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The deforestation effects of trade and agricultural productivity in Brazil ☆

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ABSTRACT

This paper quantifies the relative footprint of trade and agricultural productivity on deforestation across Brazilian municipalities between 2000 and 2017. Using remote-sensing data, we identify distinct effects of these two phenomena on land use. Greater exposure to new genetically engineered soy seeds is associated with faster deforestation through cropland expansion. We find no significant association between local exposure to Chinese demand and deforestation, but exposure to trade with China mitigates the deforestation impacts from the new soy technology. Our findings suggest that, when considered together, productivity gains altering municipalities' comparative advantage played a more significant role in driving deforestation across Brazil than Chinese demand alone.

1. Introduction

Agriculture plays a key role in driving food security and economic development in low- and middle-income countries.[1] However, it is also the main driver of deforestation and greenhouse gas emissions, especially in tropical countries.[2] This is because tropical ecosystems hold a large amount of biomass, released as carbon dioxide when converting natural vegetation into new agricultural land.[3] This paper examines the local deforestation impacts of two key factors shaping the agriculture market: trade and agricultural productivity.

The effects of trade and agricultural productivity on deforestation are theoretically ambiguous (Grossman and Krueger, 1991; Jayachandran, 2021; Balboni et al., 2023). On the one hand, heightened productivity may result in production intensification, reducing the necessity for expanding agricultural land. On the other hand, increased productivity can attract capital and labor into the agricultural sector, expanding the agriculture frontier over the forests. Furthermore, technology and trade are interconnected (Autor et al., 2015). For example, trade can yield productivity gains by offering access to cheaper inputs and stimulating innovation.[4] Simultaneously, improvements in agricultural productivity can alter a country's comparative advantage, fostering production specialization. Importantly, the full benefits of agricultural productivity gains can only be realized in the presence of domestic or international demand for those products.

This paper quantifies the relative local impact of agricultural productivity gains and the rise in international demand on the expansion of agricultural land over forested areas. Specifically, we disentangle the effects of two quasi-exogenous indicators of local exposure to new genetically engineered (GE) soy seeds and increased demand from China on deforestation and land use across Brazilian municipalities from 2000

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1 World Bank (2007), Barrett (2010), Gollin et al. (2014) and McArthur and McCord (2017).
2 IPCC (2007), Curtis et al. (2018) and Crippa et al. (2021).
3 Baccini et al. (2012), Araujo et al. (2020), Balboni et al. (2021), Hsiao (2021) and Dominguez-Iino (2021).
4 Grossman and Krueger (1991), Eaton and Kortum (2002), Bustos (2011) and Akcigit and Melitz (2021).

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to 2017. We measure local exposure to technological innovation by assessing the potential productivity gains resulting from adopting new GE soy seeds introduced in Brazil in 2003 (Bustos et al., 2016). We measure local exposure to increased export demand from China involves a two-step process (Costa et al., 2016). We first use international trade flow data to compute the differential growth in Chinese demand for each product compared to the rest of the world (excluding Brazil). Then, we allocate the China-product-specific demand growth to municipalities in Brazil based on their production composition in 1995.

Key to our identification, we show that there is variation in differential exposure to Chinese demand and productivity shocks across municipalities. This enables us to study their effects in a single equation, as in Autor et al. (2015). Our identifying assumption is that variation in suitability for GE soy seeds and exposure to China-induced export demand are uncorrelated with other factors influencing land use changes. Moreover, our method for measuring local exposure to increased Chinese demand relies on the assumption of shock exogeneity. Following Borusyak et al. (2022)'s framework, we establish that quasi-random shock assignment is a reasonable assumption in our context, and we have a sufficient number of uncorrelated shocks. Reassuringly, we find no correlations between both exposure measures and land-use patterns during the pre-treatment period from 1995 to 2000.

Our findings unveil the distinct impacts of these two shocks and underscore the necessity of considering them together. When examining the effects of trade and productivity in isolation, we find that municipalities more exposed to the rising export demand from China experienced a more rapid decline in forest cover compared to less exposed areas. Similarly, municipalities with greater exposure to productivity gains from GE soy seeds experienced increased deforestation compared to areas that did benefit from the new technology. However, when these two are considered together, we find that only the GE soy seed shock remains statistically significant and economically meaningful. This implies that one would arrive at different conclusions regarding the impact of local exposure to export demand when analyzing it in isolation from the largest agricultural technological shock during that period.

We then investigate the combined effects of being exposed to both GE soy seeds and Chinese demand by adding an interaction between the two shocks to our econometric model. We find that while Chinese demand did not seem to exert a substantial direct differential impact on deforestation, it mitigated the deforestation impacts arising from GE soy seeds. This is because municipalities highly exposed to both shocks underwent a transition from cultivating other crops to soybeans, relieving pressure on the primary ecosystem and thereby reducing the relative impact of GE soy on deforestation.

We also break down the impacts on the extensive margin of crop production. We find that exposure to GE seeds increases the likelihood that a municipality engages in soy production, with this effect being more pronounced in municipalities exposed to both shocks. Interestingly, Chinese demand appears to have decreased the probability of soy cultivation in a given municipality. These findings suggest that GE seeds pushed soy production to areas that were previously economically unviable, with the effect being stronger in areas concurrently exposed to Chinese demand shocks. However, the soy extensive margin impact of the combined shocks was not enough to drive deforestation up, because of the reduction in the area allocated to other crops and in the probability of these other crops being planted.

Our paper makes three contributions. First, we contribute to the discourse on the impact of increased agricultural productivity on deforestation (Jayachandran, 2021; Balboni et al., 2023). The Jevons Paradox, a theoretical proposition, suggests that as resource use – in our case, land – becomes more efficient, its demand increases, leading to an overall rise in resource consumption. This conjecture holds if there are no bidding constraints in factor or product markets limiting agricultural expansion. Existing literature generally refutes the Jevons Paradox, showing that agriculture extension programs aimed at small-scale agriculture in Malawi and Uganda (Abman and Carney, 2020; Abman et al., 2020), or early electrification in Brazil (Szerman et al., 2022), reduced deforestation. An exception is Hess et al. (2021), which found that community-driven development programs in Gambia increased deforestation.[5] In contrast to this literature, we explore a setting where new agricultural technology favors large-scale agriculture, and capital constraints are likely less restrictive. The period we study is characterized by substantial government-subsidized credit allocated to large agricultural producers.[6] (Bustos et al., 2016) show that the soy boom instigated a process of local structural transformation with significant implications for local capital accumulation (Bustos et al., 2020). Moreover, Pellegrina (2022) shows labor reallocation across regions and towards soy production in areas highly exposed to GE soy seeds. None of these papers investigate the expansion of the agriculture frontier into forested areas. Therefore, our main contribution lies in bringing land use to the center of discussion and providing evidence consistent with the Jevons Paradox: productivity gains lead to deforestation in a setting where production factors reallocate to expand the agricultural frontier.

Our paper also contributes to the empirical literature on the environmental implications of trade (Copeland et al., 2021; Cherniwchan and Taylor, 2022). A series of cross-country and correlational studies have documented that trade liberalization is associated with higher deforestation.[7] and Abman and Lundberg (2020) show that regional trade agreements lead to a subsequent increase in deforestation, particularly in tropical regions. Additionally, several studies link increases in international commodity prices with deforestation in Brazil (Assunção et al., 2015; Harding et al., 2021; Da Mata and Dotta, 2021). Others have used related shift-share shocks to explore the effects of greater trade demand for exports, focusing on air pollution and emissions in China and India (Bombardini and Li, 2020; Barrows and Ollivier, 2021). A growing literature incorporates environmental externalities into trade models with heterogeneous productivity (Costinot et al., 2016; Shapiro, 2016; Hsiao, 2021; Pellegrina, 2022; Dominguez-Iino, 2021; Farrokhi et al., 2023). Unlike these papers, we study the relative effects of exposure to a shock in the demand for agricultural goods on deforestation across municipalities within a large commodity-exporting country.

