Electrification, Agricultural Productivity and Deforestation in Brazil

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Abstract

We study the effects of the impressive growth in electrification in Brazil between 1960 and 2000 on changes in the structure of rural agricultural production, including adoption of irrigation, increases in agricultural productivity and investments, changes in land use, and the allocation of effort between crop cultivation and cattle grazing. The instrumental variables based identification strategy simulates a time series of hypothetical electricity grids that show how the grid would have evolved had hydro-power dams (which require intercepting water at high velocity) been allocated solely on geography-based cost considerations. Electrification allows farmers to irrigate, which leads to higher productivity, especially in areas with volatile rainfall patterns. Farming expands into frontier lands, and cultivation intensifies in existing land through investments in mechanization, fertilizer and pesticides. Crop intensification and substitution away from land-intensive cattle grazing lead to greater protection of forests and native vegetation within farms. Expansion of agriculture and this substitution have opposing effects on forest protection, and overall we estimate a net decrease in deforestation associated with electrification.

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

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 along the Amazon river basin coupled with rapid economic growth makes Brazil the single most important player in the conflict between development and environmental sustainability. While there has been a deceleration in the rate of deforestation in Brazil recently, 78,564 km2 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, and specifically, land for agricultural production in Brazil. While logging is often the proximate cause of land clearing, re-growth occurs in most moist tropical forests. For areas to remain deforested, the propensity to convert the land to agricultural use matters most. Agricultural productivity in frontier areas, and the type of agriculture that gets practiced – crop cultivation versus cattle grazing - are therefore the key determinants of long-run deforestation. Brazil produces over a hundred billions 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.

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 was less than 1 head per hectare in the 2006 agricultural census. In contrast, crop cultivation accounted for only 10.6% of total farm area, but 60% of the value of output in 2006 (IBGE). Increasing agricultural 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 agriculture, but it could also induce expansion of agriculture into frontier lands.

This paper examines the effects of the impressive growth in electrification in Brazil during the period 1960-2000 on technology use, changes in production structure and yields in the rural agricultural sector. To address the endogeneity issues inherent in infrastructure data where investment is large part follows demand, we follow Lipscomb et al. (2013) and forecast hydropower dam placement and grid expansion, which produces hypothetical maps that show how the electrical grid would have evolved had infrastructure investments been based solely on geologic cost considerations, ignoring demand-side concerns. The maps isolate the portion of the panel variation in grid expansion in Brazil that is attributable to exogenous cost considerations and are used to construct an instrument for actual electrification. This empirical strategy takes advantage of the fact that Brazil relies almost exclusively on hydropower to meet its electricity needs, and 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.

We first show that electricity permits investments in irrigation, which increases agricultural productivity more in areas that experienced more volatile rainfall over the last century. We then examine how this spurs investments and intensification, expands farming, and alters the patterns of land use within rural settlements away from cattle grazing and into crop cultivation. We find that electrification has two opposing effects on the protection of forests and native vegetation, because (a) the increase in agricultural productivity leads to an expansion of farm size and induces frontier land conversion, and (b) land use shifts away from cattle ranching, which is the most environmentally destructive, and into crop cultivation, and this allow farmers to retain more native vegetation within rural settlements. Overall, we estimate that electrification causes a small net decrease in deforestation in Brazil.

This finding on the beneficial environmental effect on 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. Our nuanced findings on the opposing effects of infrastructure development on deforestation contribute to a long-standing literature on the non-monotonic relationship between economic growth and environmental outcomes, starting with Grossman and Krueger (1991, 1995) and the 1992 World Development Report on environment and development (World Bank 1992).

The precise mechanism through which electricity benefits the environment in our setting is by permitting the adoption of productive irrigation technology. Our paper is therefore related to the literature on technology adoption (add cites). 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 growth 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 a broad range of development outcomes.

The relationship we estimate between agricultural productivity and deforestation is policy-relevant, because major policy initiatives to protect the rainforest in Brazil, Indonesia and Africa involve encouraging farmers to adopt practices that improve productivity. The conceptual model underlying these interventions is that increased productivity will allow farmers to use existing land more efficiently, thereby reduce the pressure to clear forests for new land. Economic theory suggests that such approaches can backfire if farmers choose to expand more profitable agricultural activities into frontier lands. 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, low-productivity cattle grazing makes improved cultivation productivity beneficial for the environment.

The rest of the paper is organized as follows...

2 Data

We combine three different datasets. First, we use data assembled by Lipscomb et al. (2013) containing information on electricity infrastructure, as well as the instrumental variable we use. The second dataset is formed by county-level data from the Brazilian Census of Agriculture. Finally, we use rainfall data compiled by Matsuura and Willmott (2012). Table 1 presents summary statistics.

