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Agricultural Economics 31 (2004) 241–249
AGRICULTURAL ECONOMICS
www.elsevier.com/locate/agecon

Farm size and the determinants of productive efficiency in the Brazilian Center-West

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Abstract

This paper explores the determinants of technical efficiency, and the relationship between farm size and efficiency, in the Center-West of Brazil. This is the region where agricultural production and total factor productivity have grown the fastest since 1970. It is also a region characterised by unusually large farms. Technical efficiency is studied with Data Envelopment Analysis and county level data disaggregated by farm size and type of land tenure. The efficiency measure is regressed on a set of explanatory variables which includes farm size, type of land tenure, composition of output, access to institutions and indicators of technology and input usage. The relationship between farm size and efficiency is found to be non-linear, with efficiency first falling and then rising with size. Type of land tenure, access to institutions and markets, and modern inputs are found to be important determinants of the differences in efficiency across farms.

JEL classification: Q100; O300

Keywords: Brazil; Agriculture; Productivity; Efficiency; DEA

1. Introduction

The majority of studies of agricultural productivity in developing countries support the view that there is an inverse relationship between productivity and farm size (Berry and Cline, 1979; Barrett, 1996). If correct, land reform could contribute to improving both equity and efficiency in agriculture. Most of these studies, however, are based on partial measures of productivity such as yield which are biased in favor of small producers. It is likely that the inverse relationship would be less pronounced, or perhaps even reversed, if a measure of total factor productivity (TFP) were used instead. It has also been suggested that the inverse relationship might weaken in a region characterised by rapid modernization. This paper explores the relationship between farm size and technical efficiency in exactly this type of environment. The Center-West (CW) is the region of Brazil where production and TFP have grown the fastest since 1970. Gasques and Conceição (2001) and Vicente et al. (2001) both estimate annual TFP growth rates for the CW to be in

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0169-5150/$ – see front matter
doi:10.1016/j.agecon.2004.09.021

the 4–5% range for the period 1970–1995, or about twice the national average. It is also a region characterised by unusually large farms: the average farm size in the CW is about six times the national average.

A second objective of this paper is to extend the recent Brazilian literature on total factor productivity growth in agriculture to an analysis of the determinants of productivity. We do this in two ways. First, most recent studies have limited themselves to the measurement of TFP. Only one has sought to analyse the determinants of TFP in an econometric framework (Vicente et al., 2003). In this paper we regress a measure of technical efficiency on a set of explanatory variables which includes farm size, type of land tenure, composition of output, access to institutions, and indicators of technology and input usage. Second, previous studies have been based on national or state level data. These have provided a valuable first approximation to productivity change in the past several decades. The Brazilian agricultural sector, however, is far too heterogeneous for us to be satisfied with studies conducted at this level. In this paper, we use data from 426 counties, 15 farm size classes and four types of land tenure. This permits us to avoid many of the issues of aggregation bias present in previous studies, and generates a far richer set of data for studying the determinants of efficiency.

The paper is organised as follows. Section 2 briefly presents the Data Envelopment Analysis methodology that is used to estimate technical efficiency. Section 3 describes the data and the construction of the variables. Section 4 analyses the empirical results, with an emphasis on farm size and Section 5 provides conclusions.

2. Methodology

We use Data Envelopment Analysis (DEA) to calculate productive efficiency (Färe et al., 1994). Efficiency is defined in a relative sense, as the distance between observed input–output combinations and a best practice frontier. DEA is one of several techniques that can be used to calculate a best practice production frontier (Coelli et al., 1998; Kumbhakar and Lovell, 2000). The principal advantages of DEA, as opposed to stochastic frontier estimation, are that DEA is a non-parametric technique and that it can accommodate multiple outputs and inputs. In addition, the econometric theory has yet to be developed for incorporating spatial correlation into a stochastic frontier model.

We use output distance functions to characterise the frontier of a multiple-input multiple-output production technology, and the proportional distance of each observation from the frontier. The following notation is used. The production possibilities set P is the combination of all pairs of inputs x and outputs y that are feasible, where x and y are vectors. Inputs and outputs are assumed to be freely disposable, and P is assumed to be non-empty, closed, and convex. The output distance function D_0 is

$$D_0(x, y) = \inf\left\{\theta : \left(x, \frac{1}{\theta}y\right) \in P\right\} \tag{1}$$

where θ is a non-negative scalar that measures the ratio of the observed vector of outputs to the maximum vector that could be achieved, given the input vector, if all outputs were expanded proportionally. The inverse of the output distance function, the Farrell output-oriented measure of technical efficiency, is used here as a measure of efficiency. The Farrell measure equals one for efficient firms on the frontier, and then increases with inefficiency.

