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Examining the relationship between vertical coordination strategies and technical efficiency: Evidence from the Brazilian ethanol industry

Ana Claudia Sant'Anna[1], Jason S. Bergtold[2], Aleksan Shanoyan[3], Gabriel Granco[4], Marcellus M. Caldas[5]

[1] Graduate Research Assistant, Department of Agricultural Economics, Kansas State University, Manhattan, KS, USA, acsantanna@ksu.edu

[2] Professor, Department of Agricultural Economics, Kansas State University, Manhattan, KS, USA, bergtold@ksu.edu, 785-532-0984 (Corresponding Author)

[3] Assistant Professor, Department of Agricultural Economics, Kansas State University, Manhattan, KS, USA, shanoyan@ksu.edu.

[4] Graduate Research Assistant, Department of Geography, Kansas State University, Manhattan, KS, USA, ggranco@ksu.edu.

[5] Associate Professor, Department of Geography, Kansas State University, Manhattan, KS, USA, caldasma@ksu.edu.

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Abstract

The sugarcane industry in Brazil, one of the world's leading producers of ethanol and sugar, is undergoing significant changes driven by geographic expansion and technological innovations. These changes are forcing sugarcane producers and processors to re-evaluate their vertical coordination and growth strategies. This paper presents an empirical analysis of the relationship between vertical coordination strategies at the production-processing interface of the Brazilian ethanol supply chain and technical efficiency of mills, utilizing data envelopment analysis and Tobit censored models for 204 mills that account for around half of Brazil's sugar and ethanol production. Results indicate that vertical integration and location of mill have a statistically significant impact on efficiency. Findings show that technical efficiency is not the main driver of vertical integration, implying such decisions are primarily motivated by strategic considerations. Mills are likely to forgo gains in technical efficiency in exchange for improving their strategic position through vertical integration.

Keywords: Brazil**,** data envelopment analysis, efficiency, ethanol, sugarcane industry, vertical coordination

JEL Classifications: L22, Q12, Q16

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1. Introduction

Brazil, as one of the leading producers of ethanol and sugar, was responsible for 40% of the world's sugarcane production in 2014 (FAOSTAT 2014). The sugar-energy sector in Brazil accounts for almost 2% of the country's Gross Domestic Product (Neves et al. 2011). It employs 1.2 million workers, encompassing 70,000 sugarcane producers and over 400 mills (Chaddad 2015). Over the last decade, the Brazilian sugarcane production underwent significant changes driven by geographic expansion, technological innovations, changes in public policy, as well as domestic and global market forces (Nunez et al., 2013). These changes have created unprecedented competitive dynamics in the industry forcing the players at all levels of the supply chain to re-evaluate their strategies and operations. This is particularly true for sugarcane producers and processors (Sant'Anna, Shanoyan, et al. 2016).

The production-processing interface of the Brazilian sugarcane supply chain is predominantly governed through two vertical coordination strategies: contracting – where farmers are contracted by the mills, and vertical integration – where the mills either acquire or rent the land and backward vertically integrate into sugarcane production (Moraes and Zilberman 2014; Sant'Anna, Shanoyan, et al. 2016). With the ongoing expansion of the sugarcane industry, the choice of vertical coordination strategy at the production-processing interface can have important implications not only for operational efficiency and competitive strategy of sugarcane processors, but also, for the structure of regional agricultural production and public policy.

From the operations perspective, several factors at the sugarcane production stage (e.g. distance and harvest timeline limitations) can affect the efficiency at the processing stage due to technical aspects of the refining process (Chaddad 2015; Neves et al. 1998). Thus, backward vertical integration can potentially result in efficiency gains by reducing transaction costs associated with coordinating, monitoring, and enforcing transactions with farmers to ensure timely and reliable supply of sugarcane.

From the strategy perspective, with increased control over the production stage mills can gain a potential competitive advantage by securing an adequate procurement base, while reducing or eliminating the bargaining power of suppliers. Additionally, in geographic areas with limited production resources, such vertical coordination strategies can reduce the intensity of the rivalry over access to inputs and create barriers to entry. However, the strategic and operational benefits of backward vertical integration into sugarcane production come with additional costs and risks for processors. Specifically, vertical integration into sugarcane production will: a) expose mills to additional risks that are inherent in production agriculture, and b) will require investing significant additional capital in acquiring production resources and capabilities (e.g. land, infrastructure and machinery). These additional costs and risk can have important implications for strategic decisions and the operational efficiency of the mills.

From the policy perspective, any potential effect of changes in vertical coordination strategies at the production-processing interface of the sugarcane supply chain (e.g. changes in land use, shifts in bargaining power, etc…) will be magnified over time due to the ongoing expansion of the sugarcane industry from the North-Northeast region to the Center-South region of Brazil (Granco et al. 2015). The evidence of such effects has been seen predominantly in the *Cerrado*, Brazil’s second largest biome, where over 40 sugarcane processing mills have been constructed in the states of Goiás and Mato Grosso do Sul since the early 2000s (Procana 2013). The geographic expansion has provoked a change in land use in this region historically known for livestock and soybean production (Granco et al. 2015).

Policy makers have long recognized the importance of potential long-term impacts of the expansion and placed a regulatory restriction on the extent of vertical integration with an aim to ensure a competitive market for sugarcane and to support agricultural producers. In 1941, the Brazilian government issued the Statute of Sugarcane which requires that 40% of the sugarcane processed by mills must be procured from independent sugarcane producers with exceptions granted in situations where independent producers are unable to provide an adequate supply of sugarcane for the mill (Brazil 1941). Data from 2013 suggests that the regulatory allowance for vertical integration was used by the mills up to the limit, resulting in 60% of total processed sugarcane produced by mills and the remaining 40% supplied by independent producers (Chaddad 2015). This highlights the preference towards backward vertical integration by mills and raises a number of important management and policy questions. Specifically, what is the optimal coordination strategy from the perspective of operational efficiency and strategic position; and what is the nature of the relationship between vertical coordination and technical efficiency? These questions warrant a close examination of strategic motivations for vertical integration at the production-processing interface of the Brazilian sugarcane supply-chain and the potential impact on operational efficiency of mills.

The existing literature on the relationship between vertical integration and efficiency does not provide a definitive conclusion on the impact of vertical integration on efficiency[1]. Technical efficiency is defined in the literature as the measure of the firm's ability to minimize input usage

[1] Refers to technical and cost efficiencies.

at a given level of output (Färe et al. 1994). Pieri and Zaninotto (2013) investigated the relationship between vertical integration and technical efficiency in the Italian machine tool industry. They find that, technically efficient firms tend to pursue vertical integration strategy, but did not find evidence of an impact of vertical integration on technical efficiency. Federico (2010) examined the links between productivity and vertical integration and found a positive relationship (Federico, 2010; Pieri and Zaninotto 2013). Tomiura (2007) found positive relationship between productivity and vertical integration in the study of Japanese manufacturing firms (Tomira 2007; Pieri and Zaninotto 2013). Bakhtiari (2011) examined the relationship between cost efficiency and vertical integration in the Australian manufacturing industry and found it to be positive (Pieri and Zaninotto 2013). D'Aveni and Ravenscraft (1994) found a small positive relationship between vertical integration and performance, but did not provide a conclusive evidence that the vertical integration resulted in technical efficiency gains.

While the importance of both vertical coordination and technical efficiency in the context of the Brazilian ethanol industry has been recognized by researchers, the previous studies have limited their scope by examining each of these factors separately. For example, Bastos (2013) analyzed data from 2009 to 2012 and found higher levels of vertical integration in areas where sugarcane has had recent expansion, such as in the states in the Center-West region, and lower levels in areas with a tradition of sugarcane production. Junior et al. (2014), when analyzing the technical efficiency of Brazilian mills, find a higher concentration of efficient mills in the state of São Paulo, the largest sugarcane producing state. Torquato et al. (2009) studying mill efficiency in the state of São Paulo found that mills in counties with an established tradition of growing sugarcane are more homogeneous and closer to the cost efficient frontier than those in counties where sugarcane production is more recent. Our review of the literature indicates that, to date, no study has examined the impact of vertical coordination on the technical efficiency of ethanol and sugarcane mills in Brazil.

The purpose of this study is to address the gap in the literature by providing an empirical analysis of the relationship between the vertical coordination strategy at the production-processing interface of the Brazilian ethanol supply chain and the technical efficiency of the mills. The specific objective is to estimate the impact from vertical coordination on technical efficiency. The methods involve data envelopment analysis and a Tobit censored model in combination with a unique data on 204 sugarcane processing mills that were responsible for approximately half of Brazil's recent sugar and ethanol production. The findings provide important implications for industry players and policy makers. The rest of the paper is organized as follows: section two provides background on sugarcane production and supply-chain coordination in Brazil; section three presents the data, followed by the description of empirical analysis and estimation methods; section four presents the results and discussion, and section five provides concluding remarks.

2. Coordination at the production-processing interface of the Brazilian sugarcane supply chain

The transactions at the production-processing interface of the Brazilian sugarcane supply chain are characterized by high levels of asset specificity, specifically, geographic, temporal, and physical asset specificity (Moraes and Zilberman 2014). Sugarcane procurement is limited to a certain radius of distance from the mill to minimize transportation costs and avoid sugarcane quality losses. This restricts the supply and procurement base to a specific area resulting in geographic asset specificity (Moraes and Zilberman 2014, Chaddad 2016). Additionally, the perishable nature of harvested sugarcane makes the time between harvesting and processing an important factor of the transaction resulting in temporal asset specificity (Moraes and Zilberman

2014, Neves et al. 1998). From the production perspective, the perennial nature of sugarcane implies a minimum 5-year production commitment thus resulting in physical and dedicated asset specificity (Moraes and Zilberman 2014; Khanna et al., 2017).

