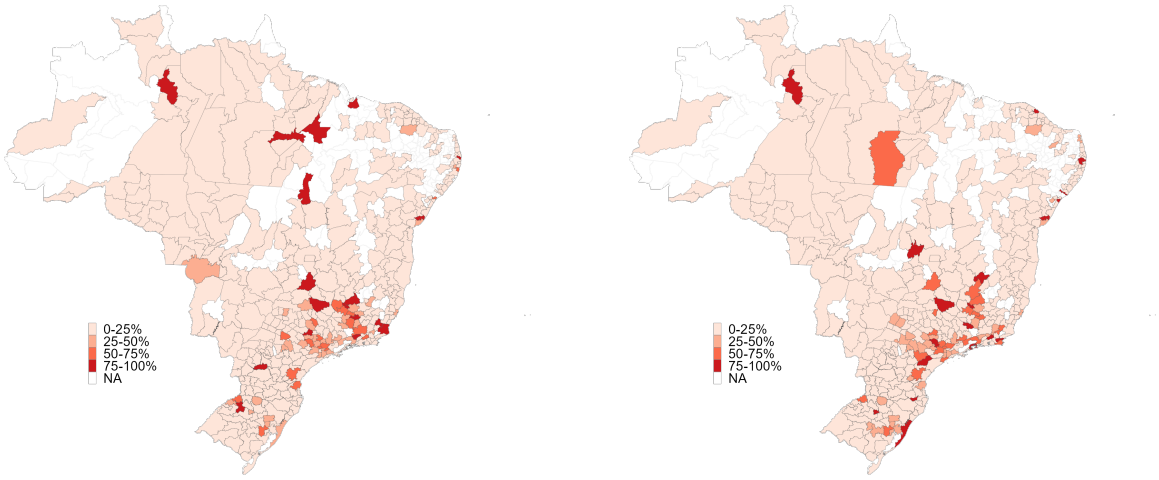
Figure B.4: Share of low-tech manufactures in exports, 2000 and 2019



(a) 2000 (b) 2019

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).

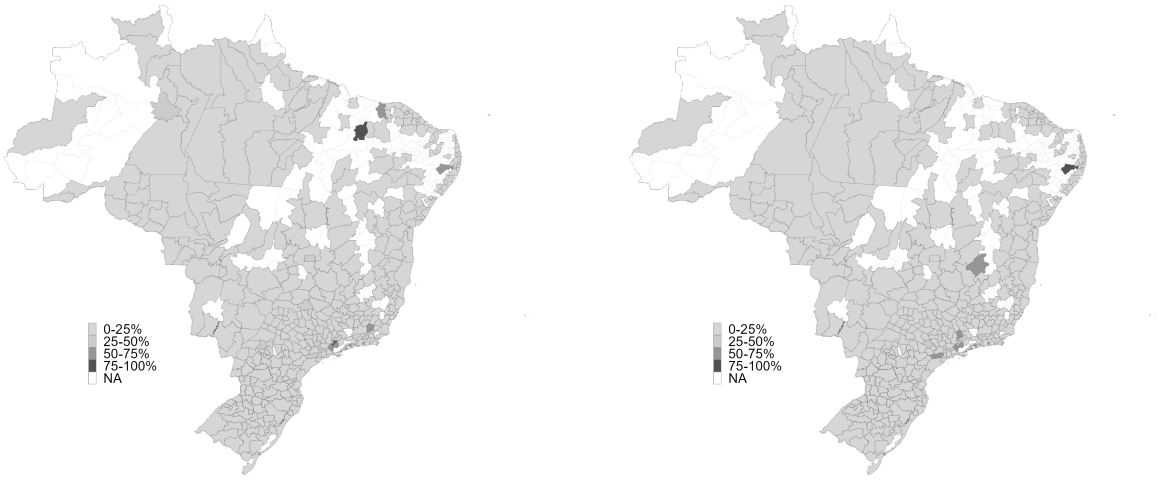
Figure B.5: Share of medium-tech manufactures in exports, 2000 and 2019



(a) 2000 (b) 2019

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).

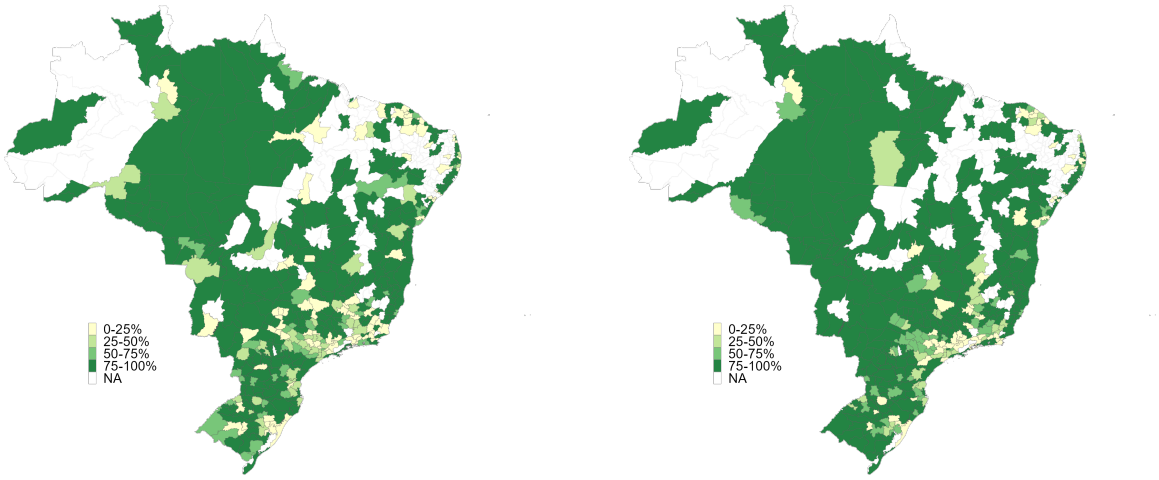
Figure B.6: Share of high-tech manufactures in exports, 2000 and 2019



