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Farm Size and Productive Efficiency in Brazilian Amazon

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Abstract:

This paper assessed the relationship between farm size and productivity performance in Brazilian Amazon. We built two productivity indicators: technical efficiency and land use efficiency. We used Stochastic Frontier Analysis and 2006 agricultural census data to derive the efficiency measures and to assess their relationship with farm size. Results pointed out that the average Amazonian farm is productivity inefficient. The average farm could increase its agricultural production in 35.3% using the current amount of inputs. For land use efficiency, results indicate that farmers could reduce agricultural land in 90% and produce the same output using the current amount of labor and capital. Our measures of productivity presented a nonlinear relationship with farm size. However, both relations possess a similar turning point around 16,500 hectares. For policy analyses purposes, the actual relationship between farm size and productive efficiency is negative, as the turning points are far above the average farm-size in the region.

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JEL Codes: Q15, Q56

#1558

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Keywords: SFA, efficiency, land use, farm size, Brazilian Amazon

JEL codes: D24, Q15, Q56.

1. Introduction

Providing food to the growing world population – while minimizing the impacts on the environment – is a challenging task for policymakers. Population is expected to increase in 2-billion over the next four decades which together with rapid urbanization and rising incomes should increase food demand in 60% compared to the current level (FAO 2013). Supply side responses to the growing food demand can trigger a process of land use change in which agricultural land replaces native vegetation. This can have harmful effects on the provision of ecosystem services as it can affect hydrological cycles, soil conservation, climate change, and biodiversity (Rudel et al. 2005; Rudel, Schneider, and Uriarte 2010). Increases in land productivity are essential to avoid further deforestation and accommodate increasing food demand and promote forest conservation.

In this paper, we investigate the impact of farm size on land productivity in Brazilian Legal Amazon (BLA). Since Sen's (1962, 1966) seminal papers, the stylized fact of an inverse relationship between farm size and productivity is relatively well-established in developing country agriculture (Henderson 2015). The main explanations of this inverse relationship rely on labor markets failures, where labor effectiveness decreases as farm size increases (Barrett, Bellemare, and Hou 2010). Thus, as small farms are more productive than larger farms, land redistribution could increase agricultural production and decrease the need for new areas. Furthermore, land redistribution could also reduce income inequality in developing world. Despite the above-mentioned consensus, Helfand and Levine (2004) found that the inverse relationship between farm size and productivity does not hold to Brazil.

Brazilian Legal Amazon (BLA)[1] is an appealing study case regarding the rational use of land for several reasons. First, Brazil has become a major player in the world agricultural market, being the fourth producer and exporter of agricultural products nowadays (FAO 2015). Second, this position is a result of an increasing agricultural production since 1970s, which is associated to a process of land use conversion from natural vegetation to agriculture as well as to a process of technological progress. A substantial share of this land conversion

[1] BLA is a socio-economic region within Brazil created in 1950s for political purposes. It spans for nine states, covers 61% of Brazilian territory and is slight smaller than Europe. The 4 million km^2 of Brazilian Amazon lies within the 5.2 million km^2 of Brazilian Legal Amazon, the remaining is mostly cerrado biome (Homma 2008; SUDAM 2010).

took place within BLA, with average deforestation rate of 15,000 km^2 over the last two decades (INPE 2015). Thus, Brazil ranked first in deforested area during 1990s and 2000s (FAO 2010). Third, land in BLA is concentrated in large farms. About 60% of the agricultural land is concentrated in farms with more than 1000 hectares in 2006 (IBGE 2014). These large farms account for 2.4% of the number of farms in BLA. In turn, only 1.33% of the agricultural area belongs to farms with less than 10 hectares. Furthermore, the number of small farms has decreased since 1980s. For instance, 55.6% of farmers in 1985 had less than 10 hectares, while this share was 35.27% in 2006. Thus, there has been land concentration in BLA over the time.

Some studies argues that smallholding agriculture has contributed less to deforestation is some BLA locations (Pacheco 2009; Ludewigs et al. 2009). Other found that smaller farmers in BLA are likely to deforest a higher proportion of their area than larger establishments (Féres and Araujo 2013). Other analyzed the relationship of agrarian structure and technical/economic efficiency. Otsuki, Hardie, and Reis (2002) found that farms facing well-defined property rights are more efficient, leading to less deforestation. In a study of the Brazilian Midwest, an overlapped region with BLA, Helfand and Levine (2004) identified that technical efficiency presents a quadratic "U" shaped relationship with farm size. Therefore, as farm size increases, technical efficiency decreases until reaching a minimum when farm size is about 1000-2000 ha. After that, technical efficiency becomes an increasing function of farm size. Marchand (2012) investigated the relation between technical efficiency and deforestation in BLA. He found a "U" shaped effect of technical efficiency on deforestation – i.e. less and more efficient farms convert more forest into agricultural land than average efficient farms.

However, these studies fail in measuring the amount of land waste (i.e. the surplus of land used in agricultural production), as they use traditional measures of efficiency such as technical and economic efficiency. For instance, Otsuki, Hardie, and Reis (2002) argued that economic inefficient farms in BLA deforest more than efficient ones. However, they did not provide information on the amount of land that can be spared. Thus, applying technical efficiency methods could lead to a misleading conclusion regarding land efficiency, as this indicator could be associated to a misuse of other inputs than agricultural land. In turn, Marchand (2012) stated that deforestation is a measure of environmental efficiency, which could also be a misleading assumption. Reinhard, Lovell, and Thijssen (1999, 2000, 2002) and Reinhard and Thijssen (2000) demonstrated that environmental efficiency related to inputs is a relative rather than an absolute measure such as deforestation. If land is the strategic environmental input in BLA, environmental efficiency is the ratio between the minimum feasible land use to observed land use, keeping constant technology and observed levels of other inputs and output. In this paper, we undertake a non-radial approach proposed by Reinhard, Lovell, and Thijssen (1999, 2002) to overcome the above-mentioned drawback and measure land use efficiency. This method allows gauging a single input technical efficiency for a firm using multiple inputs, being useful to measure waste of natural resources. For example, Karagiannis, Tzouvelekas, and Xepapadeas (2003) used this approach to measure water waste in a sample of Greek irrigated farms.

