Commodity Booms and Structural Transformation: The Role of Input Use and Land Inequality *

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Abstract

This paper studies the effects of an agricultural commodity price boom on structural transformation. I construct a shift-share measure of exposure to the commodity shock by combining climate- and soil-induced variation in agricultural production patterns among municipalities in Brazil with fluctuations in international commodity prices between 2000 and 2010. I show that labor was reallocated away from agriculture towards the manufacturing sector in locations more exposed to the commodities boom. Using data from the Population and Agricultural Censuses, I argue that the results are consistent with greater use of capital inputs in agriculture, which worked as substitutes for farm labor, and greater land inequality in more exposed locations, which ultimately displaced workers from the agricultural sector.

Keywords: Commodity Booms, Structural Transformation, Input Use in Agriculture, Land Inequality

JEL Codes: O13, O14, Q15, Q33

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1 Introduction

The relationship between agriculture and economic development has been a long-studied subject in the growth literature (Engerman and Sokoloff, 1994; Vollrath, 2011). Whether the expansion of the agricultural sector promotes or curbs structural transformation is a fundamental and highly debated question (Lewis, 1954; Rostow, 1960; Gollin et al., 2002). In particular, open economies can experience both an increase or decrease in industrialization depending on the comparative advantage of the agricultural sector and its export composition (Matsuyama, 1992). The classical theoretical models have focused on productivity changes, both in agriculture and manufacturing, as the main driver of structural change but have missed some important microeconomic mechanisms related to trade shocks and agricultural modernization that can be at play in developing economies in which agriculture is the sector with the comparative advantage (Alessandria et al., 2021).

Recently, a growing empirical literature has studied how shocks to agricultural productivity affect structural transformation in local economies. The evidence regarding the direction of structural change is, however, still scarce and ambiguous (Bustos et al., 2016; Moscona, 2018; Uribe-Castro, 2019; Fiszbein and Johnson, 2020; Gollin et al., 2021). Such studies also tend to focus on particular crops and might miss the general effects that impact the agricultural sector more generally. Isolating the forces that can operate the relationship between the expansion of the agricultural sector and structural transformation in open economies is a fundamental challenge in the literature and is, ultimately, an empirical question.

In this paper, I 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, I look at the change in employment shares across sectors and argue that differential input use (labor, capital, and land) worked as a key mechanism in driving the effects. Additionally, I explore inequality in landholdings as another important mechanism in generating structural change. Land inequality is often overlooked in the structural transformation 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, I propose a shift-share measure to isolate municipalities that were more exposed to the shock. I construct the exposure shares by using actual observed crop yields across Brazilian municipalities and data on crop potential yields from the Food and Agriculture Organization (FAO)'s Global Agro-Ecological Zones (GAEZ) project. I combine both variables into a fractional multinomial logit (FML) model of crop choice proposed by Fiszbein

(2019), which calculates predicted shares for the crops in my sample for each municipality. I then interact the predicted shares with the exogenous variation in international prices of commodities between 2000 and 2010, which represents my shift (or shock) variable.

I 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 towards the manufacturing sector. My estimates imply that the commodity price boom explains 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. I also do not observe any effect of the commodities shock on employment share in services at the local level. Using matched employer-employee data on all formal jobs in Brazil, I further show that the reallocation effect was the same between formal and informal jobs. Moreover, the increase in industrial employment was widespread across the whole manufacturing sector and did not benefited any specific industry.

Next, I explore potential mechanisms related to agricultural modernization that led to the observed reallocation of workers. First, I study how the intensity in inputs use changed in the more affected regions. The total amount of land devoted to agriculture does not change at the extensive margin, but I show that the farmland productivity increases after the shock, indicating an increase at the intensive margin. I also observe an increase in the use of capital, measured by the use of machines and genetically engineered seeds in the farms. I argue that the higher use of capital in the farms worked as substitutes to agricultural workers. I then explore how the change in land inequality after the shock might have contributed to the displacement of agricultural workers. I 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 each region. The share of land used in agricultural production was disproportionately appropriated by a small number of large properties, which displaced small landowners and workers from the agricultural sector.

My main findings are robust to a series of deviations from the baseline framework. First, I use a series of different definitions for the exposure measure and find that the general conclusions remain unaltered. Second, my main estimates remain statistically significant when I correct standard errors to account for spatial correlation and correlation across the exposure shares. Third, the estimates are stable when I introduce a series of controls that expand the baseline framework. Fourth, the results are robust to using microregions as a larger unit of observation. Fifth, I show that the main results are robust to using a placebo measure and a measure of agricultural productivity gaps between municipalities. I then conclude that the 2000s commodities boom resulted in a structural transformation process.

The use of capital inputs and rising land inequality increased in agriculture and labor was reallocated away from the agriculture sector and into manufacturing, spurring industrial growth.

Related Literature. This paper fits into different areas of the economics literature. First, it relates to research on the impacts of trade on structural transformation, including access to fertilizers (McArthur and McCord, 2017), the effect of historical trade shock across regions within the same country (Fajgelbaum and Redding, 2018), and modernization of the agricultural sector (Farrokhi and Pellegrina, 2021). I contribute to this strand of the literature by exploring the relationship between a commodity price boom and agricultural modernization in modern local economies and by looking at the changes in input use and land inequality in the farms as potential and previously unexplored mechanisms related to agricultural modernization.

My work is also related to the literature that explores the effects of agricultural productivity on structural change in open economies (Matsuyama, 1992). Within this literature, several scholars have emphasized the relative importance of the comparative advantage effect, that draws resources into agriculture, versus the push effect.[1] Empirically, our setting is closely related to that of Bustos et al. (2016) and Bustos et al. (2020a) that show how the adoption of new agriculture technologies in soy and maize production can affect structural change in different directions depending on the factor-bias of agricultural technical change.[2] In another study, Bustos et al. (2020b) show that the previous reallocation of labor away from agriculture reinforced comparative advantage in the least skill-intensive manufacturing industries. Such effect happened because the displaced workers were relatively unskilled and had lower levels of human capital. While the series of works have deepened our knowledge about the relationship between agricultural productivity and structural change, it still depends on two particular types of commodities.

There is also evidence that other types of technological changes in other agricultural crops imply different effects on trends of structural change. In a earlier work, Foster and Rosenzweig (2004) show that Indian villages with high rates of crop yield growth experienced lower industrial growth. Moscona (2018) shows that productivity growth associated

[1]The labor push effect is the main driver of structural transformation together with the labor pull effect. While the push effect is related to improvements in agricultural technology releasing labor away from agriculture, the pull effect considers improvements in industrial technology attracting labor out of agriculture (Alvarez-Cuadrado and Poschke, 2011).

[2]The authors 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 the GE soy seeds represent a labor-saving technical change in agriculture, while the new maize variety can be considered a land-augmenting technology. In the case of a labor-saving technology, labor and capital are reallocated away from agriculture and into manufacturing, while the opposite effect happens with the land-augmenting technology.

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. I contribute to this literature by providing new evidence about the relationship between the expansion of the agricultural sector, technology adoption, and structural transformation in a setting where a large set of commodities was affected by the boom, while also proposing new mechanisms related to input use and land inequality in the farms.

This paper also speak to the long-standing literature that studies the relationship between resource booms and development (Corden and Neary, 1982; Sachs and Warner, 1999, 2001; Gollin et al., 2016). In particular, my work is related to a recent strand that studies the effects of resource booms on local economies in the context of oil and gas discoveries (Allcott and Keniston, 2018; Cavalcanti et al., 2019) and coffee price shocks (Uribe-Castro, 2019). With a few exceptions, this literature has mostly focused on the extractive sector or specific crops and still lacks evidence on the widespread effects on structural transformation of a large boom across the whole agricultural sector. I contribute to this literature by exploring a boom across a wide basket of commodities that have heterogeneous patterns of production across the local economies.

2 Motivating Facts

The Brazilian economy relies heavily on agriculture and the country 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 the agricultural crops, together with cattle raising, provide the basis for the large agribusiness industry in Brazil, which represents 22% of Brazil's GDP 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 the derived products is characterized by high use of technology and agroindustry techniques. The agroindustry is, therefore, another important dimension in my analysis of the agricultural expansion, 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 agroindustry captures both farming production and 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. The 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.

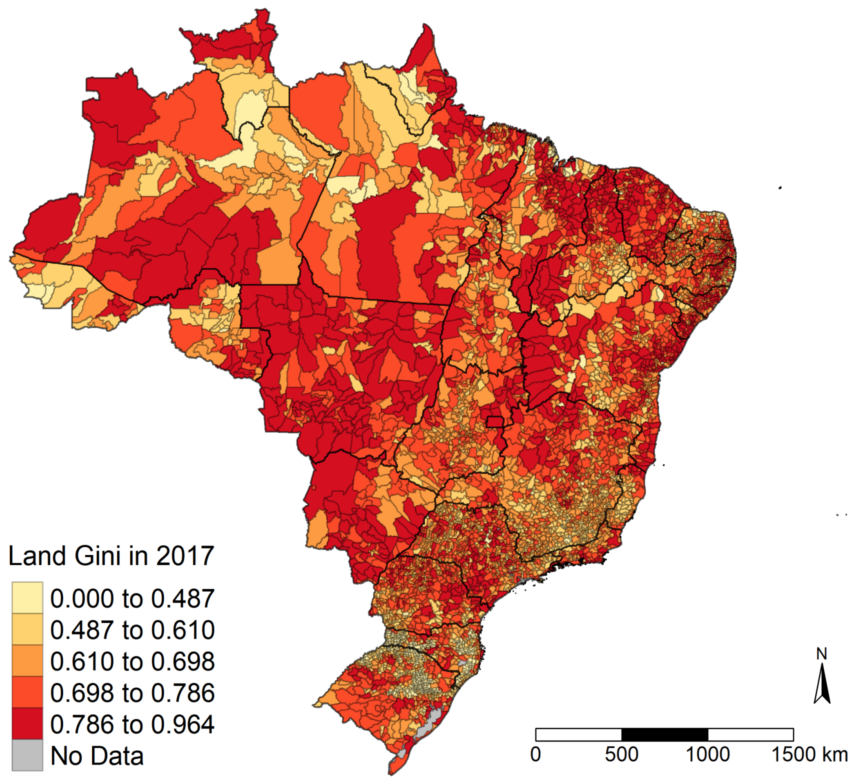


Figure 1: Land Inequality in Brazil

Notes: Author's calculations using the Brazilian Agricultural Census data from 2017. See Appendix A.1 for variable definition and sources and 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 dynamics of structural change after the 2000s commodities boom. The last commodity supercycle started in 2000 and peaked in around 2011. It's magnitude 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.

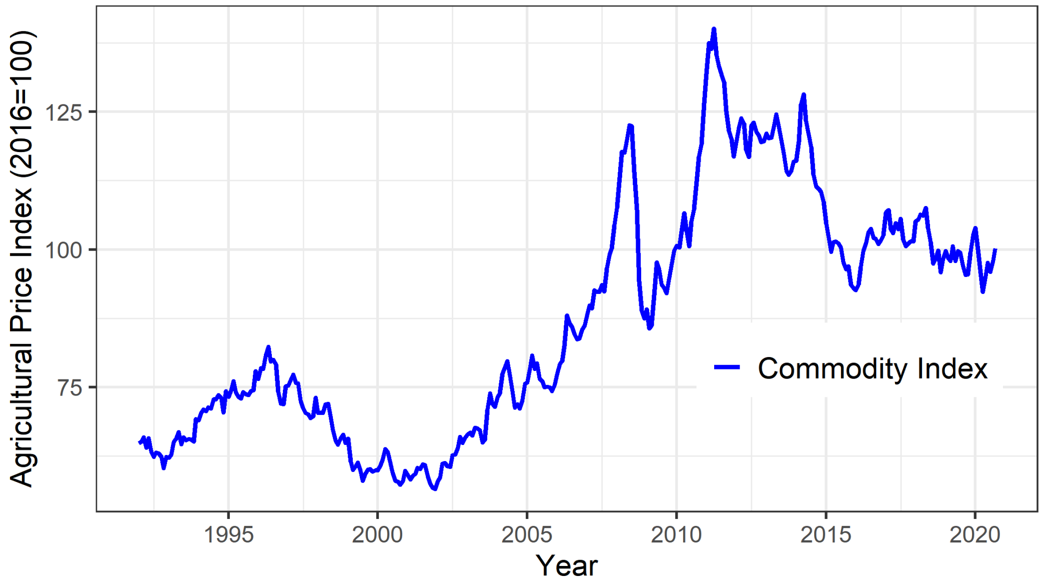


Figure 2: 2000s Commodities Supercycle

Notes: Commodity Price Index in US$ for agricultural products. Data from the World Bank's Global Economic Monitor. See Appendix A.1 for variable definition and sources.

