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AGRICULTURAL PRODUCTIVITY AND DEFORESTATION IN BRAZIL

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Agricultural Productivity and Deforestation in Brazil

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Abstract

When deforestation laws are difficult to enforce, increased agricultural productivity and intensification are used as an indirect policy tools to reduce the pressure to clear forests for new land, a strategy known as the "Borlaug hypothesis". Increasing 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 facing factor-market constraints to shift away from land-intensive cattle grazing toward less-harmful crop cultivation. We examine these predictions using five waves of the Brazil Agricultural census, 1970 - 2006. 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 cattle ranching and into crop cultivation. The latter allows farmers to retain more native vegetation within rural settlements. Overall, electrification causes a net decrease in deforestation. We also show that Brazilian farmers are credit constrained and invest more in capital following electrification, consistent with the theory we build. We address the endogeneity of electrification by developing a model that forecasts hydropower dam placement based on topographic attributes of each location, and isolate the exogenous portion of the panel variation in electrification.

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

1 Introduction

The rapid loss of major tropical forest ecosystems has been one of the major environmental disasters of the last century. Nearly 20% of recent global greenhouse gas emissions are attributed to tropical deforestation (Stern, 2008). The vast biodiversity across large, diverse ecological zones of Brazil, along with the agricultural potential that land represents, makes the country singularly important in the tension between development and environmental sustainability. While there has been a deceleration in the rate of deforestation in Brazil recently, 78,564 square kilometers of forest cover was lost in the last seven years, and the scale of the problem therefore remains enormous (MMA, 2013).

Deforestation is intricately tied to decisions on land use for agricultural production. [1] Agricultural productivity in frontier areas, and land intensity of the type of farming that gets practiced – crop cultivation versus cattle grazing – are the key determinants of deforestation. Brazil produces over a hundred billion dollars annually through large-scale crop cultivation, and ranks among the world's three largest producers of sugarcane, soybeans and maize. Crop output increased 365% between 1996 and 2006, and Brazil has been dubbed "the farm that feeds the world" (The Economist, August 26, 2010). Brazil is also the world's largest exporter of beef, with a ten-fold increase in exports during that decade. Many farmers engage in both cultivation and cattle-grazing simultaneously.

Cattle grazing and crop cultivation pose very different risks for deforestation, and this margin of land use decisions will be central to our analysis. Cattle grazing is extremely land intensive with limited use of confinement in Brazil, and the average stocking ratio reported in the 2006 agricultural census was less than 1 head per hectare. In contrast, crop cultivation accounted for only 10.6% of total farm area, but 60% of the value of output in 2006 (IBGE). Increasing crop productivity can therefore have ambiguous effects on deforestation in theory. It has the potential to curb deforestation by inducing land conversion away from grazing and into more intensive cropping, but it could also induce expansion of agriculture into frontier lands.

This paper starts by developing a framework that allows for both the intensification effect (Borlaug's hypothesis) as well as the expansion effect. In our model, farmers engage in two activities that are different with respect to their factor intensities – we label the more land-intensive activity "cattle grazing" and the capital-intensive

[1] While logging is often the proximate cause of land clearing, re-growth occurs in most moist tropical forests. For areas to remain deforested in the longer term, the propensity to convert the land to agricultural use matters most.

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 activity that is more land intensive 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. Using county-level data, we first document that electricity access increases cropping productivity more than cattle grazing productivity. Next, we show that farmers (i) allocate less land to pastures, (ii) leave more land in native vegetation, and (iii) invest in more capital following an increase in electricity infrastructure. Although cropland as fraction of total farmland remains unchanged, farmers substitute subsistence varieties for the ones that benefit most from electricity. Finally, we find weak evidence that the increase in agricultural productivity leads to an expansion in farming and induces frontier land conversion. Overall, our empirical results are consistent with our framework, and suggest that electrification causes a net decrease in deforestation in Brazil.

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). We forecast hydropower dam placement and transmission grid expansion based on exogenous topographic attributes of each location. The forecasting model produces hypothetical maps that show, given the constrained budget of generation plants for each decade, how the electrical grid would have evolved had infrastructure allocation been based solely on cost considerations, ignoring demand-side concerns. The maps isolate the portion of the panel variation in electricity grid expansion that is attributable to engineering cost considerations, and thereby provide exogenous variation in electricity access which we use as an instrument for actual electrification. Our empirical strategy takes advantage of the fact that Brazil relies almost exclusively on hydropower to meet its electricity needs. The cost of hydropower dam construction depends on topographic factors such as water flow and river gradient, since hydropower generation requires intercepting large amounts of water at high velocity. The forecasting model includes location fixed effects to control for the fixed geographic attributes, so that the identification comes only from discontinuities in the ranking of different locations' suitability for dam construction, given the decade-specific budget constraints.

An assumption underlying strategies aimed at reducing deforestation through increased investment in capital for rural farms is that increased productivity will lead to agricultural intensification which reduces the pressure to clear forests for new land, rather than expand the scope of farming. Our model indicates that this a potentially dangerous strategy, because it has ambiguous effects on land use in theory. Our empirical results indicate that productivity-enhancing strategies did allow for decreased net deforestation in Brazil over the period 1970-2000. Improvements in agricultural productivity appear to be a promising avenue for environmental protection when regulators' capacity to enforce forest protection laws is weak. Our analysis suggests that the net effect on deforestation will depend on the type of activity that gets displaced when agriculture becomes more productive. In Brazil, the proliferation of land-intensive cattle grazing makes improved cultivation beneficial for the environment.

The beneficial environmental effect of the expansion in electricity infrastructure 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 nuanced findings on the opposing effects of infrastructure development on deforestation contribute to a long-standing literature on the non-monotonic relationship, also known as the Environmental Kuznets Curve (EKC), between economic growth and environmental outcomes, starting with Grossman and Krueger (1991, 1995). The existing empirical evidence on the EKC is mixed and mostly based on cross-country regressions, see Foster and Rosenzweig (2003) and Cropper and Griffiths (1994).

Our paper is also related to the literature on technology adoption in agriculture (BenYishay and Mobarak, 2014), (Conley and Udry, 2010). It is most closely related to papers on causes and consequences of irrigation technology in the United States (Hornbeck and Keskin, 2014) and in India (Sekhri, 2011). We also contribute 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 three key datasets that we use–the Census of Agriculture in Brazil, Electricity Data from various historical archives in Brazil and elevation maps from USGS, and rainfall data. Section 5 discusses our estimation strategy and the instrumental variable technique we employ. Section 6 discusses the empirical results, and section 7 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 . 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 (citation?). 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).

