# Commodity Booms, Structural Transformation and the Natural Resource Curse

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**Abstract**

This paper explores the effects of a commodity price boom on structural transformation to test the existence of a Natural Resource Curse linked to the expansion of the agricultural sector. Combining climate- and soil-induced variation in production patterns in agriculture among municipalities in Brazil with fluctuations in international commodity prices between 2000 and 2010, we show that a natural resource boom resulted in industrial growth and reallocated labor away from agriculture. The results are consistent with greater use of capital inputs working as substitutes for labor in the farms, and also with an increase in land inequality in more exposed locations that ultimately displaced workers from the agricultural sector. We conclude that the effects usually associated with a Resource Curse were not present in the context of a commodity supercycle in Brazil.

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# 1 Introduction

The relationship between natural resource endowments and economic development has been a long studied subject in the growth literature. In particular, the existence of a Natural Resource Curse (or Dutch Disease) has been of special interest. The main idea behind this effect is that natural resource extraction could reduce growth by increasing the comparative advantage of the extractive sector and, in turn, crowding out manufacturing development.[1] Since the manufacturing sector is often associated with positive spillover effects—via learning-by-doing, for example—a natural resource boom would ultimately decrease the potential productivity spillovers and, consequently, long-run economic development.

Although the theoretical and empirical literature has extensively studied this chain of events,[2] the results are still divergent and we lack robust empirical evidence on the actual relevance of the Natural Resource Curse, especially on its mechanisms. The first studies that tried to evaluate this issue empirically—using mainly cross-sectional country data—often found that countries more affected by resource booms did not experience long-term growth gains (Sachs and Warner, 1999, 2001). But another recent strand of the literature has focused more on robust microeconometric evidence using within-country data and found that resource booms can actually generate manufacturing growth via local agglomeration effects (Allcott and Keniston, 2018) or spillover effects over the other sectors of the economy (Cavalcanti et al., 2019).[3] Nevertheless, this recent literature has concentrated mainly on oil and gas booms and few studies have been dedicated to exploring if the production of agricultural products not directly linked to mineral extraction can also cause the usual effects associated with a resource boom.[4]

In particular, commodity price shocks exogenous to the local economies are often pointed out as an important force behind a Natural Resource Curse (Prebisch, 1950; Singer, 1950). This hypothesis, usually called the Prebisch-Singer hypothesis, states that agricultural commodity exports would hurt the manufacturing sector and curb long term economic growth

[1]This general process of crowding out manufacturing growth is often related to both deindustrialization and the appreciation of the real exchange rate after the resource boom.

[2]Krugman (1987) argues that if the natural resource boom lasts long enough, it can have permanent negative impacts on the manufacturing sector. Matsuyama (1992) shows how changes in agricultural productivity can lead to different trends of structural transformation depending on whether the economy is open or closed.

[3]A large body of the literature has also focused on political factors that might worsen or alleviate the Resource Curse. In particular, diverging patterns of development after the booms might be explained by the quality of local institutions (Mehlum et al., 2006). See also Van der Ploeg (2011) and Van Der Ploeg and Poelhekke (2017) for a comprehensive discussion about the Dutch Disease literature.

[4]In a meta-analysis, Havranek et al. (2016) shows that the overall support for the resource curse hypothesis is weak, with almost the entirety of the papers in the study exploring oil, gas and mineral extraction.

via declining terms of trade and dependency on the primary sector.[5] This discussion is especially prominent in countries that rely heavily on the agricultural sector and that have experienced high rates of growth during the 2000s commodities supercycle, which also led to an observable expansion of activities associated with the primary sector, often called a process of deindustrialization of the economy—or rather, "reprimarization". It is important to note, however, that we still lack robust evidence on natural resource booms stemming from the presence of a large set of natural resource endowments.[6] Since the production of agricultural goods uses labor, capital and land in a different way in comparison with the extraction of oil, gas, minerals and precious metals, the agricultural sector structure differs in some fundamental aspects compared to these other extractive sectors.

In this paper, we explore the 2000s commodities boom as an exogenous economic shock and analyze how the underlying structure of the agricultural sector in Brazil changed after the sharp rise in the prices of a large basket of internationally traded commodities. In particular, we look at the change in employment shares in agriculture and argue that differential input usage (labor, capital and land) worked as a key mechanism in driving the effects. Additionally, we explore inequality in landholdings as another important mechanism in generating structural change. Land inequality is often overlooked in the Natural Resource Curse literature and can be important in accounting for both changes in agricultural productivity and the displacement of workers.

To empirically assess the effect of the commodity boom on local development and structural change, we construct a shift-share measure to isolate municipalities that were more exposed to the shock. We create our exposure shares by combining data on crop potential yields from the Food and Agriculture Organization (FAO)'s Global Agro-Ecological Zones (GAEZ) project and actual yields into a fractional multinomial logit (FML) model of crop choice which calculates predicted shares for the crops in our sample for each Brazilian municipality. We then interact the shares with the exogenous variation in international prices of commodities between 2000 and 2010, which represents our shift (or shock) variable.

We first explore the effect of the commodity boom on employment shares and find that regions that were more exposed to the commodity boom experienced a reallocation of labor away from agriculture and into the manufacturing sector. Our estimates imply that the commodity boom can explain 10% of the observed differences in the reduction of the agricultural share across Brazilian municipalities and 18% of the corresponding differences in the growth of the manufacturing employment share. We also do not observe any effect of

[5]For a recent discussion, see Harvey et al. (2010).

[6]Collier and Goderis (2008) compare non-agricultural vs agricultural booms in a cross-section of countries and find that they differ in their long term effects, with an agricultural boom being less detrimental to economic growth than a non-agricultural boom.

the commodities shock on employment share in services at the local level.

Next, we explore potential mechanisms that led to the observed reallocation of workers. First, we explore how the intensity in inputs usage changed in more affected regions. We observe an increase in the utilization of capital, measured by the use of machines and genetically engineered seeds in the farms. We then argue that agriculture workers were partially substituted by capital. Lastly, we explore how the change in land inequality after the shock might have contributed to the displacement of agricultural workers. We find that land inequality increased in more exposed municipalities by looking at the Land Gini and the number and area of the largest farms inside the regions. The share of land used in agriculture production was disproportionately appropriated by a small number of large properties, which possibly displaced small rural owners and workers from the agricultural sector.

Our main findings are robust to a series of deviations from our baseline framework. We first explore if our main results hold when looking only at formal jobs from a matched employer-employee dataset and find that the general conclusions remain unaltered. Next, we use different definitions for our exposure measure and also find similar results. Finally, our main estimates remain statistically significant when we correct standard errors to account for spatial correlation and correlation across the exposure shares. We then conclude that the 2000s commodities boom did not result directly in a Natural Resource Curse. The use of capital inputs increased in agriculture and labor was reallocated away from the agriculture sector and into manufacturing, spurring industrial growth.

# 2 Related Literature

There is a long tradition in economics of studying the impact of natural resource abundance on development, but no clear consensus has emerged in the literature. The large bulk of the research done in this area focuses on oil, gas and mineral endowments—across and within countries—to assess the possible existence of a Natural Resource Curse. Although the classical Dutch Disease was associated and studied in terms of oil, gas and mineral discoveries, few studies have been dedicated to exploring if the production of agricultural products can also cause the usual chain of events associated with a resource boom. In this section, we review the literature that is close to our analysis of commodity booms and structural transformation.

**Theoretical Framework:** We base our analysis on the theoretical literature that explores the relationship between natural resource boom, agricultural development and structural change in open economies. This literature is relatively scarce in comparison to the bulk of studies that analyze structural change in closed economies. We will then focus on the particular models that better approximates our scenario. Gollin et al. (2016) develop a framework in which urbanization can occur in economies even without industrialization. In their model, an exogenous increase in resource export earnings raises incomes, which then causes an increase in the urbanization rate as the rural sector contracts. Their results imply that a resource boom will ultimately generate an urbanization pattern just as effectively as industrial development, creating “consumption cities” as opposed to “production cities”.

**Natural Resource Booms and Local Development:** An important strand of the literature that explores the effects of trade induced shocks on a vast set of economic outcomes has recently emerged in applied microeconometric studies, exploring numerous settings across different countries—both in modern and historical times—and employing a wide range of identification strategies to provide robust evidence. Some of these studies are more related to our context in terms of empirical strategy, economic context or both. Allcott and Keniston (2018) revisit the question regarding the existence of a Natural Resource Curse in the context of the discoveries of natural resource and their effect on local economies in the United States.

By following a shift-share approach and interacting each county’s cross-sectional variation in initial oil and gas endowment with the time series variation in national employment, the authors study the effects of oil booms and busts on local wages and employment—while also disentangling the agglomeration and crowding-out effects of the booms—and find that both wages and manufacturing employment increase during the booms. Also, no long-run effects in terms of declining productivity are found, implying that a Dutch Disease mechanism did not occur in this setting.

Exploring the Brazilian context, Cavalcanti et al. (2019) show how oil discoveries increased local production and had spillover effects over other sectors of the economy. Workers were reallocated away from agriculture and into manufacturing and services, increasing urbanization. Following a similar empirical strategy, Dube and Vargas (2013) explore how income shocks, arising from increasing commodities prices, affect civil conflict in Colombia. Their empirical strategy interacts commodity production for coffee and oil across different municipalities with their respective international prices. The results show important heterogeneous impacts of the type of commodity on the incidence of political violence: intensification of attacks are associated with a declining price of coffee and also with a rise in the prices of oil. The channels for this different type of impact come from the relative effects of both coffee and oil on local wages and revenues. In a historical setting, Uribe-Castro (2019) studies the same Colombian agricultural sector during the 20th century and finds that coffee price shocks impacted cultivation and increased the opportunity cost of education, which reduced the supply of skilled workers, and slowed down structural transformation.

**Agricultural Productivity and Structural Change:** In a series of works starting with Bustos et al. (2016), the authors show that the adoption of new agriculture technologies can affect structural change in different directions. In particular, they explore the introduction of a new variety of genetically engineered (GE) soybean seed and of a second season in maize cultivation in Brazil. They argue that, while the GE soy seeds represent a labor-saving technical change in agriculture, the new maize variety can be considered a labor-augmenting technology. This difference is then showed to be fundamental for the effects on structural change. In the case of a labor-saving technology, labor is reallocated away from agriculture and into manufacturing, while the opposite effect happens with the labor-augmenting technology. In a subsequent work, Bustos et al. (2020a) show that the adoption of GE soy generated an increase in savings that were reinvested in urban regions and not in rural areas. Capital, therefore, has also reallocated towards the manufacturing sector and urban area.

In their last study of this trilogy, Bustos et al. (2020b) show that the previous reallocation of labor away from agriculture reinforced comparative advantage in the least skill-intensive manufacturing industries. This effect happened because the displaced workers were relatively unskilled and had lower levels of human capital. This leads to an important conclusion about long-run economic growth: it is often assumed that structural change towards manufacturing will increase the overall total productivity of the economy, but if this is an unskilled-bias reallocation, the least R&D-intensive manufacturing industries will absorb most of the labor, decreasing the size of the skill-intensive industries and slowing down the process of innovation and manufacturing productivity growth.