Last, our main contribution is to connect these two strands of the literature to assess the relative impact of agricultural productivity and trade on the expansion of agricultural land over forested areas. Our findings suggest different conclusions when analyzing the local effects of trade demand in isolation versus in conjunction with agricultural productivity gains. Specifically, we find evidence that, while Chinese demand did not seem to exert a substantial differential direct impact on deforestation, it mitigated the deforestation effects arising from GE soy seeds. This is because areas highly exposed to both shocks already had a larger area dedicated to crops. Meanwhile, GE seeds facilitated soy production in areas that were previously economically unviable, leading to a relatively larger increase in cropland in regions with less consolidated agriculture frontiers. It is crucial to note, however, that our findings speak only to relative impacts across regions differentially exposed to these shocks. We do not assert that trade had no overall impact on deforestation in Brazil as a whole. Similarly, we cannot identify productivity impacts in a world without international demand for commodities.

[5] Related, Alix-Garcia et al. (2013) shows that conditional-cash transfers in Mexico increased deforestation. Conversely, an increase in household income has been shown to reduce deforestation in India and Indonesia (Foster and Rosenzweig, 2003; Ferraro and Simorangkir, 2020).

[6] Bulte et al. (2007) argues that subsidies to large farmers are not unique to Brazil and are common in Latin America. Assunção et al. (2019) shows that credit access is a crucial mediator of deforestation in the Brazilian Amazon.

[7] E.g., Barbier and Rauscher (1994), Sohngen et al. (1999), Ferreira (2004), Faria and Almeida (2016) and Leblois et al. (2017).

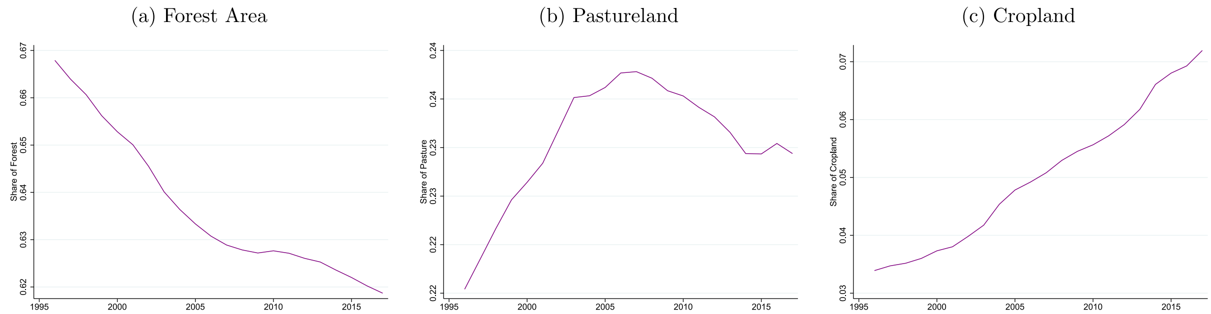

Fig. 1. Evolution of total share of forest area, cropland and pastureland. This figure shows the evolution of the share of forest areas, pastureland, and cropland in Brazil.

The remainder of the paper is organized as follows. In Section 2, we provide background information on the new GE soy seeds, the Chinese commodity boom, and describe our data. In Section 3, we present our empirical strategy and discuss our identifying assumptions. In Section 4, we present all results and a series of robustness checks. Section 5 concludes.

2. Background and data

Over the past three decades, Brazil has emerged as a major producer and exporter of agricultural products. In 2017, the country's agricultural exports amounted to approximately 73 billion dollars, marking a four-fold increase from the 19 billion dollars exported a little over two decades earlier, in 1995 (all in 2010 USD). This remarkable growth has been accompanied by substantial changes in land use, including the expansion of agricultural activities into vast forested regions of the country. While various factors may have played a role in driving this agricultural expansion, our focus in this paper is to investigate the relative contributions of a new genetically engineered soy seed and the growing demand from China to the loss of forested areas. In this section, we describe these key elements and how we measure them.

2.1. Land use in Brazil

Our main land use measure is annual remote sensing data sourced from MapBiomas, which classifies land use in Brazil based on 30-meter resolution LANDSAT images.[8] We consider four distinct land use categories: forest (encompassing native and secondary vegetation), crops, pasture, and others (the omitted category). We compute the share of each category at the municipality level i between 1995 and 2017. To ensure the consistency of municipality boundaries over time, our unit of analysis is Minimum Comparable Areas (AMCs), following the approach described by Reis et al. (2008) and Ehrl (2017). Hereinafter, we use the term "municipalities" to refer to these AMCs.

It is worth emphasizing that data reliant on remote sensing imagery for land use classification may contain measurement errors. As shown by Alix-Garcia and Millimet (2023), analyses conducted at the polygon level involving binary remotely sensed outcomes can have non-classical measurement errors. Nonetheless, they argue that data aggregation can effectively help mitigate this issue. We employ this strategy when we aggregate land use data at the municipality level. Furthermore, it is essential to underscore that MapBiomas, our main data source, employs rigorous methods aimed at minimizing classification errors by employing a series of temporal consistency rules. By combining this state-of-the-art remotely sensed land use data with data aggregation, we are confident that non-classical measurement errors do not significantly impact our analysis. Nonetheless, we present robustness checks using land use data from 1996, 2006, and 2017 Brazilian Agricultural Censuses, as provided by the Brazilian Institute of Geography and Statistics.

Fig. 1 shows the land use dynamics in Brazil from 1996 to 2017. In Fig. 1(a) we observe a substantial decline in forested areas, particularly until 2005. During this initial period, the primary driver of forest loss was the expansion of pastureland, as illustrated in Fig. 1(b) – please note the different scales across the figures. From 2005 onwards, deforestation rates began to slow down as the government implemented a series of conservation policies aimed at addressing deforestation in the Amazon region (e.g., Assunção et al., 2015; Burgess et al., 2019), curtailing the growth of pastureland. However, Fig. 1(c) shows that the areas designated for crop cultivation exhibited a steady increase from 1995, with a notable inflection point in the early 2000s when cropland expansion accelerated.

Fig. 2 presents maps illustrating the changes in land use across municipalities from 2000 to 2017. Fig. 2(a) specifically highlights the loss of forest cover, representing deforestation. Notably, the municipalities in the western part of the Amazon and the Cerrado biome (characterized by savannah-type vegetation in the central region of Brazil) experienced the largest deforestation during this period. Fig. 2(b) shows a considerable overlap between the municipalities with the highest rates of deforestation and those witnessing substantial expansion of pastureland during the same period. In Fig. 2(c), we observe some areas in the Cerrado biome (at the border of the Amazon) experiencing both a substantial increase in cropland and a decrease in forested areas. Simultaneously, the expansion of cropland in the southern part of the country overlaps with a reduction in pastureland.

2.2. Exposure to new agricultural technologies

One of the main drivers behind the expansion of crop production in Brazil in recent decades has been the introduction of genetically engineered (GE) soybean seeds. These GE soy seeds possess enhanced herbicide resistance compared to their traditional counterparts. With GE seeds, farmers can minimize soil preparation efforts, as they can directly apply herbicides to the soil to eliminate weeds without harming the soy plants. This saves time and labor, increasing potential yields. Importantly, GE seeds have enabled soy production in warmer regions that were previously unsuitable for traditional soy seeds. These GE seeds were first introduced in the United States in 1996 and were legalized in Brazil in 2003.[9] The GE seeds marked a large increase

[8] Project MapBiomas - Collection 3.0 of Brazilian Land Cover & Use Map Series, accessed on 01/09/2020 through the link: http://mapbiomas.org.

[9] While the approval of GE soy seeds may have been influenced by political factors that could also impact deforestation, there is no conclusive evidence to support such concerns. Notably, there is evidence of GE seeds being smuggled across the border from Argentina since 2001 (USDA, 2001). This was followed by lobbying from the agricultural sector based on the argument of productivity gains. The primary objections encountered were rooted in health and biodiversity concerns, not the expansion of cropland towards forests. It is worth mentioning that the approval of GE soy seeds in 2003 occurred under the same government that, in the subsequent years, implemented the most stringent environmental policy measures ever witnessed in the country (e.g., Assunção et al., 2015; Burgess et al., 2019).

