The (Other) China Shock and the Brazilian Soy Boom: Cui Bono?

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Abstract

Building upon the argument that factor endowments influence distributional outcomes, this paper examines the consequences of the China shock to global food markets for economic inequality in Brazilian municipalities from 1985 to 2020. I propose a new identification strategy that exploits plausibly exogenous variation in demand for soybeans based on fluctuations in the size of the pig stock in China and show that the proceeds of this China-driven agricultural bonanza have been rather unequally distributed. The soy boom has fueled land consolidation and economic inequality, especially in places dominated by large-scale mechanized agriculture. Income gains have been mostly limited to the top deciles of the distribution, while the poorest segments of the population have become worse off. Additionally, there is evidence that the more unequal a municipality, the more deforestation and rural conflict increase as soy expands.

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1 Introduction

One of the most significant implications of the recent rise of China as an economic power has been a large positive shock in demand for agricultural commodities—which has been labeled the "other" China shock (Hansen and Wingender, 2023). Featuring prominently on the receiving end of this shock, particularly via growing demand for soybeans, is Brazil, a country in which the production of this crop more than tripled in two decades, from around 33Mt in 2000 to almost 122Mt in 2020 (IBGE, 2023*a*). With China as its main buyer, Brazil has recently overtaken the United States to become the world's largest producer and exporter of soybeans (FAO, 2023).[1]

To what extent has this newfound prosperity trickled down to broader swaths of the Brazilian population and at what costs? This paper examines the socioeconomic and environmental consequences of this demand shock and the boom in soybean production that ensued. Following Sokoloff and Engerman's (2000) seminal contribution, the underlying premise is that factor endowments play an important role in determining (structural) inequality. Or, in the case of China and Brazil, I argue that, by its sheer scale, the former's economic rise and its growing need for certain agricultural commodities—especially after China's accession to the WTO in 2001—have significantly influenced the use of factor endowments in the latter. Not only has Chinese demand been a major force behind Brazil's consolidation as an agricultural powerhouse, but it has favored the production of certain crops more than others. In particular, it has helped making this model of large-scale, industrialized soybean cultivation—or "neo-developmentalism" (Hopewell, 2017, Sauer and Mészáros, 2017)—viable and highly profitable. Therefore, the China shock might have had unintended, but profound implications for the distribution of land and income in Brazil. More precisely, for reasons discussed below, this paper's main hypothesis is that soy expansion tends to fuel economic inequality.

The focus on soy is justified for the at least two reasons. First, although exports of other agricultural commodities produced in Brazil have also increased in the last few decades, soybeans are by far the most important crop in the country, corresponding to more than 40% of the total value of agricultural production (IBGE, 2023*a*) and taking up a larger area than any other crop (Martinelli et al., 2017).[2] Second, (modern) soybean cultivation possesses certain features that should make its expansion particularly pervasive in terms of distributional consequences. Differently from traditional, subsistence agriculture, soy is a huge business, highly capital intensive and reliant on constant technological innovation (Hopewell, 2017, Navarro and Pedroso,

[1] Soybeans are one of the world's most commercialized commodities, reaching a total trade volume of US$64 billion in 2020 (Escobar et al., 2020). Among its many uses, this legume is demanded, to a large extent, to serve as animal feed.

[2] What is more, soybeans account for approximately 14% of Brazil's export revenues (MDIC, 2022) and are planted by more than 250,000 producers in over 1,500 municipalities all over the country's territory (Martinelli et al., 2017).

2018). Importantly, it is "one of the least labor-intensive agricultural activities" (Bustos et al., 2016, p. 1328) and usually the "domain of wealthy agribusiness entrepreneurs" (Fearnside, 2001, p. 28). Because soybeans are the most important agricultural good demanded by China (Hansen and Wingender, 2023), the China shock has been an enormous incentive for the expansion of this crop in Brazil.[3]

The empirical analysis consists of two parts. First, using data for all Brazilian municipalities from 1985 to 2017 at (roughly) ten-year intervals, I provide evidence that, in the long run, land inequality has increased as soy expands. In a difference-in-differences-like setup, the results indicate that China's WTO accession has constituted an inflection point in the relationship between inequality and soy production. After 2001, the more suitable a municipality is for soy cultivation, the more unequal it has become.

To arrive at causally credible estimates, I propose a new identification strategy—used in both parts of the analysis—that exploits fluctuations in the size of the pig stock in China over time. As I explain in detail below, this is a major driver of Chinese demand for soy and is affected to a large extent by sporadic episodes of disease outbreak. For cross-sectional variation, I interact this variable with soil suitability for soybean cultivation in Brazilian municipalities, which yields a powerful instrument for municipal soy production.

In the second (and main) part of the analysis, for a more rigorous examination of the soy-inequality nexus I construct a yearly panel (2000–2020), again at the municipal level in Brazil, in which the main dependent variable is a grid-based measure of economic inequality (Galimberti et al., 2023, Weidmann and Theunissen, 2021).[4] This is a considerable improvement relative to most of the literature concerned with inequality in Brazilian municipalities, which at best relies on census-based data, available only once every decade.

Also in this case I find that soy production, fueled by Chinese demand, has substantially increased inequality in Brazilian municipalities—although with notable regional differences. These results are robust to series of tests. In particular, the effect is indeed driven primarily by soybeans, as taking other important crops into consideration barely changes the main conclusions. Furthermore, I show evidence that the instrumental variable approach does not seem to be driven by spurious correlation (Christian and Barrett, 2023). I also examine whether the reported rise in inequality is indeed driven by the (other) China shock. This does seem to be the case, as replicating the analysis for demand from the European Union (EU)—the second most important market for Brazilian soybeans—does not yield comparable results.

In line with the Sokoloff-Engerman argument, the results indicate that soy on its own is not to blame, but rather its modern—i.e., highly mechanized, large-scale—cultivation.

[3]Soybeans, together with other oilseeds as well as fats and oils, account for roughly half of China's agricultural import value (Gale, Hansen and Jewison, 2015).

[4]Because the measure of spatial inequality relies on gridded population data, it can only be constructed from 2000 onward.

Importantly, I provide evidence that the surge in inequality is linked to a broader process of land consolidation, as the median size of rural properties has increased as soy expands, while the growth in the total number of these properties has slowed down post China's WTO accession. Furthermore, based on a quantile analysis of household-level microdata, I show that it does not seem to be the case that soy has been lifting all boats, but only unevenly. Rather, it tends to benefit only those at the top deciles of the income distribution. For most of the population, soy expansion is even detrimental to household income—and the reduction in income increases the poorer one is.

Higher economic inequality has not been the only negative aspect of this process. In the Brazilian Midwest, in particular, it has also been accompanied by increases in deforestation and rural conflict. In these cases, too, inequality plays an important role, as the more (initially) unequal the place, the more harmful the soy boom is in terms of vegetation loss and conflict.

Taken together, these findings add an important dimension to the broader empirical literature on commodity booms. Existing evidence indicates that, on the one hand, the soy boom has ushered a structural transformation of the Brazilian economy, with productivity gains not only in agriculture, but also positive spillovers to the manufacturing sector and increases in capital accumulation (Bustos et al., 2016, 2020).[5] Besides, it has also contributed to improvements in local development and macroeconomic conditions via, e.g., tax and export revenues (Garrett and Rausch, 2016).

In terms of the socioeconomic impact of the soy boom in Brazil and who stands to gain from these transformations, the evidence so far is much less clear. Many descriptive studies have documented potential benefits, ranging from income gains (Weinhold et al., 2013, Garrett and Rausch, 2016, Martinelli et al., 2017) to higher well-being indicators and poverty reduction (VanWey et al., 2013, Weinhold et al., 2013, Piras et al., 2021).[6] However, consistent with the results presented here, there is also evidence that soybean production is correlated with higher economic inequality (Weinhold et al., 2013, Martinelli et al., 2017). Nevertheless—as I report below—correlations significantly underestimate the size of the effect. Therefore, an important contribution of this paper is to devote special attention to the issue of endogeneity, in particular by proposing a new identification strategy.

What is more, Falcone and Rosenberg (2022) show that the introduction of genetically engineered (GE) soybean seeds in Brazil benefited large-scale farmers to a much greater extent than smallholders and led to a reduction in rural employment between the

[5]Note that the structural transformation that Bustos et al. (2016, 2020) refer to was driven in particular by the introduction of genetically engineered soybean seeds in Brazil in 2003—and is not necessarily tied to the China shock.

[6]Importantly, a major issue associated with large-scale soybean plantation is its environmental impact. See, for instance, Fearnside (2001), Nepstad et al. (2006), Barona et al. (2010), Hargrave and Kis-Katos (2013), Dreoni et al. (2021), Song et al. (2021), and Carreira et al. (2024).

agricultural census waves of 1996 and 2006. Yet, a more rigorous assessment of who benefits and who loses from the expansion of soy is still lacking. More broadly, little is known about the consequences for local communities and the channels governing this relationship.[7]

In addition to examining the soy-inequality nexus, this paper contributes to the literature on the global consequences of China's rapid economic ascent. Although there is a rich body of work on the supply-side of this shock, which has hit mostly rich countries through import competition (Autor et al., 2013, 2016, 2020), far less is known about the consequences of China's surging demand, which has been particularly strong for agricultural commodities. Notable exceptions are Costa et al. (2016) and Hansen and Wingender (2023). The latter show that this demand shock, especially after China's WTO accession, led to significant expansion in cropland and deforestation in exporting countries. Not only is the explicit inclusion of China in the analytical framework conceptually important—in particular given the telecoupled nature of the soy trade (Pendrill et al., 2019, Meyfroidt et al., 2020)—but, as I will argue below, it also allows for a considerable improvement in the empirical identification.[8]

I proceed as follows: in Section 2, I discuss the framework upon which this paper is based. Section 3 sheds light on the long-run dynamics of land inequality in Brazil against the backdrop of China's WTO accession. In the main part of the analysis, Section 4, I examine the consequences of soy expansion for spatial inequality. I present robustness tests in Section 5 and examine potential mechanisms in Section 6. Section 7 offers some concluding remarks.

2 Framework

2.1 Brazil and the "Other" China Shock

Since the 1980s, China has embarked on a process of opening up its economy, which included its application for admission to the General Agreement on Tariffs and Trade (GATT) in 1986 and, after a lengthy procedure, culminated with its accession to the World Trade Organization (WTO) in December 2001. In a decade, from 1995 to 2005, trade (exports plus imports) as a share of China's GDP jumped from less than 39% to over 63% (Brandt and Rawski, 2008).

Not all of the global consequences of this process have been positive. In the United

[7] In particular, there is a growing concern that this agricultural boon may be contributing to further (premature) deindustrialization (and "re-primarization") in Brazil (Escher et al., 2020).

[8] To date, most of the literature concerned with identifying causal effects (on different outcome variables) of the soybean expansion in Brazil relies on the differential gains in yields, across space, in the aftermath of the adoption of GE seeds in Brazil (e.g., Bustos et al., 2016, 2020, Falcone and Rosenberg, 2022). A caveat of this strategy is that it only allows for an analysis in first differences—before and after the adoption.

States, for instance, there is evidence that the rise in exposure to Chinese manufactured goods has increased unemployment and reduced wages in affected industries (Autor et al., 2013, 2016). What is more, the reverberations of the China shock are not limited to the economic realm. Trade exposure to China—and particularly to Chinese exports—has increased ideological polarization in US electoral districts (Autor et al., 2020) and fueled economic nationalism across Western Europe (Colantone and Stanig, 2018).

The liberalizing reforms in China have also led to a surge in the country's imports of agricultural goods, although these demand-side effects have received far less attention in the literature. China went from a net exporter of agricultural goods prior to WTO accession to a net importer afterward, and it is now the destination of more than 10% of global agricultural exports (Hansen and Wingender, 2023). With soybean tariffs slashed to 3% in 2001 (Gale et al., 2015), Chinese imports of this crop jumped from 6.7Mt in 1999 to 23.2Mt in 2003—an increase of more than 246% (FAO, 2023).

These changes in the composition of Chinese imports also reflect a shift in the country's dietary habits—something that will be important for the identification strategy later on. In particular, the consumption of meat has increased substantially as Chinese citizens become more affluent. The average meat consumption per year in urban parts of China went from roughly 25kg per person in 1990 to more than 40kg in 2021. In rural parts of the country, this figure more than tripled over the sample period, reaching more than 30kg per person a year in 2021 (Ye and Leeming, 2023). This growing appetite for meat—and for pork in particular, which has long been a staple of Chinese cuisine (Grimmelt et al., 2023)—has been one of the main reasons for the rise in demand for soybeans (Da Silva et al., 2017).

Whereas the increase in exposure to Chinese exports has hit the manufacturing sector in developed countries particularly hard, the growing Chinese demand for agricultural and mineral commodities has been felt primarily in developing countries, in which the production of these goods usually accounts for a larger share of the economy. Brazil is arguably one of the countries that have been most affected by—and to some extent benefited from—this additional demand. The country rapidly became China's largest supplier of many of these commodities, including soybeans, which have become Brazil's main export crop (le Polain de Waroux et al., 2019). The share of Brazilian soybean production exported to China rose from 12% in 2004 to more than 48% in 2020 (Trase, 2022).

This boost from international trade has accelerated the process of agricultural modernization in Brazil (Farrokhi and Pellegrina, 2023), which has its roots in the 1960s, and firmly established the country as an agricultural powerhouse and a global leader in agribusiness—Brazil has become the world's largest net exporter of food (Klein and Luna, 2019).

This transformation has been accompanied by several advantages for Brazil. At the macro level, this boom in external demand has created a new stream of tax and export revenues (Garrett and Rausch, 2016) and, despite being an activity of low value added, may have generated positive spillovers to the rest of the economy (Bustos et al., 2016). There is also descriptive evidence that it is correlated with higher HDI values across Brazilian municipalities (Martinelli et al., 2017, Piras et al., 2021), and contributed to reducing poverty and raising median rural incomes in the Amazon region (Weinhold et al., 2013).

2.2 Factor Endowments and Inequality

Who has benefited and who has lost from the rapid expansion of soybean production is a more complex question, however. That is, whether these gains are reflected throughout the distribution and to what extent this applies to the country as whole. An important caveat of agricultural modernization is that frequently not all landowners are in a position to benefit from this process, as it may require certain operational scale and capacity to access (subsidized) credit lines, and invest in machinery and agricultural inputs. Those who do not fulfill these conditions are often squeezed out of the market (Pompeia, 2021).

There is indeed some evidence that this may be the case. Weinhold et al. (2013) document a positive correlation between soy production and rural inequality in municipalities in the Brazilian Amazon, a finding that is corroborated by Martinelli et al. (2017), who observe that Brazilian municipalities with higher soy production tend to also have higher Gini coefficients of income inequality. These studies, however, cover only part of Brazilian municipalities and/or a limited time period, and look solely at Gini indices of income inequality at 10-year intervals. Moreover, they do not aim to identify causal relationships nor underlying mechanisms, and do not directly take the role of China into account.