While this series of works have deepened our knowledge about agricultural productivity and structural change, it still depends on a particular type of commodity. There is also evidence that other types of technological changes in other agricultural crops imply different effects on trends of structural change. Moscona (2018) shows that productivity growth associated with the Green Revolution in the last decades has been complementary to labor, increasing the employment share in agriculture both within and across countries, while also reducing urbanization and manufacturing employment.

**2000s Commodities Supercycle and the Brazilian Labor Market:** Some recent works have also explored the Brazilian economy as a setting for studying the effects of the commodity boom on labor market outcomes. Costa et al. (2016) use the "China shock" approach to show which sectors were benefited or harmed by the increase in Chinese imports supply and exports demand. The authors find that the agricultural and extractive sector were positively affected in terms of wages, while the manufacturing sector was negatively affected. Benguria et al. (2018) show that higher commodity prices in Brazil increase the domestic demand and induce wage increases in unskilled-intensive industries. Adão (2015) finds that movements in world commodity prices explain part of the decrease in Brazilian wage inequality from 1991–2010.

**Shift-Share Instruments:** Related to our empirical identification strategy, a new body of the literature has further formalized the shift-share econometric approach pioneered in Bartik (1991) and Blanchard et al. (1992). Some of them provide very useful ways of implementing the shift-share design in our study. A priori, one must decide from which part of the instrument the exogenous variation will come from, the shocks or the shares. Goldsmith-Pinkham et al. (2020) provide a framework for working with exogeneity coming from the shares. On the other hand, Borusyak et al. (2018) and Borusyak and Hull (2020) offer a setting for working with quasi-random assignments of shock, while allowing the exposure shares to be endogenous. This is more in line with our strategy since we provide a set of international price shocks that are plausibly uncorrelated with unobserved factors affecting local outcomes.

# 3 Motivating Facts

The Brazilian economy relies heavily on agriculture. For example, Brazil is among the largest producers in the world of coffee, sugarcane, soybean, maize and beef. Furthermore, it is also characterized by regional variations in the degree of specialization in commodity output. The production of these agricultural crops, together with cattle raising, provide the basis for the large agribusiness industry in Brazil, which represents 22% of Brazil's GDP, a third of its employment, and almost 40% of its exports (PwC, 2013; FGV, 2015).

Products derived from agricultural production, like orange juice, ethanol and paper also represent an important dimension of the large agribusiness industry in Brazil. In particular, the production of these derived products is characterized by high use of technology and agroindustry techniques. This is, therefore, another important dimension in our analysis of the Resource Curse, since part of the agricultural sector in Brazil can be characterized by economies of scale that are normally associated with the manufacturing sector. Furthermore, the agribusiness industry captures not only farming production, but also the supply of farming inputs such as machinery and seeds.

Brazil has also one of the highest levels of land inequality in the world (Bauluz et al., 2020). According to the last Agricultural Census in 2017, less than 1% of all farms concentrate about half of the total rural area. This concentration of land remains surprisingly constant over time. Ever since the first Agricultural Census in 1920, the number of rural properties with more than 1000 hectares in area varied between 4% and 0.7% of the total number of agricultural establishments, but appropriated between 35% and 63% of the total area devoted to agriculture over the last 100 years. Figure 1 illustrates the differences in the

Land Gini for the Brazilian municipalities in 2017.

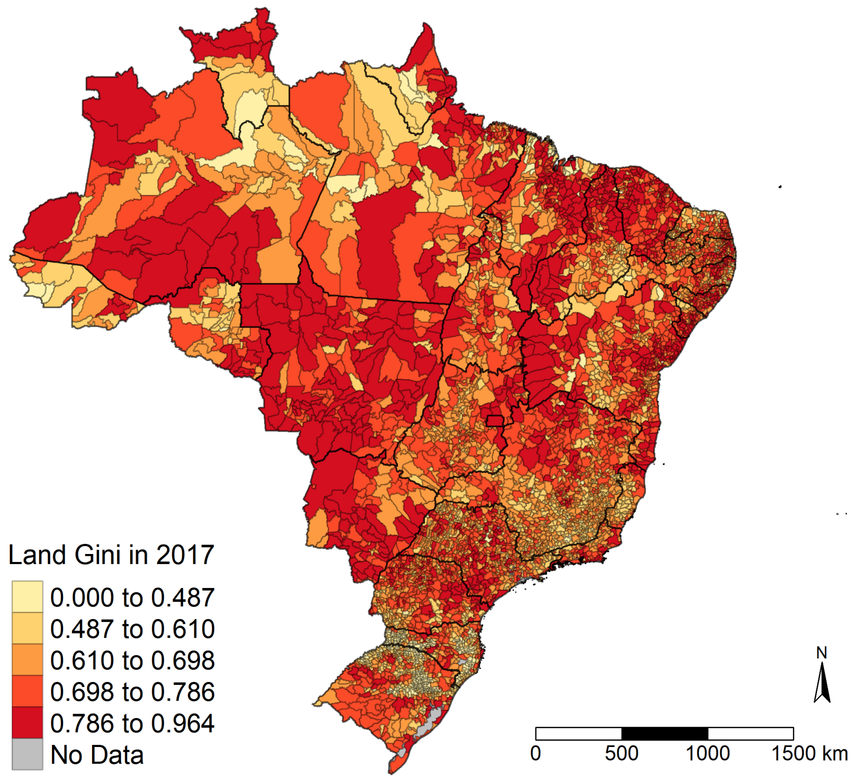



Figure 1: Land Inequality in Brazil

*Note:* Author's calculations using the Brazilian Agricultural Census data from 2017. See Appendix A.2 for details about the calculation of the Land Gini.

The characteristics of the Brazilian agricultural sector presented so far make the country a suitable setting to analyze the possible existence of a Natural Resource Curse after the 2000s commodities boom. This last commodity supercycle started in 2000 and peaked in around 2011. In terms of magnitude, it is comparable to the other two historically observed supercycles that followed the Second Industrial Revolution and the aftermath of the Second World War (Erten and Ocampo, 2013). Figure 2 illustrates how the prices of non-mineral agricultural commodities peaked very rapidly in about ten years after the 1990 decade when they were comparatively low.

In terms of local development, Brazilian municipalities have been experiencing a long process of structural transformation since the 1960s, when the economy started to grow and industrialize rapidly. Figure 3 shows the evolution of employment shares in the main sectors of the Brazilian economy over time. Observe that, although the process of structural change has consolidated in the 1980 decade, we still observe a substantial reallocation of

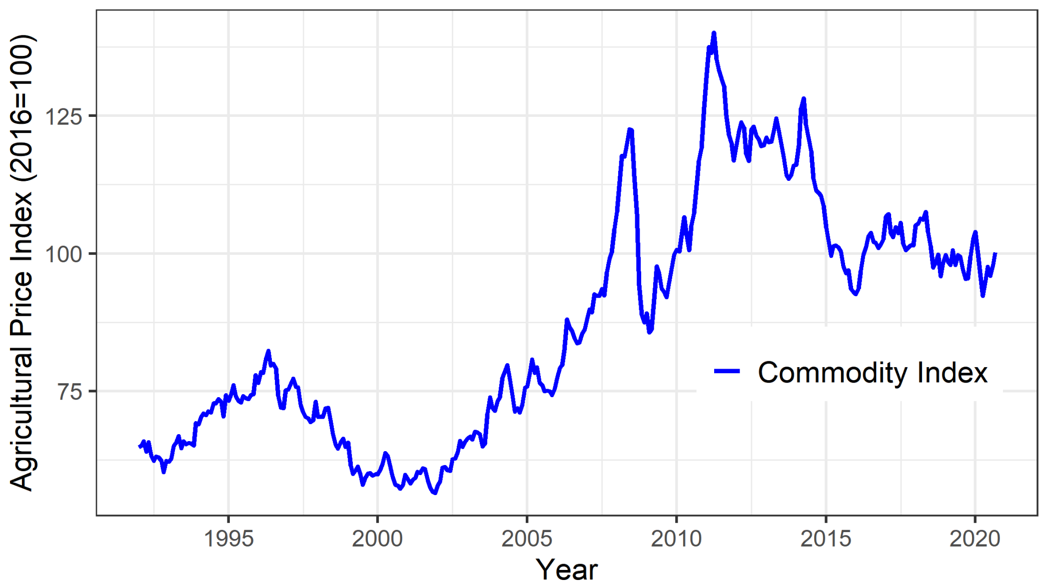



Figure 2: 2000s Commodities Supercycle

*Note:* Commodity Price Index in US$ for agricultural products. Data from the World Bank's Global Economic Monitor.

workers away from agriculture in the last decades, especially between 2000 and 2010. In particular, the distribution of these employment shares differs substantially when analyzed at the municipality level.

The facts discussed above call for a careful examination of the differential trends of local development in the municipalities. We, therefore, propose to analyze how the commodity boom affected the structure of the agriculture sector and regional development in the Brazilian economy by paying special attention to the characteristics and facts discussed above.

# 4 Data

To construct our shift-share measure of exposure to the 2000s commodities supercycle, we first obtain information on the local municipalities production of agricultural crops from the Instituto Brasileiro de Geografia e Estatística (IBGE). More specifically, we use the Produção Agrícola Municipal (PAM), which is held annually at the municipality level and has information on a set of variables such as planted area, quantities and production values for a large set of crops produced in Brazil.

To obtain beef quantities, we also use the Pesquisa da Pecuária Municipal (PPM), which is similar to the PAM and accounts for the creation of livestock in Brazil. The only drawback is that the PPM reports the number of cattle heads, not the actual weight of beef produced.

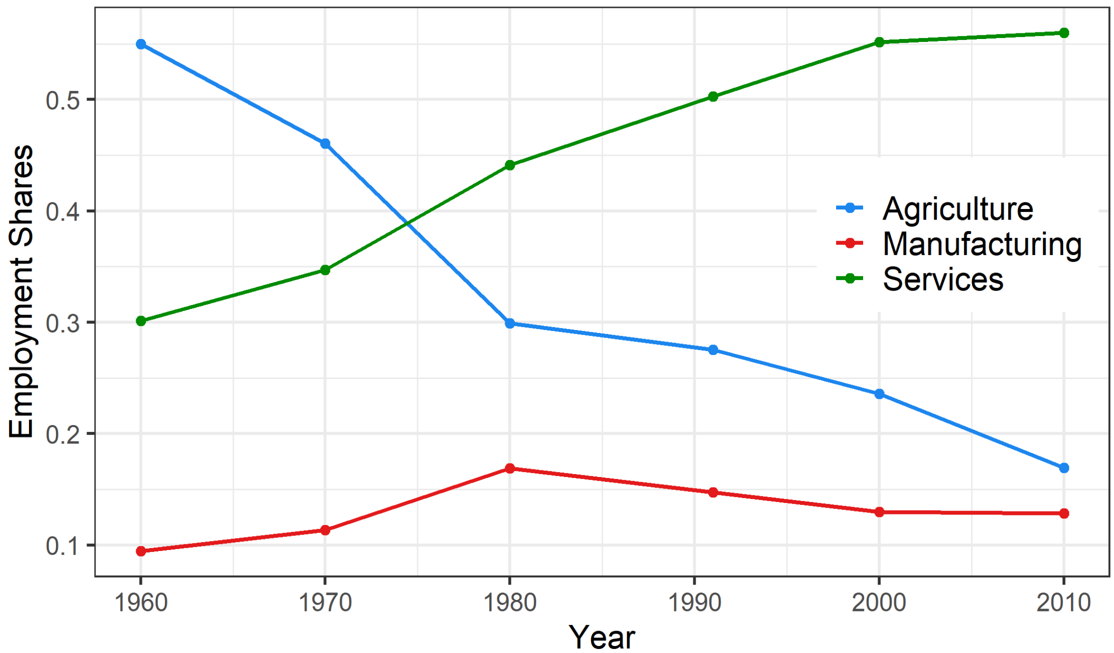



Figure 3: Employment Shares Across Sectors in Brazil

*Note:* Author's calculations from IPUMS International microdata for Brazilian Population Census.

