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Declarations

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ABSTRACT

Bush fires raged across the Brazilian Amazon in 2019. The CO_2 that was sequestered in those forests is now in the atmosphere, adding to the rate of global warming. The burned-over land will likely be converted to agriculture. Possible contributors to these events include climate change itself, creating hotter, drier conditions, and what is reportedly a reduction in the vigor of forest preservation efforts under a new government. But here we explore a third possible contributor: technical change may have been increasing the incentives to convert forests to agriculture. We examine the nature of technical change from 2003 to 2015, across 287 municipalities within Brazil's "arc of deforestation". We consider grains, livestock and timber as agricultural outputs and CO_2 emission from deforestation as an undesirable output. On average across the region, we estimate the annual rate of technical change in agriculture over this period to have been 4.9%, with a significant bias toward agricultural outputs and away from CO_2 emissions, meaning that it has been increasingly attractive to convert these forests to agriculture. This technological incentive for deforestation has thus been building up during the early part of this century, but actual deforestation was held in check somewhat by forest preservation policies until recently, when a more relaxed policy environment has allowed the increased technological incentive for deforestation to be more fully expressed. These changes have added to climate change as contributors to the recent burst in Amazon forest destruction.

Key words: CO_2 sequestration, Amazon Forest, agricultural productivity, technical change biases.

JEL: O44, Q55, Q15.

1. INTRODUCTION

Brazil encompasses the largest tropical forest in the world, corresponding to more than 10% of the world's forest area and around 60% of Brazil's surface (MacDicken *et al.*, 2016). Strong agricultural expansion in the Amazon region, starting in the 1990s, has been closely related to deforestation and therefore to deforestation-related CO_2 emissions. The increased agricultural output is a "good", but the related increase in CO_2 emissions is a "bad", given its critical role in global warming. This paper addresses the changes in the technological tradeoff (marginal rate of transformation) between increased agricultural production (goods) and increased CO_2 emissions (a bad).

In this article, we estimate the rate and biases of technical change for the "arc of deforestation" in the Brazilian Amazon during 2003-2015, including in the analysis deforestation as a proxy for CO_2 emissions. Specifically, we measure both the rate of technical change and its effect on the opportunity cost of reducing CO_2 emissions by forest preservation, i.e., whether technical change has been biased toward agricultural production or toward reductions of CO_2 emissions from reductions in deforestation. To do this we estimate a municipality-level production possibility frontier (PPF) for agriculture for the period 2003 to 2015. This permits us to identify whether technical change was progressive or regressive, and whether technical change was biased toward or against CO_2 emissions from deforestation.

Even though our analysis does not include information after 2015, in particular that which is relevant to the recent fires and deforestation, it does help understand the increasing pressure to deforest given the increasing opportunity cost we estimate.

2. BACKGROUND

In the literature, the "arc of deforestation" has been loosely defined as the set of municipalities in the agricultural frontier in the northern region of Brazil with high levels of deforestation. In this article, we investigate technical change in agriculture when deforestation as a proxy for CO_2 emissions is also considered. We use information from 287 municipalities in nine states: Acre, Amazônia, Roraima, Rondônia, Amapá, Pará, Mato Grosso, Tocantins and Maranhão. Figure 1 illustrates total deforestation by municipality during the period 2001 to 2015.

[Figure 1]

Rivero *et al.* (2009) assert that high rates of deforestation between 1995 and 2006 were caused partially by grain and livestock expansion in the North and Midwestern regions. In addition to these two activities, timber revenue has also been identified as a motivation for deforestation [Rivero *et al.* (2009); Margulis (2004); Cardille *et al.* (2003); Nepstad *et al.* (2001); Quintanilha and Lee Ho (2005)]. Other studies that also highlight the positive relationship between overall agriculture or a specific crop such as timber and deforestation in Brazil are Reis and Guzmán (1992), Andersen *et al.* (2002), Diaz and Schwartzman (2005), Nepstad *et al.* (2007), Araujo *et al.* (2009), Börner *et al.* (2010), Bowman *et al.* (2012), Assunção *et al.* (2013), Nepstad *et al.* (2014), Silva *et al.* (2019a, 2019b), and Koch et al. (2019).

Regarding the role of technical change in forest preservation, Villoria *et al.* (2014) suggest that technical change (productivity change) could lead to two opposite effects on forest preservation; higher deforestation as commercial activity is expanded, or lower deforestation due to less land-intensive production (input substitution). They argue that empirical work is needed to test which of these effects has prevailed.

Filho *et al.* (2015), for example, investigated whether Brazil can increase food supply without increasing deforestation. They assert that conversion of low-yield pasture area to crop production could offset the production effect of reducing deforestation. To obtain these results, they used a Computable General Equilibrium (CGE) model of Brazil to model land use over 20 years. Although they conclude that improved technology could provide the amount produced by deforestation, it is almost certain that increased crop productivity would lead to deforestation, as well, absent some policy restrictions to prevent it.

Koch et al. (2019) study the effect of a policy to reduce deforestation on land use, crop yields and livestock stocking rate in a subset of municipalities in the Amazon subjected to a forest protection policy. They concluded that the policy would induce increases in the livestock stocking rate and a substitution of other inputs for land in these municipalities.

There are several recent studies of productivity of Brazilian agriculture. Bragagnolo *et al.* (2010) estimate Total Factor Productivity (TFP) for Brazilian agriculture using a panel of municipalities and agricultural census data (1975, 1985, 1995 and 2006). They estimated a translog production function to obtain the TFP and its several components including technical change. They found an average annual technical progress of around 3.1%. Using their estimates of state-level average technical progress, we find the simple average rate of technical progress in the subset of states with municipalities in the "arc of deforestation" was around 6.7%, ranging from 3.9% in Maranhão to 10.2% in Roraima.

Gasques and Conceicao (1997), Gasques *et al.* (2004), Gasques *et al.* (2008) and Fuglie (2010) have all previously measured agricultural TFP rates higher than 3% for Brazil. Gasques *et al.* (2014) argue that a favorable international scenario, public research, and credit availability had important roles in these results. Rada and Valdes (2012) also found gains in TFP, mainly driven by technical change, at an annual rate of about 4% for recent decades. Mendes *et al.* (2009) and Trindade and Fulginiti (2015) measured lower TFP growth rates, 1% for 1985-2004 and 2% for 1969-2009, respectively. Gomes and Braga (2008) investigated factors associated with agricultural TFP in the Legal Amazon using state level data. They found that infrastructure and credit made available by a regional institution to promote growth (Fundo Constitutional de Financiamentos do Norte) contributed to higher TFP rates. None of these studies considered the relationship between agricultural TFP and CO_2 from deforestation.

The harmful environmental effects of the production of goods have been studied using directional output distance functions with two kinds of outputs: undesirable (e.g., pollution) and desirable (e.g., production). Chung *et al.* (1997) argue that rates of productivity change are biased when estimated using conventional methods that do not consider harmful byproduct effects on the environment. Only a few studies have included undesirable outputs to evaluate productivity change in agriculture, as we do here, for example, Rezek and Perrin (2004), Färe, *et al.* (2006) and Kabata (2011) for the United States and Flavigna, *et al.* (2013) for Italy.

