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 in Brazil between 2000 and 2017. Using remote-sensing data, we find that these two phenomena have distinct effects on land use. Greater exposure to new genetically engineered soy seeds is associated with faster deforestation through the expansion of cropland. We find no association between exposure to demand from China and deforestation – although, trade induces less conversion of forest and pastureland to cropland in areas hit by the technology shock. Our results suggest that, when taken together, agriculture productivity gains, and not trade, were the main driver of deforestation and the expansion of the agriculture sector.

JEL codes: F18, O13, Q16, Q17, Q23, Q56.

Keywords: deforestation, trade, agricultural productivity, technology, soy, Brazil.

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1 Introduction

Trade and technology are two of the main forces shaping agricultural markets worldwide. They are key factors in promoting food security and economic development in low- and middle-income countries.[1] Despite the benefits brought by greater trade integration and technological advances, agriculture is also the main driver of the loss of tropical forests and the leading source of greenhouse gas emissions outside developed economies. [2] This is because tropical ecosystems host a large amount of biomass that is released in the form of carbon dioxide in the process of converting natural vegetation into new agricultural land.[3] Thus, it is important to understand the environmental footprint of new agriculture technologies and trade in tropical ecosystems.

Moreover, technology and trade are intertwined, so it is crucial to understand how different are the impacts of the two factors (Autor et al., 2015). For instance, gains in agriculture productivity can change countries' comparative advantage, leading to production specialization and higher trade flows (Eaton and Kortum, 2002). Meanwhile, trade can generate productivity gains by providing access to cheaper inputs and by increasing innovation efforts (Akcigit and Melitz, 2021). Considering these complex relationships, how do new agricultural technologies and trade differentially impact deforestation?

In this paper, we quantify the relative footprint of new agriculture technology and increased trade demand on deforestation and land use in Brazil. In particular, we untangle the effects of new genetically engineered soy seeds (Bustos et al., 2016) and increased demand from China (Costa et al., 2016) on the loss of forest cover and land-use changes between 2000 and 2017 (MapBiomas Project). Our results reveal distinct footprints of these two phenomena. While greater exposure to the new soy technology is associated with faster deforestation through the expansion of cropland, we find no statistically significant or economically meaningful association between exposure to greater demand from China and deforestation.

The impact of increased agricultural productivity on deforestation is theoretically ambiguous (Jayachandran, 2021). On the one hand, greater productivity makes agriculture production more profitable, leading to more entry, and an expansion of the agriculture frontier over the forest (Garcia, 2020). This is known as the "Boserup Hypothesis", a special case of Jevon's Paradox. On the other hand, higher productivity may lead to an intensification of production that, under some factor market constraints, reduces the need for new agricultural land. This is known as "Borlaug Hypothesis". Evidence on the direction of the effects

[1] World Bank (2007); Goldberg and Pavcnik (2004); Barrett (2010); Gollin et al. (2014); Bustos et al. (2016); McArthur and McCord (2017).

[2] IPCC (2007); Curtis et al. (2018); Crippa et al. (2021).

[3] Baccini et al. (2012); Araujo et al. (2020); Balboni et al. (2021).

are mixed. Consistent with the latter hypothesis, Abman and Carney (2020) and Abman et al. (2020) show that agriculture extension programs targeted to small-scale agriculture in Malawi and Uganda reduced deforestation. Szerman et al. (2022) shows that electrification in Brazil between 1960 and 2000 increased agriculture productivity and preserved forest areas. Consistent with the "Boserup Hypothesis", and more aligned with our findings, Hess et al. (2021) shows that community-driven development programs in Gambia increased deforestation, likely through the community's choice to implement agricultural projects.[4]

The environmental effects of trade are also conceptually ambiguous. Grossman and Krueger (1991) shows that the net effects depend on a combination of three main mechanisms: an increase in production scale, a change in the product mix, and the adoption of cleaner and more efficient technologies. All three mechanisms are at play in our setting. Empirically, there is a series of cross-country and correlational studies documenting that trade liberalization is associated with higher deforestation.[5] Using an event study design, Abman and Lundberg (2020) shows that regional trade agreements lead to a subsequent increase in deforestation, especially in tropical regions. Also, a series of papers link increases in international commodity prices with deforestation in Brazil (Assunção et al., 2015; Harding et al., 2021; Da Mata and Dotta, 2021).

Our main contribution is to connect these two strands of the literature to evaluate the relative impact of agriculture productivity and trade on the expansion of agricultural land over forest areas. The key inputs we need to untangle these two channels are quasi-exogenous measures of exposure to agriculture technological innovations and demand from international markets. We measure the local exposure to technological shock as the local productivity gains from new genetically engineered soy seeds introduced in Brazil in 2003 as in Bustos et al. (2016). We measure the local exposure to increased export demand from China using a two-step procedure as in Costa et al. (2016). We first use country-level trade data to run regressions of country imports in the whole world (excluding Brazil) on a set of product and product-China fixed effects. The set of China-specific fixed effects captures the differential change in Chinese demand for that product relative to the rest of the world (excluding Brazil). We distribute this change in product-specific Chinese demand across municipalities in Brazil according to the local production composition in 1995.

Key to our identification, we show that there is variation in differential exposure to the trade and technology shocks across municipalities such that we can study their effects on a single equation as Autor et al. (2015). Our identifying assumption is that conditional on

[4]Related, increasing household income has been shown to increase deforestation in India, Mexico, and Indonesia (Foster and Rosenzweig, 2003; Alix-Garcia et al., 2013; Ferraro and Simorangkir, 2020).

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

controls, differential suitability to the new genetically engineered soy seed and differential exposure to the China-induced export demand are not correlated with other determinants of land use. Reassuringly, we find no strong correlations between the technology and trade shocks with land-use trends in the pre-treatment period between 1996 and 2000.

We contribute to the discussion about the effects of agriculture productivity on deforestation by providing a piece of evidence in favor of the "Boserup Hypothesis". Different from recent papers that find that agriculture productivity gains can promote conservation (Abman and Carney, 2020; Abman et al., 2020; Szerman et al., 2022), we study a setting in which the new agriculture technology favors large-scale agriculture and capital constraints are likely looser. This is a period in which the government devoted large, subsidized credit to large agriculture producers.[6] Furthermore, Bustos et al. (2016) show that the soy boom created a process of local structural transformation with substantial implications for local capital accumulation (Bustos et al., 2020).

We also contribute to the literature on the environmental implications of trade (Copeland et al., 2021; Cherniwchan and Taylor, 2022). We find no evidence that exposure to greater export demand is associated with deforestation when we account for agriculture productivity shocks that may affect local comparative advantage. Differently from the literature, we study a shock in the demand for agricultural goods on deforestation, rather than fluctuations in commodity prices (Harding et al., 2021) or regional trade agreements (Abman and Lundberg, 2020). Other papers have used related shift-share shocks to study the effects of greater trade demand for exports, but with a focus on air pollution and emissions in China and India (Bombardini and Li, 2020; Barrows and Ollivier, 2021). A growing literature embeds environmental externalities in trade models with heterogeneous productivity (Costinot et al., 2016; Shapiro, 2016; Hsiao, 2021; Pellegrina, 2022). In particular, Dominguez-Iino (2021) shows that unilateral environmental tariffs on agriculture imports from Latin America are not effective because of leakage. Our paper provides additional reduced-form evidence on the limited impact of international trade on deforestation.

The remainder of the paper is organized as follows. We describe our measures of land use in Section 2.1. We explain the new soy agriculture technology in Section 2.2, and the local exposure to trade in Section 2.3. Section 2.4 details the empirical method and discusses identifying assumptions. Section 3 presents the main results, a series of robustness, and briefly discusses potential spatial spillover. Section 4 offers concluding comments.

[6] Bulte et al. (2007) argues that subsidies to large farmers are not unique to Brazil, but abound in Latin America. Assunção et al. (2019) shows that credit access is an important mediator of deforestation in the Brazilian Amazon.

2 Measurement and Method

2.1 Land Use in Brazil

Our main measure of land use is yearly remote sensing data from MapBiomas that classifies land use in Brazil based on 30 meters resolution LANDSAT images.[7] We consider four categories of land use: forest (native and secondary vegetation), crop, pasture, and others (the omitted category). We compute the share of each category at the municipality level i between 1996 and 2017. Because new municipalities were created in this period, we use Minimum Comparable Areas (AMCs) to ensure municipality limits are consistent over time (Reis et al., 2008; Ehrl, 2017) – hereinafter, we use municipalities referring to AMCs.[8]

Figure A1 shows the evolution of land use shares in Brazil over time. Figure A1a shows that forested areas decreased sharply until 2005. In this early period, the main responsible for the loss of forest area is the expansion of pastureland – notice the difference in the scale in Figures A1b and A1c. Figure A1b shows that areas destined for crops steadily increased since 1995, there seems to be an inflection point in the early 2000s when cropland starts to expand faster. Starting in 2005, deforestation slows down as the government introduced a series of conservation policies to cope with deforestation in the Amazon region.[9]

Figure 1 shows the map of land-use changes in Brazil between 2000 and 2017. Figure 1a plots the change in forest cover (i.e., deforestation) in this period across municipalities in Brazil. We see that the municipalities in the western part of the Amazon and the Cerrado biome (savannah-type vegetation in the center of Brazil) are among those that lost the largest share of forest cover in the period. While we see an increase in cropland in these areas (Figure 1b), we see a substantial overlap between the municipalities with the highest deforestation and those with the largest expansion of pastureland (Figure 1c) in the period. This seems to be associated with pastureland moving North over time, pushed by the expansion of cropland in the Midwest and the South.

