Agricultural Productivity and Deforestation in Brazil

Juliano Assunção
PUC-Rio

Molly Lipscomb
University of Virginia

Ahmed Mushfiq Mobarak
Yale University

Dimitri Szerman
PUC-Rio

February 28, 2017

Click here for the latest version.

Abstract

Increasing agricultural productivity can have ambiguous effects on forest protection in theory: it can expand the scope of farming, which is detrimental to the forest, but it can also induce farmers to intensify their production. We examine these predictions using county-level data from five waves of the Brazilian Census of Agriculture. We identify productivity shocks using the expansion of rural electrification in Brazil during 1960-2000. We show that electrification increased crop productivity, and farmers subsequently both expand farming through frontier land conversion, but also shift away from land-intensive activities and into capital- and labor-intensive activities. The net effect depends on the county's land use prior to the increase in agricultural productivity, but it reduces deforestation in the typical county in the sample.

Keywords: Electricity, Hydro-power, Agriculture, Productivity, Deforestation, Brazil

1 Introduction

The rapid loss of tropical forests has been one of the major environmental disasters of the last century. Tropical deforestation accounts for nearly 20% of recent global greenhouse gas emissions (Stern, 2008) and has significant impacts on the world's biodiversity. The challenge of preventing the loss, and promoting the recovery, of tropical forests is immense. At its core lies the tension, perceived or real, between conservation goals and economic development. Deforestation is intricately tied to decisions on land use for agricultural production, which not only is a major source of livelihoods for the world's poorest, but also plays an important role in structural transformation of developing societies. Therefore, in balancing development and environmental goals, a key question is to what extent improvements in agricultural productivity will lead to more or less deforestation.

The link between agricultural productivity and deforestation has been the subject of debates in the literature and in policy circles alike (for an early review, see Angelsen and Kaimowitz (2001)). Enthusiasts of the Green Revolution argue that increasing yields ultimately reduced the pressure of an ever-growing demand for food on the world's forests. If true, this intensification effect, known as the Borlaug's hypothesis, provides a "win-win" solution to the conflict between environmental and development objectives that developing countries face. However, improving agricultural productivity gives individual producers the economic incentives to increase the scope of their farming. This expansion effect, sometimes referred to as Boserup's hypotheses, may offset the intensification effect and result in more deforestation. Understanding the extent of each of these effects is important for policy making in conservation. Forest protection in the tropics is hampered by regulators' inability to enforce fines or bans on deforestation (Burgess et al., 2012). Conservation policies therefore have to account for the preferences of potential users of the common pool resource, and focus on strategies that are in the economic interest of user groups. Governments and other environmental organizations are increasingly experimenting with approaches such as direct payments for ecosystem services (Porras, 2012; Jayachandran et al., 2016) or interventions that improve farm productivity.

This paper examines the link between agricultural productivity and deforestation in Brazil. To guide our empirical analysis, we first develop a simple framework that allows for both the intensification effect as well as the expansion effect. In this framework, farmers engage in two activities that are different with respect to their factor intensities – we label the land-intensive activity "cattle grazing" and the other activity "crop cultivation". The farmer faces a factor market constraint that limits growth. Any productivity shock biased towards cropping will induce farmers to switch into cultivation and decrease the land allocation to grazing. The shift away from the land-intensive activity decreases overall land use, and benefits native vegetation. On the extensive margin, increased agricultural productivity induces new people to move into farming, which has the opposite effect on deforestation. The overall effect on deforestation is therefore theoretically ambiguous, and this motivates our empirical inquiry.

The empirical exercise uses the impressive expansion of the electricity grid in Brazil during the period 1960-2000 that electrified many frontier areas and farms as a measure of a shock to agricultural productivity. To address the endogeneity issues inherent in infrastructure data (where investment may follow demand), we use the IV estimation strategy developed in Lipscomb et al. (2013). Using county-level data from the Census of Agriculture, we first document that electricity access increases productivity of cropping more than that of cattle grazing. Next, we show that farmland expands following an increase in electricity infrastructure, but also that farmers leave more of their land in native vegetation (which in Brazil is mostly composed of forests). With both the intensification and expansion effects at play, the net effect on overall native vegetation depends on land use before the improvement in agricultural productivity: in frontier (consolidated) areas, increasing agricultural productivity has negative (positive) impacts on forests. For the typical county, a 10 percent increase in electricity infrastructure causes the area in native vegetation to increase by -0.18 to 2.7 percent, depending on the prior state of native vegetation outside farms.

Brazil provides an ideal setting for our study. During our sample period, the enforcement of environmental regulation in Brazil was extremely weak, much like in the rest of the tropics today. Moreover, Brazil is a relevant case study in itself: It is home to the largest portion of rainforest in the world, at the same time that agricultural production grew enormously – the country now ranks among the world's three largest producers of sugarcane, soybeans and maize, and is also the world's largest exporter of beef. Understanding how the increases in agricultural productivity interacted with Brazilian forests can yield valuable lessons to other countries in Latin America and Africa which also ave large portions of forest, but that have not yet experienced their own Green Revolutions.

Related Literature

Starting with Grossman and Krueger (1991, 1995), a large literature in economics studies the trade-offs between economic development and environmental outcomes. Together with the 1992 World Bank Development Report, these papers popularized the concept of an Environmental Kuznets Curve (ECK) — an inverted U-shaped relationship between economic growth and environmental outcomes (see Stern (2004) and Jill L. Caviglia-Harris (2009) for critical reviews of this literature). Part of this literature (eg., Foster and Rosenzweig (2003)) focuses on the ECK for forests, forming what sometimes is called the forest transition literature, which broadly shows that afforestation takes place after a certain point of economic growth. We contribute to this literature in three ways. First, we provide well-identified effects of one aspect of economic development (agricultural productivity) on forests (native vegetation). The previous literature suffers from methodological concerns, by using cross-country regressions or simply time-series correlations. Second, we do so using Brazil as a case study, whereas most of the previous literature focuses on developed countries. Third, we provide evidence of the positive spillovers between agricultural productivity and forests at the local level; time-series evidence on the relationship between yields and area harvested is well-known at least since Dyson (1996).

We also contribute to a literature linking infrastructure and deforestation. Our findings that the expansion in the electricity grid had positive effects on deforestation stands in contrast to Pfaff (1999), Cropper et al. (1999) and Cropper et al. (2001), who show that road infrastructure aids deforestation in Brazil and Thailand, respectively. Stavins and Jaffe (1990) find that flood-control infrastructure projects account for 30 percent of forested wetland depletion in the Mississippi Valley by affecting private land use decisions.

Our paper is most closely related to papers on agricultural use of electricity and irrigation technology in the United States (Lewis and Severnini, 2015; Hornbeck and Keskin, 2014) and in India (Sekhri, 2011), and broadly related to the literatures on technology adoption in agriculture (BenYishay and Mobarak, 2014; Conley and Udry, 2010) and to a rapidly growing literature on the effects of electrification (Dinkelman, 2011; Rud, 2012; Lipscomb et al., 2013) and other forms of infrastructure (Duflo and Pande, 2007; Donaldson, ming) on development.

The paper is organized as follows: section 2 discusses historical land use in Brazil, the vast growth in the electricity network during the period 1960-2000, and the expansion of the use of irrigation. Section 3 discusses a simple theoretical model which we use to investigate the contrasting impacts of increased agricultural productivity on land use: the increased intensity of agricultural productivity, versus the potential for expansion across increased land area as agriculture becomes more profitable. Section 4 discusses the two key datasets that we use–the Census of Agriculture in Brazil, and the Electricity Data from various historical archives in Brazil and elevation maps from USGS. Section 5 discusses our estimation strategy and the instrumental variable technique we employ. Section 6 discusses the empirical results, and section 8 concludes.

2 Background

Large scale deforestation in Brazil has resulted in a 19% decrease in forest cover in the Amazon since 1970 . This deforestation was, in large part, a result of the widespread expansion of agriculture and cattle grazing (Marguilis, 2004). . The conflict between the forest and agricultural land uses is particularly pronounced in areas of Brazil with lower distances and transport costs to major markets: Northern Brazil, the Pantanal and the Cerrado (Pfaff, 1997). This expansion in farmland has occurred at the same time as a widespread increase in farm productivity stemming from improved seed varieties, improved farming techniques, and increased use of capital in farming. In this section, we discuss the increase in productivity in the agricultural sector and the reallocation in land use in farming that has occurred over the past 50 years.

2.1 The Increase in Agricultural Productivity in Brazil

Agricultural productivity in Brazil has increased significantly since 1970, as Brazil closes the gap between agricultural productivity in Brazil and the US (Viera Filho and Fornazier, 2016). This increase in productivity has depended in large part on the ability of farmers to invest in new farming technology, and has varied substantially across regions of Brazil (Viera Filho Santos and Fornazier, 2013).Over the period 1970 to 2002, average yields per hectare increased, and as a result there was also an increase in the area spared from deforestation (FAO, 2004).

Constraints in Factor Markets The ability to take advantage of productivity improvements through new technologies is often dependent on the ability of farmers to invest in new capital equipment and to hire workers with higher levels of education than traditional farm labor. One common feature of rural economies in developing countries is presence of frictions, and ensuing constraints faced by producers in factor markets (Conning and Udry, 2007). For example, between 1960 and 2006 at least 80 percent of Brazilian farmers had no access to external financing of any sort (citation?). Farmers who did obtain credit typically used it for short-term loans to finance materials — seeds, fertilizer and pesticides — or transportation, as opposed to long-term investments. Access to other financial products, such as insurance, is uncommon even today. Agricultural labor markets in general, and in developing economies in particular, are also plagued by informational frictions and strict regulations which create constraints for producers to hire labor. In Brazil, these problems have been compounded by a massive rural-urban migration which decreased labor supply in rural labor markets: the fraction of the population living in rural areas decreased from 64 percent in 1950 to 19 percent in 2000 (citation).

Electricity and Agricultural Productivity Farmers use electricity for various purposes in their agricultural production function including irrigation, processing and storage, production of fertilizer and pesticides, and production and use of farm machinery (Fluck, 1992). For example, many technologies for irrigation and storage of farm production require the use of electricity. Sprinkler irrigation systems, common throughout Brazil, require energy to lift groundwater and distribute it. Although diesel can be used to provide energy for pumps, using electricity is cheaper not only because of the equipment, but also because of fuel costs. This was particularly true after the oil price shocks in the 1970s, and the expansion of the electricity grid providing cheap energy from hydropower (World Bank, 1990; Rud, 2012). In the drier areas of the country, irrigation during the winter season allows for two, and sometimes even three harvests of grains (soybeans, maize, cotton) per growing season, significantly increasing yields.

Electricity also enables farmers to adopt various technologies to process and store their output. Post-harvest handling of grains requires an array of machinery for drying grains, including ventilators and a conveyor belt, which are energy-intensive. Drying grains is important as it enables producers to store their output and sell it when market prices are good, besides adding value to the output. Livestock production can also benefit from electricity through mechanized milking, pasteurizing and cooling of dairy products, and poultry and egg production (Lewis and Severnini, 2015). As we will see, however, the vast majority of the Brazilian cattle herd is for beef production and is not confined, leaving considerably less room for electricity to improve cattle grazing productivity.