3. THE MODEL

In this article, we seek to estimate the rate and biases of technical change for agricultural production in the Brazilian Amazon. Figure 2 illustrates the production possibilities structure we propose, in this case for a single good output such as agriculture (vertical axis) and on the horizontal axis a single undesirable (or "bad") output such as CO_2 emissions. Because direct measures of CO_2 emissions do not exist, in this study we use deforestation as a proxy for CO_2 emissions from land use change, which constitute the most important component of total greenhouse gas emissions in this region. For an undesirable output *b* that is not freely disposable, the production possibilities frontier (PPF) exhibits an upward-sloping region where it is not possible to reduce the bad output (CO_2 emissions from deforestation) without also reducing some of the desirable output. Here we interpret a rightward movement along the horizontal axis as an increase in emissions, and a leftward movement as either a decrease in emissions or an increase in CO_2 sequestration. This is a logical characterization of the agriculture/CO_2 technology in the Amazon.

Technical change is represented in Figure 2 by a shift in the frontier from the solid line to the dashed line. This outward shift of the production possibility frontier represents a progressive technical change, allowing both more agriculture and less CO_2 emissions than previously attainable from the given set of inputs. A bias in technical change is revealed here by a change in the marginal rate of transformation (MRT) along a directional line segment such as BC. In the case illustrated, the marginal rate of transformation in terms of the amount of good output y foregone to reduce a unit of bad output b has increased. This is described as a technical change bias toward good output y and away from bad output b, indicating that it is becoming relatively more expensive to sequester a unit of CO_2. Generalizing the two-output representation of technology in Figure 2, in this study we represent the municipality-level agricultural technology of this region with a directional distance function relating three desirable outputs (timber, grains, and livestock), one undesirable output (CO_2 emissions); and three inputs (labor, capital and land).

We estimate the frontier of this production set with a directional distance function. Several previous studies have used directional distance functions to represent technologies that include the joint production of both desirable and undesirable outputs: Färe *et al.* (2005); Chung, *et al.* (1997); Färe, *et al.* (2006); Macpherson, *et al.* (2010). Our results will reveal that the PPF has shifted outward (*progressive technical change*) and that the slope has increased due to technical change (a *bias toward agriculture*).

The agricultural production technology uses inputs $\boldsymbol{x} \in \Re_{+}^{S}$ to produce outputs $\boldsymbol{u} \in \Re_{+}^{P}$. Some outputs $\boldsymbol{y} \in \Re_{+}^{M}$, are desirable (such as grain, livestock and timber production), and some outputs $\boldsymbol{b} \in \Re_{+}^{R}$, are undesirable ($CO_2$). We characterize the production technology using a directional distance function:

$$\vec{D}_o(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}, t; \boldsymbol{g_y}, \boldsymbol{g_b}) = max\{\alpha: (\boldsymbol{y} + \alpha \boldsymbol{g_y}, \boldsymbol{b} - \alpha \boldsymbol{g_b}) \in P(\boldsymbol{x})\}, \quad (1)$$

where $\boldsymbol{g_y}$ and $\boldsymbol{g_b}$ constitute the directional vector $\boldsymbol{g} = (\boldsymbol{g_y}, -\boldsymbol{g_b})$ and subscripts $k = (1, 2, \ldots, N)$ representing observed units and $t = (1, 2, \ldots, T)$ representing years are dropped for simplicity. This directional distance function defines the frontier of an output possibility set at time *t*, $P(\boldsymbol{x}, t)$. On the frontier itself, the value of the frontier function (1) is zero, determined in our case by a functional estimation of *P(x)* that approximates the frontier determined by input-output bundles from the best performing units. For all observations inside the frontier the directional distance function is positive.

In general, the directional distance function is non-negative in (***y*, *b***), non-increasing and strongly disposable in ***y***, non-decreasing in ***b***, weakly disposable, and concave in (***y*, *b***). It also satisfies the translation property:

$$\vec{D}_o(\boldsymbol{x}, \boldsymbol{y} + \alpha \boldsymbol{g_y}, \boldsymbol{b} - \alpha \boldsymbol{g_b}, t; \boldsymbol{g_y}, -\boldsymbol{g_b}) = \vec{D}_o(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{b}, t; \boldsymbol{g_y}, -\boldsymbol{g_b}) - \alpha, \quad \alpha \in \Re \quad (1a)$$

which states that increasing desirable outputs by $\alpha \boldsymbol{g_y}$ and simultaneously decreasing undesirable outputs by $-\alpha \boldsymbol{g_b}$ is equivalent to subtracting the translation factor α from the original directional distance function.

Figure 2 illustrates this directional distance function for the case of one desirable output y and one undesirable output b and a fixed bundle of inputs, given a directional vector $\boldsymbol{g} = (g_y, -g_b) = (1, -1)$. The positive slope of the frontier (the locus of points for which $\vec{D}_o$= 0) indicates that the undesirable good b is weakly disposable, which means that for given input levels it is costly to dispose of b in terms of desirable good y that must be given up. The distance of observation k^t from the frontier is represented as a projection from point A along vector $\boldsymbol{g}$ = (1,-1) to point B. The directional output distance function measures this distance as α, the maximum feasible simultaneous expansion of y and contraction of b, with distance α measured in multiples of the vector $\boldsymbol{g} = (g_y, -g_b)$.

[Figure 2]

3.1 Parameters characterizing technical change

Traditionally, technical change has been characterized by two kinds of parameters: a rate of technical change and biases of technical change toward/against individual outputs and inputs. Here, an outward shift of the frontier represents a technical change of positive (progressive) rate, while an inward shift indicates a negative (regressive) rate. A pair-wise Hicks neutral[1] technical change is implied if the MRT is the same at point B and point C along the projection of the original observation between the two frontiers. If between points B and C the MRT changes, technical change is biased. In that case, technical change has altered the frontier tradeoff (the MRT) between good and bad output in the projection of observation k^t along vector $\boldsymbol{g} = (g_y, -g_b)$. In the case illustrated in figure 2, technological change is biased toward y, in accord

[1] We use the Blackorby *et al.* (1976) interpretation of Hicks neutral technical change. Specifically we have adapted their *implicit Hicks neutrality* (IHN) concept to output space with desirable and undesirable outputs.

with the notion of *implicit Hicksian neutrality* in Blackorby, *et al*. (1976). Given the algebraic specification of the distance function that we will use, both the rate and the bias of the shift in the frontier can differ depending on the location of observation k^t in $P(\boldsymbol{x})$ and depending on the directional vector along which the data point is projected. We estimate both the rate and bias of technical change at the data points for each municipality, as described below.

3.2 Primal output-based directional measure of the rate of technical change

We measure the rate of technical change following the strategy developed by Färe and Karagiannis (2014). The total differential of the distance function is

$$-\left(\nabla_b \vec{D}_o\right)' g_b d\alpha + \left(\nabla_y \vec{D}_o\right)' g_y d\alpha + \frac{\partial \vec{D}_o}{\partial t} dt + \nabla_x \vec{D}_o dx = 0 \tag{2}$$

Specifying $dx = 0$, imposing the translation property as $-\left(\nabla_b \vec{D}_o\right)' g_b + \left(\nabla_y \vec{D}_o\right)' g_y = -1$ and solving for the rate of technical change, $d\alpha/dt$:

$$\frac{d\alpha}{dt} = \frac{\partial \vec{D}_o}{\partial t} \tag{3}$$

The rate of technical change is thus measured as the common number of times the desirable output and the undesirable output vectors (g_y and g_b) can be added to the desirable output and subtracted from the undesirable output as a result of technological change, starting at a given output plan on the original *PPF*. In figure 2 it is represented by the length of the segment *BC*.

