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## Heterogeneity in the productivity of sugar-energy mills in Brazil

### REVIEW ARTICLE

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### Abstract

The development of biofuels in Brazil, and particularly of ethanol as a sustainable energy source, has enabled the strengthening of the national sugar-energy industry. The objective of this study is therefore to evaluate the evolution of the productive efficiency of sugar-energy mills in Brazil during the period of 2006 to 2015, using data envelopment analysis and the Malmquist index and its decompositions. Our results indicate that no single nor well-defined pattern of efficiency or productivity existed among the mills in the industry during the period under study; instead, we found the industry to be heterogeneous in terms of management practices and technology adoption. Furthermore, we found that differences between mills intensified over the period, and that technologically poor mills with low levels of efficiency coexisted among efficient mills employing modern management practices and technologies. Finally, we found that productivity decreased, yet varied considerably over the analyzed period.

**Keywords:** efficiency, productivity, DEA, sugar-energy industry

**JEL code:** C14, D24, L23

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## 1. Introduction

While Brazil has long been a major sugar producer, through technological innovation over the last 40 years the country has emerged as one of the world's leading biofuel – and particularly ethanol – producers. Despite this growth, the sugar and ethanol production process in Brazil has not undergone any significant changes over time. Instead, the industry has evolved through incremental technological progress that has led to a substantial reduction in production costs in both agricultural production and processing and an increase in production (Da Silva and Marques, 2017; Hall *et al.*, 2011). The National Fuel Alcohol Program (Proálcool), implemented in 1975 and that contributed to boost bioenergy production in the country, is an example of this path of technological learning based on incremental innovation (Furtado *et al.*, 2011).

The dynamism and development of the sugar-energy sector in Brazil initially occurred in the state of Sao Paulo, due to several factors that included the state's natural resources, superior logistics infrastructure, proximity to consumer markets, differential taxation of ethanol compared to gasoline, and, in particular, its innovation environment that united producers, manufacturers of capital goods, universities, and research centers.

Agricultural research in Brazil is predominantly financed by the public sector, which represents roughly 89% of research and development (R&D) efforts in this segment. Nevertheless, since the 1990s, innovation in the sugarcane industry has been marked by the intense interaction of agents outside of the public sector. Unlike other production chains in Brazilian agriculture, the private sector has contributed to troubleshooting problems in the industry, to industry financing, and to research into sugarcane production and processing. An example of a private institution working in the industry is the Sugarcane Research Center (the CTC), which is dedicated to the development of new varieties of sugarcane that are more resistant to pests and disease, and better adapted to the country's climate and soils (Beintema *et al.*, 2001; Furtado *et al.*, 2011).

Despite the country's longstanding tradition in this sector, certain technological bottlenecks remain at the top of the agenda of many mills in the industry (Salles-Filho *et al.*, 2016). Most recently, challenges for expanding sugar and ethanol production have focused on increasing agricultural productivity, innovating in the genetics for sucrose accumulation in sugarcane, reducing the levels of mineral and vegetable impurities carried from the field to processing, and developing technology for the production of second-generation ethanol. These challenges to innovation in the sugar-energy sector should be approached using instruments and technologies with a low environmental impact and low carbon emissions.

However, mills remain slow to face new technological challenges. The sugar-energy sector is competitive yet conservative in relation to innovation; mill efforts are modest, as are adjustments to internal organization structures for expanding technological capacity (Salles-Filho *et al.*, 2017).

The production of sugarcane and its derivatives (sugar and ethanol) has become increasingly vertically integrated, with higher levels of mechanization, a greater use of chemical inputs, an increased transport capacity, and a substitution of labor for capital-intensive processes (Compeán and Polenske, 2011). Technologically and economically, the sector is very heterogeneous, with mills of varying levels of efficiency. Many mills are not currently operating at maximum efficiency, but have the potential to do so by reallocating their available resources (Pereira and Silveira, 2016).

Measuring efficiency has been a matter of great interest to organizations, particularly in a context where productivity gains are sought in extremely competitive environments, such as in agribusiness chains. The identification of factors associated with productivity growth can result in technological innovation and improved productive efficiency, and are therefore fundamental to the formulation of public and private policies (Cook and Seiford, 2009; Farrell, 1957; Lovell, 1993).

Research on total factor productivity (TFP) has highlighted the country's success in obtaining competitive advantages through innovation. Gasques *et al.* (2012), analyzing the growth of the Brazilian agricultural TFP, revealed that between 1970 and 2006, the use of inputs increased by 53%, while agricultural production increased by 243%. Between 1995 and 2006, 32% of the growth in agricultural production in Brazil was explained by the increase in the use of inputs, while 68% could be attributed to innovation.

Different sugarcane production systems exist in Brazil, and the levels of technology and efficiency among the mills in the country therefore varies. For example, production in the Northeast involves an intensive use of labor due to the low levels of mechanized planting and harvest in this region, whereas production processes are nearly entirely mechanized in the Central-South. Agricultural productivity in the Northeast over the last few decades has remained at lower levels than that in the Central-South, reflected in a cost of production of the raw material in the former region that is nearly 23% higher than that in mills in the latter (Rosa *et al.*, 2017).

The technical and economic differences across sugar-energy mills in Brazil are explained by differences in technology, the quality of commercial management, the average cost of acquisition and production of raw materials, economic and institutional phenomena, research and development practices, scale, geographical location, and synergies between value chains, among other factors. In addition, the financial capacity of mills to invest in modern practices and technologies is significant. However, how exactly do these differences imply divergent technical and economic results across mills? What causes the individual disparities in efficiency among mills, and how are they reflected in the efficiency levels of mills? We have developed this study in the context of these two questions.

This study seeks to provide insight into these questions and a better understanding of the variables affecting the efficiency of mills. The objective of this study is therefore to evaluate the evolution of productive efficiency and TFP for sugar-energy mills in Brazil during the period of 2006 to 2015, using data envelopment analysis (DEA) and the Malmquist index (MI). We hypothesize that no single, well-defined efficiency standard has existed among mills in the sector over time and that mills are heterogeneous with respect to management practices and technology adoption. Specifically, the hypothesis that guides this study is the following:

**H0:** On average, mills in the Brazilian sugar-energy industry have the same levels of technical efficiency.

**H1:** On average, mills in the Brazilian sugar-energy industry have differences in levels of technical efficiency.

## 2. Literature review

Efficiency is a primary concept in neoclassical theory and is largely related to the problem of optimal resource allocation. It concerns the maximum product that can be obtained considering a given set of resources or inputs, or a target product to be obtained using a minimum level of inputs and, consequently, at a minimum cost. Specifically, measuring efficiency involves a comparison between observed values and optimal values of inputs and products. In addition, productivity is known as the relationship between the quantities of inputs and outputs (Delgado and Machado, 2007; Shirota, 1996; Tupy and Yamaguchi, 1998).

Understanding the behavior of productivity over time and the variables responsible for its trajectory are critical. Several studies have focused on understanding the factors associated with efficiency and the factors leading to economic growth using two approaches, namely: DEA and stochastic frontier analysis. The first is based on linear programming techniques, while the latter is a parametric method based on statistical techniques. DEA consists of the estimation or identification of a performance frontier of best practice, which serves as a reference for measuring the individual performance of mills.

We note that some studies have already focused on this topic, with an emphasis on the sugar-energy sector – specifically on the production of sugarcane and its derivatives (sugar, ethanol, and bioelectricity). Internationally, Onour (2015) estimated the technical efficiency (TE) of the primary sugar producers in Sudan, using a stochastic frontier and considering three inputs: capital, labor, and irrigated area. The study identified a technical inefficiency of approximately 8%, implying an average annual loss of 5,000 tons of sugar for each of the four largest producers in the country. The author identified one source of inefficiency as the mismanagement of production inputs including labor and capital, which demonstrated decreasing incomes and increasing returns, respectively. Many studies have found similar inefficiencies in sugarcane processing, including those by Ali and Jan (2017), Johnson *et al.* (1995), Khanna (2006), and Reddy and Yanagida (1999).

In Brazil, Rodrigues *et al.* (2016) analyzed the TE of sugarcane producers in the state of Sao Paulo, considering a stochastic production frontier. They found that land was the production factor that most influenced the production efficiency and TE of the sugarcane sector in the state of Sao Paulo. The authors concluded that the use of loaders, improved seeds, green fertilization, and technical assistance contributed to increases in productive efficiency.

The following studies used DEA methodology, and are summarized in Table 1: Braga (2016), Brunozi *et al.* (2012), Cano and Tupy (2005), Carlucci (2012), Lemos *et al.* (2016), Macedo *et al.* (2010), Pachiel (2009), Pereira and Silveira (2016), Pereira and Tavares (2017), Salgado *et al.* (2014), and Xavier (2014).

