How did technical change affect land use in Brazilian agriculture?

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Abstract:

How did technical change affect land use in Brazilian agriculture? We use data from the last two Agricultural Censuses of 1995/1996 and 2006 to answer this question for five different regions. We focus on the estimation of the Hicksian bias induced by technical change over this period and found that technical change was, in general, land-using. In the Southeast region, we found labor-saving behavior. Both results can be interpreted in light of the induced innovation hypothesis under Acemoglu's approach that allows testing when prices are not available.

Acknowledgment:

JEL Codes: Q18, O47

#1650
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Abstract

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Keywords: Brazilian agriculture; technical change bias; land use.

JEL: Q16; Q18; O47.
INTRODUCTION

The role of technical change and land use in agriculture is studied in this paper. Particulary, we investigate how technical change affected land use in Brazilian agriculture between the last two agricultural censuses. Brazil is one of the largest food producers\(^1\) in the world and around one fifth of its GDP comes from the agribusiness sector. Around 26% of Brazil’s total surface area is agricultural land, in which 75% are (low productive) pastures and 25% croplands (Assunção et al. 2015). Brazilian agricultural production expansion between 1970 and 2006 was based mainly on productivity gains. Gasques et al. (2010) calculated a production index that showed an increase of 243% in this period while the input index increased by 53%. During 1975 and 2011, production growth was 2.6 greater than the expansion of land use, which may indicate a significant gain in land productivity (Gasques et al., 2013). Land-saving productivity gains was markedly observed in beef production between 1950-2006, which accounted for 79% of production growth and contributed to a land-saving effect of 525 million hectares (MARTHA Jr. et al., 2012).

Why is it important to understand the relationship between technical change and land use? We consider that one of the main channels for improvement in the environmental efficiency of agricultural production is increasing land productivity. In Brazil, around 75% of national CO\(_2\) emissions are mainly from expanding agriculture through deforestation (Chen et al., 2013). The concern with forest preservation has become one of the main drivers of environmental policies\(^2\) in the country which have been effective in decreasing deforestation in the recent years. The deforestation rate decreased from 2.7 million hectares in 2004 to about 460 thousand hectares in

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\(^1\) Filho et al. (2015), reporting data from FAO, showed that 23% of sugar, 13.5% of beef, 11.3% of poultry and 8.0% of oil crops in world production for 2010 was produced in Brazil.

\(^2\) Assunção et al. (2015) highlight two main policies: 1) The Action Plan for Deforestation Prevention and Control in the Legal Amazon (Plano de Ação para a Prevenção e Controle do Desmatamento na Amazônia Legal – PPCDAm); 2) Rural credit conditional on some local environmental regulations.
2012 (Assunção et al. 2015). Due to innovation, improvements in land use can significantly decrease the pressure to convert forest or other natural areas into pasture and cropland (Byerlee et al. 2014). In addition, the recovering of degraded areas can decrease CO$_2$ emissions of at least 60% in agricultural production by increasing the production of biomass, which increases the ability of the soil to sequester CO$_2$ from the atmosphere (Chen et al., 2013). Investigating how productivity gains over time affected land use in Brazil is also relevant because we can assess whether innovations were more favourable to enhancing land productivity in the country. Being a major player in global food production increases the pressure to expand agriculture and, therefore, more incentives to increase land productivity should be addressed by agricultural and environmental policies.