2.2 Evolution of Land Use in Brazilian Farms

Land use trends over the second half of the twentieth century in Brazil are shown in Figure 1, based on data from the Census of Agriculture, described in more detail in section 4. Farmland expanded considerably, reaching 44 percent of the country's territory in 1985, from 29 percent in 1960, a 50 percent increase within 25 years, before it started slowly decreasing. Brazilian farmers allocate their land mainly between pastures, annual crops and native vegetation; at any point in time between 1960 and 2006, these three categories accounted for 80-90 percent of total land in farms.[1] As can be seen, there were major changes in the allocation of farmland between these three categories over this period. The share of

[1] The remaining land use categories include planted forests (timber), perennial crops, water bodies, and unsuitable land.

pastureland, which is almost entirely used for cattle grazing, decreased from a peak of 52 percent in 1970 to 48 percent of total farmland in 2006, while the shares of cropland and native vegetation increased from about 9 and 19 percent to 14 and 29 percent, respectively. These trends show a clear expansion of cropland and native vegetation within farmland, at the cost of pastureland and other uses.

There has been substantial growth in the cattle stock in the North and Central West areas of Brazil. In the North, cattle stock more than tripled between 1960 and 1980 and again increased by 400% by 1990, while in the center West region the cattle stock also increased by 450%. This expansion in the cattle stock came in part from increased intensity in agricultural practices, but in large part the increase came from deforestation. At the same time many of the farms in the South were converting from cattle herds to soy. (FAO, 2004, p.14).

Native Vegetation in Private Properties Native vegetation is an important component of our analysis and forms a large component of land use in Brazilian farms. [2] There are potentially many reasons why producers may decide to keep trees in their properties. Although land is a relatively abundant factor in Brazil, *land markets* are plagued with frictions, from weak property rights to regulations in rental markets. As a result, producers may leave uncultivated land for the sheer reason of not being able to hire enough labor and capital, nor being able to sell or rent their land. Second, there are regulations mandating property owners to keep trees in a fraction of their land at least since 1934.[3] This sort of legislation however can hardly explain the observed patterns for the period we analyze, as its monitoring and enforcement has been an historical challenge in Brazil in general, and in rural areas of the country in particular. Illegal deforestation in the Amazon for example only started to be more seriously tackled with command-and-control policies after peaking in 2004, therefore at the very end of our sample period. Third, agro-forestry production is a source of income and livelihood, specially for smallholders. Although this can partially explain the presence of native vegetation in farmland, it cannot explain the increase of native vegetation in farmland at the aggregate level. Over this period, Brazil's agriculture became increasingly professional, focused on commodities and export-oriented; the fact that Brazil became the world's largest soybean producer and exporter is the quintessential example of this trend. Given the increased importance

[2]The presence of trees among agricultural land is a common feature in the tropics, and not specific to Brazil. Zomer et al. (2014) find that 92 (50) percent of agricultural land in Central America had at least 10 (30) percent of tree cover in year 2000.

[3]This legislation, known as the Brazilian Forest Code, was enacted in 1934 and mandated that every rural property to keep at least 25 percent of its area in native vegetation, in order to guarantee a stock of wood fuel. The Forest Code was amended in 1965 and then in 2012 after long public debates. Enforcement of the Forest Code is only now being taken seriously with the help of high-resolution satellite technology, unavailable even in the early 2000's.

of export-oriented commodities, one would have expected the relative share of forestry production, and therefore of land allocated to forests in farmland, to *decrease* during this period. Finally, it is possible that producers realize the production benefits of having biodiversity in their land, but this is a possibility that we cannot test with our data.

Crop Cultivation and Cattle Grazing As practiced in Brazil, cattle gazing and crop cultivation mix inputs at very different rates. Specifically, cattle grazing is a relatively land-intensive activity, whereas crop cultivation requires more capital, both physical and human. For example, in 2006 the value of machinery and equipment per hectare in the typical cattle grazing farm was one-sixth of that of a typical crop farm; and crop farms had eleven times as many workers per hectare than cattle farms. These figures are not surprising when one notes that only 4 percent of cattle farms use confinement, that only 0.2 percent of producers pasteurize the milk they sell, and that the beef cattle heard is five times the dairy cattle herd. At the same time, over 60 percent of the harvested area of maize and sugar cane is mechanized, as is virtually all of the soybean production in the country. Moreover, crop cultivation demands more human skills than beef cattle grazing as practiced in Brazil, requiring experimentation with techniques and inputs, such as seeds and fertilizers. In short, the typical cattle grazing farm requires low levels of capital investments within farm gate when compared to crop farming, a fact that motivates some assumptions in the model we present in Section 3.

3 Conceptual Framework

In this section we build a simple, partial-equilibrium theoretical framework inspired by the salient features of farming and land use in Brazil, with the goal of generating predictions on how a productivity shock in crop cultivation will affect farming choices and deforestation. To mirror the language in our empirical exercise, we refer to the key productivity parameter in our model as "availability of electricity", which is denoted by Ω. Our model allows farmers to engage in both crop cultivation and cattle grazing because these are the two major categories of agricultural activities, as indicated in the previous section and in the agricultural census data.

The economy is endowed with total land of $\overline{H}$ which is initially completely covered by native vegetation. A continuum of individuals reside in this economy, and each decides whether to become a farmer and convert land to agricultural use. These agents only differ by their outside option θ, which is their individual-specific opportunity cost of operating a farm. $\theta \sim \Gamma$, with pdf γ. The opportunity cost of farming can be thought of as the wage rate in the non-agricultural sector, which may increase with the availability of electricity, and so we allow Ω to shift the distribution of outside options in the sense of first-order stochastic dominance: $\Gamma(\theta;\widehat{\Omega}) \leq \Gamma(\theta;\widetilde{\Omega})$, for all $\widehat{\Omega} > \widetilde{\Omega}$. The profit from farming activities is common across farmers and is denoted Π, and the mass of farmers is therefore $\Gamma(\overline{\theta})$, where $\overline{\theta} = \{\theta : \theta \leq \Pi\}$.

Each farm is a tract of land of size H, which is fully covered by native vegetation before farming activities commence. Each farmer can engage in both crop cultivation and cattle grazing, and the areas allocated to each type of activity are denoted H_c and H_g, respectively. We assume that the production functions for the two activities are similar, except that there is a factor other than land which is more useful in crop cultivation, which we denote N; we think of N as capital, labor, or a combination of both. Electrification improves the productivity of N. Our modeling choice reflects the fact that electrification enhances the productivity of crop cultivation more than cattle grazing. We assume the following forms for the production functions for crops and cattle grazing: $C = \Omega N F(H_c)$ and $G = F(H_g)$, with $F_H > 0$, $F_{HH} < 0$ and $F_H(0) = \infty$.[4]

Land and the factor N can be bought in the market at prices p and r, respectively. Farmers are credit constrained and need to fund their expenditures with capital and land from their own resources, M. We normalize the prices of C and G to 1[5]. Thus, each farmer's

[4] The factor Ω only entering the production function for crop but not cattle is merely a modeling simplification. The results we derive only require that electrification benefits crop cultivation relatively more.

[5] To the extent that commodity prices are exogenous to local conditions, this normalization is innocuous. In any case, making prices endogenous to the (local) productivity shock would not add predictive power to

problem can be written as:

$$\max_{N,H_c,H_g} \Pi = \Omega N F(H_c) + F(H_g) - rN - p(H_c + H_g) \tag{1}$$

subject to

$$rN + p(H_c + H_g) \leq M, \tag{2}$$
$$H_c + H_g \leq H. \tag{3}$$

Our modeling choice reflects the fact that the majority of farmers in Brazil are small and medium holders who face some factor market constraints in capital, credit or labor which affects their ability to hire non-land factors. Since the profit function is linear in N and $F_H(0) = \infty$, the resource constraint (2) always binds; this is merely a modeling device, and what is essential in this model is that farmers are constrained in their ability to hire N. Land will therefore not be the limiting factor, and the land constraint (3) will typically not bind. Again, this focus reflects reality–farming in Brazil expanded into frontier lands that just needed to be cleared and occupied during our period of study–, and makes the model informative.

In the Appendix, we show that the optimal land use and production choices for farmers, $H_c^*(\Omega), H_g^*(\Omega), N^*(\Omega)$, display the following properties:

$$\frac{\partial N^*}{\partial \Omega} > 0 \tag{4}$$
$$\frac{\partial H_c^*}{\partial \Omega} \geq 0 \tag{5}$$
$$\frac{\partial H_g^*}{\partial \Omega} < 0 \tag{6}$$
$$\frac{\partial (H_c^* + H_g^*)}{\partial \Omega} < 0 \tag{7}$$

The intuition behind equations (4)–(7) is straightforward. Since factor N and land allocated to crop cultivation become more productive with electrification, N and H_c move in the same direction as Ω in this model, as shown in equations (4) and (5). However, since the credit constraint binds, the farmer can only increase land allocated to crop cultivation and/or hire more N in response to an increase in electrification if she decreases land allocated to cattle grazing (equation 6). The total land demand for agricultural purposes within the farm, $H_c^* + H_g^*$, decreases in response to increases in electrification (equation 7): as farmers switch away from cattle grazing and into crop cultivation, they also spend

this framework.

more on N and hence must give up more of H_g than they can increase H_c.[6]

The net effect of electrification on deforestation depends not only on intensive-margin changes in land demand within each farm, but also on how the productivity shock induces extensive-margin changes in the decision to enter the agricultural sector. To analyze this net effect, we define the total area of native vegetation, H_v, as the difference between the economy's total land endowment and farmer's total land demand for agricultural purposes:

$$H_v = \overline{H} - \int_{-\infty}^{\overline{\theta}} (H_c^* + H_g^*) d\Gamma(\theta) \tag{8}$$

The derivative of the total area of native vegetation with respect to electrification has two effects:

$$\frac{dH_v}{d\Omega} = \underbrace{-\frac{d(H_c^* + H_g^*)}{d\Omega}\Gamma(\overline{\theta})}_{>0} - \underbrace{(H_c^* + H_g^*)\Gamma(\overline{\theta})\frac{d\overline{\theta}}{d\Omega}}_{\lesseqgtr 0} \tag{9}$$

The first term relates to the intensive-margin adjustment, through which electrification reduces the land demand for each farmer by inducing farmers to shift away from land-intensive cattle grazing activities. The second term is the extensive-margin effect: a positive productivity shock associated with electrification changes the threshold in the distribution of farming opportunity costs below which individuals decide to farm. Whether this threshold increases or decreases with electrification depends on the relative magnitudes of the changes in farming profits and in non-agricultural wages. If electrification increases farm profits more than the it increases farmers' outside option, the extensive-margin adjustment would lead to some deforestation as native vegetation is cleared for new farms. In this case, the overall effect on native vegetation is ambiguous. Otherwise, farmers' will leave their land, allowing native vegetation to regrow over time, and the net effect on deforestation should be unambiguously negative. The net effect on the forest is therefore theoretically ambiguous; it will depend on the relative magnitudes of the two opposing effects, including the mass of citizens who are on the margin of participation in agriculture. We will examine each of the two (intensive and extensive margin) effects in the data and infer the net implication of a productivity shock on land demand for agriculture and, hence, on deforestation.