To overcome this, we multiply the total number of livestock in each municipality by 0.23, which is the average total carcass weight at slaughter in metric tons, to obtain a proxy for the production of beef in each municipality.[7]

We use data from the FAO-GAEZ project to obtain potential yields for each crop in our sample. This database consists of maximum attainable yields for multiple crops (in tons per hectare per year), which are considered as soil- and climate-based potential yields or productivity (total production capacity) measures. These crop-specific data relies purely on exogenous geo-climatic features, such as local soil and weather characteristics, which are then incorporated into a model that predicts the maximum attainable yields for each crop in a given area under different choices of water supply methods and input levels of technology usage.

The dataset is reported on a grid cell level, with each grid representing a 5-arc-minute resolution. At the 5-arc-minute level, there are around 255,680 grid cells in Brazil, representing around 11% of all grid cells on earth excluding bodies of water and ice shelves (Costinot et al., 2016). The area of these cells ranges from 8,586 hectares at the equatorial level to

[7]The average total carcass weight at slaughter in Brazil comes from the Pesquisa Trimestral do Abate de Animais from IBGE.

6,031 hectares at the southern-most location in Brazil.

We aggregate the potential yields for each crop at the local level taking the mean value of each grid cell that falls within the border of each municipality and match all the crops present in the FAO-GAEZ with the previously obtained from the PAM/PPM dataset. We use data for rain-fed conditions under intermediate input technology—defined as a system in which "production is based on improved varieties, on manual labor with hand tools and/or animal traction and some mechanization".[8] As a robustness check, we propose to analyze the sensitivity of our results to using the high inputs.[9] With both PAM/PPM and FAO-GAEZ, we can then construct our "share" measure, consisting of the total production of crops in each municipality averaged over the 5 years preceding the start of our analysis.[10]

For the "shock" part of our measure, we use the international commodity prices from the Global Economic Monitor (GEM) Commodities database prepared by the World Bank. With this, we have monthly information over an extended period on the price of several commodities that are traded in the international markets. We then average the prices over the twelve months within each year to obtain yearly values and standardized each price to US dollars per ton.[11] In some cases, there may be a single price that matches multiple crops in the quantities dataset, so we consolidate the shift-share measure by matching each possible crop to its broad international price, leaving space to more than one commodity being assign to a single price[12], while dropping the cases in which we cannot establish a match at all.

For the main outcomes and controls, we use data from the Brazilian population census, the agricultural census, and Ipeadata. Both agricultural and population censuses are released at intervals of ten years by IBGE. We use data from the last three rounds of the censuses (1996, 2006 and 2017 for agricultural and 1991, 2000 and 2010 for population). The agricultural census variables of interest are: the total number and area of farms,[13] area planted with genetically modified seeds, number of tractors and machines employed in the farms, output value in the agroindustry, number of workers and total output of farms.

[8]For more details about the documentation of the FAO-GAEZ project, see Appendix A and IIASA/FAO (2012).

[9]Defined as being mainly market-oriented and where "production is based on improved high yielding varieties, is fully mechanized with low labor intensity and uses optimum applications of nutrients and chemical pest, disease and weed control".

[10]In the case of cattle, we use potential yields for pasture as a proxy livestock productivity. Since extensive livestock creation composes the majority of the Brazilian production, the presence of pastures is still fundamental for cattle raising. We, therefore, assume that potential yields for pastures are a good proxy for cattle breeding productivity in our scenario.

[11]Throughout the paper, all variables representing monetary values were deflated to 2010 prices using the CPI inflation index for US dollars and the IPCA index for Brazilian Reais.

[12]For example, yerba mate and indiantea were both matched with the tea price.

[13]These two variables are reported into different intervals of area measured in hectares. We use this information to calculate the Land Gini in each municipality as described in Appendix A.2.

The population census variables: are total employment, employment shares and wages in agriculture, manufacturing and services. From the population census, we also obtain start-of-period controls, such as income per capita, the share of rural population, illiteracy rate, and population density. From Ipeadata, we obtain additional geo-climatic and socio-economic characteristics such as sectoral and total GDP, latitude, longitude, municipality area, and rural and urban population. We also use historical population census microdata from IPUMS (Min, 2019) in our auxiliary analysis (to construct Figure 3, for example.) Table 1 reports summary statistics for our main variables of interest and illustrates the evolution and difference in their values between the census years at the municipality level.

Table 1: Summary Statistics on Main Variables at Municipality Level

| | 2000 | | 2010 | | Δ 2010-2000 | | |
|---|---|---|---|---|---|---|---|
| | Mean | SD | Mean | SD | Mean | SD | Observations |
| **Panel A. Sectoral GDP** | | | | | | | |
| Log Total GDP Per Capita | 1.750 | 0.720 | 2.240 | 0.704 | 0.487 | 0.321 | 5,488 |
| Log Agricultural GDP Per Capita | −0.086 | 1.252 | 0.157 | 1.350 | 0.243 | 0.662 | 5,488 |
| Log Manufacturing GDP Per Capita | −0.430 | 1.180 | −0.160 | 1.420 | 0.268 | 0.759 | 5,488 |
| Log Services GDP Per Capita | 1.142 | 0.584 | 1.690 | 0.511 | 0.545 | 0.243 | 5,488 |
| **Panel B. Population Census** | | | | | | | |
| Employment Share Agriculture | 0.422 | 0.203 | 0.354 | 0.182 | −0.068 | 0.081 | 5,475 |
| Employment Share Manufacturing | 0.100 | 0.087 | 0.100 | 0.090 | 0.002 | 0.055 | 5,475 |
| Employment Share Services | 0.317 | 0.108 | 0.325 | 0.088 | 0.008 | 0.055 | 5,475 |
| Log Wage in Agriculture | 6.167 | 0.606 | 6.390 | 0.577 | 0.222 | 0.393 | 5,475 |
| Log Wage in Manufacturing | 6.375 | 0.618 | 6.630 | 0.557 | 0.255 | 0.560 | 5,475 |
| Log Wage in Services | 6.690 | 0.457 | 6.822 | 0.340 | −0.300 | 0.422 | 5,475 |
| Urban Population Share | 0.590 | 0.233 | 0.641 | 0.219 | 0.052 | 0.063 | 5,475 |
| **Panel C. Exposure Measure** | | | | | | | |
| Commodity Exposure | 6.345 | 0.382 | 6.878 | 0.346 | 0.532 | 0.064 | 5,475 |
| | 2006 | | 2017 | | Δ 2017-2006 | | |
| | Mean | SD | Mean | SD | Mean | SD | Observations |
| **Panel D. Agricultural Census** | | | | | | | |
| Log Land Use | 10.204 | 1.247 | 10.184 | 1.293 | −0.019 | 0.471 | 5,446 |
| Log Machine Intensity | −5.896 | 1.760 | −5.500 | 1.680 | 0.392 | 0.830 | 5,446 |
| Share of Land with GE Seeds | 0.019 | 0.086 | 0.080 | 0.193 | 0.060 | 0.171 | 5,446 |
| Log Farm Productivity | −0.585 | 1.268 | −0.481 | 1.260 | 0.103 | 0.830 | 5,446 |
| Log Output per Worker | 2.065 | 1.279 | 2.091 | 1.453 | 0.025 | 0.850 | 5,446 |
| Land Gini | 0.694 | 0.130 | 0.680 | 0.117 | −0.018 | 0.084 | 5,446 |
| Log Area Farms > 1.000 ha | 3.834 | 4.926 | 3.051 | 4.720 | −0.783 | 3.521 | 5,446 |
| Log Number Farms > 1.000 ha | 1.048 | 1.286 | 1.071 | 1.310 | 0.024 | 0.530 | 5,446 |
| Log Output Value of Agroindustry | 4.392 | 2.356 | 5.595 | 2.311 | 1.202 | 2.200 | 5,446 |

*Note:* See Appendix A for a detailed description of each variable.

Finally, we also use the Relacão Anual de Informações Sociais (RAIS) to obtain disaggregated employment across different industries and alternative measures on total sectoral employment and employment shares in our analysis. RAIS is a yearly administrative database from the Brazilian Ministry of Labor (MTE), which provides matched employer-employee data at the individual level on the universe of formal sector employees.

# 5 Empirical Strategy

The first part of the empirical analysis is to construct a shift-share (Bartik) measure to estimate the causal effects of the commodity price shocks on the local reallocation of factors across the main sectors of the economy. We do so by interacting local agricultural endowment shares with the movements in global commodities prices. International prices are likely to be exogenous to local economic conditions, but local crop quantities are most likely not. Therefore, to obtain shares that are also exogenous, we combine the FAO-GAEZ potential yields with observed crop production patterns in the municipalities.

Our framework extends the settings in Dube and Vargas (2013) and Bernstein et al. (2018) by constructing exogenous agricultural shares. Following Fiszbein (2019), we construct predicted agricultural shares for each municipality by incorporating the FAO-GAEZ crop-specific attainable yields into a fractional multinomial logit (FML) model. This framework is specified as a system of equations in which the outcome variables are the observed shares of each agricultural product $k$ in total agricultural output in municipality $i$, and the regressors are the crop-specific potential yields vector $A_i$ measured in tons per hectare per year.

In our baseline specification, we use the average local crop $k$ endowment share in municipalities over the period 1995-1999 to capture the pre-period exposure to the commodity shock that started in 2000.[14] The idea behind this choice is to create a proxy for local crop endowments shares that depends only on the FAO-GAEZ soil- and climate-based productivity measures, and therefore can be considered exogenous to local economic conditions.

