Technical efficiency of the small-scale tea processors in Kenya: a stochastic metafrontier approach

Karambu Kiende Gatimbu
Department of Business and Economics, University of Embu, Embu, Kenya, and
Maurice Juma Ogada
Department of Economics, Taita Taveta University, Voi, Kenya

Received 11 October 2018
Revised 31 August 2019
11 March 2020
20 April 2020
Accepted 25 April 2020

Abstract

Purpose – Importance of small-scale tea producers in Kenya is not in doubt. They account for 60% of all tea produced in the country, serve about 560,000 tea farmers and employ about 10,000 people directly. However, the subsector faces a myriad of challenges ranging from declining yields and rising costs of production to fluctuating world prices. Thus, it is imperative that the producers entrench efficiency as a critical success factor. This makes it important for the producers to understand their relative performances to inform decisions on improving input use. Congruent with this motivation, this study sought to analyze the technical efficiency (TE) of the country's small-scale tea processors within and across the regions under the management of Kenya Tea Development Authority.

Design/methodology/approach – To allow comparison across regions, this study adopted a stochastic metafrontier approach and to be able to decompose inefficiency into persistent and time-varying components, the study adopted regression analysis.

Findings – Results showed that the small-scale tea processors operated at a mean TE level of 76% with a technology gap ratio (TGR) of 97%. This implies that the prevailing level of output could be maintained even if inputs were reduced by 24%. Persistent inefficiency could be reduced possibly through rationalization of structural and managerial components of the firms.

Research limitations/implications – While it is important to adopt yield-enhancing technologies and innovation, small-scale tea processors have the latitude to improve their earnings through enhanced TE. They can save up to 24% of their input and be able to pay farmers better even with the fluctuating global tea prices. Enhancing TE should be given priority because it is within the control of the individual firms.

Originality/value – This is a pioneering study in panel data analysis of TE of small-scale tea processors within and across regions in Kenya.

Keywords Technical efficiency, Technology gap ratio, Stochastic metafrontier, Small-scale tea processors, Kenya

Paper type Research paper

1. Introduction

Agriculture remains a key driver to ensure food security and economic development as indicated by the Sustainable Development Goals (SDGs). The role of agriculture in building the economy of many African economies is not in doubt (Akamin *et al.*, 2017). However, agricultural productivity in Africa has been low (Donkor *et al.*, 2018). The literature suggests that poverty reduction is more effective when GDP growth stems from agriculture production compared to non-agricultural production (Ngenoh *et al.*, 2015).

Kenya Vision 2030 supports development of an efficient, sustainable and competitive agricultural sector in order to ensure food security and income generation. In addition, the Kenya Vision 2030 also identifies the manufacturing sector especially the agro-processing as one of the key drivers for realizing a sustained annual GDP growth of ten percent (Ndicu,

Technical input by Prof. Hung-Jeng Wang is gratefully recognized.

Funding: This research was supported by the National Research Fund of Kenya under the grant title "*Sustainability of the smallholder tea enterprises in Kenya*".

2040-0705
DOI 10.1108/AJEMS-10-2018-0303

2015). The manufacturing sector has high, yet untapped potential to contribute to employment and GDP growth (Government of Kenya, 2013). The manufacturing sectors' average growth percentage has continued to decline from 4.3% in 2012 to 3.6% in 2016. The sectors' growth is mainly driven by processing of food products. The stagnated growth has been caused by poor performance in processing (KNBS, 2017). Accounting for about 26% of all foreign exchange earnings and 4% of the GDP, by 2010 tea was the highest foreign exchange earner in Kenya (Tea Board of Kenya, 2010). The small-scale tea subsector accounts for about 63% of the Kenyan tea production (KNBS, 2015). Thus, the sector is central to poverty alleviation, infrastructural development and nutritional security. Although Kenya is the third largest global tea exporter, the local tea industry faces severe challenges. Key among them is the perennial increase in the cost of production. In spite of the aforementioned economic importance of tea, increased factory production costs do little to alleviate poverty and contribution of tea to scaling up rural incomes falls far short of its potential.