[6]In reality, the price of cropland is higher than the price of pastureland, so the intensification effect must be even stronger–and in fact that is what our empirical results show. However, we do not assume different land prices for each activity precisely to highlight this effect. In the same vein, we assume that electrification does not increase input prices. If electrification increases (decreases) relative price p/r, farmers would adjust by spending more (less) in N and less (more) in $H_c + H_g$.

To sum up, this model makes a few assumptions about the agricultural production function that we can examine in the data, and yields a few further testable predictions, which we now summarize.

1. We make the testable assumption that electrification increases crop cultivation productivity more so than cattle grazing productivity.

2. We assume that farmers face constraints in factor markets. We will provide evidence that farmers are credit-constrained, although we cannot rule out that other constraints are at work.

3. The model predicts that electrification should lead to greater investments in capital, specifically in capital that raises crop farming productivity.

4. The model predicts that positive productive shocks induce farmers to shift land use from land-intensive cattle grazing to N-intensive cultivation.

5. The model highlights that electrification has intensive- and extensive margin effects on the demand for agricultural land. On the intensive margin, it reduces demand for agricultural land through reductions in land demand for cattle grazing. Increases in land demand for crop cultivation, if any, are not enough to offset the reduction in land demand for cattle grazing. The effects on the extensive margin are ambiguous. Land demand – hence, farmland – may or may not increase depending on the relative magnitude of farms' profits vis-a-vis farmers' outside option. Hence, the overall effect on demand for agricultural land is also ambiguous.

4 Data

We combine two datasets in order to study the impact of the vast expansion of the electricity network across Brazil from 1960-2000 on agricultural productivity, agricultural investments, and deforestation. First, we use county-level data from the Brazilian Census of Agriculture in order to track amount of land under cultivation, agricultural inputs, and total harvests. Second, we use data assembled by Lipscomb et al. (2013) for measures of electricity infrastructure in each decade and an instrumental variable which provides the exogenous variation in electricity access. Table 1 presents summary statistics from these datasets.

4.1 Census of Agriculture

The Brazilian Census of Agriculture is a comprehensive and detailed source of data on the universe of rural establishments in the country. The definition of a rural establishment is constant across the waves we use, and is similar to what would be commonly thought of as a farm: a continuous plot of land under a single operator, with some rural economic activity – crop, vegetable or flower farming, orchards, animal grazing or forestry. There are no restrictions on the size of the plot, tenure, or market participation. Common lands are excluded from this definition, as are domestic backyards and gardens. Throughout the paper, we refer to a rural establishment simply as a *farm*. We use county-level data from the following 5 waves of the Census of Agriculture: 1970, 1975, 1985, 1996 and 2006.[7] During this period, there were significant changes in the borders and number of Brazilian municipalities. We follow the methodology of Reis et al (2010), who construct minimum comparable geographical areas that are constant over this period, allowing for meaningful comparison across years. We loosely refer to these areas as *counties*.

Three sets of outcome variables are central to our analysis. First is the total land in farms (*farmland*), and how it is split in each of three land use categories: annual crops (*cropland*), pastures (*cropland*), and native vegetation. "Native vegetation" in Brazil is mostly composed of tropical rainforest although there are other types of forest, as well as Savannah-like portions in the Central parts of the country and a semiarid portion in the Northeast. By design, the Census of Agriculture collects data regarding land within farms, and to the best of our knowledge, there are no countrywide reliable sources of data on the total area under native vegetation for most of our period of analysis. Cropland excludes area for

[7] This selection was made so as to match the other available sources of data. The first wave of the Census of Agriculture was carried in 1920. From 1940 to 1970 the Census of Agriculture was decennial. From 1970 to 1985 it was carried in 5-year intervals. The last two waves were carried in 1996 and 2006.

perennial crops (many of which are in orchards) and includes forage-land. Pastures can be either natural or planted. Together, these three land use categories account for between 81% and 90% of the total land in farms in Brazil during the period 1970-2006. The remaining farm area includes orchards, planted forests, buildings and facilities, water bodies and non-arable land.[8]

Second, we construct measures to capture farm productivity as well as the productivity of crop farming and cattle grazing separately. We measure farm productivity by their gross production value divided by total farm area (*production per hectare*). Gross production value is the market value of all goods produced in farms, including production for own consumption. Crop farming productivity is measured in an analogous way: gross crop production value of divided by cropland (*crop production per hectare*). Our main measure of cattle grazing productivity is the farm inventory of cattle heads divided by hectares of pastureland (*heads per hectare*). We also breakdown the total cattle herd into beef and dairy cattle, and measure dairy cattle productivity as milk production per head of dairy cattle.

A third set of outcome variables is related to the capital stock, irrigation and input usage in farms. For capital stock, we use the number of tractor in a country. For irrigation, we have the number of farms that use irrigation as well as the irrigated area within farms. Finally, we use spending on fertilizers and pesticides as measures of input usage.

4.2 Electricity Data

The large majority of Brazil's electricity is based on hydro-power Electricity access is measured based on archival research of the location and date of construction of hydro-power plants and transmission substations in Brazil from 1950-2000. Reports, inventories, and maps from Brazil's major electricity company (Eletrobras) over the period were collected, and the data was consolidated into information about the status of the electricity grid in each decade. Eletrobras made data available on their power plants, transmission lines (which transport electricity from the power plant at which they are generated to the region in which the electricity will be used), and transmission substations (which take electricity from the high voltage transmission lines and convert the power to voltage levels that can be accepted by distribution lines and used by companies, farms, and households). The reports include tables cataloging the existing electricity network in order to determine where further expansion was necessary over the next decade.

The electricity network in Brazil developed from a base in the more developed and wealthy

[8] For our purposes in this paper, we explicitly separate planted forests from native forests. The area in planted forests is small, and bundling the two categories makes no quantitative difference in or results.

South in the 1950s and 1960s and spread Southeast in the 1960s and 70s and to the Northeast in the 1970s and 1980s. Expansion occurred further westward in the 1980s and 1990s.

As in Lipscomb et al. (2013), we focus on the transmission lines, substations, and generation plants as these are the highest cost components of the infrastructure network and the components most dependent on geographic costs. Distribution networks are very closely linked with areas where demand for electricity is highest. We merged these datasets, creating a mapping of the location of power plants and transmission substations in each decade from 1960 through 2000.

The measure of access to electricity infrastructure is generated as follows: Brazil is divided into 33,342 evenly spaced grid points. All grid points within a 50 kilometer radius of the centroid of a county containing a power plant or transmission substation are assumed to have access to electricity — it is estimated that on average the distribution networks stretch one-hundred kilometers across. The grid points are then aggregated to the county level, and the electricity access variable is defined as the proportion of grid points assigned as electrified in a county.

We match census and agricultural census data to electricity data with a time lag between the two since the development of a distribution grid around transmission stations takes several years. We match the 1970 Census data to the electricity data for the 1960s; the 1975 Census data to the 1970s electricity data; the 1985 Census data to the 1980s electricity data; the 1995 Census data to the 1990s electricity data; and 2006 Census data to the 2000s electricity data. This gives distribution networks and farms a short period of time to react to new electricity access so that we observe the changes resulting from expansion in infrastructure.

Because Brazil's electricity is based primarily on hydro-power, geographic factors play a major role in the expansion of the network. We develop an instrumental variable for electricity infrastructure based on a prediction of lowest cost areas for expansion in each decade in Lipscomb et al. (2013). This instrument is further explained in section 5.1; it is based on using geographic variation to predict the lowest cost expansion path for the electricity network over time. The instrument is developed using on geographic data collected from the USGS Hydro1k dataset. The Hydro1k dataset is a hydrographically accurate digital elevation map developed from satellite photos of the earth. Using ARCGIS, we then calculate the geographic variables most useful for predicting the cost of building a hydro-power plant: maximum and average slope and flow accumulation in the rivers near each of the 33,342 grid points. This data is then matched to each of the 33,342 evenly spaced grid points for use in the model, and then predicted access is aggregated to the level of the 2,184 standardized counties across Brazil.

5 Empirical Strategy

In order to identify the impact of access to electricity on deforestation and farm productivity, we use variation in electrification from 1960-2000 and data from the agricultural census on farm productivity and data on deforestation over that period. The principal identification concern in estimating the effect of access to electricity on farm productivity is that demand variables that attract the government to install new electricity infrastructure in some counties will also be related to farm productivity and deforestation. For example, quickly growing nearby cities may increase the demand for electricity, pushing the government to increase the power network in the area, but it could also increase the demand for agricultural products and increase the level of capital investments in agriculture because of high local demand. This would create an omitted variable bias, and we therefore need an instrumental variable which includes only variation exogenous to farm productivity and deforestation.

5.1 Predicting Electricity Expansion Based on Geographic Costs: the design of the Instrument

Our instrument takes advantage of the fact that hydropower accounts for the majority of electricity generation in Brazil. The power potential of a hydropower plant depends on the distance that the water has to fall from the top to the bottom of the turbine and the amount of water available. Hydropower plants require a steep slope and a large amount of water flow in order to create pressure from the water descending through the turbines. Areas which already have a large natural slope and a significant amount of water flow can have hydropower turbines installed relatively inexpensively, while areas in which the natural geography is less suited to hydropower generation must have large dams and huge flooded areas in order to create enough of a distance for the water to fall that power can be generated. Creating the conditions for the generation of hydropower in areas not naturally suited to it imposes costs both from the construction of the dam and from the flooding of the area. This means that topography is highly influential in determining areas that receive electricity since extending transmission lines is expensive.

We use predicted electricity availability based on the engineering cost of expanding the network to instrument for electrification. We calculate predicted availability at each grid point in each decade based on minimization of construction cost for new plants and transmission lines at the level of the national budget for new power plants using only geographic characteristics. The instrument is generated using the information considered by engineers when choosing locations for hydropower plants while omitting any demand side information which they might consider. We use the flow accumulation of water and the maximum and average slope in rivers on a grid of points across Brazil to predict low cost areas for the generation of electricity. The model varies over time since new power plants are built first in the lowest cost areas, and later in areas slightly less attractive from an engineering standpoint in order to expand the grid outward. Therefore, we identify first where the most attractive areas are for the generation of hydropower, and allow the network to expand to successively higher cost areas as Brazil invests further in its electricity grid from decade to decade.

We use the national budget for electricity plants in each decade based on the size of the expansion of the actual network in each decade, and predict where these are likely to be placed given where electricity plants and transmission networks have been placed in past decades. In the construction of the instrument, we use only topographic characteristics of the land (flow accumulation and slope in rivers) to estimate likely locations for new electricity access. This instrument is also used in Lipscomb et al. (2013). That paper demonstrates that electricity expansion had large impacts on both the Human Development Index and housing values by county.

As described in Lipscomb et al. (2013), there are three key steps to the creation of our instrument: first we calculate the budget for plants in each time period based on the actual construction of major dams in each decade across Brazil. Second, we generate a cost variable that ranks potential locations by geographic suitability. We base our suitability predictions on geographic factors of areas where hydropower plants were actually built. Finally, following the prediction on estimated construction site for each dam, we generate an estimated transmission network flowing from the new plants.

The budget of electricity plants is generated based on the actual construction of major electricity plants in Brazil over the period. This allows us to model greater expansion of electricity in years in which the national government decided to expand production of electricity, and reduced expansion in years in which the government budgeted for fewer new plants.