The functional form of the model is given by:

$$\widehat{Q}_{ki} = E[Q_{ki,99}|A_i] = \frac{e^{\beta_k A_i}}{1 + \sum_{j=1}^{K-1} e^{\beta_j A_i}} \tag{1}$$

By construction, $\sum_{i=1}^{I} \widehat{Q}_{ki} = 1$, i.e, the predicted shares for each municipality add up to 1. The parameters are estimated by quasi-maximum-likelihood. We can motivate the FML framework by considering a simple model of optimal crop choice, as discussed in Fiszbein (2019). Assume, for instance, that farms are price-takers and choose to maximize profits. The profits obtained when choosing crop $k$ for for a unit of farm resources $l$ are given by the

[14] Later, we perform robustness checks using the mean crop production over 2000-2010.

the following equation:

$$\pi_{kl} = \beta_i' A_k + \epsilon_{kl} \tag{2}$$

where $\pi_{kl}$ is the profit value for each choice of crop type and farm resource and $\epsilon_{kl}$ is an error term. Then, the estimated parameters reflect the price and cost differentials among agricultural products, as well as any other factors that affect profits for different crops. If the error term is assumed to be *iid* with type I extreme value distribution, then choice $k$ is optimal (i.e. $\pi_{kl} \geq \pi_{k'l}$ for all $k'$) with probability $\frac{e^{\beta_k A_l}}{1+\sum_{j=1}^{K-1} e^{\beta_j A_l}}$.

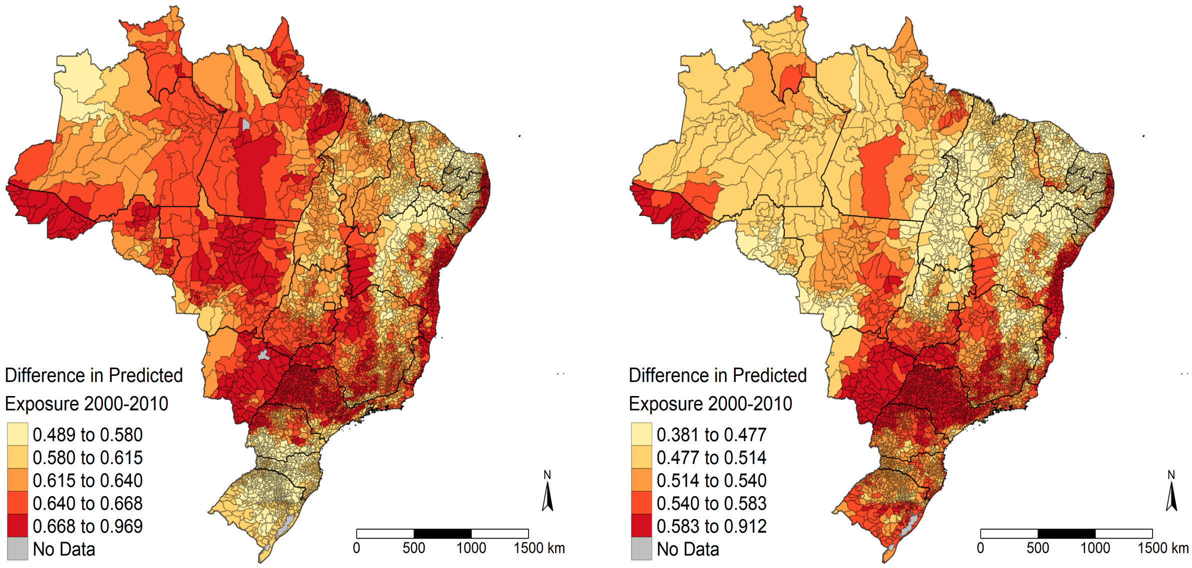
The next step is to interact the predicted shares with the international prices for each commodity. Let $P_{kt}$ be the international price of crop $k$ in year $t$. Since a municipality can be considered a small open economy, we assume that it cannot influence, in a significant manner, the yearly movements in international commodity prices. Therefore, the price variations can be considered exogenous to local outcomes related to the structure of the economy. Our measure is then given by an annual Commodity Exposure (CE) measure for municipality $i$ in year $t$:

$$CE_{it} = \sum_k \widehat{Q}_{ki} \cdot \log P_{kt} \tag{3}$$

We draw from the recent advances in the shift-share literature to guarantee that the identification assumption of this empirical design hold. In particular, our approach follows closely the assumptions in Borusyak et al. (2018), where identification is achieved via exogeneity of the shocks.[15] We choose to use the log in the prices, and not in the whole measure, to avoid omitted variable bias as discussed in Borusyak and Hull (2020). Figure 4 shows the differential exposure of each municipality to the commodity supercycle. We plot the exposure measure constructed both with and without livestock production since it could be argued that cattle is not an agricultural product per se. Nevertheless, we show in Appendix C that our results do not change if we exclude cattle from the measure. Figure 5 shows the distribution of the values for the CE measure for both years of our analysis. The values are reasonably well distributed, giving us a large sample of exposed vs non-exposed municipalities.

It is remarkable how well our measure predicts the agricultural frontier expansion that happened after 2000 in Brazil. Recall that for our baseline measure we are using pre-period crop productions combined with crop-specific attainable yields from FAO-GAEZ, which do not depend on any contemporaneous pattern of agricultural production. With this in mind,

[15] For a further discussion about the shift-share literature and different complementary frameworks—where identification is achieved via exogeneity of the shares—see Goldsmith-Pinkham et al. (2020).




(a) Excluding Cattle

(b) Including Cattle

Figure 4: Exposure to the Commodity Shock

the measure still captures how the current agricultural frontier benefited from the resource boom. Consider, for example, the Central-West portion of Brazil and the areas close to the Amazon Forest frontier, which are highly productive agricultural areas today and were also greatly exposed to the shock according to our measure (Figure 4).[16]

The last step is to estimate the main equation for our analysis, which allows us to explore the effects of the commodities shocks on outcomes related to structural change in each municipality. Formally, we estimate the following equation:

$$y_{it} = \beta CE_{it} + \alpha_i + \gamma_t + \delta X_{it} + u_{it} \tag{4}$$

where $y_{it}$ is the outcome of interest that varies across municipalities $i$ and time $t$; $CE_{it}$ is the Commodity Exposure measure as defined in Equation 3; $\alpha_i$ are municipality fixed effects and $\gamma_t$ are time fixed effects; $X_{it}$ is a vector of municipality control variables; $u_{it}$ is an error term.

Out identification assumption relies on the exogeneity of the CE measure in the following

[16] This recent expansion of the agricultural frontier also generated important concerns about the possible negative environmental effects associated with the commodity boom. For a discussion, see Assunção and Bragança (2015) and Bragança (2018).

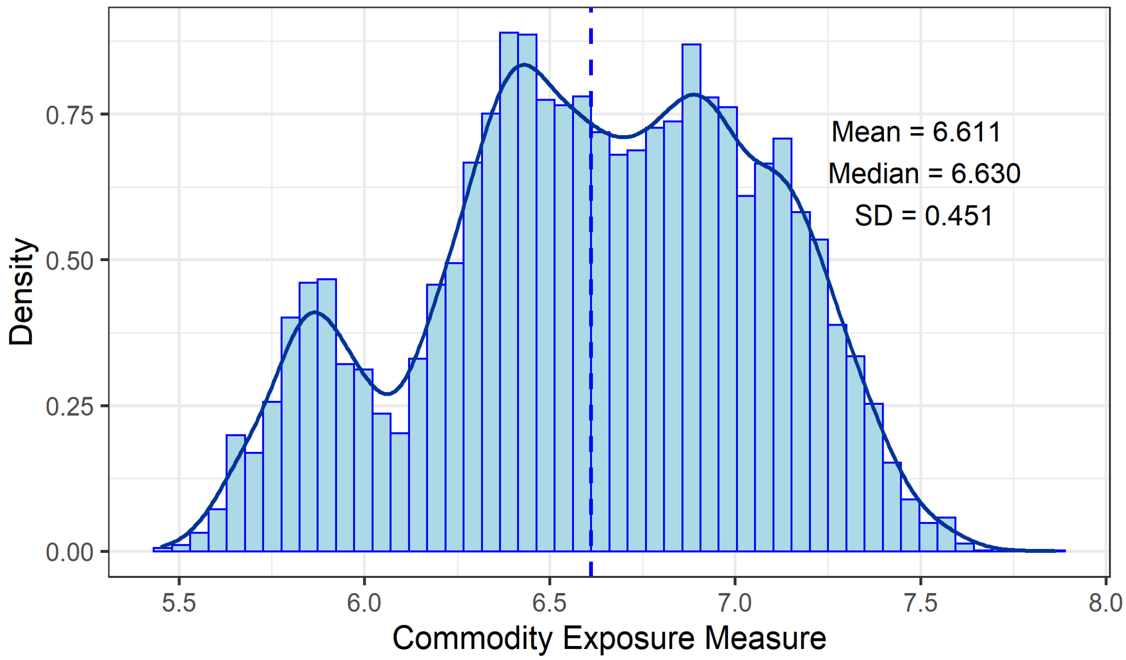



Figure 5: Histogram of the Commodity Exposure Measure

way:

$$\mathbb{E}\left[u_{it}|CE_{it}, X_{i,1991}, \alpha_i, \gamma_t\right] = 0. \tag{5}$$

Since we constructed it using a shift-share approach, we would only need either the shares or the shocks to be exogenous in relation to the outcomes, as discussed in the approaches of Goldsmith-Pinkham et al. (2020) and Borusyak et al. (2018), respectively. Nevertheless, we argued that both the shares and shocks in our measure can be considered exogenous and, therefore, that the identification assumption holds.

In the case of sectoral employment share outcomes, our period of interest spans the ten years between the last two population censuses, which took place in 2000 and 2010. Similarly, for the agricultural censuses outcomes, we also have data on an interval of about ten years between the last two rounds (2006 and 2017). We thus estimate the first-difference version of Equation 4:

$$\Delta y_i = \beta \Delta CE_i + \delta' X_{i,1991} + \Delta u_i \tag{6}$$

where the outcome of interest $\Delta y_i$ is the change in outcome variables between the last two census years and $\Delta CE_i$ is the change in the value of the exposure measure between 2000 and 2010. We also include controls for observable characteristics in the population census