Brazilian municipalities have also been experiencing a long process of structural transformation since the 1960s. Figure 3 shows the evolution of employment shares in the main sectors of the Brazilian economy over time. Although the structural change has consolidated in the 1980 decade, a substantial reallocation of workers away from agriculture was still observed in the last decades, especially between 2000 and 2010. In particular, the distribution of the 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. I, therefore, analyze how the commodity price boom affected both the structure of the agriculture sector in terms of modernization and the regional development of the Brazilian economy.

3 Data

To construct my shift-share measure of exposure to the 2000s commodities supercycle, I obtain information on the local municipalities production of agricultural crops from the Instituto Brasileiro de Geografia e Estatística (IBGE). More specifically, I use the Produção Agrícola Municipal (PAM), which is held annually at the municipality level and has infor-

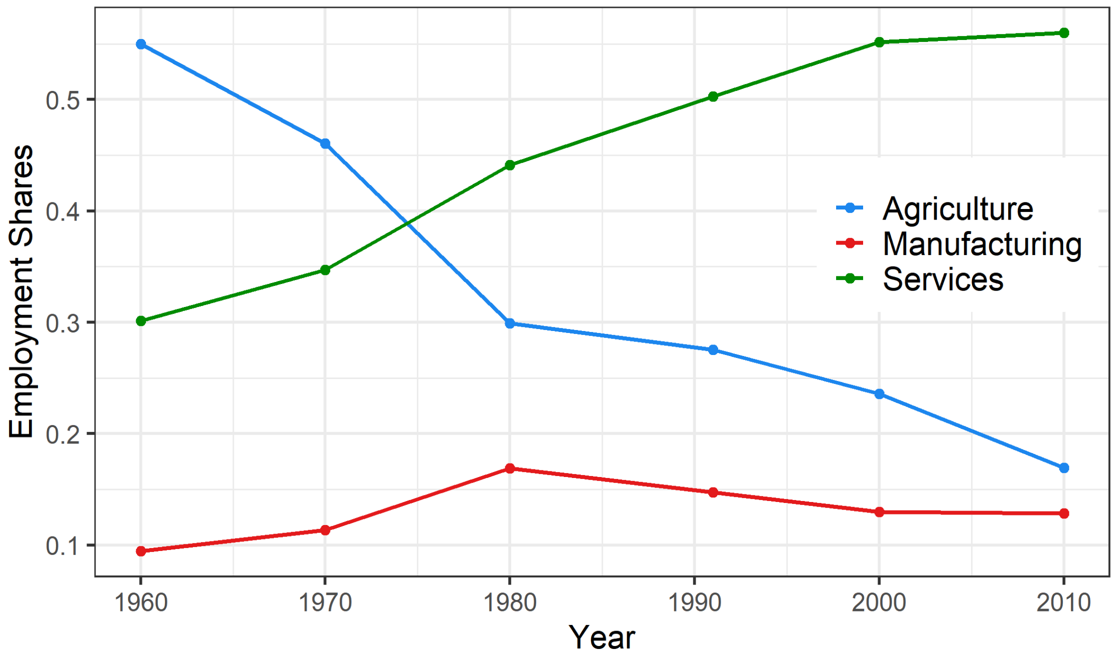


Figure 3: Employment Shares Across Sectors in Brazil

Notes: Author's calculations from IPUMS International microdata for Brazilian Population Censuses. See Appendix A.1 for variable definition and sources.

mation 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, I use the Pesquisa da Pecuária Municipal (PPM), which is similar to the PAM and accounts for cattle breeding in Brazil. The only drawback is that the PPM reports the number of cattle heads, not the actual weight of beef produced. To overcome such problem, I multiply the total number of cattle heads 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.[3]

I use data from the FAO-GAEZ project to obtain potential yields for each crop in my sample. The 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. The 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

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

use. 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 the cells ranges from 8,586 hectares at the equatorial level to 6,031 hectares at the southern-most location in Brazil.

I 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. I 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".[4] As a robustness check, I analyze the sensitivity of my results to using the high inputs.[5] With both PAM/PPM and FAO-GAEZ, I can then construct my "share" measure, consisting of the total production of crops in each municipality averaged over the 5 years preceding the start of my analysis.[6]

For the "shock" part of the exposure measure, I use the international commodity prices from the Global Economic Monitor (GEM) Commodities database prepared by the World Bank, which contains monthly information over an extended period on the price of several commodities that are traded in the international markets. I then average the prices over the twelve months within each year to obtain yearly values and standardized each price to US dollars per ton.[7] In some cases, there may be a single price that matches multiple crops in the quantities dataset, so I 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[8], while dropping the cases in which I cannot establish a match at all. Table 1 reports the number of Brazilian municipalities that produce each of the crop in our analysis and the international variation of each crop's real price between 2000 and 2010.

For the main outcomes and controls, I use data from the Brazilian Population Census, the Agricultural Census, and IPEADATA. Both agricultural and population censuses are

[4]For more details about the documentation of the FAO-GAEZ project, see Appendix A.1 and IIASA/FAO (2012).

[5]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."

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

[7]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.

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

released at intervals of ten years by IBGE. I obtain 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,[9] 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. The population census variables are: total employment, employment shares, and wages in agriculture, manufacturing, and services.

From the population census, I also obtain start-of-period controls, such as income per capita, the share of rural population, illiteracy rate, and population density. From IPEA-DATA, I obtain additional geo-climatic and socio-economic characteristics such as sectoral and total GDP, latitude, longitude, municipality area, and rural and urban population. I also use historical population census microdata from IPUMS (Min, 2019) in my auxiliary analysis (to construct Figure 3, for example).

Finally, I 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 my 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. In my analysis, I aggregate the individual level data at the municipality level. Table 2 reports summary statistics for my main variables of interest and illustrates the evolution and difference in their values between the census years at the municipality level.

4 Empirical Strategy

The first part of the empirical analysis is to construct a shift-share (Bartik) measure to estimate the effects of the commodity price shocks on the local reallocation of production factors across the main sectors of the economy. I 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, I combine the FAO-GAEZ potential yields with observed crop production patterns in the municipalities.

My framework extends the settings in Dube and Vargas (2013) and Bernstein et al. (2018) by constructing exogenous agricultural shares. Following Fiszbein (2019), I construct predicted agricultural shares for each municipality by incorporating the FAO-GAEZ crop-

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

Table 1: Agricultural Endowments and Price Variations

Crops	Number of Municipalities		International Price Variation (2010 - 2000)
	2000	2010	
Cattle	5471	5518	40.22%
Maize	5329	5176	65.83%
Rice	4071	3084	90.76%
Banana	3795	3555	61.73%
Orange	3634	3006	124.64%
Sugarcane	3483	3695	105.50%
Coffee	2008	1822	77.72%
Soybean	1446	1800	66.68%
Cotton	1272	411	38.48%
Tobacco	958	892	14.98%
Wheat	802	895	83.37%
Yerba Mate	555	474	21.43%
Sorghum	469	604	48.43%
Cocoa	264	282	173.15%
Barley	173	135	61.95%

Notes: See Appendix A.1 for variable definition and sources. The table presents the number of Brazilian municipalities that produce each of the crop in our analysis and the international variation of each crop's real price between 2000 and 2010.

specific attainable yields into a fractional multinomial logit (FML) model. The framework is specified as a system of equations in which the outcome variables Q_{ki} are the observed shares of each agricultural product k in total agricultural output[10] in municipality i, and the regressors are the crop-specific potential yields vector A_i measured in tons per hectare per year.

In my baseline specification, I use the average local crop k endowment share in municipalities over the period 1995-1999 ($Q_{ki,99}$) to capture the pre-period exposure to the commodity boom that started in 2000.[11] The idea behind this 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:

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

[10]In the analysis, I restrict the total agricultural output to the commodities in my sample.
[11]Later, I perform robustness checks using the mean crop production over 2000-2010.

Table 2: 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 Total Farmland	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

Notes: See Appendix A.1 for each variable definition and sources.

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. One 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 the following equation:

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

where π_{kl} is the profit value for each choice of crop type and farm resource and ϵ_{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 $\frac{e^{\beta_k A_l}}{1+\sum_{j=1}^{K-1} e^{\beta_j A_l}}$.[12]

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, I 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. My measure is then given by an annual Commodity Exposure (CE) measure for municipality i in year t:

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

I draw from the recent advances in the shift-share literature to guarantee that the identification assumption of the empirical design holds. In particular, my approach follows closely the assumptions in Borusyak et al. (2018), where identification is achieved via exogeneity of the shocks.[13] My identification strategy consist of a special reduced-form case of their general shift-share instrumental variable analysis. I also apply the logarithmic transformation in the prices, and not in the whole measure, to avoid omitted variable bias as discussed in Borusyak and Hull (2020).

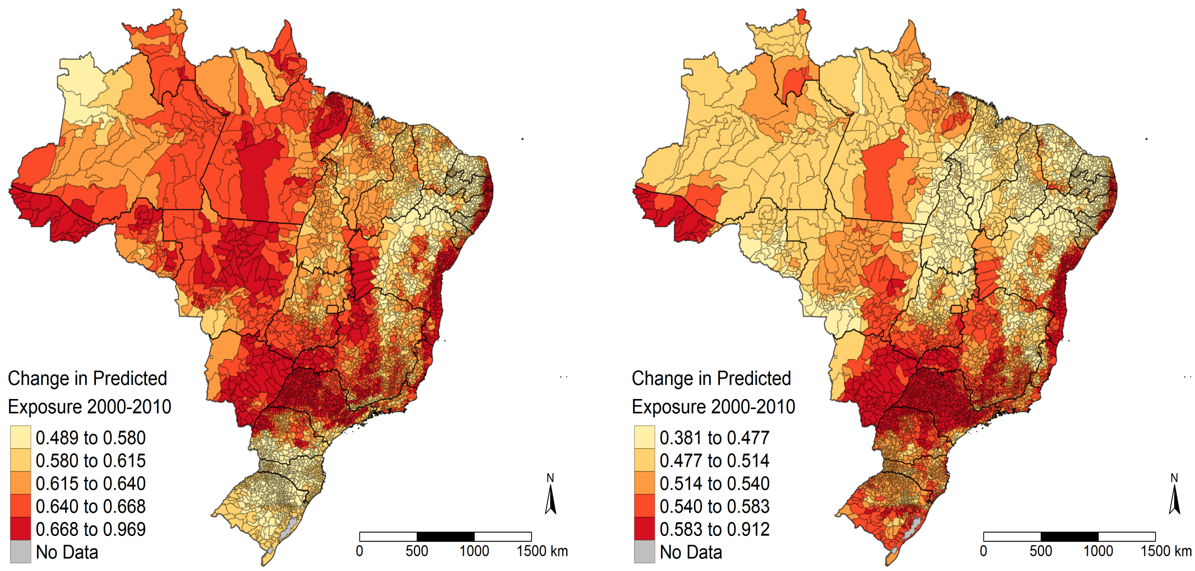
Figure 4 shows the differential exposure of each municipality to the commodity supercycle. I plot the exposure measure constructed both with and without beef quantities to give a dimension of strict farming agriculture and cattle breeding. I show in Section 7 that my results do not change if I exclude cattle from the measure. Figure 5 shows the distribution of the values for the CE measure for both years of my analysis. The values are reasonably well distributed, giving us a large sample of exposed vs non-exposed municipalities. Figure 6 shows the change in the measure between 2000 and 2010.[14]

The exposure measure also predicts the agricultural frontier expansion that happened after 2000 in Brazil. Recall that for my baseline measure I am 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. The measure, therefore, captures how the current agricultural frontier benefited from the commodities 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

[12] Figure B3 shows that the predicted shares are indeed good predictors for actual (observed) shares for all crops in the sample.

[13] 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).

[14] The predicted measure is also a good predictor of the actual measure (constructed with the observable crop shares). Figure B2 displays the scatter plot between the two measure values for all municipalities.



(a) Excluding Cattle

(b) Including Cattle

Figure 4: Exposure to the Commodity Shock

Notes: The maps display the spatial distribution of the change in the Commodity Exposure measure between 2000 and 2010, as defined in Equation 3. Figure (a) displays the measure without the shares for cattle. Figure (b) displays the baseline measure that includes cattle breeding. See Appendix A.1 for variable definition and sources.

to the shock according to the exposure measure (Figure 4).[15]

The last step is to estimate the main equation for the analysis, which allows to explore the effects of the commodity shock on outcomes related to structural change in each municipality. Formally, I 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; α_i are municipality fixed effects and γ_t are time fixed effects; X_{it} is a vector of municipality control variables; u_{it} is an error term. My identification assumption relies on the exogeneity of the CE measure in the following way:

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

[15]The 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).