Sustainability initiatives have been pursued by the tea processors with the aim of reducing production costs (Gatimbu *et al.*, 2018). Nonetheless, production costs have continued to rise. At the same time, tea prices have shown a decelerated increase over the years due to increase in global tea production (supply) and changing consumer preferences. Such developments have resulted in the collapse of tea industries in countries like South Africa and pose serious challenges to the future growth and direction of the tea industry in Kenya (Kagira *et al.*, 2012). Survival of the small-scale tea processors in Kenya greatly depends on their efficiency in the use of resources. This means that if the current trend is left unchecked, it could lead to the eventual collapse of the tea processors in Kenya.

Elsewhere, farm level technical efficiency (TE) and determinants of tea production have been studied in Vietnam (Hong and Yabe, 2015) and Sri Lanka (Basnayake and Gunaratne, 2002). Results showed that the tea farmers were technically inefficient. In Kenya, TE of maize production (Kibaara, 2005) and sweet corn (Ngenoh *et al.*, 2015) has been investigated. Results showed that the maize and sweet corn farmers were technically inefficient. The aforementioned studies focused on household units. In addition, TE of manufacturing entities has been studied in Kenya (Haron and Chellakumar, 2012; Kamande, 2010; Ndicu, 2015). It is from the foregoing that this study sought to determine TE and its determinants for the small-scale tea processors in Kenya. The absence of previous studies about the TE and its determinants of the small-scale tea processors in Kenya justified the need for this study. The following questions guided the study:

(1) Are the small-scale tea processors in Kenya technically efficient?

(2) What are the determinants of TE for the small-scale tea processors in Kenya?

(3) What is the region-specific frontier relative to the metafrontier?

Technical efficiency estimation has been of mounting interest as a means of identifying best practice performance and improving resource use efficiency (Alem *et al.*, 2017). Efficiency improvement is recognized globally as a key instrument to policy implications and reforms (Kumbhakar *et al.*, 2015). Efficiency measurement is specifically important for emerging economies where resources are paltry, and opportunities are sparse (Amornkitvikai and Harvie, 2011). Technical efficiency analysis has been found useful in identification of factors that contribute in inefficiency of different production systems (Shavgulidze *et al.*, 2017). Technical efficiency estimation has been of mounting interest as a means of identifying best practice performance and improving resource use efficiency (Alem *et al.*, 2017). Efficiency improvement is recognized globally as a key instrument to policy implications and reforms (Kumbhakar *et al.*, 2015). Efficiency measurement is specifically important for emerging economies where resources are paltry and opportunities are sparse (Amornkitvikai and

Harvie, 2011). Technical efficiency analysis has been found useful in identification of factors that contribute in inefficiency of different production systems (Shavgulidze *et al.*, 2017). The main motivation for measuring the TE is to comprehend differences in the levels of efficiency as well as differences in the context within which production takes place (Trujillo and Iglesias, 2013). In the wake of increased global tea market competition and high production costs, TE is a key determinant of the sustainability of Kenya's small-scale tea industry.

The novelty of this study is three fold. First, unlike previous studies that measured performance of tea firms in Kenya using profitability and financial ratios (Ng'ang'a, 2011; Kaimba; Nkari, 2014), this study measured firm performance by TE. In addition, previous studies on TE in Kenya have focused on the smallholder household units and the manufacturing sector. Further, the literature on TE of the small-scale tea processors in Kenya using the parametric approach is not documented. This study also used panel data models, hence is able to account for potential heterogeneity across firms. Third, the study employed region-specific frontiers for comparison rather than pooled. This is in tandem with Lundvall and Battese (2000) who found sector-based equations to be more appropriate than pooled equations. Lastly, this study employed metafrontier techniques that allow comparison of region-specific frontiers versus the metafrontier (Huang *et al.*, 2014a, b). Understanding the levels of inefficiency/efficiency can help address opportunities to improve institutional characteristics, socio-economic characteristics and management practices. The remainder of the paper is structured as follows. Section 2 presents the analytical framework used to address the aim of the paper. Section 3 describes the methodology used, next to which follows Section 4 that discusses the empirical results. The final section presents the conclusions and develops broader implications based on the findings, including areas for further research.