2.2 Exposure to New Agricultural Technologies

One of the most important factors driving the expansion of crop production in Brazil over the last decades is the arrival of genetically engineered (GE) soybean seeds. GE soy seeds are more resistant to herbicides than traditional ones. With GE seeds, farmers need little

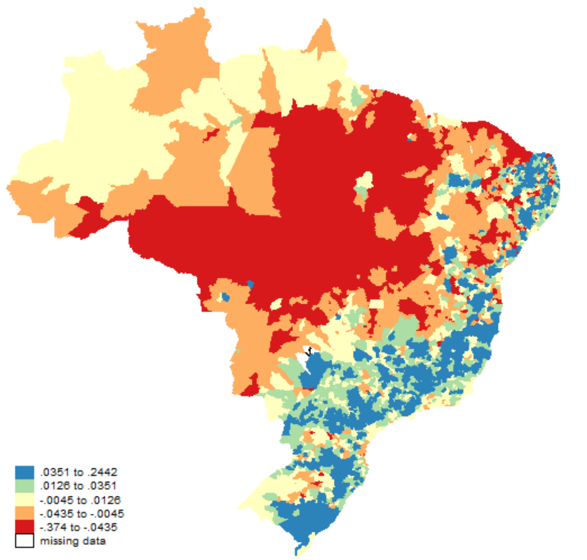
[7]Project MapBiomas - Collection 3.0 of Brazilian Land Cover & Use Map Series, accessed on 01/09/2020 through the link: http://mapbiomas.org.

[8]We also use the 1996, 2006, and 2017 Brazilian Agricultural Census from the Brazilian Institute of Geography and Statistics (IBGE), and the 1991 Demographic Census to build additional controls at the municipality level.

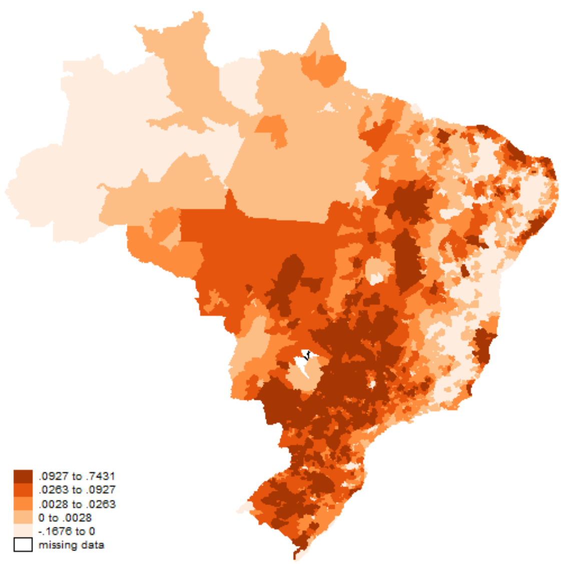
[9]E.g., Assunção et al. (2015, 2019); Alix-Garcia et al. (2018); and Burgess et al. (2019).

Figure 1: Maps of Land Use Change 2000–2017

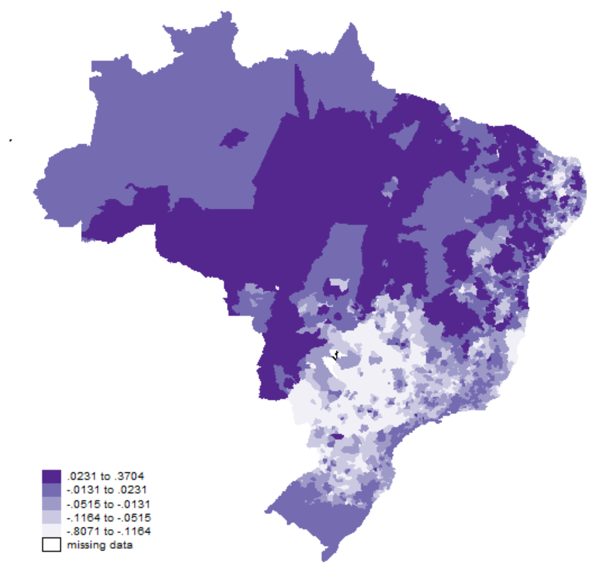
(a) Change in Forest Cover



(b) Change in Cropland



(c) Change in Pastureland



These maps show the land-use change between 2000 and 2017. These are the three main outcome variables in the paper: (a) changes in the share of municipalities with forest cover; (b) changes in the share of pastureland; and (c) changes in the share of cropland. Unit of observations are municipalities (AMCs). The intervals in the legends correspond to the quintiles of the respective variables. Table A1 Panel A presents the summary statistics of these variables.

soil preparation to separate harmful weeds from soy seeds because they can apply herbicides directly to the soil, killing unwanted weeds without harming the soy plants. This saves time and labor, increasing potential yields. Importantly, the new technology allowed the expansion of soy production to areas that were not commercially viable using traditional soy seeds. GE seeds were first commercialized in the United States in 1996, but the Brazilian government approved the use of GE soybean seeds in the country only in 2003.[10] This represented a major increase in agricultural productivity in some regions inflicting profound changes not only in the agriculture sector but in the whole economies around the new soy fields. Bustos et al. (2016) show that the technology shock of the new soy seed had triggered a process of structural transformation and capital accumulation (Bustos et al., 2020).

To measure the local exposure to the increase in agricultural productivity brought by the GE soy seeds, we follow 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 predicted yields by field based on weather and soil characteristics under different combinations of agriculture inputs. We use the difference between two measures of potential yields for soy to compute the agriculture productivity gain brought by the GE soy seed. The low input potential yields consider traditional production technology with minimal use of modern inputs such as fertilizers and herbicides. The high input potential yields consider the use of modern inputs such as GE seeds and fertilizers. We measure the local exposure to productivity gains from adopting GE soy seeds in municipality i, A_i, as the difference in potential yield in the high and low input scenarios aggregated at the municipality level (divided by 100 to facilitate visualization).[11]

Figure 2a shows the map of local agriculture productivity gains from GE soy seeds (Table A1 Panel B shows summary statistics). The regions in the Midwest and the South of the country particularly benefited from the GE soy seed. These are the areas we observe the largest increase in cropland in Figure 1b, and the largest decline in pastureland in Figure 1c.

2.3 Exposure to International Trade

A second large economic event that had a profound influence on the Brazilian agriculture sector in the last decades is China's emergence in the world market. After a decade of massive internal growth rates, China joined the World Trade Organization in 2001 and changed the dynamics of international trade (Autor et al., 2013). For developing countries in general and Brazil in particular, China rapidly became a major exporter of manufactured goods and an importer of commodities (Costa et al., 2016). This created a commodity boom of goods demanded by China, such as soybeans. The new GE soy seeds and the growing demand

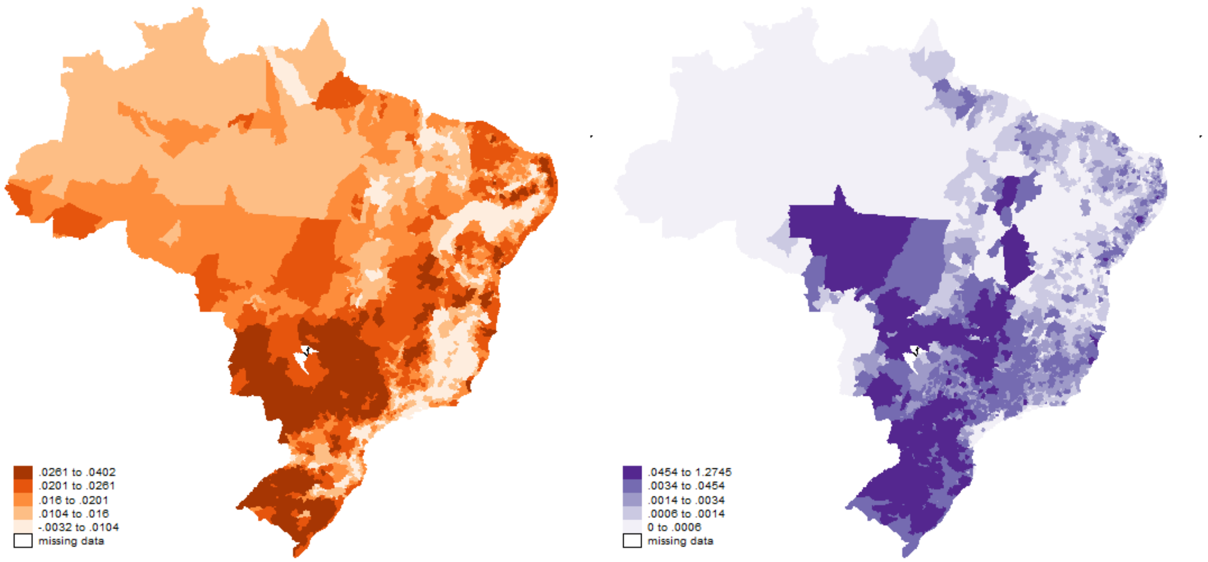
[10] However, there is evidence of smuggling of GE seeds occurred through the Brazilian border with Argentina since 2001 (USDA, 2001).

[11] We use rain-fed potential yield because irrigation is not common in soy plantations in Brazil.

Figure 2: Maps of Exposure to Agriculture Technology and Trade Shocks

(a) Productivity Gains from GE Soy seeds

(b) Exposure to Chinese Demand



These maps plot the two treatment variables used in the paper. Panel (a) plots local exposure to the potential productivity gains from GE soy seeds, described in Section 2.2. Panel (b) plots the local exposure to increased Chinese demand for products between 2000 and 2017, described in Section 2.3. Unit of observations are municipalities (AMCs). The intervals in the legends correspond to the quintiles of the respective variables.

for soybeans were a perfect storm in Brazilian agriculture. Brazil became the leading global exporter of soybeans, with China being the larger destination of Brazilian soy production. Brazilian exports of soybeans to China increased by \$2.8 billion between 1995 and 2006, and by \$17.4 billion between 2006 and 2017 - see Table A2. Brazilian exports of several other commodities and minerals to China also expanded in this period, as shown in the table.

We construct a measure of local exposure to China's growing demand for agricultural commodities in three steps. First, we use the BACI-CEPII international trade database, which provides the annual value of bilateral trade in goods classified at the 6-digit level of the Harmonized System classification from 1995 to 2017.[12] To match the agricultural products reported in the Census with the trade data, we apply the concordance from the *Comissão Nacional de Classificação* (Concla-IBGE). Since this concordance only links raw agricultural products to their trade codes, we use the direct requirements coefficients from IBGE's Brazilian input-output table to account for the changes in the demand for processed

[12] Values are denominated in thousand of current US dollars converted to thousand of 2017 US dollars using the GDP price deflator from the US Bureau of Economic Analysis.

goods.[13] This input-output table indicates the dollar amount of a raw agricultural product necessary to produce one dollar of each industry's output. We multiply the change in Chinese demand for each industry by such dollar amount to measure Chinese implicit demand for each raw agricultural product. We present a detailed description of these concordances in Appendix B. Table A3 presents the direct impact of each industry on specific agricultural products. For instance, a \$1 increase in the Chinese demand for biofuel products results in a \$0.38 increase in the demand for sugarcane and \$0.03 increase in the demand for soy.