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. 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 even less common 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.

Electricity and Agricultural Productivity Many of the new technologies for irrigation and storage of farm production require the use of electricity. In 2006, one in five Brazilian farmers reported using electricity in their production. Farmers use electricity for various purposes in their agricultural production function. One important use is irrigation. There are two main types of irrigation systems used in Brazil. Flooding or furrow irrigation typically uses gravity to channel water from a source located at higher altitudes than the field. This is a traditional, labor and water-intensive method used for flooding of lowlands in the South for rice production in the summer since the 1960s. In contrast, sprinkler irrigation systems require energy to lift groundwater and distributed 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 1973 and 1979, and the expansion of the electricity grid providing cheap energy from hydropower (World Bank, 1990; Rud, 2012). Sprinkler systems has been the preferred method for crops other than rice in the Center-West, Southeast and Northeast parts of the country. Specially in the Center-West, irrigation during the dry winters allow for two, and sometimes even three harvests of grains (soybeans, maize, cotton) per growing season, therefore significantly increasing farms' production value per hectare of land.

Electricity also enables farmers to adopt various technologies to process their output. For example, post-harvest handling of grains require an array of machinery for drying grains, including ventilators and conveyor belts, for which electricity is an important input. 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.

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 IV. 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 between three main land use categories—pastureland, cropland and native vegetation . At any point in time between 1960 and 2006, these three categories accounted for 80-90 percent of total farmland . As can be seen, there were major changes in the allocation of farmland between these three categories over this period. The share of 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.[2] These trends show a clear expansion of cropland and native vegetation within farmland, at the cost of pastureland and other uses.

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. [3] 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.[4] 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 of export-oriented commodities, one would have expected the relative share of forestry production, and therefore of land allocated to forests in farmland, to *de-*

[2]Not surprisingly, these changes mirror changes in productivity (or yield) gains: whereas gross yields in agriculture have quadrupled over the 1970-2006 period, cattle grazing yields, measured as heads per hectare, only doubled.

[3]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.

[4]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.

crease 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.

Crops vs 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 livestock farm was one-sixth of that of a typical crop farm. And although an equal fraction of farms within each activity make investments in machinery and equipment, investment per farm is also lower in livestock farms. These figures are not surprising when one notes that only 4 percent of cattle farms uses confinement, and that only 0.2 percent of producers pasteurize the milk they sell; and that 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 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 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 set 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 will denote N. Electrification improves the productivity of N. We think of N as capital, labor, or a combination of both. 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 $F_H(0) = \infty$.[5]

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. Thus,

[5]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.

each farmer's 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

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

$$H_c + H_g \leq H. \tag{3}$$

We focus on the case where the resource constraint (eq. 2) is binding, because 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 generate N. Land will therefore not be the limiting factor, and the land constraint (eq. 3) will typically not bind. 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 also makes the model interesting and informative. The credit constraint always binds because the profit function is linear with respect to N and $F_H(0) = \infty$.

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 more money on K 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 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 also compare the relative magnitudes of these estimated effects to infer the net implication of the productivity shock for deforestation.

[6] In reality, the price of cropland is higher than the price of pastureland, so this effect must be even stronger. However, we do not assume different land prices for each activity precisely to highlight this effect.

To sum up, the mechanism highlighted in 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. First, we make the testable assumption that electrification increases productivity of crop cultivation more so than cattle grazing productivity. Second, 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. Third, the model predicts that electrification should lead to greater investments in capital, specifically in capital that raises crop farming productivity. Fourth, the model predicts that positive productive shocks induce farmers to shift land use from land-intensive cattle grazing to N-intensive cultivation. Finally, our model highlights that electrification 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. On the extensive margin, it may or may not increase land demand – hence, farmland – depending on its relative magnitude in farms' profits and farmers' outside option. Hence, the overall effect on demand for agricultural land is ambiguous.

4 Data

We combine three 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. Finally, we use rainfall data compiled by Matsuura and Willmott (2012). Table 1 presents summary statistics from these datasets.

4.1 Census of Agriculture

Definition of a rural establishment and level of aggregation 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*.

Outcome variables: Area Three sets of outcome variables are central to our analysis. First is the farm area in each of three land use categories: cropland, pastures, and native vegetation. Together, these three land use categories account for between

[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.

81% and 90% of the total land in farms in Brazil during the period 1970-2006. The remaining farm area is bundled in a fourth "other" category, which includes orchards, planted forests, buildings and facilities, water bodies and non-arable land.[8] Cropland excludes area for perennial crops (many of which are in orchards) and includes forage-land. Pastures can be either natural or planted.

Outcome variables: Productivity 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 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 cattle and dairy cattle, and measure dairy cattle productivity as milk production per head of dairy cattle.

Outcome variables: Capital and Inputs 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 hydropower. Electricity access is measured based on archival research of the location and date of construction of hydropower plants and transmission substations in Brazil from 1950-2000[9]. 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

[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.

[9] This data and the related instrument was also used in Lipscomb et al. (2013).

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 cataloguing 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 South in the 1950s and 1960s and spread Southeast in the 1960s and 70s and to the Northeast in the 1970s and 80s. 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 hydropower, 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 hydropower 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 gridpoints for use in the model, and then predicted access is aggregated to the level of the 2,184 standardized counties across Brazil.

4.3 Climate Data

Finally, we use the rainfall data compiled by Matsuura and Willmott (2012) to construct various indicators of drought, dryness and rainfall volatility for each county. This dataset provides monthly precipitation estimates at each node of a 0.5×0.5 degree grid. These estimates are obtained by interpolating data from local weather stations.

To construct indicators of drought, dryness and rainfall volatility, we start by identifying all grid nodes inside each county. If there are less than four nodes with precipitation data inside the county, we then find the four closest nodes to the county's borders. For each county, we then take an weighted average of this set nodes, using the inverse of the distance to county's centroid as weights.

We define rainfall volatility of county c as the standard deviation of the residuals of the following regression:

$$r_{cmy} = \beta_0 + \theta_m + \delta_y + \epsilon_{cmy},$$

where r_{cmy} is rainfall in county c, in month m and year y, θ_m is a month fixed effect and δ_y is a year fixed-effect. In words, we calculate rainfall volatility over and above seasonality and common shocks. We then define high (low) volatility counties as those whose volatility index is above (below) the median.[10]

[10] We calculate other volatility measures, as well as indexes of droughts and dryness. We are still working on results using those other measures, and future versions of this paper should include such results either on its body or in the appendix.