Of these studies, we highlight the work done by Pereira and Silveira (2016), who use the MI to analyze the TFP and its components for 17 mills in the central-south region of Brazil during the period of 2001 to 2008. In their sample, the productivity gains observed in the mills were primarily due to technical change (TC), and specifically, to technological progress. The work of Braga (2016) analyzed the level of TE of Brazilian sugarcane mills for the 2011/2012 crop. The results suggested an average efficiency level greater than 90%. However, the author estimated that correcting for inefficiencies could save the mills more than US\$ 1.85 billion, due to the resulting increases in sugar and ethanol production. Finally, Pereira and Tavares (2017) assessed the efficiency of principal sugarcane-producing regions, based on the production costs of the 2007/2008 and 2011/2012 crops. They found average TE, under variable returns to scale, to be 99%, while the average efficiency of scale was 65%, which demonstrated problems with production scale in the regions analyzed.

As noted in Table 1, most of the studies employing DEA methodology have analyzed the efficiency of mills in the sugar-energy sector in relation to a single crop year. Our study also uses DEA methodology, in conjunction with the MI, to evaluate the productive efficiency and TFP of sugar and ethanol mills in Brazil. Furthermore, it advances the literature by including a longer period of analysis and by capturing the effects of efficiency, productivity, and their decompositions.

### 3. Methods

This section presents the tools used in our study. We first detail the DEA, which addresses the concept of the efficient frontier. We next discuss the MI, which measures the evolution of productivity over time. This section additionally presents the main concepts linked to these technical themes.

**Table 1.** Synthesis of studies from the Brazilian literature on the efficiency of the sugar-energy sector, using data envelopment analysis.<sup>1</sup>

Reference	Objective	Sample	Period	Model	Inputs (unit)	Outputs (unit)
Cano and Tupy (2005)	Assess the productive efficiency of the sugarcane agroindustry in Sao Paulo	125 mills in the state of Sao Paulo	2001/2002 crop year	VRS on an input-oriented	Sugarcane milling (t); No. of employees from industrial and admin. departments	Ethanol production (m <sup>3</sup> ); Sugar production (t)
Pachiel (2009)	Determine the efficiency of sugarcane mills	17 mills in the state of Sao Paulo	2006/2007 crop year	CRS and VRS on an input-oriented	Storage (R\$); Fixed assets (R\$); Salaries (R\$)	Gross revenue (R\$)
Macedo <i>et al.</i> (2010)	Verify the efficiency of each mill in converting investment capacity (input) into social and environmental benefits (outputs)	9 mills in Brazil	Calendar year 2004–2006	CRS on an output-oriented	Net revenue (R\$)	Investments in environment (R\$); Internal social indicators (R\$); External social indicators (R\$)
Brunozi <i>et al.</i> (2012)	Measure the performance of mills in terms of TE and scale	17 mills in the state of Sao Paulo	2008/2009 crop year	CRS and VRS on an input-oriented	Storage (R\$); Fixed assets (R\$); Salaries (R\$)	Gross revenue (R\$)
Carlucci (2012)	Verify the impact of size and location variables on the operational efficiency of sugarcane mills	355 mills in Brazil	2008/2009 crop year	VRS on an output-oriented	Sugarcane milling (t)	Ethanol production (m <sup>3</sup> ); Sugar production (t)
Xavier (2014)	Develop and apply a criterion to measure the economic efficiency of sugarcane production	67 mills in Brazil	2012/2013 crop year	CRS on an input-oriented	Land (ha); TRS (t); No. of employees from industrial and admin. departments	Ethanol production (TRS); Sugar production (TRS); Electricity prod. (MWh)
Salgado <i>et al.</i> (2014)	Develop a map of agricultural potential to invest in new sugarcane mills in Brazil	355 mills in Brazil	2008/2009 crop year	VRS on an output-oriented	Sugarcane milling (t)	Ethanol production (m <sup>3</sup> ); Sugar production (t)
Lemos <i>et al.</i> (2016)	Identify locations that obtained the highest efficiency ratios in the field-industry relationship	352 mills in Brazil	2005/2006 to 2014/2015 crop years	VRS on an output-oriented	Sugarcane milling (t)	Ethanol production (m <sup>3</sup> ); Sugar production (t)
Pereira and Silveira (2016)	Analyze TFP and its components	17 mills in the Central-South	Calendar years 2001 to 2008	VRS on an input-oriented	Sugarcane milling (t); No. of employees from the industrial department	Ethanol production (m <sup>3</sup> ); Sugar production (t)
Braga (2016)	Analyze the efficiency of Brazilian sugarcane mills, focusing on industrial efficiency	117 mills in Brazil	2011/12 crop year	VRS on an output-oriented	Sugarcane milling (t); No. employees in the mill	Ethanol production (m <sup>3</sup> ); Sugar production (t)
Pereira and Tavares (2017)	Identify the technical and scale efficiency of the main sugarcane producing regions	3 regions of Brazil	2007/2008 to 2011/2012 crop years	CRS on an input-oriented basis	Cost of production (R\$/ha): Mechanization; Labor; Inputs; Leases; Admin. expenditures	Sugarcane production (t)

<sup>1</sup> R\$ refers to the Brazilian currency, the Real (BRL). CRS = constant returns to scale; TFP = total factor productivity; TRS = total reducing sugar; VRS = variant returns to scale.



### 3.1 Data envelopment analysis<sup>1</sup>

DEA is a non-parametric method of measuring efficiency through linear programming. Coelli (1998) details its mathematical programming and the premises associated with its resolution and the efficiency scores obtained using DEA. DEA is applied to find the relative TE between the operating or decision-making units (DMUs) from resources used (multiple inputs) and goods produced (multiple outputs) (Aldamak and Zolfaghari, 2017). Its origin is associated with studies by Banker *et al.* (1984) and Charnes *et al.* (1978), both of which are based on the concept of efficiency presented by Farrell (1957).

The DEA allows each mill in the dataset to have its own production function. It then assesses the efficiency of each unit compared to that of the other units in the dataset. Specifically, it allows for each unit to be optimized individually in relation to others, forming an efficiency frontier. The frontier is defined by the Pareto-Koopmans concept, according to which no improvements in the use of any input or output are possible without worsening another input and/or output (Mirdehghan and Fukuyama, 2016).

One advantage of non-parametric DEA models is their flexibility. In addition, these models allow for the imposition of hypotheses regarding the behavior of the variables; therefore, the production frontier does not assume any *a priori* functional form, unlike conventional parametric models (Delgado and Machado, 2007). A further advantage over parametric methods is their possibility of identifying unit efficiency using efficiency scores generated by the model. Some authors therefore prefer DEA as a non-parametric technique compared to parametric models such as the stochastic production frontier (Abramo *et al.*, 2011; Bonaccorsi and Daraio, 2004; Chen *et al.*, 2015).

From a dataset containing a combination of inputs and outputs, efficiency can be defined as the distance from a certain point to its projection on the frontier function. Efficiency indices are comparative measures between the DMUs analyzed. The distance function,  $D(x,y)$ , can take values less than or equal to 1. A mill is efficient when  $D(x,y)=1$ , or when it is on the production frontier.

The analysis and measurement of efficiency using the distance function depends on its orientation (input or output). The approach originally presented by Farrell (1957) considers input orientation, which characterizes production technology according to the proportional minimization of the input vector, given a fixed level of production, known as Farrell efficiency. Meanwhile, output orientation characterizes production technology according to the proportional maximization of the product vector from a given quantity of input, and is known as Shephard efficiency (Clemente *et al.*, 2015).

The delimitation of the production frontier is based on certain microeconomic properties, with emphasis on the free availability of inputs, the possibility of a convex combination of production factors, and the type of returns to scale. In this context, the effects of increases in the scale of factors of production on the quantity of output can be represented in two models.

The first model, developed by Charnes *et al.* (1978), is known as constant returns to scale (CCR or CRS). In this model, constant returns are assumed to scale, whereby a variation in all the factors of production leads to a proportionate variation in total production. As a function of this hypothesis, the efficiency frontier is defined by the bisector of the first quadrant (a line with an angle of 45° passing through the origin of the Cartesian axes).

The second model, by Banker *et al.* (1984), known as the variant returns to scale model (BCC or the VRS), relaxes the technology hypothesis of constant returns and allows for DMUs to have variable returns to scale. In this model, an increase in input can promote an increase in output – although not necessarily proportional

<sup>1</sup> This section presents a brief methodological description, although not exhaustively. It is suggested to the reader to consult O'Donnell (2018) and Fried *et al.* (2008) for more details and theoretical depth about the efficiency analysis through DEA models.

to the increase in input. Total or productive efficiency is derived from the CCR model, while the BCC model provides TE (Pérez-López *et al.*, 2018). Scale efficiency (SE), corresponding to productivity changes as a function of changes in the production scale, may be calculated by dividing total efficiency by TE, as in Equation 1.

$$SE = \frac{TE_{CCR}(X_k, Y_k)}{TE_{BCC}(X_k, Y_k)} \quad (1)$$

Where  $TE_{CCR}(X_k, Y_k)$  is TE with CCR and  $TE_{BCC}(X_k, Y_k)$  is TE with BCC.