2. Research model

Following Kumbhakar *et al.* (2015) model, stochastic frontier analysis (SFA) was used to estimate and explain the TE of the small-scale tea processors. This parametric approach was chosen because it explicitly separates the effects of technical inefficiency and statistical noise (Le *et al.*, 2018). The SFA specifies the relationship between output and input levels and decomposes the error term into two components: a random error and an inefficiency component. The random error is assumed to follow a symmetric distribution with zero mean and a constant variance while the inefficiency term is assumed to follow an asymmetric distribution and may be expressed as a half-normal, truncated normal, exponential or two-parameter gamma distribution (Ogundari, 2008).

Two main approaches exist in the SFA literature for examining the determinants of efficiency: a one-stage and a two-stage approach. The two-stage approach estimates the efficiency score of the decision-making units (DMU) then uses these values as a dependent variable on possible independent variables in a regression model to discover the possible drivers of efficiency of the DMU (Pitt and Lee, 1981). This approach is heavily criticized because the first step assumes an independent and identically distributed relationship existing between the inefficiency terms whereas the second step tries to find factors that have some relationship with the inefficiency term. Thus, making the second step a contradiction of the first step (Danquah and Ouattara, 2015; Danquah and Quartey, 2015). This incongruity identified in the SFA literature led to the innovation of the one-stage approach that addresses the challenges of the two-stage approach by undertaking the two separate processes in one step (Battese and Coelli, 1995). The study therefore used the Battese and Coelli (1995) one-stage SFA model.

Technical efficiency estimates were derived by estimating a stochastic production frontier from each ecological region by using Equation (1). For example, given the jth region, the stochastic frontier of the ith firm can be modeled as in Equation (3).

$$Y_{ji} = f^i(X_{ji})e^{V_{ji}-U_{ji}}, \quad \text{Where } U_{ji} \sim N\left[\delta_j Z_{ji}, \sigma^2\right] \tag{1}$$

where $j = 1, 2...J$; $i = 1, 2...N$ and where Y_{ji} and X_{ji} respectively denote the output and input vector of the ith factory in the jth region. Following standard stochastic frontier modeling, V_{ji} is a normally distributed random variable with zero mean and variance σ^2 and which represents statistical noise. The non-negative random errors U_{ji} represent technical inefficiency and δj ($j = 1, 2$) is the region-specific parameters to be estimated. U_{ji}, follows a half-normal distribution and is assumed to be independent of V_{ji}. Z_{ji} is the exogenous vector of variables determining inefficiency specific to each factory unit within each region. A factory's TE is then defined by Equation (2).

$$TE_i^j \frac{Y_{ji}}{f^i(X_{ji})e^{V_{ji}}} = e^{-U_{ji}} \tag{2}$$

The ratio of the jth region's production frontier to the metafrontier is defined as the technology gap ratio (TGR) represented by Equation (3).

$$\mathrm{TGR}_i^j = \frac{f^j(X_{ji})}{f^M(X_{ji})} = e^{-U_{ji}^M} \leq 1 \tag{3}$$

At a given input level X_{ji} – a firm's observed output Y_{ji} with respect to metafrontier $f^M(X_{ji})$ – has three components: the TGR, the factory's TE and the random noise component (i.e. Equation 4).

$$\frac{Y_{ji}}{f^M(X_{ji})} = \mathrm{TGR}_i^j \times \mathrm{TE}_i^j \times e^{V_{ji}} \tag{4}$$

As the random noise component is obtained from the stochastic frontier estimation, the decomposition is shown in Equation (5).

$$\mathrm{MTE}_i^j = \frac{Y_{ji}}{f^M(X_{ji})e^{V_{ji}}} = \mathrm{TGR}_i^j \times \mathrm{TE}_i^j \tag{5}$$

Since the SFA estimates of the region-specific frontiers are $f^j(X_{ji})$ for all $j = 1, 2,...J$ regions, the estimation error of the region-specific frontier is shown in Equation (6).

$$\mathrm{In}\widehat{f}^j(X_{ji} - \mathrm{In}f^j(X_{ji}) = e_{ji} - \widehat{e}ji \tag{6}$$

Defining the estimated error as $V_{ji}^M = e_{ji} - \widehat{e}_{ji}$, the relation to the metafrontier can be written as (Equation 7).

$$\mathrm{In}\widehat{f}^j(X_{ji}) = \mathrm{In}f^M(X_{ji}) - U_{ji}^M + V_{ji}^M, \quad \forall i,j = 1, 2, \ldots, J \tag{7}$$