Therefore, we aim to analyze the relation between farm size and productivity in Brazilian Amazon. We adopt two alternative measures of productivity: an input-oriented land use efficiency and an output-oriented technical efficiency. These two efficiency measures provide information about how farm-size is associated to land waste and overall input wastes, providing different policy insights. Land use efficiency relates to the amount of land that could be spared while producing the same output quantity, whilst output-oriented technical efficiency is associated to the potential increase in output. Therefore, our study presents two analyses regarding the current process of land concentration BLA: the impact on land waste and agricultural production.

This paper is organized as follows: Section 2 briefly describes the main theoretical insights regarding the inverse relation between farm-size and productivity; Section 3 presents the empirical strategy and describes the database; Section 4 presents the estimated results; and Section 5 consolidates the main conclusions and points out the policy analysis implications.

2. The Relationship between Farm Size and Productivity

The issue of farm size and land productivity has received a great deal of attention by the rural development literature. The pioneering analyses date back to the 1920s, when Chayanov noted an inverse relation between farm size and productivity during the first years of Soviet Union (Assunção and Braido 2007; Barrett, Bellemare, and Hou 2010). Nowadays, there is a relative consensus that such inverse relation is explained by market failures. Such failures prevent the market to converge to its competitive equilibrium, in which low-productivity farmers would lease or sell land to high-productivity farmers (Assunção and Braido 2007; Barrett, Bellemare, and Hou 2010). The most frequent market failures in this literature relate to dual labor market, risk aversion and supervision of hired labor.

Sen's (1962, 1966) notion of dual labor market is the first appealing baseline to explain the inverse relationship between farm size and productivity in developing countries. This framework consists in segmented labor allocation behavior between market-oriented farmers and subsistence-oriented peasants. The market-oriented farmer behaves under the traditional production maximization assumption, equalizing marginal productivity with wages. The peasant family, instead, allocates labor to maximize its subsistence, resulting in a surplus labor compared to market equilibrium. Thus, a subsistence-oriented farmer allocates more labor per unit of land than a market-oriented one. This may occur in rural areas where unpaid-family workers supply labor, there are few job opportunities, and peasants face a lower opportunity cost of labor. These two types of farms are polar cases and intermediate cases may occur in developing countries. Sen (1966) pointed out that the proportion of market-oriented farms increases with farm size. This may lead to inverse relationship between size and productivity.

Srinivasan (1972) showed that under risk-aversion and yield risk related to weather, it is optimal for a small farmer to apply more inputs per area than for a large one. Barrett (1996) highlighted the role of price risk on the inverse farm size-productivity relationship. The author observed that if farmers are risk-averse and agricultural insurance markets are absent, net buyer farmers would over-supply labor in agricultural production to avoid food scarcity related to price fluctuations in the market (i.e. reduce their market dependence). In turn, net seller farmers would under-supply labor to reduce their exposure to price fluctuations in the market. Since households in smaller farms are likely to be net buyers whilst those in lager farms are likely to be net sellers, the inverse relationship arises again.

Another explanation to the inverse relationship between farm size and productivity relies on a principal-agent problem related to hired labor (Bardhan 1973; Eswaran and Kotwal 1986; Feder 1985). According to this approach, effectiveness – or efforts – of hired workers are positively associated to supervision of family workers and to the farm size. According to this explanation, family workers always exert the maximum effort. The greater is the proportion of family workers, the greater is the effort exerted by hired workers. Furthermore, effectiveness of family supervision of hired workers decays with farm size. Larger farms are likely to have a small proportion of family works than smaller farms. Thus, moral hazard issues would provide a possible explanation the inverse farm size-productivity relationship.

3. **Empirical Strategy**

Most of the literature on farm size and land productivity in developing countries consider yields as proxy for productivity. However, Barrett (1996) observed that yields are a partial productivity measure, since it does not account for the use of other inputs. In fact, Fried, Lovell, and Schmidt (2008) pointed out that overall productivity is broadly determined by four components: production technology, scale of operation, operating efficiency, and the environment in which production occurs. Technology and scale effects on productivity are associated to the shape of the production function, which we presume to be identical across farmers. The environmental component is a random variable exogenous to the farmer. The efficiency component is a measure of the distance from the observed production to the best production possibility. This latter component could be interpreted as agents' managerial skills and it corresponds to a performance index. Thus, efficiency measures are best suitable to assess how market failures in the previous section affect agricultural performance. For example, if we use yields instead of an efficiency measure, the inverse farm size/productivity relation could arise due to decreasing returns to scale. This may not reflect the role of market failures in the inverse relationship. We assume that market failures affect the managerial skill, especially in labor effectiveness.

In our empirical application, we use two measures of efficiency: Technical Efficiency (TE) and Land Use Efficiency (LUE). TE is a measure of efficiency related to a best practice frontier. This measure may be interpreted in terms of input-oriented and output-oriented projections. The first relates to the overall excess of input used in production and the second are the rate of potential to observed production. As we are interested in measuring the surplus of land used in agriculture, we adopt the input-oriented approach to construct out LUE indicator.

Figure 1 presents a frontier isoquant for a given level of aggregated agricultural production Y_R. A farmer producing Y_R with input quantity R is out of the frontier. This farmer is technically inefficient, once he/she could produce the same amount of output by using input bundle B at the frontier.