Overall, we obtain 54 Brazilian agricultural product categories exported to China since 1995. Table A2 shows the descriptive statistics of these product categories.[14] It shows, for example, that annual Brazilian exports of cattle to China increased by around \$476 million between 1996 and 2017.

We are interested in estimating the effect of exposure to growing demand from China on land use in Brazil. As other internal factors may have influenced Brazilian agriculture production over time, we cannot simply attribute all Brazilian export growth to China. For example, as we discuss in Section 2.2, the GE soy seed could have led to the expansion of soy production in Brazil irrespective of China's ascension. Thus, our main empirical challenge is isolating the effects of the growth of Chinese demand on Brazilian production, net of other Brazil-specific factors.

We address this challenge by constructing a plausibly exogenous measure of exposure to Chinese demand by adapting the method in Costa et al. (2016). We first remove the influence of world- and Brazil-specific shocks in the observed changes in trade between Brazil and China. We do so by running the following auxiliary regression for all countries except Brazil, weighted by the initial import values:

$$\frac{\Delta \widetilde{I}_{ij00/17}}{\widetilde{I}_{ij00}} = \beta_j + \psi_{China,j} + \upsilon_{ij} \tag{1}$$

where $\Delta \widetilde{I}_{ij00/17}/\widetilde{I}_{ij00}$ is the growth rate in imports of product j by country i from all countries other than Brazil between 2000 and 2017; β_j is the product fixed effect that captures the world average growth of *net-of-Brazil* imports of product j; $\psi_{China,j}$ is a China-product specific dummy that captures the deviation of the China import growth rate of product j in

[13]Concla's concordance includes products with minimal use of agricultural commodities as inputs. We only consider products that use raw agriculture products as inputs with direct impacts larger than 0.02.

[14]The value of production for each animal is not available in the 1995 Agricultural Census. We input the value of cattle production as equal to the value of production of large animals (in 2006, cattle production represented 99.3% of the large animals' production), and the value of production of swine and poultry as equal to the difference between the value of animal and large animals production (in 2006, swine and poultry accounted for 90.5% of this difference).

comparison to the one from the rest of the world (β_j); and υ_{ij} is the error term. The estimated $\widehat{\psi}_{China,j}$ captures the predicted change in global exports to China (excluding Brazil) induced by China-specific factors between 2000 and 2017. Table A2 shows the estimates $\widehat{\psi}_{China,j}$.

Our measure of local exposure to China-induced export demand is the following:

$$\widehat{X}_i = \frac{1}{L_{i95}} \sum_{j=1}^{54} \frac{V_{ij95}}{V_{Bj95}} \times \frac{X_{BCj00}\ \widehat{\psi}_{China,j}}{100} \tag{2}$$

where L_{i95} is the agricultural and forest land area (the sum of cropland, pastureland and forest) in municipality i in 1995; V_{ij95} is the value of production of product j in municipality i in Brazil in 1995; V_{Bj95} is the total value of product j produced in Brazil in 1995; X_{BCj00} is the Brazilian exports of product j to China in 2000; and $\widehat{\psi}_{China,j}$ are the estimates of $\psi_{China,j}$ from equation (1). Intuitivelly, we distribute the China-induced demand growth in product j ($X_{BCj00}\ \widehat{\psi}_{China,j}$) across municipalities i according to the share of that product produced in that municipality in the baseline (V_{ij95}/V_{Bj95}) normalized by the municipality area (L_{i95}). As with the technology shock, we divide by 100 to better visualize the regression coefficients. Goldsmith-Pinkham et al. (2020) clarifies that shift-share variables, such as $\widehat{X}_i$, are a weighted average of just-identified estimates considering each product category as an instrument. In our case, our identification relies on shift-exogeneity granted by the fixed effects estimates from equation (1).[15]

Figure 2b plots the map of local exposure to the Chinese demand computed from equation (2). We see that municipalities in the South, the Midwest and the Center of Brazil were among the most exposed to China-induced growth of export demand. Table A1 Panel B shows the summary statistics of $\widehat{X}_i$.

2.4 Empirical Method

We aim to untangle the impacts of exposure to agriculture productivity shocks and increased international demand for commodities on land use in Brazil. To that goal, our empirical strategy consists in estimating the effects of municipal exposure to two plausibly exogenous shocks: exposure to the new GE soy seed A_i (Bustos et al., 2016) and increased demand from China $\widehat{X}_i$ (Costa et al., 2016).

The key to our identification is that these two shocks are not highly colinear, otherwise, we would not have variation in differential exposure to both shocks that would allow us to untangle the distinct contribution of each of them to land use. The correlation between A_i and $\widehat{X}_i$ is positive but low (equal to 0.33). Important for our identification strategy, there is

[15] We cannot apply the method in Borusyak et al. (2022) as we have few product categories.

a considerable spatial variation in the intensity of exposure to the two shocks – see the maps in Figure 2 and the scatter graph in Figure A2. For example, from the set of municipalities on the top decile of most heavily exposed to either of the two shocks, only 27% are heavily affected by both shocks. That is, most of the municipalities more strongly exposed to the soy technological shock are not among the municipalities more strongly exposed to Chinese demand growth, and vice versa. This enables us to untangle the impacts of each of these shocks on land use.

In our main specification, we estimate the following equation for each year t:

$$\Delta y_{it} = \alpha_t \widehat{X}_i + \beta_t A_i + W_i' \gamma_t + \epsilon_{it}, \tag{3}$$

where Δy_{it} is the change in land-use (either forest, pastureland or cropland) in municipality i between 2000 and $t \in \{2001, ...2017\}$, and W_i is a vector of municipal controls measured at baseline. By regressing the change in land use at the municipality level, the model absorbs any municipal-level characteristics that determine land use levels. Additionally, to allow for differential trends for municipalities with different initial characteristics, we include a set of controls W_i as in (Bustos et al., 2016): literacy rate, the share of the rural population, the log of population density, log of income per capita, all in 1991 based on the demographic census. We also control for the share of available land in 1996 from MapBiomas, which is equal to the share of forest, cropland, and pasture combined – this accounts for areas that cannot be used for agriculture, such as urban areas, water sources, and rock formations. We allow for the possibility of differential state-specific trends by including state fixed effects. We adjust the standard errors by taking into account potential spatial correlation (Conley, 1999) with a 100km distance cut-off.

The coefficients of interest are β_t and α_t, which capture the effects of the technology and trade shocks, respectively, on land-use change each year. Under the assumption that, conditional on municipality level fixed effects, state-specific trends, and controls, differential suitability to the new GE soy seed and differential exposure to the China-induced export demand are not correlated with other determinants of land use, the coefficients β_t and α_t hold causal interpretation.

3 Results

We study the land-use implications of exposure to the new genetically engineered soy seed (an agriculture technological shock) and export demand from China. Figure 3 shows the estimates of equation (3). The solid lines in column (a) show the coefficients of the trade shock (α_t) and the solid lines in column (b) show the coefficients of the technology shock (β_t). The dashed lines show the 95% confidence intervals. Each row presents the estimates of a different dependent variable: changes in municipalities' area with forest cover, and changes in areas used for crop and pasture, respectively.

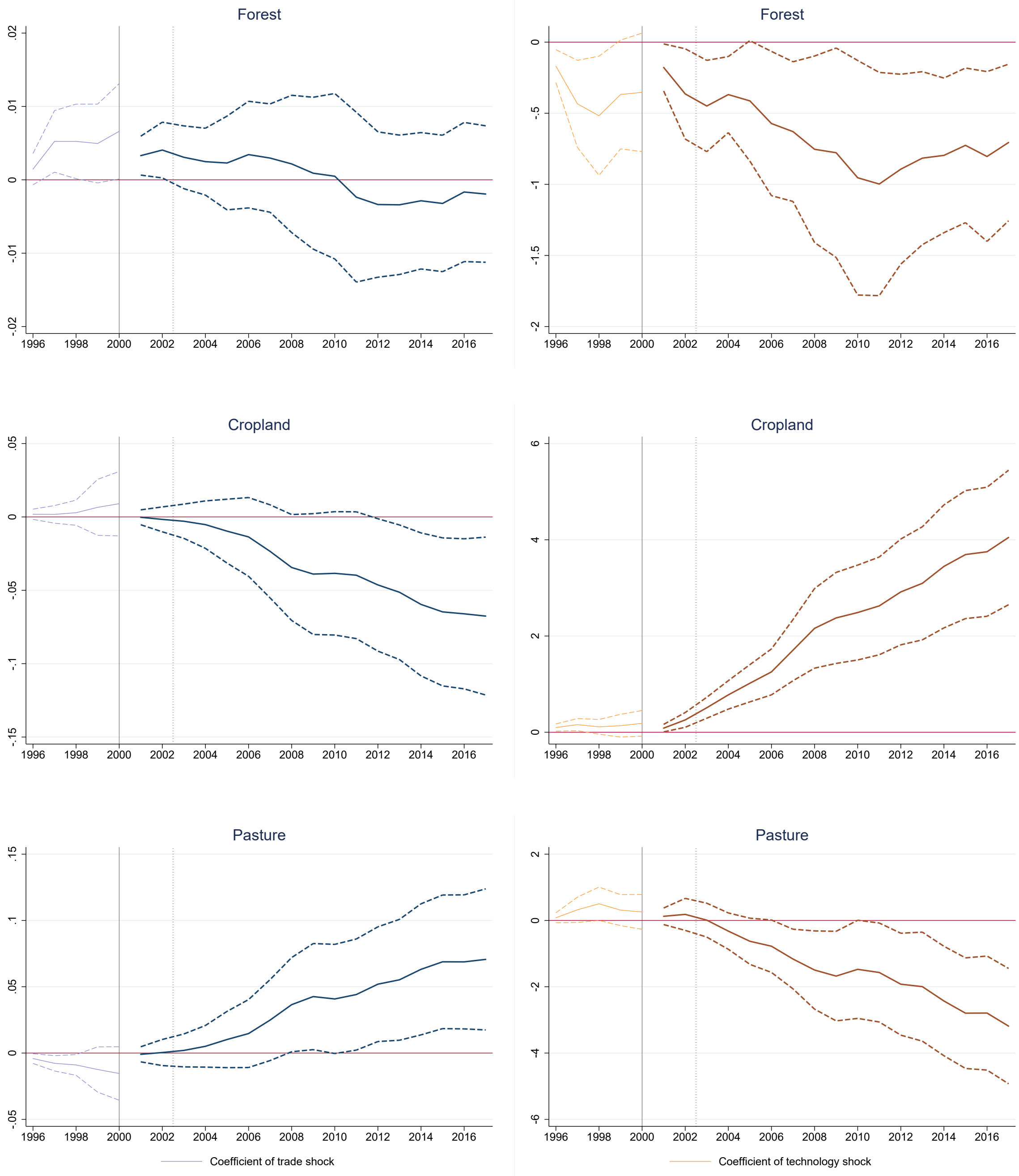
Our main exercises focus on land-use changes after 2000. To help assess our identification assumption, we investigate whether exposure to technology and trade shocks correlates with pre-treatment land use between 1995 and 2000. In this exercise, we regress changes in land use between year t and 1995 on the two shocks (and controls) – that is, we estimate equation 3 considering changes in the left-hand-side variables in the pre-period of analysis. Looking at the period from 1996 to 2000, in row 1, we observe noisy correlations between these shocks and deforestation, estimates are not statistically different from zero at 5% significance. Importantly, in rows 2 and 3 we find no differential pre-treatment effects of the technology and the trade shocks on the expansion of cropland and pastureland.Thus, reassuringly, we find no strong correlations between the technology and trade shocks with land-use trends in the pre-treatment period.