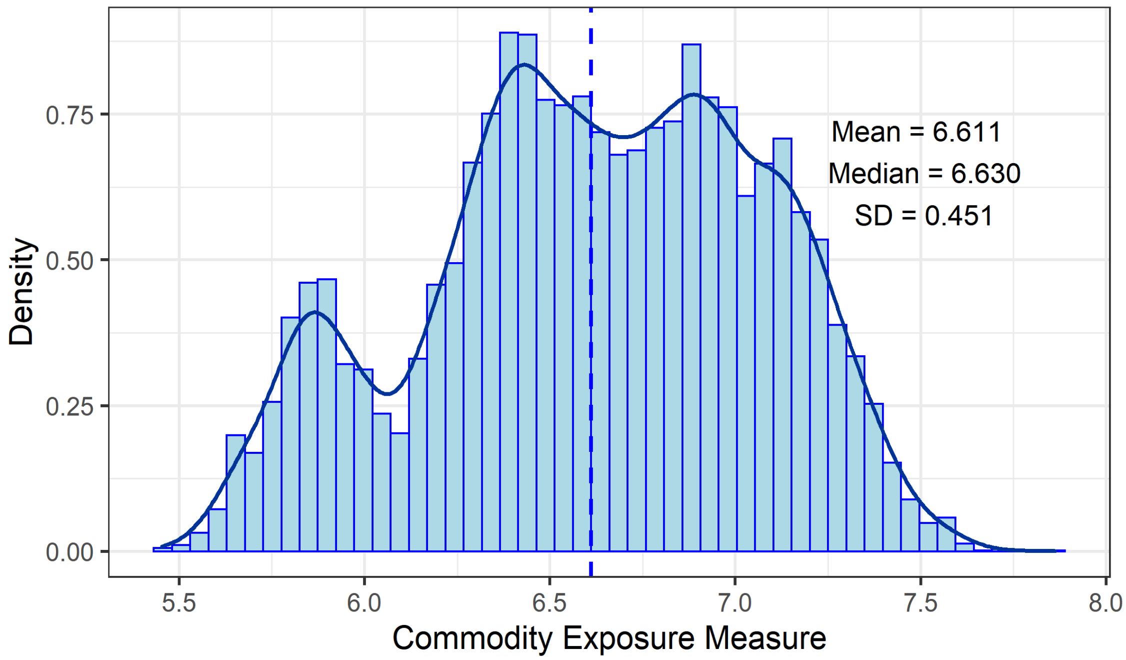


Figure 5: Histogram of the Commodity Exposure Measure

Notes: The figure displays the histogram for the Commodity Exposure measure as defined in Equation 3 for the years 2000 and 2010 together. See Appendix A.1 for variable definition and sources.

Since I constructed it using a shift-share approach, I 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). Nevertheless, I argued that both the shares and shocks in the exposure measure can be considered exogenous and, therefore, that the identification assumption holds.

In the case of sectoral employment share outcomes, my 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, I also have data on an interval of about ten years between the last two rounds (2006 and 2017). I 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 Δy_i is the change in outcome variables between the last two census years and ΔCE_i is the change in the value of the exposure measure between 2000 and 2010.

I include controls for observable characteristics in the population census of 1991 to control

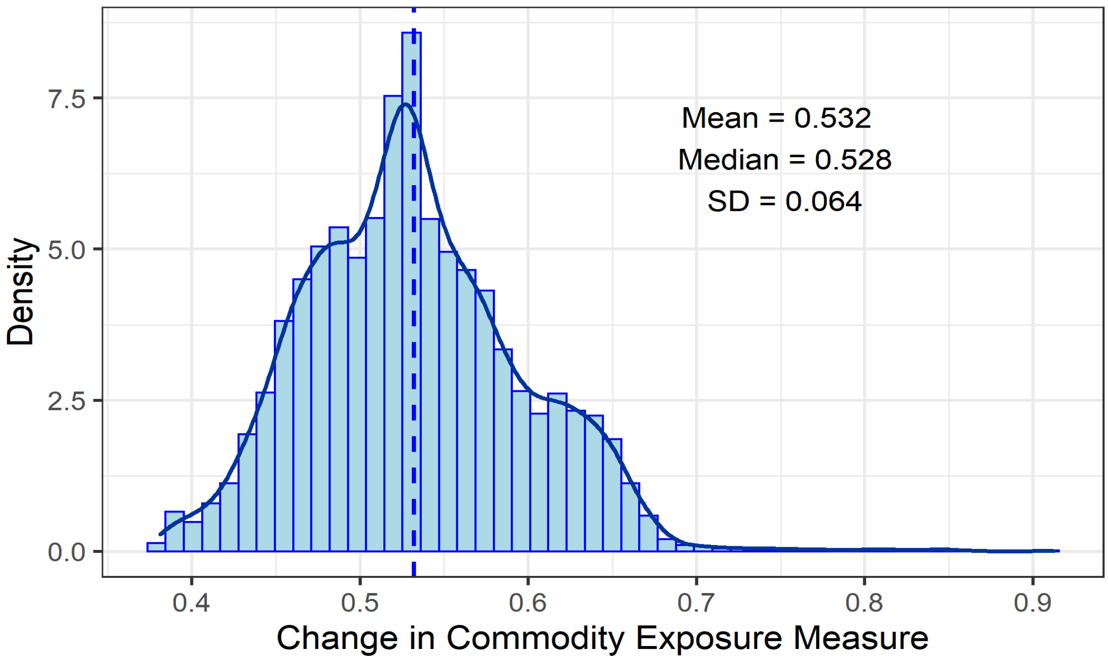


Figure 6: Histogram of the Change in the Commodity Exposure Measure Between 2000-2010

Notes: The figure displays the histogram for the Commodity Exposure measure as defined in Equation 3 for the difference in the values between 2000 and 2010. See Appendix A.1 for variable definition and sources.

for differential trends across municipalities with heterogeneous initial characteristics. In my specifications, I 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 in the vector of controls.[16] The addition of such controls is important because it can be the case that municipalities with heterogeneous initial levels of development experiences different growth paths and then my estimates could be capturing differential structural transformation trends across municipalities.[17] Table 3 displays the average values of the main observable characteristics in 1991 for municipalities that ranked below and above the median change in the exposure measure (ΔCE).[18]

Note that I do not add any geo-climatic control to the main specification. If I controlled for any variable that was used to construct the FAO-GAEZ potential yields, the variables

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

[17] 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.

[18] Figure B1 in Appendix B complements the analysis by comparing the change in employment shares between 2000 and 2010 among the same municipalities that ranked above and below the exposure measure.

would act as bad controls in our regressions. The potential yields data already incorporate climate and soil characteristics, such as rainfall, temperature, wind speed, terrain slope, and soil types. Controlling for them would lead to an amplification bias problem and reduce the precision of the estimates by decreasing the independent variation of the exposure variable.[19] In Section 7.2 I perform a robustness check and add controls for other pre-period socioeconomic characteristics; geographic characteristics not incorporated in the FAO-GAEZ potential yields; and crop-specific controls.

Table 3: Comparing Municipalities Below and Above the Median Exposure to the Commodity Shock

	Below Δ CE Median	Above Δ CE Median	Difference
Agricultural Employment Share	0.570	0.430	−0.140
			(0.006)
Manufacturing Employment Share	0.085	0.130	0.044
			(0.003)
Share Rural Population	0.611	0.410	−0.201
			(0.007)
Log Income per Capita	4.993	5.571	0.578
			(0.014)
Log Population Density	2.768	3.360	0.591
			(0.037)
Illiteracy Rate	0.385	0.238	−0.148
			(0.004)
Observations	2,738	2,737	

Notes: See Appendix A.1 for variable definition and sources. The table presents the average values of observed characteristics of municipalities that rank below and above the median of the ΔCE measure. All variables are from the population census of 1991. The third columns reports the difference between the second and first columns. Standard errors reported in parentheses.

5 Main Results

Now, I show how the commodity boom affected the growth of the major sectors in the Brazilian economy. In every table, the first column (1) displays the coefficients for the

[19] See Pearl (2011) and Cinelli et al. (2020) for a discussion about bad controls and bias amplification.

regression without any controls. In the subsequent columns (2) to (4), I 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 4 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), my preferred specification, imply that the commodity boom greatly benefited the agriculture sector by increasing its GDP. I also observe a first evidence on the existence of a spillover effect of the commodity shock on other sectors of the economy. The magnitudes 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 to the commodity shock, Agricultural GDP per capita would increase by about 16.5 log points (18%). Similarly, I 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. Table C2 in Appendix C further explores the effect of the commodity boom on GDP shares and corroborates the results discussed so far. After the shock, agriculture GDP share increases, while the services shares decreases and the manufacturing share remain unaltered.

I now explore how labor reallocated after the commodity boom. Table 5 reports the estimates of the coefficient on the commodity shock exposure measure in regressions for employment shares in agriculture, manufacturing, and services. According to my 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. The 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 2). 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.).[20]

I do not observe any significant effect on the employment share of services and hypothesize that the lack of effect could be linked with the consumption of services by the landowners. If the landowners reside in the same municipality where they own the land, one should expect an expansion of the service sector inside the municipality after the agricultural boom. On the other hand, it could be the case that the landowner decides to reside in another municipality

[20]Table C4 shows similar results when considering only formal employment from RAIS. Additionally, I show in Table C5 that the effects are similar for total employment.

Table 4: The Effect of the Commodity Shock on Sectoral GDP

	(1)	(2)	(3)	(4)
Panel A.	Δ Log Total GDP per Capita			
Δ 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.	Δ Log Agricultural GDP per Capita			
Δ 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.	Δ Log Manufacturing GDP per Capita			
Δ 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.	Δ Log Services GDP per Capita			
Δ 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: See Appendix A.1 for variable definition and sources. The table presents estimates of Equation 6. The dependent variable is the 2000-2010 change in the listed outcomes. Column (1) reports the estimates without any control. Columns (2)-(4) extend the set of controls by including the share of population living in the rural area; region fixed effect for the 5 macroregions of Brazil; log income per capita; log population density; and illiteracy rate. All municipalities controls are from the population census of 1991. The means and standard deviations (in parentheses) of the dependent variables in panels A, B, C and D are 0.487 (0.321), 0.243 (0.662), 0.268 (0.759), and 0.545 (0.243). Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

or urban center after the shock, therefore not contributing to the increase in the local service sector. I explore this hypothesis by analyzing the effect of the commodity shock on the share of landowners residing outside theirs farms, which can be constructed with data from the Agricultural Censuses. Table C3 in Appendix C shows that the municipalities that were more affected by the shock are also associated with more landowners residing outside their farms. The results show some evidence regarding the lack of effect on the service sector in the sense that the variable serves as a proxy for landowners residing in other municipalities or urban centres. It is also related to the appropriation by the landowners of the gains from the commodity boom, which will be discussed in Section 6 in terms of the changes in land inequality.

Table 5: 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: See Appendix A.1 for variable definition and sources. The table presents estimates of Equation 6. The dependent variable is the 2000-2010 change in the listed outcomes. Column (1) reports the estimates without any control. Columns (2)-(4) extend the set of controls by including the share of population living in the rural area; region fixed effect for the 5 macroregions of Brazil; log income per capita; log population density; and illiteracy rate. All municipalities controls are from the population census of 1991. The means and standard deviations (in parentheses) of the dependent variables in panels A, B and C are -0.068 (0.081), 0.002 (0.055), and 0.008 (0.055). Table C6 reports the coefficient for all the controls. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

I interpret these first results as providing evidence that supports the view that the commodity boom generated a significant structural transformation effect. As would be expected, the agricultural sector benefits heavily from the commodity shock. Since the exposure measure is constructed by multiplying prices by quantities—while also considering differentials in crop-specific agricultural productivity across locations—my results reflect how the commodity boom resulted in a significant increase in agricultural GDP. But most important than that, the boom generated a reallocation of labor away from agriculture, a result that might appear unintuitive at first.

I discuss the results in light of the recent literature that explores the localized effects of resource booms and the expansion of the agricultural sector. Bustos et al. (2016) finds that the adoption of genetically engineered (GE) soybeans across municipalities resulted in a decrease of employment share 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 my estimates are slightly lower than theirs, I also find the same sign directions after the commodity price boom.

At a first moment, the reallocation of workers away from agriculture may not be expected since I am analyzing a large set of internationally traded commodities and holding crop-specific technological change constant. Moreover, many of the commodities in my 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.[21] It could well be the case that, after the commodities boom, the agricultural sector expands its comparative advantage and draws labor in. My results imply, however, that such events did not happen, or at least were small in magnitude. My main hypothesis for the mechanism that led to the observed effect is discussed in Section 6 and is related to fundamental changes in the use of capital and land in the agricultural sector.

