Agricultural Trade and Deforestation: the Role of New Roads

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Abstract

In this paper, we study how new roads affect the spatial patterns of agricultural production and consequently impact deforestation and development outcomes, focusing on the historical experience of Brazil. We find that the expansion of Brazil's road network since the 1990s can account for up to one quarter of the total amount of deforestation that the country has experienced, with significant variation across regions. Perhaps surprisingly, our results suggest that the increase in agricultural income attributable to road construction has been more limited. Turning to the future, we examine the potential impact of Brazil's official infrastructure plans, and we quantify the ecological costs of improving market access in currently isolated areas.

Keywords: Trade Frictions ; Natural Resources ; Spatial Economics
JEL codes: F18 ; O13 ; Q10 ; R12

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1 Introduction

The destruction in recent decades of forests in the world's tropical areas stands as one of the most devastating and consequential human impacts on the biosphere. Tropical forests represent a key ecosystem, and their loss causes major environmental damages such as greenhouse gas emissions, biodiversity loss, and the degradation of ecosystem services (IPBES, 2019). Rainforest destruction also has the perverse effect of undermining the economic development that drives the process, by putting at risk agricultural productivity and undermining the livelihood strategies of those people and communities who are exposed to climate change (Lawrence and Vandecar, 2015).

In this paper, we study how new roads affect patterns of agricultural production and trade within Brazil, with implications for the extent and location of deforestation. Road construction, along with other improvements in transportation infrastructure, has typically been viewed by economists and policy makers as a key instrument to promote economic growth and development – a view that can be traced at least to Adam Smith (1776).[1] But as economists have long realized, investments in road constructions, by connecting previously isolated areas to the market, may be a key driver of forest clearing in developing countries. The trade-off between economic growth and the environment is a critical one for economists – and arguably for the planet as a whole.

In this paper, we build and calibrate a quantitative spatial general equilibrium model of agricultural trade to Brazil's 137 meso-regions. We use this model to assess the effect of new roads on the spatial equilibrium of agriculture, and, in turn, on pristine forests in Brazil. We do so by using unique data sources, based on the latest Brazilian agricultural censuses as well as high-resolution satellite data on forest cover and road networks. In contrast to many previous studies on the relationship between road construction and deforestation, we use a general equilibrium framework that allows us to consider spatially diffuse spillovers from road construction. For instance, a road built into one agricultural region may stimulate production in that location to serve distant urban markets. That may in turn alter land use patterns not only in adjacent locations but in other parts of the country that produce similar outputs. Those land use changes may, in turn, drive further impacts in other locations. In this context, a general equilibrium framework is key to understanding the overall impacts on land use and deforestation. Our model uses data on the agro-ecological properties of different meso-regions

[1] In his *Inquiry into the Nature and Causes of the Wealth of Nations*, Smith (1776) writes: "*Good roads, canals, and navigable rivers, by diminishing the expense of carriage, put the remote parts of the country more nearly upon a level with those in the neighbourhood of the town. They are upon that account the greatest of all improvements.* "

to guide our understanding of the market-mediated connections between different locations, by building in an understanding of which crops are best suited to particular meso-regions.

Our results indicate that the roads built since 1995 explain one-quarter of the total forest losses experienced in the country since that time, with important differences across regions. For instance, in a state like *Mato-Grosso*, which has become a major locus of deforestation since the 2000s, we find that reductions in transport costs (driven by road construction) explain up to 90% of the deforestation observed in the data.

To guide our modeling choices, we start by documenting four motivating facts about internal trade, deforestation and agriculture in Brazil. First, proximity to roads varies greatly across regions, suggesting important differences in market access. Second, forest cover is positively correlated to travel time to the closest international port, illustrating the links between transport costs, market access and deforestation. Third, there is substantial heterogeneity in crop suitability across space, potentially influencing specialization. Fourth, agricultural crops vary in their land intensity, with implications for the commercial pressures on standing forests in different locations.

Equipped with those facts, our model is structured as follows. The economy includes a large number of locations (corresponding in our empirical application to Brazilian meso-regions), one trade hub, and two sectors: agriculture and non-agriculture. We view the non-agricultural good as a composite good encompassing both manufacturing and service activities; for simplicity, we use the term "manufacturing" to refer to this sector. In the agricultural sector, farmers produce output using labor, imported intermediate inputs, and land. They can grow an array of crops over a continuum of plots that vary in their crop-specific land productivity. Given that crops have different land intensities, pressure on forests can vary depending on the pattern of specialization of a given region. In our setting, rural locations sell agricultural goods to the trade hub, following an Eaton and Kortum (2002) structure where transportation is subject to iceberg costs.

To open a plot for "productive use", farmers have to pay a fixed-conversion cost.[2] This cost, which is plot-specific, ultimately determines the total amount of land devoted to agriculture in a region, as in Costinot et al. (2016) or Farrokhi and Pellegrina (2021). The logic of land conversion in the model is as follows: as transport costs decrease, market prices rise

[2]Farmers in our model do not view the ecosystem services provided by forests as a productive use; any environmental benefits of forests are externalities that farmers ignore. In our model, farmers view land only as an input into agricultural production. We recognize that some farmers take seriously the environmental impacts of their actions and their responsibilities as "stewards of the land." We also recognize that some market segments and market mechanisms have emerged that encourage agricultural producers to internalize the environmental benefits of standing forests. In our analysis, we treat this as a negligible feature of the overall market.

within previously isolated areas. The increase in local prices boosts the profitability of agriculture relative to the fixed cost of land conversion, thus creating incentives for farmers to further deforest. This is the effect of improving market access. Because crops have different land intensities, the extent of forest clearing can vary depending on the production pattern of a given region. This is the effect of the nature of specialization.

In our model, deforestation is further stimulated because the decline in transport costs makes it cheaper for farmers in remote areas to "import" intermediate inputs for agricultural production. Together, the increase in output prices and the decline in input costs make agriculture more profitable and thus stimulate land clearing. These effects are spatially heterogeneous, however. The local patterns will depend on the types of crops that are most suitable in particular regions and the shape of the demand curves for those crops. For those crops with high foreign demand, expansion of production faces few limits. But where there is little foreign demand, domestic markets may become saturated. Transport cost reductions may lead to greater market integration, allowing for the intensification of production in the most favorable areas and a reduction in land pressure on the extensive margin. There is potential, in other words, for improvements in transportation infrastructure to enhance specialization and thus to reduce pressure on Brazil's land resources. Our analysis suggests that changes in the transportation network will lead to a spatial reallocation of the production of specific crops – and potentially to a reduction of the land devoted to some crops, so the aggregate effects of forest cover are unclear *ex ante*.

Taking the model to the data, we estimate trade elasticities by exploiting price differences in soybeans across space, taking advantage of the fact that soybeans are overwhelmingly exported, so that prices are determined on world markets. The rest of our key parameters are calibrated following the recent literature in the field. We calibrate the model to reproduce the observed spatial equilibrium of the economy for 2017 (the latest year for which agricultural census data are available). We then proceed to conduct three counterfactual exercises.

In our first counterfactual exercise, we examine what would be the spatial equilibrium if transport costs had remained at the level implied by the road network of the early 1990s. This allows us to quantify the impact of the roads constructed since this period. We examine the impacts on deforestation but also consider other development outcomes related to agriculture. We contextualize our results by comparing the predicted changes with the *actual* changes by exploiting data from the 1995 and 2017 agricultural censuses.

In our second counterfactual, we use our model to evaluate the potential environmental impacts and economic gains of future road networks. To do this, we exploit data from the National Ministry of Transportation about the "Brazilian's National Logistics Plan 2035"

(NLP 2035). These give us a set of plausible scenarios for future road construction. Directly related, in our third counterfactual exercise we offer an alternative scenario to the NLP 2035, where instead of decreasing transport costs in some meso-regions inside the Amazon, we propose to reallocate those same planned investments towards other areas.

Our findings highlight the sizable effects of road construction on forests in Brazil. Having estimated that transport costs decreased by around 6.5% overall since the 1990s, we find that, as a result of those changes, deforestation increased by 2.3% in the country. This represents one-quarter of the actual land clearing observed in the data over 1995-2017. Examining other outcomes, we find that aggregated exports and income in agriculture increased by 18% and 3.6%, respectively. This has had consequences on inequalities within Brazil as we find that regions in the richest quartile of income gained from reducing trade frictions, while those in the poorest quartile lost over 8% of measured agricultural income.

Our analysis also shows the importance of spatial heterogeneity as a mediator of price shocks experienced by the different Brazilian meso-regions. We document that some key locations in the Amazon biome experienced over 30% drops in transport costs since the 1990s. We show that absent these changes in transport connectivity, deforestation would have been significantly lower in those regions. While we find that greater market integration increased agricultural income, we notice that economic gains remain low in comparison to the environmental costs of the new roads.

Looking forward, we find that the 2035 National Plan would further lead to over 120 thousands hectares of forest losses. We highlight that while some regions would actually experience increases in forest cover, these are all located outside the Amazon biome. By contrast, with this plan, deforestation would increase substantially in ecologically sensitive states like *Tocantins*, belonging to the Amazon Biome. This suggests that these new roads would harm the most valuable ecosystems in the country. Our findings also show that agricultural income and exports would increase, but by a very modest extent relative to their ecological costs, which we quantify. Indeed, we estimate that the carbon cost of this project would be 276M US$ with a carbon price as the one in Columbia, and almost 3 billion US$ with the one currently used by the US government. This points out to the fact that new investments in transportation infrastructures are can be less attractive than researchers and policymakers usually think (Asher and Novosad, 2020), especially when accounting for their environment costs.

The study of an alternative investment plan (third counterfactual exercise) shows that, by avoiding road construction in meso-regions inside the Amazon, more forests can be preserved. For the exact same amount of total investment in infrastructures, we find that our

alternative scenario could lead to a 0.31% increase in total forest cover. In other words, in this particular instance, constructing roads leads to net reforestation, on average. This outcome is significantly influenced by the nature of specialization. Instead of reducing transport costs in regions with high land productivity for soybeans, our alternative plan targeted regions with high land productivity for wheat. Since the latter requires less land per unit of output than soy, it partially explains why more forests were preserved. In all, this shows the importance of taking into account several types of crop.

Our work offers new evidence on the trade-off between improving market access and preserving the forest. The topic is not a new one, but relative to previous research, our approach offers several advantages. Since locations within a country are linked by trade and markets, it is important to consider general equilibrium effects that underpin linkages between locations and across goods. This is particularly relevant for thinking about large-scale changes in transportation infrastructure, which necessarily alter the entire spatial pattern of production. Although many empirical studies look for impacts of roads within narrowly defined geographic areas, it is difficult to find contexts where "treatment" locations can be compared with untouched "control" locations. Estimates that fail to account for the spillover effects of roads may be biased (Redding and Rossi-Hansberg, 2017).

We contribute to the existing literature in several ways, as we extensively discuss in section 2 dedicated to the literature. Most obviously, we depart from a literature that has relied heavily on reduced-form empirical estimates of the impact of roads on deforestation. We also contribute to a large and growing literature making use of quantitative spatial models for thinking about issues related to agriculture; relative to this body of research, our contribution is to tackle the critical issue of forest clearing. By doing so, we also connect to the larger body of research on the effect of trade on the environment. Finally, this work relates to recent research on the importance of agriculture in development, by emphasizing the potential environmental costs of increased production.

In section 2, we discuss in details the strands of literature related to our paper. Section 3 presents empirical motivations that structure the model we present in section 4. After a calibration of the model in section 5, we expose the results of our two counterfactuals in section 6. Section 7 concludes.