5 Estimation 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 0.275 to 0.181, 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

Based on the discussion in section 2 and the model presented in section 3, we interpret the arrival of electricity as a positive productivity shock to agriculture and in particular to crop cultivation. The results presented below support our interpretation that the arrival of electricity can be thought of as a productivity shock to crop cultivation, but not to cattle grazing.

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 estimates are larger than the OLS estimates and imply that that a 10 percent increase in electricity availability increases agricultural productivity by 18.6 percent, and this result is significant at the 5 percent level. To further understand which activity benefits relatively more from new electricity infrastructure, we analyze separately the effects on crop 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 point estimate implies that a 10 percentage-point increase in electricity infrastructure increases crop productivity by 19.6 percent, and this effect is significant at the 1 percent level. The high impact of electricity on crop productivity is mirrored by a low impact on cattle grazing productivity. Columns (7)-(9) show the effects of electricity on the number of cattle heads per hectare of pastureland, or *heads per hectare*. The IV estimate in column (9) implies that a 10 percentage-point increase in electricity leads to a 0.05 increase in heads per hectare, a 4.4 percent effect on the mean. Not only this is a lower impact than that for crop cultivation, it is not statistically significant at conventional levels.

In sum, the arrival of electricity infrastructure in a county significantly increases crop productivity, but not cattle grazing productivity. Section 6.5 below gives further evidence that the effect of electricity on livestock productivity is overall small. This result corroborates our model's assumption that electricity is a positive productivity shock to crop cultivation productivity.

6.2.1 Identification concerns

As explained in section 4, the 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, Table 4 presents results of a series of sensitivity tests 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 Table 4 reports a different specification of a 2SLS regression where the dependent variable is the log of crop production value per hectare in column (1), or the number of cattle heads per hectare of pastureland in column (2). We also report the corresponding first-stage statistics in column (3). As can be seen, both the main result of Table 3 – that electricity affects crop cultivation productivity, but not cattle grazing productivity – survives all the different specifications.

6.3 Changes in Land Use and Production Decisions

Given that electricity increases overall agricultural productivity, it is natural to expect that it will lead to an expansion of farmland, as producers' will want to do more agriculture. But the arrival of electricity also changes the relative productivities of crop cultivation and cattle grazing, which implies that producers should shift away from cattle grazing into crop cultivation. In this section we explore in more details these changes in producers' decisions.

Table 5 shows the effects of electrification on land allocation within farms. Columns (1) and (2) show how farmland expands following more electricity infrastructure. The IV estimate implies that the share of farmland in the typical county increases by 1.1 percentage points following a 10 percentage point increase in electricity infrastructure. This coefficient however is not precisely estimated and hence is not statistically significant. In the remaining columns we look at changes in the shares of pastureland, cropland and area in native vegetation within farms. In Columns (3) and (4), we see that the share of pastureland in the county's farmland decreases with electricity infrastructure. The IV estimate in column (4) implies that the share of pastures in farmland decrease by 4.8 percentage points following a 10 percentage point increase in electricity, an effect of 10 percent for the typical county. Columns (5) and (6) show the same analysis for cropland. The IV estimate in column (6) implies that the share of cropland increases by 0.14 percentage points, a small and not statistically significant effect. Finally, in columns (7) and (8) we look at the share of farmland that remains in native vegetation. The IV estimate implies that a 10 percentage-point increase in electrification induces producers to increase native vegetation within rural establishments by 4.4 percentage points, a mean effect of 29 percent.

These results suggest that the arrival of electricity induce producers to reduce the share of land they allocate to pastures relative to cropland. This is not surprising once we noted that electricity increases crop farming productivity relative to cattle grazing productivity. What is more surprising is the large effect of electricity on the share of native vegetation within farms. Such large effect raises two questions. First, abstracting from potential private productive benefits of keeping native vegetation,[11] why would producers ever choose to keep land in native vegetation? In our model of land use choice, producers face constraints on input factors other than land – say, capital and/or labor. Following a positive productive shock to crop farming, producers cannot increase their crop production while keeping cattle grazing

[11]Native vegetation provides ecosystem services by increasing biodiversity and helping with pollination, plague control, providing wood fuel, increasing soil moisture and protecting water bodies.

constant. Since crop farming is less land-intensive than cattle grazing, the reduction in land demand for cattle grazing must be larger than the increase in land demand for crop farming. This intensification effect frees-up land, which then goes back into native vegetation.

Second, what is the effect of electricity in overall native vegetation, not only within farmland? Table 5 reveals two opposing effects. On one hand, new electricity infrastructure induces an expansion of farmland, which potentially has negative effects on native vegetation *outside* farms. On the other hand, there is a direct positive effect on native vegetation *inside* farms. To calculate the net effect, we would ideally have data on native vegetation outside farms. To the best of our knowledge there are no countrywide reliable sources for most of our period of analysis.[12] We therefore need to make assumptions on what was the state of native vegetation outside farms prior to the arrival of electricity. Assuming that all non-farmland is covered (not covered) with native vegetation yields the lower (upper) bound of 0.22 (0.35). That is, a 10 percentage point increase in electricity infrastructure increases the share of native vegetation in the typical county by 2.2 – 3.5 percentage points. See the appendix for details on how to calculate this estimate from the numbers presented in Table 5.

Long-run results One may wonder if the increase in native vegetation within farms concomitantly with the expansion of farmland is not an indication of 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.[13] Appendix Table 6 show the results, which remain largely unchanged, suggesting that these are not just short-run effects.

Crop choices Although the ratio of cropland to pastureland increases with electrification, the absolute share of cropland does not seem to increase. To understand why, we look into the composition of different crops choices; one possibility for cropland not to expand despite the productivity increase in crop farming is changes in the crop mix. If farmers substitute less productive crops for more productive ones, overall cropland may remain stable.[14] Specifically, we investigate the effects of elec-

[12] By design, the Census of Agriculture collects farmland data. Good countrywide remote sensing data is available starting in late 1990's and early 2000's.

[13] 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.

[14] Whereas out stylized model contemplated only two activities – labeled cattle grazing and crop farming – it could be easily extended to incorporate more activities, for instance, different crop choices.

trification 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. In contrast, cassava is a subsistence cop, with low yields and relatively more land-intensive than grains.

Table 7 reports the results. The IV estimate in column (2) implies that grain production increases by 41 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 is not statistically significant and in any case is smaller in magnitude. 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 following arrival of electricity infrastructure. These xhanges in the crop mix help explaining why we see little or no effect of electrification on cropland despite the increased crop productivity.