In Table 6, I 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. Analyzing the wages outcomes, my 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, I observe the opposite effect, with a negative effect of 2%. Again, my results for the manufacturing

[21] As already discussed in Section 1, there is still few evidence on the effects of agricultural technical change on structural transformation, which also appear to be context-specific (Moscona, 2018; Gollin et al., 2021).

sector are similar to that of Bustos et al. (2016) for the adoption of GE soy.

My 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 I do not observe localized effects on employment shares in the service sector, the rise in urbanization and employment share in manufacturing corroborate the "production cities" view. Moreover, my results also show that the commodity boom worked as a labor-push factor in agriculture.

I now turn to the possible heterogeneous effects of the commodity boom on the manufacturing sector. Since I observed a positive relationship between the shock and the employment share in manufacturing, I extend my analysis to test the hypothesis if the reallocation of labor was directed at particular types of industries. To do so, I 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. The subsectors are related to food processing, beverage production, wood processing, and clothing. The other subsectors—which I label as heavy industry—are composed of chemical industries, electronics, pharmaceutical industry, metallurgy, machinery, and automotive industry.[22]

One possible drawback in my analysis is the fact that RAIS only covers formal jobs, which do not fully represent the highly informalized Brazilian labor market. The manufacturing sector, nevertheless, relies intensely on workers with formal labor contracts—which is not the case in agriculture and services— and, therefore, I assume that the RAIS data approximates reasonably well the employment share inside the whole manufacturing sector. In Table 7 I show with the RAIS data that the commodity boom is associated with an increase in the manufacturing employment share of about the same magnitude that I have previously obtained with the population census data.

I also obtain the output value in agroindustry from the Agricultural Census to further explore how the subsector was impacted. My 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. The analysis of the employment shares outcomes shows that the reallocation of labor away from agriculture and into manufacturing appears to be equally distributed across the two subsectors that I 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.

My results imply that the 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

[22]See Appendix A for a detailed definition of the sectors and subsectors.

Table 6: The Effect of the Commodity Shock on Urbanization and Wages

	(1)	(2)	(3)	(4)
Panel A.	Δ Urban Population Share			
Δ 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.	Δ Log Wages in Agriculture			
Δ 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.	Δ Log Wages in Manufacturing			
Δ 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.	Δ Log Wages in Services			
Δ 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: See Appendix A.1 for variable definition and sources. The table presents estimates of Equation 6. The dependent variable is the 2000-2010 change in the listed outcomes. Column (1) reports the estimates without any control. Columns (2)-(4) extend the set of controls by including the share of population living in the rural area; region fixed effect for the 5 macroregions of Brazil; log income per capita; log population density; and illiteracy rate. All municipalities controls are from the population census of 1991. The means and standard deviations (in parentheses) of the dependent variables in panels A, B, C and D are 0.052 (0.063), 0.222 (0.393), 0.255 (0.560), and -0.300 (0.422). Table C6 reports the coefficient for all the controls in the regression. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

the agroindustry more specialized transformation industries. Such effect could imply that the structure of the economy has changed to a higher sustained growth path, if it is assumed that the manufacturing sector is associated with higher productivity and spillover effects, like learning-by-doing as in Matsuyama (1992) model. The scenario of an increase in the

Table 7: The Heterogeneous Effect of the Commodity Shock on the Type of Industry

	(1)	(2)	(3)	(4)
Panel A.	Δ Log Output in Agroindustry			
Δ 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.	Δ Employment Share in Manufacturing - RAIS			
Δ 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.	Δ Employment Share in Agroindustry			
Δ 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.	Δ Employment Share in Heavy Industry			
Δ 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: See Appendix A.1 for variable definition and sources. The table presents estimates of Equation 6. The dependent variable is the 2006-2017 (Panel A) or 2000-2010 (Panels B, C and D) change in the listed outcomes. Column (1) reports the estimates without any control. Columns (2)-(4) extend the set of controls by including the share of population living in the rural area; region fixed effect for the 5 macroregions of Brazil; log income per capita; log population density; and illiteracy rate. All municipalities controls are from the population census of 1991. The means and standard deviations (in parentheses) of the dependent variables in panels A, B, C and D are 1.202 (2.200), 0.001 (0.117), -0.005 (0.093), and 0.008 (0.066). Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

long-term growth of the economy is, however, unlikely to occur in my setting. My 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. Their effect is likely to be present in my analysis since agricultural labor in the Brazilian economy is characterized by low levels of human capital accumulation.

6 Mechanisms

I now turn to my analysis of possible channels and mechanisms that might be driving the reallocation of workers away from agriculture and into manufacturing. My main hypothesis is based on exploring how the structure of the agriculture sector changed after the shock. I first look at the hypothesis that the commodity boom changed the use of inputs in the agriculture sector towards a more intensive use of land and capital in the farms. I also analyze if the commodity boom increased inequality in land ownership, increasing the land appropriated by larger farms and possibly displacing small landowners from agriculture.

6.1 Use of Land, Capital Inputs, and Agricultural Productivity

In Table 8 I explore how the commodity boom impacted the use of the other two fundamental inputs used in agriculture: land and capital. My main hypothesis in the present section is that changes in input use worked as a potential margin of adjustment to the commodity price boom. My first variable of interest is the log of total farmland that measures the expansion of land use in agricultural production. To analyze the capital adoption in farms I look at the intensity of machine use[23] and the share of agricultural land planted with genetically engineered (GE) seeds in each municipality. My 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 harvested with GE seeds. The coefficients for total farmland loses significance as I control for region fixed effects and baseline controls.

Together with my main results from the previous section, I again interpret my 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 sector might have been substituted by agricultural machines.[24] Moreover, the increased

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

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

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 characteristics of GE seeds is that they are resistant to herbicides and facilitate the use of no-tillage planting techniques (Bustos et al., 2016). Therefore, one 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.

The results about the absence of effects on total farmland might seem less intuitive at a first moment. Although one could 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 are observed. I 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 the hypothesis events are indeed happening, I should at least observe the farm productivity increasing.

In Table 9 I show that it appears to be the case. I measure farm productivity as the total output of farms divided by the total farmland in hectares. My results show that the commodity boom is positively associated with farm productivity. The results also represent an important mechanism that might be driving the main results regarding structural transformation. The evidence on farmland productivity corroborates the findings in Section 5 about the commodity boom working as a labor-push factor in agriculture.

I also explore if labor productivity—measured as the log output of farms per worker—in the agricultural sector increased after the commodities boom. If I 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 land-augmenting technologies are missing from my analysis. The prevalence of one type of technological change over another might be important in explaining the structural transformation patterns I observe. I do not observe, however, any statistically significant effect in my 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 I analyze, it could be the case that their overall effect over structural transformation eventually cancels out.

6.2 Inequality in Land Ownership

I now explore how the commodities boom impacted the reallocation of farmland and land inequality across municipalities and how they might have worked as important mechanisms

agricultural machinery production.

Table 8: 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: See Appendix A.1 for variable definition and sources. The table presents estimates of Equation 6. The dependent variable is the 2006-2017 change in the listed outcomes. Column (1) reports the estimates without any control. Columns (2)-(4) extend the set of controls by including the share of population living in the rural area; region fixed effect for the 5 macroregions of Brazil; log income per capita; log population density; and illiteracy rate. All municipalities controls are from the population census of 1991. The means and standard deviations (in parentheses) of the dependent variables in panels A, B and C are -0.019 (0.471),0.392 (0.830), and 0.060 (0.171). Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

in driving the structural change effects 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. The hypothesis has been extensively tested in historical settings, implying that land inequality indeed played an important role in respect to long term economic development (Easterly, 2007; Vollrath, 2007; Cinnirella and Hornung, 2016; Wigton-Jones,

Table 9: The Effect of the Commodity Shock on Agricultural Productivity

	(1)	(2)	(3)	(4)
Panel A.		Δ Log Farm Productivity		
Δ 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.		Δ Log Output per Worker		
Δ 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: See Appendix A.1 for variable definition and sources. The table presents estimates of Equation 6. The dependent variable is the 2006-2017 change in the listed outcomes. Column (1) reports the estimates without any control. Columns (2)-(4) extend the set of controls by including the share of population living in the rural area; region fixed effect for the 5 macroregions of Brazil; log income per capita; log population density; and illiteracy rate. All municipalities controls are from the population census of 1991. The means and standard deviations (in parentheses) of the dependent variables in panels A and B are 0.103 (0.830), and 0.025 (0.850). Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

2020).

In my setting, the results regarding land inequality, institutions, and human capital are unlikely to have a significant effect, mainly because I am analyzing a modern economy that has already experienced a major industrialization and expansion of public education. Nevertheless, I still propose that land inequality might be playing an important role in the relationship between commodity 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 landholdings is negatively associated with productivity in farms. In my setting, land inequality could increase after the commodity price boom given the structure of the Brazilian agricultural sector and its high and persistent inequality in landholdings discussed in Section 2. One could also 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 land inequality and agricultural modernization. Since commodities such as soy, tobacco, cotton, sugarcane, and cattle breeding 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.[25]

In Table 10 I explore how the commodity boom affected the Land Gini by taking short and long differences. I 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. My 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). The two effects account for about 5% of a standard deviation in the observed change.

I complement the pieces of evidence by exploring in Table 11 the number of farms with more than 1000 hectares and the area appropriated by them in each municipality. I choose such arbitrary cutoff of total area because it captures the average farm size of the top 1% of agricultural establishments with respect to area appropriation, as reported in the Agricultural Census and discussed in Section 2. I 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. Analyzing the number of farms with more than 1000 hectares, I 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 9, it appears to be the case that both agricultural productivity and land inequality increased, supporting the view that farms associated with large and modern field crops increased their productivity after the commodity shock. Moreover, since I observe both the Land Gini and the area and number of top 1% farms increasing without the same happening with total farmland, I interpret the results as also supporting the view that the commodity shock impacted structural transformation via the displacement of small landowners and workers away from agriculture.

[25] Although smaller farms are usually associated with higher productivity in the empirical literature, there is a recent divergence between the microeconomic and macroeconomic evidence. For a discussion, see Sanchez et al. (2019).

Table 10: The Effect of the Commodity Shock on Land Inequality

	(1)	(2)	(3)	(4)
Panel A.		Δ Land Gini (2006-2017)		
Δ 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.		Δ Land Gini (1995-2017)		
Δ 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: See Appendix A.1 for variable definition and sources. The table presents estimates of Equation 6. The dependent variable is the 2006-2017 or 1995-2017 change in the listed outcomes. Column (1) reports the estimates without any control. Columns (2)-(4) extend the set of controls by including the share of population living in the rural area; region fixed effect for the 5 macroregions of Brazil; log income per capita; log population density; and illiteracy rate. All municipalities controls are from the population census of 1991. The means and standard deviations (in parentheses) of the dependent variables in panels A and B are -0.018 (0.084), and -0.007 (0.100). Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

7 Robustness Checks

7.1 Alternative Standard Errors

Figure 4 suggests that the Commodity Exposure measure is correlated across space. I then consider a series of possible specifications of alternative standard errors to account for spatial correlation. First, I cluster the standard errors at a higher unit of observation to allow the residuals to be correlated within geographical areas larger than a single municipality. To do so, I cluster at the microregion level, which roughly represents Brazilian local labor market regions (Adão, 2015). The approach accounts for residual auto-correlation and spatial spillovers across nearby municipalities with economic links. I also cluster at a even higher unit of observation, the mesoregion, defined by IBGE, which are larger than microregions

Table 11: The Effect of the Commodity Shock on Land Inequality

	(1)	(2)	(3)	(4)
Panel A.	Δ Log Area Farms > 1.000 ha (2006-2017)			
Δ 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.	Δ Log Area Farms > 1.000 ha (1995-2017)			
Δ 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.	Δ Log Number Farms > 1.000 ha (2006-2017)			
Δ 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.	Δ Log Number Farms > 1.000 ha (1995-2017)			
Δ 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: See Appendix A.1 for variable definition and sources. The table presents estimates of Equation 6. The dependent variable is the 2006-2017 or 1995-2017 change in the listed outcomes. Column (1) reports the estimates without any control. Columns (2)-(4) extend the set of controls by including the share of population living in the rural area; region fixed effect for the 5 macroregions of Brazil; log income per capita; log population density; and illiteracy rate. All municipalities controls are from the population census of 1991. The means and standard deviations (in parentheses) of the dependent variables in panels A, B, C and D are -0.783 (3.522), -2.790 (4.573), 0.024 (0.530), and 0.030 (0.722). Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

but smaller than the five macroregions.[26] Second, I calculate standard errors that correct for spatial dependence using different distance cutoffs as suggested by Conley (1999).[27]

My shift-share design can also suffer from a particular problem of inference that leads to

[26]In 2010, there were 558 microregions and 137 mesoregions in Brazil.
[27]I implement the Conley standard errors using *acreg* command created by Colella et al. (2019) in Stata.

a over-rejection problem. Regression residuals can be correlated across regions with similar shares, independently of their geographic location, and the OLS true variability may then be understated when using the usual clustering or heteroskedasticity-robust errors. I then apply the AKM and AKM0 corrections proposed by Adao et al. (2019) to account for the dependence between residuals generated by unobserved shift-share components.