2 Related literature

A substantial body of literature in development and environmental economics has specifically studied the links between roads and deforestation, generally by employing reduced-form

econometric models. Among these, Pfaff (1999) uses panel data on the Brazilian Amazon over the 1978-1988 period and finds that both own- and neighboring-county paved roads increase deforestation. Similarly, proximity to major national markets has been found to be positively correlated with forest clearing. Andersen et al. (2002) investigate the impact of roads on forest clearing, along with other development outcomes, for the Brazilian Amazon. Likewise, Pfaff et al. (2007) find that road investments increase deforestation in census tracts without roads and located at less than 100km from those census tracts that received investments. The authors interpret this result in terms of local spillovers. Asher et al. (2020) study the causal impact of transportation infrastructure on forest losses in India. Relying on different identification strategies, they exploit two large-scale transportation projects implemented by the Indian government in the 2000s. They find that the construction of new (last-mile) rural roads did not impact deforestation, while the upgrade of existing highways significantly increased it. They interpret this result in terms of geographical redistribution of economic activities; they argue that large highway investments lead to this kind of spatial impact, unlike last-mile roads. On rural roads, Kaczan (2020) finds that these could actually facilitate a long-term expansion of forest cover, in the context of India.

We contribute to this body of literature by employing a complementary method, based on the recent developments in the trade literature. Specifically, we use a model that allows us to take into account both spillovers and spatial reorganization of economic activities. Furthermore, by allowing prices to adjust both in space and between goods, we can avoid some of the biases that arise in reduced-form work.

We note that the question of where roads should be built, given their potential environmental costs, has also been studied outside economics – and particularly in the environmental sciences. Laurance et al. (2014) compute agricultural gains and the associated environmental costs of new roads across the world, and they map the locations where new roads would provide the largest benefits at the lowest cost for biodiversity and other environmental indicators. Vilela et al. (2020) present a similar exercise for the whole Amazon and quantify the effects of 75 planned projects over 5 years. This question of optimal road location differs from our quantification exercise, and it does not discuss how prices, output and economic activities change across space.

A fairly recent literature uses structural and quantitative spatial models to study the impact of different shocks (e.g., reductions in transport costs) on economic development and welfare (Redding and Rossi-Hansberg, 2017). Some of this literature includes models of land use choices, often in multi-country settings. For example, Costinot et al. (2016) and Gouel and Laborde (2021) study the impact of climate change on agriculture. This is also the

case of Farrokhi and Pellegrina (2021) who incorporate endogenous technology choices into a model of agricultural trade.

With these models, other authors have studied questions related to land use within countries. This is the case of Sotelo (2020), who uses a model with heterogeneous land quality in Peru to analyze a set of counterfactuals involving changes in trade costs and commodity prices. Using a similar setting, Pellegrina (2022) studies the consequences, in Brazil, of the introduction of new soybean seeds in the 1970s as well as of a rise in Chinese demand. Fajgelbaum and Redding (2022) also build a model featuring land-use competition within a country to study trade and structural transformation in Argentina. None of the papers from this quantitative literature has, to the best of our knowledge, studied the issues of deforestation and environmental harm that can accompany agricultural expansion.

Our paper touches on a macro and growth literature that poses questions about agriculture or the environment, but without directly accounting for the endogeneity of land clearing. For instance, Allen (2014), Tombe (2015), Porteous (2019) and Adamopoulos (2020) all use quantitative models with agricultural trade. In these models, there are costs associated with shipping goods, but there is not any way to evaluate environmental impacts of different policy regimes. On issues related to the environment, Desmet and Rossi-Hansberg (2015) use a multi-region dynamic model featuring two sectors to study the spatial impact of climate change. The authors quantify the importance of migration and trade restrictions, as Conte et al. (2021) do, by focusing on the patterns of specialization resulting from climate change dynamics. Desmet et al. (2018) concentrate on coastal flooding and evaluate the costs of sea-level rise worldwide while Balboni (2019) uses a dynamic spatial equilibrium model and focuses on the case of Vietnam. Given current climate change scenarios and future inundation risks, Balboni (2019) finds that coastal favoritism in investment has significant costs. For instance, she finds that avoiding the most vulnerable Vietnamese regions could have led to a 72% increase in welfare gains under a central sea level rise scenario. We contribute to this strand of the literature by studying a different environmental issue, namely deforestation. By doing so, our work is related to Farrokhi et al. (2023) who study this question at the global level.

Our work is also related to an important literature on policy interventions and deforestation in Brazil. Recent works include Souza-Rodrigues (2019) who offers a framework for measuring the cost effectiveness of alternative policies in the Amazon, or Assunção et al. (2023) who use a novel instrumental approach to study enforcement's impact on deforestation.

Finally, this work also talks to the long standing debate on the effect of transportation infrastructures on economic growth. Recent work on the topic include Donaldson and Hornbeck (2016) who study the historical impact of railroads on US in 1890. Storeygard (2016) focuses on the role of intercity transport costs for urban income in Sub-Saharan Africa while Alder (2016) focuses on India. Again in the context of India, Donaldson (2018) studies the benefits of historical railroads construction and finds that it has promoted trade and increased real income. Asher and Novosad (2020) assess the impact of a national rural road construction program and identify mixed results. Our contribution is to evaluate the economic benefits together with the ecological costs from a shock in transport costs in Brazil, which our quantitative model allows us to do.

3 Empirical background

This section describes the stylized facts that motivate the structure of our model. Data sources are detailed in Appendix B.

Road density varies across Brazil. Figure 1 shows road and port networks in Brazilian meso-regions.

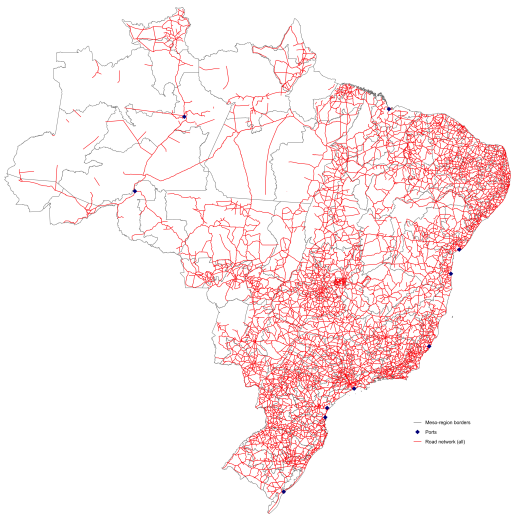


Figure 1: Access to roads and ports across meso-regions. Note: 2014 road network (IBGE) including all types of road but excluding planned roads.

Starting in the Centre-East, the North and Northeast, Brazilian meso-regions have a much lower density of paved roads than those located in the South and along the Atlantic

coast. As the capacity to transport goods at low costs influences local crop production, this unequal proximity to infrastructure also shapes land use and the pressure for agricultural expansion at the expense of standing forests.

Global market access is positively correlated to deforestation. To provide a sense of how market access can influence deforestation, we regress the share of land under forests on the distance between each meso-region's centroid and the closest international port:

$$y_i = \beta_0 + \beta_1 \log \{\text{distance}\}_i + \epsilon_i.$$

Our dependent variable y_i is computed at the meso-region level and it is the forest area divided by total area, in 2017. We use three different measures of distance to the port. One is straight-line distance between centroids and ports. The second is distance through the shortest path, using the existing road network. The third is the duration of travel, using this same network. The two latter measures are derived by exploiting the Open Source Routing Machine from OpenStreetMap (Huber and Rust, 2016). Results are shown in Table 6 of Appendix D.

The results show that the share of land under forests in a meso-region is positively correlated to each measure of distance to the closest international port. A decrease of 10% in the travel time to the closest exporting port is associated with a 1.1% decrease in forest cover. This elasticity points to the importance of global markets here as a source of the demand that is driving forest clearing. While domestic demand curves for agricultural products might be steeply downward sloping, the size of the international market is such that it exerts a strong effect on land use. In short, land in Brazil is not being cleared for agriculture to feed domestic consumers; it is being cleared in part to supply an international market, with the result that connectivity to ports matters more than connectivity to domestic urban centers. A caveat here is that Brazil's ports *are* some of its largest cities, so the two sources of demand are not separately identified. Nevertheless, the data point strongly towards the role of international markets in driving deforestation.

Heterogeneity in land productivity matters for impacts. Another factor mediating the impact of road construction is the heterogeneity of land quality for agriculture – and specifically the suitability of different plots for different crops. As an example, Figure 2 shows heterogeneity in land productivity for soybeans.

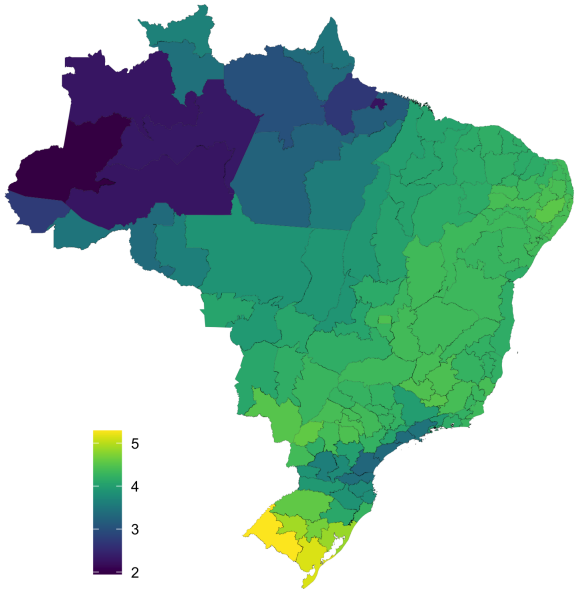


Figure 2: Soybeans Potential Yields. Note: Period: 1981-2010. Input Level: High. Data are taken from GAEZv4 (IIASA, FAO) and values are averaged by meso-regions.

As the figure shows, in some locations of southern Brazil, it is possible to obtain up to 5 tons of soybean per hectare cultivated. This is the case for instance in several *municipios* in the state of Rio Grande do Sul, and to a lesser extent in the state of Mato Grosso do Sul. By contrast, in some areas in the North, the value of potential yields is closer to 2 tons per hectare. This heterogeneity in land productivity, illustrated here with soybeans, shapes comparative advantages across regions in the production of crops. As we discuss below, this crop-specific heterogeneity creates varied patterns of pressure on forests. Deforestation in a given region will depend on the suitability of its land for particular crops and on the changes in demand for those crops.

Factor intensity varies across crops. Table 1 shows summary statistics on land intensity for four major crops at the meso-region level. For each crop, the amount of land area (in hectares) per ton produced is displayed.

Each ton of corn output requires, on average, 0.52 hectares of land. For soybeans and wheat, the land requirement is lower, at 0.38 ha for soybeans and wheat, on average. To draw a comparison, according to the data, producing one ton of sugarcane requires 0.04 hectares of land. Notice that corn and sugarcane were produced in every meso-region in 2017; this was not the case for soybeans and wheat.

Table 1: Land-area per unit of output for 4 selected crops (ha/ton). Source: 2017 IBGE Agricultural census.

	N	Mean	St. D.	Min	Max
Soybeans	88	0.38	0.35	.25	3.12
Sugarcane	137	0.04	0.036	0.01	0.23
Corn grain	137	0.52	0.51	0.12	2.34
Wheat grain	38	0.38	0.10	0.24	0.70

These land-intensity differences across crops predictably impact land clearing patterns. When a region specializes in the production of a crop, for any fixed amount of output, pressure on standing forests will vary according to the land-intensity of this crop. This justifies the importance of using a multi-crop model to understand the effect of specialization on deforestation through general equilibrium adjustments.

The empirical motivations presented in this section will guide our model in the following section.

4 The model

This section presents our spatial model of trade and land allocation between agriculture and forest. In Appendix A, we provide all the details of the derivations. In Appendix E, we show an extension of the model as a central planner's problem.