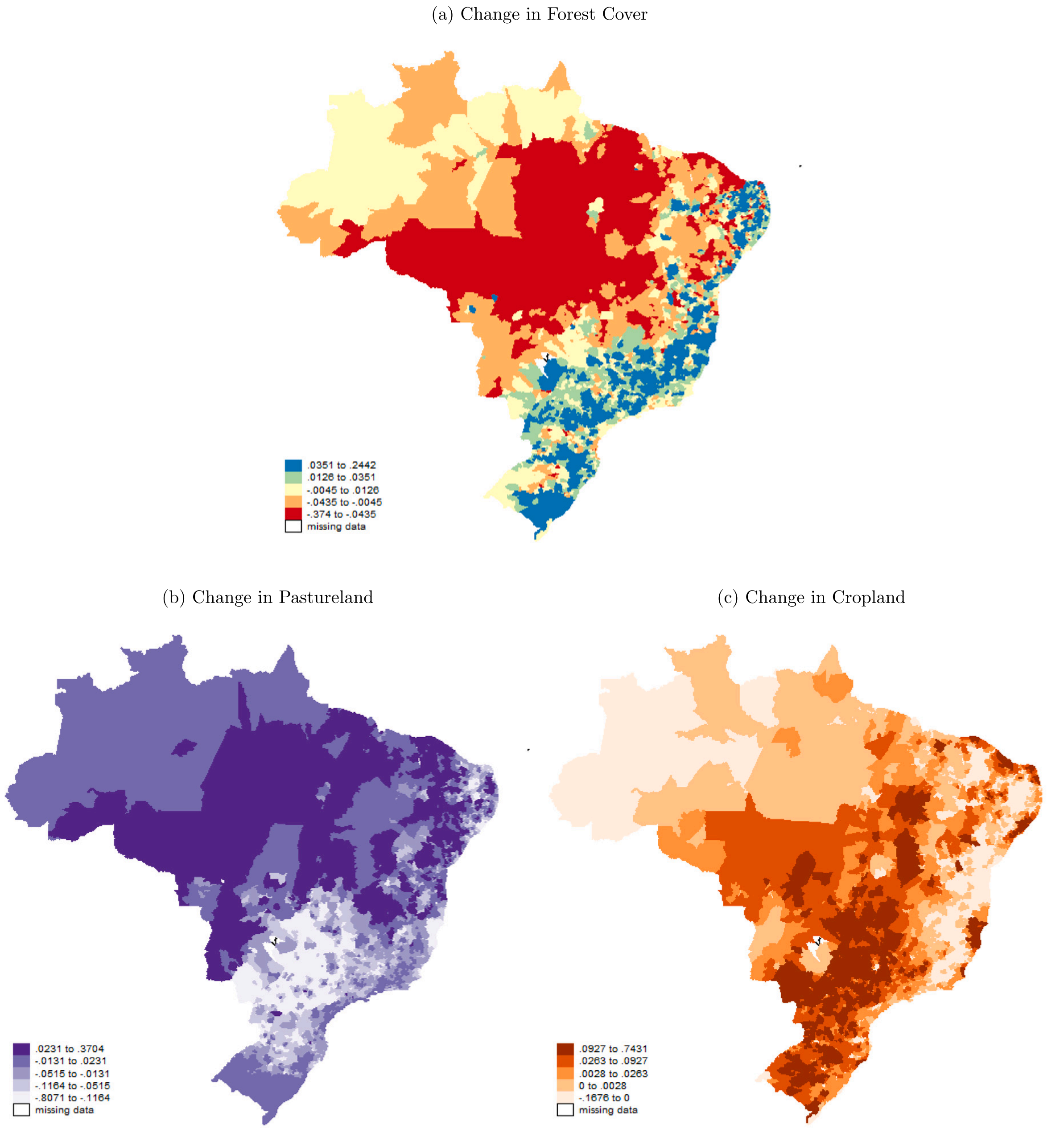

Fig. 2. Maps of land use change 2000–2017. These maps show the land-use change between 2000 and 2017 across municipalities: Panel (a) forest cover; Panel (b) pastureland; and Panel (c) cropland. The legend intervals correspond to the quintiles of the respective variables. The unit of observation is municipalities.

in agricultural productivity in certain regions, leading to profound transformations not only within the agricultural sector but also across the broader economies around the new soy fields. Bustos et al. (2016) show that the technological innovation brought about by these new soy seeds has initiated a process of structural change and capital accumulation (Bustos et al., 2020).

To measure the local exposure to the increased agricultural productivity resulting from the adoption of GE soy seeds, we adopt the approach of Bustos et al. (2016). We use data on potential soy yields from the Food and Agriculture Organization's project Global-Agroecological Zones (FAO-GAEZ). This data computes the maximum potential yields per field based on weather conditions and soil characteristics, taking into account various combinations of agricultural inputs. We compute the agricultural productivity gain brought by GE soy seeds by calculating the difference between two measures of potential soy yields. The first measure, referred to as low input potential yields, reflects traditional production methods with minimal reliance on modern inputs like fertilizers and herbicides. The second measure, known as high input potential yields, factors in the utilization of modern inputs, including GE seeds and fertilizers. To gauge the local exposure to productivity gains resulting from the adoption of GE soy seeds in each municipality i, denoted as A_i, we compute the difference in potential yields between the high and low input scenarios. This differential is aggregated at the municipality level and divided by 100 for ease of interpretation.[10]

Fig. 3(a) illustrates the potential agricultural productivity gains resulting from the adoption of GE soy seeds across municipalities (refer to Table 1, Panel B for summary statistics). Regions in the Midwest and the South of Brazil stand out as the primary beneficiaries of GE soy seeds. These are the regions where we observe the most substantial expansion of cropland (Fig. 2(c)) as well as the most significant reduction in

[10] We use rain-fed potential yield since irrigation is not commonly used in soy plantations in Brazil.

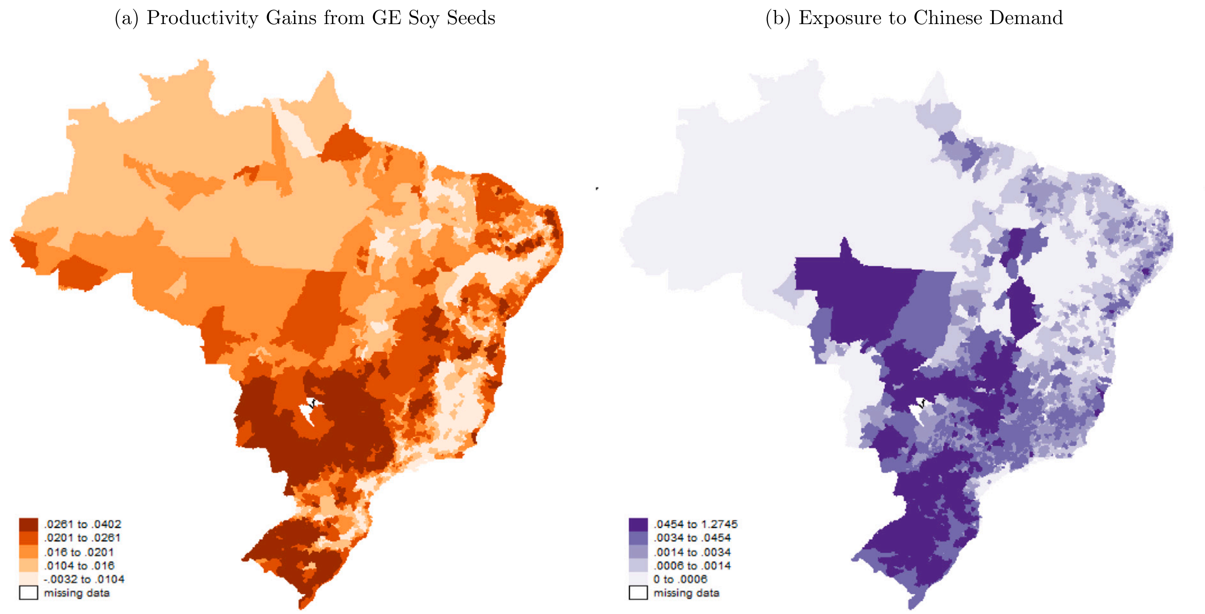

Fig. 3. Maps of exposure to agriculture technology and trade shocks. These maps show the two treatment variables employed in this study across municipalities. Panel (a) plots the local exposure to the potential productivity gains associated with GE soy seeds, as described in Section 2.2. Panel (b) plots the local exposure to increased Chinese demand between 2000 and 2017, as described in Section 2.3. The legend intervals correspond to the quintiles of the respective variables.