The distributional consequences of the recent transformation of Brazilian agriculture are arguably a central feature of this process for at least two reasons. First, because of the importance of international demand in this process, the trade-induced effects on inequality cannot be neglected (Goldberg and Pavcnik, 2007, Antràs et al., 2017). Second, as put forward by Sokoloff and Engerman (2000), factor endowments play a decisive role in shaping (structural) inequality. This implies, in particular, that the properties of the crops that a certain place produces have a significant influence on who is set to benefit the most from their cultivation. Sokoloff and Engerman's stylized historical comparison is between land endowments that favored commodities featuring economies of scale in Latin America versus an environment more suitable for crops such as wheat and corn in North America. The former is associated with plantation agriculture and land concentration, whereas the latter has been arguably more conducive to more equitable production in family farms and the like.

Adapting Sokoloff and Engerman's (2000) framework to modern Brazil, my argument is that certain key transformations in technological, political, and international conditions—and the rise of China in particular—that took place since the late 20^{th} century have fundamentally altered the use of factor endowments in Brazil and therefore may have had important consequences for socioeconomic inequality in the country. The clearest manifestation of these changes is soy. In the span of a few decades, it went from a niche crop, grown mostly in family farms in the temperate Pampas of Southern Brazil, to spearheading the country's agricultural transformation. It is now mainly cultivated in much larger rural properties in the acidic soils of the Cerrado in Midwest Brazil, where it has reached global productivity records.

What initially enabled this metamorphosis was the significant effort in agricultural research, especially in plant genetics, seed varieties, and soil correction, led by the Brazilian Enterprise for Agricultural Research (Embrapa), established in 1973. This created the conditions for the adoption of large-scale agriculture in a vast part of the Brazilian territory that was once considered unsuitable for modern agriculture.[9] As I began to argue above, however, what ultimately propelled soy production in Brazil to the heights seen today has been the seemingly unwavering Chinese demand.[10]

In this case, therefore, the typical effect of international trade on distributional outcomes is potentially magnified by its influence on the relative attractiveness of different land uses, which have tilted in favor of a particularly wealth-concentrating crop: soy cultivation is often a highly capital-intensive (and yet low value-added) activity that occupies vasts swaths of land, such that its benefits may be largely restricted to a small group of large-scale producers. According to Weinhold et al. (2013, p. 141), "soy is a relatively expensive crop to grow, needing a high level of investment in fertilizers, pesticides and machinery—it is generally held that it is not economically viable to grow soybeans on plots of less than 500 hectares."

Given the characteristics of modern soybean cultivation in Brazil, this paper's main objective is to test the hypothesis that its expansion has led to an increase in economic inequality in the country and examine which segments of society benefited the most from it. More broadly, however, although it is crucial to distinguish between the soy boom having simply lifted some boats more than others versus actually making considerable parts of the population worse off, there is a case to be made that—especially in a country such as Brazil—more inequality is *intrinsically* detrimental (Satz and White, 2024). As

[9] The agronomist Norman Borlaug once stated, in reference to the Cerrado, that "nobody thought these soils were ever going to be productive, but Embrapa was able to put all the pieces together" (Rohter, 2007). In fact, until the late 1960s, before Embrapa was created, "more than half of Brazil's territory remained untouched by agriculture" (Hopewell, 2017, p. 10).

[10] An important additional ingredient that created the conditions for Brazil's agricultural transformation were the country's own liberalizing reforms adopted during the 1990s. Domestic policies such as the Kandir Law, passed in 1996 and which exempted exports from the interstate movement tax, significantly contributed to soy's expansion.

one of the world's most unequal countries, the richest 1% of the population in Brazil account for almost 20% of the country's income and 49% of its wealth (World Inequality Lab, 2024). In terms of land inequality, less the 1% of rural properties take up almost half of the country's territory (Oxfam, 2016) and a significant share of these *latifundia* remain uncultivated (Deininger and Byerlee, 2012).

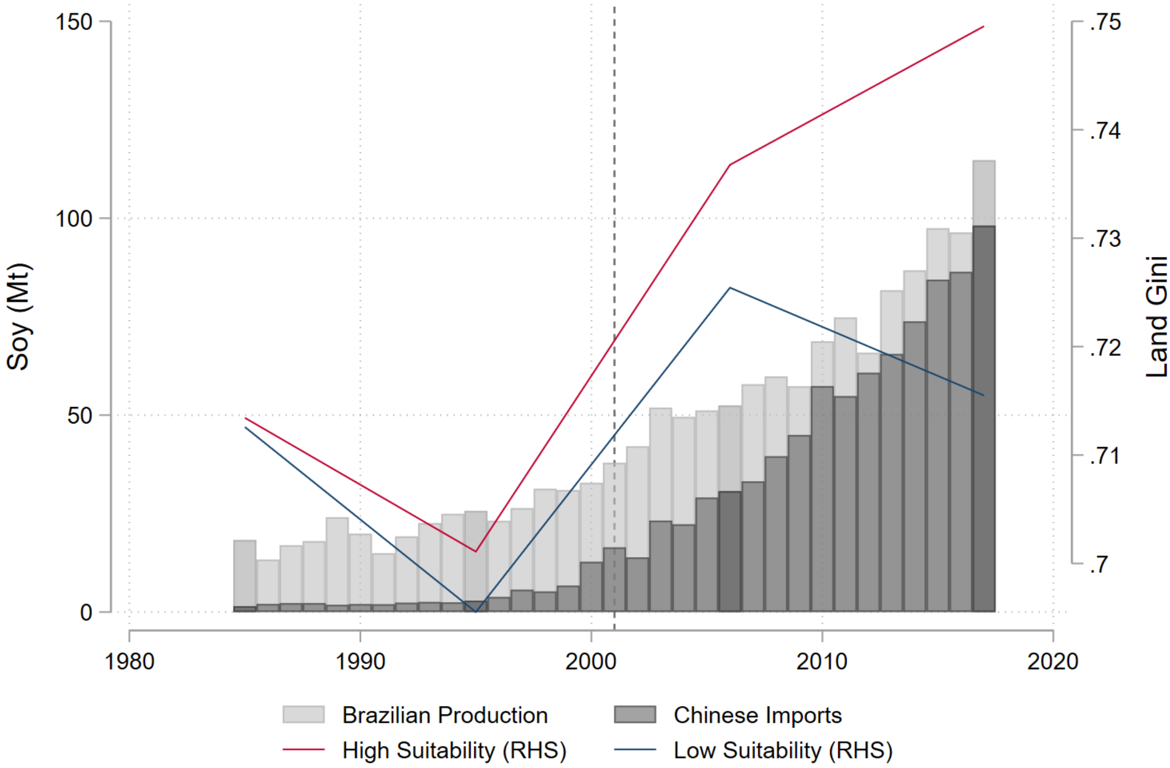
In fact, Brazil's current land configuration still owes much to its colonial heritage of hereditary captaincies (Naritomi et al., 2012, Buarque de Holanda, 2015). Despite the pressure of powerful peasant movements, political efforts toward a democratizing agrarian reform have been mostly watered down in the wake of the 1964 military coup. What followed was a process of "conservative modernization" (Klein and Luna, 2019), that is "rural modernization 'within law and order', [...] 'destroying' peasant organizations, [...] clearly benefiting the large landowners," who provided critical support for the military regime (Reydon et al., 2015, p. 511). Furthermore, in spite of a significant "march to the West" that picked up steam since the mid-twentieth century (Pellegrina and Sotelo, Forthcoming), even today access to land is still restricted—and perhaps increasingly so—to a small agrarian elite, and land regulation remains sketchy (Reydon et al., 2015).[11]

Increasing (land) inequality tends to translate into increasingly concentrated political power. The rural caucus, which represents the interests of large landowners in the Brazilian Congress, went from 73 seats in 2003 (or 14% of the total) to 324 (63%) in 2024, making it a critical force for the realization of presidents' legislative agendas, regardless of their political orientation (Helfand, 1999, Milmanda, 2022, Bragança and Dahis, 2022). This grouping has been crucial to defend the interests of their members and direct government investment toward agribusiness, ultimately consolidating the sector's hold on the economy and national politics (Sauer and Mészáros, 2017). More precisely, as has been the case through most of Brazilian history (Reydon et al., 2015), these entrenched agrarian interests often block the enactment of policies that, e.g., promote human capital formation or would make the country less dependent on exporting primary goods. In short, high inequality—and land inequality in particular—may prevent the emergence of more inclusive, human-capital promoting institutions that are crucial for long-run economic development (Sokoloff and Engerman, 2000, Acemoglu and Robinson, 2008, Ziblatt, 2008, Galor et al., 2009).

Figure 1 provides a first visual indication that the economic rise of China—especially after the country's WTO accession in 2001—and the ensuing surge in demand for soybeans

[11] As Reydon et al. (2015, p. 510) explain, "[t]he legal and institutional mechanisms developed in the 21^{st} century to deal with the critical agrarian situation in Brazil have been based on the historical pattern of occupation and development in Brazil, and seem to be insufficient to improve this situation. Formal regulations, which have never been completely enforced, make land access in Brazil both fragile and inchoate. [...] If legislation has never been able to regulate land ownership, it has much less been able to regulate land use. Brazil lacks a register of both privately owned and public unclaimed land (as defined in the 1850 Land Law) and the existing social regulation is inadequate. Land reform in Brazil has not been able to eradicate landlessness or poverty."

Figure 1 – Land Inequality and Soil Suitability for Soybeans



Notes: Figure shows the evolution of the average Gini coefficient of land inequality in Brazilian municipalities through four waves of the agricultural census (1985, 1995, 2006, 2017). Municipalities are split into two groups: below (Bottom) and above-median (Upper) soil suitability for soybean cultivation. Brazilian yearly soybean production and Chinese total imports of soybeans are in megatonnes (Mt). The vertical dashed line marks the year of China's WTO accession, 2001.

may indeed be related to rising land inequality in Brazil. By splitting municipalities by the median value of soil suitability for soy, it becomes clear that the gap in the Gini coefficient between these two groups increases in the period, with above-median places becoming significantly more unequal post 2001 ($p = 0.000$). Moreover, as the bars indicate, soybean production in Brazil and imports from China have followed a trend not too dissimilar to that of inequality (in the more suitable half of municipalities) over the same period. Therefore, I now turn to a more rigorous examination of inequality in Brazil following China's economic rise.

3 WTO Accession: Land Inequality

3.1 Main Data and Empirical Strategy

To assess how the surge in demand from China influenced land inequality in Brazil, the first part of the empirical analysis leverages longer-run data on municipal soybean production in Brazil.[12] I rely on municipal agricultural surveys (PAM), conducted yearly by the Brazilian statistical office (IBGE, 2023*a*), to compile soy production in each Brazilian municipality from 1974 to 2020.[13] Appendix Figure A1 illustrates the expansion of soybean production across the Brazilian territory between 1985 and 2020.

Because the main dependent variable of interest, the Gini coefficient of land inequality, is only available in the agricultural census (IBGE, 1985, 1996, 2006, 2017), which is conducted roughly every ten years (in four waves from 1985 to 2017), I use the average (or total) soy production in each municipality over the period of ten years that precedes the census year. Additional data sources are introduced upon use. Descriptive statistics, including all variables used in the paper, are shown in Appendix Table A1.

I begin by examining the direct relationship between the Gini coefficient of land inequality in municipality m and period p ($landgini_{mp}$) and China's accession to the WTO:

$$landgini_{mp} = \beta_1 WTO_p + \omega_m + \xi_p + u_{mp} \tag{1}$$

where WTO_p is a binary variable that takes the value 1 if period p is after 2001.[14] All specifications include municipality fixed effects (ω_m) and some also period fixed effects (ξ_p). Standard errors are clustered the at the municipality level.

Given that China's WTO accession may have affected inequality in Brazil through several different channels and that this dummy variable is likely capturing also other events that took place during the same period, there is no particular expectation with regard to β_1. To get closer to the connection to the soy boom, the next specification allows for municipalities to be differentially impacted by China's WTO accession based on their degree of involvement with the soy business, as they include an interaction term between WTO_p and a measure of such involvement, $\overline{\Theta}_{mp}$. More precisely, I estimate the following equation:

$$landgini_{mp} = \beta_1 WTO_p + \beta_2 \overline{\Theta}_{mp-1} + \beta_3 WTO_p \times \overline{\Theta}_{mp-1} + \omega_m + \xi_p + u_{mp} \tag{2}$$

Here, $\overline{\Theta}_{mp-1}$ stands for either the (log) production of soybeans in municipality m averaged over the ten years preceding the census year ($\overline{soy}_{mp-1}$), or municipality's m

[12] Because the number (and thus the borders) of Brazilian municipalities changed substantially during this period—from 3,959 municipalities in 1970 to 5,570 since 2013—I make use of "minimum comparable areas" (MCAs) to ensure that the units of analysis are consistent over time (Ehrl, 2017). Throughout this section, what I refer to as municipalities are 1970 MCAs.

[13] Roughly half of Brazil's municipalities produced a positive amount of soybeans at least during some point in the sample period.

[14] In the baseline models, due to the paucity of data available for such a long period at the municipal level and the fact that many of the most relevant variables—such as GDP per capita, population etc.—would most likely be "bad controls" (Angrist and Pischke, 2009), I refrain from including a vector of control variables.

soil suitability for soy ($soil_m$), which is a function of weather and soil characteristics and is widely used in the literature.[15] While the former has the advantage of varying over time and capturing each municipality's exact involvement with the soy business, the latter has the advantage of being less susceptible to endogeneity concerns. In either case, β_3 estimates the difference-in-differences between more or less exposed municipalities in relation to the WTO accession. Importantly, the point is not to think of the year of 2001 as a watershed moment in which China went from complete autarky to being totally integrated into world markets. As mentioned earlier, this was a gradual process that did not happen overnight. For example, in the particular case of soy, another important event took place already in 1995, when China exempted the crop from import quotas (Gale et al., 2015). Hence, the year of the accession to the WTO should not be seen as a sudden shock, but rather as the pinnacle of a bumpy and lengthy process.

Therefore, although informative, the model above is unlikely to yield causal parameters. More broadly, omitted variables and the possibility of reverse causality would compromise the interpretation of the parameters of interest. For instance, it may be the case that soy expands faster in places that are, on average, initially more equal, even if poorer, because there is not so much economic activity going on to begin with. This would be consistent with the evidence that indicates that municipalities, at least on or close to the deforestation frontier, tend to go through different stages of land use before large-scale soy plantation really kicks in (Song et al., 2021). These typically include logging followed by cattle grazing. Moreover, measurement error is another issue that could lead to underestimating the effect of soy expansion on inequality (attenuation bias).