Many studies in the economic literature have used a metafrontier production function when examining differences in technology (Chen and Song 2008; Barnes *et al.*, 2011; Chang and Tovar 2017; Nguyen *et al.*, 2018; Villano *et al.*, 2010), following the procedure proposed by Battese *et al.* (2004) and by O'Donnell *et al.* (2008). This methodology has been widely used when comparing efficiency levels and production technologies between regions.

From the perspective of agricultural production – specifically of sugarcane production – significant differences exist across Brazilian regions. Such differences include soil quality, climate, and economic infrastructure, among other variables, and they impact the efficiency of producing firms in different regional groups. Meanwhile, this study is limited to understanding solely industrial efficiency, or the efficiency of processing sugarcane into sugar, ethanol, and bioelectricity.

In this context, industrial processing, as highlighted by De Souza Dias *et al.* (2015) follows relatively similar production processes and stages, which is why we did not choose the method used by Battese *et al.* (2004) and O'Donnell *et al.* (2008) of estimating a production metafrontier.

### 3.2 Malmquist Productivity Index

Traditionally, growth in TFP is estimated by the Solow residual, which represents the portion of growth that cannot be explained by the increase in usual production factors (Hulten, 2001; Van Beveren, 2010). In their study, Nishimizu and Page (1982) suggest decomposing TFP into its components of change – TC and TE. Likewise, Caves *et al.* (1982b) introduced the MI, which generates a production frontier that represents technology and uses distance functions evaluated in different combinations of inputs and outputs to measure changes in the efficiency and productivity of companies.

Despite its popularity and wide employment in empirical research of productivity decomposition, the recent literature argues that the MI is not always a complete index of TFP (Bjurek *et al.*, 1998), especially under variable returns to scale (VRS). This instead suggests the use of the Fisher, Konus, Törnqvist, and Hicks-Moorsteen indices (Coelli *et al.*, 2005; Färe *et al.*, 2008; O'Donnell, 2010, 2012). However, these indices are infrequently used in applied research.

If we take, for example, the Hicks-Moorsteen index<sup>2</sup> and compare it to the MI, the two are found to have the same two properties: (1) constant returns to scale; and (2) inverse homoteticity (Färe *et al.*, 2008; Grifell-Tatjé and Lovell, 1995). Furthermore, empirical studies comparing both indices are extremely rare, despite the work of Bjurek *et al.* (1998) and of Simões and Marques (2012). In these empirical applications, both reported small differences between the indices and thus a strong similarity between the two, although the indices are not identical.

Compared to other indices, the MI offers insight into productivity growth, since: (1) the hypothesis of TE is relaxed; (2) it enables a decomposition into TC and TE; and (3) the calculation of this index in relation to multiple input and output technologies does not require price information (Färe *et al.*, 1995).

<sup>2</sup> We suggest the reader refer to O'Donnell (2012) for more details.



In addition, Figueiredo (2007) argues that the MI offers important advantages in relation to other measures of change in TFP, since it does not require the definition of the production function in advance nor the indication of monetary values for inputs or outputs, and therefore allows for an analysis of changes in productivity using DEA.

As a result, and following the wide range of papers in this area, this study uses the MI much more as a technology index, as highlighted by Grosskopf (2003), and presents the results of three models: the CRS, VRS, and the EE. We additionally detail and discuss the MI.

Caves *et al.* (1982a), based on Malmquist (1953), developed an index to measure the productivity variation of a DMU over time. The MI finds changes productivity as a result of changes in technology and efficiency. The index can measure the change in the TFP of a DMU at different periods and break TFP changes into efficiency and technological changes.

Many indices can be decomposed into TC, TE, SE change, and mix efficiency change. The indices that can be decomposed as such include the Fisher index, the Törnqvist index, and the Hicks-Moorsteen index, but not the MI (O'Donnell, 2010). Therefore, in this study we focus on the decomposition of the PTF using the MI, into TC and TE.

The productivity MI measures variation in the TFP of a DMU between two periods, defined as the product of changes in efficiency (catch-up) and technology (innovation). These are two factors that can change productivity over time. Given an available technology, the catch-up effect or recovery effect corresponds to the process of improvement in the use of inputs for production, bringing the DMU closer to the efficiency frontier (pure efficiency change). However, the efficiency frontier also shifts over time, reflecting a second effect and changes in technology (Maciel *et al.*, 2009).

In this study, we calculate variation in productivity using the MI, following the approach of Färe *et al.* (1994). These authors developed the MI and integrated it into the DEA. Since, several studies have analyzed changes in productivity over time or across different fields, including for energy and greenhouse gas emissions (Huang *et al.*, 2017; Pérez *et al.*, 2017) and for certain mills and sectors of the economy such as oil (Sueyoshi and Goto, 2015), semiconductors (Liu and Wang, 2008), computers (Chen and Ali, 2004), tax offices (Fuentes and Lillo-Bañuls, 2015), grain production (Odeck, 2009), and air ports (De Nicola *et al.*, 2013).

A wide range of studies discuss and apply the non-parametric frontier technique of calculating productivity based on the MI for different fields and areas of activity. In addition, the Malmquist-DEA method is particularly suitable when using panel data and can analyze changes in performance over time (Li *et al.*, 2017).

This study applies Malmquist-DEA scores to mills in the Brazilian sugar-energy sector, from 2006 to 2015, and fills a gap in the literature on DEA applications and productive efficiency modeling for this sector in this country. The following description is primarily based on the studies by Caves *et al.* (1982a), Färe *et al.* (1992) and Färe *et al.* (1994).

Based on the MI (Malmquist, 1953), Caves *et al.* (1982a), define a distance function  $D(\cdot)$  to calculate TE. Considering that  $x_0^t$  and  $y_0^t$  represent the vectors of inputs and products, respectively, in the period  $t$  for a DMU<sub>0</sub>, the relative efficiency of DMU<sub>0</sub> in period  $t$ , denoted as  $D_0^t(x_0^t, y_0^t) = \theta_0^*$ , is calculated as the quantity by which input  $x_0$  can be reduced to produce output  $y_0$  on the efficiency frontier. Similarly,  $D_0^{t+1}(x_0^{t+1}, y_0^{t+1}) = \theta_0^*$  is the measure of efficiency in  $t+1$ . For multiple periods,  $D_0^t(x_0^{t+1}, y_0^{t+1})$  and  $D_0^{t+1}(x_0^t, y_0^t)$  are the efficiency measures using a set of inputs and outputs in periods  $t+1$  and  $t$ , respectively, compared to the frontier of the periods,  $t$  and  $t+1$ , respectively.

The MI can be broken down into two components, namely: (1) the measure of change in TE; and (2) the measure of TC or equivalent changes in frontier technology (TC). Therefore, from the decomposition of the

MI, we can determine the relative efficiency increment between two periods due to the individual effort of each agent (e.g. DMU) and to the innovation of the industry. Following the approach presented by Färe *et al.* (1992), an input-oriented MI to measure productivity changes in DMU<sub>0</sub> between the periods  $t$  and  $t+1$  is given by the geometric mean of two quotients of distance-equation functions:

$$MI_0 = \left[ \frac{D_0^t(\mathbf{x}_0^{t+1}, \mathbf{y}_0^{t+1})}{D_0^t(\mathbf{x}_0^t, \mathbf{y}_0^t)} \cdot \frac{D_0^{t+1}(\mathbf{x}_0^{t+1}, \mathbf{y}_0^{t+1})}{D_0^{t+1}(\mathbf{x}_0^t, \mathbf{y}_0^t)} \right]^{1/2} \quad (2)$$

The result of the mathematical expression in Equation 2 can assume three values, namely: (1) higher than 1.0, indicating productivity growth between the analyzed periods (DMU<sub>0</sub> is more productive than in the initial period); (2) lower than 1.0, indicating a productivity decline between the analyzed periods; and (3) equal to 1.0, indicating that productivity remained constant between the analyzed periods (Liu and Wang, 2008).

The distances of the MI can be calculated by parametric techniques, as presented by Aigner and Chu (1968), or by a non-parametric approach such as DEA, and following the procedure of Färe *et al.* (1994). We will use the latter approach in this study.