The high asset specificity combined with inherent volatility in commodity markets leads to high transaction costs of coordination between the production and processing stages in the Brazilian sugarcane industrial supply chain. This in turn leads to: a) challenges in establishing reliable procurement relationships with farmers as mills expand to new geographic areas with a historically limited tradition of sugarcane production (e.g. the Center-South region of Brazil); and b) intense rivalry among mills and higher bargaining power of suppliers in areas with historically well-established sugarcane production (e.g. North-Northeast region) (Bastos 2013; Sant'Anna, Granco et al 2016). Consequently, consistent with Transaction Cost Economics (TCE) theory predictions, vertical coordination strategies with higher levels of control (e.g. vertical integration) are preferred by the mills over the spot market or contracting. Studies have found increased reliance on vertical integration both in traditional sugarcane producing regions and in new areas of expansion (Bastos 2013; Sant'Anna, Granco et al. 2016).

The extent of vertical coordination at the production and processing stages by the state in 2012 is presented in Table 1. Backwards vertical integration is reflected by the percentage of the processed sugarcane supplied through a mill's own production operations (produced on acquired or rented land). The highest extent of backward vertical integration (100%) is observed in areas with lower numbers of mills (e.g. Rio Grande do Sul and states in the North region). Relatively higher extents of backward vertical integration is also observed in states with no previous tradition of growing sugarcane (e.g. Mato Grosso do Sul, Goiás and Mato Grosso). These states also contain higher numbers of new plants. In states with historically well-established sugarcane production, such as Pernambuco and São Paulo, a relatively lower but still a significant extent of vertical integration is observed. For example, in São Paulo state, the share of sugarcane produced by the mills is about 50%. In states bordering São Paulo, such as Minas Gerais, the picture is similar. Although Minas Gerais does not have a tradition of growing sugarcane, it is likely that mills located closer to the border are able to procure from producers in the state of São Paulo (Figure 2).

Studies have shown that vertical integration facilitates the implementation of new technologies and advanced agricultural practices enhancing productivity of sugarcane production (Chaddad 2015). Increased productivity in sugarcane production can provide efficiency gains for a mill, since sugarcane accounts for 70% of total costs at the processing stage (Chaddad 2015). According to Crago et al. (2010) backward-integrated mills have higher sugarcane yields than independent farmers, 81 tons per hectare versus 75 tons per hectare, respectively. It has been argued that the technical efficiency of the mills can be enhanced through increased control over harvesting and transportation of the sugarcane (Chaddad, 2015). On the other hand, the benefits of increased control over the production and supply comes at a cost, including increased capital investments and exposure to risks inherent in production agriculture (Neves et al. 1998).

Cost inefficiencies may also occur due to the combination of price volatility and the perennial nature of sugarcane production. For example, cost inefficiencies can arise in situations where the mill is forced to rely on their own pre-committed supply versus buying from the spot market when the market prices are lower than the production costs (D'Aveni and Ravenscraft 1994). Cost and technical inefficiencies may also arise due to factors such as agency costs and underutilized capacity (D'Aveni and Ravenscraft 1994). The interrelated nature of the strategic and operation considerations in choosing vertical coordination strategy highlights the need for a closer examination of the relationship between vertical integration and technical efficiency at the production-processing interface of the Brazilian sugarcane supply chain.

3. Methods

In this paper, a two-stage analysis is utilized to examine how vertical coordination impacts technical efficiency. In the first stage, data envelopment analysis (DEA) is used to obtain efficiency scores for each of the mills. In the second stage, a Tobit model is estimated using the estimated efficiency scores, from the first stage, as the dependent variable to assess the impact of backwards vertical integration on technical efficiency.

3.1 A DEA input-oriented model

DEA is a nonparametric approach used to construct efficiency frontiers allowing for the evaluation of relative efficiency of decision making units (DMU). The benefit of using DEA is that no prior assumptions about the production relationships between inputs and outputs are needed (Zhou et al. 2008). DEA assumes that all mills have access to the same technology. This study utilizes an input-oriented DEA with variable returns to scale given the interest on sugarcane procurement by mills. The decision to allow variable returns to scale was made after testing for whether the underlying technology exhibited constant, variable returns to scale or non-increasing returns to scale using code developed by Simm and Besstremyannaya (2016). This program tests the null hypothesis of constant returns to scale against the alternative hypothesis of variable returns to scale, or the null hypothesis of non-increasing returns to scale against the hypothesis of variable returns to scale. It uses test statistics developed by Simar and Wilson (2002; 2011a). Results from both tests rejected the null hypothesis confirming with a statistical significance level of 5% the presence of variable returns to scale[2].

The DEA input-oriented model measures efficiency by focusing on the firm's ability to minimize the quantity of inputs given a fixed quantity of outputs (Fare et al. 1994). In this study, there are *N* DMUs (mills) and *M* inputs. The *M* inputs are used in the production of *S* outputs. The model determines the minimum level of input $(x_{m,k}, \theta_n)$ each DMU requires to produce a certain level of output and be technically efficient. This is done using the following minimization problem for the *nth* DMU (Färe et al. 1994):

$$\min_{\theta_n, \lambda_k} \theta_n \tag{1}$$

$$s.t. \sum_{k=1}^{N} \lambda_k x_{m,k} \leq x_{m,n}\theta_n \; for \; m = 1, \dots, M$$

$$\sum_{k=1}^{N} \lambda_k y_{s,k} \geq y_{s,n} \; for \; s = 1, \dots, S$$

$$\sum_{k=1}^{N} \lambda_k = 1$$

$$(\lambda_1, \dots, \lambda_N) \geq 0$$

where $\lambda_1, \dots, \lambda_N$ are weights estimated by the model, $x_{m,k}$ are the $m = 1, \dots, M$ inputs, and $y_{s,k}$ are the $s = 1, \dots, S$ outputs. θ_n is the input-oriented technical efficiency of mill *n* ranging from 0 to 1. The closer θ_n is to one the more efficient the mill is (Färe et al. 1994). Mills with θ_n=1 are fully

[2] The test of constant returns to scale against variable returns to scale had a p-value of 0.02, while the test of non-increasing returns to scale against constant returns to scale had a p-value of 0.01.

efficient. When θ_n is less than one it provides information on reductions in input use that could be made to produce the same level of output. DEA analysis was conducted using R-Studio using the rDEA (Simm and Besstremyannaya 2016) and benchmarking packages (Bogetoft and Otto 2015).

3.2 Estimating the effect of backwards vertical integration on technical efficiency

Once the technical efficiency for each DMU has been calculated, the effect of backwards vertical integration on the efficiency of the mill was estimated. Vertical integration can be measured as the quantity of a good transferred from one stage of production to another inside a firm (Perry 1989). In this study, vertical integration is measured as the percentage of the total crushed sugarcane used for production that came from land controlled by the mill. Thus, mills with a higher percentages of own sugarcane production are assumed to be more vertically integrated.

Prior to estimating the impact of vertical integration on technical efficiency, we checked that the assumption of separability held. Technical efficiency scores (θ_n) are only interpretable in a second-stage regression analysis when a separability condition applies (Simar and Wilson 2011b; Daraio, Simar and Wilson 2015). The separability condition assumes that environmental variables do not impact the efficiency frontier. That is, the possible set of combinations of inputs and outputs is the same regardless of the presence of environmental variables. Daraio and Simar (2005) describe environmental variables as factors that the producer has no control over but that may influence production. We tested for this condition by comparing the conditional and unconditional DEA technical efficiency scores with respect to the level of backwards vertical integration. We found that the separability condition held (see the supplemental appendix for details), allowing for the two stage analysis conducted here.

Given that the separability assumption holds, we measured the impact of vertical coordination on technical efficiency score using a two-sided Tobit regression with an upper and lower limit of censoring of 1 and 0, respectively. The efficiency score, the dependent variable, ranges from 0 to 1, such that mills with an efficiency score closer to one are more efficient and closer to the efficient frontier. In the literature, there are different views on the use of the Tobit model in the second stage regression (e.g. Simar and Wilson, 2011b). We decide, though, to follow Hoff (2007) who argues that the Tobit model is sufficient for regressing DEA scores against exogenous variables. Nevertheless, we provide estimates for two more commonly suggested models: Simar and Wilson's algorithm #1 using a truncated regression model (see Simar and Wilson 2007; Tauchmann 2016) and the fractional regression model with a logistic distribution (see Ramalho et al. 2010; Williams 2016). The Tobit model estimated in this study was:

$$\theta_n = \alpha_n + \beta_1 perown_n + \beta_2 mixed_n + \beta_3 SP_n + \beta_4 CW_n + \beta_5 ALPE_n + \beta_6 SP * perown_n + \beta_7 CW * perown_n + \beta_8 ALPE * perown_n + \beta_6 age_n + e_n \quad (2)$$

where $perown$ is the percentage of crushed sugarcane that was produced by mills; *mixed* is a dummy that is 1 if the mill produces both ethanol and sugar and 0 otherwise; *sp* is a dummy variable that is 1 if mill is in the state of São Paulo and 0 otherwise; *cw* is a dummy variable that is 1 if the mill is in the Center-West region and 0 otherwise; *alpe* is a dummy variable that is 1 if the mill is in the states of Alagoas or Pernambuco and 0 otherwise; and *age* is how old the mill is in years (see Table 2 for summary statistics of the variables). Second stage regressions were estimated using Stata 14. Standard errors are obtained through a bootstrap procedure with replacement using 5000 repetitions to correct for the serial correlation of the DEA efficiency estimates following Simar and Wilson (2007). We checked for misspecification in the Tobit model by running a link test (Pregibon 1979). The link test involves refitting the estimated model with the values of the predicted dependent value and its squared term. If the coefficient of the predicted dependent variable squared is statistically significant then the model is misspecified[3]. We also used inefficiencies (1-θ_n) as the dependent variable to run the *bctobit* test for misspecification written by Vincent (2010)[4].

The choice of exogenous variables was guided by previous studies. The region of the Center-West along with the states of São Paulo, Alagoas and Pernambuco are where most of the mills in the sample are concentrated (Figure 2). São Paulo is the largest sugar, ethanol and sugarcane producer in Brazil, where mills are reportedly less vertically integrated (Bastos, 2013) and are more efficient than in other Brazilian states (Junior et al, 2014). In terms of the Center-West, this region has experienced recent sugarcane expansion with over 40 new mills installed since 2000 (Sant'Anna, Granco, et al. 2016). The states of Alagoas and Pernambuco are in the Northeast region, where historically sugarcane production began in Brazil. Given past studies (Bastos 2013; Junior et al. 2014) it is reasonable to expect observing more technically efficient mills in São Paulo and in the Center-West, while relatively older and, perhaps, less technically efficient mills in Alagoas and Pernambuco. We interact the location dummies with the proxy for vertical integration to understand how vertical integration in these areas impacts technical efficiency.