Farrell efficiency measures can be found as the solution to a linear programming problem under alternative assumptions about returns to scale. With K farms, N inputs, M outputs and the assumption of constant returns to scale (CRS), the following linear program must be solved for every observation:

$$\begin{aligned} &[D_0(x, y)]^{-1} = \max_{(z,\theta)} \theta \\ &\text{s.t.} \quad \theta_k y_{mk} \leq \sum_{k=1}^{K} z_k y_{mk}, \quad m = 1, \ldots, M \\ &\qquad \sum_{k=1}^{K} z_k x_{nk} \leq x_{nk}, \quad n = 1, \ldots, N \\ &\qquad z_k \geq 0, \quad k = 1, \ldots, K \end{aligned} \tag{2}$$

where the z_k are variables which show the intensity with which each farm is used in order to construct the frontier of the production possibilities set. The linear program solves for the maximum value of θ given the constraints that the proportionally expanded vector of outputs and the vector of inputs are in the feasible set, and that the intensity variables are non-negative.

Two caveats are in order. First, the efficiency scores may be very sensitive to measurement error for the farms that define the best practice frontier. We explore this issue in the empirical application. Second, we use the term 'inefficiency' solely to mean the distance between a given farm and the best practice frontier. There are many reasons why a farm might not be operating on the best practice frontier, and most of these are unlikely to relate to *x*-inefficiency. Excluded variables such as land quality, market failures that lead to non-separable household decisions, credit market constraints that lead farms to choose input-output bundles that appear inefficient in relation to unconstrained farms, and different vintages of technology are all possible reasons why rational farmers might not be operating on the frontier. The challenge, it seems to us, is to identify the relative importance of these alternative sources of 'inefficiency'.

3. The data

The data for this study come from the 1995/1996 Agricultural Census in Brazil (IBGE, 1998). For the DEA analysis, we use aggregate output and five inputs. We briefly explain the construction of these variables here. In Section 4, which presents the results of the econometric analysis, we explain the variables that are used in the second stage to study the determinants of efficiency.

Output (Y): This variable is defined as the gross value of agricultural output net of three categories of items. First, to avoid the double counting of animals that takes place when animals are purchased and sold at different stages of the production process, we deducted the value of purchases of cattle, hogs, chickens and fertilised eggs. Cattle, hogs, and chickens account for over 99% of the value of animal production in the CW. Second, we deducted the value of production of 'rural industry', which accounts for 2% of the value of agricultural production in the CW. Preliminary estimates revealed that for most products the value added in rural industry was extremely close to zero. Because of data limitations, it was much simpler to exclude rural industry than estimated intermediate inputs. Finally, we excluded the value of 'extractive' and 'forestry' products to be consistent with our decision to exclude forest and woodland areas. These products only accounted for 1.6% of the value of agricultural output in the region, while forest and woodland represented 29% of the utilised area.

Utilised area (X_1): 90% of the value of output in the CW comes from temporary crops and cattle. With this in mind, we constructed the area variable to include natural and permanent pastures, land utilised for crops, and productive land that was not being used. These categories accounted respectively for 58, 7 and 2% of the utilised land. The excluded categories were forest and woodland (29%) and unusable land (4%).

Labour (X_2): First, we constructed a variable for family labour by treating males and females as equals, and by only counting half of the family labour under 14 years of age. Second, we constructed a variable for hired labour along the lines of Guanziroli et al. (2001). These authors devised an approach to correct for the fact that (a) temporary workers should not be counted as full-time equivalent workers, and (b) many farms, especially the large ones, hire contracting firms in an effort to avoid paying social security and other labour taxes. Finally, we added family and hired labour together in order to construct the labour variable in full-time equivalent units.

Tractors (X_3): Tractors are measured in the equivalent of a 75 horsepower tractor, which was the midpoint of the modal horsepower class (50–100 hp).