2.1 Electricity Data

We consider the variable on county electricity infrastructure computed by Lipscomb et al. (2013). The authors have combined data on generation plants and transmission lines, focusing on hydropower plants. Data on the distribution networks are not available and are excluded from the analysis. The measure of electricity infrastructure is built as following. 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 transmission substation are assumed to have access to electricity – it is assumed that the distribution networks stretch one-hundred kilometers across. The grid points are aggregated to the county level. The variable is defined as the proportion of electrified grid points within a county.

The instrumental variable for the electricity infrastructure variable defined above is also proposed by Lipscomb et al. (2013). This instrument is the prediction of electricity availability based on geographical characteristics and the observed expansion pace of the electricity system in Brazil. In other words, our instrument is the predicted electricity availability at each grid point in each decade, based on a model that simulates the evolution of generation plants and transmission lines in a way that minimizes construction cost based solely on geographical characteristics.

As described by Lipscomb et al. (2013), the instrument is built in three steps. First, the number of hydropower plants built in each decade in our sample is set as the budget available for the national system in that decade. Second, data on the topographic characteristics of each grid point is used to rank-order all grid points in Brazil in terms of suitability for a low-cost hydropower dam. The highest ranked grid points in terms of topographic suitability get dams as we move from the first to the last decade in the sample, according to the respective budget. Third, a cost-minimizing algorithm is used to construct two transmission lines to carry electricity from each dam that has been built in the previous step - dams are assumed to have the same capacity. The model assumes that cost increases with distance and is prohibitively high when building substations in the Amazon due to high material transport costs.

2.2 Census of Agriculture

Data on rural establishments at the county level come from tabulations of the Brazilian Agricultural Census for various years. The Census of Agriculture is a rich source of data on rural establishments and include data on land use, farm infrastructure, input choice and agricultural production. The information on Brazilian municipalities was aggregated into minimum comparable areas to allow comparisons across years – during the period considered in our analysis, there are significant changes in the municipality borders. Thus, all variables from the Agricultural Census are considered at this level of aggregation, that we are loosely referring as counties.

We match Census data to electricity data in such a way that there is a small lag between the two. As explained in Section 2.1, the electricity data is county-decade panel, not a county-year panel. For that reason, 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.

2.3 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.[1]

3 Estimation Strategy

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

$$Y_{ct} = \alpha_c + \gamma_t + \beta E_{c,t} + \varepsilon_{ct}, \tag{1}$$

where Y_{ct} is the outcome of interest i 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 (1) 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 estimates obtained by OLS to be biased.

We therefore apply an instrumental variable (IV) estimator, making use of the instrument described in Section 2.1. Specifically, we use a 2SLS model where the first stage is

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

where Z_{ct} is the fraction of grid points in county c predicted to be electrified by the forecasting model at time t – that is, Z_{ct} is our instrumental variable, described in Section 2.1. The second stage is

$$Y_{ct} = \alpha_c^2 + \gamma_t^2 + \beta \widehat{E}_{c,t} + \varepsilon_{ct}^2, \tag{3}$$

[1] 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.

where $\widehat{E}_{c,t}$ is obtained from the first stage regression (2). 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 specification, we cluster standard errors at the county level due to possible serial correlation.

Our IV strategy corrects the for the bias introduced by the endogenous placement of electricity infrastructure by isolating the supply determinants of the electricity grid evolution. These supply-side determinants are river gradient, water flow and Amazon location. The use of Amazon location in the instrument is subject to criticism, because it may introduce spurious variation in the instrument. We include as controls interactions of Amazon location and year dummies in all our specifications.[2]

The key identification assumption in our strategy is that the demand for electricity infrastructure does not independently move over time from the lowest cost locations (robust water flow with a steep river gradient) in the early decades to slightly more expensive (flatter and less water-rich) locations in later years.

4 Effects of Electrification on Agriculture

This section estimates the effects of electricity on different aspects of agriculture and land use. All results include county fixed-effects, year fixed effects, and interaction of jungle and year dummies.[3]

Table 2 relates actual electrification of rural establishments to both electricity infrastructure and the modeled instrument.

One important mechanism underlying the impacts of electrification on agricultural productivity is irrigation. Irrigation typically requires either electrical or mechanical force to pump groundwater. Table 3 reports results of the effects of electrification on irrigation. In both OLS and IV specifications, the electrification has a positive and significant impact on irrigation. The IV estimate suggests that a 10 percent increase in electrification leads to 0.66 percentage points increase on the proportion of farms with irrigation, or 11 percent at the mean. Columns (3) and (4) further explore weather this effect is different in counties with low and high rainfall volatility. Although magnitudes are the same, effects are statistically significant only in high-volatility counties.