Table 1
Descriptive statistics.

	Mean (1)	Std. Dev. (2)	Min (3)	25th Pctl. (4)	75th Pctl. (5)	Max (6)
Panel A. Land use change between 2000 and 2017 (Δy_{it})						
Forest	0.004	0.056	−0.374	−0.018	0.032	0.244
Cropland	0.056	0.098	−0.168	0.000	0.073	0.743
Pasture	−0.065	0.117	−0.807	−0.106	0.001	0.370
Panel B. Local exposure to China and GE soy						
GE soy seeds (A_i)	0.018	0.009	−0.003	0.011	0.025	0.040
Chinese demand ($\hat{X}_i$)	0.067	0.211	0.000	0.001	0.009	1.273
Interaction ($A_i \times \hat{X}_i$)	0.002	0.006	−0.000	0.000	0.000	0.047
Panel C. Controls (W_i)						
Income per capital	10.981	0.468	9.462	10.607	11.333	13.127
Literacy rate	0.657	0.175	0.131	0.494	0.804	0.965
Population density	−1.315	1.300	−7.012	−1.983	−0.663	4.795
Rural population share	0.452	0.227	0.000	0.269	0.637	0.978
Panel D. Land use change in neighboring municipalities (spillovers)						
Forest (N = 9)	−0.006	0.463	−27.652	−0.006	0.025	0.771
Cropland (N = 9)	0.059	0.161	−0.036	0.001	0.065	6.887
Pasture (N = 9)	−0.059	0.458	−2.916	−0.096	−0.000	26.422

This table presents summary statistics of the variables described in Section 2. Panel A shows statistics of land-use variables described in Section 2.1. Panel B presents statistics of the variables of interest discussed in Sections 2.2 and 2.3. Panel C displays statistics regarding control variables derived from the 1991 Demographic Census. Panel D presents statistics concerning the spillover variables utilized in Section 4.4. The unit of observation is municipalities. Number of observations: 3818.

pastureland (Fig. 2(b)). Additionally, we notice a pronounced increase in cropland in municipalities with high deforestation rates within the Cerrado biome (Fig. 2(a)).

2.3. Exposure to Chinese demand

Another large economic event that had a profound influence on the Brazilian agriculture sector was China's emergence in the global market. After a decade of remarkable internal growth, China's accession to the World Trade Organization in 2001 brought new dynamics to international trade (Autor et al., 2013). For developing countries, and Brazil in particular, China rapidly evolved into a major exporter of manufactured goods and importer of commodities (Costa et al., 2016). This shift in trade patterns led to a commodity boom, with a high demand for goods like soybeans, among others.

Combined, the new GE soy seeds and the growing demand from China created a perfect storm in the Brazilian agriculture sector. As a result, Brazil emerged as the world's leading exporter of soybeans, with China becoming the primary destination for Brazilian soybean production. Brazilian soybean exports to China saw a remarkable increase of over \$17 billion between 2000 and 2017. As indicated in Table A1, Brazilian exports of various other commodities to China also experienced significant growth during this period.

Measuring how municipalities are affected by the increasing Chinese demand is a complex task. This difficulty arises for a couple of reasons. First, we lack direct observation of where the products exported to China were originally produced within Brazil. Second, even if we had this information, bilateral trade flows can be influenced by many local factors beyond Chinese demand itself. For example, the adoption of GE soy seed could have led to the expansion of soy production across Brazil irrespective of China's ascension. Thus, our main empirical challenge is to isolate the effects of the growth of Chinese demand on agricultural production across municipalities, net of the influence of other local factors. We construct a shift-share measure of local exposure to the growth in Chinese demand in a two-step process.

Shift. First, we use the BACI-CEPII bilateral trade data to isolate China-product-specific demand growth between 2000 and 2017. To achieve this, we match BACI-CEPII's Harmonized System product classification with agricultural products reported in the 1996 Agricultural Census using the concordance provided by Concla-IBGE.[11] Since the concordance links raw agricultural products to their trade codes, we incorporate the direct requirements coefficients from IBGE's Brazilian input–output table to account for changes in the demand for processed goods, as shown in Appendix Table A2. This approach enables us to measure China's implicit demand for each raw agricultural product.[12] A comprehensive description of these concordances is available in Appendix A1.

In total, we have identified 54 distinct categories of Brazilian agricultural products. Table A1 shows the descriptive statistics for those products traded during our research period, excluding forest products.[13] The table shows that between 1995 and 2017, annual Brazilian exports of cattle to China increased by $476 million, while soybean exports to China witnessed an astounding growth of over $20 billion during the same period.

Utilizing the trade flow data, we remove the influence of world- and Brazil-specific factors in the observed changes in Chinese imports by product. Following the approach in Costa et al. (2016), we run an auxiliary regression for all countries, excluding Brazil, weighted by the initial import values:

$$I_{cj} = \gamma_j + \psi_{China,j} + \upsilon_{cj} \tag{1}$$

where I_{cj} represents the growth rate of country c's imports of product j from all countries other than Brazil between 2000 and 2017; γ_j is the product fixed effect, capturing the world average growth of imports for product j, excluding those from Brazil; $\psi_{China,j}$ are China-product-specific dummy variables that capture the differences in the growth rate of China's imports for product j compared to the rest of the world (excluding Brazil); and υ_{ij} is the error term. As a result, the estimated values $\hat{\psi}_{China,j}$ (shown in Table A1) represent the predicted China-specific import growth rates for product j between 2000 and 2017.

Share. Second, we construct the local exposure to China-induced export demand using the following equation:

$$\hat{X}_i = \frac{1}{100 L_i} \sum_{j=1}^{54} S_{ij}\, X_j\, \hat{\psi}_{China,j} \tag{2}$$

where L_i is the agricultural and forest land area in municipality i in 1995, which is the combined area of cropland, pastureland, and forest; S_{ij} is the share of Brazilian production of product j that was produced in municipality i in 1995; X_j is the Brazilian exports of product j to China in the year 2000; and $\hat{\psi}_{China,j}$ are the estimates of $\psi_{China,j}$ obtained from Eq. (1). In simple terms, this equation distributes the growth in China-induced demand for product j ($X_j\, \hat{\psi}_{China,j}$) across municipalities i based on the share of each municipality in that product's production during the baseline year (S_{ij}) normalized by the municipality's area (L_i). The division by 100 serves solely to facilitate visualizing the regression coefficients. To avoid results being driven by outliers, we winsorize $\hat{X}_i$ at the 1st and 99th percentiles.[14]

Fig. 3(b) displays a map illustrating the local exposure to Chinese demand, calculated based on Eq. (2). It shows that municipalities located in the South, Midwest, and the Cerrado biome regions were among the most exposed to the growth in export demand driven by China. Table 1 Panel B presents the summary statistics of $\hat{X}_i$.

3. Empirical methods

We aim to untangle the impacts of agricultural productivity shocks and increased Chinese demand on land use across Brazilian municipalities. Our approach involves estimating the effects of municipal exposure to two key factors: the introduction of new GE soy seeds (A_i, discussed in Section 2.2) and the rise in Chinese demand ($\hat{X}_i$, discussed in Section 2.3).

Our identification strategy hinges on the fact that these two shocks are not highly correlated. Otherwise, we would not have the variation needed to distinguish their relative contributions to land use. Fortunately, the correlation between A_i and $\hat{X}_i$ is positive but relatively low (0.33). For instance, among the municipalities in the top decile of exposure to either shock, only 27% are heavily affected by both. This means that most municipalities strongly exposed to the soy technological shock are not the same ones strongly exposed to Chinese demand growth, and vice versa. Additionally, there is significant spatial variation in the intensity of exposure to these two shocks, as evident in the maps in Fig. 3 and the scatter graph in Figure A1.