Animals (X_4): Many studies of TFP have not used animals as an input, even when they were considered part of output. We aggregated animals based on their relative prices in the CW of Brazil. We then used the stock of animals in cattle equivalents as a proxy for the stock of capital in animal production.

Purchased inputs (X_5): We created an input variable based on the expenditures for (a) fertiliser, (b) chemicals (such as pesticides and herbicides), (c) seeds, (d) fuel, and (e) feed and medicine for animals.

Finally, we created 'representative farms' for each farm size, of each type of land tenure, in each county. This was necessary because we did not have access to farm level data. We used data from all 426 counties in the CW (excluding the Federal District) that was aggregated into 15 size classes and 4 types of tenure. After removing unusable observations, the final dataset covered 237,595 establishments aggregated into 9304 representative farms, implying an average of 25 establishments per representative farm.

4. Empirical results

We first calculated the median value of output per hectare (Y/X_1) and the median value of output per unit of labour (Y/X_2) for each farm size class. The data were consistent with a broad body of international evidence on the relationship between farm size and productivity. On the one hand, there was a strong inverse relationship between value of output per hectare and farm size, reflecting the intensive use by small farms of their scarce factor of production-land. Labour productivity, in contrast, was much higher on large farms where the opportunity cost of labour is greater. The relationship between total factor productivity (or technical efficiency under CRS) and farm size is influenced by the partial productivities of land, labour, and all other inputs.

We calculated the technical efficiency scores according to the methodology in Section 2 and the assumption of constant returns to scale. We then regressed the efficiency scores on different combinations of explanatory variables as reported in Table 1. We estimated all of the regressions with county level fixed effects to take account of spatial heterogeneity, such as differences in soil quality, that was not captured in the regressors. We used a GLS procedure that allowed for heteroscedasticity across the 426 counties. Further, because each observation in our data set contains mean values of each of the variables over all farms in a given tenure type-size-county cell, we used the number of establishments represented by each observation to construct weights to correct for the heteroscedasticity (not only across counties, but also across tenure types and sizes) that otherwise arises from regression on cell means or "grouped data" (Kmenta, 1971). In practice, the estimation techniques mattered little and the estimated coefficients from all of the regressions proved quite robust to alternative specifications and to the inclusion/exclusion of different sets of variables.

Regression (1) estimates the unconditional relationship between the log of technical inefficiency and the log of farm size. We added a quadratic term to capture non-linearities that we observed in a prior graphical analysis of the mean inefficiency by farm size. Both coefficients were statistically significant at least at the 1% level. In Fig. 1 we have plotted the curve 'size' based on the coefficients from regression (1). The curve depicts a non-linear relationship between inefficiency and farm size, with inefficiency first rising and then falling as farm size grows. The modal farm size class of 20–50 ha might be considered as a target size for land reform in this region, and for this reason we have set its level of inefficiency equal to one in the figure. Relative to this group, which accounts for 21% of the farms in the region, farms in the 200–500 range are estimated to be about 20% less efficient. While farms smaller than 20 ha are even more efficient, the analysis here will focus on farms above 20 ha which represent 78% of the farms in the region and more then 95% of all variables other than labour.[1]

In addition to farm size, the next four regressions control for differences in inefficiency due to land tenure status. We included dummies for renters, sharecroppers and occupants to differentiate them from landowners. The inclusion of tenure dummies in model (2) did not change the coefficients on size. The results indicate that renters were somewhat more efficient than owners (negative coefficients indicate lower inefficiency), occupants were less efficient, and sharecroppers had mixed results. It is likely that renters were more efficient in this region because they were a more homogenous group of market oriented farmers relative to owners who were the majority. In our final model – regression (5) – the partial effect of differences in land tenure on inefficiency is relatively small compared with that of most other determinants of productivity. We estimate that renters were 14% more efficient than owners, while sharecroppers and occupants were 5 and 7% less efficient.

In addition to land tenure, regression (3) controls for differences in the composition of output. Relative to the excluded category – cattle – producers that specialised in higher value activities (temporary crops, horticulture, permanent crops, and hogs and chickens) had lower levels of inefficiency. A coefficient equal to -1 would imply that a one

[1] Some authors, such as Rezende (2003), argue that small family farms are not viable in the CW due to the long drought period and the relative scarcity of off-farm employment.