4.1 Environment

Consider a spatial economy comprising a trade hub and a set of rural locations $i \in \mathcal{L} = \{1, ...I\}$. The trade hub in the model is a central market where all rural locations exchange goods with local consumers and with the rest of the world. All rural areas produce (only) agricultural goods. The trade hub hosts a non-agricultural sector and serves as an embarkation point for all exports. In our empirical work, the trade hub will correspond to the ten largest exporting ports in Brazil.[3]

Each rural location has a total land endowment $\bar{L}_i$ and is composed by a continuum of plots ω of size one, whose set is denoted Ω_i. Those plots can be left under undisturbed forest $F_i(\omega)$ or can possibly be used for agriculture $L_i(\omega)$ to produce several crops $k = 1, ..., K$.

[3]Other models using a similar trade hub setting include Adamopoulos (2020) who study agricultural trade in Ethiopia, or Fajgelbaum and Redding (2022) who focus on structural transformation in Argentina.

Total land in region i is the sum of cultivated plots plus those left under forest:

$$\bar{L}_i = \int_{\Omega_i} \left(\sum_{k=1}^{K} L_{ik}(\omega) + F_i(\omega) \right) d\omega. \tag{1}$$

There are three types of economic agent in this economy. First, a representative farmer chooses the profit-maximizing factors for agricultural production in each rural location. This output is then shipped towards the trade hub, where it can be either locally consumed or exported. Second, the economy features a representative consumer who owns and rents out land and who supplies labor inelastically. Third, there are non-agricultural firms that hire labor to produce a composite of manufactured goods and services.

Consumers and non-agricultural firms are located in the trade hub. Trade of agricultural products from a region i to the trade hub is subject to iceberg transport costs denoted by τ: for one unit of crop k to arrive from region i to the trade hub, $\tau_i \geq 1$ units must be shipped.

4.2 Production

4.2.1 Agricultural sector

In a region $i \in \mathcal{L}$, let production of a crop k over plot ω be given by:

$$Q_{ik}(\omega) = (N_{ik}(\omega))^{\alpha_k} (h_{ik}(\omega))^{\beta_k} \left(A_{ik}(\omega) L_{ik}(\omega)\right)^{1-\alpha_k-\beta_k}, \tag{2}$$

where output depends on labor $N_{ik}(\omega)$, intermediate input $h_{ik}(\omega)$, land productivity $A_{ik}(\omega)$, and $L_{ik}(\omega)$, which is the share of plot ω allocated to crop k. Our parameters of factor-intensity, α_k and β_k, vary across crops and are constrained such that $0 < \alpha_k + \beta_k < 1$ for any $k = 1, ..., K$. The parameter $(1 - \alpha_k - \beta_k)$ thus defines each crop's land intensity. Labor is paid a real wage w_i. Intermediate inputs are entirely imported from abroad, with their local price denoted υ_i. This implies that trade frictions inside the country are affecting the economy in two distinct ways: through shipping output and importing inputs.

To "open" a plot for productive use, a representative farmer must pay a fixed-cost $A_i^0(\omega)$ expressed in units of non-agricultural good.[4] We view $A_i^0(\omega)$ as an investment, such as the supplementary labor cost required to cut down standing forest (e.g., slash and burning activities).

[4]The model of Costinot et al. (2016) displays a similar feature with its "labor intensity" requirement. In the paper of Farrokhi and Pellegrina (2021), it is an "investment requirement". Fajgelbaum and Redding (2022) also propose a fixed-cost approach in an extension of their spatial model.

In each rural location, the representative farmer chooses a crop mix and inputs (including land) to maximize profits. This gives rise to the necessary condition that the price of a commodity k equals its marginal cost of production, implying that the *net* plot-specific rental rate can be written as:

$$r_i(\omega) = A_{ik}(\omega)\psi_{ik} - p_0 A_i^0(\omega), \tag{3}$$

where:

$$\psi_{ik} = \left[\frac{p_{ik}}{w_i^{\alpha_k} v_i^{\beta_k} \tilde{\alpha}^{-1}}\right]^{\frac{1}{(1-\alpha_k-\beta_k)}}$$

is the profitability index of crop k and where $\tilde{\alpha} = \alpha_k^{\alpha_k}\beta_k^{\beta_k}(1-\alpha_k-\beta_k)^{(1-\alpha_k-\beta_k)}$.

In this formulation, Equation (3) expresses the rental rate $r_i(\omega)$ as a function of land productivity $A_{ik}(\omega)$ and crop profitability ψ_{ik}, which is itself increasing in commodity prices p_{ik} and decreasing in the wage rate w_i and the intermediate input cost v_i, for any region $i \in \mathcal{L}$. The last term on the RHS of (3) is the value of the land-clearing investment, or fixed conversion cost, $p_0 A_i^0(\omega)$. Here p_0 designates the price of the numéraire. Whenever the cost $p_0 A_i^0(\omega)$ is higher than the *gross* rental rate for all crops k, $A_{ik}(\omega)\psi_{ik}$, a given plot ω is left under forest.

As in Costinot et al. (2016) or Farrokhi and Pellegrina (2021), the productivity and investment parameter $A_i(\omega) \equiv \{A_{ik}(\omega), A_i^0(\omega)\}$ is randomly distributed from a Fréchet, with parameters $\{Z_{ik}(\omega), Z_i^0(\omega), \theta\}$. This gives:

$$\zeta_i^k(A) = \exp\left\{-\tilde{\gamma}\left[\left(\frac{A}{Z_i^0}\right)^{-\theta} + \left(\frac{A}{Z_{ik}}\right)^{-\theta}\right]\right\}, \tag{4}$$

where $\tilde{\gamma} = \left[\Gamma\left(1-\frac{1}{\theta}\right)\right]^{-\theta}$ is a normalization of the Gamma function. The parameter Z_{ik} measures land productivity, while $Z_i^0 > 0$ is the investment intensity required to open the land for agriculture (i.e., the fixed-cost). A region with a high $Z_i^0 > 0$ may thus dedicate less land to agriculture, all things being equal. The parameter θ governs the distribution of those two parameters across land, such that a larger θ implies less heterogeneity in land productivity or investment within a region.

Land Use. The representative farmer thus chooses the crop k which maximizes the land rents from (3), and deforestation in plot ω occurs whenever this rent is positive. The solution

to this problem yields the following land shares S_{ik}:

$$S_{ik} = \frac{(Z_{ik}\psi_{ik})^{\theta}}{(Z_i^0 p_0)^{\theta} + \Phi_i^{\theta}}, \tag{5}$$

with

$$\Phi_i = \left(\sum_{k'=1}^{K} (Z_{ik'}\psi_{ik'})^{\theta} \right)^{\frac{1}{\theta}}. \tag{6}$$

Equation (5) is the share of land allocated to crop k over all the plots ω open for productive use in each region $i \in \mathcal{L}$. This share increases with the crop profitability index ψ_{ik} and aggregate land-productivity Z_{ik}, relative to other crops $k' \neq k$ and to the fixed conversion cost. This implies that land is generally used where its *comparative* advantage is highest, rather than where its *absolute* advantage is strongest. The conversion cost matters here for the extensive margin: the higher the cost of converting forest to cropland, the lower is the share of land attributed to any crop $k \in K$. Finally, note that the share of land covered by forests at the regional level is total area times the share of land not allocated to any crop k:

$$F_i = \left(1 - \sum_{k=1}^{K} S_{ik} \right) \bar{L}_i. \tag{7}$$

To anticipate the role played by transport costs, it is worth examining the numerator of the land use equation (5). This expression can be viewed as the relative profitability of growing crop k in region i and is equal to:

$$\left[Z_{ik} \left(\frac{p_{ik}}{w_i^{\alpha_k} \upsilon_i^{\beta_k} \tilde{\alpha}^{-1}} \right)^{\frac{1}{(1-\alpha_k-\beta_k)}} \right]^{\theta}. \tag{8}$$

Let us focus on two important components: p_{ik} and υ_i. The spatial equilibrium in the economy is such that the price of a crop k at the trade hub is equal to the farm-gate price times transport costs; i.e., $p_k = \tau_i p_{ik}$. When a region is poorly connected to the trade hub, thus facing a high iceberg cost, the farm-gate price p_{ik} will be lower. It follows that, all things being equal, the amount of land dedicated to any crop k in that region will be lower.

Another way to appreciate the effect of iceberg costs is to examine the role of υ_i, the cost of the intermediate input. Since this input is entirely imported from the trade hub, υ_i is equal to the world price of the intermediate input times the cost τ_i of shipping it to region i. Again, keeping all other parameters constant, when a region i is isolated and τ_i is high, the cost υ_i of input use $h_{ik}\,\forall k$ will be higher. As a consequence, cultivating any crop k becomes less profitable, and the ratio of the numerator in equation (5) decreases. In our framework,

trade frictions due to transport costs thus affect agricultural expansion in at least two ways. One is through the farm-gate price, and the other is through the cost of intermediate inputs.

4.2.2 Non-Agricultural Sector

Production in the non-agricultural sector takes place in the trade hub and is based on labor only. It is given by $Q^M = \Lambda N^M$, with Λ representing a labor productivity parameter. Firms maximize profits, and labor is paid at the marginal value of its output. Hence, we obtain $p_0\Lambda = w = w_i$ as an optimality condition.

4.3 Consumer's problem

Total expenditure E for the representative consumer in the trade hub equals total income, which is the sum of wages and land rents. A constant share $b^A \in (0, 1)$ of income is spent on a composite agricultural good. From the consumer's perspective, individual crops are imperfect substitutes, and the composite is aggregated from the consumption of each crop according to the expression:

$$C^A = \left(\sum_{k=1}^{K} (\mu_k)^{\frac{1}{\sigma}} (C_k)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}.$$

In this formulation, $\sigma > 0$ represents the elasticity of substitution between crops. Different crops have utility weights, $\mu_k > 0$, and $\sum_{k=1}^{K} \mu_k = 1$. The remaining share of the consumer's income is spent on the non-agricultural good and is denoted C^M.

Provided that $p_k = \tau_i p_{ik}$, optimal consumption of crop k is given by:

$$C_k = \mu_k \left(\frac{p_k}{P} \right)^{-\sigma} \left(\frac{b^A E}{P} \right),$$

with $P = \left[\sum_{k=1}^{K} (\mu_k)(p_k)^{1-\sigma} \right]^{\frac{1}{1-\sigma}}$ the price index in the trade hub. By definition we have $b^A E = \sum_{k=1}^{K} p^k C^k$ and the consumption of manufacturing goods is simply $C^M = (1 - b^A)E/p_0$.

4.4 Competitive equilibrium

A competitive equilibrium consists of:

(a) Prices p_k in the trade hub and p_{ik} in all regions $i \in \mathcal{L}$ for all crops k, and price p_0 for the non-agricultural good ;

(b) Wage rate w_i for labor employed in both sectors ; price υ_i for the use of intermediate inputs imported from abroad in all regions $i \in \mathcal{L}$;

(c) Expenditure E divided between agriculture and manufacturing in the trade hub ;

(d) Demands for labor N_{ik} for all crops $k = \{1, ..., K\}$ produced in region $i = \{1, ..., I\}$, and N^M for manufacturing ;

(e) Agriculture imports M_k from the rest of the world, and exports X_k to the Rest Of the World ;

(f) Markets clear for labor, land and goods such that:

$$\begin{array}{lcl} \bar{N} & = & \sum_i \int_{\Omega_i} \sum_{k=1}^{K} N_{ik}(\omega) d\omega + N^M; \\ \bar{L}_i & = & \int_{\Omega_i} \left(\sum_{k=1}^{K} L_{ik}(\omega) + F_i(\omega) \right) d\omega; \\ C_k & = & \sum_i Q_{ik}/\tau_i + M_k - X_k; \\ C^M & = & Q^M. \end{array} \tag{9}$$

These six conditions define the spatial equilibrium in the economy. The equilibrium features a land allocation in each location between crops and forests, provided that consumers buy agricultural goods from the cheapest supplier.