In our main analysis, we utilize a long-difference specification, similar to Autor et al. (2015), Bustos et al. (2016), and Costa et al. (2016). We estimate the following equation:

$$\Delta y_i = \alpha \hat{X}_i + \beta A_i + \delta \hat{X}_i \times A_i + W_i' \gamma + \epsilon_i \tag{3}$$

where Δy_{it} is the change in land use (forest, pastureland, or cropland) in municipality i from 2000 to 2017. By regressing land use changes at the municipality level, we account for any factors specific to each municipality that influence land use. To accommodate differential trends in municipalities with varying initial characteristics, we incorporate a set of controls W_i measured at baseline. These controls include literacy rates, the share of rural populations, population density, and income per capita, all obtained from the 1991 Demographic Census (as in Bustos et al., 2016). Additionally, we control for the share of available land in 1995 from MapBiomas (L_i), and consider potential differential state-specific trends by including state fixed effects. To address potential spatial correlation (Conley, 1999), we adjust the standard errors using a 100 km distance cut-off.[15]

To measure the relative effects over time, we modify Eq. (3) by pooling all years (excluding 2000) and running the following regression:

$$\Delta y_{it} = \sum_{\tau=1995}^{2017} \mathbb{1}\{t=\tau\} \left[\alpha_\tau \hat{X}_i + \beta_\tau A_i + \delta_\tau \hat{X}_i \times A_i \right] + W_i' \gamma_t + \lambda_{st} + \epsilon_{it} \tag{4}$$

where λ_{st} are state-year fixed effects.

Identification Assumptions. The coefficients of interest are β and α, which quantify the relative effects of local exposure to the technology

[11] All values are converted to thousands of 2017 US dollars using the US BEA's GDP price deflator.

[12] We consider products that use raw agricultural products as inputs with direct impacts greater than 0.02. Given that Brazil's input–output structure may have evolved alongside trade flows during this period, we also measure trade flows independently of any input–output table. Appendix Table A1 shows the robustness of our results from this exercise, which remain consistent in terms of both significance and magnitude.

[13] The value of production for each animal is not available in the 1996 Agricultural Census. We imputed the value of cattle production as equal to the value of production of large animals (in 2006, cattle production constituted 99.3% of the production of large animals), and the value of production for swine and poultry was imputed as the difference between the value of animal production and the value of large animals' production (in 2006, swine and poultry accounted for 90.5% of this difference).

[14] Appendix Table A8 shows that the main findings are robust when we do not winsorize $\hat{X}_i$.

[15] Appendix Table A4 presents inference for our results using distance cut-offs ranging from 75 to 300 km.

Table 2
Results of trade and technology shocks on land use change 2000–2017.

	Land use change 2000–2017				PLACEBO	
					1995–2000	1999–2000
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Forest cover						
Chinese demand (α)	−0.009**		−0.002	−0.056*	−0.021	−0.007
	(0.004)		(0.005)	(0.029)	(0.016)	(0.005)
GE soy (β)		−0.718***	−0.705**	−0.745***	0.343	−0.019
		(0.265)	(0.281)	(0.284)	(0.216)	(0.076)
GE soy × Chinese demand (δ)				1.772*	0.458	0.163
				(0.939)	(0.489)	(0.163)
Panel B. Cropland						
Chinese demand (α)	−0.028		−0.068**	0.141**	0.014	0.004
	(0.030)		(0.027)	(0.059)	(0.070)	(0.015)
GE soy (β)		3.623***	4.050***	4.200***	−0.169	−0.045
		(0.651)	(0.713)	(0.719)	(0.144)	(0.032)
GE soy × Chinese demand (δ)				−6.828***	−0.757	−0.214
				(1.559)	(2.175)	(0.478)
Panel C. Pastureland						
Chinese demand (α)	0.040		0.071***	−0.091	0.001	−0.001
	(0.029)		(0.027)	(0.068)	(0.066)	(0.017)
GE soy (β)		−2.742***	−3.188***	−3.305***	−0.268	0.050
		(0.814)	(0.888)	(0.901)	(0.274)	(0.074)
GE soy × Chinese demand (δ)				5.290***	0.487	0.137
				(1.911)	(2.060)	(0.515)

The table shows estimates of the effects of local exposure to Chinese demand (α), GE soy (β), and the interaction between the two shocks (δ) on land-use changes between 2000 and 2017, as described in Eq. (3). There are three panels, each with a different dependent variable: changes in municipalities' forest cover (Panel A), cropland (Panel B), and pastureland (Panel C). Columns 5 and 6 show the results of a placebo pre-trend analysis. All regressions include state fixed effects and control for various factors, such as income per capita, literacy rate, population density, rural population (all in 1991), and available land in 1995. Standard errors adjusted for spatial correlation with a 100 km cut-off (Conley, 1999) in parenthesis. Number of observations: 3823.

and trade shocks, respectively, on annual land-use changes. We are also interested in δ, which captures the effects of the interaction between the two shocks. Under the assumption that differential suitability to the new GE soy seed and differential exposure to China's export demand are uncorrelated with other determinants of land use, the coefficients β, α, and δ hold causal interpretations.

In addition, our measure of local exposure to rising Chinese demand ($\widehat{X}_i$) is a shift-share variable, which requires further scrutiny. Borusyak et al. (2022) establishes a framework where shift-share identification follows from *exogenous shocks* and offers a new method for shift-share inference. In particular, Borusyak et al. (2022) set two conditions for identification: (1) quasi-random shock assignment, and (2) a sufficient number of uncorrelated shocks. In our case, our identification relies on shock exogeneity established by the fixed effects estimates in Eq. (1). Thus, a key concern is whether our 54 product categories provide enough variation to yield consistent estimates. In Appendix Section A2, we provide a detailed discussion of these issues and undertake all analyses and checks recommended by Borusyak et al. (2022) to address this concern. We also consider a related inference procedure as proposed by Adao et al. (2019). Our analysis in Tables A6 to A8 indicates that, in our context, shock exogeneity is a plausible assumption, our effective sample size is relatively large,[16] and our results are robust to different inference procedures.

4. Results

This section presents the results of exposure to GE soy seeds and rising export demand from China on land use changes across municipalities. We first present results based on the long-difference specification – Eq. (3) –, as well as their robustness and potential spillovers. Then, we present results for the dynamic specification – Eq. (4).

[16] The inverse Herfindahl concentration index (HHI) is 40.4 in our setting. Borusyak et al. (2022) show that the exposure-robust standard errors have appropriate coverage for values of inverse HHI larger than 20.

4.1. Untangling GE soy and Chinese demand

Table 2 displays the estimates of the effects of municipal exposure to the GE soy technology and growing demand from China on land-use changes between 2000 and 2017, based on Eq. (3). In Panel A, we examine the effects on changes in forest cover. Columns 1 and 2 present results for each of these shocks separately. Column 1 reveals that municipalities greatly exposed to the rise in export demand from China experienced a relatively faster decline in forest cover, indicating faster deforestation than those less exposed. Similarly, column 2 shows that forest areas have declined more rapidly in municipalities where potential productivity gains from GE soy seeds were greater.

Column 3 presents results considering both shocks together. It shows that when we include exposure to GE soy seeds, the effects of differential exposure to demand from China become closer to zero and lose statistical significance (p-value 0.68). The point estimate of local exposure to GE soy barely changes between columns 2 and 3. This suggests that one would draw different conclusions about the effects of local exposure to export demand on deforestation if analyzing it in isolation or together with the largest agriculture technological shock in that period.

Our estimates in Panel A, column 3, suggest that a municipality at the 75th percentile of exposure to the GE soy technology (A_i = 0.025) lost about 1 [=100×(−0.705)×(0.025–0.011)] percentage point of forest cover more than a municipality at the 25th percentile (A_i = 0.011). To put that into perspective, the municipality of Comodoro in the state of Mato Grosso is close to the 75th percentile of the shock. With an area of approximately 21,520 km^2, our estimates suggest that this single municipality lost about 212.6 km^2 more forest area than a municipality not so exposed to the soy technology shock — the equivalent of over a quarter of the area occupied by New York City.

Table 2 Panels B and C show how changes in crop and pasture land accompanied these effects on forest cover. Again, a comparison between columns 1 and 3 reveals different results for the effects of exposure to Chinese demand when it is considered by itself or together with the GE soy shock. In Column 3, we observe that despite no relative

Table 3
Land use in 2000 in the most exposed municipalities.