Table 1
Regression results for the determinants of technical efficiency: dependent variable = ln(inefficiency)

Variable	(1)	(2)	(3)	(4)	(5)
Farm size					
Size	0.45	0.45	0.32	0.37	0.39
Size^2	−0.04	−0.04	−0.03	−0.03	−0.03
Land tenure (relative to owners)					
Renter		−0.39	−0.11	−0.19	−0.14
Sharecropper		−0.23	0.10	−0.00[a]	0.05[a]
Occupant		0.11	0.18	0.06	0.07
Composition of output (relative to cattle)					
Temporary crops			−1.22	−1.20	−1.05
Horticulture			−1.98	−1.60	−1.25
Permanent crops			−1.36	−1.31	−1.26
Hogs and chickens			−1.39	−1.31	−1.26
Other			0.95	0.58	0.58
Access to institutions/public goods					
Credit				−0.16	−0.05[a]
Electricity				−0.55	−0.48
Technical assistance				−0.27	−0.15
Cooperatives				−0.30	−0.22
Market access				−0.56	−0.53
Technology and inputs					
Machines					−0.11
Irrigation					−0.28
Fertiliser					−0.33
Pest and disease control					−0.08[b]
Soil conservation					−0.21
Mechanical milking					−0.86[b]
Artificial insemination					−0.09[a]
Log likelihood	−4396	−4240	−2962	−2432	−2308

Notes: All regressions have county fixed effects (not reported) and allow for heteroscedasticity across counties using as GLS procedure. All coefficients are statistically significant at least at the 1% level unless designated with the following symbols:
[a] Not statistically significant at the 5% level.
[b] Statistically significant at the 5% level.

percentage point increase in the share of production coming from temporary crops, for example, translates into a 1% increase in technical efficiency. Based on the coefficients from this regression, the conditional relationship between size and inefficiency is graphed in Fig. 1 as ‘composition of output’. Because cattle production accounted for nearly half of the value of output for farms over 50 ha, but less than 25% for farms under 10 ha, controlling for these differences reduces the efficiency disadvantage of large producers. Thus, the ‘composition’ curve is higher than the ‘size’ curve below the 20–50 ha class and lower than it above this size. The advantage of farms in the 20–50 ha class over larger farms drops to a maximum of 8.4%.

Regression (4) incorporates variables intended to capture access to institutions and public goods. Thus, the variables credit, electricity, technical assistance and cooperatives all measure the share of establishments in each representative farm that uses these items. These variables range between zero and one. Market access, in contrast, is intended to capture the degree to which market oriented farms are likely to be more efficient than farms producing for their own consumption. This variable is measured as the value of sales divided by the value of production. All five variables are associated with lower inefficiency. Market orientation and use of electricity had the largest impact, followed by participation in cooperatives and use of technical assistance, with credit