In order to rank the suitability of the different sites, we generate hydrographic variables using the USGS Hydro1k dataset. We generate weights for hydrographic variables using the actual placement of hydropower plants in Brazil (for robustness we have compared these weights to those generated using US hydropower plants, and we arrive at similar results). The cost parameters are derived using probit regressions in which the dependent variable is an indicator for whether a location has a dam built on it at the end of the sample period (2000), and the explanatory variables are the topographic measures. Steep gradients and high water availability are key factors reducing dam costs.

The Matlab model then begins by placing the new budgeted hydropower plants for the decade at grid points with the predicted lowest cost from among those grid points that are not already predicted to have electricity. The model then predicts transmission lines flowing out from each plant. All plants are assumed to have the same generation capacity, as we make no assumption on demand in various areas, so we make the simplifying assumption that each plant has two transmission substations attached to it. We minimize the cost of the transmission lines based on land slope and length. We then assume that all grid points within 50km of a predicted plant or predicted transmission substation are covered by distribution networks.

In later decades, we take the existing predicted network as given and estimate additional plants and transmission lines as locating in the next lowest cost areas. We then estimate the coverage of electricity access in a county by estimating average coverage of grid points with predicted electricity across the county.

The key potential identification concern related to this instrumental variables estimation strategy would be if the geographic costs for expanding electricity access also affected the productivity of agriculture or the attractiveness of deforesting new areas. While variables like water access and slope could affect agricultural productivity in a cross-sectional framework, our identifying variation results from variation in whether the cost parameter of a gridpoint is low enough to make it among the low cost budgeted points in a given decade. This generates a non-linearity in chosen gridpoints across decades and is different from a simple ranking of lowest to highest cost gridpoints. Our identification is therefore based on discrete jumps between thresholds of suitability for electricity access between decades. The time variation in our instrument allows us to use fixed effects to separately control for factors directly impacting the suitability of land for agriculture so that our estimates are the direct impact of electricity on agricultural productivity.

5.2 Estimation Strategy

We estimate the effect of electrification on the productivity of rural establishments over the period 1960 to 2000 using county-level data. We are interested in running regressions of the form:

$$Y_{ct} = \alpha_c + \gamma_t + \beta E_{c,t} + \varepsilon_{ct}, \tag{10}$$

where Y_{ct} is the outcome of interest in county c at time t, α_c is a county fixed-effect, γ_t is a time fixed-effect, and $E_{c,t}$ is the proportion of grid points in county c that are electrified in period t – that is, $E_{c,t}$ is our measure of actual electricity infrastructure.

The main concern with (10) is that, even controlling for time and year fixed-effects, the evolution of electricity infrastructure is likely to be endogenous to a various factors also affecting the evolution of farm productivity. This causes OLS estimates to be biased.

We therefore use an instrumental variable (IV) approach, making use of the instrument described in Section 5.1. Specifically, we use a 2SLS model where the first stage is:

$$E_{ct} = \alpha_c^1 + \gamma_t^2 + \theta Z_{c,t} + \eta_{ct}, \tag{11}$$

where Z_{ct} is the fraction of grid points in county c predicted to be electrified by the forecasting model (relying only on the exogenous variation from the geographic cost variables changing according to the budgeted amount of infrastructure in each decade) at time t. The second stage is:

$$Y_{ct} = \alpha_c^2 + \gamma_t^2 + \beta \widehat{E}_{c,t} + \varepsilon_{ct}^2, \tag{12}$$

where $\widehat{E}_{c,t}$ is obtained from the first stage regression (11). Note that both $Z_{c,t}$ and $E_{c,t}$ are constructed by aggregating grid points within the county. Since the number of grid points vary in each county, we weight regressions using county area as weights. In all specifications, we cluster standard errors at the county level in order to avoid under-estimating standard errors as a result of serial correlation in electrification.

Our IV strategy corrects for the bias introduced by the endogenous placement of electricity infrastructure by isolating the impact of determinants of the electricity grid evolution unrelated to farm productivity. We present a variety of robustness checks in table 4, demonstrating that our estimates do not vary with the addition of geographic trends and other controls.

6 Empirical Results

6.1 First-stage results

Table 2 shows the first-stage results of our main analysis. As explained in section 4, our instrument is based on a engineering model that takes various inputs. Columns 1–3 show different specifications controlling directly for some of these inputs. In addition to county fixed-effects, which are included in all specifications in Table 2, column 1 uses year-fixed effects. The modeled electricity availability is highly correlated with actual electricity infrastructure, and this correlation is significant at the 1 percent level. Column 2 adds Amazon-specific year dummies to flexibly control for the region's time trend, which has significantly differed from that of the rest of the country. The point estimates decreases from from 0.326 to 0.265, but remains significant at the 1 percent level. Column 3 adds interactions of our water flow and river gradient measures with year dummies. The changes in the point estimate and standard error are negligible and, for the rest of the paper, we maintain the specification of column 2 as our preferred specification. In columns 4 and 5, we check that both our modeled instrument and measure of electricity infrastructure are indeed correlated with actual electricity provision as captured by the Census of Agriculture. The correlations are strongly significant and have similar magnitudes on the mean as those of column 2.

6.2 The effects of electricity on agricultural productivity

We start our empirical exercise by examining a central assumption of our framework, namely that the arrival of electricity is as a positive productivity shock to agriculture and that it is biased towards to crop cultivation. Table 3 reports the main effects of increasing electricity infrastructure on agricultural productivity. Columns 1–3 show respectively the OLS, reduced form, and IV estimates when the dependent variable is the log of agriculture production value per hectare of farmland. The IV estimate is larger than the OLS estimate and implies that a 10 percent increase in electricity availability increases agricultural productivity by 24 percent, and this result is significant at the 1 percent level. Next, we analyze separately the effects on crop cultivation and cattle grazing productivity. Columns 4–6 show results when the dependent variable is the log of crop production value per hectare of cropland. The IV estimate implies that a 10 percentage-point increase in electricity infrastructure increases crop productivity by 24.3 percent, and this effect is significant at the 1 percent level. The high impact of electricity on crop cultivation productivity is mirrored by a low impact on cattle grazing productivity. Columns 7–9 show the effects of electricity on log of the value of cattle production per hectare of pastureland. The IV estimate in column 9 implies that a 10 percentage-point increase in electricity leads to a 12-percent increase in this measure of productivity. Not only this is a much lower impact than that for crop cultivation, but the statistical significance is also much lower.

In sum, the arrival of electricity infrastructure in a county significantly increases productivity in crop cultivation, but not in cattle grazing. Section 6.2.1 below gives further evidence that the effect of electricity on cattle grazing productivity is small or negligible, supporting our interpretation that the arrival of electricity can be thought of as a productivity shock to crop cultivation, but not to cattle grazing.

6.2.1 Effects of electricity on cattle grazing productivity

To build confidence that electricity has little impact on cattle grazing productivity, Table 4 looks at the effect of electricity on alternative measures of cattle-related productivity.[9] Columns 1 and 2 show that the fraction of livestock production on overall farm production decreases with electrification. This is consistent with the results from Table 3 that electrification increases productivity in crop cultivation relative to cattle grazing. The next 4 columns use alternative measures of cattle grazing productivity. In columns 3 and 4, the dependent variable is the stocking ratio—heads of cattle per hectare of pastureland.[10] In columns 5 and 6, the dependent variable is fraction of young herd on overall herd, a proxy for cattle turnover – the idea being that the higher the turnover, the more productive the farm is. The results show that according to these alternative measures, electrification has no effect on cattle grazing productivity.

As explained in section 2, electricity can have effects on dairy activities by allowing for mechanical milking and refrigeration. To explore this possibility, columns 7 and 8 look at dairy cattle productivity as measured by milk production per dairy call. The IV estimate in column 8 implies that a 10 percent increase in electricity increases milk production by 56 litters per dairy cow, a 5.8 percent effect on the mean. This effect does not seem to be strong enough to induce producers to change their herd's composition towards dairy cattle. We can see this in columns 9 and 10, where the dependent variable is the fraction of dairy cattle on the herd. The IV coefficient implies that a 10 percent increase in electricity

[9] Ideally one would measure cattle grazing productivity as kilos per hectare per year. Unfortunately, to the best of our knowledge this measure is not available from any data sources, and heads per hectare is the best measure we can use.

[10] Unlike production value per hectare, heads per hectare does not capture price effects. This is an advantage because beef markets tend to be local, and electricity may raise local demand for beef through increased population and income. In turn, increased demand may translate to higher prices, spuriously increasing measures of productivity that .

increases the proportion of dairy cows 0.65 percentage point, a small effect on the mean. In sum, the effect of electrification on dairy cattle productivity, while sizable, is not sufficient to induce producers to change their herd composition, having therefore little effect on the aggregate cattle grazing productivity.

6.3 Changes in Land Use and Production Decisions

In this section we examine the effects of electrification on producers' land use decisions. In our conceptual framework, farmers to switch into crop cultivation and allocating less land to cattle grazing after receiving a productivity shock. Because of differences in land-intensity, the model predicts that overall land demand for agricultural purposes reduces in the intensive margin. But by making agriculture more attractive, the arrival of electricity may also increase land demand in the extensive margin, leading to an expansion of farmland. We therefore analyze the effect of electrification on the two adjustment margins.

6.3.1 Effects on land use

Table 5 shows the effects of electrification on land allocation. Columns 1 and 2 examine the extensive margin effects by using the proportion of farmland in the county area as the dependent variable. The IV estimate implies that the share of farmland increases by 2.88 percentage points following a 10 percentage point increase in electricity infrastructure, and this effect is statistically significant at the 1 percent level.

Next, we turn to land allocation within farms. In columns 3 and 4 of the table, we see that the share of pastures in the county's farmland decreases with electricity infrastructure. The IV estimate in column 4 implies that the share of pastures in farmland decreases by 3.29 percentage points following a 10 percentage point increase in electricity, a sizable and significant effect of 10 percent on the mean. Columns 5 and 6 show the same analysis for cropland, and find a small and not statistically significant effect. These results are consistent with our model's predictions in two ways. First, although we do not find evidence that cropland relative to farmland expands with the arrival of electricity, the results clearly show that *cropland relative to pastureland expands*, and that is the substantive prediction of the model presented in section 3. Second, because crop cultivation requires non-land factors, the decrease in pastureland should be greater than the corresponding increase in cropland. Moreover, the relative increase in cropland is not surprising given previous results that electricity increases crop farming productivity relative to cattle grazing productivity. In section 6.3.2 below, we show that electrification has effects on the crop mix, which partially explains the small effect on overall cropland.

The effect on native vegetation within farms, shown in columns 7 and 8 of Table 5, mirrors the difference between the effects on shares of pastureland and cropland. The IV estimate implies that increasing electrification in a county by 10 percentage-points causes the share of native vegetation within rural establishments to increase by 3.17 percentage points. One important aspect to this result is that it does not imply that farmland is reforested following an increase in electrification. Rather, it means that farmers in counties with increased electricity infrastructure deforest less than they would have in the counterfactual scenario where electrification does not increase. In line with our model's predictions, the positive effect on native vegetation *inside* farms contrasts with the potentially negative effect of electrification on native vegetation *outside* farms.