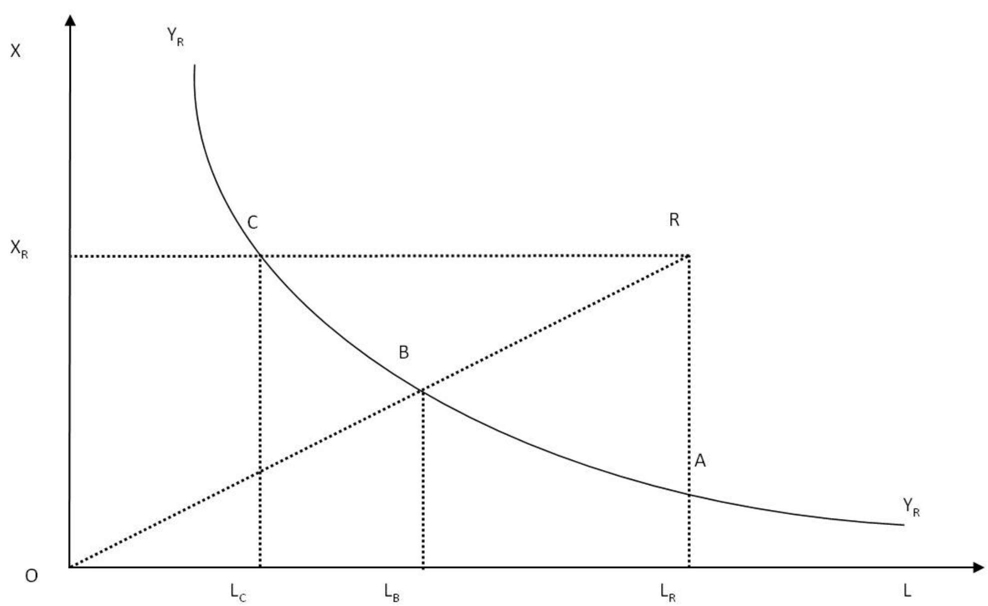

Figure 1. Production frontier for general input X, and land input (L).

LUE measures the amount of land each farm is wasting related to the best practice frontier. Reinhard, Lovell, and Thijssen (1999) built a non-radial measure to represent the amount of waste from a single input[2]. This measure consists in reducing the amount of a single input of interest while keeping the amount of other inputs and the production constant. A farmer producing an output Y_R by using an input quantity R is wasting land (L) as well as other inputs (X). This farmer could reduce the amount of land until reach the isoquant Y_R and use input bundle C. Thus, one can express LUE as

$$LUE = \min[\theta : F(X_R, \theta L_R) \geq Y_R] = |OL_C| / |OL_R| \tag{1}$$

where θ is the score of LUE; and L_R is the minimum feasible use of land, given the best practice production function $F(\bullet)$ and the observed values of output Y_R and conventional inputs X_R.

A technical efficient farmer is also land use efficient, as he/she is at the frontier. However, as Reinhard, Lovell, and Thijssen (1999) pointed out, these two measures may not be the same when farmers are not technical efficient.

We are also interested in a measure of TE to compare with LUE results and test the inverse relation. An output-oriented TE measure for a single input is illustrated Figure 2. A farmer using input X_R and producing Y_R is inefficient. He/she could increase output to Y^F at the frontier using the same amount of input X. Thus, one could express TE as

$$TE = \{\max[\phi : \phi Y_r \leq F(X_r)]\}^{-1} = |OY_R| / |OY^F| \tag{2}$$

where ϕ is the score of $F(\bullet)$ is a production function at the frontier, representing the best practice regarding the use of a given inputs vector X_r; and Y_r is the observed value of output.

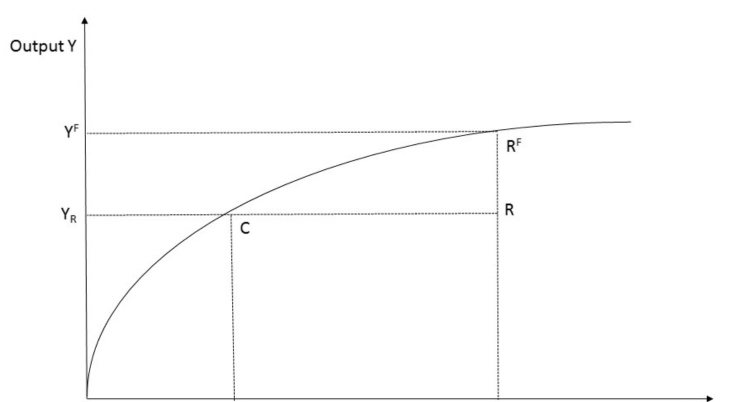

Figure 2. Production frontier in output (Y) and a single input (X).

3.1. TE and LUE Estimation

There are several approaches to estimating an efficiency index (Kalirajan and Shand 1999; Murillo-Zamorano 2004). In our empirical application, we adopt the Stochastic Frontier

[2] Reinhard, Lovell, and Thijssen (1999) created this measure to account for detrimental inputs. We adapted their approach to account for land surplus in agriculture.

Analysis (SFA) (Aigner, Lovell, and Schmidt 1977; Meeusen and van den Broeck 1977). SFA is a parametric technique with some advantages over other parametric and non-parametric techniques. First, it accounts for random variables such as weather and pests in agriculture production. Second, it presents the estimation of the production frontier, rather than a linear approximation. These two features make SFA preferable to alternative approaches like Data Envelopment Analysis (DEA) as the latter do not consider the role of random variables. Furthermore, the frontier in DEA is a piecewise linear approximation of the true frontier. Thus, this procedure tends to overstate efficiency scores and the number of efficient observations. In fact, Bravo-Ureta et al. (2007) found that DEA produces greater efficiency scores than SFA in empirical studies.

According to Greene (2008), a Maximum Likelihood estimation of a production frontier can be derived from the following expression

$$Y_i = F(L_i, X_i; \beta) \times \exp\{V_i - U_i\} \tag{3}$$

where Y_i is the aggregated output produced by farm i; L_i is the amount of agricultural land; X_i is a vector of inputs quantities; β is a vector of parameters; V_i is the error term, independently and identically distributed as $N(0, \sigma_v^2)$; U_i is a nonnegative error term, independently and identically distributed, that measures output-oriented TE. We consider that U_i could present the half-normal or an exponential distribution.