To answer our research question, we fit a production function at the municipality level using the two last agricultural censuses of 1995/1996 and 2006 by region. We calculate agricultural productivity for this period and the biases of technical change. We estimate the Hicksian measure of factor bias induced by technical change to calculate how it affected the substitution among inputs. This measure has been applied and calculated by several studies (Binswanger, 1974, Fare et al., 1994, Fulginiti and Perrin, 1993, Fulginiti, 2010, Hampf and Kruger, 2017). The estimation of biases and information on factor prices can be used to test the induced innovation hypothesis initially presented by Kennedy (1963, 1974) followed by Hayami and Ruttan (1970). This hypothesis states that when “innovation possibilities are neutral and factor prices are exogenous to the industry, a factor-saving bias should be associated with a rising factor price and vice versa” (Binswanger, 1974, p. 964). The induced innovation hypothesis can also be addressed by the scarcity (or abundance) of one input relative to another (Hayami and Ruttan, 1970). This allows to test the hypothesis when factor prices are not readily available. Acemoglu (2002) develops a model to explain the determinants of the factor-bias of technical change. His main conclusion is that the
abundance of one factor relative to another will generate factor-saving technical change towards the scarce input. We do not formally test Acemoglu’s version of the induced innovation hypothesis but use it to interpret the results of the estimated biases for the Brazilian regions. In this paper, we aim to contribute to the literature on land use in Brazil using the induced innovation hypothesis and estimating Hicksian factor biases at the regional level using municipalities data available from the agricultural census. No previous study, to our knowledge, has taken this approach and estimated the pairwise factor-bias at the regional level. In general, we found that in most regions technical change was land-using when comparing land to labor and capital. For the Southeast region, we found the pairwise bias for labor and capital to be labor-saving. We consider that both results can be interpreted in light of Acemoglu’s induced innovation framework.

The paper is organized as follows. In the next section, we review literature regarding the theories that explain technical change biases and some studies that test these theories for other countries and for Brazil. In the third section, we present our theoretical model and the empirical strategy. The fourth section presents the results of the paper. The fifth section is conclusions.

**LITERATURE REVIEW**

*Technical change biases-related literature*

The classical study of Hayami and Ruttan (1970) investigated how technical change influenced agriculture development in the U.S. and Japan between 1880 and 1960. They found that land scarcity in Japan created technical change that was land-saving while in the U.S. factor-saving technical change was observed for labor and capital, driven by the abundance of the land endowment. Binswanger (1974) was the first to estimate a multi-factor bias of technical change using a translog cost function, which is represented by the changes in factor-shares. He tested the induced innovation hypothesis for U.S. agriculture and found a strong fertilizer-using technical
change due to a decline in fertilizer prices which was consistent with the induced innovation hypothesis. In general, he concludes that factor prices can significantly affect the direction of technical change. Among other studies regarding the innovation hypothesis and technical change factor-biases are, respectively, Kawagoe, Otsuka, and Hayami (1986), Lambert and Shonkwiler (1995) and, more recently, Lambert (2017), who estimates the bias for U.S. agriculture and other related industries and finds that technical change was overall labor-saving. Hampf and Kruger (2017), using a nonparametric approach to estimate an input-specific distance function, found that since the 1980, technical change has become increasingly capital-using for developed countries. They suggest further research to evaluate empirically the relationship between input ratios and the direction of technical change as proposed in the study of Acemoglu (2002).

The study of Acemoglu (2002) is in what he defined as the “directed technical change” framework. This framework suggests that if there is low substitutability among factors of production, factor-endowments and prices will generate incentives for the development of new technologies to save the scarce inputs relative to the others and use more of the abundant and less expensive factors. These technologies will be land-saving in areas where land is relatively scarce and land-using when it is abundant in relative terms. Acemoglu’s hypothesis is in line with the induced innovation hypothesis, the theoretical model establishing that the direction of technical change will depend on the elasticity of substitution between inputs. One main contribution of this framework is that it can be tested without the information on prices but rather only on quantities. We do not provide a formal test of his hypothesis in this paper, however, we use it to shed light on the relationship between technical change and land use in Brazilian agriculture.
Brazilian agriculture and potential land use improvements

