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Productivity and Efficiency Change of Small-scale Sugarcane Growers in Amatikulu and its Policy-related Sources, South Africa

Mushoni Bulagi* and Irrshad Kaseeram

Department of Economics, University of Zululand, P. Bag X1001, KwaDlangezwa, 3886, RSA
**E-mail: Bulagimb@gmail.com*

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ABSTRACT This study aimed to decompose productivity and efficiency change and also investigated the determinants of Total Factor Productivity (TFP). Secondary data for a sample of 38 small-scale sugarcane growers was applied covering the period 2013 to 2016 in the Amatikulu region in KwaZulu-Natal Province of South Africa. The results of the Färe-Primont Index revealed technological progress–driven TFP and mix efficiency, technical and scale-efficiency has retracted annual growth in small-scale sugarcane productivity while other components revealed mixed results. The policy-related variables analysed by the Bayesian Averaging Modelling approach revealed the link between the experience and education of the farmer and sustainability investment as sources of TFP growth and further confirms that improving Research and Development (R&D) may increase TFP productivity. The paper concludes that both productivity and efficiency need to be improved without increasing the size of plots as well as increasing extensions visits to the farms.

INTRODUCTION

The recent drought in South Africa has exposed small-scale sugarcane growers to dire conditions that have resulted in many abandoning their plots. Production statistics have revealed that the Amatikulu region crushed fewer sugarcanes in 2016 than previously (SASID 2017). Empirical studies (Cockburn et al. 2014; Dubb 2015, 2016) have in the past shown interest in the contribution of sugarcane production to the well–being of rural dwellers. The interest came after policy reform aimed at uplifting small-scale farmers in the South African agricultural sector focused on increased input, technological innovation through loans schemes and regulated ownership of land. However, when agricultural policies targeted at a particular group are not fully focused, the desired outcome becomes hard to achieve.

During the last ten years, small-scale sugarcane production in Amatikulu has undergone a great decline in agricultural productivity. The decline threatens the sustainability of the farming enterprise as well as reducing output and overall food security. Moreover, the total growth in agricultural productivity results in technological innovation and overflow of resources as well as investments in all the sectors of the economy linked to agriculture (Giang et al. 2019; Nkamleu 2014; O'Donnell 2010). However, the slow adaptation of innovative technologies may result in higher inefficiencies given the available inputs. Therefore, the production of multi-outputs with the same set of inputs exacerbates the issues of performance management.

The decomposition of agricultural productivity has been well received, although was limited to labour and land. Despite the interest, there has been limited empirical research focused on the effect of performance tools and policy-related variables on agricultural productivity and efficiency change of small-scale sugarcane growers. It is worth mentioning that the existing study by Thabethe et al. (2014) in South Africa applied only the Stochastic Frontier Analysis (SFA) and used cross-sectional data to estimate productive efficiency in the Mpumalanga province. Recently, several studies (Rada et al. 2019a; Rada et al. 2019b) examined the TFP growth by decomposing technical and efficiency changes in Russia and Brazil, respectively. The latter study revealed the relationship between public education investments and faster productivity growth.

The researchers further identified policy-related variables such as research and development expenditure, extension support, education and the experience of the small-scale growers that contribute to TFP growth (Alene 2010; Fuglie and Rada 2013; Rahman et al. 2013; Kumbhakar et al. 2014) and provide the scope for policy direction and reform. However, these previous studies applied the Generalised Method of Moments (GMM) and SFA techniques that had model uncertainty and endogeneity issues. Consequently, the work of O'Donnell (2014) introduced the Bayesian Modelling Averaging (BMA) proposed by Fernandez et al. (2001) to investigate the determinants of TFP growth in agriculture. The researchers turned their attention to apply the BMA to identify sources of the TFP using policy-related variables in Northern KwaZulu-Natal. All these issues will advance the present state of knowledge by decomposing productivity and efficiency change and identifying sources of TFP growth in small-scale agriculture using farm-level data.