To overcome these issues, I propose a new instrumental variable that leverages arguably exogenous variation in an important driver of Chinese demand for soybeans: the size of the pig stock in China. More than 80% of the country's soybean imports are used for animal feed—and particularly to feed pigs.[16] This makes hog feeding the main reason for China, which is home to about half of the world's pig population (Reuters, 2017), to import soybeans.[17] Crucially, an important part of the variation in the size of the Chinese pig stock is explained by sporadic episodes of disease outbreak, which are orthogonal to economic conditions in Brazil. In 2019, for instance, China lost around half of its herd to African swine fever (Reuters, 2019). In this first part of the analysis, given that land inequality data are only available (roughly) every ten years, I use the variation in the Chinese pig stock between census waves. That is, $\Delta pigstock_p = pigstock_p - pigstock_{p-1}$. Appendix Figure A2 illustrates the evolution of China's pig stock over time. Data on the

[15] I use suitability values that consider soy cultivation under high levels of input. See FAO (2022) for more details. Note that, because this measure does not vary over time, the uninteracted term is absorbed by the municipality fixed effects.

[16] See Anand (2021) for more details.

[17] As a senior animal protein analyst at Rabobank puts it, "[t]he expectation of rapid hog restocking has been the key reason for strong imports" (Lee, 2021).

size of the Chinese pig stock come from FAO (2023).

To map how temporal variation in Chinese pig stock affects soybean production at the municipal level in Brazil, I employ FAO's index of agricultural suitability for soy cultivation ($soil_m$).[18] More precisely, I define $Z_{mp} = \Delta pigstock_p \times soil_m$, which I use as an instrument for (log) Brazilian municipal soybean production averaged over the preceding period, $\overline{soy}_{mp-1}$.[19] Thus, the first-stage regression in a 2SLS setup is as follows:

$$\overline{soy}_{mp} = \lambda(\Delta pigstock_p \times soil_m) + \omega_m + \xi_p + \nu_{mt} \tag{3}$$

Alternatively, to allow for differences before and after China's accession to the WTO, the second-stage regression may include not only $\widehat{\overline{soy}_{mp}}$, but also its interaction with WTO_p. In this case, $WTO_p \times \Delta pigstock_p \times soil_m$ enters the model as an additional exogenous variable.

Therefore, the identification strategy is again akin to a difference-in-differences comparison. In response to fluctuations in the Chinese pig stock, the first-stage regression compares within variation in Brazilian municipal soy production in places more or less suitable for cultivating this crop. Hence, the exclusion restriction is that, conditional on the control variables and fixed effects, the interaction between fluctuations in the total number of pigs in China and municipal soil suitability for soy affects inequality in Brazilian municipalities only through soy production.

Potential threats to the identification, such as the role of other crops and neighboring municipalities as well as spurious correlation (Christian and Barrett, 2023), will be discussed in detail in Section 5. Importantly, I show evidence that the size of the pig stock in China affects soybean production in Brazil, and not the other way around.

3.2 Results

Table 1 reports the OLS results for the link between China's WTO accession and the Gini coefficient of land inequality in Brazilian municipalities. Column 1 shows a positive and significant association between the two variables. Yet, this does not say much in terms of the role of soy. Including municipal soy production, in column 2, shows a positive correlation with land inequality. Interestingly, once the relationship between the two variables is allowed to vary with respect to China's WTO accession, the results indicate a negative association before 2001, which turns positive afterward. The effect is nevertheless rather small in magnitude. These findings remain largely unchanged with

[18] By its use of this kind of interacted instrument, the empirical analysis is similar to, e.g., Nunn and Qian (2014), Bustos et al. (2016), Dreher, Fuchs, Hodler, Parks, Raschky and Tierney (2021) and Cisneros et al. (2021). More broadly, this one-dimensional shift-share approach is related to the use of exogenous shock variables for identification (Borusyak et al., 2022).

[19] Using total soy production in the period preceding the census year, instead of the mean, is of little practical consequence.

the introduction of census wave fixed effects in column 4.[20]

Columns 5 and 6 use soil suitability for soy (instead of actual production) as the measure of exposure to the China shock. Again, the results indicate that more exposed municipalities have suffered more in terms of increases in land inequality. In this case, a standard deviation gain in soil suitability for soybeans implies an increase in the land inequality Gini of approximately 0.01 unit—or roughly a tenth of a standard deviation. Here too the inclusion of period fixed effects is of little consequence.

Table 1 – Land Inequality (OLS)

	Dependent Variable: Land Gini							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WTO	0.030***	0.029***	0.021***		-0.004			
	(0.001)	(0.001)	(0.001)		(0.003)			
Soy (log)		0.001***	-0.002***	-0.002***				
		(0.000)	(0.000)	(0.000)				
WTO × Soy (log)			0.004***	0.004***				
			(0.000)	(0.000)				
WTO × Soil					0.007***	0.007***		
					(0.001)	(0.001)		
Imports (log)							-0.005***	
							(0.001)	
Imports (log) × Soil							0.003***	0.003***
							(0.000)	(0.000)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	No	No	No	Yes	No	Yes	No	Yes
N	15149	15137	15137	15137	15149	15149	15149	15149

Notes: WTO is a binary variable that takes the value 1 if period p is after 2001. *Soy (log)* is the natural logarithm of municipal soybean production. *Soil* is the average soil suitability for soybeans in the municipality. *Imports (log)* stands for the natural logarithm of Chinese annual soybean imports. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors, clustered at the level of 1970 MCAs, in parentheses.

These results should be interpreted with caution. As discussed above, China's accession to the WTO is hardly unanticipated and may be correlated with other concomitant shocks that affect both soy production and inequality in Brazil. Therefore, it is not surprising that these findings are not robust to a rigorous test of parallel trends. That is, using a placebo dummy variable that takes the value 1 already in the previous census wave (1995) produces slightly weaker, but overall similar results (not reported). Somewhat reassuringly, however, a simple test of difference in mean inequality between below and above-median municipalities in terms of soil suitability does not reject the null hypothesis in the first two periods of the sample, 1985 and 1995. It is only in the first census wave after China's accession to the WTO, in 2006, that these two groups become significantly different in terms of land inequality ($p = 0.000$). This difference persists in the fourth and final wave of the sample (2017).

A way to investigate the long-run influence of Chinese demand on inequality in Brazil in a more flexible manner, that is, without having to rely on a clear cut-off point, is

[20]Note that the wave fixed effects absorb the uninteracted WTO dummy.

to use temporal variation in China's total soybean imports.[21] Once again, this provides additional descriptive evidence that the detrimental effect to inequality levels in Brazil is mediated by the soy boom. The more suitable for soy a municipality's soil, the more unequal it is expected to become as Chinese demand increases (columns 7 and 8).

Next, I turn to the results from the 2SLS approach (Table 2), in which soybean production is instrumented as described in equation (3). Columns 1 and 2 split the sample period before and after China's WTO accession, respectively. Consistent with the argument presented above, the results show that soybean cultivation leads to higher land inequality only in the post-WTO period. Accordingly, only for this second period is the instrument relevant (Stock and Yogo, 2005). That is, before 2001, the variation in the size of the Chinese pig stock does not seem to explain soybean production in Brazil, which is in line with the argument that the China shock has had a considerable influence on factor endowments in Brazil. The results imply that, post WTO, a (within) standard-deviation increase in municipal soy production (which represents a 274% increase at the mean) is expected to raise land inequality by approximately 1.6 (within) standard deviations—much larger than the previous OLS results suggest. I come to similar conclusions if, instead of splitting the sample, I allow the effect of soybean production on land inequality to vary according to China's WTO membership status (column 3). In this case, as explained previously, both municipal soy production as well as its interaction with the WTO dummy are instrumented.

To understand to what extent the increase in inequality is indeed due to soy—and not to other crops or perhaps agriculture in general—I examine the role of corn.[22] There are at least three reasons to consider that corn may be a confounding factor: (i) it is the second (after soy) most important crop in Brazil in terms of production value (IBGE, 2023*a*), (ii) it is often planted in rotation with soybeans, and (iii) it is commonly used for animal feed as well. However, differently from soybeans, China still keeps a policy of self-sufficiency in corn production (Hansen and Wingender, 2023). In any case, controlling for municipal corn production and its interaction with the WTO dummy (column 4) barely affects the main coefficient of interest—in fact, the magnitude of the soy interaction term even slightly increases. It is nevertheless interesting that the corn interaction term, although it should not be interpreted causally, indicates a reduction in inequality post 2001.

If I instrument the corn variables instead (columns 5 and 6), the F statistic drops dramatically, indicating that fluctuations in the size of the pig stock in China are not that relevant to explain variation in corn production in Brazil. Once the soy variables are

[21] Similarly to the way in which Brazilian soybean production has been defined, I use the (log) total Chinese imports of soybeans averaged over the ten years preceding the census year. Using the sum instead of the mean makes little difference (not reported). Data on Chinese soybean imports come from FAO (2023).

[22] Data on corn production also come from IBGE (2023*a*).

Table 2 – Land Inequality (2SLS)

	Dependent Variable: Land Gini						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Soy (log)	0.012	0.122***	0.006**	0.001		0.201	0.264**
	(0.018)	(0.022)	(0.003)	(0.003)		(0.665)	(0.134)
WTO × Soy (log)			0.006***	0.010***		-0.272	-0.040*
			(0.001)	(0.001)		(0.916)	(0.023)
WTO			-0.001	0.047***	-0.277***	-5.654	0.182**
			(0.002)	(0.008)	(0.052)	(18.632)	(0.083)
Corn (log)				-0.000	-0.131***	-1.548	
				(0.001)	(0.034)	(4.992)	
WTO × Corn (log)				-0.008***	0.046***	0.933	
				(0.001)	(0.008)	(3.071)	
Imports (log)							-0.075**
							(0.036)
Period	Pre WTO	Post WTO	Full	Full	Full	Full	Full
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	No	No	No	No	No
N	7556	7556	15133	15133	15133	15133	15133
KP F-stat	6.63	35.66	145.72	153.86	10.14	0.05	2.09

Notes: WTO is a binary variable that takes the value 1 if period p is after 2001. *Soy (log)* is the natural logarithm of municipal soybean production. *Corn (log)* is the natural logarithm of municipal corn production. *Imports (log)* stands for the natural logarithm of Chinese annual soybean imports. First-stage Kleibergen-Paap F-statistic reported. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors, clustered at the level of 1970 MCAs, in parentheses.

added as (non-instrumented) control variables (column 6), the F statistic becomes even smaller and all coefficients of interest become indistinguishable from zero.

Column 7 includes total Chinese imports of soybeans as a control variable. Not surprisingly, the instruments turn irrelevant. This shows that, in line with the exclusion restriction, variation in the Chinese pig stocks affect soybean production in Brazil through Chinese soy imports. Once this channel is shut down, the pig stock does not have any additional influence on Brazilian production.

Furthermore, first-stage results, reported in Appendix Table A2, indicate that, post WTO, when the Chinese pig stock increases—and demand for soy presumably goes up—soybean production in Brazil is able to expand in areas that are less suitable for cultivation. As discussed above, this changes only if Chinese soybeans imports are included as an additional control variable (columns 5 and 6).

4 Post WTO Accession: Spatial Inequality

I now proceed to analyze the distributional effects and the potential underlying mechanisms in a more granular and rigorous empirical setting using annual panel data for all Brazilian municipalities from 2000 to 2020.

4.1 Spatial Inequality

As already mentioned, conventional measures of economic inequality at the municipality level in Brazil, upon which most of the related literature relies, are based on data collected in the national census, which is conducted only every ten years or so. In order to assess inequality on a yearly basis, I follow Weidmann and Theunissen (2021) to calculate a measure of spatial inequality for each Brazilian municipality for each year in the sample. This is done as follows: I first calculate (log) average nighttime light emissions per capita in each cell. Similarly to Weidmann and Theunissen (2021), I define light per capita as follows: $lpc_{it} = \frac{ln(ntl_{it}+1)}{ln(pop_{it}+1)}$, where, for cell i in year t, ntl_{it} stands for the average nightlight radiance and pop_{it} refers to population.[23] This relies on high-resolution data on nightlights, which come from DMSP and VIIRS (harmonized as in Li et al. (2020)), and gridded population estimates, taken from WorldPop (2023).[24] Both light as well as population data are available at a spatial resolution of 30 arcsec (approximately 1km at the equator).[25]

From the distribution of light per capita in a given area, I calculate a yearly Gini index of spatial inequality at the municipal level (*spatialgini*), which yields a measure that is positively and significantly correlated with census-based Gini indices of income and land inequality in Brazil in the years in which these are available.[26] What is more, Weidmann and Theunissen (2021, p. 9) validate this measure on a sample of African countries and conclude that it is a "strong predictor of actual local [economic] inequality" for both urban as well as rural locations.

Importantly, this measure has the advantage of going beyond mere income inequality and of capturing the spread of economic activity (and its distribution) within municipalities. This is particularly valuable given soy's pattern of expansion throughout the Brazilian territory, which tends to create pockets of high light emission, but little population—given the low demand for workers. This is exemplified by the construction of soy-specific infrastructure, such as drying, storage and crushing facilities, which generates areas of high light per capita that can be captured from space. Finally, an additional benefit of measuring inequality based on remotely sensed data is that it does not suffer

[23] Note that, for cells with no inhabitants, the denominator would be zero. In these cases, light per capita is set to missing. This also ensures that the measure of spatial inequality is not affected by unpopulated areas.

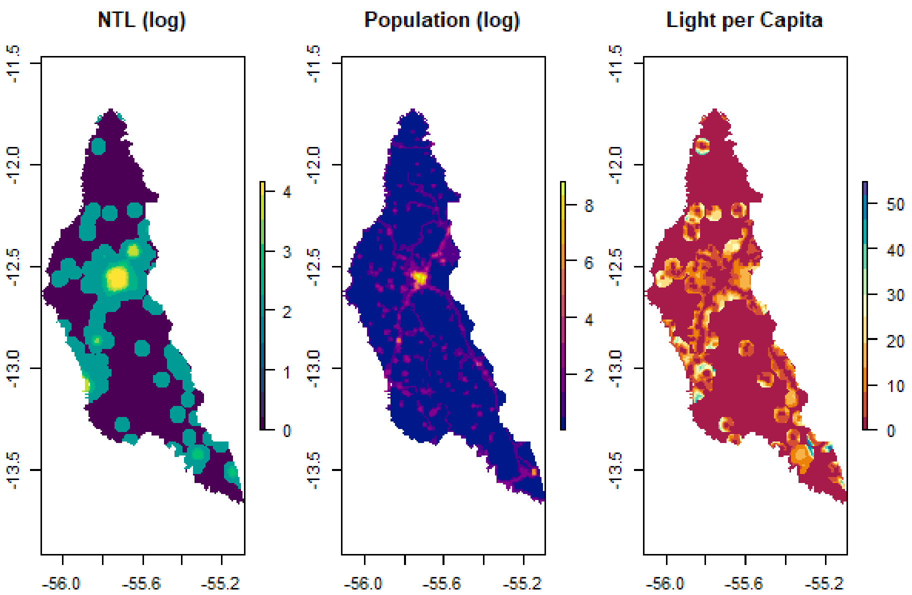
[24] Average (log) nightlight radiance by municipality-year is also used on its own, as a measure of economic activity, as luminosity per se has been shown to be a good proxy for economic activity and regional development even at small unit of analysis, such as municipalities, including in rural areas in low and middle-income countries (Pérez-Sindín et al., 2021). Gridded population data are only available from 2000, which sets the lower bound for the period of analysis in this part.