Other variables were *age* and *mixed*. The type of the mill (i.e. mixed or not) is controlled for to account for differences in the mills due to the diversity of their output production set. We

[3] The coefficient for the predicted dependent variable squared had a p-value of 0.313 and was not found to be statistically significant at a 5% level of significance, indicating no functional misspecfication.

[4] Bctobit tests the tobit specification using a Lagrange Multiplier test statistic against a model that is non-linear in the regressors with heteroskedastic and non-normally distributed errors (Vincent 2010). The test statistic for our model was 0.212. When this is compared with the critical value of 4.59 for the test at a 5% level of significance, the null hypothesis cannot be rejected.

expect *mixed* to have a positive effect (i.e. mills that produce two products instead of one are more efficient), since *mixed* mills may likely have newer technology in place in comparison to mills that produce only one type of output. We expect *age* to have a negative impact on efficiency. The older the mill, it is likely the older the technology they utilize. The impact of *perown* is ambiguous. *Perown* should have a positive effect if through backward vertical integration mills become more efficient. That is, by having more control over the coordination of planting, harvesting and hauling of sugarcane, mills can increase efficiency in ethanol and/or sugar production. On the other hand, if mills are integrating for reasons other than increasing efficiency and coordination in sugarcane production (e.g. to improve strategic position), the effect of *perown* on the efficiency of the mill is not known and could be negative.

Marginal effects were estimated after the estimation of the Tobit regression given the nonlinear nature of the model. Marginal effects allow us to evaluate the effect of a one unit change of an exogenous variable on technical efficiency (Onukwugha et al. 2015). Marginal effects for the exogenous variables, except for the interaction terms, are estimated as average partial effects. The average partial effect was estimated by obtaining separate marginal effects for each observation and then taking the average over individual marginal effects (Onukwugha et al. 2015).

Marginal effects of interaction terms are interpreted as changes in the marginal effects due to changes in another variable of interest. Generally, the marginal effect of an interaction term is the partial derivative of the marginal effect of one of the variables in the interaction (Onukwugha et al. 2015). In equation (2), the interaction terms consist of a dummy and a continuous variable. Thus, the marginal effect of the interaction term is estimated as the difference in the marginal effects of *perown* at each of the dummy values (Onukwugha et al. 2015). For example, the marginal effect (ME) of *perown*cw* on technical efficiency (θ) is the marginal effect of *perown* at cw=0 minus the marginal effect of *perown* at cw=1:

$$ME_{perown*cw} = \left.\frac{\partial\theta}{\partial perown}\right|_{cw=1} - \left.\frac{\partial\theta}{\partial perown}\right|_{cw=0} \tag{3}$$

Asymptotic standard errors for the marginal effects were estimated using the delta method (Onukwugha et al. 2015).

4. Data

Information on sugarcane processing mills in Brazil is obtained from the 2013 Brazilian Sugar and Ethanol Guide (Procana 2013). From the 422 mills included in the guide, 204 had a complete set of data required for the analysis[5]. This is a remarkable sample as the 204 firms in the study produced 48% of the ethanol and 54% of the sugar produced in 2013 in Brazil. To put it in perspective, Brazil's total production in 2013 was 38.4 million tons of sugar and 23.2 billion liters of ethanol (Procana 2013). Two inputs[6] (capacity and crushed sugarcane), and two outputs[7] (sugar and ethanol) were modeled in the input-oriented DEA model (Table 2). Of the inputs, capacity is a proxy for the capital of the mill, representing a long-term variable, while sugarcane would represent a short-term input variable of the production process. Of the 204 mills, 60 produced only ethanol and 6 only sugar, while the rest produced both ethanol and sugar. For 12 mills that did not

[5] Some of the issues encountered were: firms with more one mill only provided consolidated information; mills did not produce in 2013 or provided data; and, mills only provided partial information.

[6] Information on sugarcane yield and labor were not added. Labor was only rarely reported by the mills and would significantly reduce the sample size. Yield information is not reported and would require dividing the amount of crushed sugarcane over the total area reported which might introduce measurement errors, as well as, endogeneity issues in the second stage regressions estimated, unduly complicating analyses.

[7] The amount of energy sold by the mills was not considered as an output due to the limited information available. For the same reason, the amount of labor was not considered as an input.

report this information in the 2013 Brazilian Sugar and Ethanol Guide[8], the information on prior year capacity was used (obtained from Procana 2012). Most of the mills in the sample are in São Paulo (69 mills), a state responsible for over 50% of the sugarcane produced in the country. The North region was the region with the least number of mills (4 mills). From the Center-West, an area that has recently experienced sugarcane expansion, there were 37 mills in the sample.

Considering the sample for this study, in 2013 the amount of sugarcane used by a single mill in the production of ethanol and sugar varied from 33 thousand tons to 7 million tons. Sugarcane crushing capacity of the mills ranged from 800 to 42,000 tons of sugarcane per day. The average mill produced 62 thousand metric liters of ethanol and produced 91.5 thousand tons of sugar (Table 2).

The second stage of the analysis uses input-oriented technical efficiency scores computed for each mill and other data from the 2013 Brazilian Sugar and Ethanol Guide including the percentage of crushed sugarcane produced by mills out of the total amount of sugarcane used (*Perown*), and information on the location of the mill. The age of the mill is calculated by adding the years from when the mill started operating up to 2013. The year when the mill began operations is obtained from the websites of the individual mills, as well as, search engines for company profiles (Graphiq Inc 2017; Bloomberg 2017). In the cases where the mill was sold to another company, the year when the buying company started production is used.

The sample includes mills that are fully vertically integrated producing 100% of their own sugarcane supply (i.e. *Perown* is 100%) and mills that procure all of their sugarcane supply from third parties (i.e. *Perown* is 0%) through contracting. On average, mills produce 64% of their sugarcane supply. In geographic areas where sugarcane with production ranges from 2,808 to 10

[8] We assumed that the capacity of the mill will remain unchanged from one year to the next.

million tons, mills tend to be more integrated, producing about 99% of their sugarcane supply. Mills in the newly expanded areas (i.e. Center-West) are producing on average 80% of their own sugarcane supply. In contrast, mills in areas with more established sugarcane production (i.e. Alagoas, Pernambuco and São Paulo) produce on average 62% of their own supply. The sample includes mills with production history ranging from one year to over a century in operation (Table 2). The older mills tend to be located in Alagoas and Pernambuco with an average age of 65 years. The oldest mill in these two states has been in operation for 152 years. The relatively newer mills are located in the Center-West, where the average age of a mill is 11 years in 2013.

5. Results

The results from the input-oriented DEA illustrate that out of 204 plants analyzed, only 20 are found to be fully efficient (i.e. $\theta = 1$) (Table 3). At least one fully efficient mill is found to be present in each region (i.e. North, Northeast, Southeast, South and Center West). Similar to the findings of Junior et al. (2014), we found that most of the efficient mills were located in São Paulo. Mills in the Center-West appear to be more homogeneous in terms of efficiency, as evidenced by the low standard deviation of the efficiency scores (Table 3). One likely reason for this is that most of the mills operating in this region started their operation after 2000. Ten states are found to have no fully efficient mills. These states in general have a smaller number of mills. The low efficiency scores could be a result of the lack of market pressure to incentivize them to improve technical efficiency (D'Aveni and Ravenscraft 1994). The least efficient mill, with an efficiency score of 0.53, is found to be in the state of Minas Gerais. Mills in this state appear to be more heterogeneous in comparison to other states, as evidenced by the higher standard deviation. The standard deviation of the efficiency scores is 0.10. On average, the North region is home to the least amount of efficient mills, while the most efficient mills are located in the Center-West region (Table 3).

Considering the total sample, mills on average have an input-oriented technical efficiency score of 0.88 and a standard deviation of 0.08. There are 21 firms in the top 10^{th} percentile . Close to 10% of the mills were fully efficient, and less than 12% had an efficiency score below 0.8.

In the second stage a two-sided Tobit model is estimated to assess the impact of backwards vertical integration on technical efficiency. Following UCLA Statistical Consulting Group (2017) we calculate a rough estimate of the pseudo R^2 by squaring the correlation of the predicted efficiency scores ($\hat{\theta}_n$) with the actual efficiency scores (θ_n). The model accounts for approximately 12% of the variation in the dependent variable. A Wald test shows that the hypothesis that the sum of all the coefficients is zero is rejected at a 5% level of significance (Table 4).

Model estimates and marginal effects are presented for all three second-stage models (Tobit, Simar Wilson Algorithm #1 and fractional) in Tables 4 and 5. Corresponding coefficients of the three estimated models have the same signs though they are of different magnitudes due to varying functional specifications (Table 4). Marginal effects have the same sign and relative magnitudes between the models (e.g. *cw* has a higher marginal effect on technical efficiency followed by *alpe* then *sp*) (Table 5). Average partial effects of the interaction terms are not found to be statistically significant at a 5% level of significance for any of the models, though their signs and relative magnitudes are the same. Concern could be raised over the fact that the marginal effect of *perown* is not statistically significant in the Simar Wilson Algorithm #1 model, but it is significant in the other two models (Table 5). It can be reasonably argued though, that the size of the marginal effect of vertical integration is small enough for it not to change the findings of the paper. Furthermore, the only other significant difference is the marginal effect on *mixed*, which is only significant in the Simar and Wilson Algorithm #1 model. This model assumes a truncated versus censored regression model. Hoff (2007) finds that the tobit (censored) regression provides a suitable approximation for analysis of technical efficiency scores, which further is supported by the specification tests conducted and relative agreement with the fractional regression model estimated. Thus, the remainder of our discussion concentrates on the marginal effects of the Tobit regression.

Marginal effects of the age of the mill and whether the mill can produce both sugar and ethanol (*mixed*) were statistically insignificant, but have the expected sign (Table 5). Older mills may have older technology, potentially reducing technical efficiency. On the other hand, mill's age may not affect technical efficiency since facilities may be upgraded. Mills with an option to choose the allocation of sugarcane supplied towards ethanol and sugar production may be able to achieve higher efficiency through optimal input allocation, but this decision is made at the beginning of the production cycle each year, potentially limiting its impact on technical efficiency as other more significant factors may arise during the production cycle.