Productivity growth is commonly decomposed into two components, namely, technical change and efficiency change over time, using the Malmquist Productivity Indexes (MPI), (see Fare et al. 2001; Caves et al. 1982). Consequently, Luh et al. (2008) and Pengfei and Bing (2014) decomposed agricultural efficiency and productivity using the MPI. Other studies (Piya et al. 2012; Kumbhakar et al. 2014; Temoso et al. 2018) focused on TFP growth and decomposed agricultural productivity by applying both SFA and the Translog Production Function. Some empirical studies decomposed TFP growth into efficiency and productivity growth. Singh (2016) applied a DEA-based MPI and revealed technological regress as a consequence of negative growth in technical change and efficiency. To this end, Majiwa et al. (2018) applied both the SFA and DEA and showed that misallocation of input negatively affected agricultural productivity.

Consequently, the Hicks-Moorsteen Index (HMI) that encompasses the ratio of a Malmquist output-index over a Malmquist input-index gained attention in agricultural productivity because it satisfies determinateness under poor conditions of technology Briec et al. (2011). There is an extensive empirical literature (O'Donnell 2012a; Kerstens and Van de Woestyne 2014) on the choice between the MPI and the HMI. The Hicks-Moorsteen Index enjoys attention because it decomposes the distance of the production frontier without neglecting scale economies and the precise direction of the TFP growth. O'Donnell (2010) decomposed the Hicks-Moorsteen Index which is applied to the assumption of any return to scale. There are, however, multi-lateral and multi-temporal comparison and poor restrictive assumption concerning statistical noise issues that limit the HMI (O'Donnell 2014). The limitations of the HMI resulted in the introduction and application of the Färe-Primont Index (FPI), see studies such as Tozer and Villano (2013), O'Donnell (2014) and Khan et al. (2015) that focused on agricultural productivity. Therefore, the FPI will necessarily deliver superior results compared to the previous approaches.

There is still ambiguity in measuring the determinants and sources of agricultural efficiency and productivity change. Some empirical studies explore the sources of agricultural productivity by applying both the stochastic production frontier in a form of SFA and DEA, which is a non-stochastic production function (Alene 2010; Rahman and Salim 2013). Moreover, O'Donnell (2014) argued that SFA has a weakness when it comes to the assumption of how the error term is distributed. Moreover, the BMA technique solved the shortcomings of Generalised Least Squares (GLS) regarding its inability to resolve the endogeneity. In summary, studies have revealed mixed results on the contribution of policy-related variables to agricultural TFP growth. Public and private research and development expenditure improves TFP growth (Mullen 2007; Rahman and Salim 2013; Fuglie and Rada 2013). Other studies also reported both the positive and negative effect of education on TFP growth, (see Alene 2010; Piya et al. 2012; Kumbhakar et al. 2014). Rahman and Salim (2013) revealed that average farm size had a dominant influence on TFP growth together with scale-efficiency and technical-efficiency. Socio-economic variables such as age, size of household and the experience of farmers have an effect on efficiency (Gebrehiwot 2017).

To the researchers' knowledge, the application of the FPI and BMA to decompose productivity and efficiency change of small-scale sugarcane in South Africa has not been explored. Therefore, this study contributes to the body of knowledge and application of these methodologies represents the main novelty of this study.

Objectives

The recent occurrence of drought accompanied by poor farm management skills and lack of public support to small-scale sugarcane growers in northern KwaZulu-Natal constitute a threat to the long-term sustainability of the sugar industry. The challenges posed by low productivity and inefficiency of small-scale sugarcane growers in South Africa intensify the need for this study. The limited empirical evidence of productivity studies and the policy-related determinants of TPF makes it difficult to intervene for policymakers and role players supporting small-scale sugarcane growers to intervene. The gap in decomposing the components of productivity and efficiency change and sources that affect TFP motivated the need of this study that was aimed at estimating how productive growers were in the period 2013 – 2016 by applying aggregated input and output. It also seeks to find out which policy-related variables such as sustainability investment, land size and education affect TFP. Therefore, the findings of this study talk to stakeholders in the sugar industry who strive to formulate relevant policies and developmental programmes aimed at enhancing productivity and sustainability.