In Table 4 we present the effects of electrification on measures of agricultural productivity, allowing for heterogeneous effects by counties' rainfall volatility. In columns (1) and (2), the

[2] Lipscomb et al. (2013) discuss the introduction of these interactions, and present a series of robustness checks.
[3] For more details, see the discussion in Lipscomb et al. (2013).

dependent variable is the log of production per hectare. The IV estimate suggests that a 10 percent increase in electrification increases production per hectares by 9.8 percent in counties with low (i.e., below the median) rainfall volatility, and this effect is significant at the 1 percent level. In both the OLS and IV specifications, counties with high rainfall volatility benefit relatively more of electrification, and this differential effect is also significant at the 1 percent level. We find similar results both in magnitude and statistical significance for production per worker. The increase in labor productivity however only partially translates into an increase in wages per worker: although the effects of electrification on wages are of similar magnitude, only the differential effect in high-volatility counties is statistically significant.

Next, Table 6 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).

Given these changes, Table 7 presents the effects of electrification on farm size, farm area and land value. Column (2) show that there is a sizable and significant effect on farm size: a 10 percent increase in electrification leads to an increase in farmsize of 24 hectares, or 26 percent at the mean. The effects on farm area of a 10 percent increase in electrification is 1.5 percentage points – small in magnitude, and significant only at the 5 percent level.

These results suggest that there is consolidation of rural establishments, increase in the scale of production, and intensification. To further explore the effects on intensification, Table 8 estimates the effects of electrification on land allocation within rural establishments. The IV estimates reveal that a 10 percent increase in electrification decrease pastureland by 4.3 percentage points, or a 9 percent at the mean. For cropland, this effect is 2.2 percentage points, or 10 percent at the mean. Finally, a 10 percent increase in electrification increase native vegetation within rural establishments by 4.27 percentage points, or 24.6 percent at the mean.

To summarize, an increase in electrification leads to higher productivity, farm size, inputs usage, and intensification.

Table 1: Sample Descriptive Statistics

	count	mean	sd	min	max
Electricity Infrastructure	10,905	0.75	0.40	0.00	1.00
% of Farms with Electricity	10,894	0.34	0.33	0.00	1.00
Modeled electricity instrument	10,905	0.60	0.47	0.00	1.00
Production Per Hectare (log)	10,892	9.78	3.34	1.84	16.68
Value of Land Per Hectare (log)	8,720	0.27	1.52	-5.61	5.50
Wage Per Worker (log)	10,887	5.92	1.44	-3.47	12.18
Spending in Fertilizers Per Hectare (log)	10,576	1.45	2.98	-11.44	10.02
Spending in Pesticides Per Hectare (log)	10,768	0.77	2.26	-9.18	11.14
# of Tractors (log)	10,905	3.94	1.90	0.00	11.16
Average Farm Size	10,894	94.32	167.01	0.77	4,644.90
% of Farmland in Pastures	10,894	0.48	0.23	0.00	0.96
% of Farmland in Native Vegetation	10,894	0.17	0.15	0.00	0.99
% of Farmland in Cropland	10,894	0.22	0.18	0.00	1.00
% of Farms with Irrigation	10,894	0.06	0.11	0.00	0.93

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

Table 2: Effects of Electricity Infrastructure on Farms with Electricity

Dependent Variable	Electricity Infrastructure	% of Farms with Electricity	
	(1)	(2)	(3)
	OLS	OLS	OLS
Modeled electricity availability	0.198***	0.112***	
	[0.0443]	[0.0364]	
Electricity Infrastructure			0.107***
			[0.0234]
Year FE?	Yes	Yes	Yes
Jungle x year dummies	Yes	Yes	Yes
Observations	10,903	10,892	10,892
R^2	0.880	0.821	0.823
Mean dep. var.	0.7506	0.3414	0.3414

Notes: Standard errors clustered at county level in brackets. All specifications include county fixed effects and year fixed effects, and use county area weights.

Table 3: The Effects of Electricity on Irrigation Dependent Variable: % of Farms with Irrigation

	All Sample		High Volatility County?		Drought in Previous 5 years?	
	(1)	(2)	(3)	(4)	(5)	(6)
			Yes	No	Yes	No
	OLS	IV	IV	IV	IV	IV
Electricity Infrastructure	0.0140***	0.0666***	0.0688***	0.0688	0.267**	0.00627
	[0.00453]	[0.0194]	[0.0237]	[0.0491]	[0.109]	[0.0315]
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Jungle x year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,892	10,892	5,448	5,444	3,375	6,633
R^2	0.804	0.137	0.149	0.129	-1.172	0.212
Mean dep. var.	0.0614	0.0614	0.0501	0.0726	0.0617	0.0611

Notes: Standard errors clustered at county level in brackets. All specifications include county fixed effects and year fixed effects, and use county area weights. The dependent variables Fertilizer Per Hectare and Pesiticides Per Hectare are in logs and are measured in reais.