Results concerning the impact of backwards vertical integration (*perown*) on technical efficiency show that an increase in vertical integration by 1% implies a decrease of 0.0004 in technical efficiency. It can be argued that this negative effect is a reflection of significant differences between the processing and production activities in the supply chain. Nevertheless, the impact is negligible from a practical perspective. For example, consider an average mill that produces 64% of its sugarcane supply (i.e. extent of vertical integration). For that mill, a 10% increase in vertical integration would mean a change in technical efficiency from 0.8834 to 0.8790, which when rounded to two decimal places remains at 0.88. This result is consistent with the findings of Pieri and Zaninotto (2013) who did not find evidence of vertical integration significantly impacting technical efficiency. The results imply that the decision to backwards vertically integrate is not primarily driven by the desire to increase technical efficiency. Even if mills have higher sugarcane productivity (Chaddad 2015) or produce higher yields (Crago et al. 2010), vertical integration of the production process does not necessarily lead to gains in technical efficiency. This result does not rule out gains in efficiency from other forms of vertical coordination. Increased vertical coordination, such as mills signing supply or crop share contracts with farmers or overseeing harvesting, hauling and delivery services could possibly bring gains in technical efficiency[9].

The marginal effects associated with location dummies are all positive (Table 5). Mills located in the Center-West have 0.05 higher technical efficiency scores relative to mills in other states of Brazil not captured by the model. The marginal effect from the Center-West location is also the largest relative to the other locations controlled for (i.e. SP and ALPE). This difference could come from the fact that mills in the Center-West are newer and may have newer technology. When analyzing mills in the Center-South, Pereira et al. (2016) find that mills only adopt technologies with proven efficiency. Also, there is evidence of increased coordination through service provisions in this region. Sant'Anna, Granco, et al (2016) finds that mills in Mato Grosso do Sul and Goiás attract local farmers to sugarcane production by providing them with sugarcane seedlings, payment advances and consulting services.

The results indicate that the mills in Alagoas or Pernambuco regions are relatively more efficient compared to regions not captured by the regression model. Given the decline of the sugarcane sector in these states (Andrade 2001) it is likely that only the more efficient mills remained in operation. The findings are similar for the state of São Paulo, where it is likely that more intense rivalry has driven the inefficient mills out of business or forced them to improve. Our

[9] We were unable to account for this scenario. There was no data available on coordination strategies involving service provisions.

findings on the efficiency of the mills in Alagoas region is consistent with the previous literature and indicates higher efficiency (Junior et al., 2014).

Figures 4, 5, and 6 illustrate the impact on predicted technical efficiency of backwards vertical integration by plotting estimated efficiency scores against 1% changes in backwards vertical integration. The plots illustrate the effect on the predicted technical efficiency score of vertical integration for mixed mills, holding other factors constant. We chose mixed mills since these were the majority of mills in the sample and they represent the state-of-the-art in mill technology. Plots show that differences in technical efficiency, between mills in the Center-West and São Paulo compared to mills in other parts of Brazil, occur when mills are around 60% vertically integrated (Figures 4 and 5). That is, as vertical integration increases, the impact on technical efficiency of mills in the Center-West and São Paulo remain relatively stable and are relatively higher than the technical efficiency of firms in other regions of Brazil.

Strategic considerations underlying the choice of vertical coordination strategies are likely to be a reason for limited effect of vertical integration on technical efficiency in the Center-West (Figure 4). In this region, reliance on specification contracts is a common coordination strategy. In general, in Goiás and Mato Grosso do Sul and other states of the Center-West, farmers prefer to enter into contractual relationship with mills (Sant'Anna, Granco, et al. 2016). Hence, it is likely that the results are showing how vertical coordination through contracting may be just as beneficial, in terms of technical efficiency, as vertical integration. The occurrence of vertical integration in the Center-West may be a management strategy of incumbent mills to create barriers to entry for new entrants. Given that sugarcane has recently expanded into this region, mills establishing in the Center-West may want to control sugarcane production in surrounding lands to limit new mills from entering that geographic area and increasing competition for input procurement.

In the state of São Paulo, the presence of a well-established sugarcane spot market may explain why technical efficiency does not change with higher levels of vertical integration. As suggested by D'Aveni and Ravenscraft (1994), competitive markets may be pressuring farmers to be more efficient. If so, it may be difficult for mills to be more productive than their suppliers. This may explain why mills in São Paulo are less likely to vertically integrate than in other states (Bastos 2013). The observed extent of vertical integration in São Paulo may be a result of management strategy designed to increase mill's bargaining power with suppliers and reduce the rivalry for procurement.

The technical efficiency of mills in Alagoas and Pernambuco changes as the percentage of vertical integration increases (Figure 6). The statistically significant difference between mills in these states and those in other unmodeled states occurs from the level of 40% to 70% of vertical integration. As vertical integration increases, mills in these states start to have the same technical efficiency as those in unmodeled states, at a lower level of technical efficiency, Bastos (2013) reports a constant high level of vertical integration in the Northeastern states in past years. As Andrade (2001) reports, the sugarcane sector in Pernambuco is regressing. A declining sugarcane market may be a reason why we still see mills vertically integrating (Stuckey and White 1993). Another reason may be the costs associated with dis-integration. Stuckey and White (1993) argue that vertical integration may be difficult and costly to reverse. The state of Pernambuco, for instance, has a history of consolidated economic groups being responsible for their own sugarcane production (Andrade 2001). This suggests that mills may have decided, in the past, to vertically integrate and now find it too costly to divest from sugarcane production. In addition, current policies in place in Brazil seem to favor sugarcane production in the Center-South (e.g. the Sugarcane Agroecological Zoning identifies larger areas for sugarcane production in the Center-South states (Manzatto 2009; Sant'Anna, Granco, et al. 2016)). This discourages new farmers from entering sugarcane production or current producers from investing in sugarcane production.

6. Conclusion

The sugarcane industry in Brazil, one of the world's leading producers of ethanol and sugar, is undergoing significant changes driven by geographic expansion and technological innovations. These changes are forcing the players at all levels of the supply chain, particularly sugarcane producers and processors, to re-evaluate their vertical coordination and growth strategies. This paper contributes to the literature by presenting an empirical analysis of the relationship between the vertical coordination strategies at the production-processing interface of the Brazilian ethanol supply chain and the technical efficiency of the mills. It utilizes data envelopment analysis and a Tobit censored model in combination with a unique data on 204 mills that were collectively responsible for around half of the Brazil's sugar and ethanol production in 2013.

Results indicate that vertical integration and the location of the mill have a statistically significant impact on efficiency. Moreover, the differences in technical efficiency between mills in different locations are more significant at higher levels of vertical integration. The findings indicate that the technical efficiency is not the main driver of vertical integration though, implying that such decisions are primarily motivated by strategic considerations. Interestingly, the results indicate that the mills are likely to forgo gains in technical efficiency in exchange for improving their strategic position through vertical integration. The findings shed light on the underlying motivation for the observed level of vertical integration that accompanies the expansion of the Brazilian sugarcane industry.

The vertical integration at the production-processing interface of the Brazilian sugarcane supply chain is not a recent phenomenon. Public policies have been put in place since 1941 to mitigate potential negative effects on the structure of agricultural production, on the sustainability of natural resources, and on the balance of bargaining power and concentration within the industry. However, considering recent and ongoing expansion of sugarcane industry, many important questions remain unanswered regarding the long-term impact of those policies on operational efficiency and strategic dynamics within sugarcane processing sector. The unique contribution of this study is that it bridges the gap between two distinct and parallel strands of existing literature that are comprised of studies with a primary focus on either technical efficiency and operations or strategy and management. By examining the relationship between vertical coordination strategies and technical efficiency this study not only presents useful insights for policy and industry decision makers, but also provides a platform for future studies aiming to shed light on complex interaction between operational and strategic considerations and long-term policy and management implications for the Brazilian sugarcane and ethanol industry.

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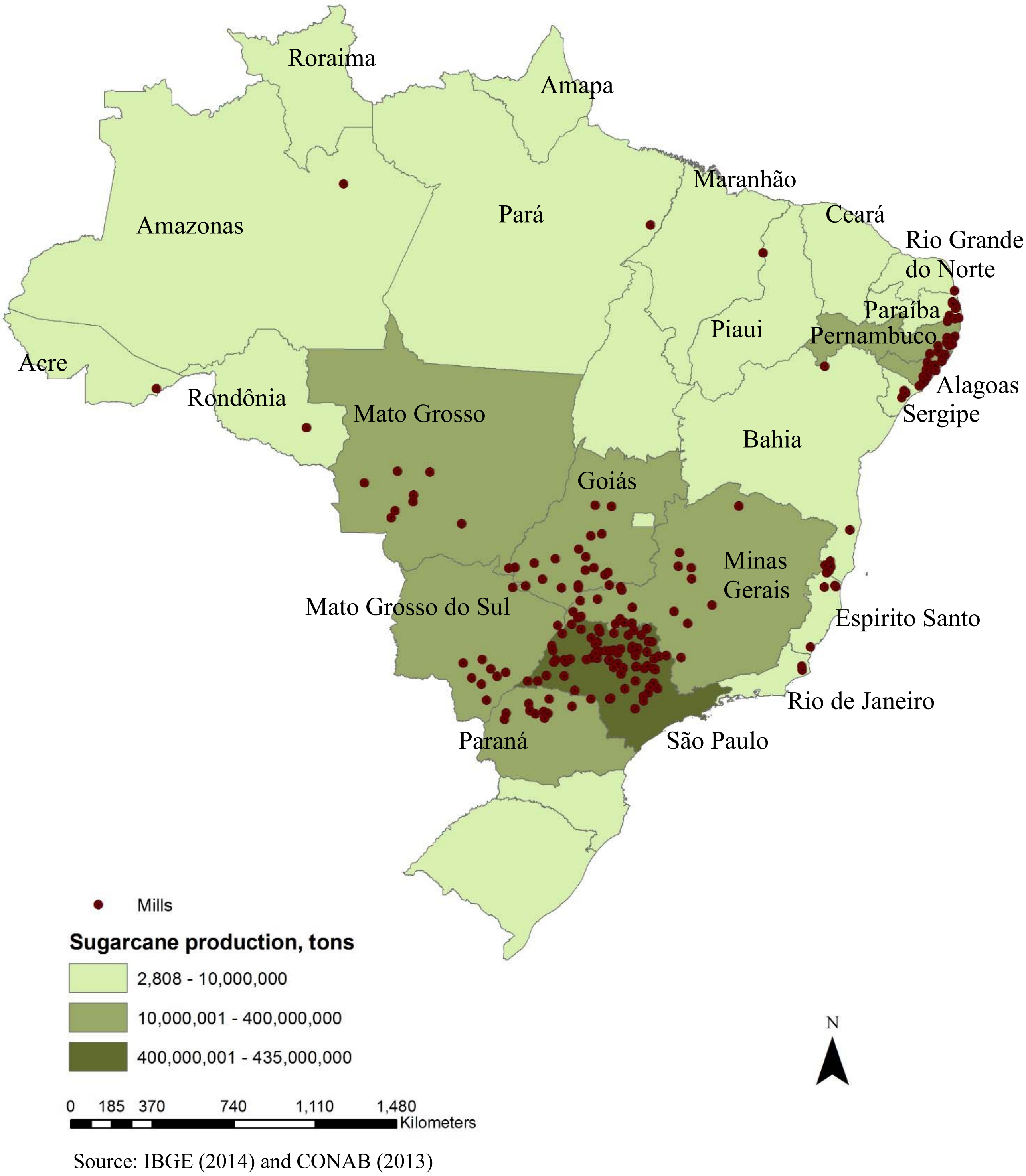