[25] Given that the size of the median (average) rural property in Brazil in 2017 was 0.43km^2 (0.95km^2), it seems reasonable to keep this resolution.

[26] Across all Brazilian municipalities, the correlation of the measure of spatial Gini is is 0.24 ($p = 0.000$) with the demographic census-based Gini of income inequality in 2010 and 0.26 ($p = 0.000$) with the agricultural census-based Gini of land inequality in 2017. These are years for which each of these censuses is available.

from reporting biases, which often distort more common measures of inequality that rely on survey data (Lakner et al., 2016, Sánchez-Ancochea, 2021).[27]

Figure 2 – Spatial Gini: Sorriso



Notes: Figure shows nighttime light (*NTL*), population, and light per capita for the municipality of Sorriso (MT) in 2020.

Figure 2 illustrates the construction of the Gini index of spatial inequality for Sorriso, one of the top soy-producing municipalities in Brazil. Combining grid-cell measures of (log) nighttime light and (log) population as explained above, it arrives at estimates of light per capita for every 1km^2 pixel. Upon aggregation at the municipal level this yields a Gini of spatial inequality of 0.796 for Sorriso in 2020.

To get a sense of what this measure is capturing, one can use satellite images to further inspect the areas of high light per capita revealed by the figure. For instance, zooming into the high light per capita pocket in the southern tip of Sorriso shows that this area is occupied by a collection of seemingly large farms. One such farm, for which online information could be found, is Fazenda Angela Tereza, which produces soybeans and maize on an area of roughly 3,000ha.[28] One can clearly see the infrastructure for storing, drying and processing grains, surrounded by vast tracts of cropland (Appendix Figure A4). Roughly speaking, another way of seeing this is to think of light and population as capital and labor. Soy brings a lot of the former, but not as much of the latter, which is

[27]See Galimberti et al. (2023) for a more detailed discussion of the advantages of using geospatial data to measure inequality.

[28]See Gazeta Digital (2023) for more information (in Portuguese).

consistent with the observed high light per capita pockets.[29]

4.2 Empirical Strategy

I then proceed to estimate the following baseline OLS model:

$$spatialgini_{mrt} = \beta soy_{mrt-1} + \mathbf{X_{mrt-1}}'\gamma + \omega_{mr} + \phi_{rt} + u_{mrt} \tag{4}$$

where $spatialgini_{mrt}$ is the measure of inequality, introduced above, for municipality m in region r and year t. The main explanatory variable of interest, soy_{mrt-1}, denotes the (log) total amount of soybeans produced in municipality m in the previous year, $t-1$, which allows for some adjustment time.[30] The data source for the production of soybeans (and other crops) remains the same, the municipal agricultural surveys (PAM), conducted by the Brazilian statistical office (IBGE, 2023*a*). This time, however, I can use (log) yearly municipal production directly (instead of using the average over the 10-year period before each census wave, as in Section 3). $\mathbf{X_{mrt-1}}$ is a vector of (lagged) control variables, including municipality's GDP (log), net tax revenues (log), value added in agriculture (log), value added in industry (log), value added in services (log)—all taken from IBGE (2023*b*)—and population (log), made available by IBGE (2021).[31] Finally, ω_{mr} and ϕ_{rt} are municipality and region-year fixed effects, respectively. The latter absorb all municipal characteristics that are constant over time and the former account for region-specific time-varying shocks.[32] Finally, u_{mrt} is the error term. Once again, the standard errors are clustered at the municipality level.

Similarly to Section 3, I again use variation in the size of the Chinese pig stock, interacted with municipal soil suitability for soy, to instrument municipal soy production and circumvent issues of endogeneity. This time, however, I can use *annual* variation in the pig stock, i.e., $\Delta pigstock_{t-1} = pigstock_{t-1} - pigstock_{t-2}$, such that the first-stage equation takes the following form:[33]

$$soy_{mrt} = \lambda(\Delta pigstock_{t-1} \times soil_{mr}) + \mathbf{X_{mrt-1}}'\pi + \omega_{mr} + \phi_{rt} + \nu_{mrt} \tag{5}$$

[29] Soy expansion may create jobs, but these tend to be low-skill occupations in services and not directly related to the soy business.

[30] Increasing the time lag (up to $t-3$) does not significantly change the results (not reported).

[31] In my preferred 2SLS specifications, I do not include these control variables because they are likely "bad controls" (Angrist and Pischke, 2009). In any case, their inclusion does not fundamentally alter any result.

[32] Brazil has five geographic regions: North, Northeast, Midwest, Southeast and South.

[33] Note that $soil_{mr}$ is absorbed by municipality fixed effects and $\Delta pigstock_{t-1}$ by region-year fixed effects.

4.3 Results

Table 3 reports the main results. In panel A, the main explanatory variable of interest is the (log) total amount of soy produced in each municipality. Column 1 starts by reporting OLS coefficients, which indicate a positive and significant—although rather small in magnitude—relationship between soy production and the spatial Gini index, which however turns insignificant upon the inclusion of region-year fixed effects (column 2). Once soy production is instrumented according to the strategy described above in equation (5) (columns 3 and 4), the coefficient's magnitude increases substantially, especially once region-year fixed effects are included. This indicates that regional heterogeneity might play an important role, which is something that will be addressed in more detail in Section 6. The coefficient in column 4 implies that a (within) standard-deviation increase in municipal soy production (about 178% at the mean) is expected to lead to more than a third of a (within) standard deviation hike in spatial inequality in the following year—no small feat given that inequality tends to change slowly over time.[34]

Furthermore, the comparison to the OLS model indicates a potential downward bias if soy is not instrumented. As discussed previously, this is consistent with the argument that soybeans tend to expand faster in places that are initially less unequal and the fact that the OLS models likely suffer for with attenuation bias.[35] Importantly, the instrumental variable far exceeds usual relevance thresholds across all specifications, as indicated by the first-stage F statistics.[36]

Panel B shows results for municipal soybean exports to China instead of total production.[37] The pattern is rather similar to the one reported in panel A. Given the distribution of each explanatory variable, the magnitude of the effect, in terms of standard deviations, is also remarkably similar. This shows that the Chinese demand for soybeans affect inequality dynamics in Brazil not only in an indirect manner, but also directly via soybeans that are actually imported by China. Whether this means that the brunt of the inequality increase is driven by Chinese demand is a question that will receive more attention in Section 6.

Importantly, Appendix Table A4 (panel A) shows that the previous results apply to most, but not all Brazilian regions. While soy production is linked to higher inequality in the Midwest, Northeast, and Southeast of the country, this is not the case in the North

[34] As discussed previously, most other variables that are relevant for the soy-inequality nexus are arguably "bad controls" and I therefore prefer not to include them in the baseline 2SLS specifications. I do so in the robustness section below, and the coefficient of interest barely changes.

[35] Another potential explanation is that, because the 2SLS model estimates a local average treatment effect, the part of soy production that responds to demand shocks in China has a different (more severe) effect on inequality.

[36] Appendix Table A3 shows first-stage results.

[37] Data on municipal soybean exports, which contains the market of destination, come from Trase (2022)—it is however only available since 2004. Restricting the period of analysis of production data (panel A) to the same range does not substantially alter any conclusion (not reported).

Table 3 – Spatial Inequality

	Dependent Variable: Spatial Gini			
	Panel A – Soy Production			
	(1)	(2)	(3)	(4)
Soy (log)	0.001***	-0.000	0.027***	0.067***
	(0.000)	(0.000)	(0.005)	(0.011)
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	-	Yes	-
Region-Year FE	No	Yes	No	Yes
Controls	Yes	Yes	No	No
Model	OLS	OLS	2SLS	2SLS
N	115994	115994	116203	116203
KP F-stat			335.99	114.53
	Panel B – Soy Exports to China			
	(1)	(2)	(3)	(4)
Soy CHN (log)	0.001***	0.000	0.045***	0.079***
	(0.000)	(0.000)	(0.008)	(0.015)
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	-	Yes	-
Region-Year FE	No	Yes	No	Yes
Controls	Yes	Yes	No	No
Model	OLS	OLS	2SLS	2SLS
N	88662	88662	88783	88783
KP F-stat			101.94	56.41

Notes: Soy (log) is the natural logarithm of municipal soybean production. *Soy CHN (log)* is the natural logarithm of municipal soybean exports to China. First-stage Kleibergen-Paap F-statistic reported. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors, clustered at the municipality level, in parentheses.

nor in the South, where the instrument proves to be quite weak. Although little soybean is planted in the North, the South is, after the Midwest, the second most important soy-producing region in the country.[38] However, as already hinted at above, soybean cultivation tends to differ greatly in the Midwest and in South. Soybeans have been cultivated in the more temperate areas of Southern Brazil for over a century, where properties are usually smaller and family farms are responsible for a significant share of total production. In Rio Grande do Sul, they account for over a third of the state's soy production (Vander Vennet et al., 2015).[39] The history of soy production in the Midwest, which is mostly characterized by the acidic soils of the Cerrado biome, is much more recent. Still virtually insignificant in the 1970s, it only consistently overtook the South

[38]Appendix Figure A5 shows the evolution of soybean production in all five Brazilian regions over time.

[39]For comparison, in Brazil as a whole, smallholders account for about 15% of total soybean production (Raleira et al., 2022).

in terms of total production in the early 2000s.

Even though other factors—notably technological progress—contributed to the transformation of the Midwest into Brazil's own "soy belt," Chinese demand is a crucial part of the explanation. Given the different nature of production in this region—usually more mechanized and on larger properties—it is not surprising that inequality has increased as soy harvests grew. The contrasting results for Brazil's two most important growing regions therefore fit remarkably well into Sokoloff and Engerman's (2000) explanation of the importance of factor endowments as a determinant of inequality.

The Northeast region, in turn, although responsible for a smaller share of production, is where most of the "Matopiba" is located.[40] This area, which has a long history of poverty and deprivation, has become (in)famous as one of the most important frontiers of soybean expansion, where speculative investments in real estate are rampant (Pitta et al., 2017, Lopes et al., 2021). These reasons may help explain the strikingly large coefficient for the Northeast, well above the national average.[41]

Furthermore, dividing the sample of Brazilian municipalities in quintiles by GDP per capita shows that soy expansion is detrimental for those in the poorest three quintiles (Table A4, panel B). For the richest group of municipalities, it may even lead to lower inequality.[42] This corroborates the interpretation that the issue seems to be not simply the expansion of soy, but rather the way it amplifies pre-existing socioeconomic deprivations and institutional frailties, such as the lack of proper land tenure regulation and enforcement.

5 Robustness

Table 4 tests the robustness of the main results (from Section 4) in several ways. First, columns 1 to 4 repeat the baseline models (without and with region-year fixed effects), but this time include a vector with the following control variables: municipal GDP, tax revenues, agriculture value added, industry value added, services value added, and population (all in logarithmic scale). Although these might be "bad controls" (Angrist and Pischke, 2009), in the sense that they may be a channel through with soy production affects inequality, the main findings barely change.

Second, as explained above, to construct the measure of spatial inequality I rely on harmonized nightlight data (Li et al., 2020), taken from two different sources: DMSP and VIIRS. Given that the latter provides more accurate data, I show results for an

[40]Matopiba is a portmanteau of the abbreviations of four Brazilian states: Maranhão (MA), Tocantins (TO), Piauí (PI), and Bahia (BA). With the exception of Tocantins, all of these states are located in the Northeast region of Brazil.

[41]For a detailed account of these differences in soy production and the characteristics of its supply chains across Brazilian regions, see Dos Reis et al. (2024).

[42]It should be noted, however, that the instrument is rather weak at the extremes of the distribution.

alternative measure of spatial inequality that relies only on VIIRS data for light emission (column 5).[43] An important drawback is that these data are only available since 2012. Regardless, this also yields a positive—although smaller in magnitude and less precisely estimated—coefficient.[44] The instrument remains highly relevant for this shorter period of analysis.

Table 4 – General Robustness

	Dependent Variable: Spatial Gini							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Soy (log)	0.026***	0.063***			0.002*		0.087***	0.158***
	(0.005)	(0.011)			(0.001)		(0.015)	(0.028)
Soy CHN (log)			0.043***	0.077***				
			(0.008)	(0.015)				
Soy (mt)						6.528***		
						(1.361)		
Corn (log)							-0.014***	
							(0.002)	
Sugarcane (log)							-0.000	
							(0.001)	
Soy Ngb. (log)								-0.004***
								(0.001)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	-	Yes	-	Yes	-	-	-
Region-Year FE	No	Yes	No	Yes	No	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Model	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
N	115994	115994	88662	88662	46240	115994	114208	110558
KP F-stat	308.01	108.85	98.47	53.88	204.49	50.55	69.55	44.06

Notes: Soy (log) is the natural logarithm of municipal soybean production. *Soy CHN (log)* is the natural logarithm of municipal soybean exports to China. *Soy (mt)* is municipal soybean production in megatonnes. *Corn (log)* is the natural logarithm of municipal corn production. *Sugarcane (log)* is the natural logarithm of municipal sugarcane production. *Soy Ngb. (log)* is the natural logarithm of the total soybean production in the neighborhood of a municipality. The neighborhood consists of all neighboring municipalities. First-stage Kleibergen-Paap F-statistic reported. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors, clustered at the municipality level, in parentheses.

Column 6 shows results for municipal soy production in megatonnes, instead of using the logarithmic form. Also in this case there is a positive and significant effect on spatial inequality. Moreover, using other variables to measure soy cultivation, such as the area planted or harvested instead of the production amount, does not affect the findings in any meaningful way (not reported).

Similarly to what has been done for the longer-run analysis above, column 7 examines the role of other crops. Controlling for the municipal production of the most important products in Brazilian agriculture after soybeans, corn and sugarcane, barely affects the main coefficient of interest.

A potential concern for the exclusion restriction is that Chinese demand for soybeans affects inequality in a given Brazilian municipality through soy production in its

[43] For a broader comparison between DMSP and VIIRS data, see Gibson (2020).