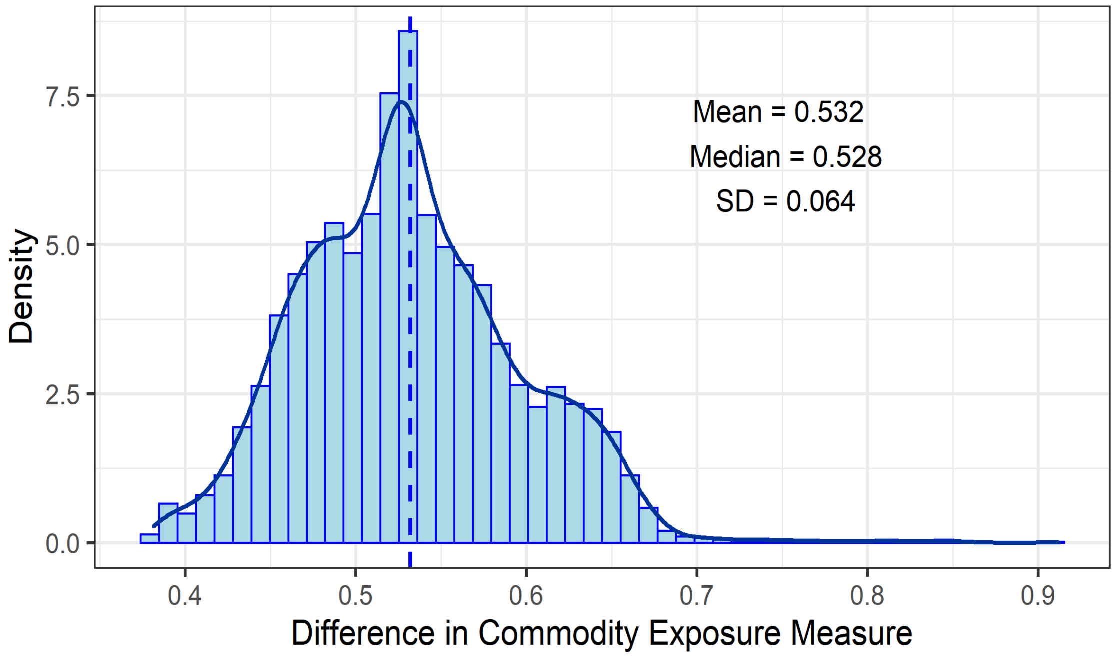



Figure 6: Histogram of the Difference in the Commodity Exposure Measure between 2000-2010

of 1991 to control for differential trends across municipalities with heterogeneous initial characteristics. In our specifications, we first add the share of rural population in 1991 and then extend the set of controls to also include population density, income per capita, illiteracy rates and region fixed effect[17] in our vector of controls. This is important because it can be the case that municipalities with heterogeneous initial levels of development experiences different growth paths and then our estimates could be capturing differential structural transformation trends across municipalities.[18]

# 6 Results

We start our analysis by exploring how the commodity boom affected the profitability and allocation of labor across the main sectors of the Brazilian economy. As discussed in Sections 1 and 2, the theoretical and empirical literature has shown that a natural resource boom can ambiguously affect agricultural and manufacturing development. It could, for instance, increase the comparative advantage of agriculture in an open economy and restrain manu-

[17] Region fixed effects include dummies variables for the five macroregions of Brazil: North, Northeast, Central-West, Southeast and South.

[18] Take, for example, the state of São Paulo in the southeast region of Brazil which is one of the regions that benefited the most from the shock (as shown in Figure 4) and also one of the most developed regions in the country.

facturing development. On the other hand, agglomeration and spillover effects might occur after the increase in the agricultural sector profitability. Some subsectors of the manufacturing sector could benefit from the commodity boom if their production chains depend on the production of agricultural goods. Consider, for example, industries linked to the processing of food and beverages, clothing, or even the supply of agricultural inputs, such as tractors or harvesters.

Now, we show how the commodity boom affected the profitability and growth of the major sectors. In every table, the first column (1) displays the coefficients for the regression without any controls. In the subsequent columns (2) to (4), we account for different specifications that sequentially expand the baseline set of pre-period socio-economic controls to include region fixed effects, the share of rural population, illiteracy rate, log income per capita and log population density.

Table 2 reports the estimates of the coefficient on the commodity shock exposure measure in regressions for total sectoral GDP across agriculture, manufacturing and services. The estimates in column (4), our preferred specification, imply that the commodity boom greatly benefited the agriculture sector by increasing its GDP. We also observe a first evidence on the existence of a spillover effect of the commodity shock on other sectors of the economy. The elasticities of the coefficients imply that if a municipality experienced an increase in the CE measure equivalent to a 1 standard deviation (0.064), from the average exposure due to the commodity shock, Agricultural GDP per capita would increase by about 16.5 log points (18%). Similarly, we would also observe an increase of 0.7-2.1 log points (0.7-2.2%) in Manufacturing GDP (columns (3)-(4)). The results for total GDP are positive and of about the same magnitude as the manufacturing sector. The results for the service sector GDP are negative and significant, implying a possible crowding out effect after the shock.

We now explore how labor reallocated after the commodity boom. Table 3 reports the estimates of the coefficient on the commodity shock exposure measure in regressions for employment shares in agriculture, manufacturing and services. According to our preferred specification, the estimates imply that a 1 standard deviation increase in the CE measure leads to a decrease of 0.8 percentage points (pp.) in the agricultural employment share. This estimate corresponds to about 10% of a standard deviation in the observed change of the agricultural employment share between 2000 and 2010 (8.1pp., see Table 1). In the case of manufacturing employment shares, the estimated coefficients in columns (4) indicate an increase of about 1pp. in manufacturing employment share, which corresponds to 18% of a standard deviation in the change between 2000 and 2010 (5.5pp.). We also do not observe any meaningful effect on the employment share of services. Additionally, we show in Appendix B that the effects were very similar for total employment.

Table 2: The Effect of the Commodity Shock on Sectoral GDP

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A.** | $\Delta$ Log Total GDP Per Capita | | | |
| $\Delta$ CE | −0.440*** | −0.291*** | 0.124 | 0.164** |
| | (0.069) | (0.074) | (0.078) | (0.079) |
| Adj. $R^2$ | 0.007 | 0.013 | 0.045 | 0.050 |
| **Panel B.** | $\Delta$ Log Agricultural GDP Per Capita | | | |
| $\Delta$ CE | 1.919*** | 2.007*** | 2.689*** | 2.580*** |
| | (0.143) | (0.153) | (0.166) | (0.169) |
| Adj. $R^2$ | 0.034 | 0.034 | 0.069 | 0.075 |
| **Panel C.** | $\Delta$ Log Manufacturing GDP Per Capita | | | |
| $\Delta$ CE | 0.516*** | 0.340** | 0.337* | 0.113 |
| | (0.158) | (0.170) | (0.185) | (0.186) |
| Adj. $R^2$ | 0.002 | 0.003 | 0.043 | 0.062 |
| **Panel D.** | $\Delta$ Log Services GDP Per Capita | | | |
| $\Delta$ CE | −1.138*** | −0.857*** | −0.546*** | −0.454*** |
| | (0.058) | (0.060) | (0.062) | (0.060) |
| Adj. $R^2$ | 0.089 | 0.124 | 0.161 | 0.181 |
| Rural Share in 1991 | | ✓ | ✓ | ✓ |
| Region FE | | | ✓ | ✓ |
| Baseline Controls | | | | ✓ |
| Observations | 5,488 | 5,488 | 5,488 | 5,488 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

We interpret these first results as providing evidence that supports the view that the commodity boom generated a relevant structural transformation effect. As would be expected, the agricultural sector benefits heavily from the commodity shock. Since our measure is multiplying prices by quantities—while also considering differentials in crop-specific agricultural productivity across locations—our results reflect how the commodity boom was fundamental in causing the high period of economic growth observed in Brazil between 2000 and 2010. But most important than that, the boom generated a reallocation of labor away from agriculture, a result that might appear not intuitive at first.

We discuss these results in light of the recent literature that explores the localized effects of natural resource booms. Bustos et al. (2016) finds that the adoption of genetically engineered (GE) soybeans across municipalities resulted in a decrease of employment share

Table 3: The Effect of the Commodity Shock on Employment Shares

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A.** | Δ Employment Share in Agriculture | | | |
| Δ CE | 0.053*** | −0.079*** | −0.095*** | −0.120*** |
| | (0.017) | (0.017) | (0.018) | (0.018) |
| Adj. $R^2$ | 0.002 | 0.071 | 0.072 | 0.086 |
| **Panel B.** | Δ Employment Share in Manufacturing | | | |
| Δ CE | 0.165*** | 0.172*** | 0.141*** | 0.151*** |
| | (0.012) | (0.012) | (0.013) | (0.014) |
| Adj. $R^2$ | 0.037 | 0.037 | 0.049 | 0.052 |
| **Panel C.** | Δ Employment Share in Services | | | |
| Δ CE | −0.152*** | −0.026** | −0.013 | 0.001 |
| | (0.012) | (0.012) | (0.013) | (0.013) |
| Adj. $R^2$ | 0.030 | 0.165 | 0.168 | 0.176 |
| Rural Share in 1991 | | ✓ | ✓ | ✓ |
| Region FE | | | ✓ | ✓ |
| Baseline Controls | | | | ✓ |
| Observations | 5,475 | 5,475 | 5,475 | 5,475 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

in agriculture of about 24% of a standard deviation., with an increase in employment share in manufacturing of 31% of a standard deviation. Since the GE soy is characterized as a labor-saving technology, their estimates also imply that a 1% increase in agricultural labor productivity corresponds to a 0.157pp. increase in manufacturing employment share. While our estimates are slightly lower than theirs, it is remarkable that we find the same sign directions after the commodity boom.

At a first moment, this could not be expected since we are analyzing a large set of internationally traded commodities and holding crop-specific technological change constant. Moreover, many of the commodities in our sample are characterized by their labor-intensity in production and, therefore, differ fundamentally from the main hypothesis of Bustos et al. (2016). In their paper, they also look at the technical change in maize, which is found to be land-augmenting. The authors then find an opposite effect to that of the GE soy, with the expansion of maize being associated with an increase in the labor share of agriculture.[19]

[19] As already discussed in Section 2, we still have little evidence on the effects of agricultural technical change on structural transformation, which also appear to be context-specific (Moscona, 2018).

It could well be the case that, after the resource boom, the agricultural sector expands its comparative advantage and draws labor in. However, our results imply that this did not happen. Our main hypothesis for the mechanism that led to this effect is discussed in Section 7 and is related to fundamental changes in the use of capital and land in the agricultural sector.

In Table 4, we explore how the commodity super-cycle impacted urbanization and wages across the same sectors. A 1 standard deviation increase in the exposure measure led to an increase of 0.2pp. in urbanization, which corresponds to 3% of a standard deviation of the change between 2000 and 2010. In terms of wages, our estimates imply that a 1 standard deviation in CE is associated with an increase of about 3% in wage in the agricultural sector and an increase of 4% in services. For wages in manufacturing, we observe the opposite effect, with a negative effect of 2%. Again, our results for the manufacturing sector are similar to that of Bustos et al. (2016) for the adoption of GE soy.

Our results are also in line with the model and cross-country evidence in Gollin et al. (2016). The expansion of the agricultural sector associated with the commodity boom generated a positive urbanization effect, as predicted by their model. Although we do not observe localized effects on employment shares in the service sector, the rise in urbanization and employment share in manufacturing corroborate the "consumption cities" view. Moreover, our results also show that the commodity boom worked as a labor-push factor in agriculture.[20]

We now turn our attention to the possible heterogeneous effects of the commodity boom on the manufacturing sector. Since we observed a positive relationship between the shock and the employment share in manufacturing, we extend our analysis to test the hypothesis if this reallocation of labor was directed at a particular types of industries. To do so, we use the RAIS dataset to divide the manufacturing sector into industries that are more linked to agriculture and consider them as being part of the agroindustry. These subsectors are related to food processing, beverage production, wood processing and clothing. The other subsectors—which we label as heavy industry—are composed of chemical industries, electronics, pharmaceutical industry, metallurgy, machinery and automotive industry.[21]

One possible drawback in our analysis is the fact that RAIS only covers formal jobs, which do not fully represent the highly informalized Brazilian labor market. Nevertheless, the manufacturing sector relies intensely on workers with formal labor contracts—which is not the case in agriculture and services— and, therefore, we assume that it approximates reasonably well the employment share inside this particular sector. In Table 5 we show

[20] For a discussion of push vs pull factors in the structural transformation literature, see Alvarez-Cuadrado and Poschke (2011).