The MI employs the distance functions of two distinct periods or technologies,  $D_0^t(\cdot, \cdot)$  and  $D_0^{t+1}(\cdot, \cdot)$  and two pairs of input-product vectors  $(\mathbf{x}_0^t, \mathbf{y}_0^t)$  and  $(\mathbf{x}_0^{t+1}, \mathbf{y}_0^{t+1})$ , and can be broken down into two components, according to Equation 3:

$$MI_0 = \frac{D_0^{t+1}(\mathbf{x}_0^{t+1}, \mathbf{y}_0^{t+1})}{D_0^t(\mathbf{x}_0^t, \mathbf{y}_0^t)} \left[ \frac{D_0^t(\mathbf{x}_0^{t+1}, \mathbf{y}_0^{t+1})}{D_0^{t+1}(\mathbf{x}_0^{t+1}, \mathbf{y}_0^{t+1})} \cdot \frac{D_0^t(\mathbf{x}_0^t, \mathbf{y}_0^t)}{D_0^{t+1}(\mathbf{x}_0^t, \mathbf{y}_0^t)} \right]^{1/2} \quad (3)$$

The quotient outside the brackets in Equation 3 is an index of change in TE. The proportions within the brackets measure an index of technological progress (TC) while shifting the technological frontier between the periods  $t$  and  $t+1$ . The TE is given by Equation 4, while Equation 5 presents the TC.

$$TE = \frac{D_0^{t+1}(\mathbf{x}_0^{t+1}, \mathbf{y}_0^{t+1})}{D_0^t(\mathbf{x}_0^t, \mathbf{y}_0^t)} \quad (4)$$

$$TC = \left[ \frac{D_0^t(\mathbf{x}_0^{t+1}, \mathbf{y}_0^{t+1})}{D_0^{t+1}(\mathbf{x}_0^{t+1}, \mathbf{y}_0^{t+1})} \cdot \frac{D_0^t(\mathbf{x}_0^t, \mathbf{y}_0^t)}{D_0^{t+1}(\mathbf{x}_0^t, \mathbf{y}_0^t)} \right]^{1/2} \quad (5)$$

TE is a function that measures the production frontier in the reduction of inputs used in the production process in the case of input orientation (Pereira and Silveira, 2016). Specifically, by isolating the effect of SE (Equation 1, the TE corresponds to the component of productive efficiency associated with the management capacity of the mill. Meanwhile, productive efficiency can be broken into SE and TE.

To facilitate the understanding of efficiency measures, Table 2 presents a summary of the variables that are presented and analyzed in this article.

### 3.3 Selected variables and data

While the DEA method allows flexibility in the process of selecting of variables (Ozcan and Luke, 1993), in this study, variables were selected according to the literature (Table 1) and considered the approach by Nataraja and Johnson (2011) and Norman and Stoker (1991).

**Table 2.** Summary of efficiency measures and their definitions.

Term	Definition	Values <sup>1</sup>
Efficiency	Efficiency is a concept related to the problem of optimal resource allocation. It concerns the maximum product that can be obtained considering a certain set of resources or inputs, or a target product to be obtained from a minimum level of inputs and, consequently, costs. Specifically, it is a comparison between observed values and optimal values of inputs and products.	–
Economic efficiency	Economic efficiency is given by setting a goal for output and defining how to achieve it without high expenditures. To understand this concept, we must distinguish between two types of efficiency: TE and allocative efficiency. Technical efficiency occurs when, given a certain quantity of inputs and a defined technology, maximum output is achieved: this means that the firm is over the production possibility frontier. Meanwhile, allocative efficiency considers the price ratio of inputs or outputs: a firm has allocative efficiency in the orientation of inputs when its marginal productivity is equal to the price ratio of its inputs.	–
Technical efficiency (TE)	Technical efficiency is the ability to produce as many products as possible from a given group of inputs. This reflects the firm's ability to maximize its production given its inputs.	0.920
Technical change (TC)	Technical change provides a measure of the change (displacement) of the technological frontier – that is, it captures innovation (changes in technology between the two periods). The change in TE can be broken down into SE and pure TE.	1.072
Scale efficiency (SE)	Scale efficiency corresponds to productivity changes as a function of changes in the production scale. It can be calculated by dividing total efficiency (constant returns to scale) by TE (variable returns to scale).	0.937
Malmquist index (MI)	The MI evaluates productivity indices during different periods, breaking them into sub-indices that reflect the variation of TE and TC.	0.985

<sup>1</sup> Reference Table 7 for the period 2014/2015. Improvements in productivity are associated with indices whose values exceed the unit.

We have included two input variables to measure the resources used in production, namely: (1) the sugarcane processed from each mill, in tons, over the years; and (2) the monetary value of fixed assets, in thousands of Brazilian Reais, at constant 2015 prices and using the centered<sup>3</sup> General Price Index – Internal Availability as a deflator. We considered two output variables: (1) total ethanol production (anhydrous and hydrous) in thousands of cubic meters (m<sup>3</sup>); and (2) total sugar production (raw sugar, white sugar, granulated, demerara, etc.) in thousands of tons. Table 3 presents the details of the variables used in the empirical model of this study.

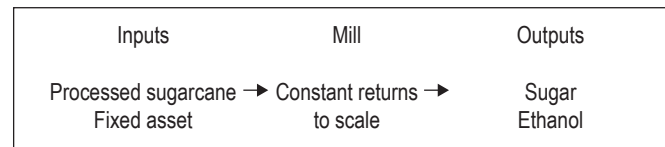
We use an input-oriented model and impose CRS to obtain the quantity of inputs that can be reduced without changing the product obtained by the mills (Figure 1). Specifically, we use the measure of input-oriented TE, since mills seek to improve their use of inputs to increase competitiveness.

All mills in the sample are legally constituted as joint-stock mills whose financial statements have been published in the official register of the federal government or the state in which the mill's office is located, as outlined in Article 289 of the Brazilian JSC Law (A Lei das Sociedades por Ações) (Brasil, 2018). We obtained the financial statements for each mill for our period of analysis (2006 to 2015), and tabulated the variables of interest for this study, including fixed assets. We obtained milling and production information per product from the sugarcane industry yearbooks published by ProCana (2018).

<sup>3</sup> Calculated from the geometric mean of values of the original General Price Index – Internal Availability series from the current and subsequent month (months  $t$  and  $t+1$ ).

**Table 3.** Details of the variables used in the empirical model.

Variable	Acronym	Description	Source
Input	Milling	M	Volume of sugarcane processed by the mill, in tons
	Fixed assets	AI	Monetary value of fixed assets, in thousands of reais
Output	Sugar	A	Total ethanol production, in thousands of cubic meters (m <sup>3</sup> )
	Ethanol	E	Total sugar production, in thousands of tons

**Figure 1.** Simplified schema of the empirical model.

Our sampling process is not probabilistic, since we selected mills according to the availability and accessibility of information essential to the study. The sample is from 32 mills, beginning in 2010, since some mills only began operating after the start of the analysis in 2006. If we take 2015 as an example, our sample consists of 32 mills – independent mills and economic groups – located primarily in the state of Sao Paulo, as shown in Figure 2.

While our sample is of 32 mills, it contains data on 101 industrial units, as the 32 mills are responsible for 19 independent mills and 13 economic groups, the latter of which had 82 mills in operation in 2015. According to Brasil (2015), 366 mills were in operation in Brazil in 2015. Our sample therefore represents 27.6% of total mills.

## 4. Results

### 4.1 Descriptive statistics

Table 4 presents the volume of sugarcane processed by the mills in the sample and the production of sugar and ethanol from 2006 to 2015. On average, over the period the mills sampled accounted for 35.7, 33.9 and 38.6%, of national sugarcane, ethanol, and sugar production, respectively.