	GE soy (A_i) (1)	Chinese demand ($\hat{X}_i$) (2)	Interaction ($A_i \times \hat{X}_i$) (3)
Forest	0.1789	0.2786	0.2626
Pasture	0.5476	0.4264	0.4358
Cropland	0.2015	0.2229	0.2258
Soy	0.0509	0.0676	0.0676
Other temporary crops	0.1504	0.1552	0.1580
Perennial crops	0.0001	0.0001	0.0001

This table presents the average share of forest, pasture, cropland, soy, other temporary crops, and perennial crops area in 2000 for the municipalities at the top quartile of exposure to each measure in the columns. Number of observations: 957 in column 1, and 956 observations in columns 2 and 3.

change in deforestation, municipalities greatly exposed to demand from China experienced some substitution of pasture for cropland. The coefficients estimated for exposure to Chinese demand in Panels B and C have opposite signs and similar magnitudes in absolute terms. The magnitude of this substitution is non-negligible. A municipality at the 75th percentile of exposure to demand from China ($\hat{X}_i = 0.009$) had, on average, 5.7 [=100×0.071×(0.009–0.001)] percentage points more pastureland and 5.4 [=100 ∗ (−0.068) ∗ (0.009 − 0.001)] percentage points less cropland than a municipality at the 25th percentile ($\hat{X}_i = 0.001$). Panels B and C also reveal that the main driver of deforestation in municipalities greatly exposed to GE soy seeds is the expansion of cropland over forest and pasture. In Panel B, Column 3 shows that a municipality at the 75th percentile of the technology shock ($A_i = 0.025$) gained 5.7 [= 100×4.05×(0.025 − 0.011)] percentage point of cropland and lost 4.5 [= 100×(−3.19)×(0.025 − 0.011)] percentage points of pastureland relative a municipality at the 25th percentile.

4.2. Interacting GE soy and Chinese demand

We consider a specification that includes an interaction between the exposures to GE soy seed and Chinese demand. Results in Table 2 column 4 show that adding this interaction does not alter the sign or magnitudes of the coefficients related to GE soy technology. However, we see a meaningful change in the coefficients associated with Chinese demand, with most of them switching signs and gaining statistical significance. The point estimates of the interaction terms suggest that areas extensively exposed to both trade and technology shocks experienced less deforestation and less cropland expansion compared to regions solely affected by GE soy. This points to an attenuation of the deforestation effects of GE soy in regions bearing a heavier exposure to both technological gains and the Chinese demand.

We examine this attenuation further. One possibility is that it could be a mechanical effect if regions initially exposed to both shocks had less forest cover. However, the data does not support this conjecture. Table 3 presents the average land use in 2000 for municipalities at the top quartiles of local exposure to GE soy, Chinese demand, and their interaction. It shows that municipalities greatly exposed to both shocks had more forest cover in 2000 than those primarily exposed to GE soy.

We then decompose the impacts on cropland dividing it into soy, other temporary cash crops, and perennial crops. The results in Table 4 show that regions significantly affected by both shocks did not exhibit a differential statistically significant increase in the share of land allocated to soy production compared to areas unaffected by both high trade and technology shocks.[17] Thus, the attenuation effect on deforestation does not result from reduced soy expansion but rather from a marked decline in the cultivation of other temporary cash crops. Hence, as shown in Table 2 Panels B and C, our results suggest that the lower deforestation rate in municipalities experiencing both shocks occurred at the expense of crops other than soy.

[17] Using agricultural Census data, Bustos et al. (2016) also find an increase in the area of soy production in regions primarily exposed to potential productivity gains.

Although the interaction of both shocks appears to have no discernible effect on the intensive margin of soy-planted area, we must delve into its impacts on the extensive margin. Table 5 shows the effect of both shocks on the change in the probability of planting various crops from 2000 to 2017. Panel A reveals no noteworthy impact on the likelihood of a municipality cultivating any type of crop. However, Panel B shows that exposure to GE seeds increases the probability that a municipality produces soy, with this effect being more pronounced in municipalities exposed to both shocks (although the results here attain significance at the 10% level). Chinese demand seems to reduce the likelihood of soy cultivation in a given municipality, despite increasing the soy-planted area, as demonstrated in Table 4. These findings suggest that GE seeds facilitated soy production in areas that were previously economically unviable, with this effect being more pronounced in areas also exposed to the Chinese demand shocks.

To summarize, municipalities with greater exposure to productivity gains from GE soy seeds experienced increased deforestation compared to areas that did not benefit from the new technology. Conversely, Chinese demand did not appear to have a substantial differential impact on forest cover, but it mitigated the deforestation effects caused by the technology shock. This is because municipalities highly exposed to both shocks underwent a more substantial transition from cultivating other temporary crops to soybeans, alleviating pressure on the primary ecosystem and thereby diminishing the overall impact of GE soy on deforestation.

4.3. Robustness

First, we assess our identification assumptions by investigating whether municipal exposure to GE soy and growing demand from China correlates with pre-treatment land use changes. As shown in Table 2, columns 5 and 6, we find no statistically significant relationship between exposure to GE soy seeds and Chinese demand and land use trends before the year 2000.

We also verify the robustness of our results to different specifications in Table 6. Column 1 presents our baseline results using the same specifications as in Table 2, column 4. To evaluate potential measurement errors arising from the use of remote sensing data, Column 2 displays results when we measure land use change using the Agricultural Census between 1996 and 2017. Column 3 weights regressions by municipality area. Column 4 excludes state-fixed effects, increasing the sample by two observations, as two states (Roraima and Distrito Federal) had fewer than three municipalities and were dropped in the specification with state fixed effects. Column 5 does not include any controls, and columns 6–10 add each control at a time. These exercises demonstrate that the estimates presented in Table 2 remain robust across specifications. The point estimates and statistical significance are relatively stable across the different specifications, with one noteworthy difference. The point estimates of GE soy seed on deforestation are larger when we measure deforestation using the Agricultural Census data (Panel A, column 2). This is likely because the census only measures land use inside private property areas, excluding indigenous land and other protected areas.

Appendix Table A3 presents results when we build local exposure to Chinese demand when we measure trade flows independently of any input–output table, i.e., by considering only direct exports. Results remain unchanged.

As a further test, we assess if our results are robust to alternative inferences. Appendix Table A4 presents inferences using alternative distance cut-offs ranging from 75 to 300 km. Appendix Table A8 reports exposure-robust shock-level standard errors proposed by Borusyak et al. (2022) and the standard errors proposed by Adao et al. (2019), which account for the correlation in the residuals of locations with similar exposure shares. Across all these specifications, the results hold regarding statistical significance. Specifically, greater exposure to the rising Chinese demand has no statistically significant impact on the area of forest cover in municipalities, but it leads to a statistically significant shift from crop cultivation to pastureland.

Table 4
Decomposing cropland results.

	Land use change 2000–2017			
	(1)	(2)	(3)	(4)
Panel A. Soy				
Chinese demand (α)	0.144***		0.135***	0.130**
	(0.021)		(0.021)	(0.066)
GE soy (β)		1.801***	0.951***	0.947***
		(0.406)	(0.254)	(0.254)
GE soy × Chinese demand (δ)				0.153
				(2.155)
Panel B. Other temporary crops				
Chinese demand (α)	−0.173***		−0.200***	−0.005
	(0.029)		(0.028)	(0.077)
GE soy (β)		1.512**	2.772***	2.913***
		(0.748)	(0.688)	(0.685)
GE soy × Chinese demand (δ)				−6.369***
				(2.390)
Panel C. Perennial crops				
Chinese demand (α)	0.001		−0.003	0.016*
	(0.001)		(0.003)	(0.009)
GE soy (β)		0.310	0.327	0.340
		(0.202)	(0.218)	(0.224)
GE soy × Chinese demand (δ)				−0.612*
				(0.323)

The table shows estimates of the effects of local exposure to Chinese demand (α), GE soy (β), and the interaction between the two shocks (δ) on land-use changes between 2000 and 2017, as described in Eq. (3). There are three panels, each with a different dependent variable: changes in municipalities' soy area (Panel A), temporary crops other than soy (Panel B), and perennial crops (Panel C). All regressions include state fixed effects and control for various factors, such as income per capita, literacy rate, population density, rural population (all in 1991), and available land in 1995. Standard errors adjusted for spatial correlation with a 100 km cut-off (Conley, 1999) in parenthesis. Number of observations: 3823.

Table 5
Cropland decomposition results — Extensive margin.