[21] See Appendix A for a detailed definition of the sector and subsector that we analyze.

Table 4: The Effect of the Commodity Shock on Urbanization and Wages

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A.** | | $\Delta$ Urban Population Share | | |
| $\Delta$ CE | −0.051*** | 0.080*** | 0.040** | 0.032** |
| | (0.014) | (0.014) | (0.016) | (0.016) |
| Adj. $R^2$ | 0.003 | 0.116 | 0.126 | 0.127 |
| **Panel B.** | | $\Delta$ Log Wages in Agriculture | | |
| $\Delta$ CE | 0.475*** | 0.354*** | 0.307*** | 0.444*** |
| | (0.080) | (0.084) | (0.092) | (0.093) |
| Adj. $R^2$ | 0.006 | 0.008 | 0.016 | 0.025 |
| **Panel C.** | | $\Delta$ Log Wages in Manufacturing | | |
| $\Delta$ CE | −0.436*** | −0.524*** | −0.359*** | −0.300** |
| | (0.117) | (0.124) | (0.133) | (0.136) |
| Adj. $R^2$ | 0.002 | 0.003 | 0.005 | 0.006 |
| **Panel D.** | | $\Delta$ Log Wages in Services | | |
| $\Delta$ CE | 1.168*** | 1.090*** | 0.572*** | 0.581*** |
| | (0.085) | (0.091) | (0.094) | (0.096) |
| Adj. $R^2$ | 0.031 | 0.032 | 0.141 | 0.145 |
| Rural Share in 1991 | | ✓ | ✓ | ✓ |
| Region FE | | | ✓ | ✓ |
| Baseline Controls | | | | ✓ |
| Observations | 5,475 | 5,475 | 5,475 | 5,475 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

that this is indeed the case. The commodity boom is associated with an increase in the manufacturing employment share of about the same magnitude that we previously obtained with the population census data.

We also obtain the output value in agroindustry from the Agricultural Census to further explore how the subsector was impacted. Our estimates imply that the production value of the agroindustry increases. After controlling for region fixed effects, the result losses significance and magnitude, but remains positive. In terms of employment shares, the reallocation of labor away from agriculture and into manufacturing appears to be equally distributed across the two subsectors that we have defined previously. A 1 standard deviation increase in the CE measure led to an increase of about 0.4pp. in agroindustry and 0.45pp. in the heavy industry.

Table 5: The Heterogeneous Effect of the Commodity Shock on the Type of Industry

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A.** | $\Delta$ Log Output in Agroindustry | | | |
| $\Delta$ CE | 3.075*** | 2.388*** | 0.276 | 0.420 |
| | (0.495) | (0.522) | (0.574) | (0.586) |
| Adj. $R^2$ | 0.008 | 0.010 | 0.040 | 0.040 |
| Observations | 5,447 | 5,447 | 5,447 | 5,447 |
| **Panel B.** | $\Delta$ Employment Share in Manufacturing | | | |
| $\Delta$ CE | 0.168*** | 0.149*** | 0.102*** | 0.112*** |
| | (0.025) | (0.027) | (0.029) | (0.030) |
| Adj. $R^2$ | 0.008 | 0.009 | 0.019 | 0.020 |
| Observations | 5,455 | 5,455 | 5,455 | 5,455 |
| **Panel C.** | $\Delta$ Employment Share in Agroindustry | | | |
| $\Delta$ CE | 0.101*** | 0.085*** | 0.042* | 0.061*** |
| | (0.019) | (0.020) | (0.022) | (0.023) |
| Adj. $R^2$ | 0.005 | 0.005 | 0.028 | 0.032 |
| Observations | 5,455 | 5,455 | 5,455 | 5,455 |
| **Panel D.** | $\Delta$ Employment Share in Heavy Industry | | | |
| $\Delta$ CE | 0.079*** | 0.070*** | 0.077*** | 0.072*** |
| | (0.014) | (0.015) | (0.016) | (0.017) |
| Adj. $R^2$ | 0.006 | 0.006 | 0.011 | 0.011 |
| Observations | 5,455 | 5,455 | 5,455 | 5,455 |
| Rural Share in 1991 | | ✓ | ✓ | ✓ |
| Region FE | | | ✓ | ✓ |
| Baseline Controls | | | | ✓ |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Our results imply that the natural resource boom associated with the commodity supercycle generated an important reallocation of labor away from agriculture and into manufacturing and, more importantly, the expansion of the manufacturing sector is equally distributed between the agroindustry more specialized transformation industries. This effect could imply that the structure of the economy has changed to a higher sustained growth path, if we assume that the manufacturing sector is associated with higher productivity and spillover effects, like learning-by-doing as in Matsuyama (1992) model. However, this scenario of an increase in the long-term growth of the economy is unlikely to occur in our setting. Our analysis abstains from human capital considerations, which is a key dimension to take into consideration. Following their early work, Bustos et al. (2020b) show that the work reallocated into manufacturing after the adoption of the GE soy was relatively unskilled, which reinforced comparative advantage in the least skill-intensive manufacturing industries and slowed down local aggregate manufacturing productivity growth. We think that this could also be the case for our analysis since agricultural labor in the Brazilian economy is characterized by low levels of human capital accumulation.

# 7 Mechanisms

We now turn to our analysis of possible channels and mechanisms that might be driving the reallocation of workers away from agriculture and into manufacturing, while also increasing the manufacturing GDP and the wages in agriculture. Our main hypothesis is based on exploring how the structure of the agriculture sector changed after the shock. In this sense, we first look at the hypothesis that the commodity boom changed the use of inputs in the agriculture sector towards a more intensive utilization of capital in the farms. We also analyze if the commodity boom increased inequality in land ownership, increasing the land appropriated by larger farms and possibly displacing small owners from agriculture.

## 7.1 Use of Land, Capital Inputs and Agricultural Productivity

In Table 6 we explore how the commodity boom impacted the utilization of the other two fundamental inputs used in agriculture: land and capital. Our main hypothesis in this section is that changes in input use worked as a potential margin of adjustment to the resource boom. Our first variable of interest is the log of total farmland, to capture the expansion of land utilization in agricultural production. To analyze the capital adoption in farms we look at the intensity of machine usage[22] and the share of agricultural land planted with genetically engineered (GE) seeds in each municipality. Our estimates in column (4) imply that an increase of 1 standard deviation in the CE measure is associated with an increase in 4.5% in machine intensity and an increase of about 1.2pp. in the share of land planted with GE seeds. The coefficients for total farmland loses significance as we control for region fixed effects and baseline controls.

Together with our main results from the previous section, we again interpret our findings as pointing to a relevant structural transformation effect after the commodity boom. In particular, the labor that was reallocated away from agriculture and into the manufacturing

[22] Defined as the total number of tractors, planters and harvesters in each municipality divided by the total farmland

sector might have been substituted by agricultural machines as our results show.[23] Moreover, the increased use of GE seeds can also explain the displacement of agricultural workers. During the last two decades, GE seeds have been extensively adopted throughout Brazil. One of the main features of GE seeds is that they are resistant to herbicides and facilitate the use of no-tillage planting techniques (Bustos et al., 2016). Therefore, we would expect that an increase in the use of GE seeds leads to a decrease in the number of workers per hectare needed to produce a fixed amount of agricultural output.

Our results about the absence of effects on total farmland might seem less intuitive at a first moment. Although we should expect an increase of land devoted to agricultural production in more exposed municipalities after the commodity boom, several factors might explain the lack of effect that we observe. We focus on a particular hypothesis that the landowners could have been inefficiently using their farmland and, after the shock, increased the efficiency of production without expanding their farmland devoted to agricultural production. If this were indeed the case, we should at least observe the farm productivity increasing.

In Table 7 we show that this appears to be the case. We measure farm productivity as the total output of agriculture divided by the total farmland in hectares. Our results show that the commodity boom is positively associated with farm productivity. This also represents an important mechanism that might be driving our main results regarding structural transformation. The evidence on farmland productivity corroborates our findings in Section 6 about the commodity boom working as a labor-push factor in agriculture.

We also explore if labor productivity in the agricultural sector increased after the resource boom. If we observed a positive and significant effect of the exposure to the commodity boom on labor productivity, it could mean that the effects of labor-saving vs labor-augmenting technologies are missing from our analysis. The prevalence of one type of technological change over another might be important in explaining the structural transformation patterns we observe, as discussed in Bustos et al. (2016). We do not observe, however, any statistically significant effect in our preferred specification. Since the literature has well-documented evidence on the adoption of both types of agricultural technical change in Brazil during the period which we analyze, it could be the case that their overall effect over structural transformation eventually cancels out.

[23] There is also a possible linkage effect that could be at play, but which we do not explore in-depth. It relates to the increase of machine intensity together with an increase in the manufacturing sector related to machine production.

Table 6: The Effect of the Commodity Shock on the Land Use and Capital Inputs

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A.** | | Δ Log Total Farmland | | |
| Δ CE | 0.579*** | 0.500*** | −0.186* | −0.111 |
| | (0.091) | (0.097) | (0.107) | (0.108) |
| Adj. $R^2$ | 0.006 | 0.007 | 0.052 | 0.062 |
| **Panel B.** | | Δ Log Machine Intensity | | |
| Δ CE | 0.264 | 0.547** | 0.582** | 0.680*** |
| | (0.206) | (0.217) | (0.234) | (0.237) |
| Adj. $R^2$ | 0.000 | 0.003 | 0.020 | 0.023 |
| **Panel C.** | | Δ Share of Land with GE Seeds | | |
| Δ CE | 0.390*** | 0.379*** | 0.188*** | 0.181*** |
| | (0.031) | (0.032) | (0.028) | (0.029) |
| Adj. $R^2$ | 0.021 | 0.021 | 0.191 | 0.193 |
| Rural Share in 1991 | | ✓ | ✓ | ✓ |
| Region FE | | | ✓ | ✓ |
| Baseline Controls | | | | ✓ |
| Observations | 5,446 | 5,446 | 5,446 | 5,446 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

## 7.2 Inequality in Land Ownership

We now explore how the commodity boom impacted the reallocation of farmland and land inequality across municipalities and how this might have worked as an important mechanism in driving the structural change effects we documented in the previous sections. Land inequality has been more extensively studied in the broad growth literature, but it is often overlooked in the structural transformation literature. One of the main hypothesis linked to the study of land inequality is related to the works of Engerman and Sokoloff (1994) and Galor et al. (2009), which suggest that inequality in the distribution of landownership had adverse effects on the emergence of public schooling during the transition from an agricultural economy to an industrial one. This hypothesis has been extensively tested in historical settings, implying that land inequality indeed played an important role in the process of long term economic development (Easterly, 2007; Vollrath, 2007; Cinnirella and Hornung, 2016; Wigton-Jones, 2020).