5 Taking the model to the data

In this section, we detail our approach to bringing the model to the data. We estimate trade costs and use parameters from the literature for factor shares. Our model includes pasture together with the following eight major crops: beans, cassava, coffee, corn, rice, soybeans, sugarcane, and wheat.

5.1 Transport costs

As we do not observe all trade flows within Brazil, we estimate the transport cost wedges by using the respective costs of shipping soybeans from each meso-region to the closest international port. This commodity was chosen since it is largely exported, following the method of Donaldson (2018) or Sotelo (2020). Formally, we estimate the following model:

$$\log \left(\frac{p_P^{\{\text{soy}\}}}{p_i^{\{\text{soy}\}}} - 1 \right) = \beta_0 + \beta_1 \log \{\text{distance}\}_{iP} + \epsilon_i, \tag{10}$$

where the dependent variable is the log of the soybean price difference between the closest exporting port P (p_P^{soy}) and location i (p_i^{soy}). Prices are taken from the 2017 agricultural

census (IBGE) as well as from the Companhia Nacional de Abastecimento (CONAB). Our variable of interest on the RHS is the log of distance between location i and the closest international port P. The error term is given by ϵ_i and we also add meso-region fixed effects to control for unobserved characteristics at this geographical scale of interest.

Equation (10) is estimated at the district level (*municipios*), rather than meso-regions, for two reasons. First, it allows us to increase the size of our sample and thus increase the precision of our estimates. Indeed, estimating equation (10) at the meso-region level leaves us with 81 observations, compared to over 1,700 at the district level. Second, since we are working on the distance from centroids to ports, the smaller the size of our administrative level, the less likely our empirical analysis is to face measurement error.

Different indexes are compared for our distance variable between a district's centroid and the closest international port. We use straight-line distances as well as shortest-path distances, measured in kilometers and travel time, based on real road infrastructure. Those two are derived by exploiting the Open Source Routing Machine from OpenStreetMap (Huber and Rust, 2016). Additionally, we also use the data provided by de Castro Victoria et al. (2021) on the cumulative cost of moving from each grid cell to the closest exporting port. This index of "Relative Distance" is also computed by using the shortest path through the existing road network.[5] Table 2 displays the results of the estimation of equation (10).

Our estimates yield similar trade cost elasticities - around 0.2 - across the different distance measures. Based on column (1), when the straight-line distance between a district's centroid and the closest exporting port increases by 10%, then the soybean price-gap also increases, by approximately 2%.

Our preferred specification is model (4), which uses travel time using the shortest-path to the closest international port. The main advantage of taking travel time instead of travel distance is that it allows us to take into account road quality. It seems reasonable to assume that driving a kilometer on a non-paved road takes more time than driving the equivalent distance on a paved highway; and it also seems reasonable to assume that the cost per mile driven is correspondingly lower, in terms of fuel, wear-and-tear on the vehicle, driver time, and potentially also spoilage of the output. Exploiting travel times between municipalities and the closest exporting port thus allows us to capture the effect of road qualities.

[5]This cumulative cost is computed by taking into account each surface type. These types include absence of road, unpaved or paved roads, which can be themselves divided into several sub-types. For instance, among paved roads, the data allow us to distinguish between single- and double-lane roads, as well as roads with a second lane under construction . Furthermore, this variable takes into account the activity of each port, *i.e.* whether agricultural commodities are exported or not over the period of study. This information is provided by Agrostat and the Ministry of Agriculture.

Table 2: Estimates of transport costs elasticities

	Dep. variable: Log of soybean prices differences			
	(1)	(2)	(3)	(4)
Straight-line Distance	0.197***			
	(0.011)			
Relative Distance		0.210***		
		(0.013)		
Minimum Distance			0.222***	
			(0.011)	
Minimum Duration				0.226***
				(0.012)
Constant	-3.858***	-3.221***	-2.706***	-1.767***
	(0.148)	(0.116)	(0.072)	(0.025)
Observations	1736	1736	1736	1736

Notes: ***, **, * significant at the 10, 5 and 1% level, respectively. Robust standard errors in parentheses. Geographical unit: municipalities. All regressions include meso-region fixed-effects. Year: 2017.

With this specification, we obtain a value of 0.226 for $\hat{\beta}_1$. This is within the range of the estimates from the literature, as Pellegrina (2022) finds 0.129 for perishable agricultural products in Brazil, and Sotelo (2020) finds 0.473 for coffee in Peru. Here, our estimate suggests that a 10% increase in the duration of travel between a district i centroid and the closest exporting port increases the soy price-gap by 2.26%.

Equipped with the estimated elasticities, we then compute iceberg transport costs τ_i for each meso-region. Figure 9 in Appendix C shows the resulting values of τ_i for our baseline.

5.2 Other key parameters

To calibrate our factor cost shares α_k and β_k for every crop k, we use the parameters from Pellegrina (2022). The author uses data on payments to labor and revenues for more than ten crops in Brazil. To give one example, we obtain $\alpha_{soy} = 0.06$ and $\beta_{soy} = 0.44$ for soybeans.[6]

The demand elasticity σ (reflecting substitutability between crops) and land heterogeneity θ are calibrated according to the estimates of Sotelo (2020). This yields values of 2.38 and 1.6, respectively. We use the GAEZ data to calibrate the productivity parameters $Z_{ik}(\omega)$

[6]To obtain values for α_k, we combine variable and non-variable labor in Pellegrina's estimates.

for all crops in our model. Finally, we back out the fixed cost $Z_i^0(\omega)$ by minimizing the difference between observed and predicted forest cover at the initial equilibrium.

For international trade, we calibrate imports M_k and exports X_k of crop k on 2017 national data, which we take from FAOSTAT. To capture the reaction of foreign demand to shocks like new roads, as well as to account for the fact that Brazil is major exporter of certain crops on the world market, we assume a constant price elasticity. This way, demand coming from foreign countries is downward-sloping. Specifically, we choose the following functional form:

$$X_k = X_{k_0} \left(\frac{p_k}{p_{k_0}} \right)^{-\sigma},$$

where p_{k_0} and X_{k_0} are respectively the world price and export value of a crop k in the baseline economy. The parameter σ is the demand elasticity, which we calibrate following the estimate of Sotelo (2020). The same approach is adopted for imports.

5.3 Model Validation

In this section we discuss the fit of estimated model with different aspects of the data important for our study. Specifically, in Figure 3 below, we display land uses, quantities and farm-gate prices in our baseline economy and in the data at year 2017.

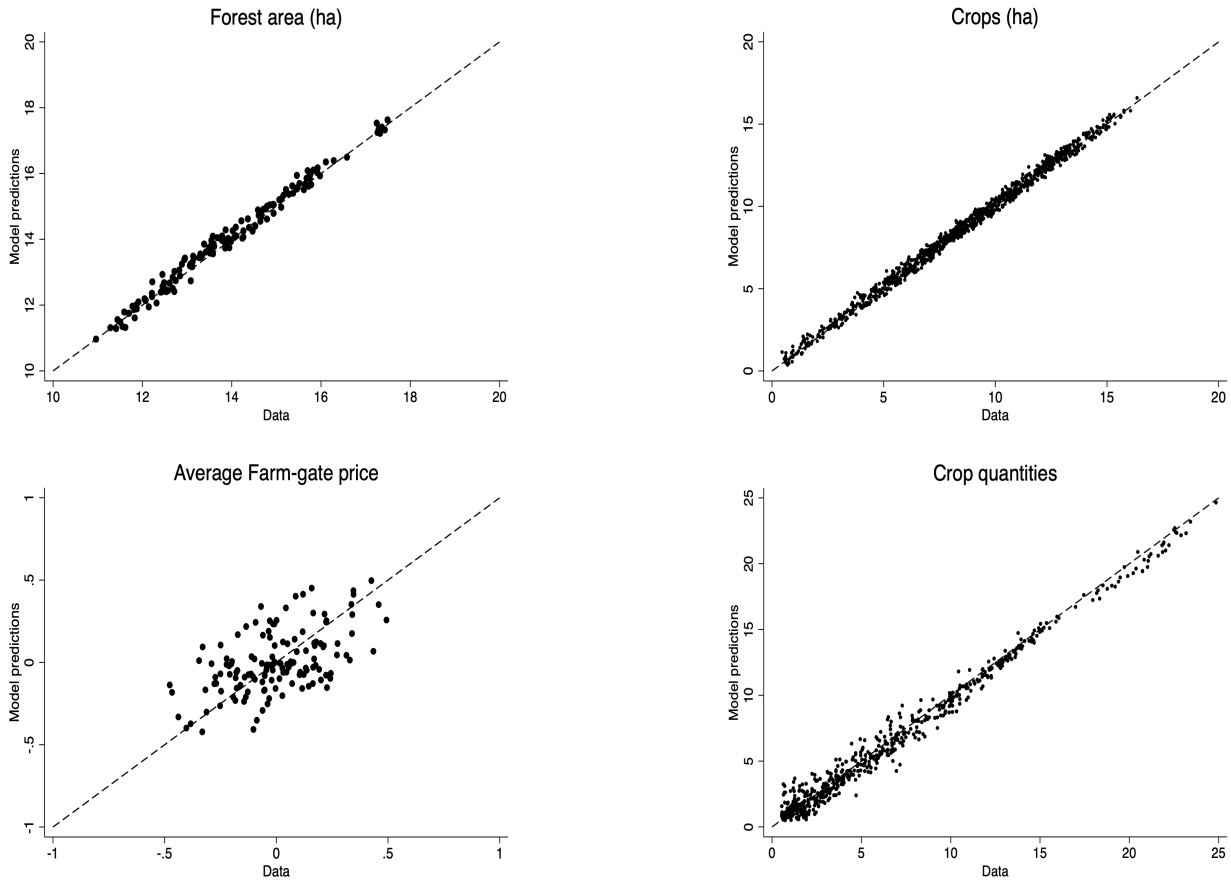


Figure 3: Model Fit. Notes: All variables are in logs. Prices are the average value of all crops per meso-region at the baseline, expressed as deviations from the mean. The dotted line line in each figure shows the 45 degree line.

By construction of the fixed cost parameter Z_i^0 and land productivity shifters Z_{ik}, the forest- and crops- land area at the baseline match the data (two upper panels of Figure 3).

The bottom left panel of Figure 3 presents the average value of the nine agricultural prices included in our analysis. It is done for each meso-region in the data and for the model's predictions. We can see that (average) crop prices are reasonably well predicted across meso-regions. Regressing the log of the price in the data over that predicted by the model yields a R-squared of 29%, with a slope of 0.58.

Regarding output quantities, displayed in the bottom right panel of Figure 3, model fit is slightly looser than for land use. This is particularly true for locations producing small amounts of output. Nevertheless, when regressing model predictions on data we find a R-squared over 90%.

Other indicators include the share of labor in agriculture. At the baseline, our model predicts a share of 5.9%, compared to 9.4 in Brazil in 2017. This is perhaps unsurprising,

given that our model accounts for only nine agricultural products (and not *all* agricultural activities) and also that we use a relatively crude representation of non-agricultural production. Together, these factors perhaps account for the model's under-prediction of the size of the labor force in agriculture.

6 Results

This section presents the results of our three counterfactual exercises. The first scenario focuses on the impact of roads that were built since 1990. We then turn to the possible effect of a national plan for transportation in 2035 and consider an alternative solution to that plan in the third scenario.

6.1 Assessing historical reductions in transport costs

As a first counterfactual exercise, we are interested in evaluating the impact of past infrastructure improvements. To do this, we focus on roads that were built from the 1990s up to our baseline year (2017).

Using historical road maps, we first calculate the iceberg transport costs that prevailed in 1995 and examine the model's predictions for both land use and a set of development outcomes. The year 1995 was chosen since it was an agricultural census year, for which we have rich data provided by IBGE. This allows us to compare the model's predictions to contemporaneous data.

To start, figure 4 shows the rate of decrease in iceberg transport costs across regions at the meso-region level.