(a) 2000 (b) 2019

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).

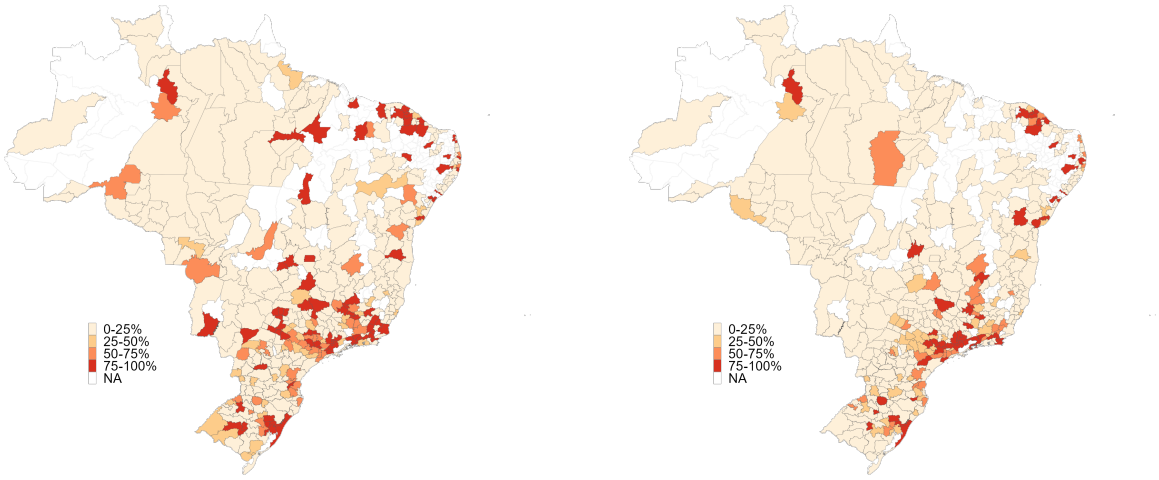
Figure B.7: Share of resource products in exports, 2000 and 2019



(a) 2000 (b) 2019

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).

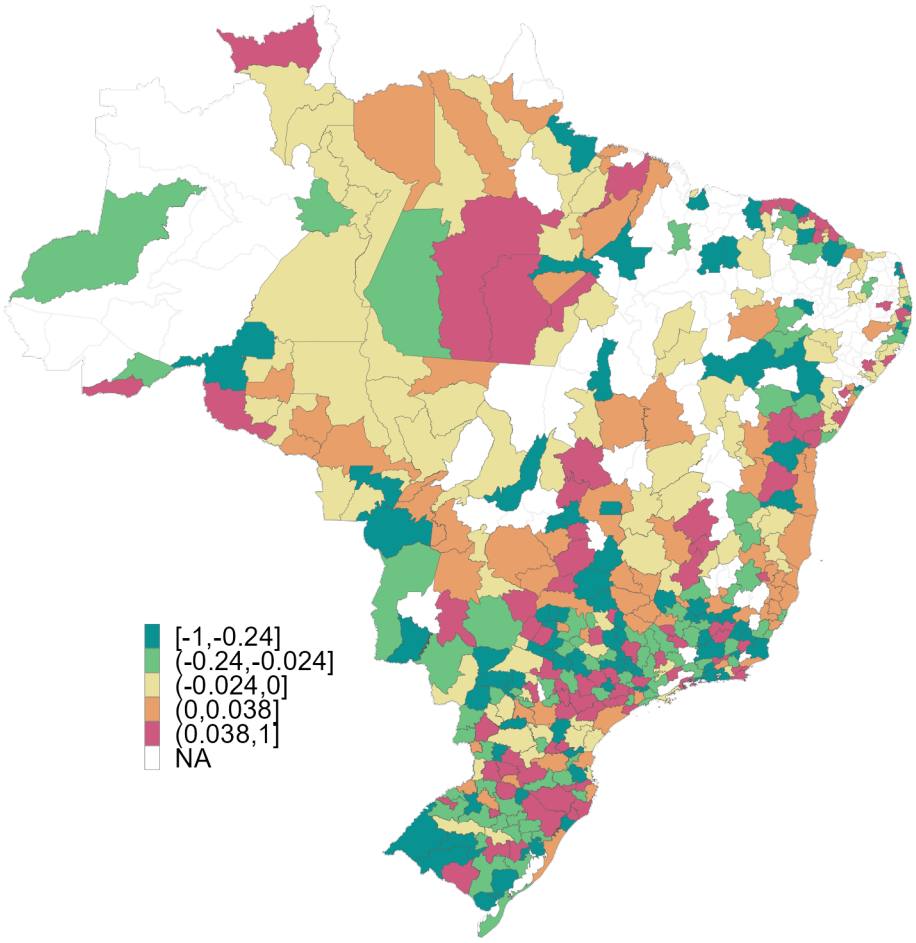
Figure B.8: Share of manufactures in exports, 2000 and 2019



(a) 2000 (b) 2019

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).