To calculate the effect of electricity on overall native vegetation, one needs to make assumptions about the state of native vegetation outside farms prior to the arrival of electricity. At given proportions of farmland in the county area and native vegetation within farms, assuming that all land outside farms is covered (not covered) with native vegetation yields the lower (upper) bound of the effect.[11] Figure 2 illustrates the bounds for the effect of electricity on overall native vegetation at varying proportions of farmland in the county area using the estimates obtained from table 5, along with confidence intervals obtained through bootstrapping. At the sample averages, the effect of a 10 percentage point increase in electricity infrastructure on the share of native vegetation ranges from -0.18 percentage points (s.e. 0.100) to 2.7 (s.e. 0.087) percentage points, depending on the initial state of native vegetation outside farms. In "frontier counties" – i.e., counties with little farmland as a proportion of the overall area – increasing agricultural productivity tends to increase deforestation.

Long-run One may wonder if the increase in native vegetation within farms concomitantly with the expansion of farmland is not just a first step towards cutting down trees in the long run. To investigate the impact of electrification in land use choices, we forward-lag the dependent variable by one decade.[12] Appendix Table 6 shows that the results remain largely unchanged, suggesting that these are not just short-run effects. In fact, the bounds on the effect of electricity in overall native vegetation implied by Table 6 are now

[11] To see this, write $V = V_I + V_O$, where V is the overall area in native vegetation, V_I is native vegetation inside farms, and V_O is native vegetation outside farms. V_0 can be written as $k(C - F)$, where C is the county area, F is the area in farmland, and $k \in [0, 1]$ is the proportion of the area outside farms in native vegetation. Algebraic manipulations and differentiating both sides with respect to Ω yields $\frac{\partial(V/C)}{\partial\Omega} = \frac{\partial(V_I/F)}{\partial\Omega} \cdot \frac{F}{C} + \frac{\partial(F/C)}{\partial\Omega} \cdot \left(\frac{V_I}{F} - k\right)$. To calculate the bounds on the effect of electricity on overall native vegetation, we use the estimated $\frac{\partial(V_I/F)}{\partial\Omega}$ and $\frac{\partial(F/C)}{\partial\Omega}$ from Table 5, as well as the sample averages for $\frac{F}{C}$ and $\frac{V_I}{F}$.

[12] As described in section 4, the outcome variables from the Census of Agriculture are already lagged, to allow for the impacts of electricity to kick in.

tighter, with a positive lower bound, suggesting that, if anything, increasing agricultural productivity has an even stronger effect in reducing deforestation in the long run.

6.3.2 Effects on crop choices

The substantive prediction of our stylized model is that, following a productivity shock, farmers will substitute away from activities that benefit less from the shock. That prediction should be true not only between cattle grazing and crops cultivation, but also across crops that benefit differently from the shock. We therefore analyze effects of electrification on the composition of different crops choices. Specifically, we investigate the effects of electrification separately on grains and cassava. Grains – which include soybeans, maize, cotton and rice – are the high-productive, capital-intensive cash crops that Brazilian farmers grow, and the ones that benefit the most from energy-intensive inputs. In contrast, cassava is a staple, commonly grown a subsistence crop across Brazil and relatively more land-intensive than grains.

Table 7 reports the results. The IV estimate in column 2 implies that grain production increases by 32 percent following a 10 percentage point increase in electricity infrastructure, and this estimate is significant at the 1 percent level. In contrast, the IV estimate for cassava production is not statistically significant and in any case has a negligible effect size. Looking at the land allocated to each of the crops, the IV estimates again imply that farmers allocate more land into grains: the IV estimates in columns 4 and 6 show that farmers allocate more land to grains and less land to cassava, both in absolute terms and relative to overall farmland, following arrival of electricity infrastructure. To sum up, the shift from land-intensive towards capital-intensive activities happens also between crops, and not only between cattle grazing and crops.

The results shown in Table 7 also help explaining why we see little or no effect of electrification on cropland relative to overall farmland, despite the increased crop productivity. By changing the crop mix towards less land-intensive crops, farmer keep overall cropland stable while responding to the productivity shock.

6.4 Mechanism: increased capital and input usage in crop cultivation

One important part of our model's mechanism is that electrification should lead to greater investments in capital, specifically in capital that raises crop farming productivity. In section 2, we highlighted that irrigation and grain storage are two energy-intensive technologies that benefit crop farmers but not cattle ranchers. We now present results that support this story and build confidence that it can explain the mechanisms underlying our results. Specifically, we examine whether farmers use more capital and inputs that are complements to those technologies, such as irrigation, tractors, and fertilizers.

Table 8 presents the effects of electrification on usage of capital and inputs that used mostly in crop cultivation. Column 1 shows that more farms adopt irrigation as electricity becomes available. The effect in grain storage capacity and in the number of tractors farmers use is also large, as shown in columns 2 and 3, respectively. Finally, columns 4 and 5 show that farmers spend more on fertilizers and pesticides per hectare of farmland. Not only these results are consistent with the intensification effect that is the key mechanism that behind our main result, but they also support the story that increased electricity infrastructure enables farmers to adopt technologies and employ capital that would not be feasible otherwise. The increase in crop cultivation productivity is accompanied by larger amounts of capital, fertilizers and pesticides.

6.5 Robustness

As explained in section 4, our instrument uses cross-sectional variation from geographical factors, and time-series variation from the national budget for construction of electricity infrastructure and suitability ranks that introduce discontinuities on the order in which new infrastructure is built. Including county fixed-effects isolates any pure cross-section variation. To further mitigate concerns that our instrument uses invalid variation for dealing of the endogeneity problems of grid placement, Appendix Tables 9 and **??** present results of a sensitivity test where we use all possible combinations of our instrument's components as explicit controls in the second-stage regressions, on top of county fixed-effects and decade dummies. Each row of the tables reports a different specification of a 2SLS regression. Appendix Table 9 assesses the sensitivity of the results from table 3 and shows that both the main result of Table 3 — that electricity affects crop cultivation productivity, but not cattle grazing productivity — survives all the different specifications and, in fact, may even get stronger in alternative specifications. Appendix table **??** does the same for 5, and shows that both the extensive and intensive margin effects are robust to different specifications.

7 Discussion on alternative mechanisms

Our stylized model in section 3 offers an explanation for the empirically observed links between electricity, agricultural productivity and deforestation. There are alternative mechanisms that could explain the empirical regularities that we document, and we now turn to a discussion of those.

Demand for Forest products One alternative explanation for the positive link between electricity and forests, is through a rise in demand for forestry products induced by an increase in income and, more broadly, development (Lipscomb et al., 2013). Foster and Rosenzweig (2003) argue that such demand mechanism was central to explain the positive association between income and forest in India, as well as in a panel of countries. One important condition for this mechanism to be captured empirically is that local demand for forestry products must be met by local supply. Thus, in their panel of countries Foster and Rosenzweig (2003) find that a positive association between income and forest growth for closed economies – Brazil included – but not for open economies. We therefore ask the question: did the shift in land use toward forests come from increases in demand for forest products?

We answer this question in Table 10. In columns 1 and 2 the dependent variable is the log of the total value of forestry goods produced. Both the OLS and IV estimates are negative, and the IV estimate is not statistically significant, indicating that production of forestry products does not increase with electricity, despite the increase in native vegetation documented in Table 5. Forestry goods however are very heterogeneous, ranging from wild fruits to timber. In columns 3 and 4 we focus on the production of wood-related products – fuelwood, charcoal and timber. The IV estimate is now positive, but not statistically significant. In columns 5 and 6 we ask whether producers make a more intensive use of the forests in their property — a natural thing to do when faced with rising demand for forestry products – and use the log of the production value of forestry produces per hectare of forest area. The negative OLS and IV estimates suggest that the rise in forest area within farmland outpaces their direct economic exploration. Finally, we ask whether producers actively plant more forests, presumably to meet demand for products that cannot be produced with native species, and use the share of planted forests in farmland as the dependent variable in columns 7 and 8. Both the OLS and IV estimates are small in magnitude and non-significant. To sum up, we find no evidence that the demand channel to be driving the growth of native vegetation in Brazil for the period we analyze.

Substitution of fuelwood for electricity An argument that runs in the opposite direction of Foster and Rosensweig's is that electricity may have induced households and firms to switch away from wood-based fuels, reducing the pace of wood extraction and hence deforestation. This could result in a positive link between electricity and native vegetation in the data. We argue that this alternative mechanism is unlikely to have played a relevant role, at least locally, for three reasons.

First, electricity did not replace wood-based fuels in the residential sector, which accounted for 70 percent of the firewood consumption in 1970. Whereas household consumption of wood-based energy reduced by 50 percent between 1970 and 2006, this reduction was due to the dissemination of bottled liquefied petroleum gas—a fossil fuel obtained from petroleum or natural gas with little or no use of electricity—, which gradually replaced firewood as a cooking fuel. Whereas we cannot formally test this due to data limitations, aggregate data make this point clear: In 1970, 49 percent of households used firewood, and 43 percent used bottled LPG for cooking, according to Census data. By 1991 (the last Census to inquire about cooking fuel), 71 percent of households used bottled LPG, and 13 percent used only firewood, with a further 14 percent using both bottled LPG and firewood. Electric stoves on the other hand have never been adopted in Brazil. In 1970, only 0.08 percent of households declared using electricity for cooking according to Census data, whereas in 1991 respondents did not even have the option to choose "electricity", which would be under the "other" category, chosen again by 0.08 percent of the households.

Second, firewood has virtually never been used to generate electricity directly in Brazil. During the period we study, at most 0.75 percent of the energy content of firewood was used to generate electricity (BRASIL, 2007). Thermal generation in Brazil has typically used fossil fuels. Therefore, the hydropower-based electric grid expansion in Brazil did not directly replace firewood for electricity generation. While in a counterfactual scenario without electricity expansion it is possible that aggregate firewood consumption would have increased, there is no evidence that electricity replaced firewood locally, because this is the variation we use to identify the link between electricity and deforestation.

8 Conclusion

We provide evidence that an increase in agricultural productivity can be good for forests. We find that rural properties in counties where electricity infrastructure increases experience more growth in native vegetation than farms located in counties where electricity did not expand. This effect is persistent, and is consistent with an intensification story whereby producers substitute away from land-intensive cattle grazing and into crop cultivation. Producers also shift away from other subsistence, land-intensive crops, such as cassava and increase the area of capital-intensive crops, such as grains.

We interpret our results as supportive for a more subtle version of the Borlaug Hypothesis. The subtlety comes from the fact that increases in agricultural production alone are not able to prevent farmland to expand; in our story, frictions in factor markets — such as credit or (local) labor markets — prevent producers to fully explore their land, leaving room for native vegetation. In absence of such frictions, it is likely that farmland expansion would dominate the intensification effect, leading to more forest loss. Yet, given the widespread presence of frictions in tropical rural economies, these findings are relevant for contexts other than the Brazilian case.

However, by using variation at the county level only, our analysis ignores the more traditional underestimates the positive effects of agricultural productivity on conservation. Because Brazil is a major commodity producer–"the world's food basket"–, it is likely that an increase in Brazilian agricultural productivity has the potential to spare land for agriculture in other countries.

Our results have important implications for policy making in conservation. Forest protection in the tropics is hampered by regulators' inability to enforce fines or bans on deforestation. Conservation policies therefore have to account for the preferences of potential users of the common pool resource, and focus on strategies that are in the economic interest of user groups. Governments and other environmental organizations are increasingly experimenting with approaches such as direct payments for ecosystem services[13] or interventions that improve farm productivity.