3.3 Primal output-based directional measure of the bias of technical change

We use a primal definition of Hicksian bias (Fulginiti, 2010) between a desirable output y_m and an undesirable output b, defined as the change in the MRT along the projection ray $\boldsymbol{g} = (g_{y_m}, -g_b)$:

$$B_{y_m,b}(\boldsymbol{y}, \boldsymbol{b}, \boldsymbol{x}, t) \equiv \frac{\partial \ln\left(MRT_{y_m,b}\right)}{\partial t} \tag{4}$$

where $MRT_{y_m,b}$ is defined as the ratio of $\partial\vec{D}_o/\partial b$ to $\partial\vec{D}_o/\partial y_m$. $B_{y_m,b}$ measures the Hicksian pair-wise bias in technical change as a change in the slope of the production possibility frontier along the directional ray $\boldsymbol{g} = (g_{y_m}, -g_b)$. $B_{y_m,b} > 0$ indicates that technical change is biased towards the production of desirable output y_m relative to undesirable output b, i.e., technical change has led to an increase in the cost of reducing a unit of undesirable output b, in terms of desirable output y_m given up. $B_{y_m,b} < 0$ indicates that technical change is biased against production of desirable output y_m relative to undesirable output b.

4. THE APPLICATION

Our sample of municipalities for analysis is selected from the 574 municipalities in the nine-state region we have identified as constituting the arc of deforestation. We first calculated total deforestation as a proxy for CO_2 emissions by municipality, over the period 2001 to 2015, using data from the National Institute for Space Research (INPE/PRODES, 2017). Because many of the smaller municipalities registered no forest or anomalous levels of deforestation, we selected for this study the 287 municipalities with deforestation above the median of 13,000 ha, which represent 94% of deforestation in this area.[2]

Annual data on desirable outputs and inputs at the municipal level for the period 2003-2015 are from the Municipal Agricultural Production (in Portuguese *Produção Agrícola Municipal* – PAM) survey[3] conducted by the Brazilian Institute of Geography and Statistics (IBGE, 2017). We obtained information on grains, livestock and timber production. Grain production is measured as the sum of corn and soybean production (in tons per year). Timber is measured in cubic meters of logged wood per year. Livestock production is measured in thousand liters of milk produced per year, given that data on cattle sold is not available on an annual basis. Descriptive statistics are in table 1.

Because direct measures of CO_2 emissions from the Brazilian Amazon at municipal scale do not exist, in this study we use deforestation as a proxy for CO_2 emissions from land use change. Although the emissions from deforestation depend on the density and type of forest, we use the average emission rate of 132.2 tons of carbon (Brazilian Ministry of Environment (MMA), 2011; Amazon Fund, 2015)[4] per hectare of forest preserved, which is used by the government of Brazil in their REDD+ contracts with Norway, Germany, Petrobras and others. Deforestation by municipality, measured in hectares per year, was obtained from the National Institute for Space Research (INPE/PRODES, 2017). Margulis (2004) suggests that deforestation of a given plot might occur over three years, and be detected only in the third year of the process, depending on

[2] We also completed the analysis for the entire set of 574 municipalities and for a set of 313 municipalities with deforestation above 10,000 ha, with no substantive change in our conclusions.
[3] Agricultural Census data was available for 1995/96 and 2006, while deforestation at municipal level was only available from 2000 to 2016 on January of 2017.
[4] The Amazon Fund (2015) raises funds to preserve the forest using this carbon content based on the Technical Committee of the Amazon Fund (CTFA), but states that it is a conservative measure considering that the carbon content in the Amazon Forest ranges from 130 tons of Carbon/ha to 320 tons of Carbon/ha.

the process of deforestation used. It is possible that agricultural activities would be occurring during this process with revenue from both agriculture and timber sales during this period. This leads us to follow Margulis and measure deforestation for a given year as the average of the current and previous two years.

Municipalities in the state of Pará and Mato Grosso have the largest average deforestation, 6,595 and 5,951 hectares, respectively. Grain production is largest in municipalities in the state of Mato Grosso averaging 273,037 tons of grains per year. Municipalities in the state of Rondônia have the largest average livestock production, 13,337 thousand liters of milk. Municipalities in the state of Pará have the largest average production of timber, 83,972 m^3.

[Table 1]

We were able to obtain information on three inputs, all from IBGE. We measure labor as the population in the municipality. Rural population is more than 70% in about 75% of the municipalities. Agricultural area is measured in hectares, obtained by subtracting forest area from the total area of the municipality. Capital is represented by stock of livestock, in number of head. Following Färe *et al.* (2005), we normalized all these variables, dividing by their means[5]. In addition to these inputs we add a time trend to capture exogenous technical change.

4.1 Empirical estimation

We specify the distance function (Eq. 1) as a quadratic flexible functional form, with the subscript $i = (1,2, \dots, N)$ representing municipalities and subscript t = (1, 2, …, T) for periods (subscripts t are dropped here, for simplicity):

[5] For a hypothetical municipality that uses mean inputs and produces mean outputs, the input and output variables would be $(x, y, b) = (1,1,-1)$.

$$\vec{D}_{o,i}(\boldsymbol{x_i}, \boldsymbol{y_i}, b_i, ; t, 1, -1) = \gamma_0 + \sum_{s=1}^{3} \gamma_k x_{si} + \theta_1 b_i + \sum_{m=1}^{3} \beta_m y_{mi} + \frac{1}{2} \sum_{s=1}^{3} \sum_{l=1}^{3} \gamma_{kl} x_{si} x_{li}$$

$$+ \frac{1}{2} \sum_{m=1}^{3} \sum_{n=1}^{3} \beta_{mn} y_{mi} y_{ni} + \frac{1}{2} \theta_{11} {b_i}^2 + \sum_{m=1}^{3} \sum_{s=1}^{3} \delta_{ms} x_{ki} y_{mi} + \sum_{s=1}^{3} \varphi_s x_{si} b_i \tag{5}$$

$$+ \sum_{m=1}^{3} \mu_m y_{mi} b_i + \upsilon_1 t + \frac{1}{2} \upsilon_{11} t^2 + \sum_{s=1}^{3} \vartheta_{s1} x_{si} t + \sum_{m=1}^{3} \eta_m y_{mi} t + \lambda_1 t b_i$$

where x_{ki} are labor, capital, and area, y_{mi} are timber, livestock and grains, and b_i is deforestation as proxy for CO_2 emissions, t is technical change measured as years, and γ's, β's, θ's, δ's, φ's, υ's, ϑ's , η's, μ's and λ_1 are parameters to be estimated. The intercept is a constant term plus municipality fixed effects (dummies). We use the directional vector = $(\boldsymbol{g_y}, -g_b) = (\mathbf{1}, -1)$, representing a simultaneous expansion in desirable outputs and contraction of undesirable output, where **1** is a 1x3 unit vector. The symmetry and translation properties in outputs and inputs are imposed before estimation, requiring the following restrictions:

$$\sum_{m=1}^{3} \beta_m - \theta_1 = -1; \quad \sum_{n=1}^{3} \beta_{mn} - \mu_m = 0; \quad \theta_{11} - \sum_{m=1}^{3} \mu_m = 0; \quad \sum_{m=1}^{3} \delta_{ms} - \varphi_s = 0$$

$$\sum_{m=1}^{3} \eta_m - \lambda_1 = 0; \quad m = 1, 2 \text{ and } 3; \text{ s} = 1, 2 \text{ and } 3; \quad \beta_{mn} = \beta_{nm}$$