Figure B.9: Change in the share of manufactures in exports, 2000–2019

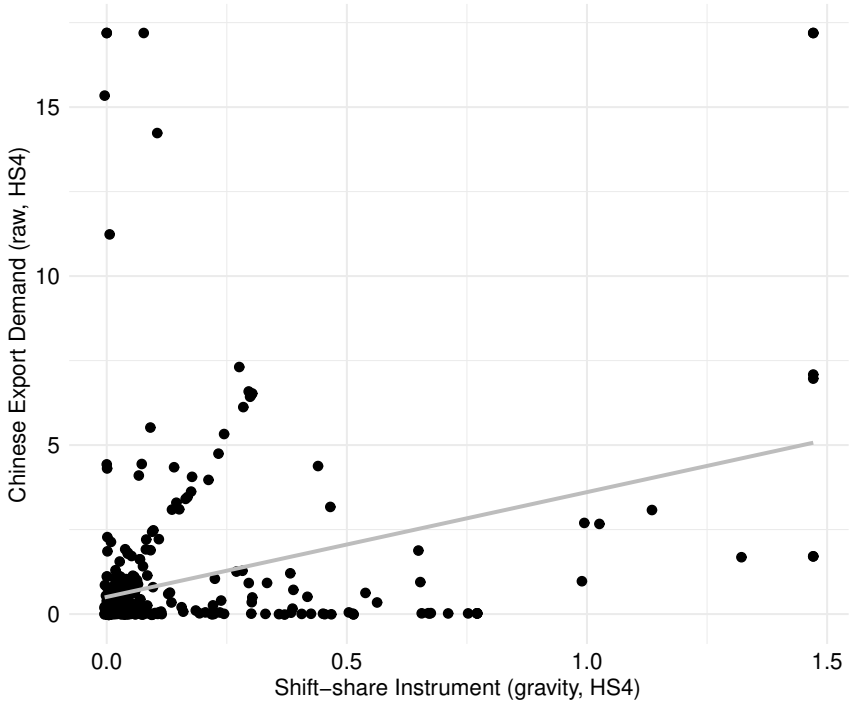


Source: Export value and composition data are based on declarations by exporters in Brazil (SISCOMEX, Ministry of Industry, Foreign Trade, and Services). Product classification follows Lall (2000).

B.2 First stage

Table B.1 reports the first-stage regressions of ΔX_r on G_r for the 424 micro-regions, with both variables built from HS2 products in Panel A, as in the main text, and from HS4 products in Panel B. Figure B.10 shows the HS4 relationship.

Figure B.10: Correlation: Chinese export demand and shift-share instrumental variable — HS4



Notes: Each dot is a micro-region. Both ΔX_r and G_r are built with HS4 products. The line is the linear fit.

B.3 2SLS estimates

Tables B.2 to B.5 report 2SLS estimates of the main results, using exposure G_r as the instrument for the growth of Chinese export demand between 2000 and 2019, ΔX_r. The first stage is in column 2 of Table 2 for the export outcomes and in column 4 for the Census outcomes.

B.4 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. Because the regional shares in G_r sum to one, each reduced form in the main text is numerically equivalent to a regression across the 96 HS2 product shocks, weighted by each product's exposure, and exposure-robust standard errors follow

Table B.1: First stage for HS2 and HS4 instruments

Dependent variable:	**Chinese export demand (ΔX_r)**			
	(1)	(2)	(3)	(4)
Panel A: HS2 (headline)				
Exposure to China's demand (G_r)	2.630***	2.995***	3.990***	4.262***
	(0.394)	(0.422)	(0.811)	(0.876)
Observations	424	424	424	424
KP F-stat	44.7	50.3	24.2	23.7
Panel B: HS4				
Exposure to China's demand (G_r, HS4)	3.426***	3.882***	3.374***	3.597***
	(0.936)	(1.176)	(0.922)	(1.051)
Observations	424	424	424	424
KP F-stat	13.4	10.9	13.4	11.7
Weighted by exports in 2000	X	X		
Weighted by population in 2000			X	X
State-year fixed effects		X		X

Notes: Unit of analysis r is a micro-region. The dependent variable is ΔX_r in Equation (18), the growth of the micro-region's exports to China between 2000 and 2019, and the regressor is exposure G_r in Equation (21). Panel B builds both with HS4 products. Columns 1–2 weight micro-regions by their exports in 2000, as in the export outcomes; columns 3–4 by their population in 2000, as in the Census outcomes. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. KP F-stat is the Kleibergen-Paap first-stage F-statistic. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.2: 2SLS estimates: export value, concentration and complexity