[13] Several developing countries are already beginning to implement payments for environmental services, including Costa Rica, Brazil, Vietnam, and Uganda(Porras, 2012).

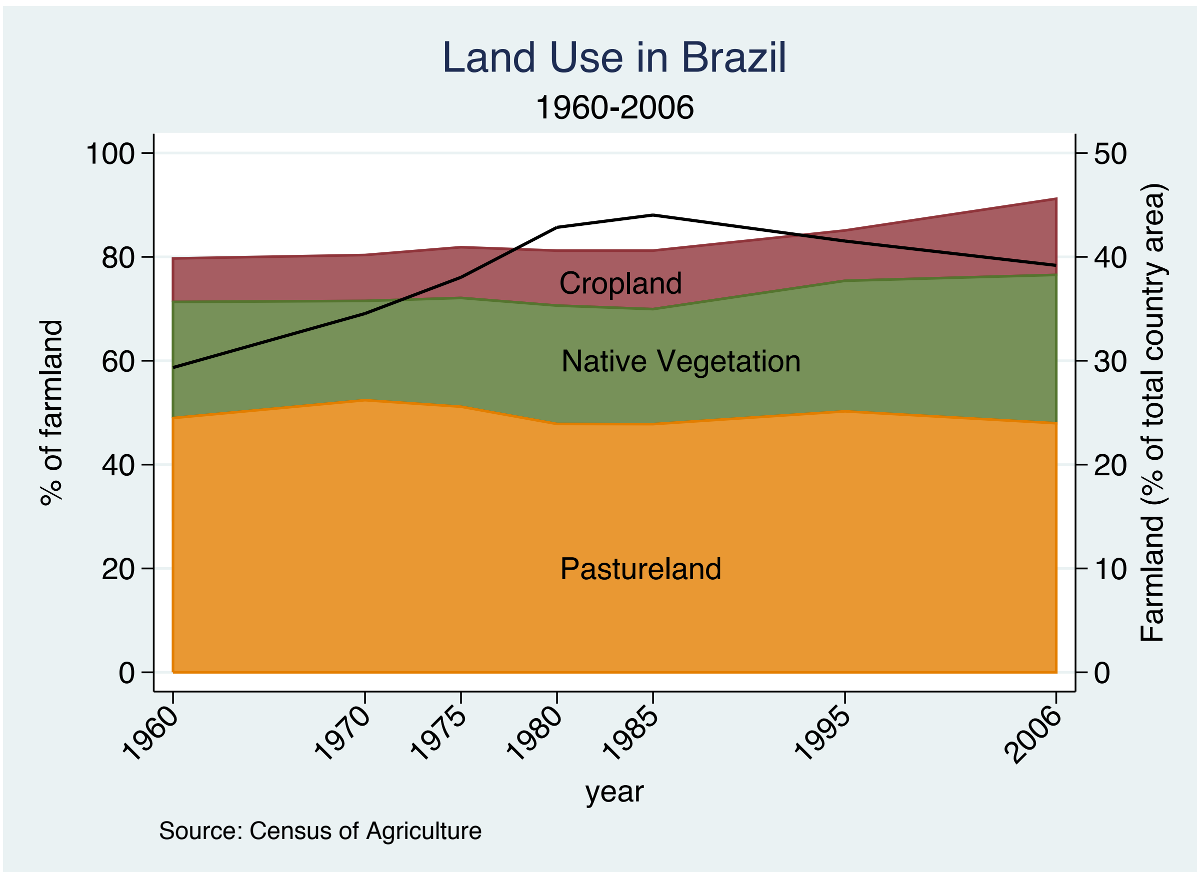

Figure 1: Proportion of Total Farmland and Allocation of Farmland Across main Land Use Categories, Brazil 1960-2006

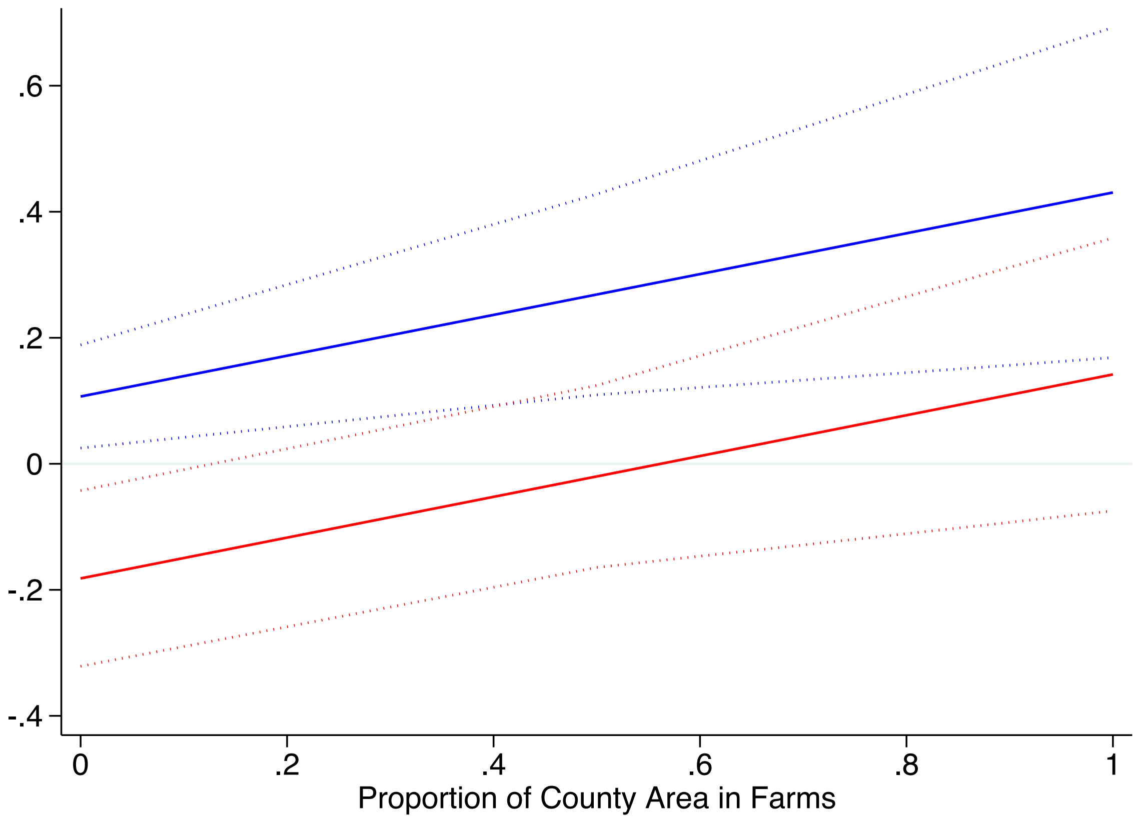

Figure 2: Bounding the Effect of Electrificaton on Native Vegetation

Notes: The figure shows the upper and lower bounds of the effect of electrificaton on native vegetation. The upper (lower) bound is calculated by assuming that none (all) of the area outside farms was in native vegetation prior to the increase in electrification. Specifically, the equation used to calculate the bounds is $\frac{\partial(V/C)}{\partial\Omega} = \frac{\partial(V_I/F)}{\partial\Omega} \cdot \frac{F}{C} + \frac{\partial(F/C)}{\partial\Omega} \cdot \left(\frac{V_I}{F} - k\right)$. $\frac{\partial(F/C)}{\partial\Omega}$ and $\frac{\partial(V_I/F)}{\partial\Omega}$ are provided in columns 2 and 6 of Table 5, respectively. For $\frac{V_I}{F}$, the figure uses the average proportion of farmland in native negetation througout our sample period (0.372). 95% confidence intervals are obtained by bootstrapping, and plotted in dotted lines.

Table 1: Sample Descriptive Statistics

	Number of Obs.	Mean	Std. Dev.	Min	Max
Electricity variables					
Electricity Infrastructure	15,460	0.74	0.41	0.00	1.00
Modeled electricity instrument	15,460	0.69	0.45	0.00	1.00
Fraction of Farms with Electricity	15,460	0.34	0.36	0.00	13.35
Productivity variables					
Production Per Hectare (log)	15,458	12.48	1.22	6.94	17.73
Crop Production per Hectare (log)	15,437	6.67	0.89	0.63	11.37
log_vProdCattlePH	15,411	4.86	1.07	-1.25	11.69
Land Use					
Fraction of County Area in Farmland	15,460	0.71	0.27	0.00	6.26
Fraction of Farmland in Pastures	15,460	0.47	0.24	0.00	0.99
fFarmCropAnnual	15,460	0.17	0.17	0.00	0.98
fFarmMataNat	15,460	0.16	0.14	0.00	0.99
Cattle stuff					
Animal Production/Total Production	15,458	0.39	0.23	0.00	1.00
fraction of cattle less than 1 year old	15,448	0.19	0.05	0.00	0.91
Heads of Cattle per Hectare	15,439	1.13	1.56	0.00	60.87
milk production per dairy cattle	15,295	0.97	0.59	0.02	9.66
fraction of dairy cattle on total herd	15,448	0.14	0.08	0.00	1.36
Capital usage					
Fraction of Farms with Irrigation	15,460	0.06	0.11	0.00	0.98
ihs_nTractor	15,460	4.18	2.09	0.00	10.53
ihs_xFertilPH	15,460	2.52	1.99	0.00	10.72
ihs_xPestPH	15,460	1.83	1.62	0.00	11.84
Number of AMCs	3,092				
Number of observations	15,460				

Notes: Monetary variables measured in thousands of reais in 2002.