We estimated equation (5) after imposing the translation property in (1a) that results in transformation of outputs and of the left hand side, at $\vec{D}_{o,i}(\boldsymbol{x_i}, \boldsymbol{y_i}, b_i, ; t, \mathbf{1}, -1) = 0$, as

$$-\alpha_i = \vec{D}_{o_i}(x_i, y_i + \alpha_i, b_i - \alpha_i; \mathbf{1}, -1) + \epsilon_i, \tag{6}$$

where α_i is the translation factor and ϵ_i is an error term. The quadratic flexible functional form with symmetry and translation properties imposed is estimated as

$$-b_i = \gamma_0 + \sum_{s=1}^{3} \gamma_s x_{ki} + \theta_1 b'_i + \sum_{m=1}^{3} \beta_m y'_m + \frac{1}{2}\sum_{s=1}^{3}\sum_{l=1}^{3} \gamma_{sl} x_{si} x_{li}$$

$$+ \frac{1}{2}\sum_{m=1}^{3}\sum_{n=1}^{3} \beta_{mn} y'_{mi} y'_{ni} + \frac{1}{2}\theta_{11} {b'_i}^2 + \sum_{m}^{3}\sum_{s=1}^{3} \delta_{ms} x_{si} y'_{mi} + \sum_{s=1}^{3} \varphi_s x_{si} b'_i \tag{7}$$

$$+ \sum_{m=1}^{3} \mu_m y'_{mi} b'_i + \upsilon_1 t + \frac{1}{2}\upsilon_{11} t^2 + \sum_{s=1}^{3} \vartheta_{s1} x_{si} t + \sum_{m=1}^{3} \eta_m y'_{mi} t + \lambda_1 t b'_i + \epsilon_i$$

where $y'_{1i} = y_{1i} + \alpha_i$, $b'_i = b_i - \alpha_i$. In our case we chose $\alpha_i = b_i$[6], so the parameters associated with b_i are recovered after estimation using the translation property restrictions. We calculate estimated technical change following equation (3), as

$$\frac{\partial \vec{D}_o}{\partial t} = \upsilon_1 + \upsilon_{11} t + \sum_{s=1}^{3} \vartheta_{s1} x_{si} + \sum_{m}^{3} \eta_m y_{mi} + \lambda_1 b_i \tag{8}$$

The biases of technical change are calculated using equation (4) as

$$B_{y_{mi},b_i}(y_{mi}, b_i, \boldsymbol{x}, t) \equiv \left[\frac{\lambda_1}{\vec{D}_{b_i}} - \frac{\eta_m}{\vec{D}_{y_{mi}}}\right] \tag{9}$$

where $\vec{D}_{b_i}$ and $\vec{D}_{y_{mi}}$ represent the first derivatives of the directional distance function for municipality *i* with respect to the undesirable and a desirable output, respectively.

Our selection of the directional vector (1,1,1,-1) for measuring technical change warrants some comment. First, recall that our output levels have been normalized by dividing by their means, so that one unit of distance is equivalent to 100% of the mean of each variable. Recall also that we measure the rate of technical change at each observation (equation 8) as the change

[6] The factor α_i used to impose the translation property of the directional distance function is chosen by the researcher and most studies have chosen one of the outputs. In this article, we have used the undesirable output but we have also estimated Eq. (6) considering $\alpha_i = y_{1i}$. Results are quite consistent with those with $\alpha_i = b_i$.

in distance evaluated for that municipality. Thus, if the change in distance is 0.10, this implies that the production frontier has shifted outward along the vector (1,1,1,-1) with each agricultural output increasing by 10% of its mean and deforestation decreasing by 10% of its mean. The 10% is thus a measure of the change in the entire bundle of outputs that is made possible by technical change, which itself is a measure of welfare that was pioneered by Allais, Debreu and others.

This directional measure is not only appealing as an economic concept, it is also completely consistent with the traditional measures of productivity change that consider a single aggregated output. This traditional approach would also measure a 10% productivity change if all subcategories of output were to increase by 10% for given levels of input.

We first use Corrected Ordinary Least Squares (COLS) to provide starting values for the parameters in the Maximum Likelihood Estimation (MLE) procedure. For the MLE estimation, the error term in equation (7) is specified as $\epsilon_i = u_i - z_i$, where u_i represents the standard error term and z_i captures the distance from the frontier, also interpreted as a measure of the inefficiency of observation *i.* We assume a half-normal distribution for $z_i \sim N^+(0, \sigma_z^2)$, as described in Kumbhakar, Wang, and Horncastle (2015). The estimation was done using Stata 14 following the command *sfmodel* suggested by Kumbhakar, *et al.* (2015) and *sfcross* suggested by Belotti, *et al.* (2012).

5. RESULTS AND DISCUSSION

We estimated the quadratic specification for the directional distance function in equation (7) using a frontier MLE approach described above[7]. Parameter estimates for the first step COLS

[7] A Likelihood Ratio test of 35.09 indicates that MLE estimates with a half-normal distribution for the one-sided error term are superior to the COLS estimates (the one percent critical value is 5.4). We also utilized the GMM method and found the results to be similar. These results can be obtained from the authors upon request.

and the MLE are shown in table A1 in Appendix A. The MLE estimation has 30 statistically significant parameters out of 36 (excluding municipality dummies).

An estimate of the distance of each municipality from the frontier is obtained from equation (7), and is interpreted as a measure of inefficiency. The average distance estimated for the region was 0.19. This means that for the average municipality, agricultural outputs (grains, timber and livestock) could be expanded by 19% each while simultaneously decreasing CO_2 by 19%. We acknowledge, however, that to the extent that the quality of resources is not homogeneous across municipalities, it may not be possible to close all of these efficiency gaps.

The estimated rate and biases of technical change vary over the production space depending on the level of inputs and outputs for individual municipalities at each point in time. We evaluated the estimated annual rate and biases for each observation, then averaged those estimates. The overall average annual rate of technical change estimated for this region during the period 2003-2015 is 4.93% (see table 2). This means that on average for given levels of inputs, technical change has shifted the frontier outward, allowing municipalities to expand agricultural outputs (grains, timber and livestock) by around 4.93% while simultaneously contracting CO_2 emissions (deforestation) by 4.93%.[8] Average estimates for each year vary from 0.042 to 0.061, following a slightly U-shaped pattern as revealed in Figure 3. At the municipality-level, estimates of this rate vary across space, as illustrated in Figure 4.