Dependent variable:	**Δ Value (US$ millions)**	**%Δ Value**	**Δ Lines**	**Δ HHI**	**Δ Log sophistication**	**Δ PCI**
	(1)	(2)	(3)	(4)	(5)	(6)
ΔX_r	2,204.134***	1.197*	-17.033	0.063**	-0.066**	-0.111
	(812.726)	(0.627)	(22.659)	(0.024)	(0.029)	(0.069)
Control mean (2000)	2,678.8	–	363.2	0.271	7.766	-0.115
Observations	424	424	424	424	424	424
KP F-stat	50.3	50.3	50.3	50.3	50.3	50.3
Weighted	X	X	X	X	X	X
State-year fixed effects	X	X	X	X	X	X

Notes: Unit of analysis r is a micro-region. 2SLS estimates using exposure G_r as the instrument for ΔX_r. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. Observations are weighted by the total exports in 2000, and all columns include state-year fixed effects. The control mean is the export-weighted average of the outcome in 2000. KP F-stat is the Kleibergen-Paap first-stage F-statistic. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

from that regression. The equivalence is exact for G_r without winsorizing, which differs from the baseline exposure in only 8 of the 424 micro-regions.

Table B.3: 2SLS estimates: resource and non-resource baskets

Dependent variable:	**Δ Value (US$ millions)**	**%Δ Value**	**Δ Lines**	**Δ HHI**
	(1)	(2)	(3)	(4)
Panel A: Resource basket				
ΔX_r	1,912.007**	1.215*	-15.298	0.041**
	(818.236)	(0.712)	(12.845)	(0.021)
Control mean (2000)	952.6	–	92.8	0.431
Observations	406	406	406	406
KP F-stat	85.6	85.6	85.6	85.6
Panel B: Non-resource basket				
ΔX_r	-10.167	-0.585	-10.913	0.087
	(273.107)	(0.794)	(13.569)	(0.074)
Control mean (2000)	2,596.2	–	313.4	0.257
Observations	314	314	314	314
KP F-stat	11.7	11.7	11.7	11.7
Weighted	X	X	X	X
State-year fixed effects	X	X	X	X

Notes: Unit of analysis r is a micro-region. 2SLS estimates using exposure G_r as the instrument for ΔX_r. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. Observations are weighted by the total exports in 2000, and all columns include state-year fixed effects. The control mean is the export-weighted average of the outcome in 2000. KP F-stat is the Kleibergen-Paap first-stage F-statistic. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4: 2SLS estimates: export shares

Dependent variable: Δ Export share	**Resource**	**Primary**	**Resource-based**	**Manufactures**	**Low-tech**	**Medium-tech**	**High-tech**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
ΔX_r	-0.012	0.063*	-0.075**	0.012	0.013	-0.001	0.001
	(0.013)	(0.034)	(0.030)	(0.013)	(0.011)	(0.018)	(0.003)
Control mean (2000)	0.493	0.211	0.282	0.507	0.121	0.258	0.129
Observations	424	424	424	424	424	424	424
KP F-stat	50.3	50.3	50.3	50.3	50.3	50.3	50.3
Weighted	X	X	X	X	X	X	X
State-year fixed effects	X	X	X	X	X	X	X

Notes: Unit of analysis r is a micro-region. 2SLS estimates using exposure G_r as the instrument for ΔX_r. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. Observations are weighted by the total exports in 2000, and all columns include state-year fixed effects. Export shares follow Lall (2000). The control mean is the export-weighted average share in 2000. KP F-stat is the Kleibergen-Paap first-stage F-statistic. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Tables B.6 to B.13 report, for each main table, the baseline estimate in column 1, the estimate with unwinsorized exposure and meso-region clustered standard errors in column 2, and the same estimate with exposure-robust standard errors in columns 3 and 4, heteroskedasticity-robust and clustered by the 21 sections of the HS classification. The

Table B.5: 2SLS estimates: employment and remuneration

Dependent variable:	Δ **Employment share**	Δ **Log average hourly wages**
	(1)	(2)
Panel A: Aggregate		
ΔX_r	0.009	0.008
	(0.006)	(0.007)
Control mean (2000)	0.585	1.754
Panel B: Primary sector		
ΔX_r	0.011	0.128***
	(0.009)	(0.028)
Control mean (2000)	0.150	1.340
Panel C: Manufacturing sector		
ΔX_r	-0.009***	-0.005
	(0.003)	(0.011)
Control mean (2000)	0.148	1.698
Panel D: Services (nontraded) sector		
ΔX_r	-0.007	0.015**
	(0.007)	(0.008)
Control mean (2000)	0.688	1.856
Panel E: Residual sector		
ΔX_r	0.004**	-0.009
	(0.002)	(0.019)
Control mean (2000)	0.013	1.743
Observations	424	424
KP F-stat	23.7	23.7
Weighted	X	X
State-year fixed effects	X	X

Notes: Unit of analysis r is a micro-region. Panel A: employment rate and log average hourly wage of the micro-region; Panels B–E: sectoral employment shares and log average hourly wages. Changes between the 2000 and 2010 Censuses. 2SLS estimates using exposure G_r as the instrument for ΔX_r. Standard errors (in parentheses) are adjusted for 129 meso-region clusters. Observations are weighted by the population in 2000, and all columns include state-year fixed effects. The control mean is the population-weighted average of the outcome in 2000. KP F-stat is the Kleibergen-Paap first-stage F-statistic. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

point estimates change little when exposure is not winsorized, and the exposure-robust standard errors are smaller than the meso-region clustered ones for most outcomes. All the estimates that are significant in the main tables remain significant with exposure-robust standard errors, and only the effect on the aggregate employment rate loses significance when the shocks are clustered by HS section.