Table 2: First-Stage Results

Dependent Variable	Electricity Infrastructure			Fractions of Farms with Electricity	
	(1)	(2)	(3)	(4)	(5)
Modeled electricity availability	0.326***	0.265***	0.264***	0.158***	
	[0.0422]	[0.0358]	[0.0359]	[0.0338]	
Electricity Infrastructure					0.107***
					[0.0187]
Year dummies	Yes	Yes	Yes	Yes	Yes
Jungle × year dummies	No	Yes	Yes	Yes	Yes
Water flow × year dummies	No	No	Yes	No	No
River gradient × year dummies	No	No	Yes	No	No
Observations	15,460	15,460	15,460	15,460	15,460
Mean dep. var.	0.740	0.740	0.740	0.338	0.338
F-stat	59.7	54.8	54.0	21.8	32.4
p-value	0.000	0.000	0.000	0.000	0.000

Notes: In columns 1–3 the dependent variable is prevalence of electricity infrastructure in the county, measured from infrastructur inventories. Each colum adds controls that soak up variation from our instrument. Adding water flow and river gradient interacted with year dummies (column 3) does not change the point estimate substatially. We therefore keep the specification in column 2 as our preferred specification througout the paper. In columns 4 amd 5, the dependent variable is the fraction of farms with electricity in the county, measured from the Censuses of Agriculture. Standard errors clustered at county level in brackets. All specifications include county fixed effects and use county area weights.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 3: The Effects of Electricity on Agricultural Productivity

	log Production Per Hectare of Farmland ($)			log Crop Production Per Hectare of Cropland ($)			log Cattle Production Per Hectare of Pastureland ($)		
	(1) OLS	(2) Reduced Form	(3) IV	(4) OLS	(5) Reduced Form	(6) IV	(7) OLS	(8) Reduced Form	(9) IV
Electricity Infrastructure	0.234**		2.408***	0.273***		2.432***	0.174		1.191*
	[0.101]		[0.544]	[0.0686]		[0.458]	[0.109]		[0.661]
Instrument		0.638***			0.644***			0.315	
		[0.148]			[0.115]			[0.192]	
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jungle x year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,458	15,458	15,458	15,437	15,437	15,437	15,411	15,411	15,409
Mean dep. var.	12.48	12.48	12.48	6.67	6.67	6.67	4.86	4.86	4.86

Notes: The table shows that electricity infrastructure is a positive productivity schock to agriculture, and that it benefits crop cultivation more than cattle grazing. The dependent variable in columns 1–3 is the log of total farm production value divided by total farmland. The dependent variable in columns 4–6 is the log of total crop production value divided by total cropland. The dependent variable in columns 7–9 is the total production value of cattle per hectare of pastureland. Standard errors clustered at county level in brackets. All specifications include county fixed effects and use county area weights.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Effects of electrification on cattle grazing productivity

	Livestock Prod./Total Prod.		Heads Per Hectare		Proportion of Cattle $\leq$ 1 yo		Milk per Dairy Cattle (1000 liters)		Proportion of Dairy Cattle	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV	(9) OLS	(10) IV
Electricity Infrastructure	0.020	-0.333^{***}	0.106	-0.073	0.003	0.022	0.050	0.561^{***}	0.010^{**}	0.065^{**}
	[0.021]	[0.117]	[0.190]	[0.593]	[0.004]	[0.019]	[0.031]	[0.171]	[0.004]	[0.026]
Observations	15,458	15,458	15,439	15,438	15,448	15,448	15,295	15,292	15,448	15,448
Mean dep. var.	0.388	0.388	1.130	1.130	0.191	0.191	0.971	0.971	0.139	0.139

Notes: The table makes the following three points: (i) consistent with the Table 3 results that electrification increases crop productivity relative to cattle grazing productivity, columns 1 and 2 show that the proportion of livestock production on overall farm production decreases with electrification; (ii) The result in Table 3 is robust to the measure of cattle grazing productivity we use. In columns 3 and 4, the dependent variable is the stocking ratio – heads of cattle per hectare of pastureland. In columns 5 and 6, the dependent variable is proportion of young herd on overall herd, which is a proxy for cattle turnover – the idea being that the higher the turnover, the more productive the farm is; (iii) Dairy cattle productivity increases with electrification, but not enough as to induce producers to change the herd's composition towards dairy cattle. The dependent variable in columns 5 and 6 is milk production in thousands of litters per dairy cattle, and in columns 7 and 8 the dependent variable is the proportion of dairy cows on the cattle herd. Standard errors clustered at county level in brackets. All specifications include county fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: The Effects of Electricity on the Allocation of Land

	$\frac{\text{Farmland}}{\text{County Area}}$		$\frac{\text{Pastures}}{\text{Farmland}}$		$\frac{\text{Cropland}}{\text{Farmland}}$		$\frac{\text{Native Vegetation}}{\text{Farmland}}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Electricity Infrastructure	0.010	0.288^{***}	0.022	-0.329^{***}	-0.016	0.037	0.024	0.317^{***}
	[0.014]	[0.110]	[0.019]	[0.112]	[0.010]	[0.047]	[0.020]	[0.109]
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jungle x year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,460	15,460	15,460	15,460	15,460	15,460	15,460	15,460
Mean dep. var.	0.709	0.709	0.470	0.470	0.167	0.167	0.156	0.156
Mean dep. var. (weighted)	0.386	0.386	0.363	0.363	0.093	0.093	0.372	0.372

Notes: The table shows how, following a productivity schock, land use changes in the extensive and intensive margins. The extensive margin is analyzed in columns 1 and 2, where the dependent variable is the county's farm area divided by the county's total area. Land use in the intensive margin (within farms) is analyzed in the remaining columns. The dependent variable in columns 3 and 4 is the farm area in pastures divided by total farm area. The dependent variable in columns 5 and 6 is farm area in crops divided by the total farm area. The dependent variable in columns 7 and 8 is farm area in native negetation divided by the total farm area. Standard errors clustered at county level in brackets. All specifications include county fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: The Effects of Electricity on the Allocation of Land: Long Run

	$\frac{\text{Farmland}}{\text{County Area}}$		$\frac{\text{Pastures}}{\text{Farmland}}$		$\frac{\text{Cropland}}{\text{Farmland}}$		$\frac{\text{Native Vegetation}}{\text{Farmland}}$	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
Electricity Infrastructure	-0.019	0.095	-0.006	-0.430^{***}	-0.011	0.074	0.054^{***}	0.331^{***}
	[0.014]	[0.107]	[0.020]	[0.117]	[0.012]	[0.047]	[0.021]	[0.126]
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jungle x year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,368	12,368	12,368	12,368	12,368	12,368	12,368	12,368
Mean dep. var.	0.706	0.706	0.471	0.471	0.172	0.172	0.157	0.157

Notes: This table is similar to table 5, except that the dependent variables are forward-lagged by one decade. The goal is to show that the increase in native vegetation within farms does not occur just a short-run. The number of observations drop because we loose one period of our panel of counties. The dependent variable in columns 1 and 2 is the county's farm area divided by the county's total area. The dependent variable in columns 3 and 4 is the farm area in pastures divided by total farm area. The dependent variable in columns 5 and 6 is farm area in crops divided by the total farm area. The dependent variable in columns 7 and 8 is farm area in native negetation divided by the total farm area. Standard errors clustered at county level in brackets. All specifications include county fixed effects.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: The Effects of Electricity on Crop Choices

	IHS Production (tons)		IHS Area (ha)		Area/Farmland	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
			Panel A: Grains			
Electricity Infrastructure	0.055	3.203***	−0.104	1.605*	0.012*	0.200***
	[0.175]	[1.084]	[0.158]	[0.919]	[0.007]	[0.046]
Observations	15,460	15,460	15,460	15,460	15,460	15,460
Mean dep. var.	8.36	8.36	8.34	8.34	0.13	0.13
			Panel B: Cassava			
Electricity Infrastructure	0.249**	0.903	0.034	0.075	−0.004	−0.032**
	[0.102]	[0.678]	[0.094]	[0.648]	[0.004]	[0.016]
Observations	15,423	15,423	15,423	15,423	15,423	15,423
Mean dep. var.	6.13	6.13	4.53	4.53	0.01	0.01

Notes: IHS stands for inverse hyperbolic sine. The table shows that the shift from land-intensive towards capital-intensive activities happens also between crops, and not only between cattle grazing and crops. To shows this, panel A shows the effects of electricity infrastructure on the production and harvested area (both in absolute terms and relative to overall farmland) of grains (cotton, maize, soybeans, rice, beans, and wheat), which benefit from electrification through irrigation, handling and storage, and mecanization in general. Panel B shows resutls for cassava, which benefits less than grains from electrification. The table shows that an increase in electricity infrastructure has an effect on the crop mix, leading to a shit into grains and out of cassava – production and area increase (respectively, decrease) for grains (respectively, cassava). This fact also helps explaining why we see little effect of electricity on the share of farmland allocated to crops in Table 5: the results suggest that farmers switch crops, keeping overall cropland as a fraction of farmland roughly constant. Standard errors clustered at county level in brackets. All specifications include county fixed effects.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: The Effects of Electricity on Inputs and Capital for Crop Cultivation

	(1) Fraction of Farms with Irrigation	(2) IHS Capacity Grain Storage	(3) IHS Number of Tractors	(4) IHS Fertilizer Expenses Per Hectare	(5) IHS Pesticides Expenses Per Hectare
IV	0.129***	42.511**	2.408**	5.620***	3.508***
	[0.047]	[17.135]	[0.990]	[1.108]	[0.848]
OLS	0.016***	2.735***	0.174	0.482***	0.243***
	[0.004]	[1.011]	[0.184]	[0.109]	[0.093]
Year dummies	Yes	Yes	Yes	Yes	Yes
Jungle x year dummies	Yes	Yes	Yes	Yes	Yes
Observations	15,460	12,368	15,460	15,460	15,460
Mean dep. var.	0.058	7.847	4.175	2.520	1.826

Notes: The table shows that electricity infrastructure increases usage of various inputs and capital that are typical of crop cultivation activities. In each column, the first row shows results from our preferred IV-fixed effect specification, and the second row shows fixed-effects results. The dependent variable in column 1 is the proportion of farms that use irrigation. The dependent variable in column 2 is the number of tractors transformed by the inverse hyperbolic sine function. The dependent variable in column 3 is the inverse hyperbolic sine of the dollar amount spent in fertilizers. The dependent variable in column 4 is the inverse hyperbolic sine of the dollar amount spent in pesticides. Standard errors clustered at county level in brackets. All specifications include county fixed effects.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A Appendix

Table 9: Sensitivity Analysis by Directly Controlling for Geographic Factors in the Second Stage

Specification (description of control set added to RHS)	(1) log Crop Production Per Hectare	(2) log Cattle Production Per Hectare of Pastureland	(3) First stage	(4) First stage F-stat
1. Water flow × decade budget	2.480*** [0.424]	0.728 [0.643]	0.323*** [0.0382]	71.24
2. River gradient × decade budget	2.484*** [0.424]	0.707 [0.635]	0.320*** [0.0368]	75.77
3. Amazon dummy × decade budget	2.583*** [0.496]	1.201* [0.683]	0.252*** [0.0327]	59.31
4. Water flow × decade budget and Amazon dummy × decade budget	2.579*** [0.503]	1.253* [0.702]	0.249*** [0.0329]	57.56
5. River gradient × decade budget and Amazon dummy × decade budget	2.589*** [0.496]	1.225* [0.680]	0.253*** [0.0326]	59.86
6. River gradient × decade budget and water flow × decade budget	2.480*** [0.424]	0.727 [0.643]	0.323*** [0.0371]	76.01
7. River gradient × decade budget, water flow × decade budget, and Amazon dummy × decade budget	2.592*** [0.504]	1.316* [0.702]	0.250*** [0.0329]	57.88
8. Water flow × year dummies	2.476*** [0.425]	0.720 [0.645]	0.323*** [0.0383]	71.05
9. Amazon dummy × year dummies	2.432*** [0.458]	1.191* [0.661]	0.264*** [0.0320]	68.16
10. River gradient × year dummies	2.484*** [0.423]	0.707 [0.635]	0.320*** [0.0368]	75.69
11. Water flow × year dummies and Amazon dummy × year dummies	2.425*** [0.465]	1.233* [0.680]	0.262*** [0.0322]	65.90
12. River gradient × year dummies and Amazon dummy × year dummies	2.446*** [0.456]	1.209* [0.656]	0.266*** [0.0318]	69.60
13. Water flow × year dummies and river gradient × year dummies	2.468*** [0.423]	0.723 [0.643]	0.324*** [0.0372]	76.02
14. River gradient × year dummies, water flow × year dummies, and Amazon dummy × year dummies	2.441*** [0.463]	1.295* [0.678]	0.263*** [0.0321]	67.21
15. Quartic suitability rank × year dummies	2.422*** [0.451]	1.062 [0.660]	0.272*** [0.0320]	72.42