Figure 1: Sugarcane production in Brazil in crop year 2011/12 and location of sugarcane mills modeled.

Table 1: Sugarcane supply share and average area cultivated by farmers and mills in the crop year 2011/12

States and Regions	Cane production share		Land cultivated by	
	Mill(%)	Farmer(%)	Mills (ha)	Farmers (ha)
North				
Acre	100%	0%	526.22	0.00
Amazonas	100%	0%	3,870.64	0.00
Para	100%	0%	12,115.82	0.00
Rondonia	84%	16%	2,328.74	437.97
Northeast				
Alagoas	66%	34%	11,732.95	6,098.28
Bahia	69%	31%	4,332.74	1,908.60
Paraiba	55%	45%	7,710.81	6,365.15
Pernambuco	60%	40%	8,559.10	5,611.60
Piaui	83%	17%	11,619.26	2,417.05
Rio Grande do Norte	79%	21%	11,385.73	3,039.37
Sergipe	74%	26%		
Southeast				
São Paulo	57%	43%	14,680.91	10,971.56
Minas Gerais	58%	42%	9,470.81	6,960.16
Espirito Santo	57%	43%	6,037.94	4,618.50
Rio de Janeiro	11%	89%	1,338.32	10,985.42
South				
Parana	90%	10%	18,272.56	2,127.75
Rio Grande do Sul	100%	0%	1,876.97	0.00
Center West				
Mato Grosso do Sul	73%	27%	16,806.98	5,671.26
Goiás	77%	23%	15,126.91	4,184.86
Mato Grosso	87%	13%	21,705.23	3,024.44
Brazil	64%	36%	13,110.12	7,348.45

Source: CONAB 2013.

Table 2: Summary statistics of inputs, outputs and exogenous variables used

Variables	Description		N	Minimum	Mean	Maximum	Standard Deviation
Inputs							
sugarcane	Amount in 1,000 tons of sugarcane crushed by the DMU		204	33.11	1,484.69	7,601.58	1,155.33
capacity	Amout of sugarcane daily crushing capacity		204	800.00	10,130.19	42,000.00	6,707.17
Outputs							
ethanol	Amount of ethanol produced in 1,000,000 liters by each DMU		204	0.00	62.00	295.85	52.37
sugar	Amount of sugar produced in 1,000 tons by each DMU		204	0.00	91.51	638.70	99.99
Exogenous							
perown	Percentage (%) of sugarcane crushed that was produced by the mill		204	0.00	64.27	100.00	29.29
mixed	Dummy that is 1 when the mill produces two goods and 0 otherweise		204	0.00	0.68	1.00	0.47
cw	Dummy that is 1 when the mill is in the Center-West and 0 otherweise		204	0.00	0.18	1.00	0.39
cw*perown	Interaction of a dummy indicating if the mill is in the Center West region with perown	cw=0	167	0.00	0.61	1.00	0.29
		cw=1	37	0.00	0.80	1.00	0.27
sp	Dummy that is 1 when the mill is in São Paulo and 0 otherweise		204	0.00	0.34	1.00	0.47
sp*perown	Interaction of a dummy indicating if the mill is in the state of Sao Paulo with perown	sp=0	135	0.00	0.66	1.00	0.30
		sp=1	69	0.00	0.62	1.00	0.27
alpe	Dummy that is 1 when the mill is either in Alagoas or Pernambuco and 0		204	0.00	0.16	1.00	0.36
alpe*perown	Interaction of a dummy indicating if the mill is in the states of Alagoas or Pernambuco with perown	alpe=0	172	0.00	0.65	1.00	0.31
		alpe=1	32	0.00	0.62	0.90	0.19
age	Age of the mill in years		204	1.00	28.33	152.00	27.84

Table 3: Input-oriented efficiency scores by region and state with variable returns to scale

States and Regions	N	Minimum	Mean	Maximum	Standard Deviation
North	4	0.70	0.82	1.00	0.13
Acre	1	1.00	1.00	1.00	.
Amazonas	1	0.75	0.75	0.75	.
Para	1	0.85	0.85	0.85	.
Rondonia	1	0.70	0.70	0.70	.
Northeast	50	0.60	0.88	1.00	0.09
Alagoas	20	0.80	0.92	1.00	0.06
Bahia	6	0.60	0.72	0.85	0.09
Paraiba	6	0.80	0.90	1.00	0.08
Pernambuco	12	0.74	0.88	1.00	0.06
Piaui	1	0.84	0.84	0.84	.
Rio Grande do Norte	1	0.72	0.72	0.72	.
Sergipe	4	0.87	0.92	0.96	0.04
Southeast	101	0.53	0.88	1.00	0.08
São Paulo	69	0.71	0.89	1.00	0.06
Minas Gerais	26	0.53	0.88	1.00	0.10
Espirito Santo	4	0.73	0.75	0.76	0.01
Rio de Janeiro	2	0.81	0.82	0.83	0.01
South	12	0.78	0.86	1.00	0.06
Parana	11	0.78	0.85	0.91	0.05
Rio Grande do Sul	1	1.00	1.00	1.00	.
Center West	37	0.77	0.91	1.00	0.06
Mato Grosso do Sul	9	0.81	0.90	1.00	0.06
Goiás	19	0.77	0.91	1.00	0.07
Mato Grosso	9	0.83	0.90	1.00	0.05
Brazil	204	0.53	0.88	1.00	0.08

Table 4: Estimation results for the Tobit, Simar Wilson and Fractional regression models

	Tobit		Simar Wilson Algorithm #1		Fractional Regression	
Perown	-0.0006		-0.0004		-0.0044	
	(0.0004)		(0.0003)		(0.0031)	
Mixed	0.0118		0.0489	***	0.1576	
	(0.0159)		(0.0160)		(0.1336)	
Cw	0.0294		0.0205		0.2536	
	(0.0665)		(0.0608)		(0.6619)	
Sp	0.0063		0.0013		0.0638	
	(0.0361)		(0.0376)		(0.3072)	
Alpe	0.1482	*	0.0964		1.6323	*
	(0.0902)		(0.0928)		(0.8485)	
Age	-0.0002		-0.0004		-0.0024	
	(0.0003)		(0.0003)		(0.00279)	
cw*perown	0.0005		0.0009		0.0047	
	(0.0008)		(0.0007)		(0.0076)	
sp*perown	0.0006		0.0008		0.0052	
	(0.0005)		(0.0005)		(0.0043)	
alpe*perown	-0.0013		-0.0004		-0.0157	
	(0.0003)		(0.0013)		(0.0115)	
Constant	0.885	***	0.8444	***	1.9624	***
	(0.0314)		(0.0250)		(0.2585)	
Sigma	0.082		0.078			
	(0.0054)		(0.0057)			
Wald Test Statistic for Overall Significance	17.94		35.282		23.47	
P-Value	0.036		0.000		0.005	

Note: Standard errors are in parenthesis.
Significant levels: *** is 1%, ** is 5%, * is 10%.

Table 5: Estimated marginal effects for Tobit, Simar Wilson and Fractional regression models

	Tobit		Simar Wilson Algorithm #1		Fractional regression	
Perown	-0.0004	*	-0.00004		-0.0004	***
	(0.0002)		(0.0003)		(0.0002)	
Mixed	0.0107		0.0489	***	0.0160	
	(0.0144)		(0.0160)		(0.0136)	
Cw	0.0526	***	0.0801	***	0.0505	***
	(0.0189)		(0.0236)		(0.0182)	
Sp	0.0401	***	0.0540	***	0.0385	***
	(0.0123)		(0.0165)		(0.0113)	
Alpe	0.0513	***	0.0723	***	0.0479	***
	(0.0161)		(0.0259)		(0.0156)	
Age	-0.0002		-0.0004		-0.0002	
	(0.0003)		(0.0003)		(0.0003)	
Interactions						
cw*perown	0.0005		0.0009		0.0005	
	(0.0006)		(0.0007)		(0.0006)	
sp*perown	0.0006		0.0008		0.0006	
	(0.0004)		(0.0005)		(0.0004)	
alpe*perown	-0.0009		-0.0004		-0.0010	
	(0.0009)		(0.0013)		(0.0009)	

Note: Standard errors are in parenthesis.
Significant levels: *** is 1%, ** is 5%, * is 10%.