[44] Restricting the sample period to 2012–2020 for the baseline measure of spatial inequality yields a positive and highly significant coefficient, but also of smaller magnitude. This indicates that the effect of soy on inequality seems to have been stronger in the first decade of the 21^{st} century (not reported).

neighboring areas. The specification in column 8 thus controls for total soy production (in logarithmic scale) in neighboring municipalities.[45] Reassuringly, the coefficient of interest even increases in magnitude and remains highly significant.

Because soybean production is correlated across space, I also rerun the main baseline specification allowing for spatial correlation within different distance cut-offs (Conley, 1999), ranging from 50km to 250km. As Appendix Table A5 shows, the results are robust to this adjustment.

5.1 Instrumental Variable

A potential concern with instrumental-variable approaches that, like mine, interact a time series variable with a measure of cross-sectional exposure is spurious correlation (Christian and Barrett, 2023). In particular, this could be caused by a co-movement between exogenous time-varying component and the endogenous variable. Following Christian and Barrett's (2023, p. 1098) recommendations, throughout the paper I use the *variation* in the size of the Chinese pig stock, because "[f]irst differencing to render the instrument, explanatory and outcome variables stationary appears a reasonably promising way to address the spurious regression problem in panel IV estimation."[46] As recommended, I also visually inspect my proposed source of exogenous variation and, reassuringly, there is no clear trend in $\Delta pigstock$ (Appendix Figure A3). The stationarity of the instrument's temporal component is further corroborated by an augmented Dickey-Fuller test for unit root, which convincingly rejects the null hypothesis ($p = 0.000$).

To further examine the validity of the instrument, Figure 3 plots the first-stage coefficient associated with the instrumental variable ($\Delta pigstock_{t-1} \times soil_{mr}$) with different lags and leads—that is, instead of instrumenting soy production in t with the variation in the size of the Chinese pig stock between $t-2$ and $t-1$ (interacted with time-invariant municipal soil suitability for soy cultivation), I try also different yearly intervals ($t-1$ is the baseline specification).

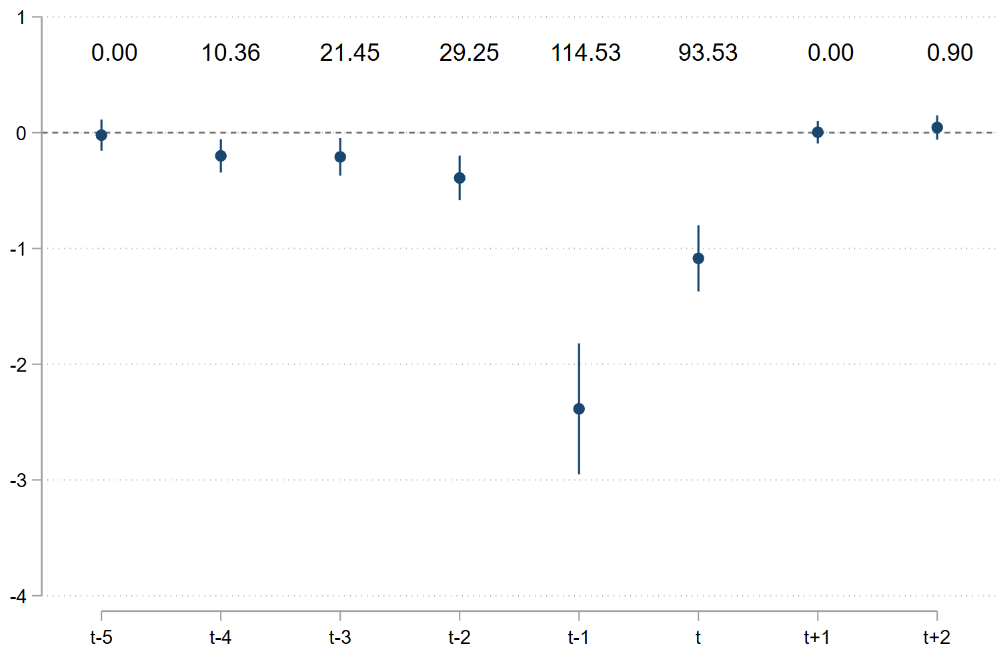
As expected, the figure shows that going back in time reduces the magnitude of the coefficient (which becomes insignificant by $t-5$ and beyond) and decreases the instrument's relevance, indicated by the first-stage F-statistics, displayed above each point estimate. That is, intuitively, the importance of variations in the pig stock as a determinant of soy production seems to wane over time.

Besides, although still powerful, instrumenting production using the current (t) change in the pig stock—that is, from $t-1$ to t— produces a considerably weaker instrument

[45]In the baseline specifications I prefer not to add this control variable because its correlation with municipal soy production is rather high (0.54).

[46]Using the size of the Chinese pig stock itself, instead of its change over time, also yields a powerful instrument (not reported). Nevertheless, I refrain from doing so given Christian and Barrett's (2023) concerns.

Figure 3 – Instrument Leads and Lags



Notes: The figure plots the first-stage coefficient for the instrumental variable ($\Delta pigstock$) from regressions with different time lags and leads in relation to the (first-stage) dependent variable, which is the logarithm of the amount of municipal soy production. Point estimates multiplied by 1e6 for presentation purposes. Figure displays 99% confidence intervals. The corresponding first-stage F statistic is reported on top of each point estimate.

and smaller first-stage coefficient. This indicates that producers might need some time to adjust production in response to demand shocks. This is also consistent with the fact that many farmers heavily rely on forward contracts to market their harvest.

Finally, in a sort of falsification test, I show results for future changes in the size of the pig stocks in China. Reassuringly, this yields extremely weak instruments and coefficients that are indistinguishable from zero, giving support to the argument of shifter exogeneity (Borusyak et al., 2022), as variation in the pig stock (partially) drives soybean production abroad, and not the other way around. This is also in line with the evidence that, to a large extent, variation in the Chinese pig stock is explained by sporadic episodes of disease outbreak (You et al., 2021).

5.1.1 Alternative Instruments

Appendix Table A6 further investigates whether the findings above are driven by a "spurious regression" problem (Christian and Barrett, 2023). To do so, it shows results using different sources of temporal variation as instruments for municipal soy production. In this case, to make sure the instrument's relevance does not come solely from soil suitability for soybean cultivation, I use uninteracted instruments that vary only over time.[47]

The table shows that using $\Delta pigstock$ on its own (i.e., uninteracted) still yields a positive and significant coefficient of interest in the second-stage regression (column 1). Not surprisingly, although still relatively strong, the instrument considerably loses in relevance. Yet, considering the other alternatives, the variation in Chinese pig stocks produces by far the highest F statistic. Relying on variation in the Chinese cattle stock—which are also mostly fed with soy-based feed but are a less preferred protein source in the Chinese diet—yields a much weaker first stage (column 2). As a falsification test, I employ, alternatively, variation in the Chinese production of crude steel, which is considered by the Chinese government to be "a strategically important commodity" (Dreher, Fuchs, Hodler, Parks, Raschky and Tierney, 2021, p. 18) and a good proxy for economic activity in the country—and in particular for its "capacity to provide physical project inputs " (Bluhm et al., 2020, p. 18).[48] This exercise shows, however, that it seems to be indeed the variation in the size of the Chinese pig stock—as theory would have it—that matters to explain soy production in Brazil, and not just any cyclical fluctuation related to the status of the Chinese economy. Finally, using variation in the size of the pig stock in the European Union—the world's second largest stock, after China's—does not yield a powerful instrument on its own (column 4). Even though the role of the EU will be discussed in more detail below, this already hints at the fact that, although it is the second most important buyer of Brazilian soybeans, feeding pigs is a less prominent reason for EU demand.

5.2 Is it really about China?

I have so far highlighted the role of the China shock as a major engine behind soy expansion in Brazil and therefore as an indirect cause of the observed increase in inequality. This begs the question of whether there is anything specific to Chinese demand of soybeans that leads to higher inequality. In fact, the existing literature on commodity shocks devotes little attention to how the consequences for the producing (origin) country might vary according to the country to which commodities are exported. In the case of soy, it becomes crucial to acknowledge the heterogeneous nature of its demand and the potential segmentation of supply chains.

Because soy trade is telecoupled by nature (Pendrill et al., 2019, Meyfroidt et al., 2020), this means that producers in Brazil may adopt different practices depending on,

[47]Note that, in this case, region-year fixed effects would absorb all of the instrument's variation. I therefore include region-5-year-period fixed effects.

[48]The temporal variation in the Chinese steel production (at times combined with that of other products or raw materials) was proposed by Dreher, Fuchs, Hodler, Parks, Raschky and Tierney (2021) as source of (arguably) exogenous variation driving Chinese foreign aid, and has since been used more widely in the literature (e.g., Humphrey and Michaelowa, 2019, Bluhm et al., 2020, Dreher, Fuchs, Parks, Strange and Tierney, 2021, Cruzatti et al., 2023, Zeitz, 2020).

e.g., the environmental awareness of their final consumers and the standards required by the importing country (Nepstad et al., 2006, Garrett, Rueda and Lambin, 2013). The fact that the two largest buyers of Brazilian soybeans, China and the European Union, differ in some important aspects makes this issue all the more relevant.

Therefore, to benchmark the findings above, I repeat the analysis for the EU. I do so in two ways. First, I use variation in the size of the European pig stock (now interacted with soil suitability for soy) as the instrumental variable. Second, I use soy exported to the EU (instead of total production) as the instrumented variable.

Importantly, as the previous results in Table A6 attest, the scale of the Chinese pig stock (more than half of the pigs worldwide) has no peer in terms of influencing the demand for soy. Besides, feeding pigs does not seem to be as important a reason behind European soy imports. Therefore, the identification strategy is probably less pertinent in the case of EU demand. Nevertheless, although less powerful than for China, the (interacted) instrument is still fairly relevant (Appendix Table A7).

In this case, there is no evidence that total soy production is linked to higher municipal inequality. This indicates that the response in production triggered by demand fluctuations in the EU do not seem to have considerable distributional implications. Increases in soybean exports to the EU, on the other hand, do lead to higher spatial inequality. A potential explanation for these contrasting results is that soy farmers who export (part of) their harvests tend to operate on larger farms. Therefore, although the EU may not possess the scale—differently from China—to influence the soy-inequality nexus as a whole, it does so via its imports. Even so, the magnitude of this effect is significantly smaller than that of exports to China.[49] As the findings from Section 3 also indicate, given the unprecedented scale—in size and tempo—of China's economic rise, it is perhaps not surprising that its consequences are rather distinct.

6 The Soy-Inequality Nexus

The analysis above presents evidence that soy expansion has increased land and spatial inequality in Brazil. This section aims to understand why this is the case.

6.1 Land Consolidation

A common consequence of processes of agricultural modernization is that farmers (or peasants), usually smallholders, who are less well positioned to exploit economies of scale and "ride the wave" of booming demand might be squeezed out of the market and end up selling their land to wealthier farmers. To better understand what may explain the

[49] Although, as discussed previously, regional differences play an important role, it does not seem to be the case that they account for the contrasting results between China and the EU, as the share of soy exported to each of these two markets is rather similar across Brazilian regions.

reported increases in land inequality, Table 5 repeats the 2SLS specification in column 3 of Table 2, but now with different outcome variables: municipality's median area of rural properties (log), the number of rural properties (log), the number of agricultural cooperatives (log), and (log) municipal population.[50]

Table 5 – Land Consolidation

Dependent Variable:	Property Area (log) (1)	No. Properties (log) (2)	No. Coop (log) (3)	Population (log) (4)
Soy (log)	0.048***	9.662***	16.673***	0.204***
	(0.018)	(0.548)	(0.959)	(0.014)
WTO × Soy (log)	0.023***	-1.792***	-3.015***	-0.030***
	(0.005)	(0.158)	(0.266)	(0.004)
WTO	-0.151***	0.669	-3.407***	0.105***
	(0.014)	(0.494)	(0.835)	(0.012)
Municipality FE	Yes	Yes	Yes	Yes
Period FE	No	No	No	No
N	15133	15171	15171	15133
KP F-stat	145.72	145.91	145.91	145.72

Notes: WTO is a binary variable that takes the value 1 if period p is after 2001. *Soy (log)* is the natural logarithm of municipal soybean production. Dependent variables: *Property Area (log)* is the median size of rural properties in a municipality in logarithmic scale (column 1); *No. Properties (log)* is the natural logarithm of the number of rural properties in a municipality (column 2); *No. Coop (log)* is the natural logarithm of the number of agricultural cooperatives in a municipality (column 3); and *Population (log)* is the natural logarithm of municipal population (column 4). First-stage Kleibergen-Paap F-statistic reported. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors, clustered at the level of 1970 MCAs, in parentheses.

First, column 1 indicates that the median size of rural properties in municipalities in Brazil increases with the amount of soy produced and even more so after 2001. This is consistent with the interpretation that, due to the crop's characteristics, soybean cultivation has a tendency to monoculture and land consolidation. Column 2 provides further evidence of land consolidation, as it indicates that, although soy expansion (perhaps mechanically) increases the number of rural properties, the effect subsides in the post-WTO period. Column 3 shows a similar pattern for the number of agricultural cooperatives, potentially reflecting the increasing financialization of the agricultural sector in Brazil and the rise of agribusiness—a model in which big trading companies dominate and cooperatives play a less important role. Finally, to assess, even if crudely, whether (intramunicipal) displacement might explain the increases in inequality, the specification in column 4 has municipal population as the outcome variable. Rather, the expansion of soybean production seems to lead to increases in population in the municipality, although the magnitude of the effect goes down after China's accession to the WTO.

Next, I analyze the components that make up the measure of spatial inequality—that is, income and population—separately. First off, Table 6 shows that there is no clear evidence that the soy boom has increased average income per capita.[51] The OLS

[50] The first three variables are taken from the four agricultural census waves between 1985 and 2017. Municipal population has already been introduced in Section 4.

[51] If run separately for each Brazilian region, the 2SLS models indicate that, perhaps unsurprisingly, soy production increases GDP per capita only in the Midwest. The coefficient is statistically insignificant for the other four regions (not reported).

coefficient is small in magnitude and only marginally significant (column 1). In the 2SLS setup, it is far from achieving statistical significance and even turns negative (column 2).[52] This makes it unlikely that the increase in inequality, reported previously, occurs simply because some benefit more then others. Rather, it suggests that some may have become worse off. This question will be examined in more detail in Section 6.2.

Columns 3 and 4 indicate in addition that average (log) cell luminosity even goes down as soy expands. As is the case in the main section of results, once again OLS significantly underestimates the effect. Finally, there is additional evidence that expanding soy production leads to (small) increases in total municipal population, also when it is measured using the gridded population data (column 6).