Rearranging (3), one could express TE as

$$TE = \frac{Y_i}{F(L_i, X_i; \beta) \times \exp\{V_i\}} = \exp\{-U_i\} \tag{4}$$

If $U_i \geq 0$, thus $0 < \exp\{-U_i\} \leq 1$. When $\exp\{-U_i\} < 1$, the farm is below the frontier (i.e. is inefficient). If $\exp\{-U_i\} = 1$, the farm is efficient and lies at the frontier. To estimate TE efficiency, we chose the TE estimator proposed by Battese and Coelli (1988). According to Murillo-Zamorano (2004, 49), this estimator is preferred to alternative approaches when U_i is not close to zero

We parametrize $F(\bullet)$ by using a translog specification

$$\begin{aligned} \ln Y_i = \beta_0 &+ \sum_k \beta_k \ln X_{ik} + \beta_L \ln L_i + \frac{1}{2}\sum_k \sum_r \beta_{kr} \ln X_{ik} \ln X_{ir} \\ &+ \sum_k \beta_{Lk} \ln L_i \ln X_{ik} + \frac{1}{2}\sum_k \sum_r \beta_{LL} (\ln L_i)^2 + V_i - U_i \end{aligned} \tag{5}$$

The translog specification is characterized as a flexible functional form, since the elasticity of substitution may vary across inputs. It is a continuous and twice differentiable function and monotonicity is verified locally. The specification also assumes symmetry in parameter for interacted variables ($\beta_{kr} = \beta_{rk}$).

A farmer is technically efficient if $U_i = 0$ in expression (5). Thus, one can express the production function of an efficient farm as

$$\begin{aligned} \ln Y_i = \beta_0 &+ \sum_k \beta_k \ln X_{ik} + \beta_L \ln L_i^F + \frac{1}{2}\sum_k \sum_r \beta_{kr} \ln X_{ik} \ln X_{ir} \\ &+ \sum_k \beta_{Lk} \ln L_i^F \ln X_{ik} + \frac{1}{2}\sum_k \sum_r \beta_{LL} \left(\ln L_i^F\right)^2 + V_i \end{aligned} \tag{6}$$

Assuming that $\ln LUE = \ln L_i^F - \ln L_i$, and equaling expressions (5) and (6), Reinhard, Lovell, and Thijssen (1999) showed that

$$\ln LUE = \left(-\varepsilon_L \pm \sqrt{\varepsilon_L{}^2 - 2\beta_{LL} U_i} \right) \Big/ \beta_{LL} \qquad (7)$$

where ε_L is the output elasticity with respect to land, which is expressed as $\partial \ln Y_i / \partial \ln L_i = \beta_L + \sum_k \beta_{Lk} \ln X_{ik} + \beta_{LL} \ln L_i$.

LUE score is calculated by the antilog of expression (7) using the positive square root. Reinhard, Lovell, and Thijssen (1999) explained that the technical efficient farm is also land use efficient. Hence, $U_i = 0 \Rightarrow \ln LUE = 0$ only if we consider the positive square root. It is noteworthy that $\ln LUE$ exists only if $\beta_{LL} < 0$ or $\beta_{LL} > 0$ and $|\varepsilon_L|$ is sufficiently large (Reinhard, Lovell, and Thijssen 1999).

3.2. Explaining LUE and TE

The so-called second-stage of efficiency analysis allows identifying the sources of efficiency. Kumbhakar and Lovell (2003) highlighted that this stage is important to capture the role of exogenous variables on production other than the inputs. These sources are associated to managerial skills, land tenure, competitive pressure, information availability, input quality, etc. In our study, the theoretical framework in section 2 assumes that farm-size is associated to labor input quality, information availability and managerial skills.

We adopt the approach proposed by Reinhard, Lovell, and Thijssen (2002) to obtain the relationship between farm-size and LUE, that consists in the ML estimation of the following stochastic frontier in the second-stage

$$\ln LUE_i = H(Z_i;\gamma).\exp\{V_i^* - U_i^*\} \qquad (8)$$

where Z_i is the exogenous variables related to farm i that explain LUE; γ is a vector of parameters; V_i^* is the error term, independently and identically distributed as $N(0, \sigma_{v*}^2)$; U_i^* is a nonnegative error term, independently and identically distributed, which is a residual measure of LUE.

The approach proposed by Reinhard, Lovell, and Thijssen (2002) presents advantages to alternative estimation methods. First, alternative methods assume that exogenous variables explain all efficiency heterogeneity among firms. Reinhard, Lovell, and Thijssen (2002) argue that the exogenous variables partly explain efficiency, and their proposed approach provides a better economic intuitive explanation. Expression (8) provides parameters estimates related to a function of explanatory variables observed by the analyst. Notwithstanding, it is likely to remain inefficiencies related to unobserved factors. These factors are represented in U_i^*. Second, Reinhard, Lovell, and Thijssen (2002) procedure is better from a statistical perspective, once it provides better estimations for the second-stage in presence of a composite error term $V_i^* - U_i^*$. For example, OLS estimates are biased and inconsistent if the real disturbance term is $V_i^* - U_i^*$ instead of V_i^*.

The main approach to explain technical efficiency is the estimation of a second-stage similar to expression (8), where U_i is regressed on the exogenous variables Z_i. However, some studies pointed out that this procedure is inappropriate because U_i is an independent and identically distributed variable (Battese and Coelli 1995; Fried, Lovell, and Schmidt 2008). Hence, parameter estimates of exogenous variables are inconsistent[3].

To overcome above-mentioned drawback, Fried, Lovell, and Schmidt (2008) suggested that the equation of TE determinants should be estimated jointly with the production function in a single-stage framework. They proposed the following estimation procedure by ML

$$Y_i = F(L_i, X_i; \beta) \times \exp\{V_i - U_i(Z_i; \alpha)\} \tag{9}$$

where $F(\bullet)$ is the translog given (5); Z_i is the vector of exogenous variables that explain technical inefficiency; and α is a vector of parameters. According to Fried, Lovell and Schmidt (2008), such procedure ensures consistent estimations. To deal with potential spatial autocorrelation, we bootstrap the errors in (3), (8), and (9) with 100 replications clustered by municipality.