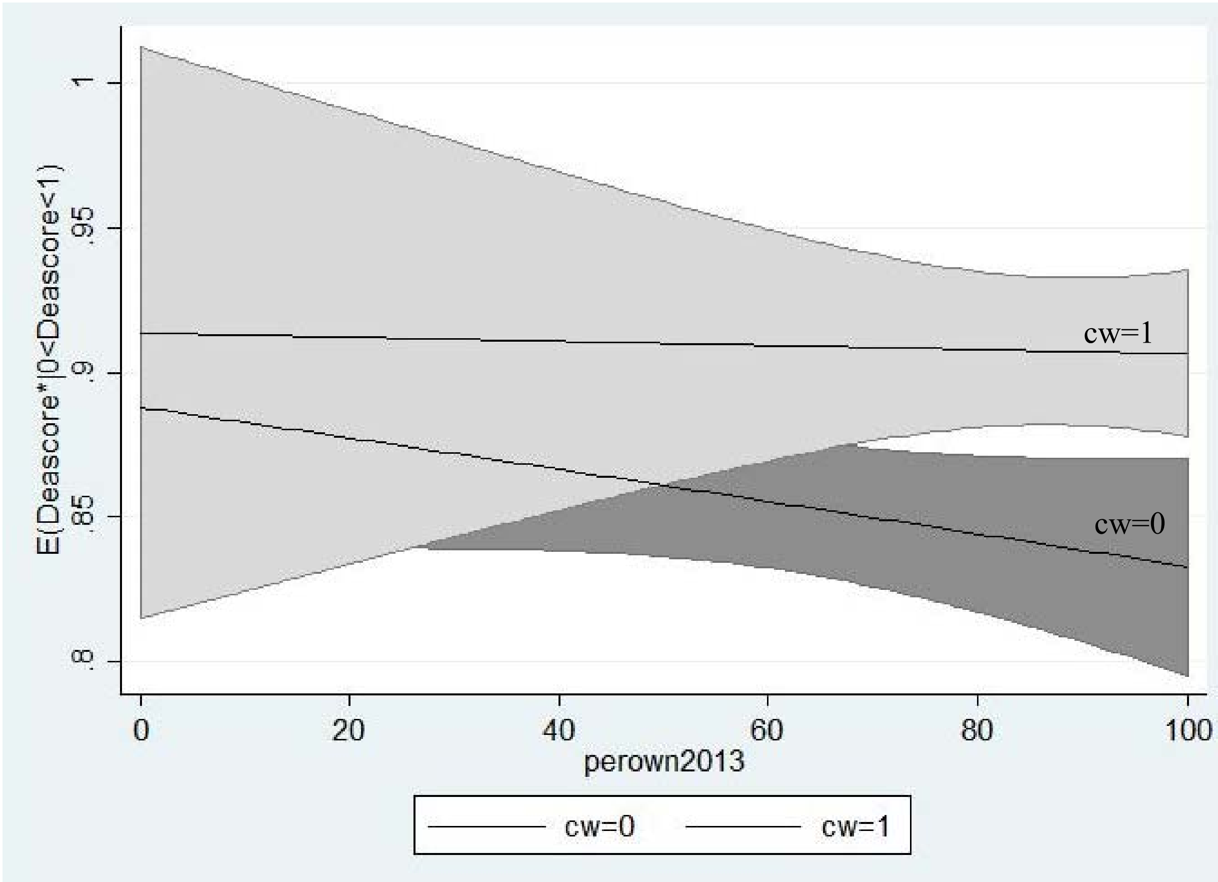

Figure 2: Predicted efficiency scores and 95% confidence interval for different levels of vertical integration for mixed mills in the Center-West (cw=1) and rest of Brazil (cw=0)

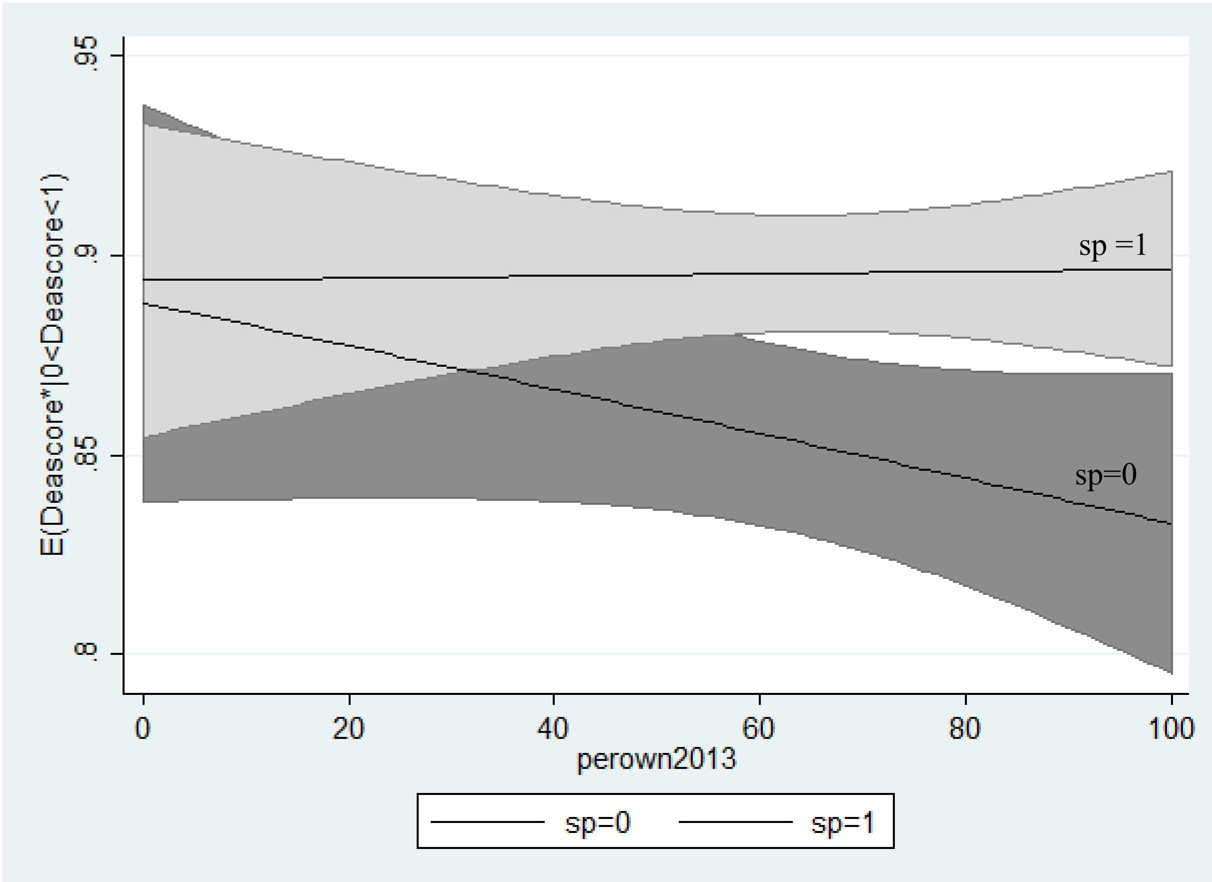

Figure 3: Predicted efficiency scores and 95% confidence interval for different levels of vertical integration for mixed mills in São Paulo (sp=1) and rest of Brazil (sp=0)

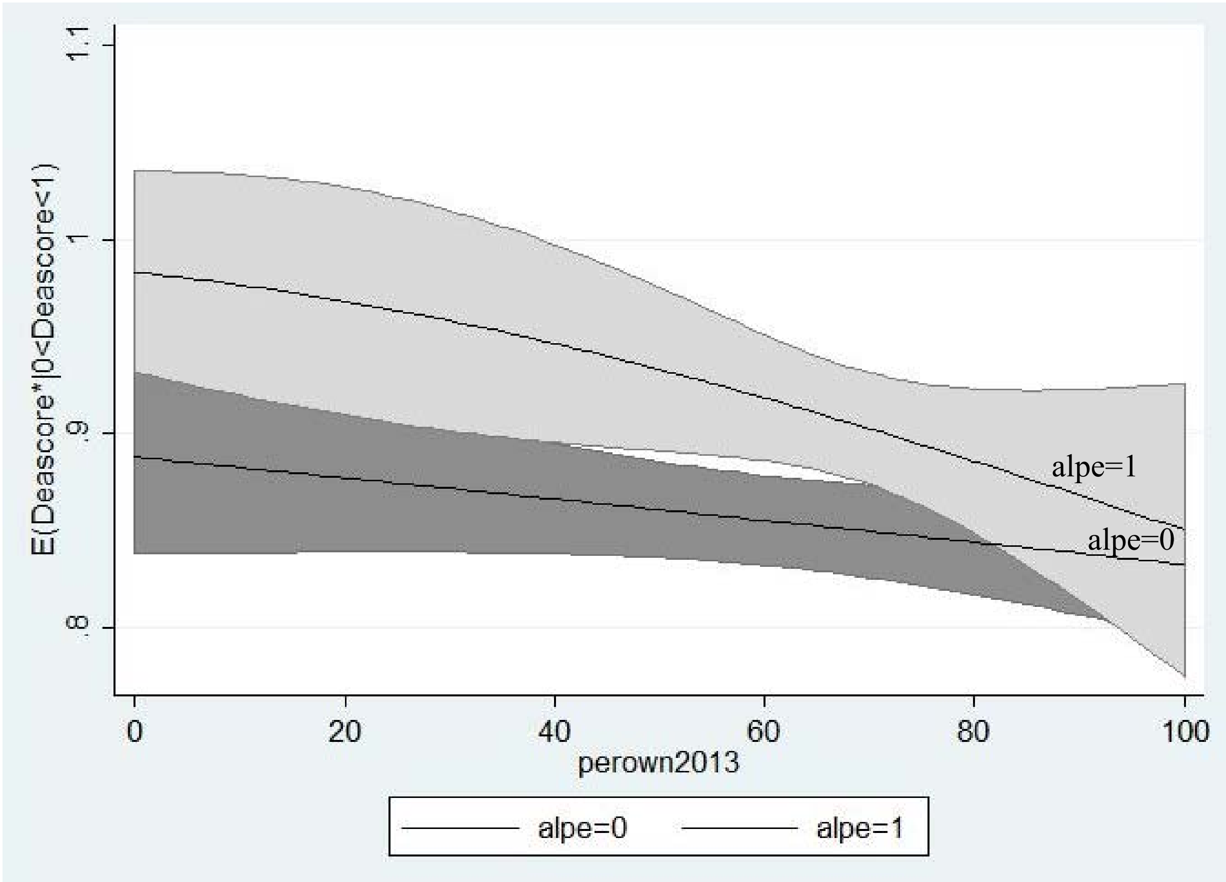

Figure 4: Predicted efficiency scores and 95% confidence interval for different levels of vertical integration for mixed mills in Alagoas or Pernambuco (alpe=1) and rest of Brazil (alpe=0)

Supplementary Appendix: Testing for separability

Prior to running a second stage regression using DEA scores, a modeler must check if the separability assumption holds. This involves estimating conditional and unconditional DEAs. If the separability assumption holds, that is, if the environmental variables (i.e. vertical integration) do not impact the efficiency frontier, then the unconditional DEA scores can be used in a second stage regression.