B.5 Sensitivity of the model to its parameters

Table B.14 reports the regional effects the model generates when each parameter in Table 11 changes, one at a time. The elasticity of world commodity markets, η_W, scales every outcome, and the labor share in commodity production, α, which sets the supply elasticity of commodities, matters moderately for the export basket. The other parameters barely move the export results, since the regional wage responds little in most regions. Labor

Table B.6: Exposure-robust inference: export value

Dependent variable:	Δ **Value of exports (US$ millions)**				%Δ **Value of exports**			
	Baseline	Unwinsorized	BHJ	BHJ, HS sections	Baseline	Unwinsorized	BHJ	BHJ, HS sections
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Exposure to China's demand (G_r)	6,600.281**	5,978.745**	5,978.745***	5,978.745***	3.584*	3.233*	3.233***	3.233***
	(2,540.742)	(2,544.061)	(453.955)	(442.328)	(1.918)	(1.887)	(0.585)	(0.551)
Weighted	X	X	X	X	X	X	X	X
State-year fixed effects	X	X	X	X	X	X	X	X
Observations	424	424	424	424	424	424	424	424

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r with state-year fixed effects, as in column 2 of Table 3. Column 1 reproduces that estimate, with G_r winsorized at the 1st and 99th percentiles and standard errors adjusted for 129 meso-region clusters. Column 2 uses G_r without winsorizing, with the same standard errors. Columns 3 and 4 report exposure-robust standard errors for the column 2 estimate, from the equivalent regression across the 96 HS2 product shocks (Borusyak et al., 2022): heteroskedasticity-robust in column 3 and clustered by the 21 sections of the HS classification in column 4. Observations are weighted by the total exports in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.7: Exposure-robust inference: export concentration

Dependent variable:	Δ **Lines**				Δ **HHI**			
	Baseline	Unwinsorized	BHJ	BHJ, HS sections	Baseline	Unwinsorized	BHJ	BHJ, HS sections
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Exposure to China's demand (G_r)	-51.007	-58.657	-58.657*	-58.657*	0.187***	0.167**	0.167***	0.167***
	(65.571)	(65.960)	(31.461)	(28.743)	(0.072)	(0.075)	(0.024)	(0.015)
Weighted	X	X	X	X	X	X	X	X
State-year fixed effects	X	X	X	X	X	X	X	X
Observations	424	424	424	424	424	424	424	424

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r with state-year fixed effects, as in column 2 of Table 4. Column 1 reproduces that estimate, with G_r winsorized at the 1st and 99th percentiles and standard errors adjusted for 129 meso-region clusters. Column 2 uses G_r without winsorizing, with the same standard errors. Columns 3 and 4 report exposure-robust standard errors for the column 2 estimate, from the equivalent regression across the 96 HS2 product shocks (Borusyak et al., 2022): heteroskedasticity-robust in column 3 and clustered by the 21 sections of the HS classification in column 4. Observations are weighted by the total exports in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.8: Exposure-robust inference: export value, resource and non-resource baskets

Dependent variable:	Δ **Value of exports (US$ millions)**				%Δ **Value of exports**			
	Baseline	Unwinsorized	BHJ	BHJ, HS sections	Baseline	Unwinsorized	BHJ	BHJ, HS sections
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: Resource basket								
Exposure to China's demand (G_r)	5,320.623**	4,777.746**	4,777.746***	4,777.746***	3.381*	3.003	3.003***	3.003***
	(2,212.388)	(2,257.105)	(445.482)	(320.389)	(1.981)	(1.964)	(0.688)	(0.558)
Observations	406	406	406	406	406	406	406	406
Panel B: Non-resource basket								
Exposure to China's demand (G_r)	-33.401	-33.380	-33.380	-33.380	-1.921	-1.921	-1.921**	-1.921**
	(893.907)	(893.869)	(727.392)	(906.809)	(2.677)	(2.677)	(0.843)	(0.853)
Observations	314	314	314	314	314	314	314	314
Weighted	X	X	X	X	X	X	X	X
State-year fixed effects	X	X	X	X	X	X	X	X

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r with state-year fixed effects, as in column 2 of Table 5. Column 1 reproduces that estimate, with G_r winsorized at the 1st and 99th percentiles and standard errors adjusted for 129 meso-region clusters. Column 2 uses G_r without winsorizing, with the same standard errors. Columns 3 and 4 report exposure-robust standard errors for the column 2 estimate, from the equivalent regression across the 96 HS2 product shocks (Borusyak et al., 2022): heteroskedasticity-robust in column 3 and clustered by the 21 sections of the HS classification in column 4. Observations are weighted by the total exports in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

mobility, ε, and the labor share in domestic tradables, α_T, change how the income gain is divided between existing residents and workers who move into the region, but real income rises in every case.