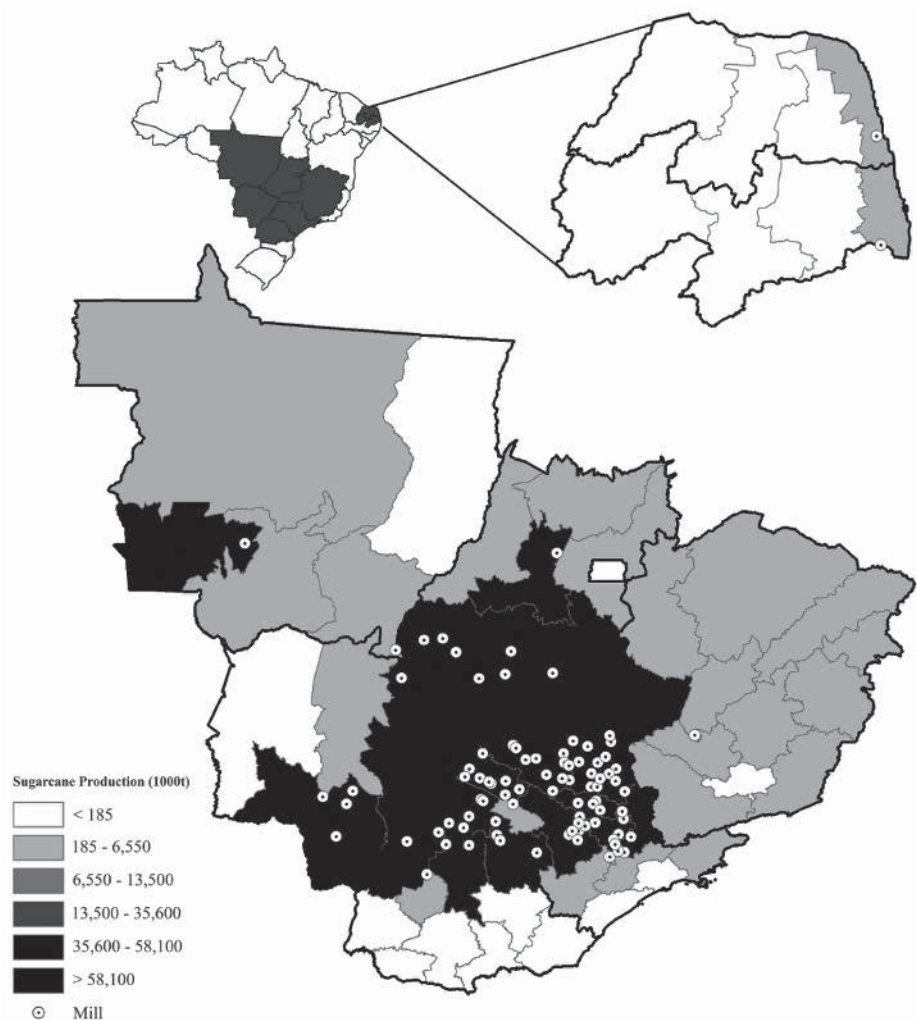
We found a very similar trend in the behavior of sugarcane processing observed in the sample. However, throughout the period, total sugarcane processing in Brazil increased at an average annual rate<sup>4</sup> of 3.84%, while our sample showed an average annual increase of 10.38%.

Table 5 presents annual descriptive statistics of the inputs and outputs used to measure the TE of sugar-energy mills between 2006 and 2015. We found the average volume of sugarcane processed by the mills in the sample increased from 2.70 million tons of sugarcane in 2006 to 4.97 million tons in 2015.

The sector experienced a period of new mill construction through 2008, benefitting from a promising scenario for sugar and ethanol in the domestic and international market. However, since 2008, a financial crisis hit the sector (De Moraes and Zilberman, 2014) and the mills analyzed consequently underwent a process of expanding their installed milling capacity, primarily through mergers and acquisitions. The fixed assets used in the process of industrial production showed an increasing trajectory, highlighting that the increase in milling was associated with the increase in fixed assets.

<sup>4</sup> The growth rate, as shown in Ramanathan (2002), was calculated using the following general regression:  $\ln y_{it} = a_i + b_i T + \varepsilon_{it}$ , where  $y$  represents the variable of interest,  $T$  is a trend variable ( $t=1$  for 2006, ...,  $t=10$  for 2015), and  $\varepsilon_{it}$  is the random error term. The compound growth rate is obtained from the relationship  $[\text{antiln}(b)-1]$ , expressed in % a.a.

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**Figure 2.** Distribution of sugarcane production by geographical mesoregion and location of sugar mills sampled. Each point represents the municipality in which the mill is located. Based on data from the Instituto Brasileiro de Geografia e Estatística (IBGE, 2015).

**Table 4.** Sugarcane processing, ethanol production, and sugar production in Brazil and in the survey sample, 2006 to 2015.<sup>1</sup>

Year	Sugarcane (million tons)			Ethanol (million m <sup>3</sup> )			Sugar (million tons)		
	Sample	Brazil	Share <sup>2</sup>	Sample	Brazil	Share <sup>2</sup>	Sample	Brazil	Share <sup>2</sup>
2006	104.1	427.7	24.3	3.9	17.8	22.0	8.0	30.0	26.7
2007	147.8	495.7	29.8	6.5	22.5	28.8	10.0	31.0	32.3
2008	170.6	569.2	30.0	8.0	27.5	29.0	10.3	31.0	33.1
2009	196.9	602.2	32.7	7.6	25.7	29.8	11.8	33.0	35.7
2010	236.8	620.4	38.2	10.0	27.4	36.5	15.8	38.0	41.6
2011	212.4	559.2	38.0	8.4	22.7	36.9	14.6	35.9	40.7
2012	241.3	588.5	41.0	9.1	23.2	39.2	16.1	38.2	42.2
2013	284.0	651.3	43.6	12.1	27.5	44.2	17.1	37.6	45.5
2014	267.1	633.9	42.1	11.3	28.5	39.7	16.3	35.6	45.9
2015	286.3	666.8	42.9	11.8	30.2	39.2	16.4	33.8	48.5
Average <sup>3</sup>	205.8	576.9	35.7	8.5	25.0	33.9	13.2	34.3	38.6

<sup>1</sup> Based on data from the União da Indústria de Cana-de-Açúcar (UNICA, 2017).  
<sup>2</sup> Sample share in relation to national production; <sup>3</sup> Corresponds to the geometric mean.



**Table 5.** Geometric mean and standard deviation of the variables used in the data envelopment analysis model.<sup>1</sup>

Variable	Year									
	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
<b>Inputs</b>										
M*	2.70	3.05	3.41	3.79	4.18	3.68	4.08	4.45	4.55	4.97
	(3.71)	(7.30)	(8.04)	(9.73)	(10.83)	(10.01)	(11.00)	(13.06)	(11.42)	(12.55)
AI*	287.95	268.94	458.15	497.04	506.38	569.00	535.89	545.15	504.62	522.68
	(821.70)	(905.53)	(1,008.18)	(1,648.94)	(1,462.48)	(2,057.98)	(2,016.18)	(1,858.10)	(1,906.23)	(1,797.33)
<b>Outputs</b>										
A*	198.55	208.03	203.46	235.04	285.72	275.73	305.86	334.42	313.53	317.02
	(345.38)	(617.53)	(614.61)	(693.82)	(798.89)	(781.48)	(836.06)	(886.46)	(796.96)	(817.60)
E*	99.58	141.46	170.26	157.82	183.43	151.55	155.32	184.60	193.02	208.47
	(125.64)	(282.44)	(323.45)	(349.30)	(436.43)	(374.69)	(410.90)	(629.87)	(476.78)	(514.21)

<sup>1</sup> \*M = volume of sugarcane processed by the mill, in million tons; AI = fixed assets, in million reais, at constant 2015 prices; A = total sugar production, in million kilograms; E = total ethanol production, in million liters. The values specified in parentheses correspond to the standard deviation.

The average sugar and ethanol production of mills in the sample increased between 2006 and 2015. During this period, average annual ethanol production of the mills increased at a rate that was 1.95% higher than that of sugar production. This finding reflects the introduction and growth of flexible-fuel vehicles in the domestic market (linked to a process of tax differentiation for ethanol compared to gasoline), a trend of increasing oil prices, and an increase in international interest in biofuels (Rodrigues and Rodrigues, 2018).

#### 4.2 Empirical model

The DEA method allows mills to be organized and analyzed in terms of their efficiency, while the MI allows for the dynamic estimation of variations in productivity. Thus, in this section, we present the average efficiency scores of mills from the input-oriented DEA model, followed by the MI and its decompositions for the mills under analysis.

Table 6 presents the average scores of the mills evaluated between 2006 and 2015. The short-term efficiency scores for each mill were calculated in relation to a best-practice frontier – or, a best performance frontier. All efficiency scores were measured relative to the frontier of the same year.

The average efficiency scores of the mills in the sample over the period of analysis were 0.922, 0.951, and 0.970 for the CRS, VRS, and SE models, respectively. This means that in the CRS model, mills could reduce their input consumption by an average of 7.80% without necessarily compromising their sugar and ethanol production. In the VRS model, which includes a restriction on convexity, a 4.91% reduction<sup>5</sup> in use of factors of production would make the mills in the sugar-energy sector part of this frontier. However, according to the results of the SE model, mills can expand their production scales by 3.03%. An important finding identified in this study is that of inefficiencies, which can be corrected by mills in the Brazilian sugar-energy industry, whose benchmarking practices can mitigate these distortions.

DEA methodology is one tool used for benchmarking to identify efficiency frontiers. Graphically, the Pareto-efficient frontier is defined by DMUs (in this case, mills in the sugar-energy sector) to delimit a linear envelopment surface that represents the best-practice frontier. We obtained an operational performance indicator using DEA to benchmark sugar and ethanol mills in Brazil based on their operating efficiencies.

<sup>5</sup> The potential for economizing inputs in the VRS model is smaller than that in the CRS model (Grilo and Santos, 2015).