MATERIAL AND METHODS

Decomposing Productivity and Efficiency Change

The DEA method can be applied to estimate the distance-based index of the Färe-Primont Index, which assumes that the frontier of a firm follows the linear form in the neighbouring of the technically efficient point (O'Donnell 2012b). The small-scale sugarcane growers were treated as firms. The output distance function holds only in the neighbourhood of the technically efficient point (x_{nt}, q_{nt}/OTE_{nt}) and takes the form:

$$D_O(x_{nt}, q_{nt}, t) = (q_{nt}'\alpha)/(\gamma + x_{nt}'\beta) \qquad (1)$$

The standard output-oriented DEA problem involves finding the solutions for the unknown parameters in Equation (1) to minimize technical efficiency: $OTE_{nt} = D_o(x_{nt}, q_{nt}, t)$ If α and β are non-negative, then the only constraint that needs to be satisfied is 1. $D_0(x_{nt}, q_{nt}, t) \leq$ Setting an additional constraint $q'_{nt}\alpha = 1$, the DEA problem takes the following linear programming form:

$$D_O(x_{nt}, q_{nt}, t)^{-1} = OTE_{nt}^{\ -1} = \min\{\gamma + x_{nt}'\beta : \gamma\tau + X'\beta \geq Q'\alpha;\ q_{nt}'\alpha = 1;\ \alpha \geq 0;\ \beta \geq 0\} \qquad (2)$$

where Q is a vector of observed outputs, X is a vector of observed inputs, and τ is a unit vector. Henceforth, the computation of the Färe-Primont aggregates was solved by applying the variant of LP as:

$$D_O(x_o, q_o, t_o)^{-1} = \min\{\gamma + x_o'\beta : \gamma\tau + X'\beta \geq Q'\alpha;\ q_{nt}'\alpha = 1;\ \alpha \geq 0;\ \beta \geq 0\} \qquad (3)$$

Estimates of aggregate outputs, Q_{nt} and aggregated input, X_{nt} for all i and t are then estimated as:

$$Q_{nt} = (q_{nt}'\alpha_o)/(\gamma_o + x_o'\beta_o) \qquad (4)$$

$$X_{nt} = (x_{nt}'\eta_o)/(q_o'\phi_o - \delta_o) \qquad (5)$$

where α_0, β_0, γ_0 solve Equations 4 and 5. The computer software DPIN[1] 3.0 was used to decompose productivity into various efficiency indexes as applied by (Rahman and Salim 2013), which estimated the FPI assuming that the production technology exhibits variable returns to scale (VRS).

Sources of TFP

For factors that affect TFP, the policy-related variables were analysed using the Bayesian Modelling Average technique. Suppose a linear model structure with the dependent variable y**,** a constant expressed as α, while coefficients expressed as β and a normally distributed error term ε with variance σ^2, expressed as follows:

$$y = \alpha + \beta_i Z_i + \varepsilon \qquad \varepsilon \sim N(0; \sigma^2) \quad (6)$$

However, when several potential explanatory variables in a matrix X exist, then it becomes difficult for us to see which variables to include. Suppose Z contains G possible variables, then an estimate of 2^G models will be made to imply the anticipated number of explanatory variables in a model will show G/2 as proposed by (Fernandez et al. 2001). Therefore, the model weights over models S was expressed as:

$$P(S_G|\ y, Z) = \frac{P(y|M_G,Z)P(M_G)}{P(y|Z)} = \frac{P(y|M_G,Z)P(M_G)}{\sum_{S=1}^{2K} P(y|M_S,Z)P(M_S)} \qquad (17)$$

where $P(y|M_G,Z)$ expresses the posterior model probability, $P(y|Z)$ is the integrated likelihood, which is a multiplicated term, and p(M) denotes the prior model probability. Therefore, the posterior model probability of a given model will be specified as the model likelihood conditional on the assumed model M times a prior model probability. Hence, the weighted posterior distribution for any data is expressed as:

$$\theta\colon \sum_{S=1}^{2K} p(\theta|M,Y)p(M|X,y) \quad (8)$$

Data and Variables

This study used both survey and secondary data on small-scale sugarcane production and policy-related factors to quantify input and output variables in order to use a weighted aggregative method. The survey data consisted of livestock, sugarcane seeds stalk output, fertiliser, capital and labour. Secondary data consisted of sugarcane output data sourced from the Tongaat Hullett extension services department in the Amatikulu regional office. Livestock, sugarcane seeds stalk output and input data were collected using structured questionnaires covering the period 2013–2016. Furthermore, the survey collected production information from 38 small-scale sugarcane growers. The survey was from a project that tracked 300 small-scale sugarcane growers in two sugar-producing regions in Northern KwaZulu-Natal.