Other studies reporting rates of technological change in Brazilian agriculture have not considered deforestation or emissions, and analyze the whole country except for the Bragagnolo et al. (2010), who provide estimates by state. Bragagnolo's estimates of the rate, for an earlier

[8] Estimated average rates of technical change for the entire set of 574 municipalities is 0.045 and for the 313 municipalities with deforestation above 10.000 hectares is 0.048, compared with 0.049 for the sample in this study.

period (1975-2006), averaged 3.1% for the country, but for the states in which the municipios of our study are located, the simple average estimate of the rate was 6.7%. Gasques and Conceicao (1997), Gasques et al. (2004), Gasques et al. (2008), Fuglie (2010) and Rada and Valdes (2012) all measured country-wide rates exceeding 3%, but Trindade and Fulginiti (2015) estimated rates of only 1% for 1985-2004 and 2% for 1969-2009. Gomes and Braga (2008) investigated factors associated with agricultural TFP in the Legal Amazon using state level data and found that infrastructure contributed to higher rates.

[Table 2]

[Figure 3]

[Figure 4]

Our primary interest for this study is in the biases of technical change between agricultural production and CO_2 emissions, because they indicate changes in trade-offs due to technical change. We evaluate this issue by estimating Hicksian pairwise technical change biases as defined in equation (4) and equation (9). Our results indicate that municipalities in the "arc of deforestation" have experienced technical change that is biased toward each agricultural output and against CO_2 emissions. This means that as a result of technical change, for a given level of efficiency, less CO_2 emissions from deforestation is now necessary to increase a unit of agricultural output. Expressed as the inverse, it means that the opportunity cost to farmers of reducing CO_2 emissions by one unit has increased in terms of agricultural output foregone. An interpretation of this is that the cost to farmers of legal restrictions intended to reduce CO_2/deforestation has increased, an issue that we discuss below.

[Figure 5]

From equation (8), the estimate of parameter λ_1, +0.017, indicates that the estimate of the rate of technical change is higher in areas with more emissions from deforestation, and the positive values of coefficients for grain, livestock and timber indicate that the rate of technical change is also higher in areas with more of each of the agricultural outputs.

For each of the desirable outputs we evaluate pairwise technical change biases relative to CO_2 emissions from deforestation using equation (9). As indicated earlier, a pairwise bias in favor of, say grains, relative to CO_2 would be reflected by a steeper MRT_{t+1} in Figure 2. To evaluate whether technical change has on average been biased toward grains and against CO_2 from deforestation, we evaluate B_{y_1,b_1} at each observation using equation (9), then calculate the average across municipalities. We proceed in the same manner to estimate average technical biases with respect to timber and livestock. Using the maximum likelihood estimates (MLE in Table 2), we find that the average bias for grains relative to CO_2 is $B_{y_1,b_1} = 0.15$, for timber relative to CO_2 is $B_{y_3,b_1} = 0.11$ and for milk relative to CO_2 is $B_{y_2,b_1} = 0.17$. These estimates indicate that as a result of bias in technical change, more of each of these agricultural outputs must be foregone to decrease one unit of CO_2 emission from deforestation, as illustrated by the increased slope of the MRT in Figure 2.

In 2007, the Brazilian government identified a list of priority municipalities with high levels of deforestation and high rates of growth of agricultural output, where strict monitoring would take place. These 40 municipalities, clustered in the states of Pará and Mato Grosso, are all included in our sample. Our results show that the average rate of technical change in the priority municipalities was 10.3%, significantly higher than the 3.8% in the rest of the municipalities in these states (the null hypothesis of no difference in these means was rejected at the 1% level). Koch *et al.* (2019) using a diff-in-diff approach study the impact of this monitoring policy on crop yields and livestock stocking rates in priority municipalities versus others. They conclude that this policy resulted in substitution of land by other inputs and increased livestock stocking rates in priority municipalities; results that do not contradict our broader multifactor productivity estimates for these municipalities.

Brazilian policies to reduce CO_2 emissions by controlling deforestation, such as the 2004 Action Plan for Deforestation Prevention and Control in the Legal Amazon[9] and others mentioned below, may be related to these results in two ways. First, these programs have focused attention on the tradeoff between deforestation and agricultural production, providing incentives and enforcement to reduce deforestation and therefore emissions. These incentives or penalties would increase the slope of the iso-revenue line (not shown in Figure 2) that agents would presumably use as a target to adjust the MRT to the profit-maximizing point on the production possibilities frontier in Figure 2. The policies would thus lead us to observe municipalities with less deforestation (and emissions) than was profitable (reductions in both desirable and undesirable output along the transformation frontier in the vicinity of B and C in figure 2). Second, the policies may have also affected the nature of technical change by inducing development and adoption of innovations that allowed both yield increases and reduced deforestation and therefore emissions (Nepstad *et al.*, 2014). Therefore the relationship between policies, their impacts on behavior, and their impact on the nature of technical change, although important, cannot be entirely disentangled. In this analysis we do not examine any explicit impact of policies on the technology set itself, given the extended period of time required for such an impact to occur.

[9]Plano de Ação para a Prevenção e Controle do Desmatamento na Amazônia Legal – PPCDAm found at http://www.mma.gov.br/florestas/controle-e-preven%C3%A7%C3%A3o-do-desmatamento/plano-de-a%C3%A7%C3%A3o-para-amaz%C3%B4nia-ppcdam

Among the other policies mentioned above are the Soy Moratorium (SoyM) in 2006, and the Cattle Agreement in 2010, which constituted obstacles to deforestation and the concomitant reductions in emissions despite the fact that they are voluntary (Nesptad *et al.*, 2014; Gibbs *et al.*, 2015). The enforcement of newer regulations such as the Brazilian Forest Code (FC), the Rural Environmental Registry of private property (CAR), and surveillance by the Brazilian Institute of the Environment and Renewable Natural Resources (IBAMA), have been shown to have positive impacts as deforestation and therefore to be effective emission control mechanisms (Gibbs *et al.*, 2015; Soares-Filho *et al.*, 2014; Hargrave and Kis-Katos, 2013). The impact of these regulations on the rate and bias of technical change has not been explicitly studied in this research, but we speculate that the intensification measured by the bias in technical change might have been, in part, a result.

The Brazilian government has also invested in infrastructure, public research and extension, and has promoted agricultural production via increased credit availability (Gomes and Braga (2008); Gasques *et al.* (2014)). From 1999 to 2009, credit availability through the Program to Support Family Farms (PRONAF)[10] has increased, on average, at a rate of 24% annually for the states considered in this article. The total credit made available by the government to this region increased six-fold between 2001 and 2009. These incentives would appear to favor increased agricultural production, presumably to some extent at the cost of higher CO_2 emissions.

[10] Programa Nacional de Fortalecimento da Agricultura Familiar. This information is for all municipalities in the Legal Amazon region and can be found at http://www.mda.gov.br/sitemda/pagina/acompanhe-a%C3%A7%C3%B5es-do-mda-e-incra

6. CONCLUSIONS

In this article we evaluate whether the high measured rates of technical change reported in the literature for Brazilian Amazon agriculture remain high when CO_2 emissions, considered as an undesirable output, are included in the estimation. We are more specifically interested in the nature of the biases in technical change, to determine whether innovations have made it less or more costly to reduce CO_2 emissions from deforestation. Our analysis of these issues is based on a sample of 287 municipalities in the "arc of deforestation" in Brazil over the period 2003-2015. We estimated an aggregate municipality-level technology using a directional output distance function with data on grains, livestock and timber production from IBGE and CO_2 emissions from deforested area from INPE. The directional distance function was specified as a flexible quadratic form and estimated using a stochastic frontier approach.