6.4 Testing mechanisms and other model predictions

We now empirically evaluate our model's predictions to build confidence that it can explain the mechanisms underlying our results. First, in our model there are two opposing forces following a productivity shock to agriculture productivity – an intensification and one expansion effects. We argue that these opposing effects come from different groups of producers, as it would be inconsistent for one single group of producers to display both forces. The mechanism we outline is one where new, incoming operators open new farms (or, equivalently, fewer operators leave). In Table 8, columns (1)-(2) show a large effect on the number of farms above 10 hectares in a county. We exclude very small farms from the dependent variable for conceptual reasons.[15] Our model's prediction is about new operators attracted by an increase in productivity. While our model's prediction is silent on farm size, very small farms are typically operated by families for subsistence, and therefore do not fit into our model.

Second, we test one important link between electricity and agricultural productivity – irrigation. One of our model's implications is that producers respond to an increase in the availability of electricity by making crop-related investments. Irrigation is a

[15] While farms of 10 hectares may be considered large for some countries, like Bangladesh or India, they are considered small in Brazil where the average farm size ranged from 60 to 73 hectares in our sample period. For example, land redistribution programs grant no less than 5 hectares for a family to produce at subsistence levels. Depending on the county, the estimated minimum size of plot of land for subsistence may be as large as 100 hectares.

strong candidate, as explained in section 2. Columns (3) and (4) show that both the number of farms as well as irrigated farm area grow substantially with an increase in electricity infrastructure. A 10 percentage point increase increase in electricity leads to 27 percent more farms with irrigation and a 70 percent increase in irrigated land.

Next, Table 8 presents the effects of electrification usage of inputs. In the IV specification, a 10 percent increase in electrification leads to a 53 percent in crease in fertilizer spending (Column (2)), and a 28.7 percent increase in pesticides (Column (4)), and both effects are significant at the 1 percent level. Electrification also leads to more tractors being used, as shown in columns (5) and (6).

6.5 Further evidence that cattle grazing productivity does not increase with electricity

Is it really the case that the arrival of electricity does not increase productivity in cattle-related activities, as found in section 6.2?[16] To further explore this question, Table 9 looks at the effect of electricity on alternative productivity measures of cattle-related activities. In columns (1) and (2), the dependent variable is the fraction of the herd that is younger than one year-old, a proxy for cattle turnover. The idea is that there can be productivity gains by increasing cattle turnover, which translates in a younger the heard. The IV coefficient in column (2) implies that a 10 percent increase in electricity infrastructure increases the fraction of calves by 0.48 percentage points, a 2.5 percent effect on the mean. The effect is significant at the 10 percent level. In the same vein, columns (3) and (4) look at the effect on fraction of the herd that is younger than two years old. The IV coefficient is not statistically significant, and represents an effect of 1.5 percent on the mean. Overall these effects are small in magnitude and weakly significant when compared to the effects found on crop productivity.

Electricity can have an important effect on dairy activities by allowing for mechanical milking and refrigeration. To explore this possibility, columns (5) and (6) look at dairy cattle productivity as measured by milk per dairy call. The IV estimate in column (6) implies that a 10 percent increase in electricity increases milk production by 60 litters per dairy cow, a 6 percent effect on the mean. Is this effect strong

[16]Ideally one would measure cattle grazing productivity as kilos-per hectare/year, since ultimately it is not the number of heads of cattle that matter, but their weight. And, by reaching a given weight using the same amount of land in a smaller period of time would increase productivity. 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.

enough to induce producers to change their herd's composition towards dairy cattle? In columns (7) and (8) we answer this question by looking at the fraction of dairy cattle on the herd. The IV coefficient is not significant and represents an small effect on the mean. Taken together, the results from columns (5)-(8) imply that the effect on dairy cattle productivity, while sizable, is not sufficient to induce producers to change their herd's composition, having therefore little effect on the aggregate cattle grazing productivity.

Finally, columns (9) and (10) look at the ratio of animal production to total production (i.e., crop production plus animal production). The idea is that there can be other livestock activity other than cattle grazing, or other ways to measure cattle grazing production not captured previously. The IV estimates indicate that electricity benefits animal production less than it benefits crop production: following an a 10 percent increase in electricity infrastructure, the share of animal production declines 4.3 percentage points, a 13.7 percent effect on the mean, and strongly significant.

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.[17] 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

[17](Lipscomb et al., 2013) find positive links between electricity and income.

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, there is no evidence that either farms or industrial plants, which together accounted for the remainder 30 percent of firewood consumption in 1970, directly replaced wood-based energy for electricity. During the period we analyze, industrial plants actually increased their consumption of wood-based energy, while farms decreased it. The agricultural census data allows us to check whether farms substituted firewood for electricity. The results are in Table XXXX.

Finally, 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.

Better enforcement of property rights Arguably, property rights may be locally better enforced with the arrival of electricity — for example, counties with electricity may have more and better courts and policing, protecting landowners from each other and from invasions. Better "contracting institutions" (Acemoglu and Johnson, 2005) may have enabled producers to invest in more productive technologies and crop choices (Hornbeck, 2010), thus explaining the intensification of the agricultural activity that we find.

While the presence of the state may have improved conflict resolution between private parties, in Brazil it may also represent a higher risk of expropriation. Starting in 1964, land reform programs explicitly targeted unproductive properties for expropriation and redistribution.[18] Historians have noted that the presence of native vegetation signaled unused land, increasing the probability of expropriation. Landowners would clear their land and populate it with some cattle to protect against the risk of expropriation. As a result, the arrival of electricity (and the state) may have induced a reduction in native vegetation within private properties and increased the share of (low productivity) pastureland.