	Land use change 2000–2017			
	(1)	(2)	(3)	(4)
Panel A. Cropland				
Chinese demand (α)	−0.004		0.013	0.014
	(0.011)		(0.018)	(0.046)
GE soy (β)		−1.618	−1.699	−1.698
		(0.999)	(1.081)	(1.091)
GE soy × Chinese demand (δ)				−0.026
				(1.533)
Panel B. Soy				
Chinese demand (α)	−0.183***		−0.216***	−0.429***
	(0.048)		(0.054)	(0.148)
GE soy (β)		2.021	3.382**	3.228**
		(1.628)	(1.576)	(1.621)
GE soy × Chinese demand (δ)				6.968*
				(4.067)
Panel C. Other temporary crops				
Chinese demand (α)	−0.013		0.001	−0.008
	(0.012)		(0.019)	(0.049)
GE soy (β)		−1.451	−1.458	−1.465
		(1.033)	(1.121)	(1.131)
GE soy × Chinese demand (δ)				0.290
				(1.589)
Panel D. Perennial crops				
Chinese demand (α)	−0.033		−0.107	0.229*
	(0.065)		(0.070)	(0.137)
GE soy (β)		6.956***	7.627***	7.870***
		(2.057)	(2.132)	(2.169)
GE soy × Chinese demand (δ)				−10.969**
				(4.353)

The table shows estimates of the effects of local exposure to Chinese demand (α), GE soy (β), and the interaction between the two shocks (δ) on land-use changes between 2000 and 2017, as described in Eq. (3). There are four panels, each with a different dependent variable. We regress changes in the probability of planting: crops in general (Panel A), soy (Panel B), temporary crops other than soy (Panel C), and perennial crops (Panel D). All regressions include state fixed effects and control for various factors, such as income per capita, literacy rate, population density, rural population (all in 1991), and available land in 1995. Standard errors adjusted for spatial correlation with a 100 km cut-off (Conley, 1999) in parenthesis. Number of observations: 3823.

Table 6
Robustness with alternative specifications and dependent variables.

	Land use change 2000–2017									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Forest cover										
Chinese demand (α)	−0.056*	−0.024	−0.150***	−0.065**	−0.052	−0.052	−0.054*	−0.053*	−0.056*	−0.049
	(0.029)	(0.033)	(0.057)	(0.031)	(0.032)	(0.032)	(0.033)	(0.031)	(0.030)	(0.031)
GE soy (β)	−0.745***	−1.133***	−2.538***	−0.744**	−0.717**	−0.693**	−0.749***	−0.718***	−0.680**	−0.742**
	(0.284)	(0.415)	(0.811)	(0.307)	(0.278)	(0.279)	(0.284)	(0.277)	(0.284)	(0.292)
GE soy × Chinese demand (δ)	1.772*	0.862	5.501***	2.193**	1.615	1.622	1.656	1.638*	1.727*	1.534
	(0.939)	(0.964)	(1.953)	(0.999)	(1.010)	(1.000)	(1.026)	(0.994)	(0.965)	(0.983)
Panel B. Cropland										
Chinese demand (α)	0.141**	0.090	0.310***	0.135**	0.165**	0.166**	0.166**	0.155**	0.146**	0.133**
	(0.059)	(0.089)	(0.090)	(0.060)	(0.071)	(0.070)	(0.071)	(0.066)	(0.068)	(0.067)
GE soy (β)	4.200***	4.124***	2.787***	5.524***	4.255***	4.339***	4.285***	4.246***	4.437***	4.481***
	(0.719)	(0.717)	(0.468)	(0.982)	(0.805)	(0.817)	(0.816)	(0.736)	(0.839)	(0.833)
GE soy × Chinese demand (δ)	−6.828***	−3.440	−9.130***	−6.392***	−7.345***	−7.321***	−7.384***	−7.080***	−6.797***	−6.616***
	(1.559)	(2.746)	(2.915)	(1.756)	(1.912)	(1.895)	(1.906)	(1.788)	(1.815)	(1.705)
Panel C. Pastureland										
Chinese demand (α)	−0.091	−0.023	−0.138*	−0.063	−0.134*	−0.134*	−0.128	−0.128*	−0.127*	−0.099
	(0.068)	(0.082)	(0.080)	(0.059)	(0.079)	(0.078)	(0.080)	(0.076)	(0.076)	(0.071)
GE soy (β)	−3.305***	−3.249***	−0.126	−4.630***	−3.320***	−3.371***	−3.219***	−3.315***	−3.382***	−3.569***
	(0.901)	(0.716)	(1.150)	(1.135)	(0.943)	(0.961)	(0.970)	(0.908)	(0.991)	(0.979)
GE soy × Chinese demand (δ)	5.290***	1.991	2.979	4.253**	6.322***	6.307***	6.189***	6.171***	6.136***	5.516***
	(1.911)	(2.632)	(2.908)	(1.836)	(2.252)	(2.237)	(2.285)	(2.180)	(2.144)	(1.978)
Data	Mapbio	Census	Mapbio	Mapbio	Mapbio	Mapbio	Mapbio	Mapbio	Mapbio	Mapbio
State FE	Yes	Yes	Yes		Yes	Yes	Yes	Yes	Yes	Yes
Income p.c$_{91}$	Yes	Yes	Yes	Yes		Yes				
Literacy rate$_{91}$	Yes	Yes	Yes	Yes			Yes			
Population density$_{91}$	Yes	Yes	Yes	Yes				Yes		
Rural population$_{91}$	Yes	Yes	Yes	Yes					Yes	
Available Land$_{95}$	Yes	Yes	Yes	Yes						Yes
Weighted			Yes							

The table shows alternative specifications for the estimates of the effects of local exposure to Chinese demand (α), GE soy (β), and the interaction between the two shocks (δ) on land-use changes between 2000 and 2017, as described in Eq. (3). See description in Section 4.3. Standard errors adjusted for spatial correlation with a 100 km cut-off (Conley, 1999) in parenthesis. Number of observations: 3761 (column 2), 3825 (column 4), and 3823 (remaining columns).

Table 7
Results on the effects of trade and technology shocks — Spillovers.

	Land use change 2000–2017 in the 9 closest municipalities			
	(1)	(2)	(3)	(4)
Panel A. Forest cover				
Chinese demand (α)	−0.013		−0.016	−0.011
	(0.014)		(0.015)	(0.034)
GE soy (β)		0.443	0.524	0.530
		(1.302)	(1.326)	(1.329)
GE soy × Chinese demand (δ)				−0.187
				(1.291)
Panel B. Cropland				
Chinese demand (α)	0.003		0.008	0.191***
	(0.019)		(0.020)	(0.056)
GE soy (β)		−0.713	−0.753	−0.552
		(0.644)	(0.670)	(0.691)
GE soy × Chinese demand (δ)				−6.454***
				(1.894)
Panel C. Pastureland				
Chinese demand (α)	0.007		0.007	−0.170**
	(0.025)		(0.026)	(0.076)
GE soy (β)		0.010	−0.024	−0.219
		(1.391)	(1.428)	(1.443)
GE soy × Chinese demand (δ)				6.247**
				(2.597)

The table shows estimates of the effects of local exposure to Chinese demand (α), GE soy (β), and the interaction between the two shocks (δ) on land-use changes between 2000 and 2017, as described in Eq. (3). There are three panels, each with a different dependent variable: changes in forest cover (Panel A), cropland (Panel B), and pastureland (Panel C) in the nine closest municipalities. Specifications are similar to those in Table 2 with additional controls for neighbors' available land and neighbors' exposure to China and GE soy. Standard errors adjusted for spatial correlation with a 100 km cut-off (Conley, 1999) in parenthesis. Number of observations: 3818.