Our results reveal that the rate of technical change (the percentage increase in agricultural outputs and decrease in emissions achievable while holding inputs constant) averaged about 4.9% per year across these municipalities during the period from 2003 to 2015. These estimates of technical change are as high or higher than other estimates for Brazil that have ranged between 1% to 4%, even though in our case we included reduction of emissions in the analysis.

The most significant of our results are that technical change was biased toward agricultural production relative to emissions indicating a change in the marginal rate of transformation along the production possibility frontier between CO_2 emissions and agricultural outputs. This possibility has not been examined before, and it indicates that for given levels of inputs, more agricultural production must be foregone per unit of CO_2 sequestered in the forest. For future agricultural/environmental policies, these results imply that incentives for decreasing deforestation-related CO_2 emissions will need to increase well above the current \$5/t in Brazil's

REDD+ agreements, and will need to continue to increase if preservation of the forest is to be financially attractive relative to agricultural production.

The observed rates of deforestation in this region were decreasing during the period of analysis. We take this as indirect evidence of the success of Brazilian policies during this period intended to reduce deforestation and therefore emissions. Our results show that meanwhile the technology was changing in such a way as to make it more ever expensive to reduce deforestation. However, news media have reported recently that deforestation in 2016 was higher than in 2015, the last year of our study. Deforestation in the state of Mato Grosso for example, increased by 190% during the first months of 2016 compared to 2015[11]. In fact there has been an increase of 58% in the annual deforestation rate in the last four years, from 6.2 thousand km^2 in 2015 to 9.8 thousand km^2 in 2019[12]. Our interpretation is that during the early years of the century, policies were effectively inhibiting deforestation, despite the increasing incentives to deforest because of the nature of technical change. More recent relaxation of the enforcement of the policies has allowed the accumulating deforestation incentive to be expressed as a catching-up of the rate of deforestation consistent with this technological change. When combined with the hotter, drier conditions accompanying climate change, this has resulted in a burst of deforestation. Clearly these events are evidence that the REDD+ payments of $5 per ton of CO_2 preserved are no longer high enough to reduce emissions, relative to the growing value of the agricultural production foregone.

[11] http://g1.globo.com/mato-grosso/noticia/2016/05/desmatamento-da-amazonia-legal-aumenta-190-em-mt-diz-imazon.html

[12] Information available at TerraBrasilis (http://terrabrasilis.dpi.inpe.br/app/dashboard/deforestation/biomes/legal_amazon/rates).

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FIGURES AND TABLES

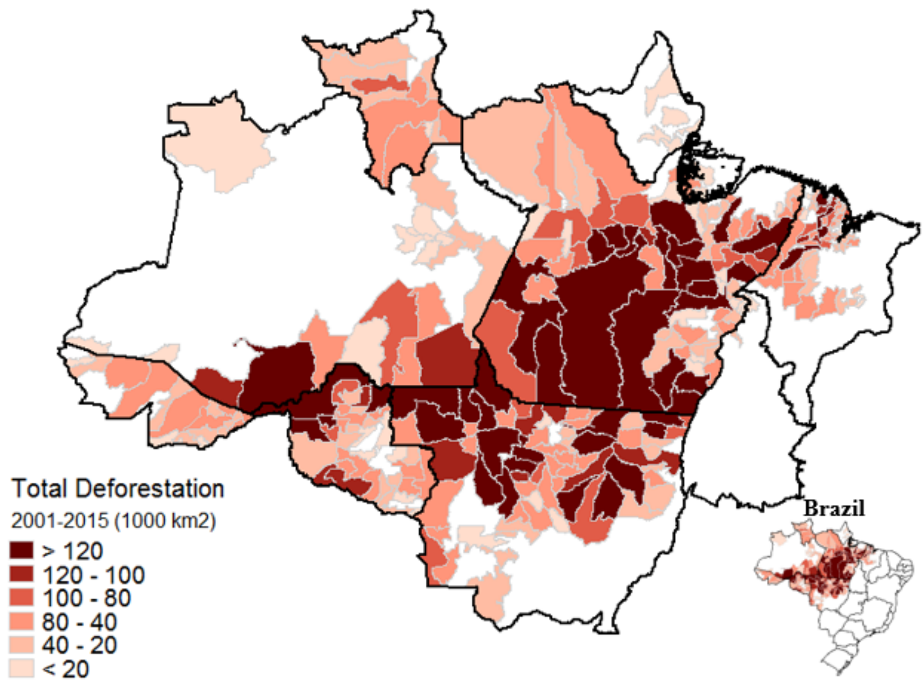

Figure 1. Total deforestation (in km^2), 2001-2015, in each of the 287 municipalities in the "arc of deforestation" in the northern region of Brazil

Note: White are municipalities not included in the estimation of equation (1). In the application section we describe how we identified the two-hundred eighty seven municipalities.
Source: Authors' estimates using Stata 14, using data obtained from the National Institute for Space Research (INPE/PRODES, 2017).

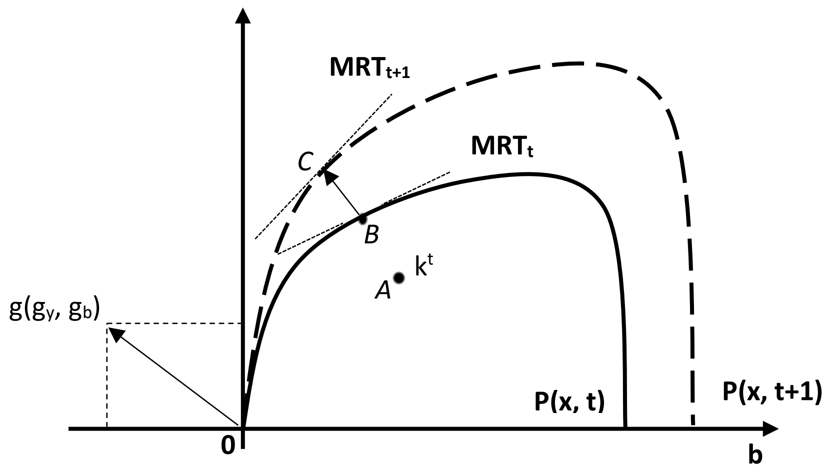

Figure 2. Output Set - *P(x)*, and directional output distance function

Table 1. Descriptive statistics for agricultural outputs, inputs and deforestation in 287 municipalities with 13,000 ha or more deforested (94% of total deforestation) in the arc of deforestation, Brazil, 2003-2015.

	Variable	Mean	Standard Deviation	Minimum	Maximum
Outputs					
Grains (tons)	y_1	69,112	275,835	0	4,584,870
Livestock (1000 liters)	y_2	5,414	8,917	0	91,953
Timber (m^3)	y_3	40,845	114,683	0	1,521,233
GHGemissions(as deforestation, in ha)	b_1	4,621	8,683	0	142,463
Inputs					
Labor (population)	x_1	43,544	126,735	1225	2,020,301
Capital (head of livestock)	x_2	167,987	203,354	0	2,282,445
Agricultural area (ha)	x_3	372,896	425,683	420	7,193,020

Source: Desirable outputs and inputs were obtained from SIDRA/IBGE and deforestation from INPE/PRODES.

Table 2. Average rate and biases of technical change in 287 municipalities with 13,000 ha or more deforested (94% of total deforestation) in the arc of deforestation, Brazil, 2003-2015.