The improvements of property rights enforcement accruing from the arrival electricity could therefore have ambiguous effects on deforestation. The fact that these two forces partially offset each other mitigate

Table 12 suggests that electrification has had ambiguous effects on property rights. We use two measures to proxy different types of property rights. In columns (1) and (2), we use the fraction of land under tenancy or shareholder contracts. We believe this measure captures institutions that protect private parties from each other. The results show that the fraction of land under tenancy contracts increase significantly with electricity. We interpret this as evidence that

In columns (3) and (4), we use the fraction of untitled farmland

Functioning land tenancy and shareholder markets are a sign of well established property rights

[18] Although expropriations averaged 8 properties per year in the the 1964–1984 period, the threat existed (Hidalgo et al., 2010). After 1984,

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 and (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,

Our results have important implications for policy making in

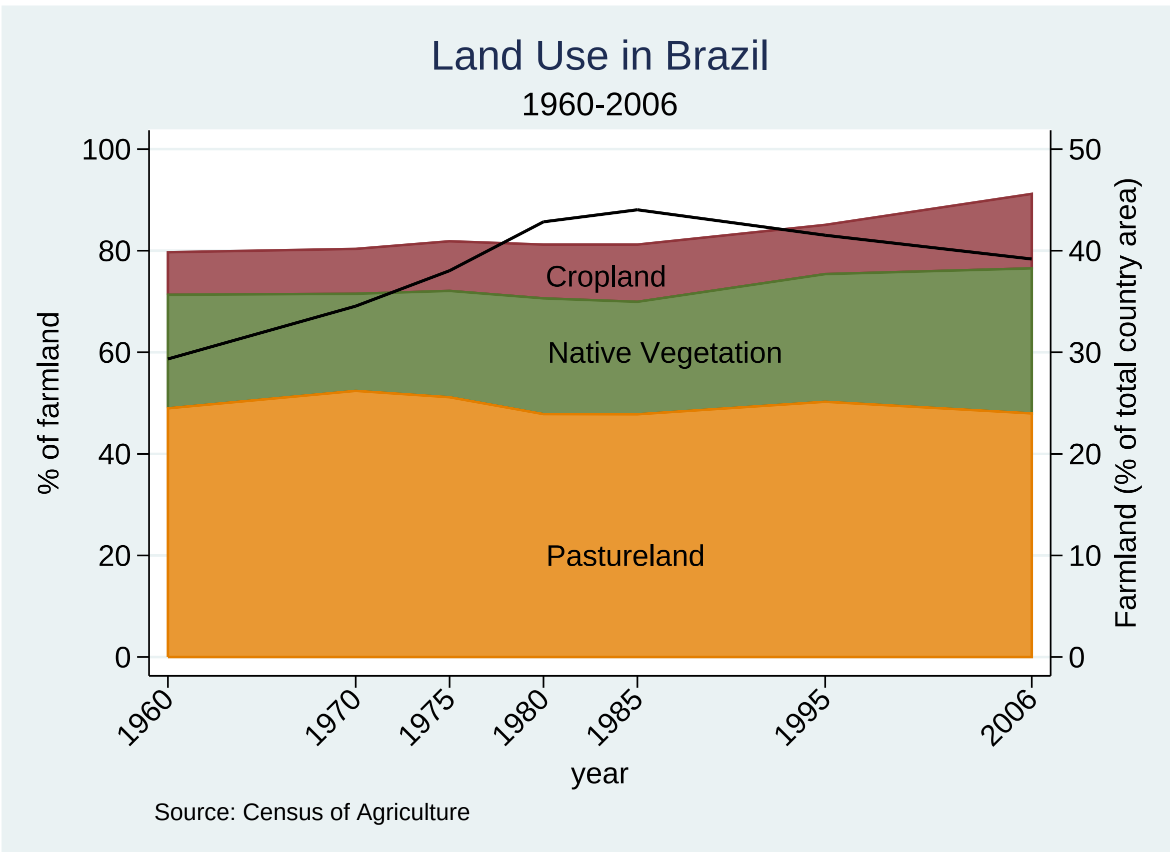

Figure 1: Proportion of Total Farmland and Allocation of Farmland Across main Land Use Categories, Brazil 1960-2006

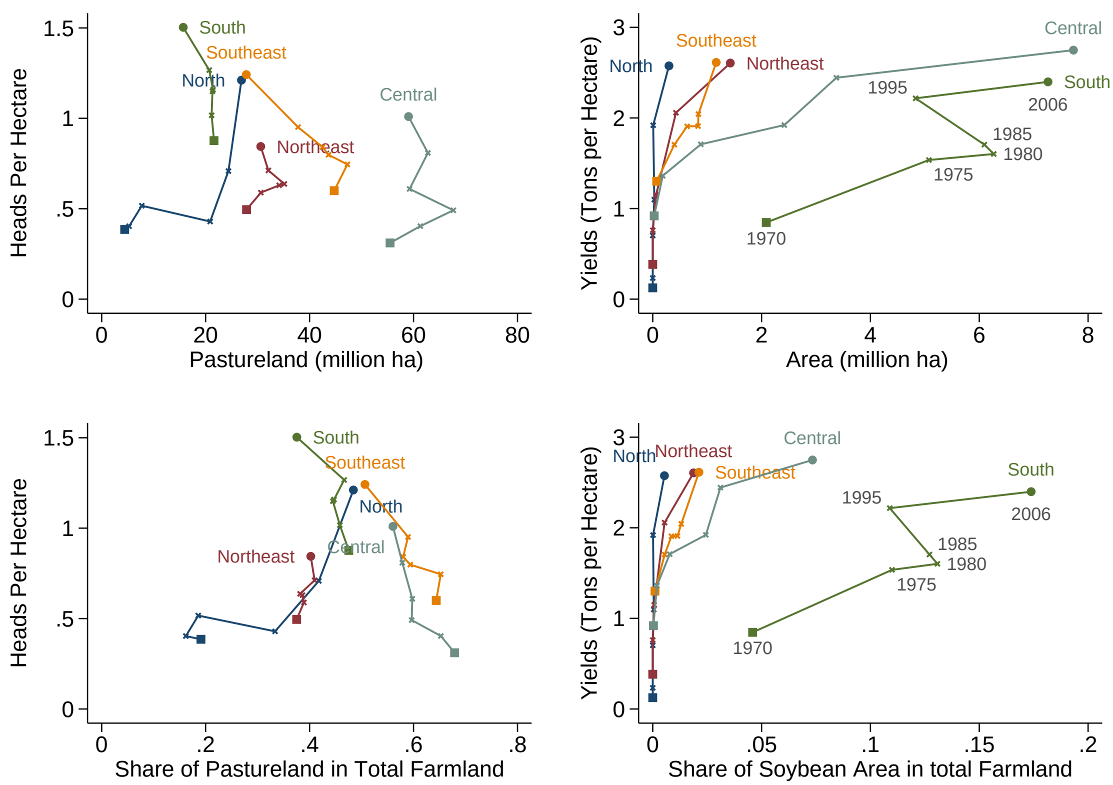

Figure 2: Evolution of Cattle Grazing and Soybean Cultuvation: Area and Productivity, Brazil 1960-2006