I also calculate the simulated rejection probabilities to account for possible over-rejection problems as proposed by Ferman (2021). This assessment method assumes that the null hypothesis holds and simulates the probability that the test is rejected when errors are homoscedastic. I simulate errors drawn from a standard normal distribution and calculate the rejection probabilities for tests of sizes 5% and 10% for the main specification.

Tables 12, 13 and 14 report the alternative standard errors for my main results regarding the effects of the commodity boom on structural change, input use, and land inequality. I report coefficients for my main specification (column (4) in the previous tables), as well as the coefficients for the main specification but without region fixed effects. I remove the region fixed effects because the *reg_ss* package developed by Adao et al. (2019) that implements the AKM and AKM0 corrections does not allow for fixed effects regressions.

The significance of my results remains the same in respect to employment shares and wages. Only the effects on urban population share appear to loose significance when I account for spatial correlation. The significance of the coefficients for input use also remain mostly the same, with only the coefficient for spatial correlation above 200km losing significance. The results for land inequality also remain statistically significant with the exception of the coefficient for the short difference in the Land Gini for the 400km cutoff. With respect to the simulated rejection probabilities, the results show no overall sign of substantial over-rejection in the main specification.

7.2 Additional Controls

A potential concern regarding my analysis is that specific commodities, such as soy, meat, or sugarcane, are driving the results. Moreover, municipalities more exposed to the commodities boom can also have higher overall agricultural productivity or different labor force composition prior to the shock. My estimates could then be capturing specific specialization in commodity production or differential trends of structural transformation across locations. To address the differential trends, I report estimates of Equation 6 including the following additional controls: share of women in the labor force in 1991; land productivity in 1995 (measured as the log value of output per total farmland); a dummy variable if a commodity represents individually more than 30% of a municipality's total agricultural production; and a dummy variable if a group of commodities (meat, coffee, maize, soybean, and sugarcane) represents together more than 50% a municipality's total agricultural production. I also add a control for altitude—which is an important geographical characteristic not incorporated in the FAO-GAEZ potential yields model—and other proxies for access to markets, such as distance to the federal capital; distance to the state capital; and state capital dummy.

Tables C7 and C8 report the coefficients for the main regressions with the full set of additional controls. The sign of estimated coefficients remains the same, while also remaining significant and of similar magnitude for the main outcomes (the only exception is the coefficient for urbanization). Overall, my results remain stable over the inclusion of a set of additional variables that controls for initial agricultural development, labor force composition, geographical characteristics, and prevalence of specific commodities.

7.3 Alternative Measures

I now consider alternative definitions for my Commodity Exposure Measure. Based on the continuous measure defined in Equation 3, I construct dummy variables that equal one if the difference in the CE measure is in some given top or bottom percentile of its distribution. One could then interpret that a municipality is "treated" if the dummy variable equals one. For the percentile thresholds, I construct dummy variables for the top and bottom 10th and 25th percentiles, as well as for the values above and below the median of the distribution.

Tables 15, 16 and 17 report the coefficients for my preferred specification on the main outcomes using the alternative measures. Overall, the results remain qualitatively the same, but the interpretation of the coefficients is different. Now, I am comparing the municipalities above or below an arbitrary threshold of the CE measure distribution with the rest of the municipalities. In respect to employment shares, the results show that if a municipality is in the top 10% or top 25% of the Δ CE measure distribution, it experiences a decrease in employment share in agriculture of 2.1-2.4 pp. and an increase of 2.5-2.7pp. in employment share in manufacturing. The bottom dummies also corroborate my main findings. Being in the bottom distribution of the Δ CE measure is associated with no effect on employment shares, urbanization, and wages. In some cases there are even opposite effects in comparison with the municipalities in the top of the distribution. The results on input use and land inequality also remain qualitatively the same except for the machine intensity variable.

I also perform robustness check regarding the definition of the Commodity Exposure measure constructed in Equation 3. First, I use the actual mean commodity production in PAM for the supercycle period (2000-2010) to construct the shares in the FML model. Second, I exclude cattle shares from the baseline measure. Third, I use the FAO-GAEZ high inputs in the FML model. Tables C9, C10 and C11 report the estimates for the three different definitions for the CE measure. The results remain consistent with the main estimates in both magnitude and significance.

7.4 Observations at a Large Aggregation Level

A potential issue in the empirical analysis performed so far is that some municipalities might be to small to capture flows between rural and urban areas, which are usually associated with agricultural and manufacturing labor. I then aggregate the municipality-level observations at the microregion level, which represents a larger unit of observation and, as discussed previously, also represents Brazilian local labor markets. Tables C12, C13 and C14 report the baseline estimates at the microregion-level. The results have similar magnitude and are consistent with the estimates reported in Section 5.

7.5 Placebo Measure

I now construct a placebo measure to explore if the main results are robust to a different definition of the exposure measure based on a previous period of commodity price variations. I construct the placebo measure by interacting the predicted shares related to the agricultural production of 1985-1989 with the changes in the international commodity prices between 1990 and 2000. This period was characterized by stable or falling international prices and thus can serve as a good placebo with respect to our baseline price boom period (see Figure 2). I then re-estimate equation Equation 6 using the placebo measure. Tables C15, C16 and C17 report the results for the placebo exercise. The estimates imply that the placebo measure is associated with effects that are insignificant or with different signs with respect to the baseline result of the 2000s commodity boom. Overall, the main results remain robust to the placebo exercise.

7.6 Technological Adoption and Productivity Gaps

One potential concern about the identification strategy is that possible effects of new technology adoption on agricultural productivity are missing out in the analysis, which in turn could affect structural transformation as discussed in Section 6. For example it could be the case that the regions that adopted the GE seeds faster did it because their gap between the potential yields for intermediate and high levels of technology was higher then other regions and this made the new technological adoption faster, despite the occurrence of the commodity shock. To examine such issue, I consider the gap between our baseline exposure measure, constructed using the FAO-GAEZ potential yields for intermediate levels of technology, and the analogous one based on potential yields for advanced technology (high input levels). Tables C18, C19 and C20 report the results for productivity gap. The estimates imply that the a higher productivity gap does not lead to a sizeable difference to our main results using the baseline measure.

Table 12: 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)***
Cluster at mesoregion	(0.046)**	(0.047)***	(0.019)	(0.025)	(0.162)***	(0.161)*	(0.209)***
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)*
Simulated Rejection Probability - 5% test	0.058	0.051	0.046	0.045	0.065	0.038	0.053
Simulated Rejection Probability - 10% test	0.106	0.098	0.090	0.084	0.082	0.097	0.084
Observations	5,475	5,475	5,475	5,475	5,475	5,475	5,475

Notes: See Appendix A.1 for variable definition and sources. The table presents the main specification estimates of Equation 6 as reported in column (4) of Tables 5 and 6. Conley (1999) standard errors are computed using the *acreg* command created by Colella et al. (2019). AKM and AKM0 corrections are computed using the *reg_ss* command created by Adao et al. (2019). Estimates of the main specification without region fixed effects are also reported since *reg_ss* does not allow for fixed effects. Simulated rejection probabilities of 5% and 10% t-tests are computed using Ferman (2021) assessment method. Simulations assume the null hypothesis and that residuals are homoscedastic. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table 13: Alternative Standard Errors for Input Use

	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)**
Cluster at mesoregion	(0.211)	(0.340)**	(0.084)**
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)
Simulated Rejection Probability - 5% test	0.037	0.039	0.046
Simulated Rejection Probability - 10% test	0.090	0.100	0.095
Observations	5,446	5,446	5,446

Notes: See Appendix A.1 for variable definition and sources. The table presents the main specification estimates of Equation 6 as reported in column (4) of Table 8. Conley (1999) standard errors are computed using the *acreg* command created by Colella et al. (2019). AKM and AKM0 corrections are computed using the *reg_ss* command created by Adao et al. (2019). Estimates of the main specification without region fixed effects are also reported since *reg_ss* does not allow for fixed effects. Simulated rejection probabilities of 5% and 10% t-tests are computed using Ferman (2021) assessment method. Simulations assume the null hypothesis and that residuals are homoscedastic. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table 14: Alternative Standard Errors for Land Inequality

	Δ Land Gini (2006-2017)	Δ Land Gini (1995-2017)
Δ 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)***
Cluster at mesoregion	(0.033)*	(0.051)**
Conley 50km	(0.027)**	(0.044)**
Conley 100km	(0.033)*	(0.056)**
Conley 200km	(0.032)*	(0.059)*
Conley 400km	(0.039)	(0.062)*
Δ 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)
Simulated Rejection Probability - 5% test	0.056	0.055
Simulated Rejection Probability - 10% test	0.119	0.095
Observations	5,446	4,919

Notes: See Appendix A.1 for variable definition and sources. The table presents the main specification estimates of Equation 6 as reported in column (4) of Table 10. Conley (1999) standard errors are computed using the *acreg* command created by Colella et al. (2019). AKM and AKM0 corrections are computed using the *reg_ss* command created by Adao et al. (2019). Estimates of the main specification without region fixed effects are also reported since *reg_ss* does not allow for fixed effects. Simulated rejection probabilities of 5% and 10% t-tests are computed using Ferman (2021) assessment method. Simulations assume the null hypothesis and that residuals are homoscedastic. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%

Table 15: 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: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Tables 5 and 6 substituting the continuous Δ CE measure with dummy variables that indicate if a municipality is at the top and bottom 10th and 25th percentiles and above the median in the distribution of the Δ CE measure. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table 17: 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: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Table 10 substituting the continuous Δ CE measure with dummy variables that indicate if a municipality is at the top and bottom 10th and 25th percentiles and above the median in the distribution of the Δ CE measure. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table 16: 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: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Table 8 substituting the continuous Δ CE measure with dummy variables that indicate if a municipality is at the top and bottom 10th and 25th percentiles and above the median in the distribution of the Δ CE measure. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

8 Conclusion

I showed that the 2000s commodity supercycle led to a significant structural change in Brazilian municipalities between 2000 and 2010. My identification strategy relied on constructing a shift-share measure by interacting climate- and soil-based measures of crop-specific potential yields with the international prices of commodities. The shift-share measure then reflects an exogenous variation of local exposure to the commodity shock by combining both the cross-sectional and time dimensions. I find that, after the boom, labor was reallocated away from agriculture and towards the manufacturing sector. The reallocation of labor was widespread and did not benefited any specific industrial sector. It also impacted formal and informal jobs in the manufacturing sector symmetrically. I explore the possible mechanisms that are driving the observed 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 results. The mechanisms suggest an increase of large and mechanized farms, pointing to a relevant agricultural modernization process in the Brazilian economy after the agricultural boom.

I also interpret the results in terms of the impact of trade on structural transformation. The results show that the interaction between trade and agricultural productivity after the commodities boom resulted in a structural transformation process that relied heavily on the agricultural modernization of the farms. Taking 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 and overcome the comparative advantage effect of drawing labor into agriculture.

Although deindustrialization and low trends of growth and productivity are salient features in the Brazilian economy during the last decades, my work provides evidence that the commodity boom is not one of the fundamental causes of such issues. I 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. I do not, however, test directly for the human capital hypothesis and leave it for future work.

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Appendix

A Data

This section contains a detailed description and the sources of the main variables used in the paper.

A.1 Definitions and Sources

Variables for Constructing the Commodity Exposure Measure

Observed shares of each crop ($Q_{ki}, 99$): Data on the observed shares of each crop between 1995 and 1999 is from the Produção Agrícola Municipal (PAM) and Pesquisa da Pecuária Municipal (PPM) and it is sourced from the IBGE online data repository SIDRA. I construct this variable by dividing the quantities of each crop in each municipality-year observation by the total quantity of all crops used in our sample for each observation. Data for the quantities of seasonal and permanent crops in PAM is from Tabela 5457. Data for the number of cattle heads in PPM if from Tabela 3939.