There are several studies that studied Brazilian agricultural productivity such as Gasques et al. (2010), Rada and Buccola (2012), Bragagnolo et al. (2010) and Bustos et al. (2016). All these studies use more than one agricultural census data and, to our knowledge, no previous study investigated the Hicksian factor-bias for the country and try to link it with the induced innovation hypothesis. Gasques et al. (2010) calculated a production index, using vegetal production, cattle production and agribusiness industry production, and also calculated an input index to generate an index of total factor productivity from 1970 to 2006. Rada and Buccola (2012) focused on the determinants of total factor productivity in Brazil and found that research investments, rural credit, education and infrastructure investments were responsible for the high average productivity growth from 1985-2006, mainly in the southern region of the country, around 4.5% per year. Bragagnolo et al. (2010) found that total factor productivity in Brazil over the period between 1975-2006 increased mainly due to labor reduction in production while land reduction was observed in states where agriculture share in GDP decreased. However, land expansion was observed in the Northern region, which was a result of the expansion of the agricultural frontier. Bustos et al. (2016) estimate the effect of agricultural productivity in Brazil on structural change. Specifically, they want to test whether labor-saving technical change increases labor supply in the industrial sector. They measure technical change by the adoption of new technologies such as genetically engineered seeds in soy production and a second harvesting season in maize production. They find that for the former technical change was labor-saving, while for the latter, it was land-saving. They conclude that factor-bias is crucial to determine the effect of agricultural productivity on industrialization. We claim that studying factor-bias is also important to improve land productivity and its implications on the environmental efficiency of the sector.
Brazil has potential to improve land use. Assunção et al. (2015) establishes that Brazil can improve agricultural production at no cost to the environment through increasing land productivity. They present three examples from the Brazilian agriculture in which land efficiency was improved including the mechanism through which this change was possible. It is possible to change land use patterns based on technical change, private investment, and environmental policies. First, in central Brazil, the experience with technological innovation and skilled labor in soybean production decreased deforestation. Second, private investment in sugarcane turned low productivity pastures to high productivity crops. The last example was the adoption of monitoring and law enforcement to contain deforestation in the Brazilian Amazon. Filho et al. (2015) aimed to identify if there was a trade-off between deforestation reduction and agricultural output. They concluded that there are several mechanisms that allow greater food production without increasing land supply.

MODEL AND ESTIMATION

General model

Consider a production function \( F(X) = \max\{Y: (X, Y) \in T\} \) where \( Y \) is the output index, \( X \) is the input index and \( T \) is the technology set. In the case of an agricultural production with three inputs, we can represent the production function as:

\[
Y = F(L, K, Z, A)
\]

where \( Y \) represents the value of agricultural output, \( L \) represents labor, \( K \) is capital, \( Z \) represents land and \( A \) is the technical change index. Technical change is proxies by a time trend. We are interested in how technical change affects land use over time, so we want to calculate the its factor-bias. The Hicksian bias can be measured as the percent change in the marginal rate of technical
substitution between two factors of production due to a change in $A$. The factor-bias between land and labor is:

$$B_{Z,L} = \frac{\partial \ln(MR\bar{T}S_{Z,L})}{\partial A} = \frac{\partial \ln\left(\frac{\partial F}{\partial L} - \frac{\partial F}{\partial Z}\right)}{\partial A}$$

(2)

If $B_{Z,L} > 0$, a progressive technical change will increase the marginal product of labor more than that of land, this will cause a shift in the demand for labor, and therefore, technical change will be land-saving. If $B_{Z,L} < 0$, the marginal product of land increases more relative to the marginal product of labor, and technical change will be land-using. If $B_{Z,L} = 0$, technical change will be Hicks land-neutral.

Data

Data is from the Brazilian Agricultural Census, published by the Brazilian Institute of Geography and Statistics (Instituto Brasileiro de Geografia e Estatística-IBGE) for the years 1996 and 2006. We used the last two agricultural censuses available on the online database SIDRA\(^3\). The data are available at the municipality level, we use a balanced panel of 4,946 municipalities. Output $Y$ is the “value of agricultural production” which is the sum of the values of production for seasonal crop, permanent crop, horticulture product, forestry product, vegetable extraction products, production of bovines, swine, and poultry. We converted the 1996 values to 2006 Reais using the price index Índice Geral de Preços - Disponibilidade Interna (IGP-DI) collected from the IPEADATA online database\(^4\). The IGP-DI was set to 1 in 2006 and then we divided the value of 1996 by this index.