The variables used in the analysis of productivity and efficiency change were sugarcane output, quantified in terms of a weighted aggregate quantity of sugarcane harvested, with weights based on revenue shares of sugarcane. The livestock output corresponded to a weighted aggregate of the number of cattle and goats during the survey period using revenue share as a weight. Seed cane output was the total seed cane stalk produced during the survey period in kilograms. To construct the land input variable all the land area operated for the production of sugar whether owned or rented by the growers was used in terms of hectares. The fertiliser was calculated by the aggregate quantity of all fertiliser used in kilograms. Capital corresponded to the average of the total closing value of capital on the closing of business and opening value of capital. It included the value of all assets used on the farm including leased equipment with the exception of machinery contractors' equipment. Lastly, labour corresponds to the total number of hours worked by all farm workers including family members.

Variables as determinants of TFP were defined and quantified as follows: Education- the total number of years of schooling. Experience–the total number of years a particular grower has been producing sugarcane for crushing by the mill and other stakeholders involved in the business. Extension visits–the number of days constituting a direct visit to the growers' production plot by extension officers for any kind of advice. Land size- the extent of millable agricultural land available for sugarcane production. Sustainability investment–the total expenditure on operating costs incurred by the mill in terms of subsidies for a particular small-scale sugarcane grower.

The average sugarcane yield was 96767.7 kilograms per season for small-scale sugarcane growers in the Amatikulu region. Out of which, 20483.07 kilograms per season was certified by the mill to be used as seed cane stalks and was sold to other growers. It is very difficult to compare these figures to the annual estimated average yield in the Northern KwaZulu-Natal region of 6000 kg/ha when the average rainfall is 1000 – 1300 mm/annum. The average revenue share for livestock was R116835.90 for the aggregated cattle and goat that a particular small-scale sugarcane grower owns. On average, the total 2.62

Table 1: Summary statistics of production data

	Sugarcane output	*Livestock*	*Seed cane*	*Land*	*Fertiliser*	*Capital*	*Labour*
Mean	96767.70	116835.90	20483.07	2.62	633.61	14186.52	556.49
SD	85929.51	73011.93	23284.51	2.28	436.50	9028.36	335.57
Min	9141	15000	668	0.20	50	875	100
Max	765564	360000	152152	15	2250	42300	1698

hectares of land was milled for sugarcane production with the minimum and maximum hectares standing at 0.2 and 15 respectively. With regard to fertilisers, the average of 633.61 kilograms was applied in the production of sugarcane. The average of 633.61 kilograms of fertilisers was applied with a minimum of 50 kg and the maximum kilograms applied been 2250. Lastly, the total of 556.49 hours was allocated on average for the production of the three outputs.

RESULTS

Results of Färe-Primont Index

Table 2 in the appendix illustrates summary of annual input growth rate for the years 2013–2016 as follows: input technical efficiency reduction of 7 percent, input scale efficiency decreases of 12 percent, input mix efficiency increases of 31 percent, residual input scale efficiency decreases of 47 percent and input scale mix efficiency increase of 45 percent. These results reveal low input mix efficiency, which corresponds to a sub-optimal combination of inputs as experienced by the sugarcane growers. The sub-optimal combination of inputs leads to inefficiencies as a consequence of failure to apply inputs optimally.

Tables 3 and 4 present the TFP and efficiency levels, TFP change and its components, respectively, of the 38 small-scale sugarcane growers using the Färe-Primont Index. Table 3 in the appendix shows that the sugarcane growers ought to improve productivity by producing at the optimal point. Thus, despite grower's higher efficiency levels on both technical and scale efficiency growers. Moreover, there is a need to focus on improving residual scale, scale mix and residual mix efficiency to a level higher than or equal to technical and scale efficiencies. Overall, the results revealed the mean scores for technical efficiency ranging between 28 percent and 95 percent. The results show that these sugarcane growers experience challenges in maintaining the use of inputs. The results also revealed the gap between the observed TFP (71%) and the maximum frontier TFP (57%) as a consequence of low mix efficiency (77%) compared to the technical efficiency (81%) levels of the sugarcane growers. The gap is a concern for these growers' quest to achieve economies of scope over the long-run by applying an optimum combination of input and output mixes.