Crop-specific potential yields: Data on potential yields comes from the Global Agro-Ecological Zones project v3.0 (IIASA/FAO (2012)), which is publicly available on their website.[28] This variable measures agricultural suitability as the maximum attainable yields for a crop in a certain geographical area and are reported in tons per hectare per year for each crop in each grid cell of 0.083x0.083 degrees. FAO uses information on climatic conditions—including precipitation, temperature, wind speed, sunshine hours, and relative humidity—together with data on soil, topography and elevation to determine the maximum attainable yields. FAO's data also enable us to choose different types of inputs and water supply conditions. I use data on intermediate levels of inputs/technology and rain-fed conditions, which better approximates our scenario.

The definition of each inputs/technology in the FAO-GAEZ dataset documentation is as follows. Low-level inputs/traditional management: "Under a low level of inputs (traditional management assumption), the farming system is largely subsistence based. Production is based on the use of traditional cultivars (if improved cultivars are used, they are treated in the same way as local cultivars), labor intensive techniques, and no application of nutrients, no use of chemicals for pest and disease control and minimum conservation measures." Intermediate-level inputs/advanced management: "Under an intermediate level of

[28] http://www.gaez.iiasa.ac.at/.

input (improved management assumption), the farming system is partly market oriented. Production for subsistence plus commercial sale is a management objective. Production is based on improved varieties, on manual labor with hand tools and/or animal traction and some mechanization, is medium labor intensive, uses some fertilizer application and chemical pest disease and weed control, adequate fallows and some conservation measures." High-level inputs/advanced management: "Under the high input, advanced management assumption, the farming system is mainly market oriented. Commercial production is a management objective. 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."

International commodity prices: Data on international commodity price comes from the Global Economic Monitor (GEM) Commodities database published by the World Bank, which is publicly available on their website.

Outcome Variables

Total GDP per capita: Data on Total Gross Domestic of Municipalities is from the *Produto Interno Bruto dos Municípios* series by IBGE. I use the values for 2000 and 2010 in our analysis. The values are reported in current values in Reais in the respective years. In order to deflate all 2000 values to 2010 Reais, I used the annual IPCA (Índice Nacional de Preços ao Consumidor Amplo). In order to obtain per capita values, I divide the real values by the total population in each municipality taken from the Population Census.

Agricultural GDP per capita: Data on Agricultural GDP per Capita is obtained in the same way as Total GDP per Capita

Manufacturing GDP per capita: Data on Agricultural GDP per Capita is constructed in the same way as Total and Agricultural GDP per Capita.

Services GDP per capita: Data on Agricultural GDP per Capita is constructed in the same way as Total, Agricultural and Manufacturing GDP per Capita.

Employment share in agriculture: Data on employment share in agriculture come from the Brazilian Population Censuses of 2000 and 2010. The variable is calculated as total number of people who reported working in the agricultural sector divided by the total number of people that reported being employed in any sector of the economy. Sector of employment is reported according to the first version of the CNAE-Domiciliar in both 2000 and 2010. The agricultural sector is defined as any sector with the codes ranging from 01 to 05, which encompasses the Sections A: Agriculture, Livestock, Silviculture and Forest Production and B: Fishing. Original data come at the individual level and I use the municipality-level aggregation provided by the Atlas do Desenvolvimento Humano no Brasil (PNUD, 2020).

Employment share in manufacturing: Data on employment share in manufacturing come from the Brazilian Population Censuses of 2000 and 2010. The variable is calculated and aggregated in the same way as employment share in agriculture. The manufacturing sector is defined as Sections C: Extractive Industries and D: Transformation Industries, with the codes ranging from 10 to 37.

Employment share in services: Data on employment share in services come from the Brazilian Population Censuses of 2000 and 2010. The variable is calculated and aggregated in the same way as employment share in agriculture and manufacturing. The service sector is defined as Sections G: Commerce; H: Transportation; I: Accommodation and Food; J: Information and Communication; K: Financial Activities; L: Real Estate; M: Professional, Scientific and Technical Activities; N: Administrative Activities; O: Public administration, defense and social security; P: Education; Q: Health; R: Arts, Culture, Sport and Recreation; S: Other Services; T: Domestic Services, with the codes ranging from 45 to 97.

Wages in agriculture: Data on the wage in agriculture come from the Brazilian Population Censuses of 2000 and 2010. All wages are reported in current values in Reais in the respective years of the two Censuses. In order to deflate all 2000 values to 2010 Reais, I used the annual IPCA (Índice Nacional de Preços ao Consumidor Amplo).

Wages in manufacturing: Data on the wage in manufacturing come from the Brazilian Population Censuses of 2000 and 2010. The variable is constructed in the same way as the wages in agriculture.

Wages in services: Data on the wage in services come from the Brazilian Population Censuses of 2000 and 2010. The variable is constructed in the same way as the wages in agriculture and manufacturing.

Urban population share: Data on the urban population share come from the Brazilian Population Censuses of 2000 and 2010. The variable is constructed by dividing the total population living in urban areas with the total population in each municipality.

Output in agroindustry: Data on the output value in the agroindustry is from the Brazilian Agricultural Census of 2006 and 2017 and is sourced from the IBGE online data repository SIDRA.[29] Data of 2006 is from Tabela 4081 and of 2017 from Tabela 6960.

[29] www.sidra.org.br.

Employment share in manufacturing - RAIS: Data on alternative employment share in manufacturing come from the Relação Anual de Informações Sociais (RAIS) from the Brazilian Ministry of Labor.[30] The manufacturing sector is defined the same way as before, using Sections C: Extractive Industries and D: Transformation Industries from CNAE, with the codes ranging from 10 to 37.

Employment share in agroindustry: Data on employment share in agroindustry come from the Relação Anual de Informações Sociais (RAIS) from the Brazilian Ministry of Labor. The agroindustry sector is defined using codes 152 to 214, which include the processing of food; beverage production; manufacturing of textile products; clothing; wood and paper processing.

Employment share in heavy industry: Data on employment share in agroindustry come from the Relação Anual de Informações Sociais (RAIS) from the Brazilian Ministry of Labor. The heavy industry sector is defined using codes 24 to 37, which include the chemical industry; pharmaceuticals; metallurgy; machinery; electronics; automotive industry; and furniture.

Total farmland: Data on the total farmland is from the Brazilian Agricultural Census of 2006 and 2017 and is sourced from the IBGE online data repository SIDRA. Data of 2006 is from Tabela 787 and of 2017 from Tabela 6878.

Machine intensity: Data on the machine intensity is from the Brazilian Agricultural Census of 2006 and 2017 and is sourced from the IBGE online data repository SIDRA. I construct this variable by obtaining the total number of tractors, seeders, planters, harvesters and fertilizers used in the agricultural establishments (farms) in each municipality. I then divide the total number of machines by the total farmland. Data of 2006 is from Tabela 860 (tractors) and Tabela 861 (other machines). Data of 2017 is from Tabela 6898 (tractors) and Tabela 6872 (other machines).

Share of land with GE seeds: Data on the share of land harvested with GE seeds is from the Brazilian Agricultural Census of 2006 and 2017 and is sourced from the IBGE online data repository SIDRA. Data of 2006 is from Tabela 824 and of 2017 from Tabela 6958.

Farm productivity: Data on farm productivity is from the Brazilian Agricultural Census of 2006 and 2017 and is sourced from the IBGE online data repository SIDRA. I construct this variable by dividing the total value of output in agricultural for each municipality by the total farmland. Data of 2006 for Total value of production in agriculture is from Tabelas:

[30] As of 2020, the Ministry of Labor has been incorporated into the Ministry of Economy.

1823 (value of production by seasonal crop), 1177/1178 (value of production by permanent crop), 818 (value of production by horticulture product), 815 (value of production by forestry product), 816 (value of production by vegetable extraction product), 782 (value of bovines), 937 (value of swines), 943 (value of poultry). Data for 2017 is from Tabelas: 6957 (value of production by seasonal crop), 6955 (value of production by permanent crop), 6953 (value of production by horticulture product), 6949 (value of production by vegetable extraction product), 6947 (value of production by forestry product), 6940 (value of poultry), 6927 (value of swines), 6910 (value of bovines).

Output per worker: Data on output per worker is from the Brazilian Agricultural Census of 2006 and 2017 and it is sourced from the IBGE online data repository SIDRA. I construct this variable by dividing the total value of output in agricultural for each municipality by the number of workers in agriculture. Data for the number of workers in 2006 is from Tabela 956 and in 2017 from Tabela 6889.

Land Gini: Data on Land Gini is from the Brazilian Agricultural Census of 1995, 2006 and 2017 and it is sourced from the IBGE online data repository SIDRA. I detail the construction of this variable in Appendix A.2. I use data for the total area and number of farms in each municipality. Data for the area of agricultural establishments in 1995 is from Tabela 315, of 2006 is from Tabela 787 and of 2017 from Tabela 6878. Data for the number of farms in 1995 is from Tabela 312, of 2006 is from Tabela 860 and of 2017 from Tabela 6880.

Area of farms > 1.000 ha: Data on the area of farms with more than 1.000 ha is from the Brazilian Agricultural Census of 1995, 2006 and 2017 and it is sourced from the IBGE online data repository SIDRA. The data is from the same tables used in the Land Gini.

Number of farms > 1.000 ha: Data on the number of farms with more than 1.000 ha is from the Brazilian Agricultural Census of 1995, 2006, and 2017 and is sourced from the IBGE online data repository SIDRA. The data is from the same tables used in the Land Gini.

Share of landowners residing outside the farms: Data on the share of landowners residing outside the farms is from the Brazilian Agricultural Census of 2006 and 2017 and it is sourced from the IBGE online data repository SIDRA. To construct the variable I divide the total number of landowners who do not reside in their own farm by the total number of landowners in each municipality. Data in 2006 is from Tabela 843, and in 2017 from Tabela 6778.

Control Variables

Share of rural population: Data on the share of rural population come from Brazilian Population Census of 1991. This variable is constructed by dividing the total number of people that reported living in rural area with the total population in each municipality. Original data come at the individual level and I use the municipality-level aggregation provided by the Atlas do Desenvolvimento Humano no Brasil (PNUD, 2020).

Illiteracy rate: Data on the illiteracy come from Brazilian Population Censuses of 1991. The variable is calculated considering only people 10 years or older, as the total number of people who is able to read and write divided by the total number of people. Original data is at the individual level and I use the municipality-level aggregation provided by the Atlas do Desenvolvimento Humano no Brasil (PNUD, 2020).

Income per capita: Data on income per capita come from Brazilian Population Census of 1991. Income is defined for every person as the sum of income coming from all sources. Original data come at the individual level and I use the municipality-level aggregation provided by the Atlas do Desenvolvimento Humano no Brasil (PNUD, 2020).

Population density: Data on population density come from Brazilian Population Census of 1991 and IpeaData. I construct this variable by dividing the total population of each municipality by its total area in square kilometers. Data on municipality area is from IpeaData.

Share of women in the labor force: Data on share of women in the labor force come from the Brazilian Population Census of 1991. I construct this variable by dividing the total number of women in the labor market by the total number of people that reported being employed in any sector of the economy.

Farmland productivity in 1995: Data on land productivity come from the Brazilian Agricultural Census of 1995. I construct this variable by dividing the total value of output in agricultural for each municipality by the total farmland in the same way I did for the previous farm productivity variable.

Commodity prevalence dummies: I construct the dummies of commodity prevalence by assigning a dummy variable equal to one to municipalities that have any crop representing more than 30% of its total agricultural production and a dummy variable equal to one if the group of commodities composed by meat, coffee, maize, soybean, and sugarcane represent more than 50% of its total agricultural production.

Altitude: Data on altitude at the municipality level is from Ipeadata.

Distance to federal and state capitals: I obtain data on the distance to the federal and state capitals for each municipality from Ipeadata.

Variables Used in Figures and Additional Results

Employment shares from Figure 3: Data on employment shares since 1960 in Brazil come from IPUMS International microdata for the Brazilian Population Census (Min, 2019). This dataset enables us to construct employment shares in the usual way, but also keeping the variables in each year harmonized throughout the different definitions of occupations in the Censuses using ISCO and SIC codes, which follow a similar structure than that of CNAE.