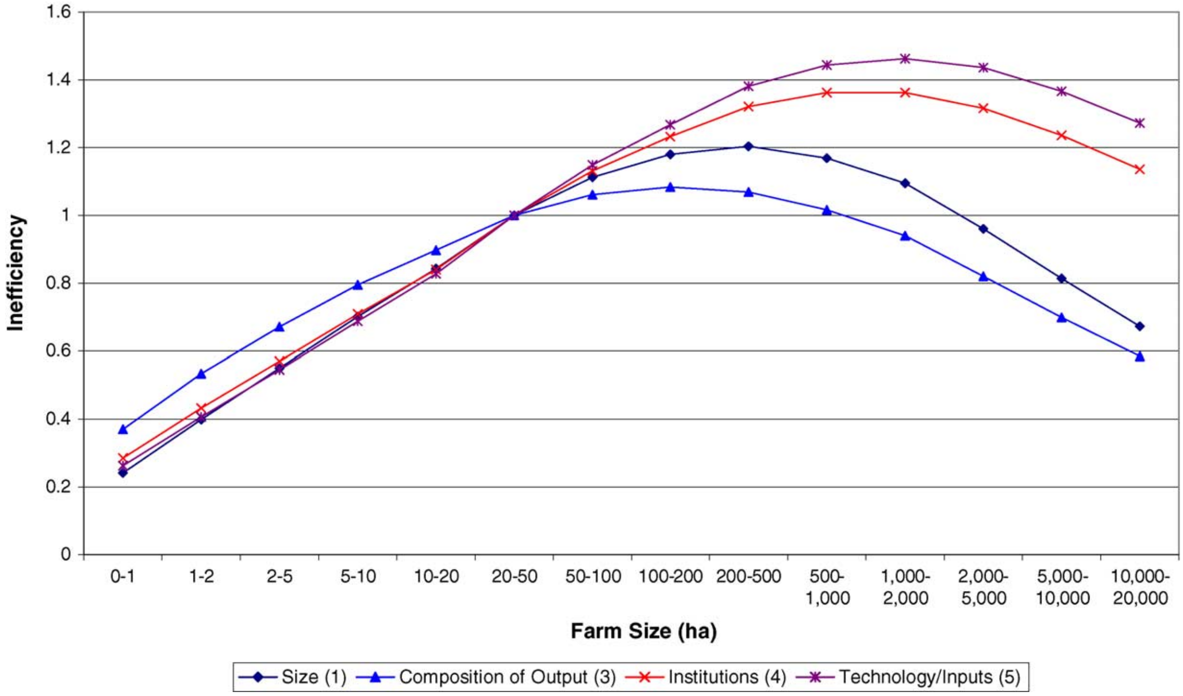

Fig. 1. Conditional effect of farm size on inefficiency (normalized as a fraction of the 20–50 ha group).

having the smallest impact.[2] Based on the coefficients from this regression, the curve 'institutions' in Fig. 1 shifts up substantially relative to the previous scenario, reflecting the fact that large farms tended to have preferential access to these institutions, and controlling for this advantage would increase the relative inefficiency of these farms. Thus, farms in the 1000–2000 range were now estimated to be the least efficient. They were 36% less efficient than farms in the 20–50 ha class, or nearly twice the maximum efficiency difference that was observed in the base case. This is powerful evidence of the importance of providing small farms with access to these institutions.

Regression (5) controls, in addition, for a variety of factors related to the level of technology and the use of inputs. All variables are measured as the share of establishments that report using the designated item. Thus, an increase in the share of farms using machines, irrigation, fertilisers, pest and disease control or soil conservation, all contribute to reducing inefficiency. Mechanical milking has the largest effect of all of these variables. Based on the coefficients from this regression, the curve 'technology/inputs' in Fig. 1 shows that when we also control for differences in the use of technology and inputs, the relative inefficiency of large farms is even greater than in the previous scenarios. The relative disadvantage of farms in the 1000–2000 ha class rises to 46% in this case. However, due to the indivisibilities that exist with certain technologies, such as tractors, providing small and medium farmers with greater access to these inputs might require institutional innovations such as the development of rental markets for the services provided by these inputs.

Finally, we estimated a number of variations on our models to check the robustness of the results and to examine the spatial nature of our data. Due to space limitations, we restrict ourselves to summarising the most important conclusions.

[2] We are surprised by the small size of the coefficient on credit. This was the most important difference from earlier, unweighted results. However, separate regressions using credit/size interaction terms, revealed that the effect of credit on inefficiency varies substantially across size groups. We hope to shed additional light on these results in future research.

First, to evaluate the quadratic specification of the size-inefficiency relationship, we estimated our five models using a series of farm size dummies in place of the log of size and square of log of size, and graphed the results. The resulting graphs did, indeed, approximate an inverted, U-shaped curve fairly closely, indicating that the quadratic specification is appropriate.

Second, to test the sensitivity of the DEA results to measurement error for the observations that define the frontier, we removed the 0.5% (or 47) most efficient observations, re-ran DEA, and re-estimated the model. With only a few exceptions, the signs of the estimated coefficients remained the same, as did their magnitudes relative to the others in the same 'group' (e.g. composition of output). Most importantly, the shape of the size-inefficiency relationship represented in Fig. 1 remained similar, although inefficiency now reached a maximum in the 2000–5000 farm size category rather than in the 1000–2000 class. Thus, it is unlikely that measurement error on the frontier substantially affected our results.

Third, we considered whether the exclusion of forest and woodland areas as inputs understated the relative inefficiency of large farms, because these farms may hold large amounts of undeveloped land for speculation, as a hedge against inflation or for prestige, and therefore do not use it efficiently for production. To test this, we recomputed our DEA results, excluding only 'unusable land' (4% of land in the CW) from our land input variable, and without excluding extractive products, forestry products or rural industry from our output variable. The new coefficients were, again, similar in sign and magnitude in nearly every case, and the quadratic relationship between size and inefficiency was essentially unchanged. The efficiency advantage of farms in the 20–50 ha group (in model 5) was still 46% over the 1000–2000 class. Thus, the exclusion of forest and woodland does not appear to bias downward the efficiency disadvantage of large farms. We want to be cautious about generalising this result, given the unique features of this region: the unusual dynamism of agricultural growth in the region, driven principally by large farms.