Table 4: The Effects of Eletrification on Land and Labor Productivity: Heterogeneity by Rainfall Volatility

	Production Per Hectare		Production Per Worker		Wages Per Worker	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Electricity Infrastructure	0.0469	0.988**	-0.0615	1.411***	-0.0476	0.843*
	[0.0844]	[0.402]	[0.0704]	[0.382]	[0.0808]	[0.474]
elecinf_x_highvol	0.238**	1.111***	0.374***	1.460***	0.288***	1.377***
	[0.106]	[0.277]	[0.0985]	[0.264]	[0.109]	[0.326]
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Jungle x year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,890	10,890	10,890	10,890	10,885	10,885
R^2	0.974	0.966	0.980	0.969	0.863	0.342
Mean dep. var.	9.7840	9.7840	12.3705	12.3705	5.9219	5.9219

Notes: Standard errors clustered at county level in brackets. All specifications include county fixed effects and year fixed effects, and use county area weights. All dependent variables are in logs and are measured in reais. We have no information on Land Values in the 1970 census.

Table 5: The Effects of Irrigation on Productivity

	Production Per Hectare (log)		Production Per Worker (log)		Wages Per Worker (log)	
	(1) OLS	(2) IV	(3) OLS	(4) IV	(5) OLS	(6) IV
% Farms with irrigation	0.762**	15.68**	0.372	22.11**	0.689	14.48*
	[0.301]	[7.636]	[0.269]	[9.227]	[0.453]	[8.365]
fFarmIrr_x_highvol	1.008	16.15***	1.746*	21.59***	1.380*	18.87***
	[0.877]	[4.586]	[0.930]	[5.542]	[0.831]	[5.030]
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Jungle x year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,890	10,890	10,890	10,890	10,885	10,885
R^2	0.974	0.928	0.980	0.891	0.864	-0.215
Mean dep. var.	9.7840	9.7840	12.3705	12.3705	5.9219	5.9219

Notes: Standard errors clustered at county level in brackets. All specifications include county fixed effects and year fixed effects, and use county area weights. All dependent variables are in logs and are measured in reais. We have no information on Land Values in the 1970 census.

Table 6: The Effects of Electricity on Input Usage

	Fertilizers Per Hectare		Pesticides Per Hectare		Number of Tractors (log)	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Electricity Infrastructure	0.234	5.323***	0.0406	2.874***	0.382**	3.893***
	[0.308]	[1.034]	[0.203]	[0.814]	[0.149]	[0.830]
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Jungle x year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,575	10,567	10,766	10,764	10,903	10,903
R^2	0.817	0.439	0.805	0.460	0.846	0.342
Mean dep. var.	1.4452	1.4452	0.7655	0.7655	3.9437	3.9437

Notes: Standard errors clustered at county level in brackets. All specifications include county fixed effects and year fixed effects, and use county area weights. The dependent variables Fertilizer Per Hectare and Pesiticides Per Hectare are in logs and are measured in reais.

Table 7: The Effects of Electricity on Farmland and Farm Size

	Farm Size (hectares)		% of County Area in Farmland		Land Value Per Hectare (log)	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Electricity Infrastructure	2.842	247.5***	0.0137	0.154**	-0.0302	1.353***
	[19.07]	[76.29]	[0.0146]	[0.0680]	[0.121]	[0.444]
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Jungle x year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,892	10,892	10,903	10,903	8,718	8,718
R^2	0.934	-0.041	0.914	0.139	0.867	0.701
Mean dep. var.	94.3402	94.3402	0.7234	0.7234	0.2682	0.2682

Notes: Standard errors clustered at county level in brackets. All specifications include county fixed effects and year fixed effects, and use county area weights. All dependent variables are in logs and are measured in reais. We have no information on Land Values in the 1970 census.

Table 8: The Effects of Electricity on the Allocation of Land within Rural Establishments

Activity	Pastures		Crops		Native Vegetation	
	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	IV	OLS	IV	OLS	IV
Electricity Infrastructure	0.0335*	-0.434***	-0.0316**	-0.226***	0.0167	0.427***
	[0.0202]	[0.0780]	[0.0133]	[0.0592]	[0.0216]	[0.0905]
Year FE?	Yes	Yes	Yes	Yes	Yes	Yes
Jungle x year dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,892	10,892	10,892	10,892	10,892	10,892
R^2	0.850	-0.279	0.712	0.118	0.753	-0.104
Mean dep. var.	0.4784	0.4784	0.2209	0.2209	0.1731	0.1731

Notes: Standard errors clustered at county level in brackets. All specifications include county fixed effects and year fixed effects, and use county area weights. Each dependent variable is divded by the country's total farmland.

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