As illustrated in the appendix Table 4 shows the results of TFP productivity change and its components for the period under review. The results revealed the positive annual rate of TFP

Table 2: Summary of input usage

Year	*Input technical efficiency*	*Input scale efficiency*	*Input mix efficiency*	*Residual input scale efficiency*	*Input scale mix efficiency*
2013	0.91	0.95	0.71	0.51	0.38
2014	0.85	0.91	0.70	0.41	0.28
2015	0.74	0.76	0.77	0.50	0.40
2016	0.85	0.83	0.79	0.64	0.51
Geomean	0.84	0.86	0.74	0.51	0.39
Growth (%)	- 0.07	- 0.12	0.31	- 0.47	0.45

Table 3: Total factor productivity and efficiency levels

	Maximum TFP 1	*Technical-efficiency 2*	*Scale-efficiency 3*	*Mix-efficiency 4*	*Residual scale-efficiency 5*	*Scale mix efficiency 6*	*Residual mix-efficiency 7*	*TFP efficiency 8*	*Average TFP= (1*2*3*7)*
2013	0.56	0.90	0.95	0.76	0.50	0.80	0.40	0.74	0.19
2014	0.69	0.83	0.93	0.69	0.45	0.78	0.31	0.73	0.17
2015	0.68	0.67	0.84	0.82	0.53	0.73	0.53	0.68	0.20
2016	0.41	0.82	0.88	0.87	0.63	0.74	0.63	0.70	0.19
Geomean	0.59	0.81	0.90	0.79	0.53	0.76	0.47	0.71	0.19

Table 4: Total factor productivity change and its components

Year	*Technical change 1*	*Technical-efficiency change 2*	*Scale-efficiency change 3*	*Mix-efficiency change 4*	*Residual scale-efficiency change5*	*Residual mix-efficiency change 6*	*TFP change 7 =(1*2*3*6)*
2013	0.57	0.90	0.96	0.81	0.81	0.64	0.32
2014	0.39	0.83	0.93	0.68	0.73	0.50	0.15
2015	0.48	0.67	0.84	0.83	0.86	0.85	0.23
2016	0.72	0.81	0.89	0.87	1.04	1.01	0.52
Geomean	0.54	0.80	0.91	0.80	0.86	0.75	0.29
Growth (%)	0.42	- 0.06	- 0.17	0.10	0.28	0.67	0.55

growth, which is encouraging because of harsh climatic conditions that have affected yields. The observed technological progress estimated by technical change grew at an annual rate of 42 percent, which indicates that the positive TFP growth is influenced by technological progress and mix efficiency. Moreover, the results also revealed a decline in technical efficiency and scale-efficiency annual growth. This finding translates as revealing the poor maintenance of technical efficiency and scale-efficiency over a short period of 4 production seasons. The residual scale-efficiency and residual mix-efficiency grew at an annual rate of 28 percent and 67 percent, respectively.

Results of Bayesian Modelling Averaging

Table 5 in the appendix presents the results from BMA relating to determinants of TFP growth of the growers to various socio-environmental variables. The results of the coefficients averaged over all models were presented by the post mean. To give a possible explanation for the representatives of the variables, the Posterior Inclusion Probabilities (PIP) is considered. The coefficient sign for all models that contained experience of the small-scale sugarcane grower showed a positive association with TFP growth and PIP of 0.534 indicating the confidence of 53.4 percent. This means that the posterior model mass rests on models that included experience. Likewise, sustainability investment also showed a positive association with TFP growth, but a fairly low rate of PIP of 0.343 implying the confidence of 34.3 percent. Moreover, education revealed a positive association with TFP growth with a PIP of 0.308, implying, the confidence of 30.8 percent. In contrast, both land size and extension visit revealed PIP of 0.197(19.7%) and 0.167(16.7%), respectively. Therefore, all models that included both land size and extension visit, revealed negative coefficient sign.