3.3. Variables and Data

Most of our data come from Brazilian Agricultural Census of 2006 provided by the Brazilian Institute of Geographic and Statistics (*Instituto Brasileiro de Geografia e Estatística* – IBGE). IBGE provides Agricultural Census data on municipal level segmented into five land tenure groups (owner, sharecropper, renter, occupant and farmers recently granted in land reform (less than five years)) and eleven farm-size groups. We created representative farms from averages of each group formed from a municipality "i", land tenure "j" and farm size group "k". Thus, each municipality could present up to 55 of these representative farms.

Output is measured by the value of agricultural production expressed in Brazilian currency *real.* We construct this variable as a residual procedure, by subtracting the value of extractive, forestry and rural industry production from total production value. As extractive and forestry products are from stand forest and rural industry uses less land than agricultural production, we assume that the output variable measures the production that takes place in deforested areas in BLA.

We consider that farmers in BLA use three fixed inputs: agricultural land, labor and capital. Agricultural land is the total area of the representative farm less areas with buildings, covered with water, unsuitable to agriculture, natural forests, and planted forests. The proxy for labor is a variable created by IBGE that corresponds to an adult working eight hours per day, 260 days per year. Capital is the declared value in *reais* of machines and improvements (mainly buildings).

Some variables in the second-stage are also extracted from the 2006 Agricultural Census. Farm-size is the area of the establishment, including agricultural land, forests, buildings, covered with water, and unsuitable to agriculture. As our observations refer to a single year, we add some variables to control heterogeneity among representative farms. The first set of controls is dummy variables representing the tenure structure groups: owners, sharecropper, renter, occupant and farmers recently granted in land reform. The second set of variables refers to output composition. We calculated the share of output value related to cattle, permanent crops, temporary crops and other activities such as horticulture, dairy, poultry, etc. We excluded cattle proportion and expose results relative to this activity. The third set of control variables correspond to social and demographic-related characteristics. These are the proportion of farms within a group with the following features: managed by

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[3] It should be remarked that this is not a problem to estimate the sources of $\ln LUE$ in (8), as it is calculated from estimated parameters that describes the structure technology and the one-sided error component (Karagiannis, Tzouvelekas, and Xepapadeas 2003; Reinhard, Lovell, and Thijssen 2002).

women, the manager is younger than 25, the manager is older than 55, the manager has more than ten years of experience in agriculture, the manager studied less than eight years.

To control for institutions, we used a dataset provided by Catholic Pastoral Land Commission for 2005. These variables include the number of rural conflicts per municipality, the number of murders and murders attempts related to land per municipality and the number of farms caught with slavery and poor work conditions per municipality. Finally, the last set of variables represents agronomic features such as soil, topography, and latitude. The first two variables are the percentage of the municipality area covered by eight soil and five topography classes. These classes range to less suitable to more suitable to agriculture. The reference for soil is soil class 1 and the reference for topography is topography class 2[4]. Soil and topography data were provided by Center for Studies and Spatial Systemic Models (*Núcleo de Estudos e Modelos Espaciais Sistêmicos* - NEMESIS). The variable latitude controls for the incidence of solar radiation and other geographic related factors. This variable is the absolute latitude of municipalities centroids provided by IBGE.

After discarding missing values, our data set covered 1,287,358 farms aggregated into 5564 representative farms. Table 1 presents summary statistics of all variables used in this paper. We applied the natural logarithm to output and input variables to estimate the translog production function. We add quadratic term to farm-size in efficiency equations to capture non-linearities.

Table 1. Descriptive statistics of variables of interest in BLA

	mean	sd	cv	min	max
Output	37725.81	601516.93	15.94	3.32	26677700.00
Land	148.87	737.54	4.95	0.00	17544.00
Labor	1.40	2.95	2.11	0.74	121.80
Capital	74486.60	628561.13	8.44	0.91	24680400.00
Size	256.66	1355.48	5.28	0.01	33329.83
Owner	0.79	0.41	0.52	0.00	1.00
Settled	0.10	0.29	3.08	0.00	1.00
Renter	0.02	0.14	6.85	0.00	1.00
Sharecropper	0.01	0.10	10.30	0.00	1.00
Occupant	0.09	0.28	3.27	0.00	1.00
Cattle	0.35	0.31	0.89	0.00	1.00
Permanent crops	0.09	0.19	2.13	0.00	1.00
Temporary crops	0.29	0.31	1.05	0.00	1.00
Other	0.26	0.28	1.08	0.00	1.00
Education	0.30	0.11	0.35	0.00	1.00
Experience	0.19	0.10	0.55	0.00	1.00
Woman	0.03	0.04	1.04	0.00	0.40
Young than 25	0.01	0.02	1.54	0.00	0.40
Older than 55	0.13	0.08	0.57	0.00	1.00
Conflicts	0.76	1.75	2.30	0.00	15.00
Slavery/Poor work conditions	0.61	2.06	3.36	0.00	20.00
Murder/Attempts	0.08	0.47	5.76	0.00	5.00
Latitude	8.31	4.43	0.53	0.03	17.83
% soil type 1	5.43	18.25	3.36	0.00	100.00
% soil type 2	4.28	17.26	4.03	0.00	100.00
% soil type 3	2.74	12.74	4.65	0.00	100.00
% soil type 4	45.79	38.85	0.85	0.00	100.00
% soil type 5	1.80	10.92	6.08	0.00	99.42
% soil type 6	4.76	17.35	3.65	0.00	100.00
% soil type 7	0.43	4.23	9.92	0.00	72.04
% soil type 8	34.77	37.96	1.09	0.00	100.00
% topography type 2	34.77	37.96	1.09	0.00	100.00
% topography type 3	4.35	16.99	3.90	0.00	100.00
% topography type 4	58.71	38.17	0.65	0.00	100.00
% topography type 5	1.75	10.91	6.22	0.00	99.42

sd – standard deviations; cv – coefficient of variation; min – minimum; max – maximum.

[4] We did not use topography 1 in estimations because it is rare class within Amazon, which leaded to multicolinearity.