Fourth, we conducted two tests to explore the impact on efficiency of transportation costs, location and spatial correlation of the errors in our regression models. First, we computed the correlation coefficient between the 426 fixed effects in model (5) and an estimate of transportation costs between each county and São Paulo, the economic center of Brazil.[3] The correlation coefficient of only 0.11 indicates that the fixed effects mainly capture other county level fixed factors, such as soil quality and rainfall, which appear to be much more important in explaining efficiency than county level economic distance from São Paulo. Second, the version of this paper presented in South Africa in August, 2003, reported results for a model that allowed for spatial correlation in the errors across counties using a SUR framework. The results were almost identical to model (5) reported here. We conclude that the spatial nature of our data does not appear to be biasing our results.

Finally, to determine whether the dummies for land tenure types were sufficient to control for differences between owners, renters, sharecroppers and occupants, we estimated our models separately for each of the tenure types. Fig. 2 shows the relationship between size and inefficiency implied by the coefficients of model (5) for each of the four tenure types. Although we did find some differences in the coefficients across models, the U-shaped relationship between size and inefficiency remained in every case.

Interestingly, Fig. 2 shows that the relative inefficiency of large renters was less than that of large owners. In fact, renters of farms greater than 5000 ha were actually *more efficient* than those in the 20–50 ha group. Unlike in many other parts of the world where renters might be more like sharecroppers, renters in the Brazilian Center-West were a relatively homogeneous group of market oriented farmers. Surprisingly, renters made greater use than owners of those modern inputs, technologies and institutions recorded by the Agricultural Census that were associated with lower levels of inefficiency.[4] It is

[3] We would like to thank Newton de Castro, a professor at the UFRJ in Rio de Janeiro, Brazil and a Co-PI on the research project NEMESIS for graciously providing us with this transportation cost variable. Because of perfect multicollinearity between this county-level variable and our fixed effects, we could not include it in our models.

[4] Not only did renters sell a larger share of their value of output to the market than owners in each size category, they also specialised much more heavily in temporary crops (rather than cattle) and were more likely to use credit, technical assistance, machines, fertilisers and soil conservation measures.