Our input variables are number of workers in agriculture ($L$), the number of tractors in the farms ($K$, as our proxy for capital) and the number of hectares in agricultural production ($Z$). The proxy


for technical change is a dummy variable equal to 0 for 1996 and 1 for 2006. The other control variables are: share of irrigated land and share of cropland in agricultural land and seasonal average precipitation and temperature\(^5\). Table A1, in the appendix, presents the descriptive statistics of the variables used in the study for the whole sample.

In our sample, the Southeast and South regions produced 58% of the Brazilian agricultural value of production while the North and Northeast produces 24%, and the Midwest produced around 18% in 2006. However, the Southeast and the South regions of Brazil are less labor intensive with a share of 38% compared to North and Northeast with a share of 56% in 2006. On the other hand, the South and Southeast regions are more capital intensive with a share higher than 70% of the tractors used in agriculture in 2006. The North and the Northeast only accounted for 10% and Midwest for 15% in 2006. The most land intensive, which also observed an increase from 1995 to 2006, was the Midwest with a share of agricultural land of 33% in 2006 followed by the Northeast with a 20% share. These numbers show a clear regional disparity in agricultural production in Brazil, while the Southeast and South regions are capital intensive the Northeast and North are labor intensive and the Midwest is land intensive. Therefore, we study how technical change affected land use by region.

**Empirical Specification**

We consider a general translog specification for our production function:

\[
y = \alpha_0 + \sum_{i=1}^{2} \alpha_i x_i + \gamma_0 t + \frac{1}{2} \sum_{i=1}^{2} \sum_{j=1}^{2} \alpha_{ij} x_i x_j + \frac{1}{2} \sum_{i=1}^{2} \gamma_i t x_i
\]

\(^{5}\) We insert these variables to capture differences in climatic zones in Brazil. We use the averages of temperature and precipitation for winter and summer seasons from 1960 to 1990 as proxies for municipality climatic zone. The source of these variables is www.ipeadata.gov.br. Accessed: January, 5, 2018.
where $y = \ln(Y/Z)$, $x_i = \{\ln(X_2/Z), \ln(X_3/Z)\}$ for $X_2 = L$ and $X_3 = K$ and $i,j=1,2$ are the indices for the factors of production, and $\alpha_0, \alpha_i, \gamma_0, \alpha_{ij}$, and $\gamma_i$ are the first and second order parameters to be estimated. The subscripts for municipalities (units of observation) are omitted from eq. (3). Our proxy for technical change is expressed by $t$, which is a dummy variable that aims to capture the changes in intercept, $\gamma_0$, and changes in slope, $\gamma_i$, of the production function due to technical change between the two agricultural censuses. We use land, $Z$, as our normalizing input, thus we recover the parameters for land from the homogeneity restrictions: $\sum_{i=1} x_i = 1$ and $\sum_{i=1} x_{ij} = \sum_{j=1} x_{ij} = 0$. Symmetry constraints hold for the translog production function: $\alpha_{ij} = \alpha_{ji}$. We included in the empirical model dummy variables for the Brazilian states to control for differences in land and other state-specific characteristics.