What are the effects of exposure to the rise in Chinese demand for land use? Figure 3 column (a) shows the results. In row 1, we see that exposure to the rise in export demand is not associated with changes in the share of municipalities' area with forests after 2000. The point estimates are positive until 2010 and negative afterward but are all statistically insignificant. We find, however, that exposure to Chinese demand leads to some substitution of pasture for crops. Results in column (a) rows 2 and 3 show a negative and a positive association between export demand and share of cropland and pastureland, respectively, with similar magnitudes in absolute terms. The magnitude of this substitution is non-negligible. By 2017, a municipality at the 75^{th} percentile of exposure to the trade shock ($\widehat{X}_i = 0.009$, see in Table A1) 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 25^{th} percentile ($\widehat{X}_i = 0.001$).

What are the effects of exposure to the soy technology shock on land use? Figure 3 column (b) row 1 provides evidence that areas of forest have declined more rapidly in municipalities where potential productivity gains from GE soy seed have increased more strongly. All the point estimates are negative, and most of them are statistically significant at the 5% level. Our estimates suggest that, by 2017, a municipality at the 75^{th} percentile of the technology shock ($A_i = 0.025$) lost about 1 [= 100×(-0.706)×(0.025 - 0.011)] percentage point of forest more than a municipality at the 25^{th} percentile ($A_i = 0.011$). To put that into perspective, the municipality of Comodoro in the state of Mato Grosso is close to the 75^{th} percentile of the shock. With an area of approximately 21,520 km^2, our estimates suggest that this single

Figure 3: Results on the Effects of Trade and Technology Shocks

(a) China Export Demand (b) GE Soy Technology



The figures show the estimates of the effects of the trade shock (α_t) and technology shock (β_t) from equation (3) on land-use change over time. Each row presents a different dependent variable: changes in municipalities' forest cover area, changes in areas used for crops, and pasture, respectively. The solid lines plot the point estimates and the dashed lines the 95% confidence (using Conley, 1999, standard errors). We plot pre shocks (1996-2000) and post shocks (2001-2017) regressions. The points to the right of the solid vertical line consider post trade shock regressions (2001 onwards), while points to the right of the dashed vertical line consider post trade and technology shocks regressions (2003 onwards). All regressions include state fixed effects and the following controls: income per capita, literacy rate, population density, and rural population all in 1991, and available land in 1995. N=3,823.

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.

The estimates in Figure 3 column (b) rows 2 and 3 show that the main driver of deforestation is the expansion of cropland over forest and pasture. Row 2 shows that, by 2017, a municipality at the 75^{th} 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)] pastureland relative a municipality at the 25^{th} percentile.

Robustness We verify the robustness of our results to different specifications. First, Figure A3 shows that our results are robust to applying an inverse hyperbolic sine transformation to our dependent variables.[16] Table 1 presents a series of different specifications. All regressions in the table consider the last year of our analysis – that is, land-use changes between 2000 and 2017. Panels show results using different land use as the dependent variable. Column 1 shows our baseline results using the same specifications from Figure 3. Column 2 uses Agricultural Census data to calculate the dependent variables (instead of MapBiomas). Column 3 weights regressions by the municipality area. Column 4 excludes state fixed effects.[17] Column 5 does not include any regressor apart from state fixed effects, while columns 6-10 consider state fixed effects and add each control one at a time. This table shows that the estimates presented in Figure 3 are robust to most of these specifications. Almost all coefficients remain statistically significant and their magnitudes are relatively stable across the different specifications. The two noteworthy differences are relative to the estimates of the effect of technology on deforestation (Panel A). The point estimates are larger when we use the Agricultural Census data (column 2), likely because it only includes private property areas (e.g., it excludes indigenous land and other protected areas). Point estimates are statistically insignificant when we weigh the regression by municipalities area (column 3).

Interaction We also consider a specification that includes an interaction between the two shocks. The results are presented in Figure 4. We can see that adding the interaction does not change the sign or magnitudes of the coefficients of the technology shock. However, most of the coefficients of the trade shock become statistically insignificant. The interaction coefficients in the last column of the figure suggest that the trade shock alleviated the

[16] More precisely, we take the inverse hyperbolic sine transformation of land use before taking differences over time to construct our new dependent variables. This transformation plays the same role as a logarithmic transformation (before taking time differences). Its main advantage is that it incorporates zeros, which are relevant in our case.

[17] This increases the sample by two observations, as two states (Roraima and Distrito Federal) had fewer than three municipalities and could not be included in the regression with state fixed effects.

Table 1: Robustness Results on the Effects of Trade and Technology Shocks 2000-2017

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Change in share of forest 2000-2017										
Trade Shock (α)	-0.002	0.003	-0.009	0.001	-0.003	-0.003	-0.003	-0.003	-0.003	-0.002
	(0.005)	(0.009)	(0.010)	(0.007)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Technology Shock (β)	-0.706**	-1.114***	-0.505	-0.695**	-0.671**	-0.648**	-0.702**	-0.672**	-0.638**	-0.702**
	(0.281)	(0.409)	(0.363)	(0.305)	(0.275)	(0.275)	(0.281)	(0.273)	(0.281)	(0.288)
Panel B. Change in share of cropland 2000-2017										
Trade Shock (α)	-0.068**	-0.015	0.034	-0.057**	-0.059*	-0.057*	-0.059*	-0.061**	-0.061**	-0.069**
	(0.027)	(0.025)	(0.032)	(0.027)	(0.031)	(0.030)	(0.031)	(0.028)	(0.030)	(0.030)
Technology Shock (β)	4.050***	4.047***	3.431***	5.381***	4.048***	4.133***	4.074***	4.046***	4.271***	4.307***
	(0.713)	(0.710)	(0.479)	(0.982)	(0.797)	(0.810)	(0.809)	(0.731)	(0.834)	(0.827)
Panel C. Change in share of pastureland 2000-2017										
Trade Shock (α)	0.071***	0.038*	-0.024	0.065**	0.059*	0.058*	0.060**	0.060**	0.059**	0.069**
	(0.027)	(0.021)	(0.030)	(0.029)	(0.030)	(0.030)	(0.030)	(0.029)	(0.030)	(0.029)
Technology Shock (β)	-3.188***	-3.204***	-2.763***	-4.535***	-3.142***	-3.193***	-3.042***	-3.141***	-3.232***	-3.424***
	(0.888)	(0.707)	(0.645)	(1.130)	(0.928)	(0.946)	(0.953)	(0.895)	(0.981)	(0.965)
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							