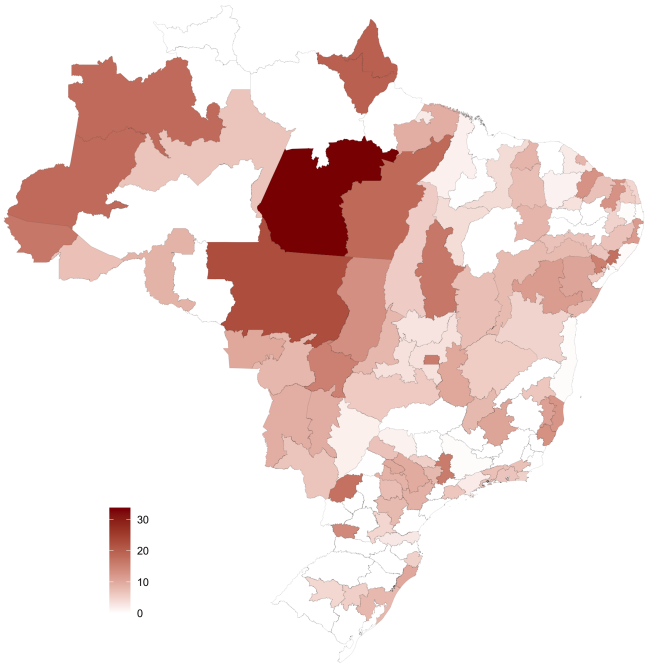


Figure 4: Decrease in iceberg transport costs between 1995 and 2017 across the Brazilian meso-regions (%)

While iceberg transport costs decreased on average by 6.47% across all Brazilian meso-regions over 1995-2017, the map shows that the meso-regions that experienced the largest reductions were mainly located in the Central-West and North regions. For instance, we find that the *Norte Mato-Grossense* (MT) meso-region experienced a 22.5% decrease over the period. In the meso-region of *Sudoeste Paraense*, in the state of *Parà*, transport costs dropped by 33.7% over the period, as a result of road construction. By contrast, in many other locations, we observe no variation.

Let us now assess the effect of these shocks by introducing 1995 transport costs to our baseline economy as a first counterfactual exercise. We discuss the results by separating the aggregated outcomes from the spatially explicit ones.

Aggregate results. Table 3 displays the results in two parts: the first column shows the economy when transport cost variations affect both inputs and output (i.e., τ_i and υ_i) ; the second column shows the economy when only the cost of shipping goods τ_i varies, but not that of importing modern inputs, υ_i. This approach allows us to isolate the effect of changes

in transport costs for the adoption of intermediate inputs in agriculture. It informs us about the role of modernization in the deforestation and agricultural development process.

Table 3: The economy with past transport costs: predicted rates of change

		Output and Inputs	Output only
Forest cover	$\Delta\left(\sum_i F_i\right)$	2.270	1.837
Gross ag. income	$\Delta\left(\sum_i \sum_k p_{ik} Q_{ik}\right)$	-3.650	-3.255
Q1 income	-	-0.692	-1.262
Q4 income	-	8.254	5.788
Ag. exports	$\Delta\left(\sum_k X_k\right)$	-18.082	-14.185
Ag. consumption	$\Delta\left(\sum_k C_k\right)$	-10.109	-8.653
Input adoption	$\Delta\left(\sum_i h_i\right)$	-7.318	-2.772
Non-ag. workers	ΔN^M	0.205	0.201

Notes: Column "Output and inputs" reports rates of change when transport costs change for shipping goods and importing intermediate. In column "Output only", the iceberg cost from importing intermediate goods is the same as in the baseline economy. Q1 and Q4 designate change in income in the richest and poorest (respectively) quartiles of meso-regions.

Compared with the baseline economy, we find that forest cover would be 2.3% higher than its actual 2017 level, if transport costs had remained at the level of 1995. As we detail below, some meso-regions even peak slightly above 80% of additional forest cover. In the counterfactual economy, agricultural consumption nationally (aggregated across all nine of our crops) would have been 10.1% lower than in our baseline for 2017. Agricultural exports would have been 18% lower. These declines in agricultural production and exports reflect the negative price shock faced by the economy as a whole, and particularly by more remote meso-regions. In comparison with the baseline, in the counterfactual economy some locations would have become less attractive for agriculture, as both τ_i and υ_i are affected by transport costs. Locations remote from the transportation hubs would have seen substantial increases in their cost of production, as well as decreases in farm-gate prices. Put differently, the actual road investments during this period had a major impact on increasing agricultural output – but did so at a significant cost in terms of forest loss.

The model predicts that the new roads constructed during this period caused a loss of 2.3% of Brazil's forest cover. This is 25.6% of the total loss observed in the data over 1995-2017. This assumes that the observed allocation of land in 2017 fully incorporates all the land use changes associated with the expansion of the transport network and thus reflects

the new spatial equilibrium. To the extent that land conversion may take some time, it is possible that transport expansion from the past few years may not yet be fully embedded in observed land use. In that sense, our model gives us a lower-bound prediction of the deforestation impacts.

The quantification exercise thus reveals that as much as a quarter of the land cleared in Brazil over these two decades may be due to changes in transport costs. Let us now examine other economic outcomes in the counterfactual economy.

One topic for analysis is the allocation of labor across sectors. The reduction in transport costs between 1995 and 2017 led, according to the model, to a reduction of labor in the non-agricultural sector by 0.205% (compared to the baseline model values in 2017). This suggests that the improvement in transport connectivity had the paradoxical effect of reducing movements of labor out of agriculture. Because agriculture was made more profitable by the reductions in transport cost, the movement of labour into cities was somewhat muted, relative to what might have happened. This effect is quantitatively small, however.

Had transport costs remained at their 1995 levels, agricultural income would be 3.6% lower than the 2017 baseline. This average result hides important disparities. Indeed, the richest quartile of the agricultural income distribution would be 0.7% worse off, in terms of income, while the poorest quartile would be better off by more than 8%. This suggests that roads construction since the 1990s has deepened inequalities across space and benefited mostly those regions that already had a relatively high level of agricultural income. Road construction in general made the already prosperous parts of Brazil more prosperous. Increased output in those regions actually led to a reduction in the prices received in other regions, making farmers in those places worse off.

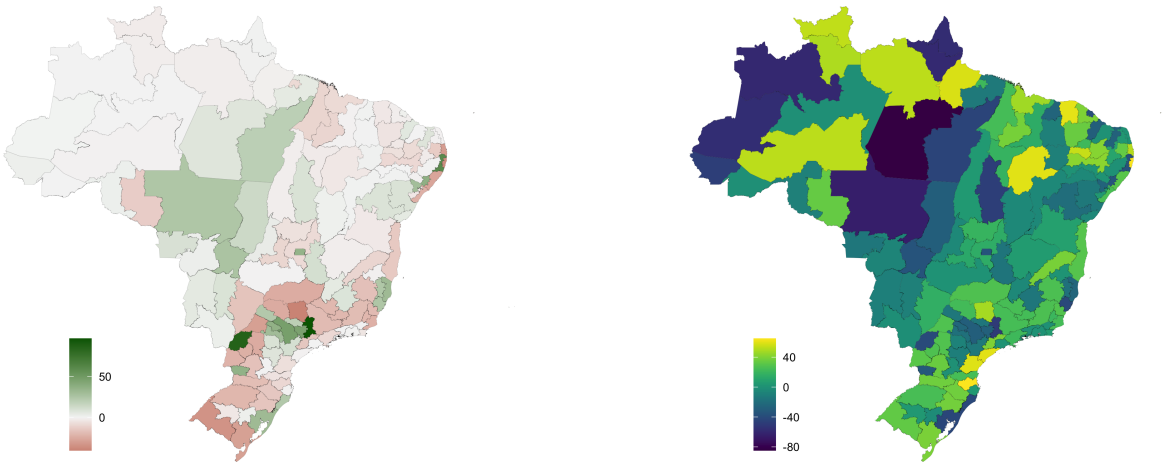
To understand the role played by input adoption, we examine the column labeled "Output only". It displays results from an economy in which intermediate inputs still face the transport costs prevailing in 2017, but output faces those from year 1995. In this counterfactual, forest cover would be higher than at the baseline by 1.8% in average, instead of 2.3% when both inputs and outputs are affected by transport cost variations. The difference between those two rates of change points to the role played by modern input adoption in land conversion. The result shows that, when adopting inputs is more costly, more forest cover is preserved. The construction of new roads drives greater uptake of intermediate inputs for agriculture. Although, in principle, it seems plausible that this intensification might actually reduce land pressure and forest clearing, our analysis suggests that prices will not drop sufficiently on the extensive margin. Our quantification exercise suggests that decline

in inputs accounted for only one-fifth of the total deforestation caused by improvement in market access; the bulk of the impact came from higher farmgate prices for crop output.

Looking at agricultural income as an outcome, input adoption accounts for a relatively modest fraction of the impact of transport cost reductions. The overall effect of the road improvements between 1995 and 2017 was to raise agricultural incomes by 3.6%, as noted above. When road improvements are restricted to affect only the prices of crop outputs, agricultural income drops by 3.2%, compared with 3.6% when the transport costs shock affects the prices of both outputs and intermediate inputs. This implies that 11% of the improvements in agricultural income over this period can be attributed to the lower prices of intermediate inputs.

We now go further and disentangle the spatial disparities of these results.

Regional results. Figure 5 presents the growth rate in forests and in agricultural income predicted by the model when we return the model economy to 1995 iceberg costs.



(a) Predicted Change in Forest Cover. (b) Predicted Change in agricultural income.

Figure 5: Spatial impacts of reversion to 1995 levels of transport costs. Note: Figure 5a plots predicted rate of change in forests per meso-region with 1995 transport costs compared to the baseline equilibrium, and Figure 5b for the change in income.

Figure 5a shows the spatially heterogeneous distribution of deforestation across Brazilian meso-regions. It is important to keep in mind that the Figure shows what would happen relative to the baseline 2017 economy when historical transport costs (from 1995) are re-introduced. Some locations exhibit a rate of forest gain up to 80%, while some others

actually lose forest stock. In the latter case, this means that new roads from 1995 to 2017 appear to have led to reforestation in some regions.

Consider first a location where road construction led to forest clearing. In the meso-region of *Norte Mato-grossense* (MT), we find that forest cover in 2017 would have been 24.5% higher had Brazil's road network stayed as it was in 1995. The land clearing that the model attributes to road improvements is actually 93.3% of what we observe in the data: the model tells us that changes in the road network accounted for the vast majority of the forest clearing that took place in this meso-region.

Figure 5b allows us to discuss further our results about the impacts on the top and bottom quartiles of meso-regions, in terms of agricultural income distribution.[7] As shown by the figure, compared to the baseline, many locations in the economy would have experienced lower agricultural incomes in 2017 had iceberg costs remained at their 1995 levels. Put differently, this means that new roads have contributed to an increase in agricultural income in some meso-regions where a change in agricultural activities has taken place due to spatial changes in prices. For instance, following the new road network implemented between 1995 and 2017, the state of *Mato Grosso* saw a 34.4% increase in the price of soybeans.[8]

At the economy-wide level, however, the changes in agricultural income due to roads appear to have been modest. Some regions gained and others lost, but we find that gross agricultural revenues, $\sum_i \sum_k p_{ik} Q_{ik}$, only grew by 3% as a result of new roads. The gains in remote regions were offset to some degree by losses in other areas that were undercut by the expansion of agricultural production into previously forested areas. The net gains in agricutlural income are thus substantially smaller than the gains in the regions that were most favored. And the welfare gains would arguably be much smaller still, especially if measured against the local and global environmental costs.

To better grasp the consequences of improvements in market access, Figure 6 plots the predicted change in total cropland in the model and in the data vs the change in iceberg transport costs per meso-region between the baseline and year 1995.