Differentiating eq. (3) with respect to $x_i$ yields the output elasticity of input $i$ because the output and inputs are expressed in logs, $s_i$, expressed as:

$$s_i = \frac{\partial y}{\partial x_i} = \alpha_i + \frac{1}{2} \sum_{j=1}^2 \alpha_{ij}x_i + \frac{1}{2} \gamma_i t$$

(4)

Technical change can be calculated in a similar way, by differentiating eq. (3) with respect to $t$.

$$TC = \frac{\partial y}{\partial t} = \gamma_0 + \frac{1}{2} \sum_{j=1}^2 \gamma_i x_i$$

(5)

For the translog, the Hicksian pair-wise factor bias between inputs $i$ and $j$ can be expressed as:

$$B_{i,j} = \frac{s_i}{s_j} - \frac{s_j}{s_i}$$

(6)

where $s_i$ and $s_j$ are the estimated output elasticities. If $B_{i,j} > 0$, then technical change is $i$-saving; $B_{i,j} = 0$, technical change is $i$-neutral and, for $B_{i,j} < 0$, technical change is $i$-using.
Results and discussion

We use the stochastic frontier approach (SFA) to estimate the production function, in equation 3, for Brazil and the five regions. We added two error terms to the production function, one to account for random errors and the other to account for inefficiencies. We follow Battese and Coelli (1995) and decompose the error term of the stochastic frontier in two random variables. For the \( kth \) observation, we have: \( e_{kt} = v_{kt} - u_{kt}. \) Where \( v_{kt} \) is assumed to be iid \( N(0, \sigma_v^2) \) and \( u_{kt} \) is iid, following a half-normal distribution (i.e. \( N(\mu, \sigma_u^2) \)). The term \( \mu \) is associated with technical inefficiency or heterogeneity of municipalities over time. To account for sources of heterogeneity that may affect efficiency levels, we also included state-level dummy variables in the estimation of the inefficiency random term. The SFA approach has been broadly used in the literature to estimate agricultural productivity. A recent application of this method is found in Trindade and Fulginiti (2015), where they estimate agricultural productivity between 1969-2009 for a group of 10 South American countries.

We first estimated the frontiers using COLS (Corrected Ordinary Least Squares) to obtain initial values that are then used in MLE (Maximum Likelihood estimation). A log-likelihood ratio test suggested that the MLE is more adequate to estimate the stochastic frontier compared to COLS. We present in the paper only the results of the MLE. Table A2, in the appendix, shows the estimated coefficients of the translog stochastic frontiers: 11 out of the 15 coefficients were significant for the whole sample, 10 at 1% and 1 at 1%. The results for the whole country is valid if we assume a metafrontier for Brazilian regions. We also estimated a frontier for each region. For the Northern region, 10 out of the 15 parameters were significant, 9 at 1% and 1 at 10%. For the Northeast region, 11 out of the 15 estimated parameters were significant at 1%. For the Southeast region, we observe 9 significant at 1% and 2 at 5%. The results for the Southern were 9 out of 15 parameters significant at 1% while for the Midwest, 4 were significant at 1%, 4 at 5% and 3 at 10%.
Monotonicity was violated in 90 (0.9%) observations for land, 8 (0.08%) for labor and 1079 (10.91%) for capital out of the 9,892 observations\(^6\) for the whole sample. For the subsamples, monotonicity was violated in 39 observations for land, 1 observation for labor and 134 observation for capital out of the 796 observations of the North region. It was violated only for capital in 272 observations out of the 3115 for the Northeast. It was violated for land (45) and capital (206) out of the 3012 observations in the Southeast region. For the South monotonicity was violated in 53, 270 and 2 for land, labor and capital, respectively, out of the 2115 observations. While for the Midwest, it was violated for 30, 245 and 1, for land, labor and capital, respectively, out of the 854 observations\(^7\). The average efficiency scores for North (0.62), Northeast (0.88), Southeast (0.70), South (0.91), and Midwest (0.76), reflect the heterogeneity within the regions, indicating that some municipalities are below the frontier which can be due to inefficiency/heterogeneity or other random effects not captured by the variables in the model.