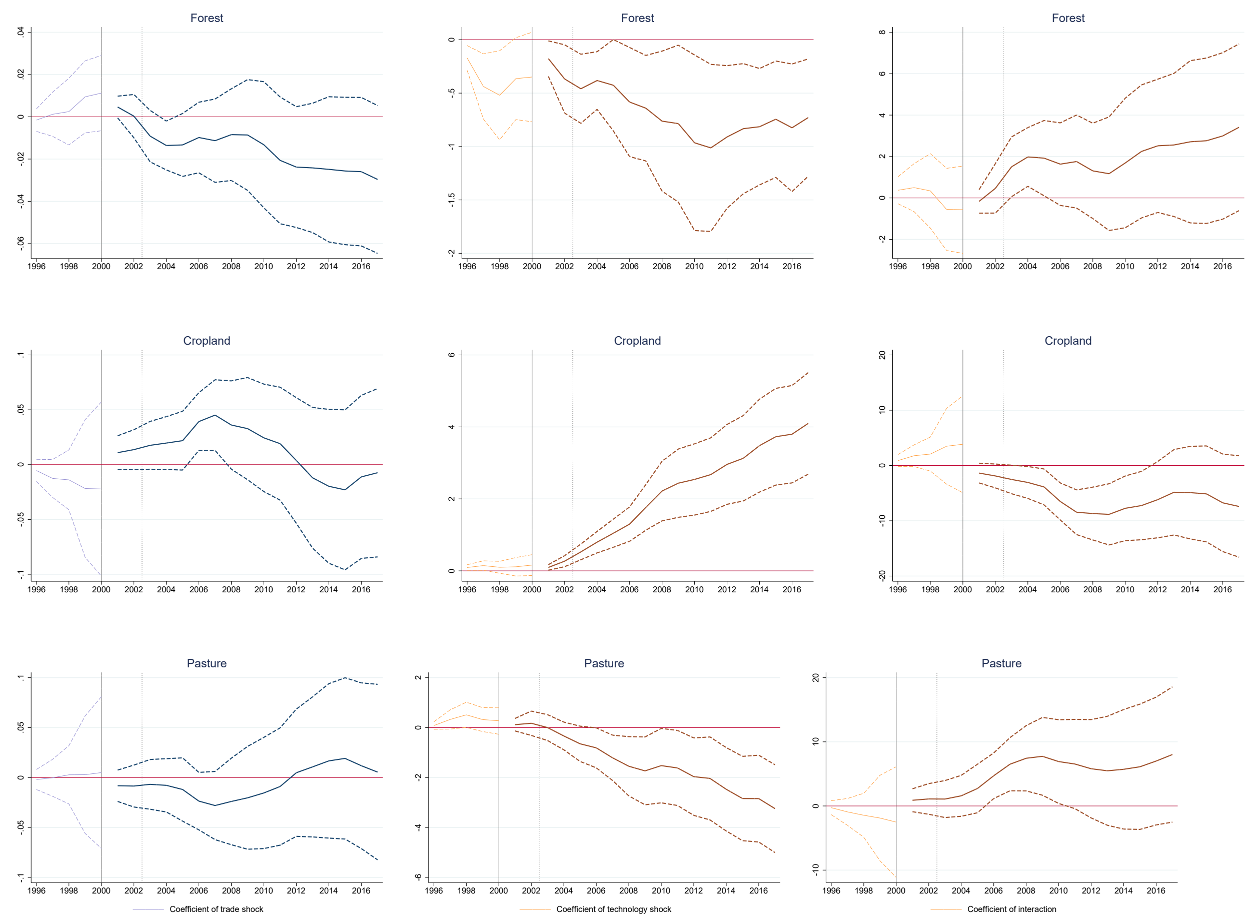
This table presents alternative specifications for the effects of the trade shock (α_t) and technology shock (β_t) from equation (3) on land use changes between 2000 and 2017. See description in the **Robustness** segment in Section 3. Conley (1999) standard error in parenthesis. Number of observations: 3,784 (column 2), and 3,823 (remaining columns).

deforestation effects arising from the technology shock. Although many coefficients are not statistically significant, the point estimates of the interaction terms suggest that areas extensively exposed to both trade and technology shocks experienced less deforestation and less conversion from cropland to pastureland compared to areas that experienced only large technology shocks. One possible explanation is that regions more exposed to trade were already major commodities producers (including soy) even before the technology shock. On the other hand, adopting GE soy seeds likely constituted a more extensive productivity shock in regions that did not grow export-oriented crops, leading to greater crop expansion and deforestation in these regions – the "Boserup Hypothesis".

Spillovers A potential concern about our empirical method is that local exposure to trade and technology shocks could have spatial spillovers and affect land use in the neighboring municipalities (De Sá et al., 2013). We provide some evidence on the effect of these shocks on land use in nearby regions. The first challenge is to determine the reach of such potential spillovers. As an effort in this direction, we study how exposure to the trade and technology shocks in municipality i affects land use in the N closest municipalities to i.

Figure 4: Results on the Effects of Trade and Technology Shocks with an Interaction

(a) China Export Demand (b) GE Soy Technology (c) Interaction



The figures show the estimates of the effects of the trade shock (α_t) and technology shock (β_t) from equation (3) on land-use change over time, as well as of the interaction between the two shocks. Each row presents a different dependent variable: changes in municipalities' forest cover area, changes in areas used for crops, and pasture, respectively. The solid lines plot the point estimates and the dashed lines the 95% confidence (using Conley, 1999, standard errors). We plot pre shocks (1996-2000) and post shocks (2001-2017) regressions. The points to the right of the solid vertical line consider post trade shock regressions (2001 onwards), while points to the right of the dashed vertical line consider post trade and technology shocks regressions (2003 onwards). All regressions include state fixed effects and the following controls: income per capita, literacy rate, population density, and rural population all in 1991, and available land in 1995. N=3,823.

Figure 5 presents the estimates from equation (3) using as dependent variable land-use change in the nine closest municipalities to i (that is, N =9). We control by the neighbors' available land, as well as to neighbor's exposure to the trade and technology shocks. We find no robust evidence that trade or technology shocks to a particular municipality spillover to the nearby areas – all coefficients are statistically indistinguishable from 0 at standard significance values.

Considering an inverse hyperbolic sine transformation does not produce substantially different results - see Figure A4 in the Appendix. Moreover, Table A4 shows that specifications considering a different number of closest municipalities (N = 3, 6, and 15) or using Census data also produce statistically insignificant results. This suggests that our estimates are not entirely driven by local spillovers.

4 Conclusion

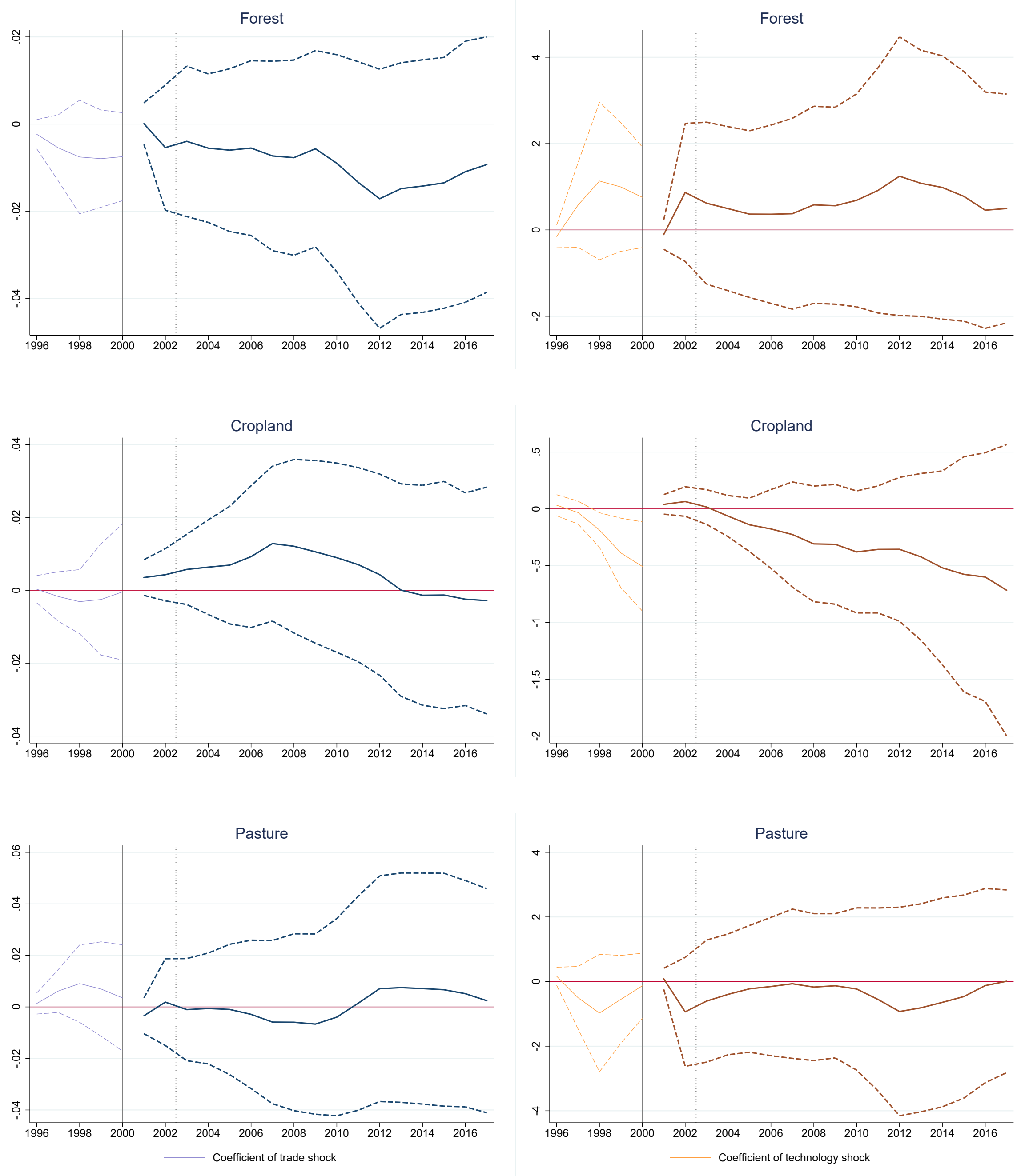
We estimate the impacts of new agriculture technology and greater demand from trade on deforestation and land use in Brazil between 2000 and 2017. We measure local exposure to an agriculture technological shock based on the productivity gains from new genetically engineered soy seeds introduced in Brazil in 2003, and exposure to increased export demand from China using a shift-share strategy based on the growth of China-product-specific demand. We quantify the distinct effects of local exposure to these shocks using remote-sensing data of land use from MapBiomas.

In the Brazilian case, a setting where the technology shock mostly benefitted large-scale farmers with low capital constraints, we find evidence supporting the "Boserup Hypothesis". That is, we find that municipalities with greater suitability to new genetically engineered soy seeds experience a loss of forest cover driven by the expansion of cropland area. In contrast, we find no effect of exposure to demand from China on deforestation. If anything, we find weak evidence that trade reduces the loss of forest cover generated by the technology shock. This suggests that the main driver of land-use change in Brazil was productivity gains that changed the country's comparative advantage in global markets.

It is important to highlight that our findings do not suggest that large trade shocks should not be a source of concern for conservationists around the globe. In fact, trade relationships may be a good way to demand environmental actions from trade partners in order to mitigate the potential negative externalities from those relationships. This may be the case of Brazil, where trade partners constantly threaten to disrupt commercial flows if environmental protection is not taken seriously (Gibbs et al., 2015). Moreover, the evidence provided here show-cases the need for trade models incorporating deforestation that can

Figure 5: Results on Spillovers of Trade and Technology Shocks

(a) China Export Demand (b) GE Soy Technology



The figures show the estimates of the effects of the trade and technology shocks on land-use change spillovers over time. Each row presents the estimates of a different dependent variable: changes in forest cover area, cropland, and pastureland considering the nine closest municipalities. See further description in the **Spillovers** segment in Section 3. The solid lines plot the point estimates and the dashed lines the 95% confidence (using Conley, 1999, standard errors). We plot pre shocks (1996-2000) and post shocks (2001-2017) regressions. The points to the right of the solid vertical line consider post trade shock regressions (2001 onwards), while points to the right of the dashed vertical line consider post trade and technology shocks regressions (2003 onwards). Regressions include all controls from Figure 3 plus controls for neighbors' available land and neighbor's exposure to the trade and technology shocks. N=3,818.

account for general equilibrium effects of agriculture productivity gains on global trade flows and on land-use.