Consider a vector of input quantities $X \epsilon R_{+}^{p}$, a vector of output quantities $Y \epsilon R_{+}^{q}$and a vector of environmental variables $Z \epsilon R^{r}$. The environmental variables are variables not present in the vector of inputs or outputs but, nevertheless, may affect the distribution of the efficiency scores and location of the efficiency frontier (Daraio et al. 2015). The environmental variables can impact the production process through: (1) the set of feasible input and output combinations ψ^{Z}; (2) through the joint density function $f_{XYZ}(x, y, z)$; or (3) both (1) and (2) (Daraio et al. 2015). Let ψ^{Z} be the set of possible pairs of inputs and outputs for a firm when there are environmental variables *Z*. In this case (Daraio et al. 2015):

$$\psi^{Z} = \{(X, Y) | X\ produces\ Y\ when\ Z = z\} \tag{C.1}$$

That is, the efficiency frontier will be determined in part by the value of the environmental variable(s). In this case, the efficient frontier is not separable from the level of *Z*. If environmental factors do not impact the location of the efficient frontier, then the set of possible pairs of inputs and outputs for a firm becomes:

$$\psi = \{(X, Y) | X\ produces\ Y\} \tag{C.2}$$

Tests of separability are important to determine if second-stage regression results are not biased and inconsistent by not taking account of the effect of environmental variables of interest in estimating the efficient frontier.. These tests compare the null hypothesis of separability $H_0: \psi^Z = \psi$ against the alternative hypothesis $H_A: \psi^Z \neq \psi, for\ some\ z \in Z$ (Daraio et al. 2015). If the null hypothesis is rejected, meaning that the seperability assumption does not hold, the environmental variables must be accounted for in first stage estimation of technical efficiency using DEA. This is done by using conditional DEA (Daraio et al. 2015) or correction procedures as proposed by Simar and Wilson (2007).

To check for separability we follow methods in Daraio et al. 2015 and compared the conditional efficiency scores with the unconditional efficiency scores using the level of backward vertical integration as the conditioning environmental factor. Conditional efficiency scores were obtained by splitting the sample into groups that have similar levels of the environmental variable factor *Z*. This means that DMU's were split into groups according to the percentage of sugarcane that was crushed that came from land under their control. First the unconditional DEA was estimated followed by the estimation of the conditional DEA. For the conditional DEA, the minimization problem described in (1) was run separately for each group. Conditional and unconditional scores were compared, as in Bădin et al. (2012), by taking the ratio (R_0) of the efficiency scores:

$$R_0(x, y|z) = \frac{\theta(x,y|z)}{\theta(x,y)} \tag{C.3}$$

Conditional DEAs were run by splitting the sample into groups of 3, 4 and 5 depending on their percentage of crushed sugarcane that was produced by the mill. The groups and their sizes are presented in Table SA1. In all cases the conditional efficiency scores matched that of the unconditional DEA. Groups contain over 30 DMUs in each subgroup to ensure that the DEA is relevant. Since the efficiency scores from the conditional DEAs and the unconditional DEAs were close to identical we decided that there was no need to run statistical tests. Results from the pooled and conditional DEA are presented in Table SA2.

Table SA1: Conditional DEA groupings by level of backward vertical integration.

Group Size	Category	N
3	[0%-50%]	52
	(50%-80%]	81
	(80%-100%]	75
4	[0%-50%]	52
	(50%-70%]	53
	(70%-85%]	46
	(85%-100%]	57
5	[0%-45%]	44
	(45%-65%]	44
	(65%-80%]	42
	(80%-95%]	38
	(95%-100%]	36

Table SA2: Comparison of the conditional and unconditional DEA efficiency scores

dmu	Unconditional	Conditional DEA in groups of			Ratios		
	DEA (1)	Three (3)	Four (4)	Five (5)	(1)/(3)	(1)/(4)	(1)/(5)
1	0.965	0.965	0.965	0.965	1.000	1.000	1.000
2	0.850	0.850	0.850	0.850	1.000	1.000	1.000
3	0.903	0.903	0.903	0.903	1.000	1.000	1.000
4	0.534	0.534	0.534	0.534	1.000	1.000	1.000
5	0.808	0.808	0.808	0.808	1.000	1.000	1.000
6	0.747	0.747	0.747	0.747	1.000	1.000	1.000
7	1.000	1.000	1.000	1.000	1.000	1.000	1.000
8	0.923	0.923	0.923	0.923	1.000	1.000	1.000
9	1.000	1.000	1.000	1.000	1.000	1.000	1.000
10	0.710	0.710	0.710	0.710	1.000	1.000	1.000
11	0.878	0.878	0.878	0.878	1.000	1.000	1.000
12	0.775	0.775	0.775	0.775	1.000	1.000	1.000
13	0.793	0.793	0.793	0.793	1.000	1.000	1.000
14	0.847	0.847	0.847	0.847	1.000	1.000	1.000
15	0.806	0.806	0.806	0.806	1.000	1.000	1.000
16	0.814	0.814	0.814	0.814	1.000	1.000	1.000
17	0.858	0.858	0.858	0.858	1.000	1.000	1.000
18	0.929	0.929	0.929	0.929	1.000	1.000	1.000
19	0.927	0.927	0.927	0.927	1.000	1.000	1.000
20	0.877	0.877	0.877	0.877	1.000	1.000	1.000
21	0.872	0.872	0.872	0.872	1.000	1.000	1.000
22	0.898	0.898	0.898	0.898	1.000	1.000	1.000
23	0.911	0.911	0.911	0.911	1.000	1.000	1.000
24	0.894	0.894	0.894	0.894	1.000	1.000	1.000
25	0.839	0.839	0.839	0.839	1.000	1.000	1.000
26	0.891	0.891	0.891	0.891	1.000	1.000	1.000
27	0.878	0.878	0.878	0.878	1.000	1.000	1.000
28	0.891	0.891	0.891	0.891	1.000	1.000	1.000
29	0.845	0.845	0.845	0.845	1.000	1.000	1.000
30	0.817	0.817	0.817	0.817	1.000	1.000	1.000
31	0.852	0.852	0.852	0.852	1.000	1.000	1.000
32	0.931	0.931	0.931	0.931	1.000	1.000	1.000
33	0.903	0.903	0.903	0.903	1.000	1.000	1.000
34	0.959	0.959	0.959	0.959	1.000	1.000	1.000
35	0.874	0.874	0.874	0.874	1.000	1.000	1.000
36	0.870	0.870	0.870	0.870	1.000	1.000	1.000
37	0.883	0.883	0.883	0.883	1.000	1.000	1.000
38	0.842	0.842	0.842	0.842	1.000	1.000	1.000
39	0.967	0.967	0.967	0.967	1.000	1.000	1.000
40	0.855	0.855	0.855	0.855	1.000	1.000	1.000
41	0.953	0.953	0.953	0.953	1.000	1.000	1.000
42	0.708	0.708	0.708	0.708	1.000	1.000	1.000
43	0.810	0.810	0.810	0.810	1.000	1.000	1.000
44	0.858	0.858	0.858	0.858	1.000	1.000	1.000
45	0.892	0.892	0.892	0.892	1.000	1.000	1.000
46	0.971	0.971	0.971	0.971	1.000	1.000	1.000
47	0.847	0.847	0.847	0.847	1.000	1.000	1.000
48	0.811	0.811	0.811	0.811	1.000	1.000	1.000
49	0.801	0.801	0.801	0.801	1.000	1.000	1.000
50	0.986	0.986	0.986	0.986	1.000	1.000	1.000
51	0.978	0.978	0.978	0.978	1.000	1.000	1.000

(continued)