In our setting, these results regarding land inequality, institutions and human capital are unlikely to have a significant effect, mainly because we are analyzing a modern economy

Table 7: The Effect of the Commodity Shock on Agricultural Productivity

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A.** | | $\Delta$ Log Farm Productivity | | |
| $\Delta$ CE | 1.012*** | 1.009*** | 0.399** | 0.567*** |
| | (0.180) | (0.196) | (0.193) | (0.194) |
| Adj. $R^2$ | 0.006 | 0.006 | 0.096 | 0.118 |
| **Panel B.** | | $\Delta$ Log Output per Worker | | |
| $\Delta$ CE | 1.324*** | 1.434*** | 0.033 | 0.215 |
| | (0.191) | (0.207) | (0.197) | (0.197) |
| Adj. $R^2$ | 0.010 | 0.010 | 0.124 | 0.144 |
| Rural Share in 1991 | | ✓ | ✓ | ✓ |
| Region FE | | | ✓ | ✓ |
| Baseline Controls | | | | ✓ |
| Observations | 5,446 | 5,446 | 5,446 | 5,446 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

that has already experienced a major process of industrialization and expansion of public education. Nevertheless, we still propose that land inequality might be playing an important role in the relationship between natural resource booms and structural transformation, in particular via productivity changes and displacement of small landowners.

The relation between land inequality and agricultural productivity has been studied in Vollrath (2007). In a cross-sectional study of countries, the author finds that the Gini coefficient for land holdings is negatively associated with productivity in farms. In our setting, the relation between the resource boom, land inequality and structural change could go plausibly in different directions. We expect that, after the commodity shock, land inequality increases given the structure of the Brazilian agricultural sector and its high and persistent inequality in landholdings discussed in Section 3. The relationship between land inequality and agricultural productivity would then be ambiguous a priori. We could expect that productivity decreases given the rise in land inequality, supporting Vollrath's findings. On the other hand, productivity could also be positively related to productivity in our case. Since commodities such as soy, tobacco, cotton, sugarcane and cattle raising are associated with large and productive farms, it could be the case that, after the shock, both land inequality and farm productivity increase in Brazil.[24]

[24] Although smaller farms were usually associated with higher productivity in the empirical literature, there is a recent divergence between the microeconomic and macroeconomic evidence. For a discussion, see

In Table 8 we explore how the commodity boom affected the Land Gini taking short and long differences. We choose to report both types of results because land inequality, as a particular form of wealth inequality, is very persistent and changes slowly over time. Our results imply that an increase of 1 standard deviation in the exposure measure led to an increase of 0.004 points in the short difference Land Gini (between the 2006 and 2017 Agricultural Censuses) and an increase of about 0.007 points in the long difference (between 1995 and 2017). These two effects account for about 5% of a standard deviation in the observed change.

We complement these pieces of evidence by exploring in Table 9 the number of farms with more than 1000 hectares and the area appropriated by them in each municipality. We choose this arbitrary cutoff of total area because it captures the average farm size of the top 1% of agricultural establishments in terms of area appropriation, as reported in the Agricultural Census and discussed in Section 3. We find that an increase of 1 standard deviation in the exposure measure is associated with an increase of 0.42% in the area of the top 1% farms in the short difference. The coefficient associated with the long difference is not statistically significant, although higher in magnitude. In terms of the number of farms that have more than 1000 hectares, we find that an increase of 1 standard deviation in the CE measure leads to an increase of 2.1pp. in the short difference and an increase of 8pp. in the long difference.

Together with the evidence in Table 7, it appears to be the case that both agricultural productivity and land inequality increased, supporting the view that farms associated with large field crops increased their productivity after the commodity shock. Moreover, since we observe both the Land Gini and the area and number of top 1% farms increasing without the same happening with total farmland, we interpret these results as also supporting the view that the commodity shock impacted structural transformation via the displacement of small landowners and workers away from agriculture.

# 8 Conclusion

This paper shows that the 2000s commodity supercycle led to a sizeable structural change in Brazilian municipalities between 2000 and 2010 and did not generate what is usually called a Natural Resource Curse. Our identification strategy relies on a shift-share measure that is constructed interacting climate- and soil-based measures of crop-specific potential yields with the international prices of commodities. This measure gives us cross-sectional and time variation of local exposure to the commodity shock. We find that, after the boom, labor was reallocated away from agriculture and towards the manufacturing sector. We also

Sanchez et al. (2019).

Table 8: The Effect of the Commodity Shock on Land Inequality

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A.** | | $\Delta$ Land Gini (2006-2017) | | |
| $\Delta$ CE | 0.179*** | 0.163*** | 0.072*** | 0.065*** |
| | (0.017) | (0.018) | (0.021) | (0.021) |
| Adj. $R^2$ | 0.018 | 0.019 | 0.065 | 0.071 |
| Observations | 5,446 | 5,446 | 5,446 | 5,446 |
| **Panel B.** | | $\Delta$ Land Gini (1995-2017) | | |
| $\Delta$ CE | 0.217*** | 0.229*** | 0.127*** | 0.111*** |
| | (0.022) | (0.023) | (0.025) | (0.025) |
| Adj. $R^2$ | 0.019 | 0.019 | 0.106 | 0.111 |
| Observations | 4,919 | 4,919 | 4,919 | 4,919 |
| Rural Share in 1991 | | ✓ | ✓ | ✓ |
| Region FE | | | ✓ | ✓ |
| Baseline Controls | | | | ✓ |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

explored the possible mechanisms that are driving this effect and find that substitution of labor by capital in the farms and increasing inequality among landowners are important and previously unexplored factors that might be driving the observed effects.

We interpret our results in terms of both the broad Dutch Disease literature and the Prebisch-Singer hypothesis. The resource boom did not appear to crowd out the manufacturing sector, which shows that the usual Resource Curse effects were not present in the context analyzed. If we take into account the evidence presented in this paper together with that in Bustos et al. (2016), it appears that changes in the structure of the modern agricultural sector in Brazil—via exogenous prices variations or technological change—can indeed generate structural transformation.

Although deindustrialization and low trends of growth and productivity are indeed salient features in the Brazilian economy during the last decades, our work provides evidence that the commodity boom is not one of the fundamental causes of these issues. We raise the hypothesis that the usual suspects, such as the overall quality of institutions and the accumulation and quality of human capital might be the key factor preventing the betterment of productivity and economic growth in the economy. However, we do not test directly for the human capital hypothesis in this paper and leave it for future work.

Table 9: The Effect of the Commodity Shock on Land Inequality

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A.** | $\Delta$ Log Area Farms > 1.000 ha (2006-2017) | | | |
| $\Delta$ CE | 0.179*** | 0.163*** | 0.072*** | 0.065*** |
| | (0.017) | (0.018) | (0.021) | (0.021) |
| Adj. $R^2$ | 0.018 | 0.019 | 0.065 | 0.071 |
| **Panel B.** | $\Delta$ Log Area Farms > 1.000 ha (1995-2017) | | | |
| $\Delta$ CE | 1.267 | 6.090*** | 2.087* | 1.544 |
| | (0.970) | (1.022) | (1.094) | (1.114) |
| Adj. $R^2$ | 0.000 | 0.030 | 0.086 | 0.094 |
| **Panel C.** | $\Delta$ Log Number Farms > 1.000 ha (2006-2017) | | | |
| $\Delta$ CE | 0.848*** | 0.827*** | 0.294** | 0.336** |
| | (0.117) | (0.125) | (0.134) | (0.136) |
| Adj. $R^2$ | 0.010 | 0.010 | 0.031 | 0.033 |
| **Panel D.** | $\Delta$ Log Number Farms > 1.000 ha (1995-2017) | | | |
| $\Delta$ CE | 1.009*** | 1.839*** | 1.323*** | 1.228*** |
| | (0.148) | (0.156) | (0.165) | (0.169) |
| Adj. $R^2$ | 0.008 | 0.043 | 0.073 | 0.079 |
| Rural Share in 1991 | | ✓ | ✓ | ✓ |
| Region FE | | | ✓ | ✓ |
| Baseline Controls | | | | ✓ |
| Observations | 5,446 | 5,446 | 5,446 | 5,446 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

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# Appendix

## A Data

### A.1 Definitions and Sources

Table A.1: Agricultural Endowments Across Municipalities

| | Number of Municipalities | |
|---|---|---|
| | 2000 | 2010 |
| Cattle | 5471 | 5518 |
| Maize | 5329 | 5176 |
| Rice | 4071 | 3084 |
| Banana | 3795 | 3555 |
| Orange | 3634 | 3006 |
| Sugarcane | 3483 | 3695 |
| Coffee | 2008 | 1822 |
| Soybean | 1446 | 1800 |
| Cotton | 1272 | 411 |
| Tobacco | 958 | 892 |
| Wheat | 802 | 895 |
| Yerba Mate | 555 | 474 |
| Sorghum | 469 | 604 |
| Cocoa | 264 | 282 |
| Barley | 173 | 135 |

### A.2 Land Gini Calculation

The three rounds of the Agricultural Census (1995, 2006 and 2017) divide the area of rural properties into different intervals, reporting the total number and total area of properties across this different brackets. With this we able to calculate the mean property size within each interval. We then follow Nunn (2008) and use the Stata program *ineqdec0* written by Stephen P. Jenkins, to obtain the Gini coefficient as follows:

$$\text{Gini} = 1 + \left(\frac{1}{n}\right) - \frac{2\sum_1^n (n-i+1)\, a_i}{n\sum_i^n a_i}$$

where $n$ is the number of farms, $a_i$ is farm size in acres, and $i$ denotes the rank in ascending order of $a_i$.