We present our main results only for the regional models. Table 1 shows the output elasticities and technical change. The elasticity of land varies from 0.33 in the South to 0.42 in the Northeast. In general, land elasticity is high for all the regions which indicate that production was increased mainly through land expansion in Brazil. The elasticity of labor is highest for the North region followed by the Northeast, which indicates that production was more responsive to changes in labor in these regions; this result makes sense given the lower levels of mechanization in these regions relative to the others. The lowest elasticity of labor is for the Midwest; this region has experience the highest development in agriculture in Brazil in terms of mechanization during the period

\(^6\) We did not include observations that had missing values for the value of production.

\(^7\) Even though the percentage of violations of the regularity conditions of the technology are small we intend to do additional work to impose these theoretical properties on estimation.
This result is also reflected in the elasticity of capital, which is 0.57 for the Midwest. Therefore, production was highly dependent on increasing the level of capital in agriculture.

Table 1. Estimated Output Elasticities at the mean levels by Region.

<table>
<thead>
<tr>
<th>Inputs\Region</th>
<th>South</th>
<th>Southeast</th>
<th>Midwest</th>
<th>North</th>
<th>Northeast</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labor</td>
<td>0.329***</td>
<td>0.353***</td>
<td>0.112***</td>
<td>0.485***</td>
<td>0.438***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.019)</td>
<td>(0.029)</td>
<td>(0.031)</td>
<td>(0.018)</td>
</tr>
<tr>
<td>Land</td>
<td>0.335***</td>
<td>0.406***</td>
<td>0.320***</td>
<td>0.384***</td>
<td>0.422***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.021)</td>
<td>(0.039)</td>
<td>(0.031)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Capital</td>
<td>0.335***</td>
<td>0.240***</td>
<td>0.567***</td>
<td>0.131***</td>
<td>0.139***</td>
</tr>
<tr>
<td></td>
<td>(0.021)</td>
<td>(0.014)</td>
<td>(0.047)</td>
<td>(0.015)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Technical change</td>
<td>0.139***</td>
<td>0.079***</td>
<td>0.188***</td>
<td>0.217***</td>
<td>0.309***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.025)</td>
<td>(0.035)</td>
<td>(0.050)</td>
<td>(0.026)</td>
</tr>
</tbody>
</table>

Note: (***), (**) and (*) indicates significance at 1%, 5% and 10%, respectively. Standard errors are in parentheses.

Technical change is found to be highest in the Northeast, 3.1% per year, followed by the North (2.17%) and Midwest (18.8%). Our results reflect the expansion of the agricultural frontier in the Midwest and North regions; it is most interesting to observe that these regions had higher average rates of productivity, but most of this gain seems to have been stimulated by growth through land and labor use in the North and Northeast and by capital use in the Midwest. The Southest region had the lowest average productivity gain during 1996-2006, 0.79%. The South also presented lower levels of technical change which reflects the earlier development of agriculture in these two regions in Brazil. We now discuss the mean Hicksian biases for the regions in Table 2.
Table 2. Estimated pairwise factor-bias at the mean levels by Region.

<table>
<thead>
<tr>
<th>Input\Region</th>
<th>South</th>
<th>Southeast</th>
<th>Midwest</th>
<th>North</th>
<th>Northeast</th>
</tr>
</thead>
<tbody>
<tr>
<td>Land, Labor</td>
<td>-0.227**</td>
<td>-0.395***</td>
<td>0.083</td>
<td>-0.329***</td>
<td>-0.120*</td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.088)</td>
<td>(0.424)</td>
<td>(0.087)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>Land, Capital</td>
<td>-0.324***</td>
<td>0.0006</td>
<td>-0.454***</td>
<td>-0.455***</td>
<td>-0.206**</td>
</tr>
<tr>
<td></td>
<td>(0.098)</td>
<td>(0.085)</td>
<td>(0.104)</td>
<td>(0.120)</td>
<td>(0.100)</td>
</tr>
<tr>
<td>Labor, Capital</td>
<td>-0.096</td>
<td>0.395***</td>
<td>-0.538</td>
<td>-0.126</td>
<td>-0.086</td>
</tr>
<tr>
<td></td>
<td>(0.180)</td>
<td>(0.139)</td>
<td>(0.474)</td>
<td>(0.178)</td>
<td>(0.139)</td>
</tr>
</tbody>
</table>

Note: (***) , (**) and (*) indicates significance at 1%, 5% and 10%, respectively. Standard errors are in parentheses.