Table 6 – Income, Lights and Population

Dependent Variable:	GDP pc (log)		NTL		Population (log)	
	(1)	(2)	(3)	(4)	(5)	(6)
Soy (log)	0.003*	-0.003	-0.002*	-0.106***	-0.001	0.049***
	(0.002)	(0.036)	(0.001)	(0.022)	(0.001)	(0.008)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No	No
Model	OLS	2SLS	OLS	2SLS	OLS	2SLS
N	116774	116774	116858	116858	116780	116780
KP F-stat		113.97		118.14		113.96

Notes: Soy (log) is the natural logarithm of municipal soybean production. Dependent variables: *GDP pc (log)* is municipal GDP per capita in logarithmic scale (columns 1 and 2); *NTL* is the natural logarithm of municipal average nightlight radiance (column 3 and 4); and *Population (log)* is the natural logarithm of municipal population (columns 5 and 6). First-stage Kleibergen-Paap F-statistic reported. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors, clustered at the municipality level, in parentheses.

Taken together, these results paint a picture that is consistent with a process of land consolidation. While the increase in soy production brings benefits to the agricultural sector, these do not seem to extend to other parts of the economy.[53] The reduction in average light emission is in line with the anecdotal evidence that indicates that small-holder farmers, who tend to live on the outskirts of municipalities, are pushed to the urban center (or elsewhere) as agriculture consolidates. This would concentrate light both at the rural part (as land consolidates) as well as in the urban center. Given that the latter is usually already well lit, this movement may decrease luminosity in the rural part without necessarily creating more (observable) light in the center. This does not necessarily mean that the soy business does not create additional light through its machinery and dedicated facilities, but rather that this seems to be more than offset by intra-municipal flows and the lack of activity being created in other capital-intensive sectors of the economy.

The increase in population, on the other hand, is in line with the creation of

[52] Using (log) GDP, instead of (log) GDP per capita, yields similar findings (not reported).

[53] Appendix Table A8 shows that soy production increases the share of value added in agriculture, but has no influence on the industrial or service sector.

(potentially low value-added) activity in services, such as small shops and restaurants. Moreover, this is embedded in a deeper process of reorganization of Brazil's population. Mirroring the growing dominance of agribusiness in the Brazilian economy, millions of people have been moving toward the interior of the country after centuries of concentration along the coastal areas. In any case, it is important to note that an increase in total population does not mean that soy is not linked to displacement, a phenomenon widely discussed in the related literature, "as large-scale mechanized agriculture uses less labor per hectare than small-scale farming techniques" (Weinhold et al., 2013, p. 133). This process could still be taking place within municipalities, something which intermunicipal migration data would not be able to capture.[54]

Not only is luminosity decreasing—or at least growing at a slower pace—as soybean expands, but it seems to do so in such a way that light becomes more concentrated. Again, this is consistent with the pattern of land consolidation and the displacement of small-holder farmers. As Appendix Table A9 shows, the increase in spatial Gini seems to be driven by the distribution of nighttime light becoming more unequal—although it has also been accompanied by a decrease in the population Gini. Summing up: lights get more concentrated, while population increases and spreads.

6.2 Quantile Analysis: Who Benefits?

To complement the findings on inequality, it is important to understand the impact of soy expansion on different strata of society. It is possible that all groups have become better off, with some just benefiting more than others. But it could also be the case that parts of the population have actually become worse off. To address this question, I make use of microdata on household monthly income for all Brazilian municipalities available in the last three rounds of the Brazilian demographic censuses (IBGE, 1991, 2000, 2010).[55] I thus calculate the average household monthly income per resident (henceforth income per capita) for each decile of the distribution in each Brazilian municipality during each census wave. Appendix Figure A6 illustrates how income per capita evolves, both in monetary values (constant 2000 BRL) as well as the share of total municipality-wave income, from 1991 to 2010.

To understand how the expansion of soy affects income across all deciles, I estimate the following model:

[54]Using census data, available roughly every ten years, Bustos et al. (2016) find that Brazilian municipalities which experienced large increases in potential soy yields after the introduction of GE soy saw higher net outflows of migrants between 2000 and 2010.

[55]Throughout this subsection, what I refer to as municipalities are 1980 MCAs.

$$y_{dmrp} = \beta_1 \overline{soy}_{mrp-1} + \sum_{d=2}^{10} \beta_d \, \overline{soy}_{mrp-1} \times \mathbb{1}[D_{dmrp} = d] + \eta_{rp} + \psi_{dmr} + \epsilon_{dmrp} \tag{6}$$

in which y_{dmrp} stands for decile d's mean income in each municipality m in region r during each census wave p. It is measured either in constant 2000 BRL or as a share of total municipality-year income across all deciles. Similarly to Section 3, $\overline{soy}_{mrp-1}$ stands for the (log) production of soybeans in municipality m averaged over the ten years preceding the census year. Here, it also enters the equation interacted with a binary variable for each municipality-period income decile, D_{dmrp} (the first decile is the omitted category). On top of region-period fixed effects (η_{rp}), because this analysis is at the municipality-decile-period level, I include also municipality-decile fixed effects (ψ_{dmr}), such that I exploit income variation within each municipality-decile over time.

For identification purposes, in addition to instrumenting $\overline{soy}_{mrp-1}$ with $Z_{mrp} = \Delta pigstock_p \times soil_{mr}$ (similarly to equation (3)), now the first-stage equation includes also the interaction between Z_{mrp} and each decile indicator variable, D_{dmrp} ($d \in [2, 10]$), as regressors.

Figure 4 plots the marginal effect associated with a 1% increase in municipal soy production (implied by the estimation in equation (6)) for each outcome variable: decile income per capita in BRL (Panel A) and as a share of the total income in a municipality-period (Panel B).[56] The former shows that, in absolute terms, the higher one is at the income distribution, the more one tends to benefit from increases in municipal soy production. Given the amount of capital usually required to be a competitive soy producer, it is quite likely that most of these farmers are in the top income deciles in their home municipalities.[57]

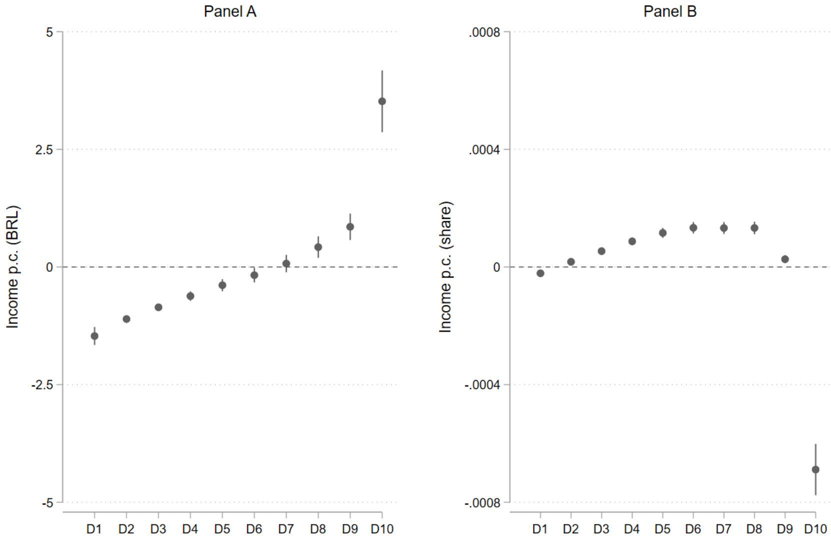
But soy seems far from lifting all boats. Strikingly, for the bottom six deciles—that is, for more than half of the population—soy expansion is even detrimental to one's income, and the reduction in income increases the poorer one is. These findings are in line with the results above of rising inequality and no benefit in terms of average municipal GDP per capita. The groups at the bottom of the distribution, to which smallholders most likely belong, tend to be the ones who often get the short end of the stick, for instance by losing access to their land.

Considering the effects on deciles' income shares offers some additional insights (Panel B). Because the top decile historically owns a considerable share of the total income—aproximately 44% in 1991 (Appendix Figure A6)—even though this is the group that

[56] Appendix Table A10 shows the full results.

[57] In fact, the level of income per capita necessary to be in the tenth decile is relatively low. Across all municipalities in 2010, the mean monthly income per capita of the top decile is BRL 2,267 (in current values), or about USD 1,288 according to the exchange rate at the time.

Figure 4 – Marginal Effect of Soy Expansion by Income p.c. Deciles



Notes: The figure plots the marginal effect associated with a 1% increase in municipal soy production for each per-capita income decile according to the estimation strategy described in equation (6). The outcome variables are income per capita in constant 2000 BRL (Panel A), and the decile's share of total municipal income per capita in each census wave (Panel B). Figure displays 99% confidence intervals. All regression models include decile-municipality and region-period fixed effects. Robust standard errors clustered at the level of 1980 MCAs. The first-stage Kleibergen-Paap F-statistic is 16.39.

benefits the most from the expansion in soy, the part of the additional income that it amasses is not high enough to sustain its share. Moreover, because the bottom deciles suffer particularly large losses, those at the middle of the distribution might even see their decile's income share increase, even though their income has not increased (and may have even decreased, but less so).[58]

6.3 Deforestation and Conflict

The rise in economic inequality is likely to be closely related to other important dimensions of the soy boom: the impact on the environment (and deforestation in particular) and rural conflict. More precisely, these elements may function as escape valves when economic opportunities become scarcer. That is, as inequality increases and land becomes more consolidated, (smallholder) farmers and peasants might start looking for land elsewhere, in turn increasing pressures on the local native vegetation and making the occurrence of land conflicts more likely.

The link between soy, considered "the second largest agricultural driver of deforestation worldwide" (WWF, n.d.), and environmental damage in Brazil is well

[58]This might explain why there is no clear effect on the Gini coefficient of income inequality. Appendix Table A11 shows OLS and 2SLS results for regressing the municipal Gini of income inequality (taken from the 1991, 2000 and 2010 censuses) on average (log) municipal soy production over the ten-year period preceding the census year. In the 2SLS setup, the explanatory variable of interest is, as above, instrumented with $Z_{mrp} = \Delta pigstock_p \times soil_{mr}$. All models include municipality fixed effects and either period or region-period fixed effects. The 2SLS results indicate even a small reduction in income inequality, which is however driven only by the municipalities in the South of Brazil.

documented in the literature. While cattle ranching is usually the ultimate cause of land-use change in Brazil, the expansion of the soy frontier—which has been moving North toward the Amazon in what is referred to as the "arc of deforestation"—is frequently an underlying force behind pasture displacement and hence deforestation (Fearnside, 2001, Barona et al., 2010, Song et al., 2021). In short, soy production has been a major driver of forest and biodiversity loss in the country (Nepstad et al., 2006, Hargrave and Kis-Katos, 2013, Carreira et al., 2024).[59]

However, it remains unclear to what extent this has been driven by rising Chinese demand.[60] To address this question, I apply the empirical strategy outlined in Section 4, but now with (log) annual deforested area in each Brazilian municipality, between 2000 and 2020, as the outcome variable (Base dos Dados, 2023). This measure is constructed based on satellite data provided by Brazil's National Institute for Space Research (INPE, 2023).

Consistent with Hansen and Wingender (2023), the China shock does seem to be an important part of the story (Table 7, Panel A). The 2SLS results show that increasing municipal soy production by a (within) standard-deviation is expected to increase deforestation by approximately 3.7% (column 5). What is more, the effect, once again, is much larger than what is implied by a naive OLS estimation (column 1).

Moreover, in line with the argument that deforestation should increase more in more unequal municipalities, adding an interaction term between soy production and spatial inequality yields a positive coefficient in both setups: OLS (column 3) and 2SLS (column 7)—in which case an additional instrumental variable is added to the first-stage regression, namely: $W_{mrt} = \Delta pigstock_{t-1} \times soil_{mr} \times spatialgini_{mrt-1}$. A drawback of this exercise is that inequality itself is also affected by soybean production. To at least mitigate this issue, I repeat the analysis using the initial level of inequality (that is, the spatial Gini in the year 2000) in each municipality instead of its lagged value. The results again indicate that soy production leads to higher deforestation in (initially) more unequal places (columns 4 and 8).[61] However, in this case, soy production would actually slow down deforestation in a small group of observations (approximately 10% of Brazilian municipalities) that have a rather low level of initial inequality.

As suggested above, another potential implication of the distributional consequences of the soy boom is the intensification of social grievances. This is "rooted in the idea that because access to land is the cornerstone of rural life, a skewed distribution of

[59]See Hänggli et al. (2023) for a systematic review of the literature on deforestation drivers in the Amazon biome.

[60]Perhaps surprisingly, based on a long-difference model, Carreira et al. (2024) show that differential exposure to the *aggregate* China shock does not seem to be linked to deforestation rates in Brazilian municipalities. However, this only holds as long as the effect of the shock is mediated by the introduction of GE soy technology.

[61]Measuring initial inequality with the 1995 land Gini instead leads to similar conclusions (not reported).

Table 7 – Deforestation and Rural Conflict

	Panel A – Dependent Variable: Deforestation (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Soy (log)	0.007***	0.007***	0.004***	-0.026***	0.035***	0.001	0.069***	-0.091***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.010)	(0.005)	(0.012)	(0.020)
Spatial Gini		0.051***	0.040***			0.053***	-0.150***	
		(0.007)	(0.008)			(0.007)	(0.028)	
Spatial Gini × Soy (log)			0.004***				0.070***	
			(0.001)				(0.010)	
Initial Spatial Gini × Soy (log)				0.038***				0.166***
				(0.004)				(0.018)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	No	No	No	No
Model	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS
N	116606	110477	110477	114943	116858	110646	110646	115157
KP F-stat					118.14	132.76	32.21	71.76
	Panel B – Dependent Variable: Land Invasion (log)							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Soy (log)	0.008***	0.009***	0.009***	-0.025***	-0.095***	-0.104***	0.277***	-0.245***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.024)	(0.024)	(0.091)	(0.043)
Spatial Gini		0.128***	0.130***			0.130***	-0.781***	
		(0.025)	(0.029)			(0.025)	(0.201)	
Spatial Gini × Soy (log)			-0.001				0.294***	
			(0.003)				(0.067)	
Initial Spatial Gini × Soy (log)				0.038***				0.205***
				(0.011)				(0.041)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	No	No	No	No
Model	OLS	OLS	OLS	OLS	2SLS	2SLS	2SLS	2SLS
N	61106	61050	61050	60215	61215	61159	61159	60324
KP F-stat					105.99	108.39	8.25	60.92

Notes: Soy (log) is the natural logarithm of municipal soybean production. *Spatial Gini* is the Gini coefficient of municipal light per capita inequality. First-stage Kleibergen-Paap F-statistic reported. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors, clustered at the municipality level, in parentheses.

landholdings can fuel rural grievances and unrest" (Albertus et al., 2018, p. 558). Rural conflict, therefore, can be seen as a typical symptom of an unequal society (Russett, 1964, Brockett, 1992). To test if this is the case in the context of the China shock, I conduct a similar analysis, but this time with rural conflict as the dependent variable. I use the (log) annual number of land invasions that occurred in each municipality, taken from Comissão Pastoral da Terra (CPT, 2020), to measure rural conflict.