**Table 6.** Descriptive statistics for annual estimated efficiency scores for input-oriented empirical models.<sup>1</sup>

Year	No. of mills <sup>2</sup>	Model	Average <sup>3</sup>	Std. dev.	Minimum	Maximum	No. of 1s
2006	28	CRS	0.936	0.104	0.471	1.000	8
		VRS	0.964	0.078	0.634	1.000	16
		SE <sup>4</sup>	0.971	0.054	0.743	1.000	8
2007	30	CRS	0.932	0.062	0.825	1.000	10
		VRS	0.956	0.054	0.827	1.000	14
		SE <sup>4</sup>	0.975	0.038	0.858	1.000	10
2008	31	CRS	0.970	0.042	0.854	1.000	14
		VRS	0.978	0.040	0.868	1.000	20
		SE <sup>4</sup>	0.992	0.016	0.922	1.000	16
2009	31	CRS	0.938	0.076	0.645	1.000	11
		VRS	0.954	0.072	0.663	1.000	16
		SE <sup>4</sup>	0.984	0.024	0.891	1.000	12
2010	32	CRS	0.937	0.051	0.812	1.000	7
		VRS	0.957	0.050	0.844	1.000	15
		SE <sup>4</sup>	0.979	0.024	0.921	1.000	9
2011	32	CRS	0.925	0.051	0.838	1.000	7
		VRS	0.954	0.049	0.841	1.000	15
		SE <sup>4</sup>	0.970	0.034	0.882	1.000	9
2012	32	CRS	0.900	0.112	0.378	1.000	8
		VRS	0.929	0.112	0.386	1.000	16
		SE <sup>4</sup>	0.969	0.036	0.880	1.000	11
2013	32	CRS	0.918	0.062	0.780	1.000	9
		VRS	0.945	0.060	0.781	1.000	14
		SE <sup>4</sup>	0.971	0.034	0.871	1.000	9
2014	32	CRS	0.916	0.069	0.749	1.000	8
		VRS	0.944	0.066	0.749	1.000	14
		SE <sup>4</sup>	0.971	0.034	0.892	1.000	10
2015	32	CRS	0.853	0.097	0.702	1.000	7
		VRS	0.930	0.076	0.770	1.000	14
		SE <sup>4</sup>	0.917	0.075	0.750	1.000	8

<sup>1</sup> CRS = constant returns to scale; EE = scale efficiency; Std. dev. = standard deviation; VRS = variant returns to scale model.

<sup>2</sup> Number of mills (DMUs).

<sup>3</sup> Geometric mean of the Malmquist indexes.

<sup>4</sup> Calculated using Equation 1.

We were thereby able to identify the mill (or economic group) that most efficiently operated its resources (inputs) to obtain its outputs (sugar and ethanol).

A portion of the inefficiency of mills in the Brazilian sugar-energy industry, as identified in this study, can be mitigated by mills adopting best operational practices, defined by the mills on the efficiency frontier. Specifically, benchmarking consists of a systematic and continuous process of adopting best practices (operational and administrative) to achieve a higher performance and, consequently, a lower level of inefficiency.

All three models (CRS, VRS, SE) indicate a similar reduction in average efficiency levels over time. Averaging the results of the mills in the CRS model, the inefficiency of mills increased from 6.40% in 2006 to 14.72% in 2015 ( $EME^{CRS}$ ), with the worst efficiency level observed in 2015 ( $EME^{CRS}=0.853$ ). This efficiency score suggests that 14.72% of conventional variable inputs could have been saved by the mills by improving their

management and by restructuring according to the best practices observed among the mills. Eliminating these inefficiencies would improve the use of scarce resources and contribute to a reduction in the costs of production of each mill.

In the CRS model, 21.87%, or seven of the 32 mills in the sample in 2015, were classified as fully efficient due to the higher productivity of their factors of production, as reflected in their maximum efficiency scores. This signals that these mills do not have a problem with allocating their factors of production, since they are under the frontier of variable returns to scale; however, they face obstacles in relation to an inadequate productivity scale.

The average efficiency scores fluctuated and tended to decrease over the period of analysis. The fluctuations were linked to several factors whose impacts on harvests differed among mills and throughout the period of analysis. The fluctuations in efficiency may be linked to difference in weather, and reflect, for example, periods of water deficit that may have compromised sugarcane quantity or quality, as measured in kilograms of total recoverable sugars (TRS).

Assessing the coefficients of variation of the average efficiency scores over the period, we found a lower variability in the efficiency indicators for production scale compared to those for inputs. That is, we found less heterogeneity in scale of production than in the use of production factors. This result confirms the findings of Brunozi *et al.* (2012) and Pachiel (2009), who identified TE as the greatest bottleneck in the sugar-energy industry, particularly with respect to the incorrect use of factors of production.

Separating inefficient mills ( $EME^{VRS} < 1$ ) from fully efficient mills ( $EME^{VRS} = 1$ ), we found that efficient mills obtained higher levels of production with fewer inputs, resulting in a higher productivity of factors of production. For example, between 2006 and 2015, the fixed assets (here, a proxy for capital) of efficient mills was on average R\$<sup>6</sup> 130.73 per ton of processed sugarcane, while this value was R\$ 198.41 per ton of processed sugarcane for the group of inefficient mills.

This result suggests an opportunity for certain mills in the sector to reduce their monetary resources immobilized in assets, and seek a more optimized structure associated with higher levels of sugar and ethanol recovery per ton of sugarcane. This process may result in a reduction in the volume of resources linked to the remuneration of fixed capital and the depreciation of these assets. Thereby, the potential exists for mills to obtain a higher productivity of their factors of production and consequently reduce their costs of production.

The inefficiencies observed in the mills in the sugar-energy industry cannot be solely attributed to poor industrial management (TE). While this factor is partly responsible for inefficiency, other variables also play a role, including technology, scale, and production mix, among others. Our period of analysis, between 2006 and 2015, corresponds to a time during which significant changes were observed in sugarcane production, including a shift in harvest practices from manual burning to mechanized harvest without burning, and changes in planting practices from manual to mechanized planting. If we consider only the changes in harvest and planting, we find an impact on the allocation of capital (in this study, measured by fixed capital) and labor; an impact on the volume of mineral and vegetable impurities taken from the field to industry; and, consequently, a loss of milling capacity, a wearing of equipment, a difficulty in the treatment of sugarcane juice, and a reduction in the fermentation yield, among other impacts.

The model captures industrial efficiency by measuring the conversion of input into product, given the level of technology employed by the mill. However, this efficiency is affected by other variables (particularly agronomic variables). Nevertheless, we note that using the MI, we are limited to decomposing the TFP into TC and TE – or what is explained by either the quantity of processed sugarcane or the amount of capital employed in production. In addition, we should emphasize that the motivation for the study is to analyze

<sup>6</sup> R\$ refers to the Brazilian currency, the Real (BRL).

industrial productive efficiency. Specifically, we ask: given a quantity of inputs, do mills exploit all the potential of the industry and adopt the latest best practices and technology available in the sector?

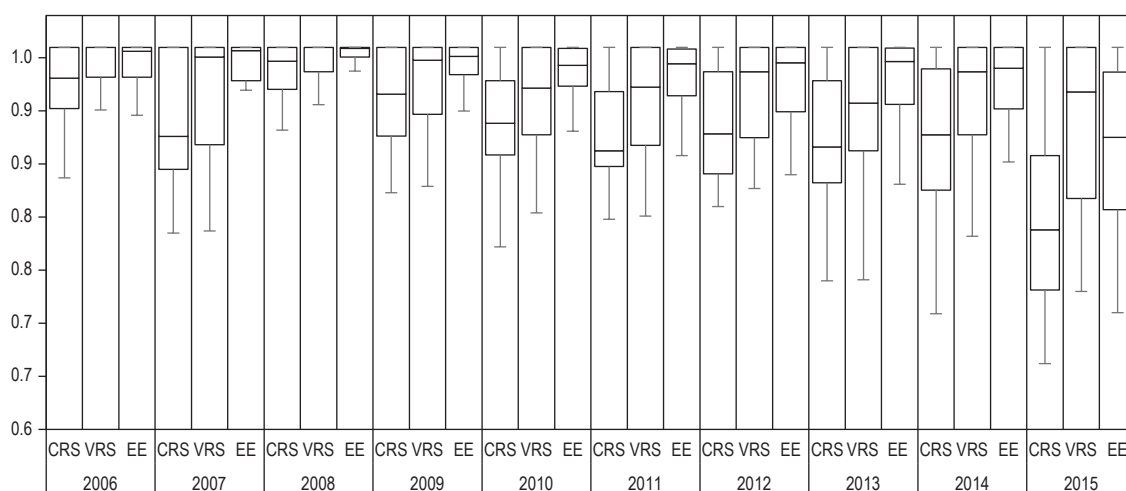
Figure 3 displays the empirical distribution of efficiency indicators (scores) obtained by the DEA (CRS, VRS, and EE) models in the form of boxplot diagrams.