Notes: This table shows that the IV results presented in Table 3 are robust to the inclusion of controls which are used in the construction of the instrument. Each row represents a different sensitivity test. All specifications include county fixed effects and year dummies. The dependent variable in column 1 is the log of gross crop production value divided by cropland (the same as in columns 4–6 in Table 3). The dependent variable in column 2 is the total production value of cattle per hectare of pastureland (the same as in columns 7–9 in Table 3). Column 3 reports the first-stage coefficient associated with the instrument, and column 4 reports the associated F-statistic. See section 4 and the Appendix for precise definitions of the control variables included in this table. Standard errors clustered at county level in brackets.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: The Effects of Electricity on Forestry Production

	log Forestry Production Value		log Production Value of Wood Products		log Forestry Production Value Per Hectare of Forest		Share of Planted Forests on Farmland	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
Electricity Infrastructure	-0.371**	0.129	-0.300	-0.177	-0.383***	-2.508	-0.00174	-0.0133
	[0.150]	[1.874]	[0.202]	[1.982]	[0.140]	[1.728]	[0.00221]	[0.0244]
Observations	15,510	15,510	15,510	15,510	15,462	15,462	15,496	15,496
Mean dep. var.	8.664	8.664	4.309	4.309	0.165	0.165	0.0172	0.0172

Notes: Standard errors clustered at county level in brackets. All specifications use county area weights and include county fixed effects, year fixed effects, and Amazon-year dummy interactions.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Appendix

B.1 Model Derivation

Proposition 1. *The optimal land use and production choices for farmers,* $H_c^*(\Omega), H_g^*(\Omega), N^*(\Omega)$, *satisfy equations* (4)–(7) *in section* 3.

Proof. The solution to the farmer's problem is given by the set of first-order conditions

$$\begin{aligned}
&\text{wrt } H_c: && \Omega N F_H(H_c^*) = (1+\lambda)p && (13)\\
&\text{wrt } H_g: && F_H(H_g^*) = (1+\lambda)p && (14)\\
&\text{wrt } N: && \Omega F(H_c^*) = (1+\lambda)r && (15)\\
&\text{constraint} && \lambda(rN^* + p(H_c^* + H_g^*) - M) = 0 && (16)
\end{aligned}$$

where λ is the Lagrange multiplier associated with equation (2).

To prove equation (4), note that equations (13) and (15) imply that $N^* = \frac{p}{r}\frac{F(H_c^*)}{F_H(H_c^*)}$ and thus $\frac{\partial N^*}{\partial H_c^*} > 0$.

To prove equation (5), note that combining equations (14) and (15) and taking derivatives with respect to Ω gives

$$\frac{r}{p} F_{HH}(H_g)\frac{dH_g}{d\Omega} - \Omega F_{HH}(H_c)\frac{dH_c}{d\Omega} = F_H(H_c) \tag{17}$$

Furthermore, taking derivatives with respect to Ω in equation (16) and re-arranging yields

$$\Big(1 + \frac{r}{p}\frac{dN}{dH_c}\Big)\frac{dH_c}{d\Omega} = -\frac{dH_g}{d\Omega} \tag{18}$$

Now, substituting (18) into (17), we can see that $dH_c/d\Omega > 0$:

$$-\frac{r}{p} F_{HH}(H_g)\Big(1 + \frac{r}{p}\frac{dN}{dH_c}\Big)\frac{dH_c}{d\Omega} - \Omega F_{HH}(H_c)\frac{dH_c}{d\Omega} = F_H(H_c) \tag{19}$$

Electrification therefore increases the productivity of N and induces farmers to invest in more N. N is useful for cultivation, which increases the land allocated to cultivation. This necessarily leads credit constrained farmers to lower land allocated to cattle grazing, because a larger share of their budget is spent on cultivation.

The net effect on native vegetation within the farm will depend on farmers' total land demand across cultivation and grazing. We define the farmer's total land demand as $H_f = H_c + H_g$, equation 18 can be rearranged to:

$$\frac{dH_f}{d\Omega} = \frac{dH_c}{d\Omega} + \frac{dH_g}{d\Omega} = -\frac{r}{p}\frac{dN}{dH_c}\frac{dH_c}{d\Omega} < 0 \tag{20}$$

The total land demand for all forms of agricultural activities decreases, because farmers have to spend more money on N. In summary, the model predicts that electrification (i.e. increasing the productivity of the limited factor) will: (i) increase use of N, (ii) induce farmers to shift land use from land-intensive cattle grazing to N-intensive cultivation; and (iii) reduce farmers' total land demand.

The net effect of electrification on deforestation will depend not only on intensive-margin changes in land demand within each farm, but also on how the productivity shock induces extensive-margin changes in the decision to enter the agricultural sector. To analyze this net effect, we define the total area of native vegetation as

$$\begin{aligned} H_v &= \overline{H} - \int_{\theta<\Pi} H_f d\Gamma(\theta) \\ &= \overline{H} - H_f \Gamma(\Pi). \end{aligned} \tag{21}$$

The total derivative of the forest with respect to electrification displays two opposing effects:

$$\begin{aligned} \frac{dH_v}{d\Omega} &= \underset{}{-\frac{d\Gamma(\Pi)}{d\Pi}\frac{d\Pi}{d\Omega}H_f} \quad -\Gamma(\Pi)\frac{dH_f}{d\Omega} \\ &= \underset{<0}{-\gamma(\Pi)KF(H_a)H_f} \quad \underset{>0}{-\Gamma(\Pi)\frac{dH_f}{d\Omega}} \end{aligned} \tag{22}$$

□

Proposition 2. *The effect of electrification on overall native vegetation defined in equation* (8) *is ambiguous.*

Proof. The total derivative of the forest with respect to electrification displays two opposing effects:

$$\frac{dH_v}{d\Omega} = -\frac{dH_c + dH_g}{d\Omega}\Gamma(\bar{\theta}) - (H_c + H_g)\Gamma(\bar{\theta})[\frac{d\Pi}{d\Omega} - \frac{d\theta}{d\Omega}] \tag{23}$$

$$\begin{aligned} \frac{dH_v}{d\Omega} &= \quad -\frac{d\Gamma(\Pi)}{d\Pi}\frac{d\Pi}{d\Omega}H_f \quad -\Gamma(\Pi)\frac{dH_f}{d\Omega} \\ &= \underbrace{-\gamma(\Pi)KF(H_a)H_f}_{<0} \quad \underbrace{-\Gamma(\Pi)\frac{dH_f}{d\Omega}}_{>0} \end{aligned} \tag{24}$$

□

References

Angelsen, A. and Kaimowitz, D., editors (2001). *Agricultural Technologies and Tropical Deforestation*. CABI Publiching.

BenYishay, A. and Mobarak, A. M. (2014). Social Learning and Communication. NBER Working Papers 20139, National Bureau of Economic Research, Inc.

BRASIL (2007). Balanco energetico nacional 2007: ano base 2006. Technical Report 194 p, Ministerio de Minas e Energia, EPE, Rio de Janeiro. available at https://ben.epe.gov.br/downloads/BEN2007_Versao_Completa.pdf.

Burgess, R., Hansen, M., Olken, B. A., Potapov, P., and Sieber, S. (2012). The political economy of deforestation in the tropics. *The Quarterly journal of economics*, 127(4):1707–1754.

Conley, T. G. and Udry, C. R. (2010). Learning about a new technology: pineapple in Ghana. *American Economic Review*, 100(1):35–69.

Conning, J. and Udry, C. (2007). *Rural Financial Markets in Developing Countries*, volume 3 of *Handbook of Agricultural Economics*, chapter 56, pages 2857–2908. Elsevier.

Cropper, M., Griffiths, C., and Jyotsna (2001). Predicting Spatial Patterns of Deforestation: The Role of Roads and Protected Areas in North Thailand. *Land Economics*, May.

Cropper, M., Griffiths, C., and Mani, M. (1999). Roads, Population Pressures, and Deforestation in Thailand, 1976-1989. *Land Economics*, 75 (1):58–73.

Dinkelman, T. (2011). The Effects of Rural Electrification on Employment: New Evidence from South Africa. *American Economic Review*, 101(7):3078–3108.

Donaldson, D. (forthcoming). Railroads of the raj: Estimating the impact of transportation infrastructure. *American Economic Review*.

Duflo, E. and Pande, R. (2007). Dams. *The Quarterly Journal of Economics*, 122(2):pp. 601–646.

Dyson, T. (1996). *Population and Food: Global Trends and Future Prospects*. Routledge.

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

Grossman, G. M. and Krueger, A. B. (1991). Environmental impacts of a north american free trade agreement. *National Bureau of Economic Research Working Paper 3914, NBER, Cambridge MA.*

Grossman, G. M. and Krueger, A. B. (1995). Economic growth and the environment. *Quarterly Journal of Economics*, 110:353–377.

Hornbeck, R. and Keskin, P. (2014). The historically evolving impact of the ogallala aquifer: Agricultural adaptation to groundwater and drought. *American Economic Journal: Applied Economics*, 6(1):190–219.

Jayachandran, S., de Laat, J., Lambin, E. F., and Stanton, C. Y. (2016). Cash for carbon: A randomized controlled trial of payments for ecosystem services to reduce deforestation. Working Paper 22378, National Bureau of Economic Research.

Jill L. Caviglia-Harris, Dustin Chambers, J. R. K. b. (2009). Taking the "u" out of kuznets: A comprehensive analysis of the ekc and environmental degradation. *Ecological Economics*, (68):1149–1159.

Lewis, J. and Severnini, E. (2015). The value of rural electricity: Evidence from the rollout of the us power grid. Technical report, Mimeo.

Lipscomb, M., Mobarak, A. M., and Barham, T. (2013). Development Effects of Electrification: Evidence from the Topographic Placement of Hydropower Plants in Brazil. *American Economic Journal: Applied Economics*, 5(2):200–231.

Pfaff, A. (1999). What Drives Deforestation in the Brazilian Amazon? Evidence from Satellite and Socioeconomic Data. *Journal of Environmental Economics and Management*, 37(1):26–43.

Porras, I. (2012). Payments for environmental services in costa rica: from rio to rio and beyond. *iied Briefing*.

Rud, J. P. (2012). Electricity provision and industrial development: Evidence from india. *Journal of Development Economics*, 97:352–367.

Sekhri, S. (2011). Public provision and protection of natural resources: Groundwater irrigation in rural india. *Amercian Economic Journal: Applied Economics*, 3(4):29–55.

Stavins, R. N. and Jaffe, A. B. (1990). Unintended Impacts of Public Investments on Private Decisions: The Depletion of Forested Wetlands. *The American Economic Review*, 80(3):pp. 337–352.

Stern, D. I. (2004). The rise and fall of the environmental kuznets curve. *World Development*, 32(8):1419–1439.

Stern, N. (2008). The economics of climate change. *American Economic Review*, 98(2):1–37.

World Bank (1990). Brazil - irrigation subsector review. Sector Report 7797, World Bank.

Zomer, R. J., Trabucco, A., Coe, R., and Place, F. (2014). Trees on farms: an update and reanalysis of agroforestry's global extent and socio-ecological characteristics. *World Agroforestry Center Working Paper 179*.