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	0.265***	0.168***	0.167***	0.0831**	
	[0.0397]	[0.0380]	[0.0383]	[0.0333]	
Electricity Infrastructure					0.106***
					[0.0187]
Year dummies	Yes	Yes	Yes	Yes	Yes
Jungle $\times$ year dummies	No	Yes	Yes	Yes	Yes
Water flow $\times$ year dummies	No	No	Yes	No	No
River gradient $\times$ year dummies	No	No	Yes	No	No
Observations	15,510	15,510	15,510	15,496	15,496
Mean dep. var.	0.740	0.740	0.740	0.338	0.338
F-stat	44.7	19.4	18.9	6.2	32.3
p-value	0.000	0.000	0.000	0.013	0.000

Notes: In columns (1)–(3) the dependent variable is prevalence of electricity infrastructure in the county, measured from infrastructur inventories. In columns (4)–(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 ($)			log Crop Production Per Hectare ($)			Heads Per Hectare		
	(1) OLS	(2) Reduced Form	(3) IV	(4) OLS	(5) Reduced Form	(6) IV	(7) OLS	(8) Reduced Form	(9) IV
Electricity Infrastructure	0.235**		1.826**	0.274***		2.084***	0.107		0.327
	[0.101]		[0.827]	[0.0686]		[0.568]	[0.190]		[0.875]
Instrument		0.306*			0.349***			0.0546	
		[0.159]			[0.0888]			[0.164]	
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	15,493	15,493	15,493	15,469	15,469	15,469	15,468	15,468	15,465
Mean dep. var.	9.73	9.73	9.73	3.91	3.91	3.91	1.13	1.13	1.13

Notes: Standard errors clustered at county level in brackets. All specifications include county fixed effects. 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 number of cattle heads per hectare of pastureland.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: 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) Heads Per Hectare	(3) First stage	(4) First stage F-stat
1. Water flow × decade budget	2.227***	-0.691	0.263***	273.0
	[0.246]	[0.632]	[0.0159]	
2. River gradient × decade budget	2.227***	-0.709	0.260***	270.5
	[0.250]	[0.640]	[0.0158]	
3. Amazon dummy × decade budget	2.281***	0.196	0.157***	107.0
	[0.422]	[1.071]	[0.0152]	
4. Water flow × decade budget and Amazon dummy × decade budget	2.273***	0.239	0.155***	104.6
	[0.427]	[1.084]	[0.0152]	
5. River gradient × decade budget and Amazon dummy × decade budget	2.302***	0.287	0.158***	108.8
	[0.419]	[1.063]	[0.0152]	
6. River gradient × decade budget and water flow × decade budget	2.225***	-0.695	0.261***	273.2
	[0.248]	[0.637]	[0.0158]	
7. River gradient × decade budget, water flow × decade budget, and Amazon dummy × decade budget	2.299***	0.397	0.156***	105.7
	[0.425]	[1.079]	[0.0152]	
8. Water flow × year dummies	2.230***	-0.694	0.264***	274.3
	[0.246]	[0.630]	[0.0159]	
9. Amazon dummy × year dummies	2.084***	0.327	0.167***	125.0
	[0.386]	[1.009]	[0.0149]	
10. River gradient × year dummies	2.221***	-0.707	0.260***	271.7
	[0.248]	[0.639]	[0.0158]	
11. Water flow × year dummies and Amazon dummy × year dummies	2.079***	0.365	0.165***	123.0
	[0.389]	[1.016]	[0.0149]	
12. River gradient × year dummies and Amazon dummy × year dummies	2.114***	0.399	0.168***	126.8
	[0.384]	[1.003]	[0.0149]	
13. Water flow × year dummies and river gradient × year dummies	2.219***	-0.700	0.262***	276.3
	[0.246]	[0.634]	[0.0158]	
14. River gradient × year dummies, water flow × year dummies, and Amazon dummy × year dummies	2.115***	0.510	0.166***	123.4
	[0.390]	[1.016]	[0.0149]	
15. Quartic suitability rank × year dummies	2.070***	-0.0284	0.185***	150.3
	[0.347]	[0.909]	[0.0151]	

Notes: Standard errors clustered at county level in brackets. The goal of this Table is to show 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. The dependent variable in column (1) is the log of gross crop production value divided by cropland (the same in columns 4–6 in Table 3). The dependent variable in column (2) is the number of cattle heads per hectare of pastureland (the same in columns 7–8 in Table 3). Column (3) reports the first-stage coefficient associated with the instrument. Column (4) reports the associated F-statistic. See section 4 and the Appendix for precise definitions of the control variables included in this table.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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	0.00987	0.288***	0.0223	−0.329***	−0.0157	0.0369	0.0236	0.317***
	[0.0140]	[0.110]	[0.0191]	[0.112]	[0.0105]	[0.0466]	[0.0201]	[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.	0.71	0.71	0.47	0.47	0.17	0.17	0.16	0.16

Notes: Standard errors clustered at county level in brackets. All specifications include county fixed effects. The dependent variable in columns (1)-(2) is the county's farm area divided by the county's total area. The dependent variable in columns (3)-(4) is the county's area in pastures divided by the county's farm area. The dependent variable in columns (5)-(6) is the county's area in crops divided by the county's farm area. The dependent variable in columns (7)-(8) is the county's area in pastures divided by the county's farm area

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

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

	Farmland / County Area		Pastures / Farmland		Cropland / Farmland		Native Vegetation / Farmland	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
Electricity Infrastructure	-0.0189	0.0948	-0.00580	-0.430^{***}	-0.0110	0.0744	0.0543^{***}	0.331^{***}
	[0.0136]	[0.107]	[0.0195]	[0.117]	[0.0116]	[0.0474]	[0.0206]	[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.	0.71	0.71	0.47	0.47	0.17	0.17	0.16	0.16

Notes: Standard errors clustered at county level in brackets. All specifications include county fixed effects. This table is similar to Table 6, except that the dependent variables are forward-lagged by one decade. The dependent variable in columns (1)-(2) is the county's farm area divided by the county's total area. The dependent variable in columns (3)-(4) is the county's area in pastures divided by the county's farm area. The dependent variable in columns (5)-(6) is the county's area in crops divided by the county's farm area. The dependent variable in columns (7)-(8) is the county's area in pastures divided by the county's farm area