Regardless of the model analyzed, an increase in variability over the years is evident for the entire sample and for each mill individually. Specifically, the range of efficiency levels widened over the period, reflecting a growing gap between mills in the sector in terms of efficiency. This result supports our hypothesis of a heterogeneous sector with respect to efficiency, and corroborates similar findings in the economic literature from the 1990s and 2000s by Shikida *et al.* (2011). Throughout its history, the sector has assumed the characteristic of heterogeneity in terms of management practices, technical performance, and economic results, and recently, this heterogeneity has become even more pronounced.

Since its formation, the Brazilian sugar-energy sector has been marked by intense heterogeneity in terms of management practices and technological diffusion. Recently, in the face of severe financial difficulties, yet a commitment to productivity levels, differences in the sector have intensified and mills that are technologically poor and have low efficiencies coexist alongside mills with modern management practices, productive technologies, and resulting high levels of efficiency. We therefore reject the null hypothesis ( $H_0$ ) of this study: no single nor well-defined standard for efficiency or productivity has ever existed among mills in the sector.

We note that since 2008, a significant number of mills have ceased their operations (declared bankruptcy) or are in receivership. This situation reflects a scenario that includes high levels of debt, depressed prices or the presence of government control, and low levels of investment in the sector.

It additionally reflects the existing inefficiencies in the sector and, as found in the study, the high level of technical and economic heterogeneity among mills. In this context, we expect to see a movement toward mergers and acquisitions in the Brazilian sugar-energy sector, which may result in increased efficiency and growth in the scale of agricultural and industrial production, reduced costs in the sector, and lower volatility in sugar and ethanol production. Moreover, the sugar and ethanol mills in Brazil are likely to undergo further structural changes that will contribute to the long-term development of the sector.



**Figure 3.** Boxplots of efficiency indicators obtained from the DEA (CRS, VRS, and EE) models between 2006 and 2015. Outliers – values 1.5 times higher than the 3<sup>rd</sup> quartile + interquartile range or 1.5 times lower than the 1<sup>st</sup> quartile (interquartile range) – are not represented nor identified in the respective boxplots.

In summary, the Brazilian sugar-energy sector is one in which mills of varying technological and economic situations coexist. This scenario is likely to lead to consolidation and concentration in the sector in the short term, with an emphasis on the absorption and acquisition of mills in difficulty by those presenting superior operational results and greater cash generation.

Following an analysis of efficiency scores, Table 7 presents the TFP variation index of the MI for each of the mills analyzed between the years 2006 and 2015. We can observe that, on average, productivity decreased by 2.18% between 2006 and 2015, with fluctuations in productivity during the period. For example, while productivity increased 0.88% between 2013 and 2014, it decreased roughly 1.46% between 2014 and 2015.

**Table 7.** Malmquist index for mills in the Brazilian sugar-energy sector, annual change between two consecutive time periods,  $t$  and  $t+1$ , from 2006 to 2015.

Mill <sup>1</sup>	Period $t$ and $t+1$									Average <sup>2</sup>	Std. dev. <sup>3</sup>
	06/07	07/08	08/09	09/10	10/11	11/12	12/13	13/14	14/15		
1	1.01	0.98	1.03	1.28	0.74	0.87	0.94	0.99	1.07	0.98	0.14
2	0.94	1.00	0.89	1.13	0.92	1.04	1.00	0.97	1.02	0.99	0.07
3	1.50	0.35	0.63	1.48	1.00	0.98	0.99	1.01	0.98	0.92	0.36
4	1.16	0.93	0.92	1.11	0.97	0.98	0.97	1.02	0.96	1.00	0.08
5	0.89	0.86	0.95	1.04	1.10	0.42	2.09	0.93	1.01	0.96	0.44
6	0.98	0.99	0.93	1.12	0.94	0.98	0.99	0.98	1.11	1.00	0.07
7	0.93	0.90	0.94	0.99	1.14	1.02	1.01	1.28	0.81	0.99	0.14
8	0.97	0.94	0.78	1.27	1.00	0.95	1.02	0.98	1.01	0.98	0.13
9	0.97	0.99	0.88	1.09	1.14	1.11	0.98	0.85	1.71	1.06	0.25
10	1.83	0.90	1.01	1.11	0.94	1.00	1.08	0.84	1.05	1.06	0.29
11	—	0.04	0.87	1.16	0.98	0.99	1.05	0.91	0.96	0.66	0.35
12	1.02	1.01	0.92	1.09	0.97	1.01	1.02	1.07	0.95	1.01	0.05
13	0.99	0.93	1.11	1.04	0.94	0.97	1.00	1.01	0.94	0.99	0.06
14	0.95	1.03	0.93	1.06	0.96	1.01	1.00	1.03	0.91	0.98	0.05
15	0.99	0.90	0.89	1.13	0.97	1.02	1.01	1.02	0.95	0.98	0.07
16	—	—	—	—	1.02	1.03	0.91	0.97	1.00	0.98	0.05
17	0.97	0.95	0.94	1.21	0.88	0.85	1.14	1.07	0.97	0.99	0.12
18	0.96	1.03	0.88	1.07	0.99	1.00	0.98	1.03	0.96	0.99	0.05
19	0.91	0.96	1.05	1.06	1.03	0.96	0.93	1.12	0.95	0.99	0.07
20	0.92	1.01	0.99	1.11	1.03	0.98	1.00	0.99	0.97	1.00	0.05
21	0.95	1.03	0.88	1.09	1.06	0.97	0.97	1.07	1.00	1.00	0.07
22	0.97	0.99	0.97	1.05	0.91	1.03	1.00	1.06	0.96	0.99	0.05
23	0.92	0.94	0.91	1.07	0.97	1.03	1.00	1.05	0.91	0.97	0.06
24	0.85	1.03	0.84	1.15	1.13	1.00	0.94	1.03	0.83	0.97	0.12
25	0.97	0.97	1.02	1.18	0.92	0.97	1.02	1.01	0.92	0.99	0.08
26	0.95	1.01	0.98	1.07	0.97	0.98	1.00	0.99	0.94	0.99	0.04
27	0.99	0.97	1.01	1.05	0.92	1.01	1.00	0.97	1.01	0.99	0.04
28	—	—	0.93	1.09	1.02	1.01	0.95	1.00	1.02	1.00	0.05
29	—	0.95	0.97	1.07	0.96	1.01	0.94	1.04	1.01	0.99	0.05
30	1.14	0.98	0.97	1.07	0.97	1.02	0.97	1.11	1.01	1.03	0.07
31	1.01	0.90	0.94	0.98	1.00	0.99	1.00	1.00	0.96	0.98	0.04
32	0.94	0.84	0.95	1.09	1.04	1.01	1.00	0.95	0.93	0.97	0.07
Average <sup>2</sup>	1.01	0.83	0.93	1.11	0.98	0.96	1.02	1.01	0.98	0.98	0.09
Std. dev. <sup>3</sup>	0.20	0.21	0.09	0.10	0.08	0.11	0.20	0.08	0.14	0.06	

<sup>1</sup> Mill began operating after the period of analysis.

<sup>2</sup> Corresponds to the geometric mean of the MI.

<sup>3</sup> Std. dev. = standard deviation.



In a similar analysis, Pereira and Silveira (2016) found that between 2001 and 2008, the TFP index of mills located in the Central-South had a negative annual average of 0.2%. This shows that the sector has not followed a path of productivity gains, and that while productivity has fluctuated both positively and negatively during the period, it saw an overall decrease between 2001 and 2008.

Table 8 presents the average MI and the MI decomposition into TE, TC, pure TE, and SE. This decomposition provides a more detailed view of the nature of the change in productivity of the sampled sugar mills.

One advantage of the DEA method is that it allows changes in productivity to be analyzed individually, providing more information than simply sample averages. For example, nearly one in seven of the mills sampled demonstrated a trend of progression or regression of the MI in at least three consecutive periods. Most mills experienced relatively unstable productivity during the sampling period.

The pairs of years of 2006 and 2007, 2009 and 2010, and 2014 and 2015 demonstrated a similar behavior – a decline in TE levels followed by gains in TC. This process can partially be explained by organizational theory, since production inefficiency may be correlated with a failure to seize new opportunities for achieving productivity growth.