	COLS	MLE
Rate of technical change		
Median	0.0323	0.0334
Mean	0.0491*** (0.0043)	0.0493*** (0.0042)
Bias Grains-emissions (B_{y_1,b_1})	0.1573*** (0.0029)	0.1480*** (0.0027)
Bias Livestock-emissions (B_{y_2,b_1})	0.1383*** (0.010)	0.1673*** (0.0169)
Bias Timber-emissions (B_{y_3,b_1})	0.1132*** (0.0033)	0.1055*** (0. 0035)

Note: The biases were calculated only on the estimates that satisfy monotonicity. Monotonicity for both grains and livestock was satisfied at 98%, for timber at 92%, and for emissions (deforestation) at 88% of the 3731 observations. The standard errors for the average technical change were estimated using the Delta method, *** for p-value smaller than 0.01, ** smaller than 0.05, and * smaller than 0.1.

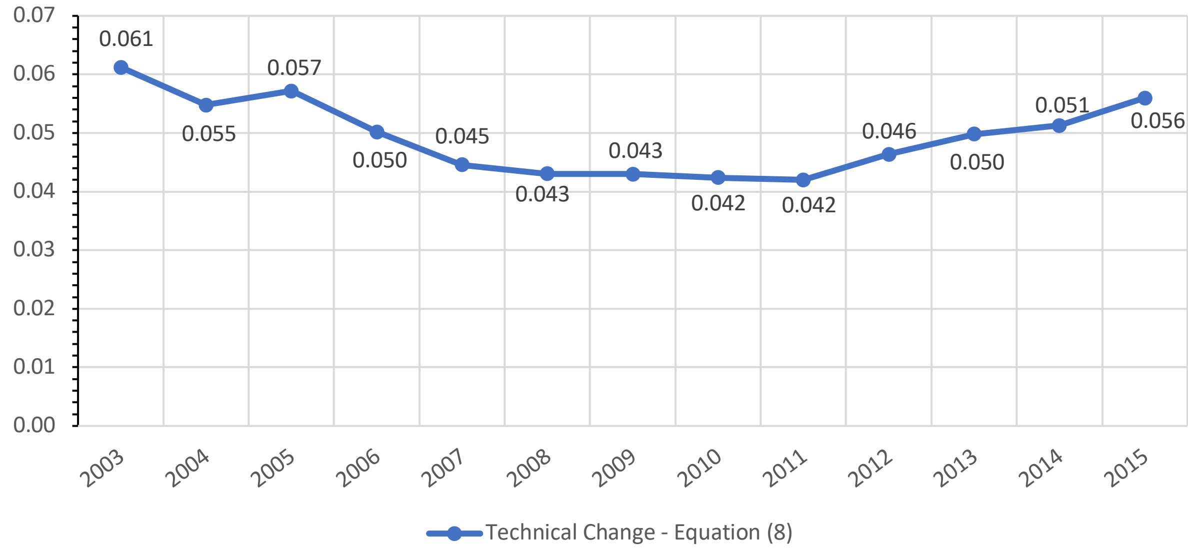

Figure 3. Average rates of technical change in the arc of deforestation, Brazil, from 2003 to 2015.

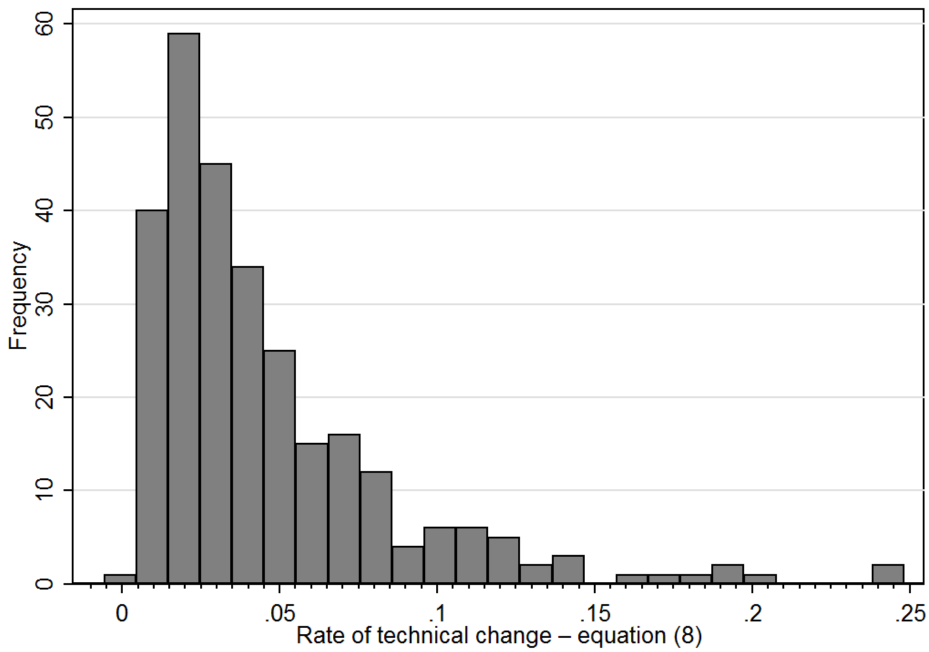

Figure 4. Histogram of average rates of technical change by municipality in the arc of deforestation, Brazil, 2003 to 2015.

Note: The top and bottom 1% of the sample were dropped to simplify the figure.

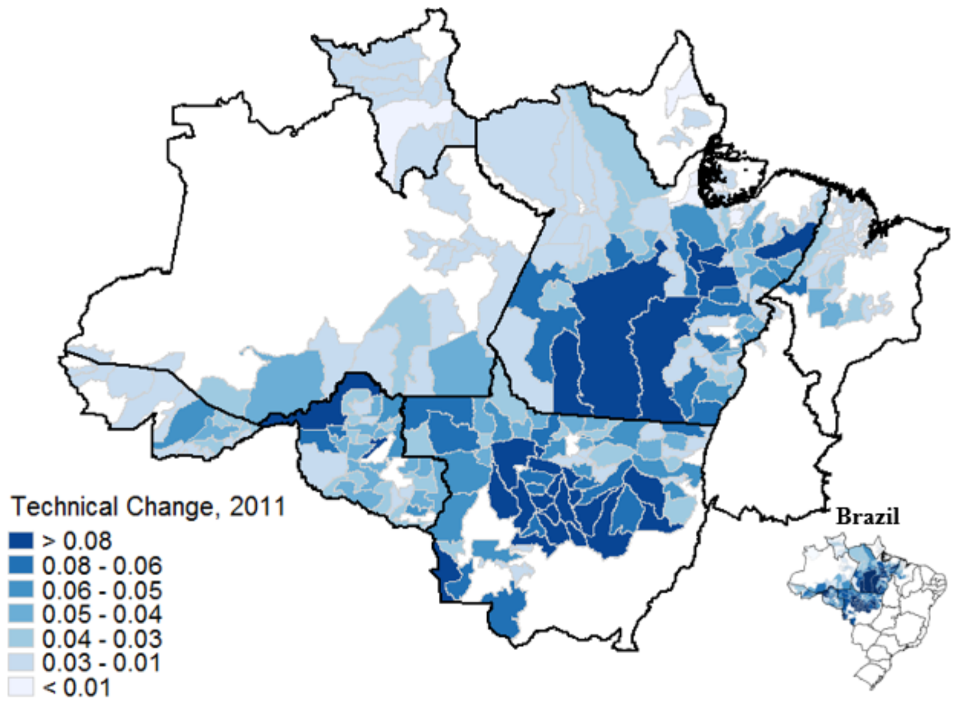

Figure 5. Average rate of technical change in 2011 by municipality in the arc of deforestation, Brazil.