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

Table 7: The Effects of Electricity on Crop Choices

	log Production (tons)		log Area (ha)		Area/Farmland	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
			Panel A: Grains			
Electricity Infrastructure	0.206	3.752***	0.042	2.155**	0.012*	0.200***
	[0.230]	[1.227]	[0.215]	[1.071]	[0.007]	[0.046]
Observations	15,460	15,460	15,460	15,460	15,460	15,460
Mean dep. var.	7.57	7.57	7.54	7.54	0.13	0.13
			Panel B: Cassava			
Electricity Infrastructure	0.332***	0.494	0.082	−0.426	−0.004	−0.032**
	[0.112]	[0.863]	[0.105]	[0.827]	[0.004]	[0.016]
Observations	15,423	15,423	15,423	15,423	15,423	15,423
Mean dep. var.	4.87	4.87	3.18	3.18	0.01	0.01

Notes: The table shows that electrification has effects on the crop mix. Some crops benefit more from electrification than others. Grains, in particular, benefit from electrification through irrigation, handling and storage, and mecanization in general. Cassava, on the other hand, benefits less from electrification, as it is a typical subsistence crop. Consistent with this, the table shows that an increase in electricity infrastructure leads to a shit into grains and out of cassava – production and area increase (respectively, decrease) for grains (respectively, cassava). The table makes the point that the shift from land-intensive towards capital-intensive activities happens also between crops, and not only between cattle grazing and crops. This fact helps explaining why we see little effect of electricity on the share of farmland allocated to crops in Table 5. Farmers may be switching crops, keeping overall cropland as a fraction of farmland roughly constant.

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

Table 8: The Effects of Electricity on Capital and Inputs

	Fraction of Farms using Irrigation		Number of Tractors (log)		Expenditures in Fertilizers Per Hectare (log)		Expenditures in Pesticides Per Hectare (log)	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
Electricity Infrastructure	0.02***	0.13***	0.17	2.41**	0.48***	5.62***	0.24***	3.51***
	[0.00]	[0.05]	[0.18]	[0.99]	[0.11]	[1.11]	[0.09]	[0.85]
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.	0.06	0.06	4.18	4.18	2.52	2.52	1.83	1.83

Notes: Standard errors clustered at county level in brackets. All specifications include county fixed effects. The dependent variable in columns (1)-(2) the fraction of farms that use irrigation. The dependent variable in columns (3)-(4) is number of tractors in a county-year transformed by the inverse hyperbolic sine function. The dependent variable in columns (5)-(6) is the inverse hyperbolic sine of the dollar amount spent in fertilizers in a county-year. The dependent variable in columns (7)-(8) is the inverse hyperbolic sine of the dollar amount spent in pesticides in a county-year.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Cattle grazing productivity really doesn't go up with electrification?

	Animal Prod./Total Prod.		Fraction Cattle $\leq$ 1 yo		Heads Per Hectare		Milk per Dairy Cattle (1000 liters)		Fraction 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	0.0205	-0.333^{***}	0.00337	0.0216	0.106	-0.0728	0.0497	0.561^{***}	0.0100^{**}	0.0650^{**}
	[0.0210]	[0.117]	[0.00355]	[0.0194]	[0.190]	[0.593]	[0.0310]	[0.171]	[0.00402]	[0.0260]
Observations	15,458	15,458	15,448	15,448	15,439	15,438	15,295	15,292	15,448	15,448
Mean dep. var.	0.388	0.388	0.191	0.191	1.130	1.130	0.971	0.971	0.139	0.139

Notes: The table makes the following three points: (i) consistent with the story that electrification increases crop productivity relative to cattle grazing productivity, columns 1-2 show that the fraction of animal production on overall farm production decreases. (Note that includes poltry production which is likely affected by electricity); (ii) the result in Table 3 is robust to the measure of cattle grazing productivity we use. In this table, we use two alternative measures of cattle grazing productivity instead of Cattle Production Per Hectare of Pastureland. Columns 3-4 use the fraction of young herd on overall herd – the idea being that the younger the herd becomes ready for the slaughterhouse, the more productive the farm is (unfourtunately we don't have the herd's age). Columns 5-6 use the stocking ratio – heads of cattle per hectare of pastureland. The IV estimates are not significant, not have meaninful magnitudes when either measure is used. (iii) Dairy cattle productivity does go up – columns 7-8 show that a 10% increase in electrification increases milk per cow by 60 liters, a 6% increase on the mean. However, this effect is small for it does not induce producers to change the herd's composition towards dairy cattle, as shown in columns 9-10.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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

Table 11: Teting for the presence of credit constraints: Do past rainfall schocks affect productivity and investments?

	Number of Tractors			log Production Per Hectare ($)		
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall at t	28.97*	23.31	49.27**	0.0225	0.00647	0.0252
	[17.37]	[17.25]	[19.52]	[0.0240]	[0.0239]	[0.0242]
Rainfall at t-1	24.85***			0.108***		
	[4.813]			[0.0156]		
Rainfall at t-3		57.67***			0.0717***	
		[16.38]			[0.0268]	
Rainfall at t-5			113.7***			0.0745***
			[19.01]			[0.0185]
Observations	15,510	15,510	15,510	15,493	15,493	15,493
Mean dep. var.	169.9	169.9	169.9	9.725	9.725	9.725

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

Table 12: The Effects of Electricity on Property Rights

	Fraction of Farmland under Tenancy or Sharecropping contracts		Fraction of Farms under Tenancy or Sharecropping contracts		Fraction of Untitled Farmland		Fraction of Untitled Farms	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV	(7) OLS	(8) IV
Electricity Infrastructure	0.0240***	0.215***	0.00884	0.0184	0.0593***	0.413***	0.110***	0.786***
	[0.00861]	[0.0793]	[0.0115]	[0.121]	[0.0175]	[0.135]	[0.0208]	[0.233]
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Jungle x year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,496	15,496	15,496	15,496	15,496	15,496	15,496	15,496
Mean dep. var.	0.07	0.07	0.12	0.12	0.05	0.05	0.12	0.12

Notes: Standard errors clustered at county level in brackets. All specifications include county fixed effects.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

9 Appendix

9.1 Calculating the effect of electricity on native vegetation

Column (10) of Table 5 gives us the effect of electricity on native vegetation *inside* farms. Because we do not have explicit data on native vegetation *outside* farms, we need one assumption to be able to back out the effect of electricity on overall native vegetation. To see this, first note that $V(e) = V_I(e) + V_O(e)$, where V is total native vegetation, V_I denotes native vegetation inside of farms, and V_O denotes native vegetation outside of farms. Denoting county area by C, we are interested in

$$\frac{\partial}{\partial e}\frac{V(e)}{C} = \frac{\partial}{\partial e}\frac{V_I(e)}{C} + \frac{\partial}{\partial e}\frac{V_O(e)}{C} \tag{13}$$