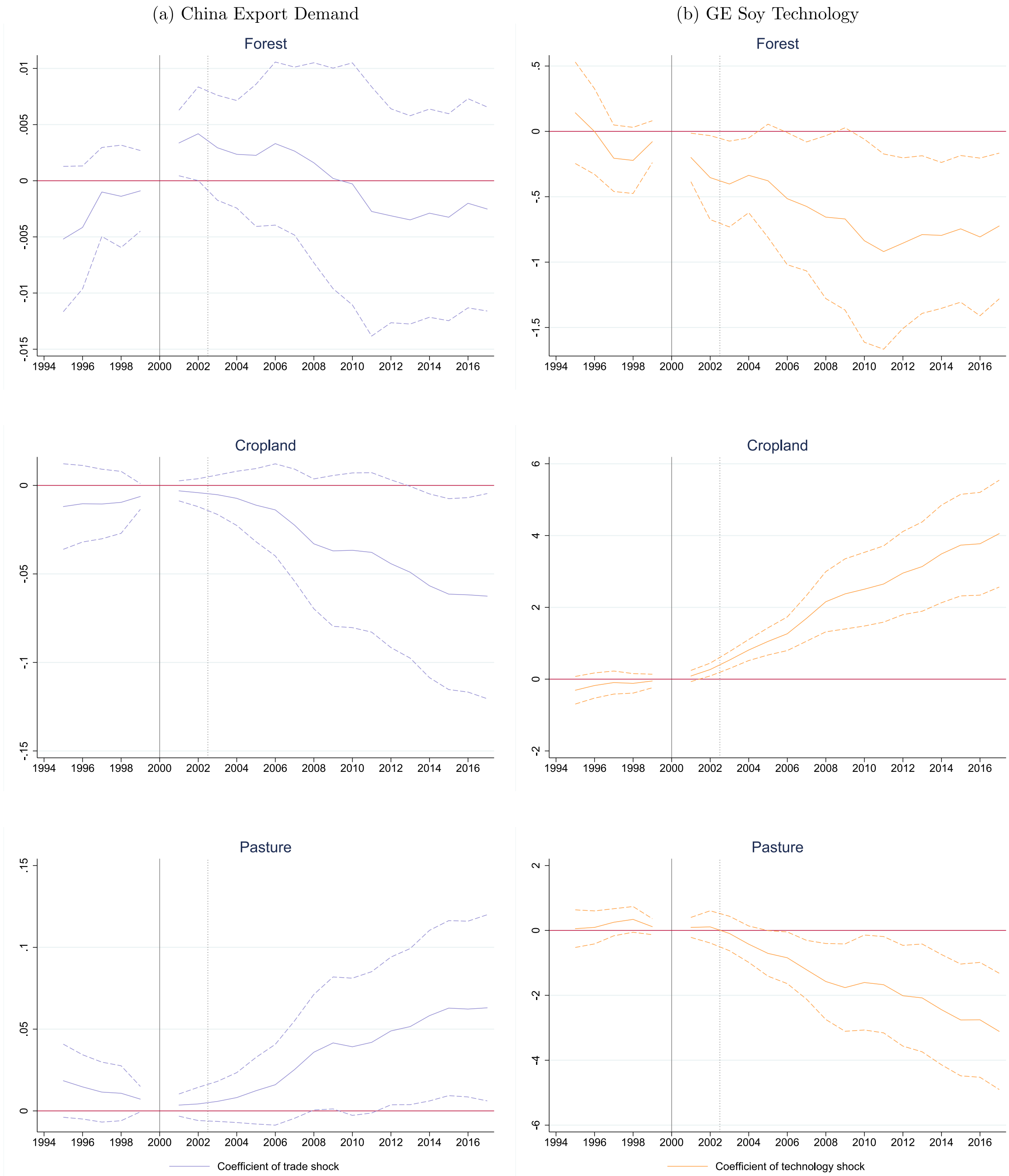

Fig. 4. Dynamic results on the effects of trade and technology shocks. The figures show estimates of the effects of local exposure to Chinese demand (α) and GE soy (β) on land-use changes over time, as described in Eq. (4), removing the interaction term ($\hat{X}_i \times A_i$). Each row presents a different dependent variable: changes in municipalities' forest cover, cropland, and pastureland, respectively. Column (a) presents the coefficients of exposure to Chinese demand (α_t), and column (b) shows the coefficients of exposure to GE soy seeds (β_t). All regressions specifications as in Table 2 column 3. The solid lines plot the point estimates and the dashed lines the 95% confidence interval. Standard errors adjusted for spatial correlation with a 100 km cut-off (Conley, 1999) in parenthesis. Number of observations: 84,106.

4.4. Spillovers

A potential concern about our empirical method is the possibility of spatial spillovers, where local exposure to trade and technology shocks might affect land use in neighboring municipalities (De Sá et al., 2013). To address this concern, we investigate how exposure to these shocks in municipality i influences land use in the N closest municipalities to i.

Table 7 presents the estimates from Eq. (3) using land-use change in the nine closest municipalities to i as the dependent variable (i.e., N = 9).[18] We include controls for the available land in the neighboring areas, as well as the exposure of these neighbors to the trade and technology shocks. The results reveal no robust evidence that trade or technology shocks in one municipality spill over to affect nearby areas. This suggests that our estimates are not significantly influenced by local spillovers.

[18] Appendix Table A5 considers a different number of closest municipalities (N = 3, 6, and 15) or using Census data, also producing statistically insignificant results.

4.5. Dynamic effects

Finally, we pool data from all years to examine the year-by-year changes in land use over the 17 years studied in the previous section. Fig. 4 displays the estimates from the pooled regression Eq. (4), removing the interaction term ($\widehat{X}_i \times A_i$). Column (a) presents the coefficients of exposure to Chinese demand (α_t), and column (b) shows the coefficients of exposure to GE soy seeds (β_t). Appendix Figure A2 provides the dynamic coefficients of the regression with the interaction term (δ_t). Solid lines represent point estimates, while dashed lines indicate the 95% confidence intervals. Each row displays the estimates for a different dependent variable: changes in municipalities' forest cover, cropland, and pastureland. Please note the different scales across the panels.

The results in Fig. 4 column (a), row 1, indicate that the relative effects of exposure to Chinese demand on deforestation are consistently close to zero and noisy throughout the entire period. The results in rows 2 and 3 reveal that the conversion of cropland to pastureland gained momentum only after 2006.

In Fig. 4 column (b), row 1, we find evidence that forest areas declined more rapidly in municipalities with higher potential productivity gains from GE soy seeds, with an apparent inflection point after 2003. This is consistent with the timing of the legalization of the use of these seeds in Brazil. The effects on deforestation reached a plateau around 2011 and became more precise over time. The results in rows 2 and 3 exhibit a different dynamic, with the effects on faster conversion of pastureland to cropland continuing to grow until the end of our study period. This suggests a sustained expansion of cropland, initially at the expense of forests and subsequently at the expense of pastureland, in municipalities with significant exposure to GE soy seeds.

5. Conclusion

We estimate the impacts of new agriculture technology and increased demand from China on deforestation and land use across Brazilian municipalities between 2000 and 2017. Local exposure to the agriculture technological shock is measured based on the productivity gains from new genetically engineered (GE) soy seeds introduced in Brazil in 2003. Local exposure to increased exports to China is measured using a shift-share strategy based on the growth of China-product-specific demand. We estimate the distinct effects of local exposure to these shocks and their interaction using remote-sensing data on land use from MapBiomas.

In the Brazilian context, where the technology shock primarily benefited large-scale farmers with low capital constraints, we find support for the Jevons Paradox. Municipalities with greater suitability to new GE soy seeds experienced faster deforestation driven by the expansion of cropland. In contrast, we find no robust association between local exposure to Chinese demand and deforestation. This suggests that the main driver of land-use change across Brazil was productivity gains that changed municipalities' comparative advantage in global markets. Even so, deforestation was slower in areas experiencing both high technology and Chinese demand shocks relative to areas affected only by the former. The technology shock seems to have enabled soy cultivation in previously non-commercially viable areas, while areas exposed to both shocks showed substitution of soy for other crops, likely mitigating soy's relative deforestation effects.

It is crucial to emphasize that our findings do not imply that large trade shocks should not concern global conservationists. We focus on a specific episode – the surge in Chinese demand for commodities in recent decades – which may not necessarily extend to more general trade arrangements. Indeed, trade relationships could serve as a means for demanding environmental actions from trade partners to alleviate potential negative externalities (Harstad, 2023). This is evident in Brazil, where trade partners consistently threaten to disrupt commercial flows if environmental protection is not prioritized (Gibbs et al., 2015). Moreover, the evidence presented underscores the necessity for trade models incorporating deforestation, capable of accounting for the general equilibrium effects of agricultural productivity gains on global trade flows and land use (e.g., Farrokhi et al., 2023).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jdeveco.2023.103217.

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