dmu	Unconditional DEA (1)	Conditional DEA in groups of Three (3)	Four (4)	Five (5)	Ratios (1)/(3)	(1)/(4)	(1)/(5)
52	0.879	0.879	0.879	0.879	1.000	1.000	1.000
53	0.847	0.847	0.847	0.847	1.000	1.000	1.000
54	0.947	0.947	0.947	0.947	1.000	1.000	1.000
55	0.888	0.888	0.888	0.888	1.000	1.000	1.000
56	0.783	0.783	0.783	0.783	1.000	1.000	1.000
57	1.000	1.000	1.000	1.000	1.000	1.000	1.000
58	0.778	0.778	0.778	0.778	1.000	1.000	1.000
59	0.905	0.905	0.905	0.905	1.000	1.000	1.000
60	0.858	0.858	0.858	0.858	1.000	1.000	1.000
61	0.908	0.908	0.908	0.908	1.000	1.000	1.000
62	0.898	0.898	0.898	0.898	1.000	1.000	1.000
63	0.894	0.894	0.894	0.894	1.000	1.000	1.000
64	0.859	0.859	0.859	0.859	1.000	1.000	1.000
65	0.930	0.930	0.930	0.930	1.000	1.000	1.000
66	0.856	0.856	0.856	0.856	1.000	1.000	1.000
67	0.834	0.834	0.834	0.834	1.000	1.000	1.000
68	0.857	0.857	0.857	0.857	1.000	1.000	1.000
69	0.910	0.910	0.910	0.910	1.000	1.000	1.000
70	0.794	0.794	0.794	0.794	1.000	1.000	1.000
71	0.809	0.809	0.809	0.809	1.000	1.000	1.000
72	0.919	0.919	0.919	0.919	1.000	1.000	1.000
73	0.812	0.812	0.812	0.812	1.000	1.000	1.000
74	0.898	0.898	0.898	0.898	1.000	1.000	1.000
75	0.882	0.882	0.882	0.882	1.000	1.000	1.000
76	0.842	0.842	0.842	0.842	1.000	1.000	1.000
77	0.912	0.912	0.912	0.912	1.000	1.000	1.000
78	0.770	0.770	0.770	0.770	1.000	1.000	1.000
79	0.931	0.931	0.931	0.931	1.000	1.000	1.000
80	0.886	0.886	0.886	0.886	1.000	1.000	1.000
81	0.883	0.883	0.883	0.883	1.000	1.000	1.000
82	0.837	0.837	0.837	0.837	1.000	1.000	1.000
83	0.818	0.818	0.818	0.818	1.000	1.000	1.000
84	0.918	0.918	0.918	0.918	1.000	1.000	1.000
85	0.827	0.827	0.827	0.827	1.000	1.000	1.000
86	0.912	0.912	0.912	0.912	1.000	1.000	1.000
87	0.845	0.845	0.845	0.845	1.000	1.000	1.000
88	0.885	0.885	0.885	0.885	1.000	1.000	1.000
89	0.894	0.894	0.894	0.894	1.000	1.000	1.000
90	0.977	0.977	0.977	0.977	1.000	1.000	1.000
91	0.880	0.880	0.880	0.880	1.000	1.000	1.000
92	0.833	0.833	0.833	0.833	1.000	1.000	1.000
93	0.844	0.844	0.844	0.844	1.000	1.000	1.000
94	0.872	0.872	0.872	0.872	1.000	1.000	1.000
95	0.920	0.920	0.920	0.920	1.000	1.000	1.000
96	0.937	0.937	0.937	0.937	1.000	1.000	1.000
97	0.985	0.985	0.985	0.985	1.000	1.000	1.000
98	0.853	0.853	0.853	0.853	1.000	1.000	1.000
99	0.937	0.937	0.937	0.937	1.000	1.000	1.000
100	0.789	0.789	0.789	0.789	1.000	1.000	1.000
101	0.853	0.853	0.853	0.853	1.000	1.000	1.000
102	0.862	0.862	0.862	0.862	1.000	1.000	1.000

(continued)

dmu	Unconditional DEA (1)	Conditional DEA in groups of Three (3)	Four (4)	Five (5)	Ratios (1)/(3)	(1)/(4)	(1)/(5)
103	0.973	0.973	0.973	0.973	1.000	1.000	1.000
104	1.000	1.000	1.000	1.000	1.000	1.000	1.000
105	1.000	1.000	1.000	1.000	1.000	1.000	1.000
106	0.939	0.939	0.939	0.939	1.000	1.000	1.000
107	0.859	0.859	0.859	0.859	1.000	1.000	1.000
108	0.890	0.890	0.890	0.890	1.000	1.000	1.000
109	0.903	0.903	0.903	0.903	1.000	1.000	1.000
110	1.000	1.000	1.000	1.000	1.000	1.000	1.000
111	0.885	0.885	0.885	0.885	1.000	1.000	1.000
112	0.891	0.891	0.891	0.891	1.000	1.000	1.000
113	0.938	0.938	0.938	0.938	1.000	1.000	1.000
114	0.847	0.847	0.847	0.847	1.000	1.000	1.000
115	0.874	0.874	0.874	0.874	1.000	1.000	1.000
116	0.919	0.919	0.919	0.919	1.000	1.000	1.000
117	0.961	0.961	0.961	0.961	1.000	1.000	1.000
118	0.904	0.904	0.904	0.904	1.000	1.000	1.000
119	0.957	0.957	0.957	0.957	1.000	1.000	1.000
120	0.954	0.954	0.954	0.954	1.000	1.000	1.000
121	0.879	0.879	0.879	0.879	1.000	1.000	1.000
122	0.981	0.981	0.981	0.981	1.000	1.000	1.000
123	0.893	0.893	0.893	0.893	1.000	1.000	1.000
124	1.000	1.000	1.000	1.000	1.000	1.000	1.000
125	0.969	0.969	0.969	0.969	1.000	1.000	1.000
126	0.997	0.997	0.997	0.997	1.000	1.000	1.000
127	0.983	0.983	0.983	0.983	1.000	1.000	1.000
128	0.911	0.911	0.911	0.911	1.000	1.000	1.000
129	0.904	0.904	0.904	0.904	1.000	1.000	1.000
130	0.974	0.974	0.974	0.974	1.000	1.000	1.000
131	0.941	0.941	0.941	0.941	1.000	1.000	1.000
132	0.929	0.929	0.929	0.929	1.000	1.000	1.000
133	1.000	1.000	1.000	1.000	1.000	1.000	1.000
134	0.905	0.905	0.905	0.905	1.000	1.000	1.000
135	1.000	1.000	1.000	1.000	1.000	1.000	1.000
136	0.906	0.906	0.906	0.906	1.000	1.000	1.000
137	1.000	1.000	1.000	1.000	1.000	1.000	1.000
138	0.942	0.942	0.942	0.942	1.000	1.000	1.000
139	0.854	0.854	0.854	0.854	1.000	1.000	1.000
140	0.981	0.981	0.981	0.981	1.000	1.000	1.000
141	1.000	1.000	1.000	1.000	1.000	1.000	1.000
142	0.990	0.990	0.990	0.990	1.000	1.000	1.000
143	1.000	1.000	1.000	1.000	1.000	1.000	1.000
144	1.000	1.000	1.000	1.000	1.000	1.000	1.000
145	1.000	1.000	1.000	1.000	1.000	1.000	1.000
146	1.000	1.000	1.000	1.000	1.000	1.000	1.000
147	0.854	0.854	0.854	0.854	1.000	1.000	1.000
148	0.977	0.977	0.977	0.977	1.000	1.000	1.000
149	0.830	0.830	0.830	0.830	1.000	1.000	1.000
150	0.872	0.872	0.872	0.872	1.000	1.000	1.000
151	0.803	0.803	0.803	0.803	1.000	1.000	1.000
152	0.900	0.900	0.900	0.900	1.000	1.000	1.000
153	1.000	1.000	1.000	1.000	1.000	1.000	1.000

(continued)

dmu	Unconditional DEA (1)	Conditional DEA in groups of Three (3)	Four (4)	Five (5)	Ratios (1)/(3)	(1)/(4)	(1)/(5)
154	0.940	0.940	0.940	0.940	1.000	1.000	1.000
155	0.892	0.892	0.892	0.892	1.000	1.000	1.000
156	0.991	0.991	0.991	0.991	1.000	1.000	1.000
157	0.858	0.858	0.858	0.858	1.000	1.000	1.000
158	0.891	0.891	0.891	0.891	1.000	1.000	1.000
159	0.967	0.967	0.967	0.967	1.000	1.000	1.000
160	0.910	0.910	0.910	0.910	1.000	1.000	1.000
161	1.000	1.000	1.000	1.000	1.000	1.000	1.000
162	0.912	0.912	0.912	0.912	1.000	1.000	1.000
163	0.976	0.976	0.976	0.976	1.000	1.000	1.000
164	0.845	0.845	0.845	0.845	1.000	1.000	1.000
165	0.747	0.747	0.747	0.747	1.000	1.000	1.000
166	0.848	0.848	0.848	0.848	1.000	1.000	1.000
167	0.680	0.680	0.680	0.680	1.000	1.000	1.000
168	0.677	0.677	0.677	0.677	1.000	1.000	1.000
169	0.764	0.764	0.764	0.764	1.000	1.000	1.000
170	0.776	0.776	0.776	0.776	1.000	1.000	1.000
171	0.603	0.603	0.603	0.603	1.000	1.000	1.000
172	0.749	0.749	0.749	0.749	1.000	1.000	1.000
173	0.763	0.763	0.763	0.763	1.000	1.000	1.000
174	0.739	0.739	0.739	0.739	1.000	1.000	1.000
175	0.731	0.731	0.731	0.731	1.000	1.000	1.000
176	0.850	0.850	0.850	0.850	1.000	1.000	1.000
177	0.898	0.898	0.898	0.898	1.000	1.000	1.000
178	0.983	0.983	0.983	0.983	1.000	1.000	1.000
179	1.000	1.000	1.000	1.000	1.000	1.000	1.000
180	0.910	0.910	0.910	0.910	1.000	1.000	1.000
181	0.831	0.831	0.831	0.831	1.000	1.000	1.000
182	0.805	0.805	0.805	0.805	1.000	1.000	1.000
183	0.744	0.744	0.744	0.744	1.000	1.000	1.000
184	0.904	0.904	0.904	0.904	1.000	1.000	1.000
185	1.000	1.000	1.000	1.000	1.000	1.000	1.000
186	0.869	0.869	0.869	0.869	1.000	1.000	1.000
187	0.902	0.902	0.902	0.902	1.000	1.000	1.000
188	0.842	0.842	0.842	0.842	1.000	1.000	1.000
189	0.902	0.902	0.902	0.902	1.000	1.000	1.000
190	0.892	0.892	0.892	0.892	1.000	1.000	1.000
191	0.913	0.913	0.913	0.913	1.000	1.000	1.000
192	0.894	0.894	0.894	0.894	1.000	1.000	1.000
193	0.848	0.848	0.848	0.848	1.000	1.000	1.000
194	0.872	0.872	0.872	0.872	1.000	1.000	1.000
195	0.844	0.844	0.844	0.844	1.000	1.000	1.000
196	0.807	0.807	0.807	0.807	1.000	1.000	1.000
197	0.827	0.827	0.827	0.827	1.000	1.000	1.000
198	0.716	0.716	0.716	0.716	1.000	1.000	1.000
199	1.000	1.000	1.000	1.000	1.000	1.000	1.000
200	0.699	0.699	0.699	0.699	1.000	1.000	1.000
201	0.867	0.867	0.867	0.867	1.000	1.000	1.000
202	0.906	0.906	0.906	0.906	1.000	1.000	1.000
203	0.956	0.956	0.956	0.956	1.000	1.000	1.000
204	0.944	0.944	0.944	0.944	1.000	1.000	1.000