From the numbers in Table 5 we can back out the term $\frac{\partial}{\partial e}\frac{V_I(e)}{C}$ using the chain rule. But since we do not have data on $\frac{V_O}{C}$, we must make one assumption to fully recover the effect of electricity on overall native vegetation. Note that we can write $V_O(e) = k(C - F(e))$, that is, native vegetation outside of farms is a fraction k of the county area (C) that is not in farms ($F(e)$). Plugging that on the second term on the RHS of (13),

$$\frac{\partial}{\partial e}\frac{V_O(e)}{C} = \frac{\partial}{\partial e}\frac{k(C - F(e))}{C} = -k\frac{\partial}{\partial e}\frac{F(e)}{C} \tag{14}$$

We have $\frac{\partial}{\partial e}\frac{F(e)}{C}$ from column (2) of Table 5. The only information we do not have is k, the fraction of the county area outside of farms that is in native vegetation. Assuming $k = 1$ ($k = 0$) gives us a lower (upper) bound on the effect of electricity on overall native vegetation.

To calculate $\frac{\partial}{\partial e}\frac{V_I(e)}{C}$, note that the IV coefficient in column (10) of Table 5 gives us $\frac{\partial}{\partial e}\frac{V_I(e)}{F(e)}$ which, by applying the chain rule, is $\frac{\frac{\partial V_I}{\partial e}\cdot F(e) - V_I(e)\cdot\frac{\partial F}{\partial e}}{F(e)^2}$. Solving for $\frac{\partial V_I}{\partial e}$ and dividing both sides by C yields

$$\frac{\partial}{\partial e}\frac{V_I}{C} = \frac{\partial}{\partial e}\frac{V_I(e)}{F(e)}\cdot\frac{F(e)}{C} + \frac{V_I}{F(e)}\cdot\frac{\partial}{\partial e}\frac{F(e)}{C} \tag{15}$$

Plugging equations (14) and (15) into (13),

$$\frac{\partial}{\partial e}\frac{V(e)}{C} = \frac{\partial}{\partial e}\frac{V_I(e)}{F(e)}\cdot\frac{F(e)}{C} + (\frac{V_I}{F(e)} - k)\cdot\frac{\partial}{\partial e}\frac{F(e)}{C} \tag{16}$$

If we evaluate this derivative at the sample means, Table 5 gives all the terms on the RHS of this equation except for k. The effect of electricity on the share of farmland in native vegetation, $\frac{\partial}{\partial e}\frac{V_I(e)}{F(e)}$ is 047. The fraction of the county area in farmland, $\frac{F(e)}{C}$ is 0.70 for the typical municipality. The fraction of farmland in native vegetation is $\frac{V_I(e)}{F(e)}$ is 0.16 for the typical municipality. Finally, the effect of electricity on farmland 0.13. Assuming $k = 1$ gives a lower (upper) bound of 0.22 (0.35). That is, a 10 percentage point increase in electricity infrastructure increases the share of native vegetation in the typical county by 2.2 – 3.5 percentage points.

9.2 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

$$\begin{aligned}
&\text{wrt } H_c: && \Omega N F_H(H_c^*) = (1+\lambda)p && (17)\\
&\text{wrt } H_g: && F_H(H_g^*) = (1+\lambda)p && (18)\\
&\text{wrt } N: && \Omega F(H_c^*) = (1+\lambda)r && (19)\\
&\text{constraint} && \lambda(rN^* + p(H_c^* + H_g^*) - M) = 0 && (20)
\end{aligned}$$

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

To prove equation (4), note that equations (17) and (19) 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 (18) and (19) and taking derivatives with respect to Ω gives

$$\frac{r}{p}F_{HH}(H_g)\frac{dH_g}{d\Omega} - \Omega F_{HH}(H_c)\frac{dH_c}{d\Omega} = F_H(H_c) \tag{21}$$

Furthermore, taking derivatives with respect to Ω in equation (20) and re-arranging yields

$$\Big(1 + \frac{r}{p}\frac{dN}{dH_c}\Big)\frac{dH_c}{d\Omega} = -\frac{dH_g}{d\Omega} \tag{22}$$

Now, substituting (22) into (21), we can see that $dH_c/d\Omega > 0$:

$$-\frac{r}{p}F_{HH}(H_g)\Big(1 + \frac{r}{p}\frac{dN}{dH_c}\Big)\frac{dH_c}{d\Omega} - \Omega F_{HH}(H_c)\frac{dH_c}{d\Omega} = F_H(H_c) \tag{23}$$

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 22 can be rearranged to:

$$\frac{dH_f}{d\Omega} = \frac{dH_c}{d\Omega} + \frac{dH_g}{d\Omega} = -\frac{r}{p}\frac{dN}{dH_c}\frac{dH_c}{d\Omega} < 0 \tag{24}$$

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

$$\begin{aligned} H_v &= \overline{H} - \int_{\theta<\Pi} H_f d\Gamma(\theta) \\ &= \overline{H} - H_f\Gamma(\Pi). \end{aligned} \tag{25}$$

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

$$\begin{aligned} \frac{dH_v}{d\Omega} &= -\frac{d\Gamma(\Pi)}{d\Pi}\frac{d\Pi}{d\Omega}H_f \quad -\Gamma(\Pi)\frac{dH_f}{d\Omega} \\ &= \underbrace{-\gamma(\Pi)KF(H_a)H_f}_{<0} \quad \underbrace{-\Gamma(\Pi)\frac{dH_f}{d\Omega}}_{>0} \end{aligned} \tag{26}$$

□

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:

$$\frac{dH_v}{d\Omega} = -\frac{dH_c + dH_g}{d\Omega}\Gamma(\bar{\theta}) - (H_c + H_g)\Gamma(\bar{\theta})[\frac{d\Pi}{d\Omega} - \frac{d\theta}{d\Omega}] \tag{27}$$

$$\begin{aligned} \frac{dH_v}{d\Omega} &= \quad -\frac{d\Gamma(\Pi)}{d\Pi}\frac{d\Pi}{d\Omega}H_f \quad -\Gamma(\Pi)\frac{dH_f}{d\Omega} \\ &= \underbrace{-\gamma(\Pi)KF(H_a)H_f}_{<0} \quad \underbrace{-\Gamma(\Pi)\frac{dH_f}{d\Omega}}_{>0} \end{aligned} \tag{28}$$

□

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