References

Abman, R. and Carney, C. (2020). Agricultural productivity and deforestation: Evidence from input subsidies and ethnic favoritism in malawi. *Journal of Environmental Economics and Management*, 103:102342.

Abman, R., Garg, T., Pan, Y., and Singhal, S. (2020). Agriculture and deforestation. *Available at SSRN 3692682*.

Abman, R. and Lundberg, C. (2020). Does free trade increase deforestation? the effects of regional trade agreements. *Journal of the Association of Environmental and Resource Economists*, 7(1):35–72.

Akcigit, U. and Melitz, M. (2021). International trade and innovation. Working Paper 29611, National Bureau of Economic Research.

Alix-Garcia, J., McIntosh, C., Sims, K. R., and Welch, J. R. (2013). The ecological footprint of poverty alleviation: evidence from mexico's oportunidades program. *Review of Economics and Statistics*, 95(2):417–435.

Alix-Garcia, J., Rausch, L. L., L'Roe, J., Gibbs, H. K., and Munger, J. (2018). Avoided deforestation linked to environmental registration of properties in the brazilian amazon. *Conservation Letters*, 11(3):e12414.

Araujo, R., Costa, F., and Sant'Anna, M. (2020). Efficient forestation in the brazilian amazon: Evidence from a dynamic model. *working paper*.

Assunção, J., Gandour, C., Rocha, R., and Rocha, R. (2019). The effect of rural credit on deforestation: Evidence from the brazilian amazon. *The Economic Journal*, 130(626):290–330.

Assunção, J., Gandour, C. C., and Rocha, R. (2015). Deforestation slowdown in the legal amazon: Prices or policies? *Environment and Development Economics*, 20(6):697–722.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The china syndrome: Local labor market effects of import competition in the united states. *American Economic Review*, 103(6):2121–68.

Autor, D. H., Dorn, D., and Hanson, G. H. (2015). Untangling trade and technology: Evidence from local labour markets. *Economic Journal*, 125(584):621–646.

Baccini, A., Goetz, S. J., Walker, W., Laporte, N. T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P., Dubayah, R., Friedl, M., Samanta, S., and Houghton., R. A. (2012). Estimated carbon dioxide emissions from tropical deforestation improved by carbon-density maps. *Nature Climate Change*.

Balboni, C., Burgess, R., and Olken, B. A. (2021). The origins and control of forest fires in the tropics. *working paper*.

Barbier, E. B. and Rauscher, M. (1994). Trade, tropical deforestation and policy interventions. *Environmental and Resource Economics*, 4(1):75–90.

Barrett, C. B. (2010). Measuring food insecurity. *Science*, 327(5967):825–828.

Barrows, G. and Ollivier, H. (2021). Foreign demand, developing country exports, and co2 emissions: Firm-level evidence from india. *Journal of Development Economics*, 149:102587.

Bombardini, M. and Li, B. (2020). Trade, pollution and mortality in china. *Journal of International Economics*, 125:103321.

Borusyak, K., Hull, P., and Jaravel, X. (2022). Quasi-experimental shift-share research designs. *The Review of Economic Studies*, 89(1):181–213.

Bulte, E. H., Damania, R., and Lopez, R. (2007). On the gains of committing to inefficiency: corruption, deforestation and low land productivity in latin america. *Journal of Environmental Economics and Management*, 54(3):277–295.

Burgess, R., Costa, F., and Olken, B. A. (2019). The brazilian amazon's double reversal of fortune. *SocArXiv*.

Bustos, P., Caprettini, B., and Ponticelli, J. (2016). Agricultural productivity and structural transformation: Evidence from brazil. *American Economic Review*, 106(6):1320–65.

Bustos, P., Garber, G., and Ponticelli, J. (2020). Capital accumulation and structural transformation. *The Quarterly Journal of Economics*, 135(2):1037–1094.

Cherniwchan, J. M. and Taylor, M. S. (2022). International trade and the environment: Three remaining empirical challenges. *NBER Working Paper*.

Conley, T. (1999). Gmm estimation with cross sectional dependence. *Journal of Econometrics*, 92(1):1–45.

Copeland, B. R., Shapiro, J. S., and Taylor, M. S. (2021). Globalization and the environment. *NBER Working Paper*, (w28797).

Costa, F., Garred, J., and Pessoa, J. P. (2016). Winners and losers from a commodities-for-manufactures trade boom. *Journal of International Economics*, 102:50–69.

Costinot, A., Donaldson, D., and Smith, C. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, 124(1):205–248.

Crippa, M., Solazzo, E., Guizzardi, D., Monforti-Ferrario, F., Tubiello, F., and Leip, A. (2021). Food systems are responsible for a third of global anthropogenic ghg emissions. *Nature Food*, 2(3):198–209.

Curtis, P. G., Slay, C. M., Harris, N. L., Tyukavina, A., and Hansen, M. C. (2018). Classifying drivers of global forest loss. *Science*, 361(6407):1108–1111.

Da Mata, D. and Dotta, M. (2021). Commodity booms and the environment. *working paper*.

De Sá, S. A., Palmer, C., and Di Falco, S. (2013). Dynamics of indirect land-use change: empirical evidence from brazil. *Journal of Environmental Economics and Management*, 65(3):377–393.

Dominguez-Iino, T. (2021). Efficiency and redistribution in environmental policy: An equilibrium analysis of agricultural supply chains. Technical report, working paper.

Eaton, J. and Kortum, S. (2002). Technology, geography, and trade. *Econometrica*, 70(5):1741–1779.

Ehrl, P. (2017). Minimum comparable areas for the period 1872-2010: an aggregation of brazilian municipalities. *Estudos Econômicos (São Paulo)*, 47(1):215–229.

Faria, W. R. and Almeida, A. N. (2016). Relationship between openness to trade and deforestation: Empirical evidence from the brazilian amazon. *Ecological Economics*, 121:85–97.

Ferraro, P. J. and Simorangkir, R. (2020). Conditional cash transfers to alleviate poverty also reduced deforestation in indonesia. *Science Advances*, 6(24):eaaz1298.

Ferreira, S. (2004). Deforestation, property rights, and international trade. *Land Economics*, 80(2):174–193.

Foster, A. D. and Rosenzweig, M. R. (2003). Economic growth and the rise of forests. *The Quarterly Journal of Economics*, 118(2):601–637.

Garcia, A. (2020). The environmental impacts of agricultural intensification. Technical Note N.9, Rome: Standing Panel on Impact Assessment.

Gibbs, H. K., Rausch, L., Munger, J., Schelly, I., Morton, D. C., Noojipady, P., Soares-Filho, B., Barreto, P., Micol, L., and Walker, N. F. (2015). Brazil's soy moratorium. *Science*, 347(6220):377–378.

Goldberg, P. K. and Pavcnik, N. (2004). Trade, inequality, and poverty: What do we know? evidence from recent trade liberalization episodes in developing countries. NBER working paper, (w10593).

Goldsmith-Pinkham, P., Sorkin, I., and Swift, H. (2020). Bartik instruments: What, when, why, and how. *American Economic Review*, 110(8):2586–2624.

Gollin, D., Lagakos, D., and Waugh, M. E. (2014). The agricultural productivity gap. *The Quarterly Journal of Economics*, 129(2):939–993.

Grossman, G. M. and Krueger, A. B. (1991). Environmental impacts of a north american free trade agreement. *NBER working paper*, (w3914).

Harding, T., Herzberg, J., and Kuralbayeva, K. (2021). Commodity prices and robust environmental regulation: Evidence from deforestation in brazil. *Journal of Environmental Economics and Management*, 108:102452.

Hess, S., Jaimovich, D., and Schündeln, M. (2021). Environmental effects of development programs: Experimental evidence from west african dryland forests. *Journal of Development Economics*, 153:102737.

Hsiao, A. (2021). Coordination and commitment in international climate action: Evidence from palm oil. *working paper*.

IPCC (2007). *Climate Change 2007: Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*. Geneva, Switzerland.

Jayachandran, S. (2021). How economic development influences the environment. NBER working paper, (w29191).

Leblois, A., Damette, O., and Wolfersberger, J. (2017). What has driven deforestation in developing countries since the 2000s? evidence from new remote-sensing data. *World Development*, 92:82–102.

McArthur, J. W. and McCord, G. C. (2017). Fertilizing growth: Agricultural inputs and their effects in economic development. *Journal of Development Economics*, 127:133–152.

Pellegrina, H. S. (2022). Trade, productivity, and the spatial organization of agriculture: Evidence from brazil. *Journal of Development Economics*, 156:102816.

Reis, E., Pimentel, M., Alvarenga, A. I., and Santos, M. (2008). Áreas mínimas comparáveis para os períodos intercensitários de 1872 a 2000. *Rio de Janeiro: Ipea/Dimac*, page 40.

Shapiro, J. S. (2016). Trade costs, co2, and the environment. *American Economic Journal: Economic Policy*, 8(4):220–54.

Szerman, D., Assunção, J., Lipscomb, M., and Mobarak, A. M. (2022). Agricultural productivity and deforestation: Evidence from brazil. *working paper*.

USDA (2001). Agriculture in brazil and argentina: developments and prospects for major field crops. *United States Department of Agriculture Report WRS-01-3*.

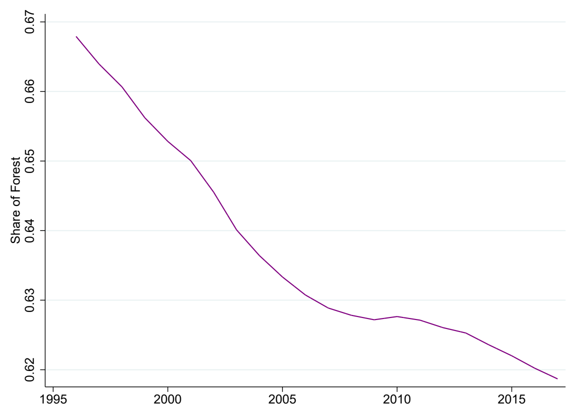
World Bank (2007). *World development report 2008: Agriculture for development*. The World Bank.