Some key findings emerge from this analysis (Panel B). First, on its own, there is no evidence that the soy boom has increased rural conflicts in Brazil. In fact, the 2SLS results indicate that, in aggregate terms, it may have even reduced land invasions.[62] However, this masks important regional heterogeneity. In the Midwest in particular, where these

[62] This may be partially explained by the fact that information on rural conflict is only available from 2010 to 2020. Therefore, this part of the analysis does not include the period just after China's accession to the WTO, such that tensions may have already dwindled once data become available. Relatedly, Falcone and Rosenberg (2022) show convincing evidence that agricultural modernization (driven by soy) increased land occupations in Brazil between 1988 and 2014.

tensions are most present, soybean production significantly increases rural conflict.[63]

Moreover, as for deforestation, the findings on rural conflict reiterate the importance of taking inequality into consideration. Regardless of how inequality is measured (varying over time or using its initial value), it shows that also the effect on land invasions increases substantially with the level of inequality, and thus emphasizes that the consequences of soy production vary significantly depending on local conditions. Therefore, bringing both deforestation as well as rural conflict into the analysis not only highlights other important aspects of the China shock, but also shed more light on the role of inequality. More broadly, it suggests that it is not possible to make sense of soy's environmental impact without taking its socioeconomic consequences into account.

7 Final Remarks

While the recent rise of China as a global economic power has brought opportunities for countries around the world, it has also contributed to some worrying developments. Relying on plausibly exogenous variation in Chinese demand for causal identification, this article shows that the "other" China shock—that is, China's growing demand for agricultural commodities (and soybeans in particular)—inadvertently worsened economic inequality in Brazilian municipalities. The process of land consolidation that ensued benefited mostly the richest parts of the population at the expense of everyone else, leading also to an increase in deforestation and, in some cases, a surge in land invasions. The results show that the more unequal a municipality, the more it tends to suffer in terms of forest loss and violence as soy expands.

Given the characteristics of modern soy cultivation, these findings are not that surprising. In fact, they reiterate the importance of factor endowments in shaping the distribution of land and income (Sokoloff and Engerman, 2000). In a country such as Brazil, which due to its colonial history has long struggled with high levels of inequality, this recent turn of events can be especially damaging. As economic inequality tends to translate into political inequality, the entrenched interests of an increasingly powerful agrarian elite may make the enactment of more inclusive policies ever more difficult (Acemoglu and Robinson, 2008, Ziblatt, 2008, Galor et al., 2009).

This paper thus underscores the need of harnessing the productive potential of Brazilian agriculture in a fairer and more sustainable manner. While domestic challenges such as land reform cannot be overlooked (Reydon et al., 2015), initiatives for more responsible global agricultural supply chains may be an important catalyst for change (Garrett, Lambin and Naylor, 2013, Gardner et al., 2019). In particular, this requires putting additional emphasis on the welfare of smallholders, who often lack the scale and

[63] Appendix Table A12 shows the results for deforestation (Panel A) and rural conflict (Panel B) for each Brazilian region separately.

the resources to compete against more consolidated producers. As the evidence presented here indicates, this can help not only to tackle inequality, but also to curb deforestation and rural conflict.

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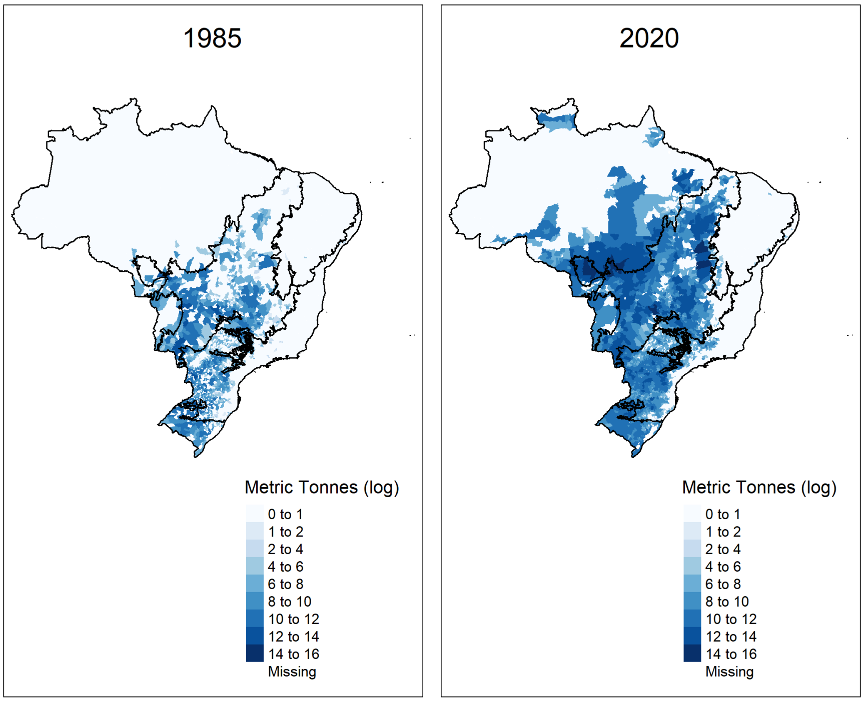
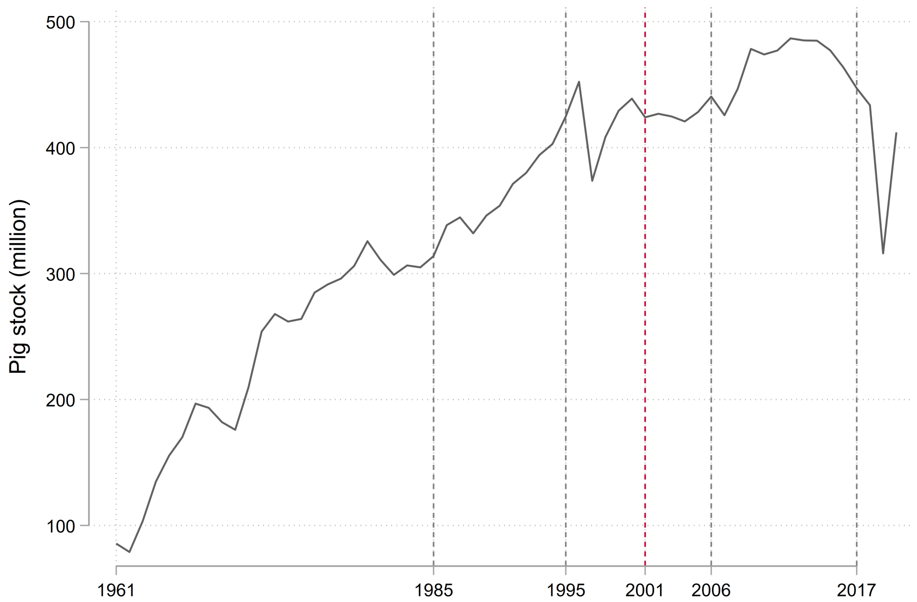
Appendix

Figure A1 – Municipal Soybean Production



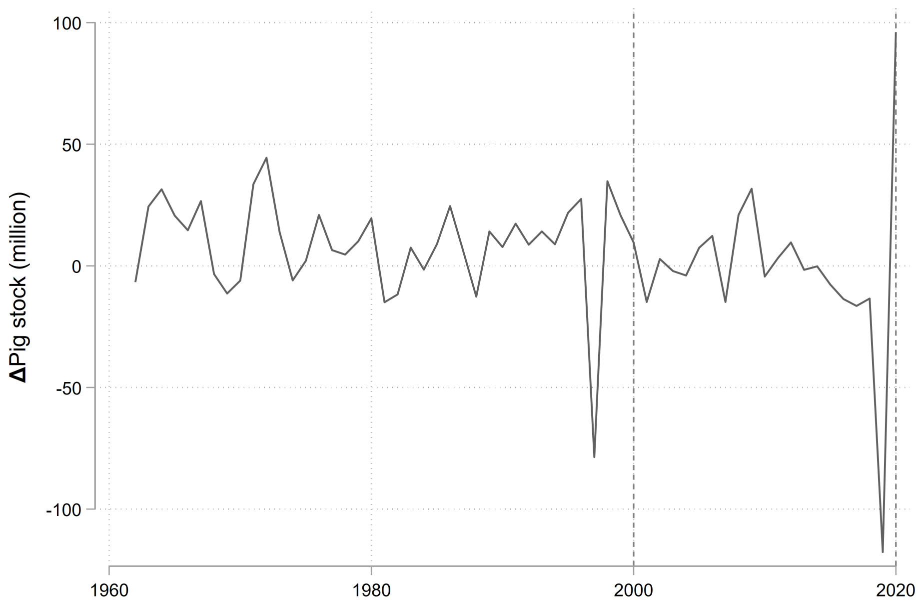
Notes: Figure shows soybean production (log) in each Brazilian municipality in 1985 (left) and 2020 (right). A unit (metric tonne) is added to each municipality before the log transformation to avoid losing observations.

Figure A2 – Chinese Pig Stock



Notes: Figure shows the size of the Chinese pig stock (in million) over time. Vertical gray lines indicate the four census waves used in Section 3. The vertical red line marks the year of China's accession to the WTO.

Figure A3 – Chinese Pig Stock: Annual Variation

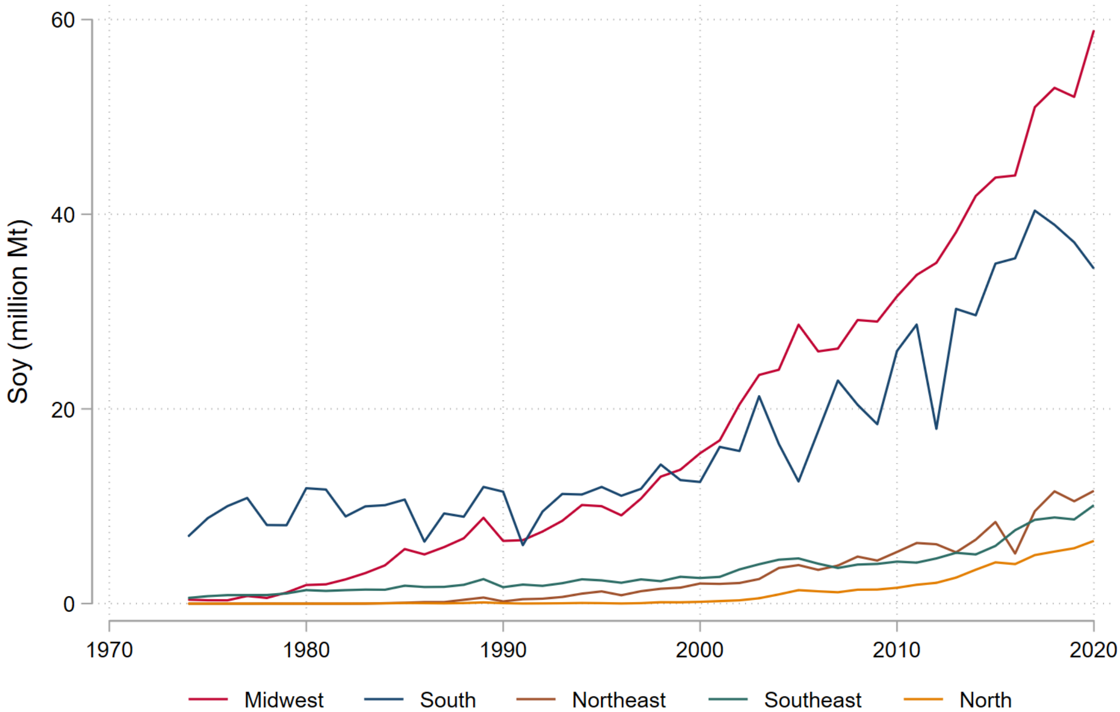


Notes: Figure shows the annual variation in size of the Chinese pig stock (in million) over time. Vertical gray lines indicate the period of analysis in Section 4.

Figure A4 – Fazenda Angela Tereza

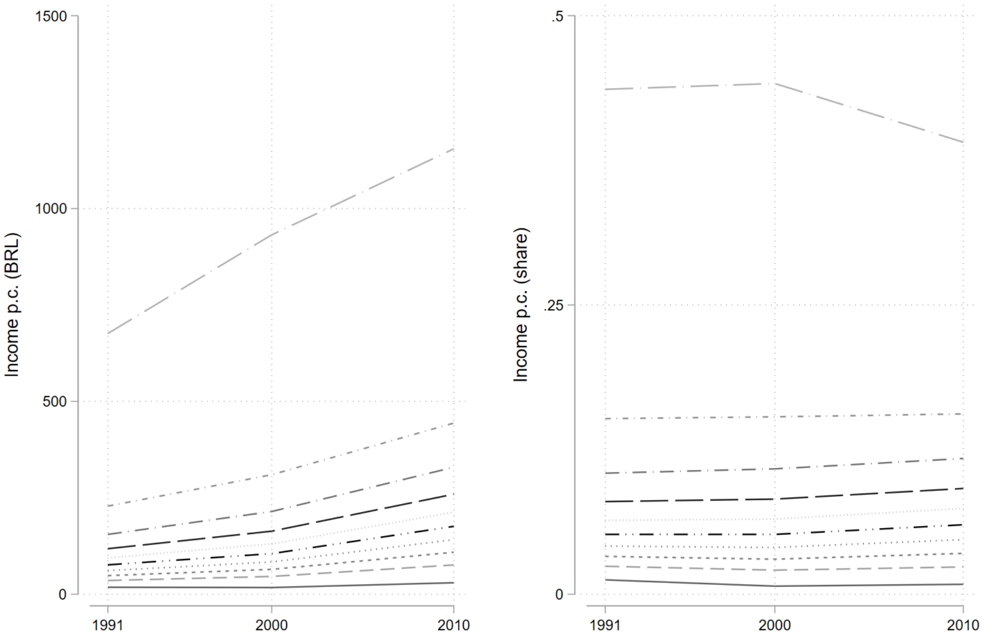
Notes: Satellite images, from Google maps, of Sorriso (MT). Fazenda Angela Tereza is located at 13° 16' 54" S, 55° 22' 27" W.

Figure A5 – Total Soybean Production by Region



Notes: Figure shows total annual production of soybeans across all five Brazilian major regions over time.

Figure A6 – Income p.c.: Trends by Decile



Notes: The figure plots, for each income decile, the evolution of average per-capita income by decile in constant 2000 BRL (left-hand side) and each decile's share of the total municipal income (right-hand side) during the last three demographic census waves (1991, 2000, 2010).