4. Results

Results of the first-stage are presented in Table 2. Specifications differ according to the statistical distribution assumed for TE (Half-normal and Exponential) and the presence of state dummies. The translog functions in Table 2 differ from the proposed specification in expression (6). The coefficient of land squared was not significant at 10% when we estimated the full translog specification as in (6) (i.e. with inputs interactions)[5]. This coefficient is a necessary condition to calculate land use efficiency. Thus, we opted to the specification in Table 2 in order to enable the proposed analysis.

Table 2. Estimation of technical efficiency with special case of translog production function for BLA in 2006

	(1)	(2)	(3)	(4)
Land	0.129^{***}	0.141^{***}	0.127^{***}	0.138^{***}
	(0.0132)	(0.0163)	(0.0135)	(0.0137)
Labor	0.830^{***}	0.813^{***}	0.842^{***}	0.823^{***}
	(0.144)	(0.0872)	(0.144)	(0.149)
Capital	-0.297^{***}	-0.289^{***}	-0.346^{***}	-0.344^{***}
	(0.0918)	(0.107)	(0.108)	(0.105)
Land^2	-0.0317^{***}	-0.0318^{***}	-0.0311^{***}	-0.0308^{***}
	(0.00853)	(0.00968)	(0.00863)	(0.00862)
Labor^2	0.0390	0.0403	0.0309	0.0325
	(0.108)	(0.0685)	(0.104)	(0.104)
Capital^2	0.0694^{***}	0.0672^{***}	0.0755^{***}	0.0741^{***}
	(0.0121)	(0.0137)	(0.0142)	(0.0138)
Constant	7.478^{***}	7.386^{***}	7.997^{***}	7.940^{***}
	(0.354)	(0.465)	(0.505)	(0.481)
AIC	16500.8	16420.7	16497.7	16413.6
BIC	16560.4	16533.3	16557.3	16526.2
TE distribution	Half-normal	Half-normal	Exponential	Exponential
State FE	no	yes	no	yes
Lambda	0.00709	0.00599	0.342^{***}	0.371^{***}

Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Coefficient estimates in Table 2 are quite robust, with little variation across the distinct specifications. Statistical significance of the lambda parameter in columns 3 and 4 indicates that exponential distribution captures the inefficiency in agricultural production in BLA. According to Aigner, Lovell and Schmidt (1977), lambda is the ratio of standard deviation of U_i and V_i. When lambda is statically different from zero, the inefficiency term U_i is relevant to explain agricultural production. In addition to that, bayesian (BIC) and Akaike (AIC) information criteria indicate that column 4 provides the most adequate specification. Therefore, we use the specification in column 4 to develop our analysis.

Table 3 presents results regarding elasticities of production, returns to scale and technical and land use efficiencies. We build these indicators for each representative farm weighted by the number of observation within the group. Elasticities indicate that agricultural production in BLA is more sensitive to labor variations than capital and land. In average, 1% increase in land endowment will lead to a 0.08% increase in agricultural output. In general, land has low elasticities and about 7.3% of farms in BLA present negative elasticities of production, violating theoretical assumptions. Labor elasticity of production is constant in BLA, as coefficient of labor squared is not statistically significant at 10%. This higher value indicates that production in BLA would greatly increase if farmers allocate more labor units in production. Capital elasticity is negative for 2.5% of BLA farms. For the average farm, an

[5] See Table A1 in appendix.

increase in capital endowment in 1% leads to an increase in 0.26% in agricultural production. Summary statistics for returns to scale indicates that he average farm in BLA operates with increasing returns. In fact, about 95% of BLA farms present increasing returns to scale. This result agrees with Marchand's (2012) results, which also found increasing returns to scale in BLA utilizing data from 1995/1996 Brazilian Agricultural Census.

Table 3. Elasticities of production, returns to scale, technical and land use efficiencies in BLA[6]

	mean	sd	min	max
Land	0.080	0.061	-0.163	0.391
Labor	0.823	0.000	0.823	0.823
Capital	0.259	0.120	-0.351	0.918
Returns to scale	1.162	0.091	0.543	1.658
TE	0.739	0.051	0.061	0.900
LUE	0.096	0.080	0.000	0.598

Table 3 also reports summary statistics for technical efficiency (TE) and land use efficiency (LUE). These two efficiency scores present a Spearman rank correlation of 0.3228 and the null hypothesis that theses efficiency scores are not correlated is rejected at 1%. Albeit the correlation is positive and significant, it has a low value. Therefore, Otsuki, Hardie, and Reis (2002) conclusions regarding efficiency and deforestation may not hold for BLA, as TE is not a good measure of land use waste.

Average technical efficiency means that the actual agricultural production in BLA represents 73.9% of its potential. This means that the average BLA farm could increase its agricultural production in 35.3% using the current amount of inputs. Land use efficiency is much lower than technical efficiency. The average LUE value means that BLA farmers could reduce agricultural land in 90.4% and produce the same output using the current amount of labor and capital. In general, studies using this methodology have found smaller values for non-radial efficiency (like LUE) compared to technical efficiency scores (Karagiannis, Tzouvelekas, and Xepapadeas 2003; Reinhard, Lovell, and Thijssen 1999). Nevertheless, our findings are quite low in comparison to literature. We attribute this low LUE to the also low land elasticity of production, which enters directly in LUE formula in expression (7). This finding partly agrees with Ferreira Filho, Ribera, and Horridge (2015) study for Brazil. Using a General Equilibrium model, these authors have found that the reduction of agricultural land related to a slowing or halt in deforestation would have a minimum negative impact on agriculture output growth in the period 2005-2025. They argued that the reduced land supply leads to an effective use of the existing land. Our results confirm their conclusion, as a great extent of land is far below its effective use in BLA.