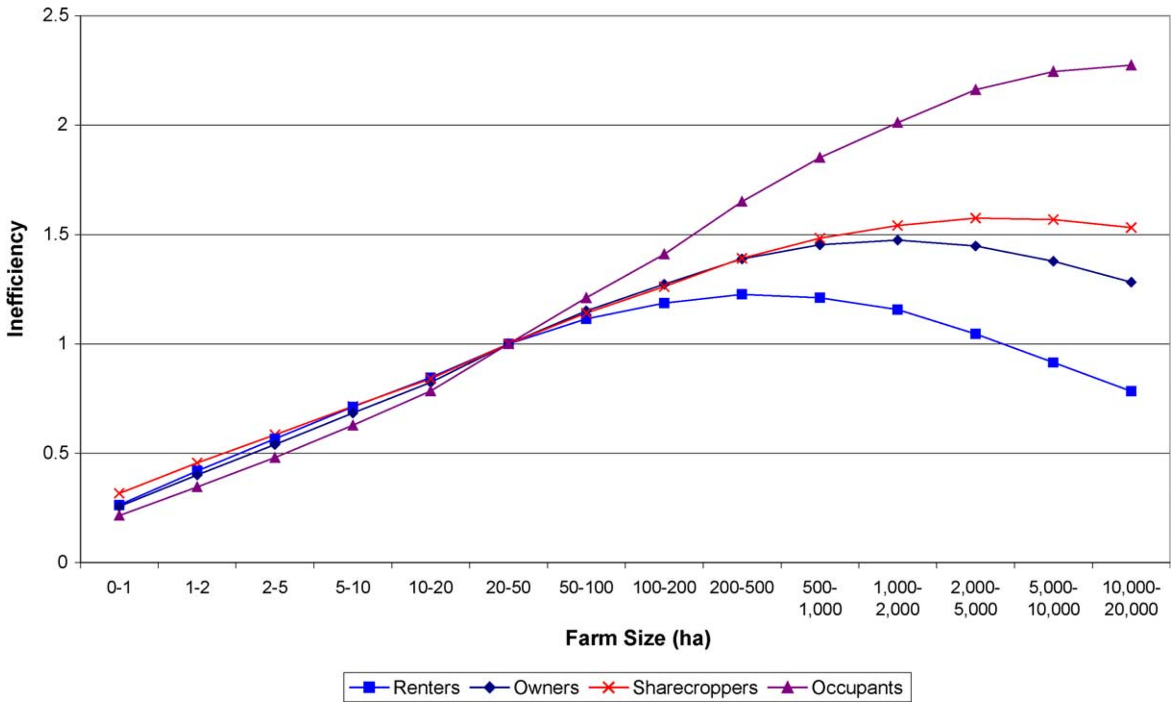

Fig. 2. Conditional effect of farm size on inefficiency by tenure type (normalized as a fraction of the 20–50 ha group).

likely that large renters also made greater use of unobserved factors, which could explain the relative efficiency advantage of this group.

In general, the inverse relationship between size and efficiency weakened as we moved from tenure types associated with lower technologies (occupants) to those associated with greater market orientation and greater use of modern technologies, inputs and institutions (renters). Thus, while our pooled regression results accurately represented the situation of owners, which accounted for 88% of the establishments in this region, there were important differences across tenure types in the size-inefficiency relationship. These differences merit further study.

5. Conclusions

In this paper we used Data Envelopment Analysis (DEA) to estimate the technical efficiency of farms in the Center-West of Brazil, and then studied the determinants of efficiency with regression techniques. Future research should explore the robustness of the results presented here by comparing them with estimates from a stochastic frontier production function.

There are important policy implications that can be derived from the analysis in this paper. The results indicate that access to institutions and goods that are often provided by the public sector, such as market access via infrastructure creation and rural electrification, were among the most important determinants of differences in efficiency. Other important determinants included the use of inputs such as irrigation and fertilisers, and differences in the composition of output. These results identify the types of policies and production practices that could contribute to increased technical efficiency in this region.

We also showed the relationship between farm size and technical efficiency to be more complex than what is normally believed. Rather than an inverse relationship, where productivity falls as farm size rises, we found a U-shaped relationship. For farms up to about 1000–2000 ha, efficiency did fall as farm size rose, but beyond this size it started to rise again. The most important reasons why the inverse relationship broke down relate to preferential access by large farms to institutions and services that help lower inefficiency (such as rural electricity, technical assistance and access to markets) as well more intensive use of the technologies and inputs that raise productivity. The access of large farmers to such efficiency-improving inputs and institutions may partially explain the dramatic TFP growth in this region relative to the rest of Brazil. However, if one could create an environment in which small to medium size farms had equal access to productivity enhancing institutions, and improved access to modern technologies and inputs, then these farm could still produce more efficiently than farms in the 2000–20,000 ha range. Thus, even in the Center-West of Brazil, a region characterised by extremely large farms and relatively high levels of technology, land reform continues to provide the possibility of simultaneously improving equity and efficiency. Its success, however, is strongly conditioned by the complementary institutions, investments and services that permit small and medium size farms to compete on a level playing field.

Finally, we found important differences in the size–efficiency relationship across land tenure types. While all types exhibited a U-shaped relationship, the U-shape was most pronounced for renters, which was the most market oriented type and which made the greatest use of the institutions and modern inputs associated with higher levels of efficiency. The U-shape attenuated, more closely approximating a monotonic inverse relationship, as we moved to the land tenure type (occupants) associated with lower market orientation and lower technology. These results lend further support to the view that differential access to institutions, and use of technologies and inputs, can significantly alter the usual findings of an inverse relationship between farm size and productivity.

Acknowledgements

This paper was written as part of a larger project on spatial economics called NEMESIS (www.nemesis.org.br). The project is based at IPEA in Rio de Janeiro and has been supported by a grant from the Brazilian government under a program called PRONEX. We would like to thank Gervásio Castro de Rezende, Eustáquio Reis, Keith Griffin, and Tim Coelli for valuable comments on an earlier draft.

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