[7] Recall that each region in the model has a single representative consumer. Thus the only distributional issue that we can address is the distribution across meso-regions; i.e., the spatial inequality of our economy. Recall also that all consumption takes place in the (urban) transportation hub, so all consumers face the same prices, regardless of the region in which they produce output. Our measure is thus simultaneously a measure of inequality in agricultural income and a measure of inequality in consumption.

[8] This reflects an average change across the five meso-regions that make up the state.

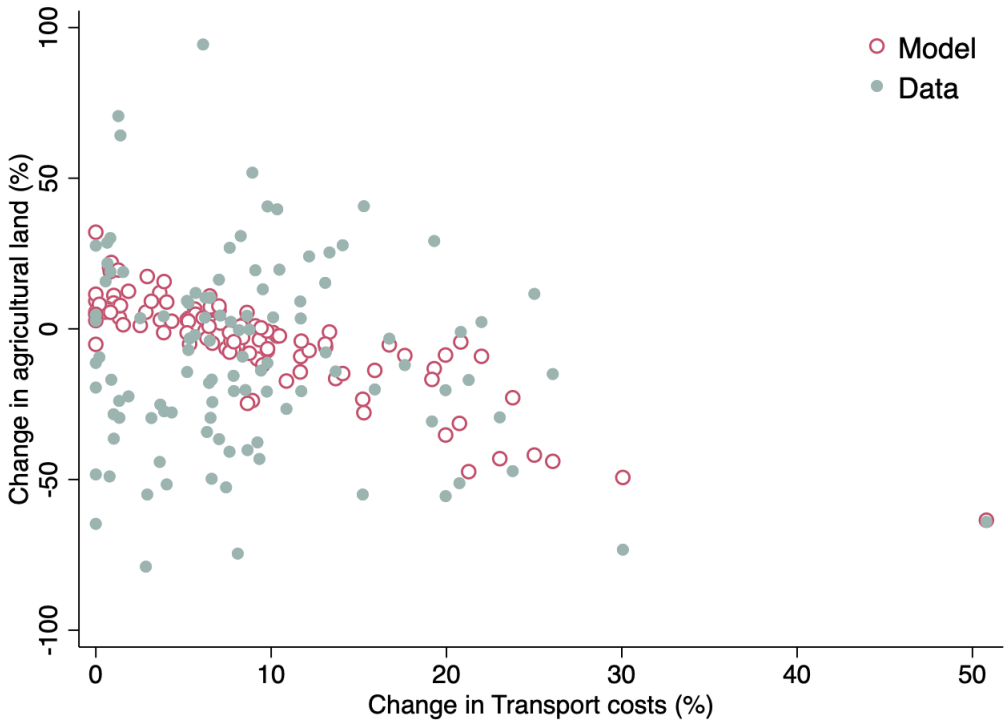


Figure 6: Agricultural land expansion and changes in transport costs

Variations in land use and in transport costs seem to be correlated, both in the data and in the model. Since there are many other factors taking place and potentially affecting the spatial patterns of forest changes (e.g., logging, mining and other forms of extraction, mediated through varying degrees of local regulatory effectiveness), we do not expect our model to explain all the variation observed in the data. Keeping this in mind, Figure 6 shows the linear relationship between the removal of trade frictions and land expansion from 1995 to 2017. The broad pattern is clear: the more frictions diminish, the more land is converted into cropland.

In the model, changes in forest cover are mainly linked to soy and pasture production, as shown by Figure 11 in Appendix C. In some meso-regions, the changes in iceberg transport costs have led to increases in the land area devoted to soya of greater than 50%. Some locations in Northern Brazil have nearly 40% more land under pasture with 2017 transport costs than would have been the case had transport costs remained at their 1995 levels. While the changing spatial patterns of agricultural production do highlight the "positive" impacts of specialization, the clear cost in this case is that livestock production has been moving to previously forested regions in the Central-West part of Brazil. In the counterfactual economy,

a state like *Mato-Grosso* would in 2017 have had 78% less land under soybeans if transport costs had remained at their 1995 levels.

Note that these changes do not affect only those regions that experienced direct changes in their own transport costs. Because of spatial spillovers and general equilibrium effects, there appear to have been substantial changes even in locations that had little change in transport costs. Consider the meso-region of *Centro Ocidental Paranaense* (PA) in the Amazonian Biome: the land allocated to pasture would have been 23.9% lower in 2017 if transport costs had remained at their 1995 levels, according to our model. Interestingly, the data show a change of 23.1% in pasture coverage during this period, suggesting that the model closely matches the data in this case, and allows us to capture the general equilibrium effects.

New roads thus threaten forests also in locations indirectly connected to a decrease in transport costs. Note that we would not be able to take into account these effects using a standard empirical analytical framework. Among the advantages of our framework and approach is that we can assess these general equilibrium effects. It is critical when studying a policy like infrastructure improvements where many outcomes are likely to vary, often simultaneously, including in non-treated locations.

6.2 Brazilian National Plan for 2035

For our second counterfactual exercise, we use data on the planned 2035 Road network. Those are provided by the National Observatory of Transports and Logistics. This office provides several scenarios of infrastructure improvements that include all types of transportation modes (e.g., air, maritime, national vs international) around what has been named the "Brazilian's National Logistics Plan 2035" (NLP 2035). We selected the most exhaustive scenario (number 8) and kept changes in road networks only.[9] We compute iceberg transport costs as for our baseline economy and retain meso-regions with lower τ_i than at the baseline.

Figure 7 displays the change in iceberg transport costs between our baseline and NLP 2035.

[9]Supplementary details regarding the report can be found at https://ontl.epl.gov.br/wp-content/uploads/2022/05/PNL-English-version.pdf

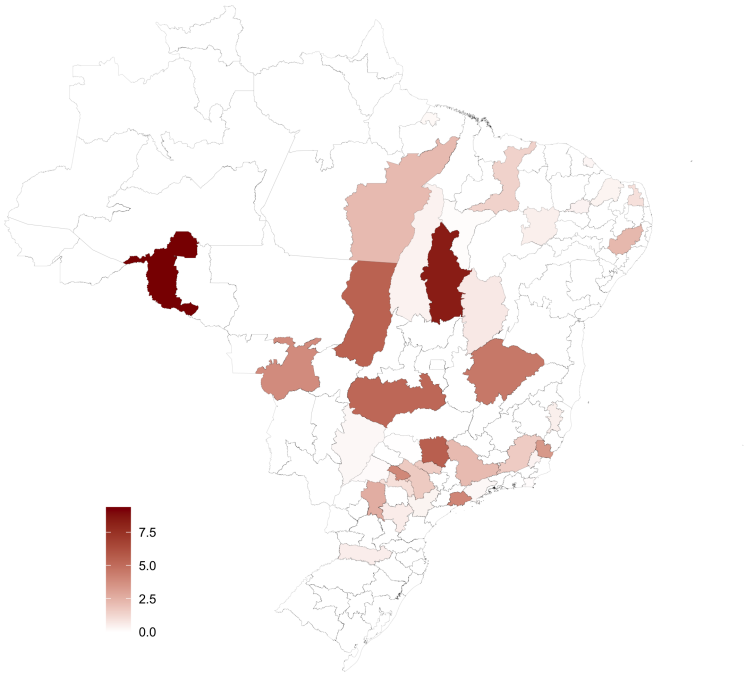


Figure 7: Estimated reduction in transport costs 2017-2035.

According to this plan, a mesoregion like *Madeira-Guaporé*, in the state of Rondonia, which currently has almost 70% of total land under forest, will experience a transport cost reduction of over 9%. Similarly, assuming the transportation plan goes through, we estimate a reduction in iceberg transport costs by 8.4% in *Oriental do Tocantins* (TO), a meso-region with almost 60% of land under forest.

For our second set of counterfactuals, we now introduce the predicted τ_i of 2035 in our baseline economy. Table 4 presents the aggregated results.

The overall effect on deforestation is relatively small compared to the baseline economy, with a rate of forest losses of 0.024%. Again, this result hides important spatial heterogeneities. To see it, we plot the spatially explicit results for forest cover changes in Figure 8. In comparison with the baseline economy, the 2035 National Plan would negatively affect forests in many locations. This is the case of *Oriental do Tocantins* (TO), cited before, where deforestation would reach 6.5% compared to the baseline. Offsetting this deforestation to some degree, we note that many meso-regions would reforest. However, it is important to notice that these positive rates of forest change would remain low, below 10%. More importantly, reforestation occurs in locations mostly outside of the Amazon biome. The potential

Table 4: The economy with future transport costs: predicted rates of change

		Output and Inputs
Forest cover	$\Delta\left(\sum_i F_i\right)$	-0.024
Gross ag. income	$\Delta\left(\sum_i \sum_k p_{ik} Q_{ik}\right)$	0.283
Q1 income	-	-0.270
Q4 income	-	-8.319
Ag. exports	$\Delta\left(\sum_k X_k\right)$	3.175
Ag. consumption	$\Delta\left(\sum_k C_k\right)$	1.562
Input adoption	$\Delta\left(\sum_i h_i\right)$	1.969
Non-ag. workers	ΔN^M	-0.086

Notes: Column "Output and inputs" reports rates of change when transport costs change for shipping goods and importing intermediate. Q1 and Q4 designate change in income in the richest and poorest (respectively) quartiles of meso-regions.

ecological benefits from the growth of those forests are unlikely to compensate the loss of primary forest in the Amazon.[10]

Regarding economic outcomes, we find that agricultural exports would be 3.2% higher than in the baseline economy. The share of workers outside of agriculture would actually decline by almost 1%, and agricultural income would rise by 0.3%. These positive impacts need to be balanced against the potential environmental costs of deforestation.

A simple calculation can compare the income gains with the carbon price of lost CO_2 sequestration in Brazil's forests. This infrastructure scenario would lead to 0.02% of deforestation overall, which corresponds to slightly more than 120 thousands hectares of forests. In 2022, the carbon price in a geographically close country, such as Columbia, was $5.01 per ton, according to the Carbon Pricing dashbord from the World Bank. Even on the basis of this *particularly* low carbon price, the 0.02% of forest losses represents a huge carbon cost. For example, Paniagua-Ramirez et al. (2021) recently estimate that carbon storage in tropical forests vary from 204 tonnes per hectare (secondary forest) to 447 tonnes per hectare (mature forest). This implies that, with a carbon price as low as the one provided by the World Bank for Columbia, deforestation caused by the NLP 2035 would incur a total cost comprised between 126M and 276M of US$. When one considers that the carbon price used by the US government is 51 US$ (Rennert et al., 2022), this yields an upper-bound to the

[10]On the imperfect substitution between primary and secondary forests, see, for instance, Angelsen and Rudel (2013) or Wolfersberger et al. (2021).

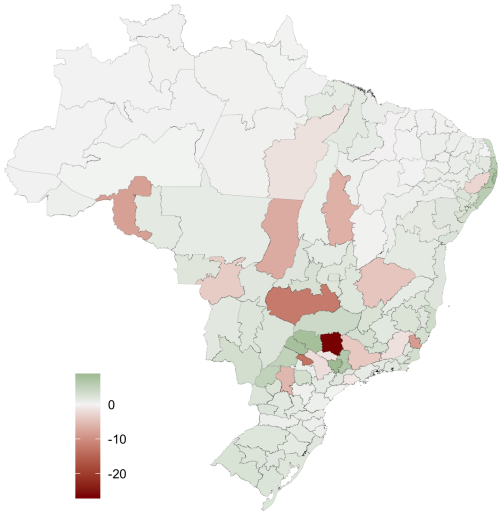


Figure 8: Predicted rate of variation in forest cover with 2035 transport costs compared to the baseline economy

deforestation cost of new roads of almost 3 billion US$. This is not to mention that other costs, such as biodiversity losses, are not taken into account in this simple exercise.