The pairwise biases indicate that technical change was land-using in all regions except the Midwest, when comparing labor and land. For all the regions, technical change was also land-using when comparing with capital, except for the Southeast. For the Southeast, technical change was labor-saving when comparing labor and capital. Our estimates for this region, the most industrialized in the country, indicates that agricultural labor is scarce given the higher opportunities to work in other industries. Our results indicate that technical change in the regions that expanded agriculture the most during the 1995-2006 period was land-using. This is consistent with Acemoglu’s version of the induced innovation hypothesis that states that technical change will be factor-using in the abundant factor. The same can be claimed for labor in the Southeast where technical change was labor-saving relative to capital.

CONCLUSION

Agricultural production growth in Brazil was stimulated by productivity gains over the last years. In this study, we aimed to answer if technical change was land-using or land-saving in Brazilian
agricultural production. We fit a translog production function by region using the Agricultural censuses of 1995/1996 and 2006. This allowed us to estimate the Hicksian bias of technical change by region.

Our findings showed a progressive technical change that varied by region, ranging from an average of 8% in the Southeast to 31% in the Northeast from 1996-2006. Our answer to the research question in this paper is that technical change was overall land-using for the regions. When comparing the labor and capital in the Southeast, we found that technical change was labor-saving. Both results can be interpreted in light of the induced innovation hypothesis under Acemoglu’s approach that allows testing when prices are not available. The country has an abundant resource of land and the market conditions or other factors may have important effects on how technical change is increasing the productivity of the other factors of production other than land.

For future research, we aim to test empirically Acemoglu’s approach to the induced innovation hypothesis for the Brazilian agriculture. This research sheds light on how innovations in agriculture affect land use, which are related to other policy issues such as forest preservation, and could help guide the design of new policies on land use in Brazil.