Table 5: Determinants of TFP growth

Variable	*PIP*	*Post mean*	*Post SD*	*Cond Pos Sign*	*Idx*
Land size	0.197	-0.004	0.151	0.000	1
Sustainability Investment	0.343	0.113	0.219	1.000	2
Extension visit	0.167	0.014	0.081	0.000	3
Experience	0.537	0.190	0.218	1.000	4
Education	0.308	0.068	0.136	1.000	5

DISCUSSION

This study is one of the first attempts in South Africa to decompose productivity and efficiency change as well as investigating the determinants of TFP. The FPI developed by O'Donnell (2010) and BMA proposed by Fernandez et al. (2001) were applied in the small-scale agricultural sector. Finer components of TFP index were decomposed (that is, Maximum TFP, Technical efficiency, Scale-efficiency, Mix-efficiency, Residual scale-efficiency, Scale mix efficiency, Residual efficiency, TFP efficiency and Average TFP). The small-scale sugarcane growers demonstrated varying efficiency scores, with a very low average TFP followed by residual efficiency, similar findings were earlier discovered by Rada et al. (2019a) in the Russian agricultural sector. An examination of input growth showed both an increase in input mix efficiency and input scale mix efficiency and also the decrease in input technical efficiency, input scale efficiency and residual input scale efficiency. The reduction of efficiency accompanied by low input mix efficiency in agricultural productivity is associated with the sub-optimal optimal combination of inputs. The considerably lower mix efficiency compared to technical efficiency over this period can also be attributed to the gap between the TFP and the maximum frontier TFP. Thus far Majiwa et al. (2018) argue that misallocation of inputs hinders crop productivity. Therefore, proper allocation of inputs is necessary in order to attain the desired yields of sugarcane. The findings of the FPI contribute to the findings by Rada and Schimmelpfennig (2018) and O'Donnell (2012b) that revealed technical progress and productivity growth by stating mixed findings on the role of TFP on agricultural development.

Findings on the determinants of TFP growth showed the link between the experience and education of the farmer as well as sustainability investment. Their positive relationship means that growers with particular years of schooling and years of growing sugarcane are more productive. One may relate this finding to the proper allocation of resources based on previous experience of the grower. The study by Giang et al. (2019) proposed agricultural reforms aimed at improving investments to improve productivity. In terms of development, the mills' sustainability investment also improves TFP. Hence, the stakeholders may need to strengthen and improve research and development in small-scale sugarcane production to increase efficiency and productivity. Since land size and extension visits revealed a negative association with TFP growth, there is need to focus on improving efficiency and productivity without increasing the size of plots because small-scale growers are failing to maximise productivity given their small plots. Moreover, increasing the number of extensions of visits and direct contact with the growers will improve TFP growth.

Overall, technological progress is driven by technical and mix efficiency TFP productivity, while technical and scale-efficiency have retracted annual growth in small-scale sugarcane productivity. These findings support empirical studies that decomposed efficiency in agriculture see (Rahman and Salim 2013).

CONCLUSION

The paper concludes that sugarcane grower's productivity and efficiency growth need to be improved without altering the size of the plots. Also, the paper concludes that the proper allocation of inputs is important for growers to maintain their optimal production. In relation to the determinants of TFP growth, the study concludes that strengthening R&D focused on small-scale production may lead to TFP growth. Furthermore, the study concludes that the land size and extension visit negatively affect TFP growth. This explains that increasing the size of plots and farm extension visits without proper allocation of inputs and adaptation of innovative technologies result in less productive and inefficient sugarcane growers.

RECOMMENDATIONS

This study discovered that small-scale sugarcane growers need to improve productivity and efficiency growth by allocating proper inputs in the production of sugarcane optimally. Therefore, the study recommends policies focused on improved technological progress, and focus on optimal application of inputs to improve productivity, and sustainability of the sugarcane growers through focused subsidies for inputs. Further estimation of farm-level data will bring a better understanding of productivity and efficiency change in small-scale farming and contribute to this body of knowledge. Nevertheless, it is clear that sources of TFP growth will provide precision on policy reforms. The formulation and implementation of policies aimed at improving productivity, sustainability and efficiency of small-scale sugarcane growers could result in the improvement of their livelihoods and curb poverty.

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