Appendix (for online publication)

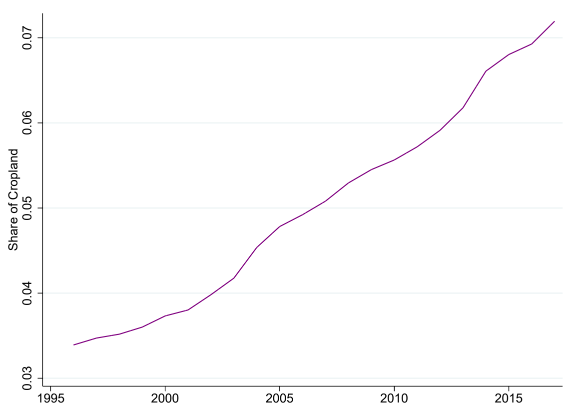
A Additional Figures and Tables

Figure A1: Evolution of Total Share of Forest Area, Cropland and Pastureland

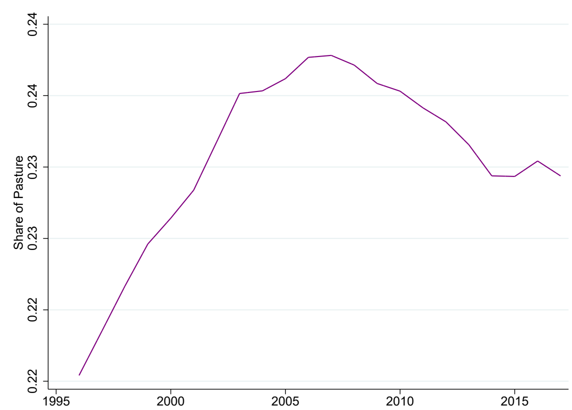
(a) Forest Area



(b) Cropland

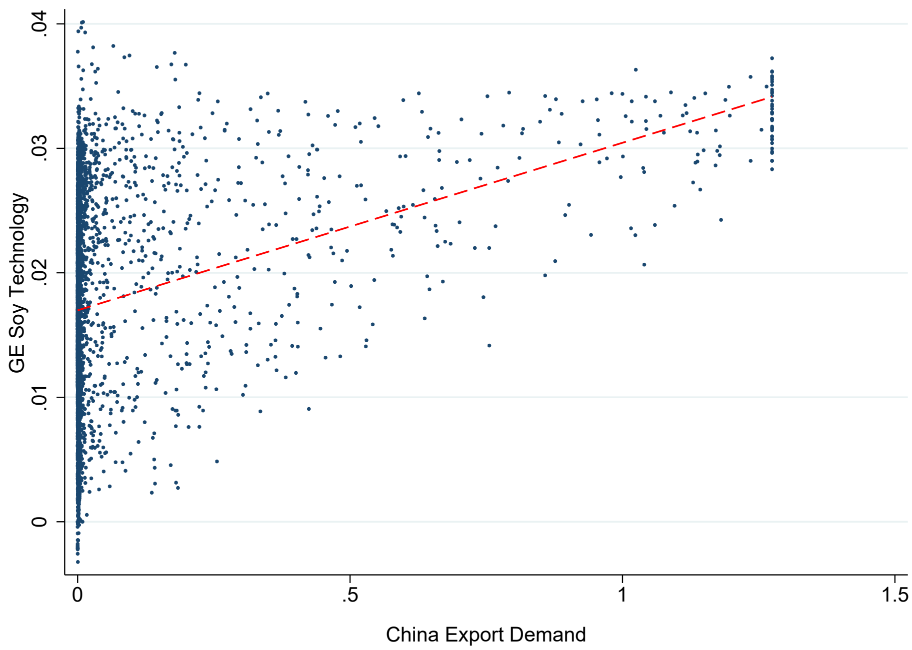


(c) Pastureland



This figure shows the evolution of the share of forest areas, cropland, and pastureland in Brazil. Data from MapBiomas.

Figure A2: Exposure to Agricultural Technology vs. Export Demand



This graph presents scatter plots of municipal-level soy technology shock A_i against the Chinese demand shock $\widehat{X}_i$. The line depicts the results of a simple regression of A_i on $\widehat{X}_i$ (coefficient .0134, s.e. .0006).

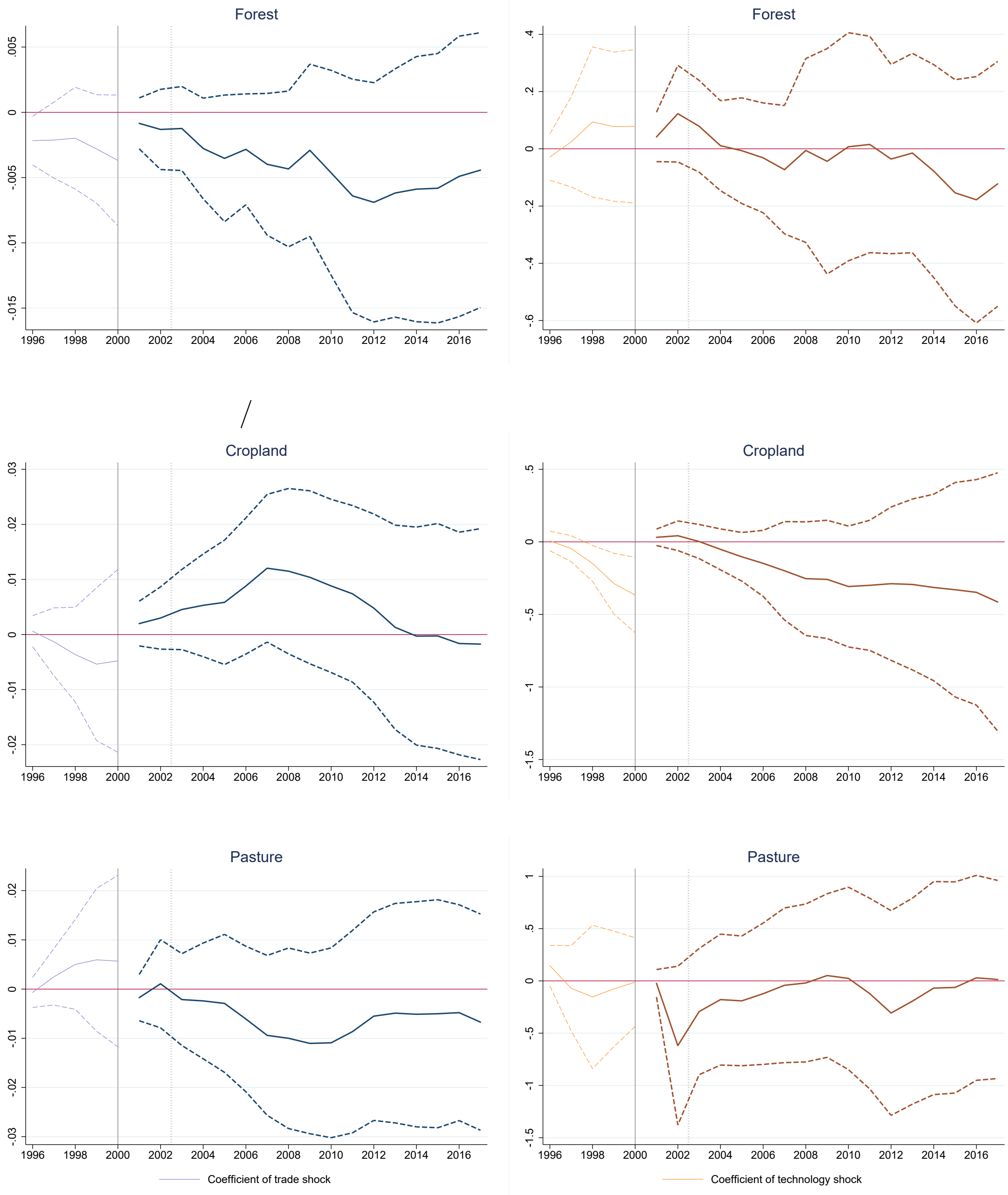
Figure A3: Robustness Results – Inverse Hyperbolic Sine Transformation

(a) China Export Demand (b) GE Soy Technology

These figures show the estimates of the effects of the trade shock (α_t) and technology shock (β_t) from equation (3) on land-use change over time using inverse hyperbolic sine transformation of the share of land-use change. We take the inverse hyperbolic sine transformation of land use shares before taking differences over time to construct the dependent variables. Remaining notes and descriptions are analogous to Figure 3. Number of observations: 3,818.

Figure A4: Robustness Spillover Results (N=9) – Inverse Hyperbolic Sine Transformation

(a) China Export Demand (b) GE Soy Technology



These figures show the estimates of the effects of the trade shock (α_t) and technology shock (β_t) from equation (3) on land use change of the nine closest municipalities using inverse hyperbolic sine transformation of the share of land use change. We take the inverse hyperbolic sine transformation of land use shares before taking differences over time to construct the dependent variables. Remaining notes and descriptions are analogous to Figure 5. Number of observations: 3,818.