Table B.9: Exposure-robust inference: export concentration, resource and non-resource baskets

Dependent variable:	Δ Lines				Δ HHI			
	Baseline	Unwinsorized	BHJ	BHJ, HS sections	Baseline	Unwinsorized	BHJ	BHJ, HS sections
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: Resource basket								
Exposure to China's demand (G_r)	-42.571	-44.340	-44.340***	-44.340***	0.115**	0.101*	0.101***	0.101***
	(34.026)	(32.924)	(12.473)	(12.010)	(0.054)	(0.058)	(0.037)	(0.029)
Observations	406	406	406	406	406	406	406	406
Panel B: Non-resource basket								
Exposure to China's demand (G_r)	-35.853	-35.840	-35.840	-35.840	0.286	0.286	0.286***	0.286***
	(53.926)	(53.922)	(38.811)	(50.667)	(0.179)	(0.179)	(0.092)	(0.097)
Observations	314	314	314	314	314	314	314	314
Weighted	X	X	X	X	X	X	X	X
State-year fixed effects	X	X	X	X	X	X	X	X

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r with state-year fixed effects, as in column 2 of Table 6. Column 1 reproduces that estimate, with G_r winsorized at the 1st and 99th percentiles and standard errors adjusted for 129 meso-region clusters. Column 2 uses G_r without winsorizing, with the same standard errors. Columns 3 and 4 report exposure-robust standard errors for the column 2 estimate, from the equivalent regression across the 96 HS2 product shocks (Borusyak et al., 2022): heteroskedasticity-robust in column 3 and clustered by the 21 sections of the HS classification in column 4. Observations are weighted by the total exports in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

B.6 Projected net effects on GDP per capita

Figure B.11 shows the paths behind the break-even elasticities in Table 14. Through 2019, the net effect n_t is the observed effect of exposure on GDP per capita from Figure 13. After 2019, the projections follow Equation (26) with catch-up ($\rho = 0.98$), holding the observed gain at its 2015–2019 average and subtracting the further capability loss implied by each published elasticity. Panel (a) measures the export basket with the complexity index and panel (b) with sophistication. With complexity, the net effect turns negative in 2088, 2050, and 2032 under the estimates of Hausmann et al. (2007) and the cross-section and fixed-effects estimates of Jarreau and Poncet (2012), and stands at 1.2, 0.0, and -3.0 percent per standard deviation of exposure in 2050. With sophistication, it turns negative in 2070, 2044, and 2030, and stands at 0.9, -0.6, and -4.0 percent in 2050. With catch-up as in the fixed-effects regression of Jarreau and Poncet (2012) ($\rho = 0.82$), the net effect under that estimate remains positive throughout.

Table B.10: Exposure-robust inference: export shares

Classification	Baseline	Unwinsorized	BHJ	BHJ, HS sections
	(1)	(2)	(3)	(4)
Resource	-0.035	-0.037	-0.037	-0.037
	(0.039)	(0.037)	(0.064)	(0.056)
Primary	0.190*	0.177*	0.177***	0.177***
	(0.113)	(0.105)	(0.033)	(0.034)
Resource-based	-0.225**	-0.214**	-0.214**	-0.214***
	(0.102)	(0.093)	(0.084)	(0.075)
Manufactures	0.035	0.037	0.037	0.037
	(0.039)	(0.037)	(0.064)	(0.056)
Low-Tech	0.038	0.035	0.035	0.035
	(0.036)	(0.033)	(0.045)	(0.046)
Medium-Tech	-0.004	0.001	0.001	0.001
	(0.054)	(0.051)	(0.025)	(0.021)
High-Tech	0.002	0.002	0.002	0.002
	(0.008)	(0.007)	(0.015)	(0.013)
Weighted	X	X	X	X
State-year fixed effects	X	X	X	X
Observations	424	424	424	424

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r with state-year fixed effects, as in column 2 of Table 7. Column 1 reproduces that estimate, with G_r winsorized at the 1st and 99th percentiles and standard errors adjusted for 129 meso-region clusters. Column 2 uses G_r without winsorizing, with the same standard errors. Columns 3 and 4 report exposure-robust standard errors for the column 2 estimate, from the equivalent regression across the 96 HS2 product shocks (Borusyak et al., 2022): heteroskedasticity-robust in column 3 and clustered by the 21 sections of the HS classification in column 4. Observations are weighted by the total exports in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.11: Exposure-robust inference: export sophistication and complexity

Dependent variable:	**Δ Log export sophistication (PWT)**				**Δ Export complexity (PCI)**			
	Baseline	Unwinsorized	BHJ	BHJ, HS sections	Baseline	Unwinsorized	BHJ	BHJ, HS sections
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Exposure to China's demand (G_r)	-0.198**	-0.194**	-0.194**	-0.194***	-0.332	-0.299	-0.299***	-0.299***
	(0.083)	(0.078)	(0.078)	(0.057)	(0.227)	(0.208)	(0.059)	(0.057)
Weighted	X	X	X	X	X	X	X	X
State-year fixed effects	X	X	X	X	X	X	X	X
Observations	424	424	424	424	424	424	424	424

Notes: Unit of analysis r is a micro-region. Reduced-form estimates on exposure G_r with state-year fixed effects, as in column 2 of Table 8. Column 1 reproduces that estimate, with G_r winsorized at the 1st and 99th percentiles and standard errors adjusted for 129 meso-region clusters. Column 2 uses G_r without winsorizing, with the same standard errors. Columns 3 and 4 report exposure-robust standard errors for the column 2 estimate, from the equivalent regression across the 96 HS2 product shocks (Borusyak et al., 2022): heteroskedasticity-robust in column 3 and clustered by the 21 sections of the HS classification in column 4. Observations are weighted by the total exports in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.12: Exposure-robust inference: employment and remuneration