6.3 An alternative Plan

In this section, we propose a policy scenario that differs from the 2035 National Plan, specifically regarding the meso-regions targeted by reductions in transport costs. According to the NLP 2035, two meso-regions located inside the Amazon biome are expected to experience reductions in iceberg costs. Those are *Madeira-Guaporé* in the state of *Rondonia*, and *Sudeste Paraense* in *Parà*, as shown in Figure 10 of Appendix C. Their expected reductions in τ_i, relative to the 2017 values, are by 9.4% and 2.2%, respectively.

Here, we build an alternative scenario in which we keep their transport costs unchanged between 2017 and 2035, and instead apply the exact same reductions that were initially planned but to two other regions outside the Amazon biome. We choose two regions that were not supposed to be affected by NLP 2035, and that are relatively more productive in wheat, instead of soybeans. By doing this, we can illustrate the importance of specialization across crops on deforestation patterns. We proceed by applying a 9.4% reduction in iceberg cost to the meso-region *Noroeste Paranaense* in the state of Paranà, and a 2.2% reduction to *Sudoeste de Mato Grosso do Sul* in Mato Grosso do Sul.

The results are displayed in Table 5.

Table 5: The economy with future transport costs: alternative scenario of road construction

		Output and Inputs
Forest cover	$\Delta\left(\sum_i F_i\right)$	0.310
Gross ag. income	$\Delta\left(\sum_i \sum_k p_{ik} Q_{ik}\right)$	-0.212
Q1 income	-	2.473
Q4 income	-	-13.865
Ag. land productivity	$\Delta\left(\sum_i \sum_k Q_{ik}/L_{ik}\right)$	1.900
Ag. exports	$\Delta\left(\sum_k X_k\right)$	3.731
Ag. consumption	$\Delta\left(\sum_k C_k\right)$	1.217
Input adoption	$\Delta\left(\sum_i h_i\right)$	2.880
Non-ag. workers	ΔN^M	-0.718

Notes: This table shows the rate of change in aggregate outcomes of the economy between 2017 and our alternative scenario of roads construction for 2035. Column "Output and inputs" reports rates of change when transport costs change for shipping goods and importing intermediate. Q1 and Q4 designate change in income in the richest and poorest (respectively) quartiles of meso-regions.

Redirecting road investments towards meso-regions outside the Amazon changes dramatically the outcome of the policy. Overall, instead of decreasing, the level of forest cover actually increases with the shock. This means that this alternative Plan leads to net reforestation instead of deforestation. For example, in *Madeira-Guaporé* we find that forest cover is 1.1% higher than at the baseline with this alternative Plan, and as much as 12.6% higher than with the NLP 2035. This shows the importance of avoiding key areas when investing in road infrastructures.

Turning to economic outcomes, we observe sizeable and positive changes. The share of workers in agriculture decreases by 0.7%, consecutively to the shock. While gross agricultural income slightly decreases on average, the output per hectare as well as the value of exports, consumption and input adoption all increase. Importantly, we find that relative to the NLP 2035 scenario presented in section 6.2, the share of land under soybeans decreases by 0.342%, and that used for pasture by 0.536%. On the contrary, the share of land under wheat increases by 0.032% (relative to the NLP 2035 scenario).

All in all, this shows that for an exact same given amount of infrastructure investments, it is possible to obtain comparable economic outcomes while preserving more natural habitats.

This can be done thanks to two forces. First, by targeting regions with comparative advantages in less land-intensive crops (e.g., wheat instead of soy or cattle), thus taking advantage of specialization patterns. Second, by avoiding the most ecologically sensitive locations.

7 Conclusion

In this paper, we have studied how new roads may disrupt the spatial equilibrium of an economy and affect both environmental and development outcomes. To do this, we built a quantitative spatial model of agricultural trade that takes into account several crops, trade frictions and fixed-costs to convert forest into cropland. We then took our model to the data to quantify the effect of infrastructure improvements in Brazil, both in the past and for the next 10 years.

In a first counterfactual exercise we found that roads that were built between 1995 and 2017 did contribute to up to one quarter of total forest clearing in the country over that period. Importantly, the impacts were highly heterogeneous across Brazilian meso-regions. New roads, by increasing market access and dropping the adoption cost of intermediate inputs, increased the profitability of agriculture in many locations previously isolated. In locations benefiting from a comparative advantage due to high land productivity, the increase in market access pushed prices up to a level high enough that converting more land into agriculture was now profitable. Our model, for example, captured this reasonably well in a state like Mato-Grosso. In this state, which has become a major deforestation hotspot since the 2000s, reductions in transport costs explain up to 90% of the deforestation observed in the data.

In a second counterfactual exercise we made use of data provided by the Brazilian Ministry of Transportation on infrastructure plans for 2035. We found that the future reductions in transport costs from this plan, although relatively modest, will affect some locations currently largely covered with forests. While other regions would potentially reforest thanks to specialization, these are mostly locations outside the Amazon biome, likely less ecologically valuable (though perhaps equally significant for carbon sequestration). In a third counterfactual exercise, we propose an alternative plan that avoids meso-regions inside the Amazon for a same given level of investments. We find that, by improving market access in those regions elsewhere and that are better at producing other crops than soy, this leads to greater forest conservation, especially in the Amazon biome, while still enabling development as measured by agricultural income, exports and employment share.

Our findings depend on assumptions regarding foreign demand in our baseline economy. In this analysis, we have assumed a downward-sloping global demand curve for soybeans and other agricultural commodities. A cynical view might be that global demand for soybeans is almost perfectly elastic, from the vantage point of Brazil. In this case, soya expansion will not be limited by declining prices. Similarly, there is no guarantee that pressure on forests, from international consumption for soybeans or other products, will not increase in the future. This would potentially threaten the reforestation results found here.

Our counterfactual exercises, whether with past or future transport costs, shed light on the environmental impact of new roads. The project emphasizes the importance of general equilibrium effects in assessing the environmental impact of new roads. Roads do not only alter production in the places they traverse; they also alter incentives in locations much farther away. Our results highlights the need to think carefully about the land use impacts of investment in infrastructure. While roads are widely viewed in economic and policy work as a key tool for growth, their environmental impacts, especially in ecologically sensitive locales, call for caution. Regions with the largest ecological reserves could potentially be negatively affected, sometimes for rather modest economic benefits.

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Online Appendix

A Solving the Model

We detail the steps to solve the model.

A.1 Agricultural output

Over a given plot ω in region i, the representative farmer minimizes the following total cost:

$$\min_{\{N_{ik},h_{ik},L_{ik}\}} \left[w_i N_{ik}(\omega) + \upsilon_i h_{ik}(\omega) + r_i(\omega) L_{ik}(\omega)\right], \tag{11}$$

subject to:

$$\left(N_{ik}(\omega)\right)^{\alpha_k} \left(h_{ik}(\omega)\right)^{\beta_k} \left(A_{ik}(\omega) L_{ik}(\omega)\right)^{1-\alpha_k-\beta_k} \geq \bar{Q}_k.$$

In the objective function (11), w_i is wage, υ_i is the price of the intermediate input, and $r_i(\omega)$ is the plot-specific rental rate. Denoting by λ the Lagrangian multiplier, the first-order-conditions of the above problem are the following:

$$\begin{aligned} \lambda \alpha_k \frac{Q_{ik}(\omega)}{N_{ik}(\omega)} &= w_i, \\ \lambda \beta_k \frac{Q_{ik}(\omega)}{h_{ik}(\omega)} &= \upsilon_i, \\ \lambda (1-\alpha_k-\beta_k) \frac{Q_{ik}(\omega)}{L_{ik}(\omega)} &= r_i(\omega). \end{aligned}$$

We thus obtain the following labor- and intermediate input-to-land ratio:

$$\begin{aligned} \frac{N_{ik}(\omega)}{L_{ik}(\omega)} &= \frac{\alpha_k}{(1-\alpha_k-\beta_k)} \frac{r_i(\omega)}{w_i}, \\ \frac{h_{ik}(\omega)}{L_{ik}(\omega)} &= \frac{\beta_k}{(1-\alpha_k-\beta_k)} \frac{r_i(\omega)}{\upsilon_i}. \end{aligned}$$

Note that given the distributional assumptions regarding $A_{ik}(\omega)$, when a plot is open for productive use, the representative farmer uses all land area available in that plot for the most productive crop k, such that $L_{ik}(\omega) = 1$. Substituting each of the above first-order-conditions in the technology constraint, provided that in equilibrium $Q_{ik}(\omega) = \bar{Q}_k$ holds, we

can write the marginal cost $MC_{ik}(\omega)$ of producing k in plot ω in region i as:

$$MC_{ik}(\omega) = \frac{w_i^{\alpha_k} v_i^{\beta_k} r_i(\omega)^{(1-\alpha_k-\beta_k)}}{A_{ik}(\omega)^{(1-\alpha_k-\beta_k)} \alpha_k^{\alpha_k} \beta_k^{\beta_k} (1-\alpha_k)^{(1-\alpha_k-\beta_k)}}.$$

As profit maximization over each plot imposes that the price p_{ik} of a commodity k in region i equals its marginal cost of production $MC_{ik}(\omega)$, we obtain the following rental rate per plot net of the fixed conversion cost:

$$r_i(\omega) = A_{ik}(\omega)\psi_{ik} - p_0 A_i^0(\omega),$$

with:

$$\psi_{ik} = \left[p_{ik} \frac{\alpha_k^{\alpha_k} \beta_k^{\beta_k} (1-\alpha_k-\beta_k)^{(1-\alpha_k-\beta_k)}}{w_i^{\alpha_k} v_i^{\beta_k}} \right]^{\frac{1}{(1-\alpha_k-\beta_k)}}$$

as expressed in (3). Combining this result with the ratios of labor-to-land and intermediate input-to-land we obtain the optimal factors' demand per plot:

$$N_{ik}(\omega) = A_{ik}(\omega)\psi_{ik} \frac{\alpha_k}{(1-\alpha_k-\beta_k)} w_i^{-1}, \tag{12}$$

$$h_{ik}(\omega) = A_{ik}(\omega)\psi_{ik} \frac{\beta_k}{(1-\alpha_k-\beta_k)} v_i^{-1}. \tag{13}$$

The land shares are then derived by making use of the Fréchet assumption regarding investment $A_i^0(\omega)$ and productivity $A_{ik}(\omega)$, with $A_i(\omega) \equiv \{A_{ik}(\omega), A_i^0(\omega)\}$, as in Costinot et al. (2016) or Farrokhi and Pellegrina (2021). We obtain equation (5).

Finally, aggregating (12) and (13) over all plots ω in region i gives the regional demand for labor and intermediate inputs, respectively. The regional amount of output per crop can then be easily obtained.

A.2 Non-agricultural output

In our setting the production of a composite good of manufacturing and services requires labor only. The producer problem is:

$$\max_{\{N^M\}} \left\{ p_0 \Lambda N^M - w N^M \right\},$$

whose first-order-condition is given by $p_0\Lambda = w = w_i$.

A.3 Consumers

Total expenditures are given by the sum of wages and income from the land:

$$E = w_i \sum_i N_i^A + wN^M + \sum_i \int_{\Omega_i} r_i(\omega) d\omega. \tag{14}$$

Consumption for all crops k can be found by solving the following maximization problem:

$$\max_{\{C_k\}} \left(\sum_{k=1}^{K} (\mu_k)^{\frac{1}{\sigma}} (C_k)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \text{ s.t. } \sum_{k=1}^{K} p_k C_k \leq b^A E.$$

Provided that $p_k = \tau_i p_{ik}$. The maximization problem for outside good consumption is choosing the level of consumption C^M subject to the constraint $p_0 Q^M \leq (1 - b^A)E$.

B Data Sources

Geographic features and infrastructures. We work at the meso-region level, a formal political boundary defined by the Brazilian statistical bureau (IBGE). We collect data on road network from the Ministry of Transportation, and ports are taken from the WFPGeoNode.