APPENDIX A

Table A1. Parameter estimates for the directional distance function under alternative econometric approaches, municipalities in the arc of deforestation, Brazil, 2003-2015.

Coefficient	Variable	COLS	MLE
$\boldsymbol{\beta_1}$	y_1	-0.2401***	-0.2418***
		(0.0103)	(0.0102)
$\boldsymbol{\beta_2}$	y_2	-0.1011***	-0.0939***
		(0.0067)	(0.0065)
$\boldsymbol{\beta_3}$	y_3	-0.5326***	-0.5254***
		(0.0105)	(0.0104)
$\boldsymbol{\beta_{11}}$	y_1^2	0.0021***	0.0022***
		(0.0003)	(0.0003)
$\boldsymbol{\beta_{22}}$	y_2^2	0.0056***	0.0053***
		(0.0004)	(0.0004)
$\boldsymbol{\beta_{33}}$	y_3^2	0.0558***	0.0572***
		(0.0022)	(0.0021)
$\boldsymbol{\beta_{12}}$	y_1y_2	0.0164***	0.0170***
		(0.0013)	(0.0013)
$\boldsymbol{\beta_{13}}$	y_1y_3	-0.0401***	-0.0401***
		(0.0016)	(0.0015)
$\boldsymbol{\beta_{23}}$	y_2y_3	-0.0140***	-0.0150***
		(0.0014)	(0.0013)
$\boldsymbol{\gamma_1}$	x_1	-0.0275	-0.0156
		(0.0494)	(0.0466)
$\boldsymbol{\gamma_2}$	x_2	0.3531***	0.3776***
		(0.0389)	(0.0367)
$\boldsymbol{\gamma_3}$	x_3	0.0074	0.0069
		(0.0271)	(0.0256)
$\boldsymbol{\gamma_{11}}$	x_1x_1	0.0021*	0.0019*
		(0.0012)	(0.0011)
$\boldsymbol{\gamma_{22}}$	x_2x_2	-0.0304***	-0.0855***
		(0.0088)	(0.0147)
$\boldsymbol{\gamma_{33}}$	x_3x_3	0.0419***	0.0002
		(0.0118)	(0.0026)
$\boldsymbol{\gamma_{12}}$	x_1x_2	-0.0815***	-0.0336***
		(0.0159)	(0.0083)
$\boldsymbol{\gamma_{13}}$	x_1x_3	-0.0553***	0.0394***
		(0.0143)	(0.0116)

$\boldsymbol{\gamma_{23}}$	x_2x_3	0.0001	-0.0473***
		(0.0026	(0.0133)
$\boldsymbol{\delta_{11}}$	y_1x_1	-0.0607***	-0.0619***
		(0.0040)	(0.0038)
$\boldsymbol{\delta_{12}}$	y_1x_2	-0.0350***	-0.0328***
		(0.0054)	(0.0052)
$\boldsymbol{\delta_{13}}$	y_1x_3	0.0389***	0.0401***
		(0.0044)	(0.0042)
$\boldsymbol{\delta_{21}}$	y_2x_1	-0.0086***	-0.0070***
		(0.0013)	(0.0014)
$\boldsymbol{\delta_{22}}$	y_2x_2	0.0074***	0.0069***
		(0.0024)	(0.0023)
$\boldsymbol{\delta_{23}}$	y_2x_3	0.0008	-0.0005
		(0.0020)	(0.0018)
$\boldsymbol{\delta_{31}}$	y_3x_1	0.0597***	0.0580***
		(0.0044)	(0.0042)
$\boldsymbol{\delta_{32}}$	y_3x_2	0.0136**	0.0090*
		(0.0056)	(0.0054)
$\boldsymbol{\delta_{33}}$	y_3x_3	-0.0430***	-0.0388***
		(0.0060)	(0.0057)
$\boldsymbol{\upsilon_{1}}$	t	0.0129**	0.0016
		(0.0053)	(0.0054)
$\boldsymbol{\upsilon_{11}}$	t^2	-0.0004	0.0011*
		(0.0007)	(0.0007)
$\boldsymbol{\vartheta_{11}}$	x_1t	-0.0022**	-0.0022***
		(0.0009)	(0.0009)
$\boldsymbol{\vartheta_{21}}$	x_2t	0.0095***	0.0103***
		(0.0018)	(0.0017)
$\boldsymbol{\vartheta_{31}}$	x_3t	-0.0027*	-0.0025*
		(0.0015)	(0.0014)
$\boldsymbol{\eta_{1}}$	y_1t	0.0112***	0.0112***
		(0.0006)	(0.0006)
$\boldsymbol{\eta_{2}}$	y_2t	0.0022***	0.0023***
		(0.0005)	(0.0005)
$\boldsymbol{\eta_{3}}$	y_3t	0.0037***	0.0035***
		(0.0009)	(0.0009)
$\boldsymbol{\theta_{1}}$	b	0.1263***	0.1388***
		(0.0090)	(0.0096)

$\boldsymbol{\mu_1}$	y_1b	-0.0216***	-0.0209***
		(0.0013)	(0.0012)
$\boldsymbol{\mu_2}$	y_2b	0.0080***	0.0073***
		(0.0011)	(0.0011)
$\boldsymbol{\mu_3}$	y_3b	0.0016	0.0021*
		(0.0011)	(0.0011)
$\boldsymbol{\theta_{11}}$	bb	-0.0119***	-0.0115***
		(0.0012)	(0.0012)
$\boldsymbol{\varphi_1}$	bx_1	-0.0096***	-0.0109***
		(0.0026)	(0.0025)
$\boldsymbol{\varphi_2}$	bx_2	-0.0140***	-0.0169***
		(0.0033)	(0.0032)
$\boldsymbol{\varphi_3}$	bx_3	-0.0033	0.0008
		(0.0053)	(0.0051)
$\boldsymbol{\lambda_1}$	bt	0.0171***	0.0170***
		(0.0010)	(0.0010)
$\boldsymbol{\gamma_0}$	*Constant*	-0.2065**	-0.0774
		(0.0945)	(0.0899)
$\boldsymbol{\sigma_u}$		-	-2.7958***
			(0.1457)
$\boldsymbol{\sigma_v}$		-	-3.5791***
			(0.1033)
$\boldsymbol{\lambda_{MLE}}$		-	1.4794***
			(0.0262)

Note: COLS parameters used as starting values for MLE. Standard error in parenthesis; *** for p-value smaller than 0.01, ** smaller than 0.05, and * smaller than 0.1. The dependent variable is the negative of average deforestation. $\boldsymbol{\lambda_{MLE}}$ refers to the estimated $\boldsymbol{\sigma_u/\sigma_v}$ instead of the parameter associated with the interaction between undesirable output and time trend (Eq. 7). In the two methods, we include municipality dummies, available upon request. Parameters for deforestation, are recovered using the translation property. 3731 observations were used in these regressions.