Dependent variable:	Δ Log average hourly wages				Δ Employment share			
	Baseline	Unwinsorized	BHJ	BHJ, HS sections	Baseline	Unwinsorized	BHJ	BHJ, HS sections
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Exposure to China's demand (G_r)	0.032	0.033	0.033*	0.033*	0.039*	0.034	0.034**	0.034
	(0.029)	(0.027)	(0.019)	(0.016)	(0.021)	(0.022)	(0.016)	(0.020)
Weighted	X	X	X	X	X	X	X	X
State-year fixed effects	X	X	X	X	X	X	X	X
Observations	424	424	424	424	424	424	424	424

Notes: Unit of analysis r is a micro-region. Changes between the 2000 and 2010 Censuses. Reduced-form estimates on exposure G_r with state-year fixed effects, as in column 2 of Table 9. Column 1 reproduces that estimate, with G_r winsorized at the 1st and 99th percentiles and standard errors adjusted for 129 meso-region clusters. Column 2 uses G_r without winsorizing, with the same standard errors. Columns 3 and 4 report exposure-robust standard errors for the column 2 estimate, from the equivalent regression across the 96 HS2 product shocks (Borusyak et al., 2022): heteroskedasticity-robust in column 3 and clustered by the 21 sections of the HS classification in column 4. Observations are weighted by the population in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.13: Exposure-robust inference: sectoral employment and remuneration

Dependent variable:	Δ Employment share				Δ Log average hourly wages			
	Baseline	Unwinsorized	BHJ	BHJ, HS sections	Baseline	Unwinsorized	BHJ	BHJ, HS sections
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Panel A: Primary sector								
Exposure to China's demand (G_r)	0.049	0.043	0.043**	0.043	0.548***	0.505***	0.505***	0.505***
	(0.032)	(0.032)	(0.021)	(0.027)	(0.127)	(0.127)	(0.064)	(0.077)
Panel B: Manufacturing sector								
Exposure to China's demand (G_r)	-0.038***	-0.035***	-0.035***	-0.035**	-0.021	-0.022	-0.022	-0.022
	(0.012)	(0.012)	(0.010)	(0.012)	(0.046)	(0.044)	(0.024)	(0.030)
Panel C: Services (nontraded) sector								
Exposure to China's demand (G_r)	-0.028	-0.024	-0.024	-0.024	0.066**	0.064***	0.064***	0.064***
	(0.029)	(0.028)	(0.022)	(0.028)	(0.026)	(0.024)	(0.018)	(0.017)
Panel D: Residual sector								
Exposure to China's demand (G_r)	0.017**	0.016**	0.016***	0.016***	-0.040	-0.036	-0.036	-0.036
	(0.007)	(0.007)	(0.004)	(0.005)	(0.087)	(0.081)	(0.054)	(0.054)
Weighted	X	X	X	X	X	X	X	X
State-year fixed effects	X	X	X	X	X	X	X	X
Observations	424	424	424	424	424	424	424	424

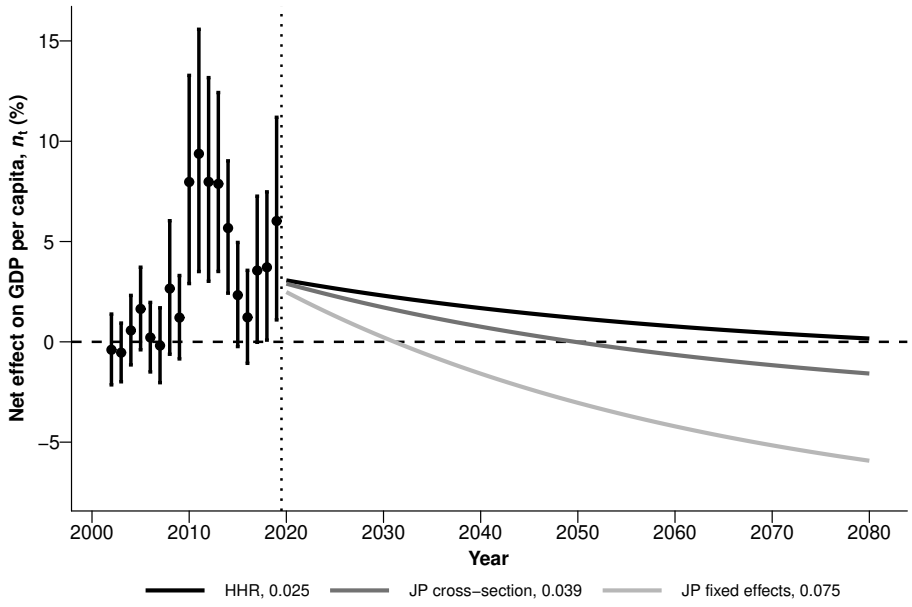
Notes: Unit of analysis r is a micro-region. Changes between the 2000 and 2010 Censuses. Reduced-form estimates on exposure G_r with state-year fixed effects, as in column 2 of Table 10. Column 1 reproduces that estimate, with G_r winsorized at the 1st and 99th percentiles and standard errors adjusted for 129 meso-region clusters. Column 2 uses G_r without winsorizing, with the same standard errors. Columns 3 and 4 report exposure-robust standard errors for the column 2 estimate, from the equivalent regression across the 96 HS2 product shocks (Borusyak et al., 2022): heteroskedasticity-robust in column 3 and clustered by the 21 sections of the HS classification in column 4. Observations are weighted by the population in 2000. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table B.14: Sensitivity of the model-implied regional effects to the parameters