Forests. Our data on forest cover are satellite data taken from the MapBiomas project. This project reconstructs annual land use and land cover information between 1985 and 2017 for Brazil. It provides detailed mapping for forests and other land covers (e.g., pasture) at a 30m pixel resolution based on Landsat archive (Souza et al., 2020).

Agriculture. Our main source of agricultural data are the agricultural censuses from 1995 and 2017 provided by IBGE. Among other variables, we obtain the amount of hectares cultivated for each crop, quantities produced and sold, or the number of agricultural workers at different administrative levels. For data on the rest of the world, we use FAOSTAT. To inform us on estimated potential yields per crop in each location we use the GAEZ data (IIASA, FAO).

Other variables. Data for the non-agricultural sector are taken from the Economic Transformation Database (de Vries et al., 2021). We collect information on the number of persons engaged in the non-agricultural sector as well as on the value-added of this sector.

C Supplementary Figures

Year 2017 Transport Costs. Figure 9 presents the estimated iceberg costs of transportation towards the closest international port for each meso-region centroid.

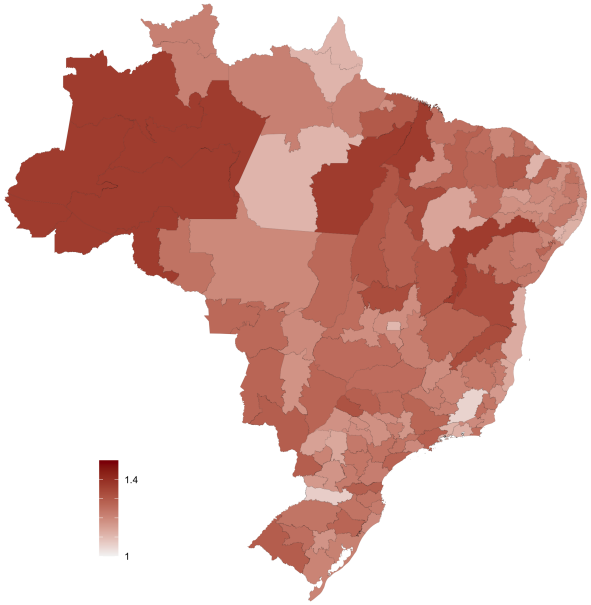


Figure 9: Estimated iceberg transport costs in 2017

The figure makes clear that meso-regions along the Atlantic Coast as well as in the Southern part of Brazil are well connected to the international market. On the contrary, the meso-regions in some states such as Acre or Mato-Grosso face higher trade costs. In a meso-region like *Vale do Juruá*, in the state of Acre, our estimate of the iceberg transport cost reaches a score slightly above 1.35 in 2017.

Year 2035. Figure 10 shows the meso-regions where iceberg are supposed to decrease with the 2035 Brazilian National Plan.

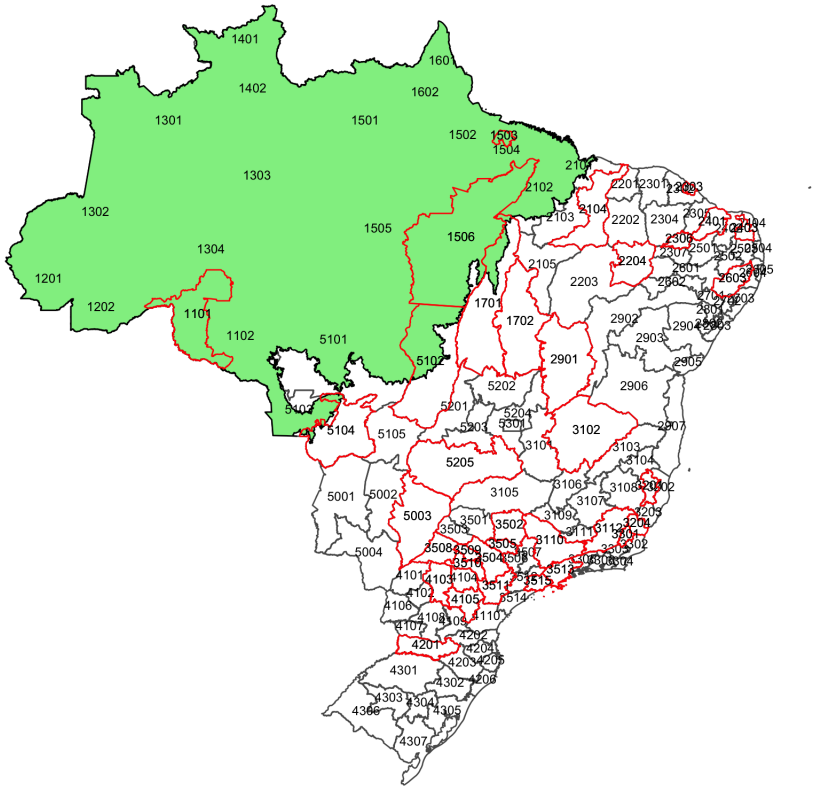
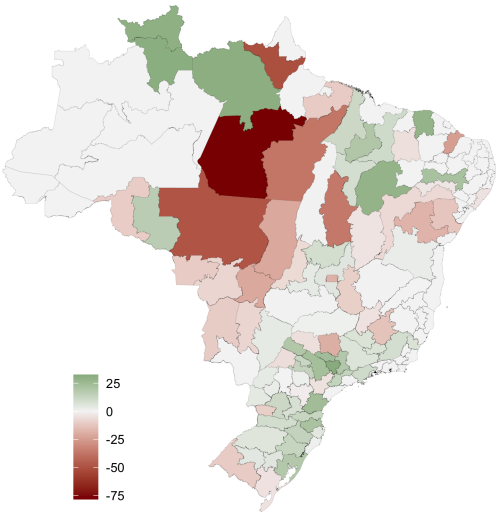
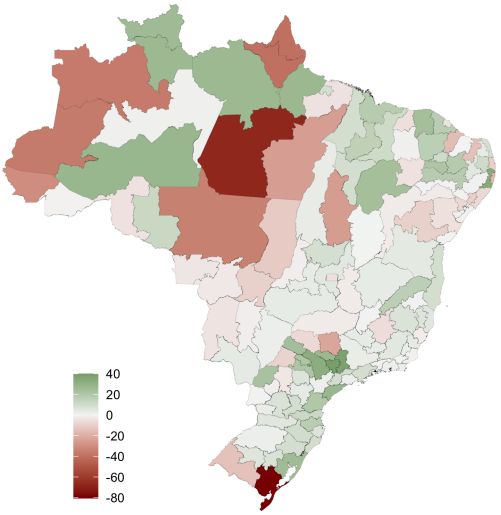


Figure 10: Meso-regions with transport costs reduction according to the NLP 2035.

Additional results, first counterfactual



(a) Predicted Change in Soybeans area.



(b) Predicted Change in Pasture area.

Figure 11: Soybeans and Pasture expansion. Note: this Figure plots the predicted rate of change in hectares allocated to soybeans and pasture activities per meso-region with 1995 transport costs compared to the baseline economy.

D Empirical results

Table 6: Correlation between forest cover and distance to the closest international port

	Dep. Var.: Share of land under forests		
Straight-Line Distance	0.039		
	(0.024)		
Minimum Distance		0.071**	
		(0.029)	
Minimum Duration			0.114***
			(0.023)
Constant	-0.074	-0.515	-0.285*
	(0.314)	(0.381)	(0.145)
Observations	137	137	137

Notes: ***, **, * significant at the 10, 5 and 1% level, respectively. Robust standard errors in parentheses. Geographical unit: meso-regions. Year: 2017.

E Extension: Planner's problem

In this section we describe an extension of the model as a social planner's problem that values the existence of the forest. We focus on the agricultural sector only and drop the plot-level index.

For $\forall\, k \in \{1, ..., K\}$ and $\forall\, i = \{1, ..., \mathcal{L}\}$, the objective function is:

$$\max W = \left[\left(\sum_{k=1}^{K} (\mu_k)^{\frac{1}{\sigma}} (C_k)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} + \sum_i \log (F_i) \right] \tag{15}$$

Forest land F_i is integrated to the preferences of the representative agent. It reflects the services provided by standing forests, which may be ecological, for example by maintaining soil quality, preserving local biodiversity or ensuring the perpetuation of precipitation cycles. These may be social too, by preserving the living conditions of local tribes. This objective function is subject to:

$$\begin{aligned} bE &\geq \left(\sum_{k=1}^{K} (\mu_k)^{\frac{1}{\sigma}} (C_k)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \\ F_i &\leq \bar{L}_i - \sum_{k=1}^{K} L_{ik} \end{aligned}$$

Agricultural production in all region i:

$$\sum_{k=1}^{K} Q_{ik} = N_{ik}^{\alpha_k} h_{ik}^{\beta_k} \left(A_{ik} L_{ik} \right)^{1-\alpha_k-\beta_k},$$

subject to:

$$\begin{aligned} \bar{N} &= \sum_{k=1}^{K} N_{ik} + N^M \\ \bar{L}_i &= \sum_{k=1}^{K} L_{ik} + F_i \end{aligned}$$

Clearing for all crops k implies:

$$C_k = \sum_i Q_{ik}/\tau_i + M_k - X_k$$

The Lagrangian of this problem is:

$$\begin{aligned}
\mathcal{L} &= \left[\left(\sum_{k=1}^{K}(\mu_k)^{\frac{1}{\sigma}}(C_k)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{\sigma}{\sigma-1}} + \sum_i \log(F_i)\right] \\
&- \sum_i \sum_k P_k \left[C_k - Q_{ik}/\tau_i - M_k + X_k\right] \\
&- W\left[\sum_i \sum_{k=1}^{K} N_{ik} + N^M - \bar{N}\right] \\
&- \Upsilon_i \left[\sum_{k=1}^{K} h_{ik}\right] \\
&- \sum_i R_i \left[\sum_{k=1}^{K} L_{ik} + F_i - \bar{L}_i\right]
\end{aligned}$$

Where P^k, W, Υ_i and R_i are the multipliers for the trade, labor, intermediate input and land constraints, respectively. The first-order conditions of the problem are:

$$\frac{\partial \mathcal{L}}{\partial C_k} = 0 : P_k = \left(\sum_{k=1}^{K}(\mu_k)^{\frac{1}{\sigma}}(C_k)^{\frac{\sigma-1}{\sigma}}\right)^{\frac{1}{\sigma-1}} \mu_k^{\frac{1}{\sigma}} C_k^{-\frac{1}{\sigma}} \tag{16}$$

$$\frac{\partial \mathcal{L}}{\partial F_i} = 0 : R_i = \left(\frac{1}{F_i}\right) \tag{17}$$

$$\frac{\partial \mathcal{L}}{\partial N_{ik}} = 0 : W = P_k \tau_i^{-1} \alpha_k \frac{Q_{ik}}{N_{ik}} \tag{18}$$

$$\frac{\partial \mathcal{L}}{\partial h_{ik}} = 0 : \Upsilon_i = P_k \tau_i^{-1} \beta_k \frac{Q_{ik}}{h_{ik}} \tag{19}$$

$$\frac{\partial \mathcal{L}}{\partial L_{ik}} = 0 : R_i = P_k \tau_i^{-1} (1 - \alpha_k - \beta_k) \frac{Q_{ik}}{L_{ik}} \tag{20}$$

Condition (20) illustrates land use competition between forest and agriculture. It can be rewritten as:

$$P_k \tau_i^{-1} (1 - \alpha_k - \beta_k) \frac{Q_{ik}}{L_{ik}} = \left(\frac{1}{F_i}\right)$$

It states that at the equilibrium, in each location i, the marginal return from growing crop k (LHS) must equal the marginal utility of having land under forest (RHS). When transport cost τ_i decreases, the marginal return on agriculture increases and the forest stock F_i in region i decreases.