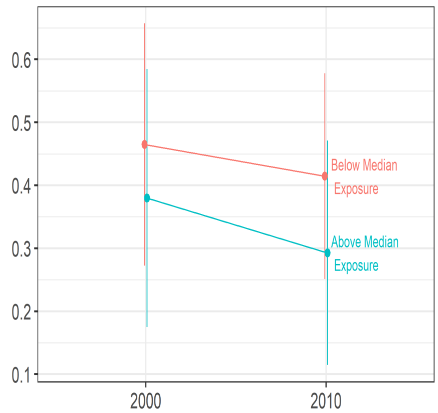
A.2 Land Gini Calculation

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 different bins of total area. With this I am able to calculate the mean property size within each interval. I then follow Nunn (2008) and use the Stata program *ineqdec0* written by Stephen P. Jenkins, to obtain the Gini coefficient as follows:

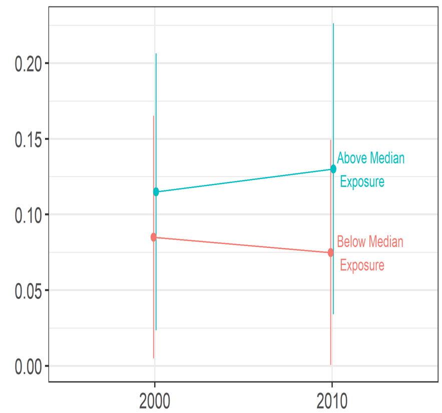
$$\text{Gini} = 1 + \left(\frac{1}{n}\right) - \frac{2\sum_{1}^{n}(n-i+1)\,a_i}{n\sum_{i}^{n} a_i}$$

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.

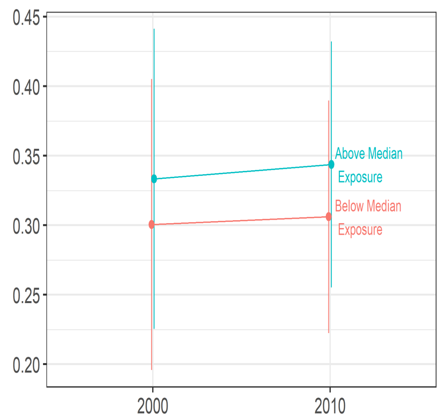
B Additional Figures



(a) Agriculture



(b) Manufacturing



(c) Services

Figure B1: Employment Shares (Mean and 1SD Error Bars)

Notes: The figures display the average employment shares, and their respective 1 standard error bars, in Brazilian municipalities that were ranked above and below the ΔCE measure. Data are from the 2000 and 2010 Population Census. See Appendix A.1 for variable definition and sources.

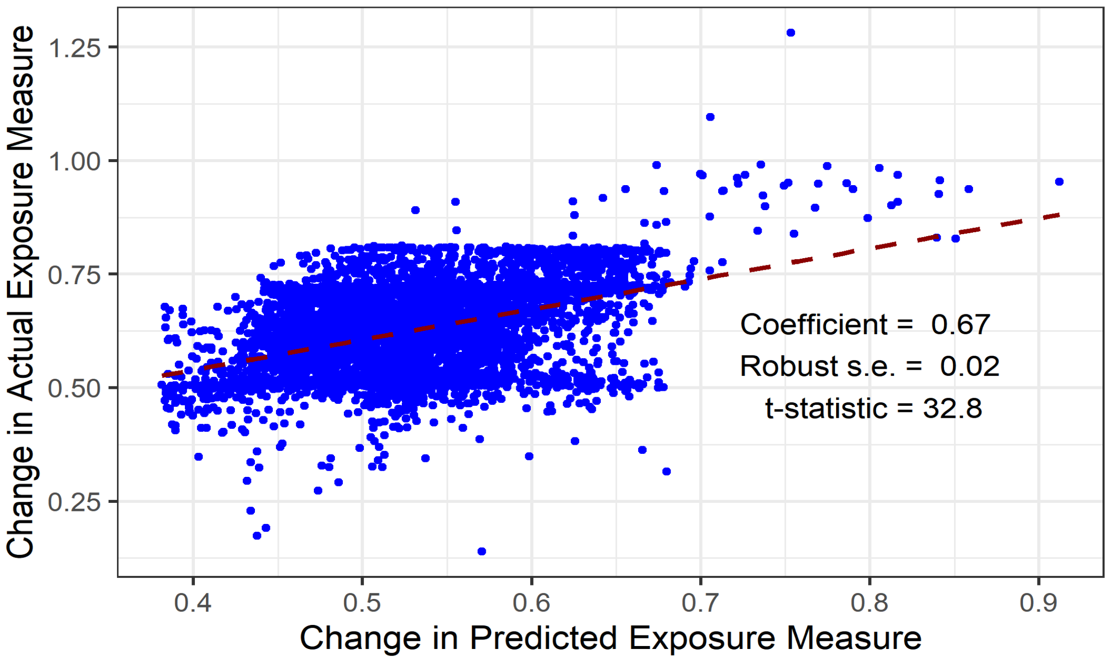


Figure B2: Actual and Predicted Exposure Measure

Notes: The figure displays the scatter plot of actual and predicted ΔCE measure constructed in Equation 3. Predicted shares are obtained from the FML model. The figure reports the coefficient, robust standard error, and t-statistic of the bivariate regression between the two variables. See Appendix A.1 for variable definition and sources.

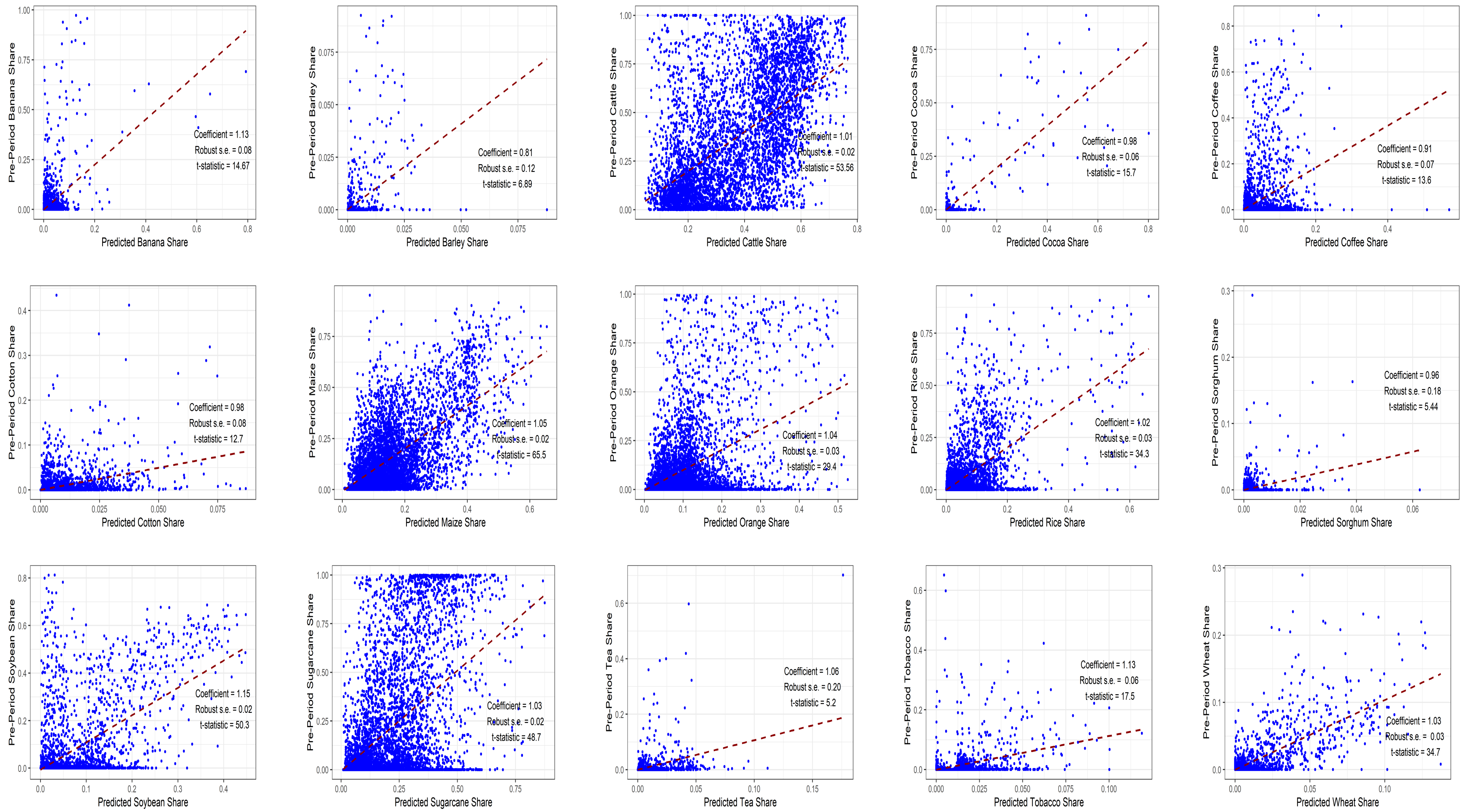


Figure B3: Actual and Predicted Agricultural Shares

Notes: The figures display the scatter plot of actual and predicted shares for all crops in the sample. The figure reports the coefficients, robust standard errors, and t-statistics of the bivariate regression between the two variables in each graph. Predicted shares are obtained from the FML model. See Appendix A.1 for variable definition and sources.

C Additional Results

Table C1: Summary Statistics on Crop Shares

Crops	Mean	Standard Deviation	Min.	Max.	Observations	Mean Price (2000-2010)
Banana	0.013	0.063	0.000	0.973	5,494	695
Barley	0.001	0.005	0.000	0.093	5,494	135
Cattle	0.361	0.361	0.000	1.000	5,494	2856
Cocoa	0.005	0.047	0.000	0.909	5,494	2059
Coffee	0.021	0.082	0.000	0.847	5,494	2597
Cotton	0.005	0.021	0.000	0.434	5,494	1536
Maize	0.165	0.181	0.000	0.952	5,494	144
Orange	0.107	0.196	0.000	0.994	5,494	875
Rice	0.052	0.121	0.000	0.932	5,494	355
Sorghum	0.001	0.007	0.000	0.294	5,494	140
Soybean	0.044	0.125	0.000	0.813	5,494	349
Sugarcane	0.215	0.308	0.000	1.000	5,494	273
Tea	0.002	0.021	0.000	0.702	5,494	2183
Tobacco	0.005	0.028	0.000	0.651	5,494	3561
Wheat	0.005	0.021	0.000	0.290	5,494	183

Notes: See Appendix A.1 for each variable definition and sources.

Table C2: The Effect of the Commodity Shock on GDP Shares

	(1)	(2)	(3)	(4)
Panel A.		Δ Agriculture GDP Share		
Δ CE	0.466***	0.360***	0.424***	0.392***
	(0.024)	(0.025)	(0.027)	(0.028)
Adj. R^2	0.070	0.093	0.117	0.122
Panel B.		Δ Manufacturing GDP Share		
Δ CE	0.042**	0.054**	0.028	0.015
	(0.020)	(0.021)	(0.024)	(0.024)
Adj. R^2	0.001	0.001	0.017	0.023
Panel C.		Δ Services GDP Share		
Δ CE	−0.444***	−0.357***	−0.401***	−0.356***
	(0.023)	(0.024)	(0.027)	(0.027)
Adj. R^2	0.065	0.081	0.116	0.132
Rural Share in 1991		✓	✓	✓
Region FE			✓	✓
Baseline Controls				✓
Observations	5,488	5,488	5,488	5,488

Notes: See Appendix A.1 for variable definition and sources. The table presents estimates of Equation 6. The dependent variable is the 2000-2010 change in the listed outcomes. Column (1) reports the estimates without any control. Columns (2)-(4) extend the set of controls by including the share of population living in the rural area; region fixed effect for the 5 macroregions of Brazil; log income per capita; log population density; and illiteracy rate. All municipalities controls are from the population census of 1991. The means and standard deviations (in parentheses) of the dependent variables in panels A, B and C are -0.041 (0.112), -0.011 (0.093), and 0.037 (0.111). Table C6 reports the coefficient for all the controls. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table C3: The Effect of the Commodity Shock on Landowner Residence

	(1)	(2)	(3)	(4)
Panel A.	Δ Share of Landowners Residing Outside the Farm			
Δ CE	0.273***	0.215***	0.143***	0.123***
	(0.029)	(0.031)	(0.036)	(0.037)
Adj. R^2	0.016	0.021	0.049	0.051
Rural Share in 1991		✓	✓	✓
Region FE			✓	✓
Baseline Controls				✓
Observations	5,446	5,446	5,446	5,446

Notes: See Appendix A.1 for variable definition and sources. The table presents estimates of Equation 6. The dependent variable is the 2006-2017 change in the listed outcomes. Column (1) reports the estimates without any control. Columns (2)-(4) extend the set of controls by including the share of population living in the rural area; region fixed effect for the 5 macroregions of Brazil; log income per capita; log population density; and illiteracy rate. All municipalities controls are from the population census of 1991. The mean and standard deviation (in parentheses) of the dependent variable are 0.058 (0.135). Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10% level.