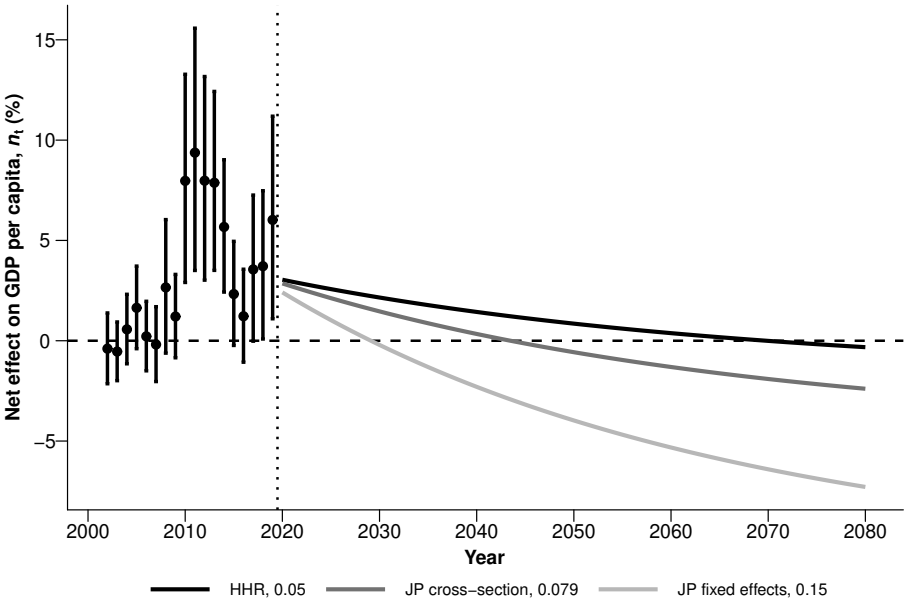
	Export basket				Regional income (%)		
	%Δ Value	Δ HHI	Δ Log sophistication	Δ PCI	Nominal income per worker	Real income	Real income per worker
Baseline	0.323	0.031	-0.010	-0.008	3.8	4.6	2.1
$\eta_W = 0.5$	1.705	0.055	-0.022	-0.017	7.6	9.1	4.2
$\eta_W = 2$	0.096	0.015	-0.004	-0.002	1.9	2.3	1.1
$\alpha = 0.15$	0.266	0.028	-0.009	-0.007	3.8	4.3	2.3
$\alpha = 0.40$	0.457	0.038	-0.014	-0.011	3.9	5.1	1.9
$\gamma = 0.3$	0.323	0.031	-0.010	-0.008	3.8	4.6	2.2
$\gamma = 0.7$	0.323	0.031	-0.010	-0.009	3.8	4.6	2.1
$c_L = 0.2$	0.324	0.030	-0.010	-0.008	3.8	4.6	2.1
$c_L = 0.6$	0.323	0.032	-0.010	-0.008	3.8	4.5	2.2
$\sigma_k = 3$	0.324	0.030	-0.010	-0.008	3.8	4.6	2.1
$\sigma_k = 7$	0.322	0.032	-0.010	-0.008	3.8	4.6	2.1
$\varepsilon = 0$	0.305	0.032	-0.010	-0.008	5.3	3.4	3.4
$\varepsilon = 3$	0.336	0.031	-0.010	-0.008	2.7	5.4	1.2
$\alpha_T = 0.35$	0.317	0.031	-0.010	-0.008	3.6	4.7	1.8
$\alpha_T = 0.65$	0.330	0.031	-0.010	-0.008	3.9	4.4	2.5
$\alpha_N = 0.45$	0.324	0.031	-0.010	-0.008	3.9	4.4	2.0
$\alpha_N = 0.75$	0.322	0.031	-0.010	-0.008	3.7	4.7	2.3

Notes: Effects of a one-standard-deviation increase in exposure G_r on the changes the model generates from each region's 2000 export basket, estimated with the regression of Table 12. The baseline uses the parameters in Table 11, and each row changes one of them. Nominal and real income per worker exclude the income of workers who move into the region. All variants set $\eta_k = 1$.

Figure B.11: Net effect of China's demand shock on GDP per capita



(a) Complexity (PCI)



(b) Sophistication

Notes: HHR refers to Hausmann et al. (2007) and JP to Jarreau and Poncet (2012). Effects of a one-standard-deviation increase in exposure G_r, in percent. Points to the left of the dotted line are the coefficients of Figure 13 for 2002–2019, with 95% confidence intervals. They already contain any capability loss to date. Lines are projections of n_t following Equation (26) with catch-up ($\rho = 0.98$). Elasticities are per unit of the complexity index in panel (a), converted from the published estimates, and per log point of sophistication in panel (b).