Table A1: Descriptive Statistics

	Mean	Std. Deviation	Min	25^{th} Pctl.	75^{th} Pctl.	Max
Panel A. Main dependent variables: land use						
$\Delta_{00/06}Forest_i$	-0.003	0.036	-0.290	-0.014	0.012	0.196
$\Delta_{00/06}Cropland_i$	0.017	0.037	-0.105	0.000	0.020	0.306
$\Delta_{00/06}Pasture_i$	-0.016	0.052	-0.307	-0.039	0.008	0.289
$\Delta_{00/17}Forest_i$	0.004	0.056	-0.374	-0.018	0.032	0.244
$\Delta_{00/17}Cropland_i$	0.056	0.098	-0.168	0.000	0.073	0.743
$\Delta_{00/17}Pasture_i$	-0.065	0.117	-0.807	-0.106	0.001	0.370
Panel B. Main exogenous variables						
Exports ($\hat{X}$)	0.067	0.211	0.000	0.001	0.009	1.275
Productivity gain from GE soy seed (A)	0.018	0.009	-0.003	0.011	0.025	0.040
Panel C. Controls						
Income per capital 1991	10.981	0.468	9.462	10.607	11.333	13.127
Literacy rate 1991	0.657	0.175	0.131	0.494	0.804	0.965
Population density 1991	-1.315	1.300	-7.012	-1.983	-0.663	4.795
Rural population share 1991	0.452	0.227	0.000	0.269	0.637	0.978
Panel D. Land use in neighboring municipalities (spillovers)						
$\Delta_{00/06}Forest_{n=9}$	-0.010	0.311	-18.848	-0.006	0.007	0.372
$\Delta_{00/06}Cropland_{n=9}$	0.017	0.049	-0.322	0.000	0.016	1.613
$\Delta_{00/06}Pasture_{n=9}$	-0.011	0.313	-1.267	-0.031	0.002	18.746
$\Delta_{00/17}Forest_{n=9}$	-0.006	0.463	-27.652	-0.006	0.025	0.771
$\Delta_{00/17}Cropland_{n=9}$	0.059	0.161	-0.036	0.001	0.065	6.887
$\Delta_{00/17}Pasture_{n=9}$	-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 the dependent variables in Section 3 described in Section 2.1. Panel B presents statistics if the two exogenous variables discussed in Sections 2.2 and 2.3. Panel C shows statistics of control variables computed using the 1991 Demographic Census. Panel D shows statistics on the spillover variables used in Section 3. Unit of observation are municipalities (AMCs). Number of observations: 3,818.

Table A2: Agricultural Products Exported from Brazil to China

	Change in Exports to China (Thousands of US$)			
	Between 1995-2006	Between 1995-2017	Share of Agricultural Production in 1995 (%)	$\widehat{\psi}_{China,j}$
Agave	21,812.3	10,680.7	0.02	120.9
Apple	36.6	0	0.45	1.4
Avocado	0	2.1	0.04	12,889.9
Bamboo	-30.2	-30.2	.	-0.8
Banana	25.9	0	1.33	1.6
Bean	0	45.8	2.19	12.5
Brazil nut	592.4	-26.2	.	0
Cashew nut	-69.2	-66.2	0.13	-0.4
Cattle	8,181.3	476,095.5	25.89	3.5
Cereals (ex-maize)	-20,620.6	-13,732.7	4.07	7.5
Citron	110.3	0	0	42.5
Coffee	596.6	10,309.6	5.31	15.0
Cotton	12,689.7	112,565.3	0.81	12.6
Forest production	42,750.0	140,460.4	.	2.9
Garlic	40.2	0	0.10	1.2
Grape	171.9	0	0.60	6.1
Guava and Mango	0	3.0	0.37	23.5
Maize	0	2,707.2	6.96	1069.6
Mandarin	127.2	0	0.18	23.2
Mate	1.2	25.4	0.15	949.9
Natural gum resin	0	2.3	.	1.3
Nut	142.3	319.1	.	9.0
Orange	14.8	0	2.06	5.7
Other root vegetables	17.5	0	0.12	34.2
Pepper	20.3	1,287.7	0.05	1.8
Plants (live)	33.7	119.6	0.34	4.4
Plants (pharmacy and perfume)	44.0	226.6	0.06	-1.2
Soybean	2,856,979.3	20,296,222.0	9.15	5.4
Spices	1.3	39.9	0.01	-0.3
Sugarcane	-66,186.4	-26,245.4	11.57	5.9
Swine and Poultry	2,396.0	139,400.3	14.75	3.5
Tobacco	34,741.9	101,821.4	1.70	0.06
Vegetable fibre	-37.5	-37.5	0.01	0
Vegetable for tanning	23.4	0	.	0
Vegetable waxes	1,583.9	15,283.9	.	0.9
Walnut	300.8	0	0.02	8.2
Wood	-2.3	3,440.2	.	8.0

Columns (1) and (2) show the change in exports from Brazil to China in thousands of $ between 1995 and 2006, and between 1995 and 2017, respectively. It includes the impacts of changes in exports of processed goods on the demand for raw agricultural goods, according to the coefficients of the direct requirement (Table A3). Column (3) indicates the share of the agricultural production (the value of production in Brazilian Reals) for each product. It does not sum up to 1 because many agricultural products were not traded between Brazil and China. The share of agricultural production in 1995 is missing for forest products. The table does not contain products that were not traded in 1995, 2006 or 2017.

Table A3: Industry Exports Impact on Agricultural Products

	Meat and dairy	Sugar	Other food products	Beverage	Tobacco products	Textile	Biofuel	Forest products	Wood products	Paper products
Cereals (ex-maize)	-	-	0.03	-	-	-	-	-	-	-
Maize	-	-	0.03	-	-	-	-	-	-	-
Cotton	-	-	-	-	-	0.06	-	-	-	-
Sugarcane	-	0.52	-	0.02	-	-	0.38	-	-	-
Soybean	-	-	0.11	-	-	-	0.03	-	-	-
Tobacco	-	-	-	-	0.39	-	-	-	-	-
Cattle	0.26	-	-	-	-	-	-	-	-	-
Swine and Poultry	0.08	-	-	-	-	-	-	-	-	-
Forest production	-	-	-	-	-	-	-	0.04	0.10	0.05

This table presents the direct impact of each industry on specific agricultural products based on IBGE's Brazilian input-output table, as discussed in Section 2.3. Each coefficient represents the value of the row's commodity necessary for the production of one dollar of the column's industry. Coefficients lower than 0.02 are represented by a dash (-).

Table A4: Robustness Results on the Spillovers of Trade and Technology Shocks 2000-2017

	Number of neighboring municipalities (N)				
	N=9	N=9	N=3	N=6	N=15
	(1)	(2)	(3)	(4)	(5)
Panel A. Change in share of forest 2000-2017					
Trade Shock (α)	-0.016	-0.011	-0.001	-0.004	-0.002
	(0.015)	(0.024)	(0.003)	(0.007)	(0.020)
Technology Shock (β)	0.524	3.080	-0.118	-0.649	-0.844
	(1.326)	(3.470)	(0.360)	(1.213)	(3.306)
Panel B. Change in share of cropland 2000-2017					
Trade Shock (α)	0.008	-0.003	0.007	0.005	0.018
	(0.020)	(0.020)	(0.007)	(0.010)	(0.023)
Technology Shock (β)	-0.753	1.785**	-0.255	-0.114	-1.043
	(0.670)	(0.708)	(0.245)	(0.473)	(1.067)
Panel C. Change in share of pastureland 2000-2017					
Trade Shock (α)	0.007	0.010	-0.007	-0.000	-0.016
	(0.026)	(0.020)	(0.008)	(0.011)	(0.029)
Technology Shock (β)	-0.024	-1.421	0.221	0.607	1.768
	(1.428)	(2.109)	(0.390)	(1.267)	(3.091)
Data	MapBio.	Census	MapBio.	MapBio.	MapBio.
N	3818	3756	3818	3818	3818

This table presents alternative specifications for the spillover effects of the trade shock (α_t) and technology shock (β_t) from equation (3) on land-use changes in the neighboring municipalities between 2000 and 2017. See description in the **Spillovers** segment in Section 3. All regressions include state fixed effects and the following controls: income per capita, literacy rate, population density, and rural population all in 1991, and available land in 1995. Conley (1999) standard error in parenthesis. Number of observations: 3,784 (column 2), and 3,823 (remaining columns).

B Concordances

The concordance between the Agricultural Census data from IBGE to the trade data from BACI-CEPII is the result of the following procedures:

Raw agricultural products: The Concla-IBGE provides a correspondence table linking the agricultural products to a list of products (PRODLIST). Then, another classification links the PROLIST data to the 2003 *Nomenclatura Comum do Mercosul* (NCM) trade codes. The final step to match the products to the trade data is to remove the last two digits from the NCM trade codes (this classification is more specific than the HS), and use the UN Trade Statistics correspondence table between the HS 2002 and HS 1992 trade codes – the BACI-CEPII trade data is classified in the 6-digit Harmonized System (HS) 1992 nomenclature. The Concla concordance includes some products with minimal processing that use agricultural commodities as inputs. However, it does not include all processed goods and does not indicate which raw agricultural products are being used in the production of these processed products. So we will take an alternative approach to account for changes in the demand for processed goods.

Goods that use agricultural products as input: Using the direct requirements coefficients from the 2015 Brazilian Input-Output Table released by IBGE (Table 11 - *Matriz dos coeficientes técnicos dos insumos nacionais*), we can account for the dollar amount of an agricultural commodity necessary to produce one dollar of the industry's output. For instance, a one-dollar increase in the demand of the biofuel industry results in the use of 0.38 dollars of sugarcane (Table A3). We impose a threshold of 0.02 on the direct requirements coefficients. This is not an arbitrary choice. Ignoring coefficients lower than this threshold avoids an arbitrary choice of how to split the production of industry among "Other temporary crops", since it is not possible to know which specific agricultural product is being used as an input. The only exception is the case in which 0.39 dollars of "Other temporary crops" is required to produce one dollar of the tobacco products industry. In this situation, we assume that "Other temporary crops" means tobacco. To construct the contribution of an industry to the China Shock, we multiply the change in the industries' exports by their respective input coefficients and by the local exposure to the agricultural inputs, summing over all the inputs used in that industry. To link the Input-Output table industries to the trade data, we use the international trade/national accounts correspondence table from IBGE (*Tradutor Nomenclatura Comum do Mercosul (NCM) - Comércio Exterior/Contas Nacionais (2016)*).

Agricultural products linked to the trade data: We include crops, livestock and forest products in the list of products used to calculate the exposure of each municipality to the trade shock. The value of production for each animal is not available in the 1995

Agricultural Census. Therefore, to measure the exposure to trade shocks we consider the "Large animals production" as the output value for "Cattle" and the difference between "Animal production" and "Large animals production" as the value of production for "Swine and Poultry". Based on the 2006 Agricultural Census, this is a reasonable assumption. Cattle production represented 99.3% of the large animals' production, while poultry and swine accounted for 90.5% of the difference in the value of animal production and large animals' production.