The estimated relationship between farm-size and LUE is in Table 4. The results in Table 4 refer to land use inefficiency expressed in equation (8) ($-\ln LUE_i$). Thus, a variable that is positively associated to land use inefficiency is negatively associated to LUE. We proceed this way to compare results of LUE and TE sources, as the latter is by definition for technical inefficiency ($-U_i(Z_i;\alpha)$). We successively add group of controls in each column to check robustness of farm-size and LUE relationship. Column 1 considers only farm-size as explanatory variables. We add land tenure dummies in column 2, composition of output in column 3, demographic variables in column 4, institutions in column 5, and agronomic variables in column 6. We suppressed results for agronomic variables to save space. The coefficients of lambda are significant at 1% in all specifications. Thus, farm-size and controls

[6] We weighted summary statistics by the number of respondents. Alternative results for a full translog specification are in Table A2.

are not sufficient to explain the whole land use inefficiency in BLA, and U_i^* is relevant to explain LUE. The results in Table 4 have exponential distribution for U_i^*, as it was the distribution utilized to calculate TE and LUE.

Overall, results for farm-size are robust to the six specifications. Coefficients of farm-size decay as we introduce controls. However, the signs and statistical significance do not change across specifications. Therefore, there is an inverse "U" relationship between farm-size and land use inefficiency. The farm-size at the point of maximum is about 16,400 hectares in all 6 specifications. For farm-size smaller that this number, land use inefficiency increases (LUE decreases) as farm-size increases. Land use inefficiency is a decreasing function of farm-size for values greater than 16,400 hectares. For policy analysis purposes, results indicate that the prevailing farm-size/LUE relationship is negative, as the bulk of farmers in BLA is far smaller than 16,400 hectares. Therefore, the current land concentration process will diminish LUE in BLA.

Table 4. Regression results for the sources of land use inefficiency in BLA

	(1)	(2)	(3)	(4)	(5)	(6)
Farm size						
Size	0.00334***	0.00320***	0.00332***	0.00293***	0.00292***	0.00290***
	(0.000275)	(0.000275)	(0.000234)	(0.000270)	(0.000268)	(0.000275)
Size^2	-1.02e-08***	-9.80e-08***	-9.98e-08***	-8.93e-08***	-8.90e-08***	-8.84e-08***
	(1.61e-08)	(1.58e-08)	(1.52e-08)	(1.51e-08)	(1.50e-08)	(1.51e-08)
Land tenure						
Settled		-0.247***	-0.238***	0.0412	0.0344	0.0269
		(0.0683)	(0.0639)	(0.0727)	(0.0725)	(0.0720)
Renter		-0.0580	0.238	0.280	0.267	0.244
		(0.362)	(0.314)	(0.282)	(0.256)	(0.253)
Sharecropper		-1.217***	-0.424***	-0.308***	-0.295***	-0.269***
		(0.0992)	(0.0838)	(0.0876)	(0.0884)	(0.0899)
Occupant		-0.616***	-0.341***	-0.267***	-0.268***	-0.254***
		(0.0752)	(0.0653)	(0.0713)	(0.0709)	(0.0682)
Composition of output						
Permanent crops			-2.016***	-1.925***	-1.912***	-1.859***
			(0.0999)	(0.0918)	(0.0881)	(0.0933)
Temporary crops			-1.524***	-1.444***	-1.436***	-1.434***
			(0.0727)	(0.0678)	(0.0672)	(0.0708)
Other			-0.952***	-0.762***	-0.746***	-0.725***
			(0.107)	(0.104)	(0.101)	(0.109)
Demographics						
Education				-1.814***	-1.841***	-1.886***
				(0.293)	(0.291)	(0.306)
Experience				1.799***	1.859***	1.948***
				(0.260)	(0.269)	(0.285)
Women				-6.809***	-6.811***	-6.790***
				(0.692)	(0.695)	(0.704)
Younger than 25				4.223***	4.236***	4.404***
				(1.127)	(1.140)	(1.147)
Older than 55				1.153***	1.170***	0.948**
				(0.372)	(0.373)	(0.380)
Institutions						
Conflicts					0.0341**	0.0296**
					(0.0135)	(0.0135)
Slavery					0.0129	0.0104
					(0.0166)	(0.0184)
Murders					-0.0750	-0.0797
					(0.0599)	(0.0626)
Constant	3.659***	3.747***	4.546***	4.646***	4.606***	-37.66
	(0.0507)	(0.0547)	(0.0710)	(0.101)	(0.0935)	(65.61)
Lambda	0.885***	0.861***	0.952***	0.870***	0.869***	0.868***

Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Coefficients for sharecroppers and occupant dummies decay substantially as we introduce controls. Nonetheless, their signs and statistical significance do not change. This land tenure classes are more land use efficient than owners. This is an unexpected result for occupant farmers and other studies have found a different relation. For instance, Mendelsohn's

(1994) theoretical model pointed out that landowner without titles tend to perform a less sustainable economic activity than a titled owner. Otsuki, Hardie and Reis (2002) and Helfand and Levine (2004) found a negative relationship between occupant and technical efficiency. All classes of composition of output are more land use efficient than cattle. Farmers with higher education and farms managed by woman are more land use efficient. Manager experience is negatively associated to LUE. Older and younger farmers are less land use efficient than middle-aged farmers. Finally, farmers in municipalities with a higher incidence of rural conflicts present smaller LUE.

Results for TE efficiency are in Table 5 and were calculated using expression (9). We estimated six specifications to check coefficient robustness, as we proceed for LUE. Coefficients in the second equation explain technical inefficiency as we estimated the $-U_i(Z_i;\alpha)$ function. Thus, a negative sign indicates that a variable is positively associated to TE. Results for farm-size are again robust to specifications. There is an inverse "U" relationship between farm-size and technical inefficiency. The point of maximum is very close to the results for land use inefficiency, about 16,600 hectares. Thus, technical inefficiency is an increasing function of farm-size for values smaller than 16,600 hectares, and a decreasing function of farm-size for greater values. Notwithstanding, there is a negative relation between farm-size and TE for policy analysis purposes, as an increase in the present values of farm-size will lead to less agricultural production in BLA. Unlike the results for LUE, our results do not show a comprehensive relation between TE and other variables.