Table C4: 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: See Appendix A.1 for variable definition and sources. The table presents estimates of Equation 6. The dependent variable is the 2000-2010 change in the listed outcomes. Column (1) reports the estimates without any control. Columns (2)-(4) extend the set of controls by including the share of population living in the rural area; region fixed effect for the 5 macroregions of Brazil; log income per capita; log population density; and illiteracy rate. All municipalities controls are from the population census of 1991. The means and standard deviations (in parentheses) of the dependent variables in panels A, B, and C are -0.023 (0.125), 0.001 (0.117), and 0.021 (0.170). Robust standard errors reported 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 Total Employment Across Sectors

	(1)	(2)	(3)	(4)
Panel A.		Δ Log Total Employment		
Δ 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.		Δ Log Total Employment in Agriculture		
Δ 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.		Δ Log Total Employment in Manufacturing		
Δ 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.		Δ Log Total Employment in Services		
Δ 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: See Appendix A.1 for variable definition and sources. The table presents estimates of Equation 6. The dependent variable is the 2000-2010 change in the listed outcomes. Column (1) reports the estimates without any control. Columns (2)-(4) extend the set of controls by including the share of population living in the rural area; region fixed effect for the 5 macroregions of Brazil; log income per capita; log population density; and illiteracy rate. All municipalities controls are from the population census of 1991. The means and standard deviations (in parentheses) of the dependent variables in panels A, B, C and D are 0.190 (0.220), -0.009 (0.342), 0.173 (0.666), and 0.927 (0.818). Robust standard errors reported 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 Structural Transformation - Main Specification Coefficients

	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	−0.120***	0.151***	0.001	0.032**	0.444***	−0.300**	0.581***
	(0.018)	(0.014)	(0.013)	(0.016)	(0.093)	(0.136)	(0.096)
Log Income per Capita in 1991	0.018***	−0.005*	−0.009***	0.006*	−0.010***	−0.056**	0.013
	(0.004)	(0.003)	(0.003)	(0.003)	(0.020)	(0.029)	(0.021)
Log Population Density in 1991	0.0004	−0.001*	−0.001	0.0007	−0.021***	−0.006	−0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.006)	(0.007)	(0.006)
Share of Rural Population in 1991	−0.054***	−0.004	0.062***	0.094***	−0.196***	−0.114***	0.006
	(0.006)	(0.004)	(0.004)	(0.006)	(0.030)	(0.042)	(0.030)
Illiteracy Rate in 1991	−0.0007***	0.0002*	0.0003***	0.00008	−0.0008	−0.002	−0.002**
	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.001)	(0.001)	(0.001)
Northeast Region Dummy	0.001	0.016***	−0.012***	0.00003	0.136***	0.010**	−0.024
	(0.006)	(0.004)	(0.004)	(0.004)	(0.028)	(0.041)	(0.030)
Southeast Region Dummy	−0.010*	0.029***	−0.004	0.009**	0.163***	0.028	0.065**
	(0.006)	(0.004)	(0.003)	(0.004)	(0.024)	(0.036)	(0.027)
South Region Dummy	−0.019***	0.032***	0.003	0.013***	0.182***	0.026	0.182***
	(0.006)	(0.004)	(0.004)	(0.005)	(0.027)	(0.038)	(0.029)
Central-West Region Dummy	−0.0112*	0.025***	−0.011***	−0.006	0.195***	0.006	0.379***
	(0.006)	(0.004)	(0.004)	(0.005)	(0.028)	(0.040)	(0.029)
Adj. R^2	0.086	0.052	0.176	0.127	0.025	0.006	0.145
Observations	5,475	5,475	5,475	5,475	5,475	5,475	5,475

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Tables 5 and 6, reporting all the coefficients for the controls. The North region dummy is omitted in the set of region dummies. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C7: The Effect of the Commodity Shock on Structural Transformation - Additional Controls

	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	−0.101***	0.125***	0.006	0.0294	0.293***	−0.214	0.434***
	(0.020)	(0.016)	(0.014)	(0.018)	(0.108)	(0.158)	(0.112)
Adj. R^2	0.113	0.107	0.167	0.154	0.057	0.015	0.209
Observations	4,865	4,865	4,865	4,865	4,865	4,865	4,865

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 with additional controls. I now add both the baseline controls reported in column (4) of Tables 5 and 6 and the following variables: share of women in the labor force in 1991; log value of output per total farmland in 1995; altitude; state capital dummy; distance to the state capital; distance to the federal capital; dummies for individual and groups of commodities. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C8: The Effect of the Commodity Shock on Input Use and Land Inequality - Additional Controls

	Δ Log Total Farmland	Δ Log Machine Intensity	Δ Share of Land with GE Seeds	Δ Land Gini (2006-2017)	Δ Land Gini (1995-2017)
Δ CE	0.030	0.551**	0.133***	0.092***	0.116***
	(0.125)	(0.271)	(0.034)	(0.024)	(0.029)
Adj. R^2	0.078	0.035	0.260	0.089	0.137
Observations	4,841	4,841	4,841	4,841	4,841

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 with additional controls. I now add both the baseline controls reported in column (4) of Tables 8 and 10 and the following variables: share of women in the labor force in 1991; log value of output per total farmland in 1995; altitude; state capital dummy; distance to the state capital; distance to the federal capital; dummies for individual and groups of commodities. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C9: The Effect of the Commodity Shock on Structural Transformation - Alternative Shares for the Exposure Measure

	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 - Actual Shares	−0.159***	0.207***	−0.008	0.042***	0.526***	−0.248*	0.814***
	(0.019)	(0.014)	(0.013)	(0.016)	(0.098)	(0.138)	(0.096)
Adj. R^2	0.091	0.070	0.176	0.127	0.027	0.006	0.150
Δ CE - No Cattle	−0.159***	0.167***	0.004	0.019	0.715***	−0.367**	0.964***
	(0.023)	(0.017)	(0.016)	(0.021)	(0.107)	(0.167)	(0.116)
Adj. R^2	0.088	0.048	0.176	0.126	0.028	0.006	0.149
Δ CE - High Inputs	−0.111***	0.149***	−0.004	0.021	0.346***	−0.264**	0.409***
	(0.018)	(0.013)	(0.012)	(0.016)	(0.087)	(0.130)	(0.091)
Adj. R^2	0.086	0.053	0.176	0.127	0.024	0.006	0.142
Observations	5,475	5,475	5,475	5,475	5,475	5,475	5,475

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Tables 5 and 6 substituting the shares used in the construction of the Δ CE measure with: the mean production of each crop during the ten years between 2000 and 2010 (Actual Shares); the pre-period shares excluding cattle (No Cattle); the high inputs potential yields from FAO-GAEZ. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C10: The Effect of the Commodity Shock on the Land Use and Capital Inputs - Alternative Shares for the Exposure Measure

	Δ Log Total Farmland	Δ Log Machine Intensity	Δ Share of Land with GE Seeds
Δ CE - Actual Shares	−0.185*	0.212	0.279***
	(0.108)	(0.213)	(0.036)
Adj. R^2	0.063	0.021	0.198
Δ CE - No Cattle	0.074	1.687***	0.322***
	(0.134)	(0.316)	(0.042)
Adj. R^2	0.062	0.029	0.197
Δ CE - High Inputs	−0.014	0.670***	0.135***
	(0.104)	(0.220)	(0.033)
Adj. R^2	0.062	0.023	0.192
Observations	5,446	5,446	5,446

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Table 8 substituting the shares used in the construction of the Δ CE measure with: the mean production of each crop during the ten years between 2000 and 2010 (Actual Shares); the pre-period shares excluding cattle (No Cattle); the high inputs potential yields from FAO-GAEZ. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C11: The Effect of the Commodity Shock on Land Inequality - Alternative Shares for the Exposure Measure

	Δ Land Gini (2006-2017)	Δ Land Gini (1995-2017)
Δ CE - Actual Shares	0.082***	0.123***
	(0.020)	(0.025)
Adj. R^2	0.075	0.111
Δ CE - No Cattle	0.067***	0.077**
	(0.025)	(0.032)
Adj. R^2	0.073	0.108
Δ CE - High Inputs	0.053***	0.075***
	(0.019)	(0.024)
Adj. R^2	0.073	0.109
Observations	5,446	4,919

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Table 10 substituting the shares used in the construction of the Δ CE measure with: the mean production of each crop during the ten years between 2000 and 2010 (Actual Shares); the pre-period shares excluding cattle (No Cattle); the high inputs potential yields from FAO-GAEZ. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C12: The Effect of the Commodity Shock on Employment Shares - Observations at the Micro-Region Level

	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	-0.169***	0.143***	0.046*	0.046	0.432**	-0.264	0.246
	(0.040)	(0.029)	(0.024)	(0.035)	(0.173)	(0.199)	(0.199)
Adj. R^2	0.170	0.105	0.392	0.242	0.131	0.071	0.345
Observations	558	558	558	558	558	558	558

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Tables 5 and 6 and aggregates the municipality-level variables at the microregion-level. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C13: The Effect of the Commodity Shock on the Land Use and Capital Inputs - Observations at the Microregion Level

	Δ Log Total Farmland	Δ Log Machine Intensity	Δ Share of Land with GE Seeds
Δ CE	-0.223	1.137***	0.201***
	(0.246)	(0.428)	(0.078)
Adj. R^2	0.129	0.105	0.265
Observations	557	557	557

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Table 8 and aggregates the municipality-level variables at the microregion-level. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C14: The Effect of the Commodity Shock on Land Inequality - Observations at the Micro-Region Level

	Δ Land Gini (2006-2017)	Δ Land Gini (1995-2017)
Δ CE	0.028	0.116*
	(0.048)	(0.069)
Adj. R^2	0.194	0.262
Observations	557	557

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Table 10 and aggregates the municipality-level variables at the microregion-level. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C15: The Effect of the Commodity Shock on Employment Shares - Placebo Check

	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 - Placebo	0.103***	−0.111***	−0.009	−0.024	−0.322***	0.043	−0.514***
	(0.018)	(0.013)	(0.012)	(0.016)	(0.098)	(0.136)	(0.098)
Adj. R^2	0.067	0.052	0.146	0.153	0.033	0.007	0.178
Observations	4,411	4,411	4,411	4,411	4,411	4,411	4,411

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Tables 5 and 6 using the placebo exposure measure. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C16: The Effect of the Commodity Shock on the Land Use and Capital Inputs - Placebo Check

	Δ Log Total Farmland	Δ Log Machine Intensity	Δ Share of Land with GE Seeds
Δ CE - Placebo	−0.095	−0.513**	−0.175***
	(0.116)	(0.228)	(0.029)
Adj. R^2	0.059	0.025	0.196
Observations	4,380	4,380	4,380

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Table 8 using the placebo exposure measure. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C17: The Effect of the Commodity Shock on Land Inequality - Placebo Check

	Δ Land Gini (2006-2017)	Δ Land Gini (1995-2017)
Δ CE - Placebo	−0.063***	−0.087***
	(0.021)	(0.027)
Adj. R^2	0.076	0.118
Observations	4,380	4,376

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Table 10 using the placebo exposure measure. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C18: The Effect of the Commodity Shock on Employment Shares - Productivity Gaps

	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 - High and Intermediate Gap	−0.019	0.078**	−0.030	−0.046	−0.312	0.039	−0.667***
	(0.047)	(0.035)	(0.030)	(0.036)	(0.235)	(0.235)	(0.238)
Adj. R^2	0.080	0.032	0.176	0.126	0.022	0.005	0.141
Observations	5,475	5,475	5,475	5,475	5,475	5,475	5,475

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Tables 5 and 6 using the gap between the high and intermediate exposure measures. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C19: The Effect of the Commodity Shock on the Land Use and Capital Inputs - Productivity Gaps

	Δ Log Total Farmland	Δ Log Machine Intensity	Δ Share of Land with GE Seeds
Δ CE - High and Intermediate Gap	0.505	0.356	−0.162
	(0.314)	(0.480)	(0.106)
Adj. R^2	0.063	0.021	0.191
Observations	5,446	5,446	5,446

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Table 8 using the gap between the high and intermediate exposure measures. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.

Table C20: The Effect of the Commodity Shock on Land Inequality - Productivity Gaps

	Δ Land Gini (2006-2017)	Δ Land Gini (1995-2017)
Δ CE - High and Intermediate Gap	−0.023	−0.151**
	(0.050)	(0.060)
Adj. R^2	0.076	0.118
Observations	5,446	4,919

Notes: See Appendix A.1 for variable definition and sources. The table presents then main specification estimates of Equation 6 as reported in column (4) of Table 10 using the gap between the high and intermediate exposure measures. Robust standard errors reported in parentheses. *** Significant at the 1% level; ** Significant at the 5% level; * Significant at the 10%.