# B Additional Results and Other Channels

Table B1: The Effect of the Commodity Shock on Employment Shares in the Formal Sector

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A.** | Δ Employment Share in Agriculture | | | |
| Δ CE | –0.355*** | –0.353*** | –0.176*** | –0.195*** |
| | (0.033) | (0.040) | (0.052) | (0.056) |
| Adj. $R^2$ | 0.026 | 0.026 | 0.050 | 0.171 |
| **Panel B.** | Δ Employment Share in Manufacturing | | | |
| Δ CE | 0.135*** | 0.067** | 0.051 | 0.098** |
| | (0.029) | (0.032) | (0.039) | (0.045) |
| Adj. $R^2$ | 0.009 | 0.012 | 0.044 | 0.059 |
| **Panel C.** | Δ Employment Share in Services | | | |
| Δ CE | 0.222*** | 0.289*** | 0.155** | 0.128* |
| | (0.043) | (0.055) | (0.068) | (0.074) |
| Adj. $R^2$ | 0.012 | 0.013 | 0.052 | 0.062 |
| Rural Share in 1991 | | ✓ | ✓ | ✓ |
| Region FE | | | ✓ | ✓ |
| Baseline Controls | | | | ✓ |
| Observations | 5,455 | 5,455 | 5,455 | 5,455 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table B2: The Effect of the Commodity Shock on Total Employment Across Sectors

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| **Panel A.** | $\Delta$ Log Total Employment | | | |
| $\Delta$ CE | 0.442*** | 0.155*** | 0.198*** | 0.107** |
| | (0.045) | (0.048) | (0.071) | (0.053) |
| Adj. $R^2$ | 0.016 | 0.060 | 0.157 | 0.124 |
| **Panel B.** | $\Delta$ Log Total Employment in Agriculture | | | |
| $\Delta$ CE | −0.076 | −0.267*** | −0.215*** | −0.279*** |
| | (0.073) | (0.076) | (0.083) | (0.084) |
| Adj. $R^2$ | 0.000 | 0.008 | 0.033 | 0.039 |
| **Panel C.** | $\Delta$ Log Total Employment in Manufacturing | | | |
| $\Delta$ CE | 2.238*** | 2.075*** | 1.562*** | 1.449*** |
| | (0.144) | (0.156) | (0.167) | (0.172) |
| Adj. $R^2$ | 0.046 | 0.047 | 0.061 | 0.064 |
| **Panel D.** | $\Delta$ Log Total Employment in Services | | | |
| $\Delta$ CE | 0.523*** | 0.156 | 0.326** | 0.392** |
| | (0.089) | (0.106) | (0.129) | (0.157) |
| Adj. $R^2$ | 0.014 | 0.020 | 0.050 | 0.060 |
| Rural Share in 1991 | | ✓ | ✓ | ✓ |
| Region FE | | | ✓ | ✓ |
| Baseline Controls | | | | ✓ |
| Observations | 5,475 | 5,475 | 5,475 | 5,475 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

# C Robustness Checks and Alternative Measures

## C.1 Alternative Measures

Table C1: Alternative Standard Errors for Population Census Outcomes

| | Δ Employment Share Agriculture | Δ Employment Share Manufacturing | Δ Employment Share Services | Δ Urban Population Share | Δ Log Wages Agriculture | Δ Log Wages Manufacturing | Δ Log Wages Services |
|---|---|---|---|---|---|---|---|
| Δ CE - Main Specification | −0.120*** | 0.151*** | 0.001 | 0.0325** | 0.444*** | −0.300** | 0.581*** |
| | (0.018) | (0.014) | (0.013) | (0.016) | (0.093) | (0.136) | (0.096) |
| Adj. $R^2$ | 0.086 | 0.052 | 0.176 | 0.127 | 0.025 | 0.006 | 0.145 |
| Cluster at microregion | (0.033)*** | (0.033)*** | (0.015) | (0.021) | (0.136)*** | (0.141)** | (0.182)*** |
| Conley 50km | (0.036)*** | (0.031)*** | (0.018) | (0.023) | (0.137)*** | (0.165)* | (0.173)*** |
| Conley 100km | (0.049)** | (0.044)*** | (0.022) | (0.028) | (0.173)** | (0.167)* | (0.236)** |
| Conley 200km | (0.065)* | (0.061)** | (0.024) | (0.032) | (0.186)** | (0.157)* | (0.267)** |
| Conley 400km | (0.071)* | (0.073)** | (0.020) | (0.014)** | (0.141)*** | (0.194) | (0.171)*** |
| Δ CE - No Region FE | −0.138*** | 0.174*** | 0.006 | 0.045*** | 0.524*** | −0.345*** | 0.575*** |
| | (0.018) | (0.014) | (0.012) | (0.016) | (0.089) | (0.131) | (0.094) |
| Adj. $R^2$ | 0.082 | 0.037 | 0.171 | 0.123 | 0.014 | 0.005 | 0.100 |
| AKM | (0.035)*** | (0.044)*** | (0.021) | (0.015)*** | (0.121)*** | (0.086)*** | (0.224)** |
| AKM0 | (0.055)** | (0.070)** | (0.033) | (0.027) | (0.189)** | (0.143)* | (0.353)* |
| Observations | 5,475 | 5,475 | 5,475 | 5,475 | 5,475 | 5,475 | 5,475 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table C2: Alternative Standard Errors for Input Usage

| | Δ Log Total Farmland | Δ Log Machine Intensity | Δ Share of Land with GE Seeds |
|---|---|---|---|
| Δ CE - Main Specification | –0.111 | 0.680*** | 0.181*** |
| | (0.108) | (0.237) | (0.029) |
| Adj. $R^2$ | 0.062 | 0.023 | 0.193 |
| Cluster at microregion | (0.168) | (0.295)** | (0.073)** |
| Conley 50km | (0.153) | (0.313)** | (0.074)** |
| Conley 100km | (0.194) | (0.331)** | (0.093)* |
| Conley 200km | (0.254) | (0.466) | (0.084)** |
| Conley 400km | (0.300) | (0.624) | (0.087)** |
| Δ CE - No Region FE | 0.238** | 0.597*** | 0.110*** |
| | (0.102) | (0.226) | (0.030) |
| Adj. $R^2$ | 0.042 | 0.006 | 0.082 |
| AKM | (0.144)*** | (0.298)** | (0.155) |
| AKM0 | (0.187) | (0.518)** | (0.246) |
| Observations | 5,446 | 5,446 | 5,446 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table C3: Alternative Standard Errors for Land Inequality

| | $\Delta$ Land Gini (2006-2017) | $\Delta$ Land Gini (1995-2017) |
|---|---|---|
| $\Delta$ CE - Main Specification | 0.065*** | 0.111*** |
| | (0.021) | (0.025) |
| Adj. $R^2$ | 0.071 | 0.111 |
| Cluster at microregion | (0.031)** | (0.042)*** |
| Conley 50km | (0.027)** | (0.044)** |
| Conley 100km | (0.033)* | (0.056)** |
| Conley 200km | (0.032)* | (0.059)* |
| Conley 400km | (0.039) | (0.062)* |
| $\Delta$ CE - No Region FE | 0.062*** | 0.108*** |
| | (0.020) | (0.024) |
| Adj. $R^2$ | 0.067 | 0.083 |
| AKM | (0.030)** | (0.048)** |
| AKM0 | (0.053) | (0.078) |
| Observations | 5,446 | 4,919 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

## C.2 Alternative Measures

Table C4: The Effect of the Commodity Shock on Employment Shares - Alternative Measures

| | Δ Employment Share Agriculture | Δ Employment Share Manufacturing | Δ Employment Share Services | Δ Urban Population Share | Δ Log Wages Agriculture | Δ Log Wages Manufacturing | Δ Log Wages Services |
|---|---|---|---|---|---|---|---|
| Top 10% Δ CE | −0.024*** | 0.027*** | −0.002 | 0.005** | 0.077*** | −0.007 | 0.077*** |
| | (0.003) | (0.003) | (0.002) | (0.003) | (0.017) | (0.023) | (0.016) |
| Adj. $R^2$ | 0.088 | 0.052 | 0.176 | 0.127 | 0.025 | 0.005 | 0.142 |
| Top 25% Δ CE | −0.021*** | 0.025*** | −0.002 | 0.003 | 0.074*** | −0.018 | 0.098*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.013) | (0.019) | (0.013) |
| Adj. $R^2$ | 0.091 | 0.061 | 0.176 | 0.127 | 0.027 | 0.005 | 0.147 |
| Above Median Δ CE | 0.0002 | 0.009*** | −0.005*** | 0.003* | 0.033*** | −0.035** | 0.077*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.012) | (0.017) | (0.013) |
| Adj. $R^2$ | 0.080 | 0.036 | 0.177 | 0.127 | 0.023 | 0.006 | 0.145 |
| Bottom 10% Δ CE | 0.007* | 0.000 | −0.008*** | 0.003 | −0.011 | 0.019 | 0.0303 |
| | (0.004) | (0.002) | (0.003) | (0.003) | (0.019) | (0.029) | (0.020) |
| Adj. $R^2$ | 0.081 | 0.031 | 0.178 | 0.126 | 0.022 | 0.005 | 0.140 |
| Bottom 25% Δ CE | 0.001 | −0.006*** | 0.000 | −0.004* | 0.012 | 0.054** | 0.012 |
| | (0.003) | (0.002) | (0.002) | (0.003) | (0.015) | (0.023) | (0.016) |
| Adj. $R^2$ | 0.080 | 0.033 | 0.176 | 0.127 | 0.022 | 0.006 | 0.139 |
| Observations | 5,475 | 5,475 | 5,475 | 5,475 | 5,475 | 5,475 | 5,475 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table C5: The Effect of the Commodity Shock on the Land Use and Capital Inputs - Alternative Measures

| | Δ Log Total Farmland | Δ Log Machine Intensity | Δ Share of Land with GE Seeds |
|---|---|---|---|
| Top 10% Δ CE | –0.0240 | –0.093*** | 0.001 |
| | (0.019) | (0.029) | (0.007) |
| Adj. $R^2$ | 0.062 | 0.022 | 0.190 |
| Top 25% Δ CE | –0.027* | –0.026 | 0.028*** |
| | (0.015) | (0.023) | (0.007) |
| Adj. $R^2$ | 0.063 | 0.021 | 0.194 |
| Above Median Δ CE | –0.004 | 0.040* | 0.021*** |
| | (0.016) | (0.025) | (0.004) |
| Adj. $R^2$ | 0.062 | 0.022 | 0.193 |
| Bottom 10% Δ CE | 0.012 | –0.309*** | –0.004** |
| | (0.022) | (0.058) | (0.001) |
| Adj. $R^2$ | 0.062 | 0.032 | 0.190 |
| Bottom 25% Δ CE | 0.003 | –0.209*** | –0.008*** |
| | (0.021) | (0.039) | (0.002) |
| Adj. $R^2$ | 0.062 | 0.029 | 0.191 |
| Observations | 5,446 | 5,446 | 5,446 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table C6: The Effect of the Commodity Shock on Land Inequality - Alternative Measures

| | Δ Land Gini (2006-2017) | Δ Land Gini (1995-2017) |
|---|---|---|
| Top 10% Δ CE | 0.014*** | 0.011*** |
| | (0.004) | (0.004) |
| Adj. $R^2$ | 0.075 | 0.108 |
| Top 25% Δ CE | 0.009*** | 0.01*** |
| | (0.003) | (0.003) |
| Adj. $R^2$ | 0.074 | 0.108 |
| Above Median Δ CE | 0.005* | 0.009*** |
| | (0.003) | (0.003) |
| Adj. $R^2$ | 0.073 | 0.108 |
| Bottom 10% Δ CE | 0.008** | –0.008* |
| | (0.004) | (0.005) |
| Adj. $R^2$ | 0.073 | 0.108 |
| Bottom 25% Δ CE | 0.001 | –0.013*** |
| | (0.003) | (0.004) |
| Adj. $R^2$ | 0.072 | 0.109 |
| Observations | 5,446 | 4,919 |

*Notes:* Robust standard errors in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.