Table A1 – Descriptive Statistics

Variable	Mean	SD	Min	Max	Count
Panel A: Data used in Section 3					
Land Gini	0.72	0.11	0.16	0.99	15,149
WTO	0.50	0.50	0.00	1.00	15,196
Soy (log)	2.57	3.86	0.00	16.41	15,176
Soil	4.83	1.93	0.00	9.89	15,196
Population (log)	9.70	1.18	6.57	16.30	15,196
Imports (log)	15.73	1.50	14.09	17.87	15,196
Δ Pigstock	45.79	40.92	6.59	110.93	15,196
Property Area (log)	3.84	1.04	0.05	8.44	15,149
No. Properties (log)	1.70	2.44	0.00	11.60	15,190
No. Coop (log)	2.41	3.31	0.00	12.51	15,190
Panel B: Data used in Section 4					
Spatial Gini	0.70	0.27	0.02	1.00	116,210
Soy (log)	3.01	4.34	0.00	14.64	116,970
Soy CHN (log)	1.58	3.38	0.00	14.30	94,690
Soy EU (log)	1.19	2.88	0.00	13.45	94,690
Soil Suitability	4849.59	1934.24	0.00	9995.00	116,865
Δ Pigstock	-0.82	35.26	-117.68	96.11	116,970
NTL	1.03	0.97	0.00	4.16	116,865
Δ Cattle (CHN)	-1.94	3.08	-12.43	2.64	116,970
Δ Steel (CHN)	4478.60	2834.81	-1848.13	8925.67	116,970
Δ Pigstock (EU)	-0.63	2.32	-5.33	2.77	116,970
GDP pc (log)	7.81	1.05	-0.17	12.34	116,821
Spatial Gini (VIIRS)	0.34	0.17	0.02	1.00	50,084
Corn (log)	6.59	2.90	0.00	15.16	116,970
Sugarcane (log)	5.53	4.74	0.00	16.14	115,059
Soy Ngb. (ln)	8.91	20.02	0.00	150.83	116,970
Deforestation (log)	5.53	1.13	0.00	9.55	116,970
Land Invasion (log)	0.04	0.47	0.00	9.50	61,270

Table A2 – Land Inequality (1^{st} Stage)

Instrumented Variable:	Soy (log)	Soy (log)	Soy (log)	WTO × Soy (log)	Soy (log)	WTO × Soy (log)
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Pigstock × Soil	0.000**	-0.007***	-0.003***	-0.011***	-0.001***	-0.007***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
WTO × Δ Pigstock × Soil			-0.007***	0.002***	0.006***	0.041***
			(0.001)	(0.001)	(0.001)	(0.001)
WTO			1.130***	2.729***	-1.145***	-4.194***
			(0.058)	(0.072)	(0.127)	(0.159)
Δ Pigstock			0.014***	0.051***	0.004***	0.021***
			(0.001)	(0.001)	(0.001)	(0.001)
Imports (log)					0.485***	1.476***
					(0.028)	(0.037)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	No	No	No	No
N	7556	7556	15133	15133	15133	15133

Notes: Δ *Pigstock* is the annual change in the size of the total pig stock in China. *Soil* is the average soil suitability for soybeans in the municipality. *WTO* is a binary variable that takes the value 1 if period p is after 2001. *Imports (log)* stands for the natural logarithm of Chinese annual soybean imports. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors, clustered at the level of 1970 MCAs, in parentheses.

Table A3 – Spatial Inequality (1^{st} Stage)

Instrumented Variable:		Soy (log)			Soy CHN (log)	
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Pigstock × Soil	-0.004***	-0.002***	-0.002***	-0.003***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
GDP (log)			0.006			-0.001
			(0.005)			(0.008)
Tax (log)			0.008			0.018**
			(0.006)			(0.008)
VA Industry (log)			0.007			-0.006
			(0.006)			(0.008)
VA Services (log)			0.004			0.020**
			(0.006)			(0.008)
VA Agro (log)			0.055***			0.010
			(0.006)			(0.008)
Population (log)			-0.255**			0.290*
			(0.120)			(0.152)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	-	-	Yes	-	-
Region-Year FE	No	Yes	Yes	No	Yes	Yes
N	116203	116203	115994	88783	88783	88662

Notes: Δ *Pigstock* is the annual change in the size of the total pig stock in China. *Soil* is the average soil suitability for soybeans in the municipality. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors, clustered at the municipality level, in parentheses. Note that the point estimates and standard errors relative to the instrumental variable ($\Delta Pigstock \times Soil$) are multiplied by 1,000 for presentation purposes.

Table A4 – Spatial Gini: Quintiles and Regions

	Dependent Variable: Spatial Gini				
	Panel A – Regions				
	(1)	(2)	(3)	(4)	(5)
Soy (log)	0.030***	0.085	0.820***	0.019***	-0.270
	(0.006)	(0.191)	(0.298)	(0.004)	(0.344)
Region	Midwest	South	Northeast	Southeast	North
Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Model	2SLS	2SLS	2SLS	2SLS	2SLS
N	9717	24563	37549	34994	9380
KP F-stat	35.09	0.50	8.09	353.47	0.59
	Panel B – GDP per capita (Quintiles)				
	(1)	(2)	(3)	(4)	(5)
Soy (log)	0.264*	0.585**	0.041***	-0.015	-0.151**
	(0.154)	(0.260)	(0.014)	(0.018)	(0.066)
Quantile	Q1	Q2	Q3	Q4	Q5
Municipality FE	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
N	23037	23054	22976	22975	23059
KP F-stat	4.21	5.43	38.64	20.74	6.23

Notes: Soy (log) is the natural logarithm of municipal soybean production. First-stage Kleibergen-Paap F-statistic reported. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors, clustered at the municipality level, in parentheses.

Table A5 – Spatial Autocorrelation

	Dependent Variable: Spatial Gini				
	(1)	(2)	(3)	(4)	(5)
Soy (log)	0.067***	0.067***	0.067***	0.067**	0.067**
	(0.016)	(0.021)	(0.025)	(0.027)	(0.029)
Municipality FE	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
Model	2SLS	2SLS	2SLS	2SLS	2SLS
SE	Conley (50km)	Conley (100km)	Conley (150km)	Conley (200km)	Conley (250km)
N	116203	116203	116203	116203	116203
KP F-stat	73.30	40.15	25.67	18.72	15.51

Notes: Soy (log) is the natural logarithm of municipal soybean production. First-stage Kleibergen-Paap F-statistic reported. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Conley standard errors for different distance cut-offs in parentheses.

Table A6 – Alternative Instruments

	Dependent Variable: Spatial Gini			
	(1)	(2)	(3)	(4)
Soy (log)	0.798***	1.359**	-6.661	-1.410
	(0.205)	(0.593)	(8.958)	(1.030)
Instrument	Δ Pig Stock (China)	Δ Cattle Stock (China)	Δ Steel (China)	Δ Pig Stock (EU)
Municipality FE	Yes	Yes	Yes	Yes
Region-Period FE	Yes	Yes	Yes	Yes
Controls	No	No	No	No
Trend	Yes	Yes	Yes	Yes
N	116203	116203	116203	116203
KP F-stat	15.19	5.23	0.55	1.88

Notes: Soy (log) is the natural logarithm of municipal soybean production. Instrumental variable: Δ *Pig Stock (China)* is the annual change in the size of the total pig stock in China (column 1); Δ *Cattle Stock (China)* is the annual change in the size of the total cattle stock in China (column 2); Δ *Steel (China)* is the annual change in the total Chinese production of crude steel (column 3); and Δ *Pig Stock (EU)* is the annual change in the size of the total pig stock in European Union (column 4). First-stage Kleibergen-Paap F-statistic reported. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors, clustered at the municipality level, in parentheses.

Table A7 – European Demand

	Dependent Variable: Spatial Gini			
	(1)	(2)	(3)	(4)
Soy (log)	0.002	-0.006		
	(0.010)	(0.011)		
Soy EU (log)			0.029***	0.027***
			(0.010)	(0.010)
Municipality FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes
Controls	Yes	No	Yes	No
Model	2SLS	2SLS	2SLS	2SLS
N	115994	116203	88662	88783
KP F-stat	41.28	30.96	29.69	29.39

Notes: Soy (log) is the natural logarithm of municipal soybean production. *Soy EU (log)* is the natural logarithm of municipal soybean exports to the European Union. First-stage Kleibergen-Paap F-statistic reported. Significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01. Robust standard errors, clustered at the municipality level, in parentheses.

Table A8 – Sectoral Value Added

Dependent Variable:	VA Agriculture		VA Industry		VA Service	
	(1)	(2)	(3)	(4)	(5)	(6)
Soy (log)	0.037	2.544***	-0.538*	3.927	-0.437	-3.841
	(0.031)	(0.487)	(0.289)	(7.335)	(0.394)	(12.525)
GDP	0.000	0.000	0.021	0.021	-0.068***	-0.068***
	(0.000)	(0.000)	(0.016)	(0.016)	(0.025)	(0.025)
Population	0.000**	0.000**	-0.002*	-0.002*	0.003*	0.003*
	(0.000)	(0.000)	(0.001)	(0.001)	(0.002)	(0.002)
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Model	OLS	2SLS	OLS	2SLS	OLS	2SLS
N	116775	116775	116775	116775	116775	116775
KP F-stat		114.95		114.95		114.95

Notes: Soy (log) is the natural logarithm of municipal soybean production. First-stage Kleibergen-Paap F-statistic reported. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors, clustered at the municipality level, in parentheses.

Table A9 – Inequality: Light and Population

Dependent Variable:	NTL Gini		Pop. Gini	
	(1)	(2)	(3)	(4)
Soy (log)	-0.000	0.069***	-0.000***	-0.008***
	(0.001)	(0.013)	(0.000)	(0.002)
Municipality FE	Yes	Yes	Yes	Yes
Region-Year FE	Yes	Yes	Yes	Yes
Controls	No	No	No	No
Model	OLS	2SLS	OLS	2SLS
N	116204	116204	116858	116858
KP F-stat		114.43		118.14

Notes: Soy (log) is the natural logarithm of municipal soybean production. First-stage Kleibergen-Paap F-statistic reported. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors, clustered at the municipality level, in parentheses.

Table A10 – Quantile Analysis

	Income p.c. (BRL) (1)	Income p.c. (share) (2)	Income p.c. (BRL) (3)	Income p.c. (share) (4)
Soy (log)	-13.618***	-0.000***	-147.306***	-0.002***
	(0.666)	(0.000)	(7.464)	(0.000)
Soy × D2	3.425***	0.000***	36.236***	0.004***
	(0.196)	(0.000)	(1.686)	(0.000)
Soy × D3	5.605***	0.001***	61.311***	0.008***
	(0.306)	(0.000)	(2.846)	(0.000)
Soy × D4	7.887***	0.001***	85.230***	0.011***
	(0.406)	(0.000)	(3.952)	(0.001)
Soy × D5	10.331***	0.001***	108.456***	0.014***
	(0.502)	(0.000)	(5.015)	(0.001)
Soy × D6	12.261***	0.002***	129.919***	0.016***
	(0.580)	(0.000)	(6.000)	(0.001)
Soy × D7	13.842***	0.001***	154.684***	0.015***
	(0.676)	(0.000)	(7.211)	(0.001)
Soy × D8	16.509***	0.001***	189.799***	0.015***
	(0.823)	(0.000)	(8.881)	(0.001)
Soy × D9	20.500***	0.000***	233.178***	0.005***
	(1.085)	(0.000)	(10.939)	(0.001)
Soy × D10	40.504***	-0.007***	501.144***	-0.067***
	(4.140)	(0.001)	(25.622)	(0.003)
Decile-Municipality FE	Yes	Yes	Yes	Yes
Region-Period FE	Yes	Yes	Yes	Yes
Model	OLS	OLS	2SLS	2SLS
N	114373	114373	114364	114364
KP F-stat			16.39	16.39

Notes: Soy (log) is the natural logarithm of municipal soy production. D2 to D10 stand for each municipality-period income decile. Monetary values in constant 2000 BRL. Income per capita share represents each decile's share of the total income per capita in a given municipality-period pair. First-stage Kleibergen-Paap F-statistic reported. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors, clustered at the level of 1980 MCAs, in parentheses.

Table A11 – Income Gini

	Dependent Variable: Income Gini					
	Panel A – OLS					
	(1)	(2)	(3)	(4)	(5)	(6)
Soy (log)	-0.000	0.001	0.001	-0.001*	0.003*	-0.003**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Region	Brazil	Midwest	South	Southeast	Northeast	North
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	No	Yes	Yes	Yes	Yes	Yes
Region-Period FE	Yes	No	No	No	No	No
N	11472	768	2016	4200	3972	516
	Panel B – 2SLS					
	(1)	(2)	(3)	(4)	(5)	(6)
Soy (log)	-0.007**	-0.047	-0.009**	-0.003	0.677	0.011
	(0.003)	(0.163)	(0.004)	(0.003)	(8.366)	(0.022)
Region	Brazil	Midwest	South	Southeast	Northeast	North
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	No	Yes	Yes	Yes	Yes	Yes
Region-Period FE	Yes	No	No	No	No	No
N	11472	768	2016	4200	3972	516
KP F-stat	164.12	0.09	56.71	170.88	0.01	1.80

Notes: Soy (log) is the natural logarithm of municipal soy production. First-stage Kleibergen-Paap F-statistic reported. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors, clustered at the level of 1980 MCAs, in parentheses.

Table A12 – Deforestation and Rural Conflict: Regions

	Panel A – Dependent Variable: Deforestation (log)				
	(1)	(2)	(3)	(4)	(5)
Soy (log)	0.115***	1.289	1.010***	-0.012***	-0.026
	(0.023)	(17.538)	(0.356)	(0.003)	(0.257)
Region	Midwest	South	Northeast	Southeast	North
Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Controls	No	No	No	No	No
Model	2SLS	2SLS	2SLS	2SLS	2SLS
N	9786	24948	37674	35022	9428
KP F-stat	35.18	0.01	8.13	353.02	0.51

	Panel B – Dependent Variable: Land Invasion (log)				
	(1)	(2)	(3)	(4)	(5)
Soy (log)	0.167***	-0.012	-0.337	-0.001	-1.705
	(0.058)	(0.044)	(0.257)	(0.005)	(1.376)
Region	Midwest	South	Northeast	Southeast	North
Municipality FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Region-Year FE	No	No	No	No	No
Controls	No	No	No	No	No
Model	2SLS	2SLS	2SLS	2SLS	2SLS
N	5126	13068	19734	18348	4939
KP F-stat	26.12	1.65	6.83	266.56	1.73

Notes: Soy (log) is the natural logarithm of municipal soy production. First-stage Kleibergen-Paap F-statistic reported. Significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors, clustered at the municipality level, in parentheses.