REFERENCES


## APPENDIX


<table>
<thead>
<tr>
<th>Variable</th>
<th>Units</th>
<th>North Mean</th>
<th>SD</th>
<th>Northeast Mean</th>
<th>SD</th>
<th>Southeast Mean</th>
<th>SD</th>
<th>South Mean</th>
<th>SD</th>
<th>Midwest Mean</th>
<th>SD</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Production</strong></td>
<td>R$1 million</td>
<td>15.96</td>
<td>26.16</td>
<td>13.37</td>
<td>42.64</td>
<td>27.41</td>
<td>50.15</td>
<td>32.87</td>
<td>36.32</td>
<td>47.02</td>
<td>76.09</td>
</tr>
<tr>
<td><strong>Land</strong></td>
<td>1000 ha</td>
<td>69.57</td>
<td>86.86</td>
<td>28.33</td>
<td>35.55</td>
<td>29.49</td>
<td>40.66</td>
<td>29.70</td>
<td>51.39</td>
<td>160.96</td>
<td>235.62</td>
</tr>
<tr>
<td><strong>Labor</strong></td>
<td># employee (1000)</td>
<td>4.29</td>
<td>4.56</td>
<td>4.93</td>
<td>4.43</td>
<td>2.17</td>
<td>2.32</td>
<td>2.89</td>
<td>2.55</td>
<td>2.30</td>
<td>1.92</td>
</tr>
<tr>
<td><strong>Tractors</strong></td>
<td>Number of tractors</td>
<td>53.31</td>
<td>68.07</td>
<td>36.56</td>
<td>75.03</td>
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<td>312.47</td>
<td>323.44</td>
<td>274.98</td>
<td>313.37</td>
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<td><strong>Share of land with crop</strong></td>
<td>[0,1]</td>
<td>0.26</td>
<td>0.29</td>
<td>0.39</td>
<td>0.25</td>
<td>0.32</td>
<td>0.25</td>
<td>0.55</td>
<td>0.24</td>
<td>0.14</td>
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<td><strong>Share of Irrigated land</strong></td>
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<td>0.04</td>
<td>0.03</td>
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<td>0.04</td>
<td>0.09</td>
<td>0.03</td>
<td>0.08</td>
<td>0.01</td>
<td>0.03</td>
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<tr>
<td><strong>Temp. summer</strong></td>
<td>Average °C</td>
<td>26.18</td>
<td>0.54</td>
<td>26.14</td>
<td>1.21</td>
<td>23.47</td>
<td>1.73</td>
<td>23.17</td>
<td>1.52</td>
<td>25.15</td>
<td>1.07</td>
</tr>
<tr>
<td><strong>Temp. winter</strong></td>
<td>Average °C</td>
<td>25.93</td>
<td>0.87</td>
<td>23.70</td>
<td>2.00</td>
<td>18.43</td>
<td>2.13</td>
<td>15.08</td>
<td>1.65</td>
<td>22.45</td>
<td>1.68</td>
</tr>
<tr>
<td><strong>Prec. summer</strong></td>
<td>Average mm</td>
<td>260.96</td>
<td>39.18</td>
<td>92.24</td>
<td>49.06</td>
<td>218.99</td>
<td>40.06</td>
<td>154.49</td>
<td>21.67</td>
<td>255.08</td>
<td>41.16</td>
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<tr>
<td><strong>Prec. winter</strong></td>
<td>Average mm</td>
<td>73.51</td>
<td>72.74</td>
<td>63.70</td>
<td>62.75</td>
<td>27.09</td>
<td>15.66</td>
<td>118.07</td>
<td>31.45</td>
<td>18.19</td>
<td>16.60</td>
</tr>
<tr>
<td><strong>N (observations)</strong></td>
<td>-</td>
<td>796</td>
<td>3115</td>
<td>3012</td>
<td>2115</td>
<td>854</td>
<td>-</td>
<td>19</td>
<td>-</td>
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Table A2: Translog ML estimation results.

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<th>Variables</th>
<th>Brazil</th>
<th>North</th>
<th>Northeast</th>
<th>Southeast</th>
<th>South</th>
<th>Midwest</th>
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<tbody>
<tr>
<td>lx2</td>
<td>0.46***</td>
<td>16.32</td>
<td>0.59***</td>
<td>9.15</td>
<td>0.60***</td>
<td>11.43</td>
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<tr>
<td>lx3</td>
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<td>-0.36***</td>
<td>-9.01</td>
<td>-0.27***</td>
<td>-10.99</td>
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<td>t</td>
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<td>1.86</td>
<td>-0.10</td>
<td>-0.75</td>
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<td>0.11***</td>
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<td>0.09***</td>
<td>4.08</td>
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<tr>
<td>lx33</td>
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<td>-0.07***</td>
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<tr>
<td>lx2t</td>
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<td>-2.82</td>
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<td>2.06</td>
<td>-0.0437</td>
<td>-1.06</td>
<td>0.0338</td>
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<td>share_cop</td>
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<td>-0.039*</td>
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<tr>
<td>share_irr</td>
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<td>37.00</td>
<td>0.99***</td>
<td>7.09</td>
<td>0.75***</td>
<td>10.76</td>
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<td>-3.53</td>
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<td>5.09</td>
<td>-0.08***</td>
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<td>0.001</td>
<td>1.29</td>
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<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
<td>yes</td>
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</tbody>
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* p<0.10,  ** p<0.05,  *** p<0.01. The variables are: x2=labor; x3=tractors; share_cop=share of cropland; share_irr=share of irrigated area; tempsummer=average temperature in the summer; tempwinter=average temperature in the winter; precsummer=average precipitation in the summer; and, precw=average precipitation in the winter.