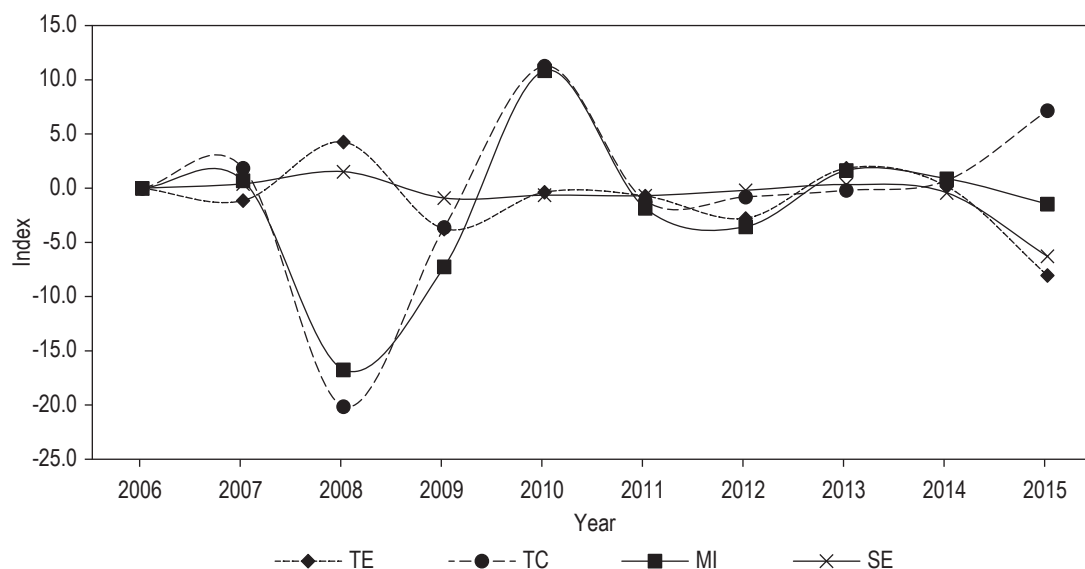
Table 8 contains the geometric mean of the MI and its decompositions by pairs of years. The differences in indices over a shorter period – such as from one year to the next – are relatively small. We calculated the annual changes in TE, TC, SE, and MI for each mill and for each pair of years using the methodology described in Section 3.2. We have converted these individual measures (TE, TC, SE, and MI) into annual averages, and subsequently into indices of accumulated percentage changes<sup>7</sup> by multiplying the indicators for each year, as shown in Figure 4.

<sup>7</sup> For more detail, see Klein *et al.* (1992), who modified Färe *et al.* (1992) to calculate cumulative indices of productivity change, considering a fixed base year.

**Table 8.** Geometric mean of the Malmquist index and its decompositions.<sup>1</sup>

Period	Malmquist index	Technical efficiency	Technical change	Pure technical efficiency	Scale efficiency
2006/07	1.007 (7/0/21)	0.989 (8/4/16)	1.019 (16/0/12)	0.985 (3/11/14)	1.004 (11/4/13)
2007/08	0.833 (8/0/22)	1.043 (18/6/6)	0.799 (0/0/30)	1.027 (14/13/3)	1.015 (16/6/8)
2008/09	0.928 (6/0/25)	0.963 (6/7/18)	0.964 (3/0/28)	0.971 (6/12/13)	0.991 (6/7/18)
2009/10	1.108 (29/0/2)	0.996 (11/3/17)	1.113 (31/0/0)	1.003 (8/11/12)	0.994 (10/4/17)
2010/11	0.981 (11/0/21)	0.993 (10/6/16)	0.988 (12/0/20)	1.000 (11/11/10)	0.993 (11/6/15)
2011/12	0.965 (14/3/15)	0.972 (13/6/13)	0.992 (8/1/23)	0.974 (12/13/7)	0.998 (13/6/13)
2012/13	1.016 (12/1/19)	1.018 (8/6/18)	0.998 (18/0/14)	1.015 (8/13/11)	1.003 (11/7/14)
2013/14	1.009 (18/1/13)	1.002 (14/7/11)	1.007 (17/0/15)	1.006 (11/12/9)	0.996 (10/9/13)
2014/15	0.985 (12/0/20)	0.920 (3/4/25)	1.072 (28/0/4)	0.981 (8/11/13)	0.937 (5/4/23)

<sup>1</sup> The indicators in parentheses correspond to the number of mills with the highest index (showing progress), with an index equal to 1 (without change), and with an index less than 1 (regressing).



**Figure 4.** Indices of the cumulative percentage change in technical efficiency, technical change, scale efficiency, and the Malmquist index. MI = Malmquist index; SE = scale efficiency; TC = technical change; TE = technical efficiency.

We can conclude that the mills in the Central-South saw a loss in accumulated productivity throughout the period of analysis. However, we cannot define a common or clear trend toward a change in SE and productive efficiency for the mills in the Central-South. Instead, the period is marked by fluctuations in efficiency, and various factors impacted productivity during the period.

As noted in Figure 4, the factors contributing to changes in productivity varied from year to year. For example, in 2009, all three components of the MI contributed to a decline in productivity, whereas in 2013, changes in SE and productive efficiency offset the external change of the technology frontier, resulting in productivity growth.

Between 2006 and 2015, the cumulative change in the TFP of the MI decreased by 1.5%. This reduction in productivity is associated with negative scale effects (-6.3%) and TE (-8.0%). Meanwhile, external changes to the technological frontier demonstrated a positive change of 7.2%. Thus, the aggregate decline in productivity was primarily due to a worsening of productive efficiency, although TC mitigated this process. This decline in productivity has translated into a deleterious effect on the fixed cost of production over the period, when mills experienced significant increases in their costs of production (PECEGE, 2017).

The portrait of the Brazilian sugar-energy sector captured by this study emphasizes the deterioration of productivity of the sector, compared to other Brazilian agriculture industries. The sugar-energy sector has not seen continuous increases in productivity, but instead, a reduction and significant fluctuation in productivity throughout the period of analysis.

The cumulative decline in productivity of 1.5% between 2006 and 2015, measured by the MI, was largely due to negative results for SE and TE. Unfortunately, technological gains in the sector did not compensate for declines in productive efficiency. The greater heterogeneity and variability of the two components of productive efficiency (SE and TE) were mainly due to TE. This reflects how over the period, instead of certain mills meeting the efficiency of the most efficient mills, differences regarding management practices and the optimal use of inputs were only amplified.

## 5. Conclusions

This study aimed to analyze the evolution of the TE and SE of certain mills in the sugar-energy sector between 2006 and 2015. It additionally studied the impacts of TC and TE over the period, using variables explaining productivity behavior. While the sample is not probabilistic, and therefore presents certain limitations for inference, the findings are relevant.

The frontier mills demonstrated technological advances between 2006 and 2015, which were reflected in a reduction in factors of production (e.g. capital and labor). However, inefficient mills did not undergo TCs of the same intensity, and by the end of the period lagged further behind those with best practices. Technological changes, mainly due to changes in the production system from the 2011/2012 crop year, contributed positively to productivity development. However, certain mills have also seen a regression in their technology, underlining how factors of production are not adequately allocated in the sector.

Brazilian sugar-energy mills maintain a high degree of heterogeneity in the allocation of productive inputs, which is reflected in varying costs among mills, in a sector whose profitability is characterized by a low level of product differentiation. The competitiveness of the sector, and consequently the security of production, therefore depends increasingly on the efficient management of mills.

Despite its relevance in the Brazilian agribusiness sector, the sector lacks public and private policies aimed at technological development and the dissemination of best productivity practices and management among mills. Without such policies, the gap between mills is likely to widen, exacerbating the imbalance in mill performance.

Possibilities for expansion of the Brazilian sugar-energy sector in the medium and long term exist, mainly due to the goals established by Brazil at the 21<sup>st</sup> Conference of the Parties (COP 21) at the United Nations Conference on Climate Change, and by new policies – such as *RenovaBio*<sup>8</sup> – to stimulate biofuel production in the country. However, in the short term, problems remain that can potentially limit growth in the sector and drive consolidation based on mergers and acquisitions, given the strong technical and economic heterogeneity between mills.

Training programs continue to target growth in the sector, the incorporation of new technologies that drive the recovery of productivity of production factors, and the improvement of management and organization practices to encourage adequate input allocation. In the latter case, this study has highlighted the impact of technical inefficiency among mills in the sector for the period of 2015 to 2016.

This study contributes to the empirical literature and provides further insight into the performance of the sugar-energy sector in recent years. In addition, it generates robust findings by taking a medium- to long-term view of sectoral efficiency that has not been captured in other studies, whose scope is generally limited to a specific harvest year.

Productivity and efficiency are intrinsically related to performance. In this study, we analyzed these two variables to better understand the performance of mills in the Brazilian sugar-energy sector and to provide an analysis of sectoral benchmarking. However, future research could provide further insight into this topic by comparing the results of parametric and non-parametric models, and by identifying further performance factors, including microeconomic variables and others that capture the effects of the location of the mills.

<sup>8</sup> *RenovaBio* is the National Biofuel Policy (Política Nacional de Biocombustíveis) established by Brazilian Law 13.576/2017, whose objective is to expand biofuel production in Brazil based on demand trends and environmental, economic, and social sustainability. As a result of this expansion, biofuels are expected to make an important contribution to reducing greenhouse gas emissions in the country.

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