Table 5. Regression results for the sources of technical inefficiency in BLA

	(1)	(2)	(3)	(4)	(5)	(6)
Farm size						
Size	0.627^{***}	0.625^{***}	0.619^{***}	0.602^{***}	0.601^{***}	0.579^{***}
	(0.0626)	(0.0603)	(0.00236)	(0.0845)	(0.0842)	(0.00590)
Size^2	$-1.88e-05^{***}$	$-1.87e-05^{***}$	$-1.86e-05^{***}$	$-1.81e-05^{***}$	$-1.80e-05^{***}$	$-1.74e-05^{***}$
	(2.90e-06)	(2.84e-06)	(2.04e-06)	(3.34e-06)	(3.33e-06)	(1.90e-06)
Land tenure						
Settled		0.174	0.221	0.322^{*}	0.249	-0.335
		(0.401)	(0.335)	(0.166)	(0.158)	(1.780)
Renter		0.0751	0.125	0.168^{*}	0.155	-0.150
		(0.438)	(0.250)	(0.0934)	(0.0962)	(3.881)
Sharecropper		0.278	0.290^{**}	0.261	0.304	1.688
		(0.254)	(0.114)	(0.180)	(0.199)	(2.402)
Occupant		0.241^{***}	0.273^{***}	0.266^{***}	0.306^{***}	0.424
		(0.0486)	(0.0581)	(0.0996)	(0.107)	(1.191)
Composition of output						
Permanent crops			0.221	0.336	0.344	0.506
			(0.279)	(0.804)	(0.827)	(1.695)
Temporary crops			0.0195	0.184	0.138	-0.428
			(0.487)	(0.654)	(0.652)	(1.090)
Other			0.184	0.244^{*}	0.292^{**}	1.037
			(0.201)	(0.128)	(0.137)	(0.747)
Demographics						
Education				0.295	0.167	-0.340
				(0.442)	(0.411)	(1.436)
Experience				-0.0393	-0.612	-5.509
				(1.211)	(1.182)	(4.803)
Women				0.856	1.428	7.111
				(1.303)	(1.475)	(6.703)
Younger than 25				-0.257	-0.584	-6.904
				(1.095)	(1.086)	(6.482)
Older than 55				0.0781	-0.371	-2.905
				(1.009)	(1.016)	(4.313)
Institutions						
Conflicts					0.131	-0.0563
					(0.103)	(0.295)
Slavery					0.106	-0.0594
					(0.128)	(0.427)
Murders					0.0461	0.107
					(0.242)	(1.554)
Constant	0.0353	0.0284	0.113	0.256^{*}	0.189	-0.143
	(0.468)	(0.602)	(0.437)	(0.155)	(0.151)	(0.681)

Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

5. Conclusion

This paper investigated the relationship between farm size technical efficiency in Brazilian Legal Amazon. Our results indicate that TE is not a good indicator to gauge land waste in BLA. Thus, the statement that a lower TE fosters deforestation is not necessarily true. We also found that land is inefficiently used in BLA, and an expressive reduction in land would not necessary decrease agricultural production in the region. Hence, there is no need to convert forest into agricultural land to increase agricultural production in the future. Furthermore, the historically process of deforestation would be avoided if farmers used land in an efficient way in the region.

Our measures of productivity, TE and LUE, presented a nonlinear relationship with farm size. However, we did not rule out the inverse relationship between farm size and productivity. Both relations possess a similar turning point around 16,500 hectares. For policy analyses purposes, the actual relationship is the inverse as the turning points are far above the average farm-size in the region. Thus, the current trend of land concentration in BLA will lead to worse environmental and economic scenarios. More land will be wasted as the farms become larger. Furthermore, agriculture supply side responses to the growing future demand will come from conversion of natural vegetation into agricultural uses.

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APPENDIX

Table A1. Estimation of technical efficiency with full translog production function for BLA in 2006

	(1)	(2)	(3)	(4)
Frontier				
Land	0.270***	0.268***	0.279***	0.274***
	(0.0849)	(0.0755)	(0.0856)	(0.0830)
Labor	0.482	0.503	0.273	0.277
	(0.651)	(0.667)	(0.673)	(0.663)
Capital	-0.367***	-0.351***	-0.420***	-0.404***
	(0.116)	(0.111)	(0.129)	(0.125)
Land^2	-0.00365	-0.00402	-0.00137	-0.00172
	(0.00942)	(0.00915)	(0.00945)	(0.00934)
Labor^2	0.226	0.240	0.188	0.200
	(0.214)	(0.212)	(0.221)	(0.211)
Capital^2	0.0812***	0.0773***	0.0880***	0.0841***
	(0.0163)	(0.0152)	(0.0180)	(0.0173)
Land*Labor	-0.177**	-0.184**	-0.194**	-0.201**
	(0.0837)	(0.0819)	(0.0849)	(0.0832)
Land*Capital	-0.0206*	-0.0188*	-0.0221**	-0.0200*
	(0.0110)	(0.00983)	(0.0111)	(0.0109)
Labor*Capital	0.105	0.104	0.135	0.135
	(0.0818)	(0.0824)	(0.0856)	(0.0836)
Constant	7.629***	7.556***	8.183***	8.108***
	(0.434)	(0.428)	(0.515)	(0.496)
AIC	16465.0	16384.3	16457.5	16373.3
BIC	16544.5	16516.8	16537.0	16505.7
TE distribution	Half-normal	Half-normal	Exponential	Exponential
State FE	no	yes	no	yes
Lambda	0.00592	0.00758	0.371***	0.390***

Standard errors in parentheses: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A2. Elasticities of production, returns to scale, technical and land use efficiencies for the full translog specification for BLA in 2006[7]

	mean	sd	min	max
Land	0.101	0.069	-1.026	0.292

[7] We weighted summary statistics by the number of respondents. We used all coefficients in

APPENDIX

Table A1 to construct the indicators.

Labor	1.004	0.288	-0.505	2.802
Capital	0.247	0.131	-0.469	1.397
Returns to scale	1.352	0.323	-0.525	3.263
TE	0.732	0.054	0.040	0.900
LUE	0.079	0.069	0.000	0.489