Thus, the metafrontier estimation approach proposed by Huang *et al.* (2014a, b) can be summarized in the estimation of the two following regressions (Equations 8 and 9)

$$\mathrm{In}Y_{ji} = \mathrm{In}f^j(X_{ji}) + V_{ji} - U_{ji}, \quad i = 1, 2, \ldots, N_j \tag{8}$$

$$\mathrm{In}\widehat{f}^j(X_{ji}) = \mathrm{In}f^M(X_{ji}) + V_{ji}^M - U_{ji}^M. \tag{9}$$

where $\mathrm{In}\widehat{f}^j(X_{ji})$ is the estimates of the region-specific frontier. This should be estimated j times, one for each region. The estimates from all j regions are then pooled to estimate the metafrontier (Equation 10). To ensure that the metafrontier is larger than or equal to the region-specific frontiers ($\text{In}f^j(X_{ji}) \leq \text{In}f^M(X_{ji})$), the estimated TGR must always be less than or equal to unity (Equation 10).

$$T\widehat{G}R_i^j = \widehat{E}(e^{-U_{ji}^M}|\widehat{e}_{ji}^M) \leq 1 \tag{10}$$

where $\widehat{e}_{ji}^M = \text{In}\widehat{f}^j(X_{ji}).\text{In}\widehat{f}^M(X_{ji})$ are the estimated composite residuals of Equation (3). The corresponding estimated meta-technical efficiency (MTE) is equal to the product of the estimated TGR and the estimated individual firm's TE (Equation 11).

$$M\widehat{T}E_i^j = T\widehat{G}R_i^j X\widehat{T}E_i^j \tag{11}$$

Identifying the magnitude of persistent inefficiency is important, especially in short panels, because it reflects the effects of inputs like management as well as other unobserved inputs that vary across firms but not over time. Previous models never considered the aspect of persistent technical inefficiency (Kumbhakar *et al.*, 2015). The error term is decomposed into technical inefficiency and statistical noise. The technical inefficiency component is further decomposed into two: persistent component and residual component. Such a decomposition is desirable from a policy point of view because the persistent component is unlikely to change over time without any change in government policy or management, whereas the residual component changes both across firms and over time (Kumbhakar *et al.*, 2015). Unfortunately, if the persistent inefficiency component is large for a firm, then it is expected to operate with a relatively high level of inefficiency over time, unless some changes in policy and/or management take place. Thus, a high value is of more concern from a long-term point of view because of its persistent nature (Kumbhakar *et al.*, 2015).

The models are specified in Equations (12)–(14).

$$y_{it} = \beta_o + X_{it}^t\beta + \in_{it} \tag{12}$$

$$\in_{it} = V_{it} - U_{it}, \tag{13}$$

$$U_{it} = U_i + \tau_{it} \tag{14}$$

The error term $\in_{it}$ is decomposed to $V_{it} - U_{it}$, as where U_{it}, is technical inefficiency and V_{it} is statistical noise. The technical inefficiency part is further decomposed to $U_i + \tau_{it}$, where U_i is the persistent component (for example, time-invariant management effect) and τ_{it} is the residual (time-varying) component of technical inefficiency. It is worth mentioning that the former is only firm-specific, while the latter is both firm- and time-specific. This new model improves upon the previous models in several ways. First, the model takes into account presence of some factors that might have permanent (i.e. time-invariant) effects on a firm's inefficiency. We refer to them as persistent/time-invariant components of inefficiency. Models proposed by Greene (2005a, 2005b), Kumbhakar and Wang (2005), Wang and Ho (2010) and Chen *et al.* (2014) decompose the error term in the production function into three components: a producer-specific time-varying inefficiency term; a producer-specific random- or fixed-effects capturing latent heterogeneity; and a producer- and time-specific random error term. The model can be rewritten in a single equation (Equation 15). $U_{it} > 0$ and $\tau_{it} > 0$ are inefficiency while the other two are firm effects (U_i) and voice (V_{it}). This model confounds persistent/time-invariant inefficiency with firm effects (heterogeneity). Models proposed by Greene (2005a, 2005b), Kumbhakar and Wang (2005), Wang and Ho (2010) and Chen *et al.* (2014) decompose the error term in the production function into three components: a producer-specific time-varying inefficiency term; a producer-specific random- or fixed-effects capturing latent heterogeneity; and a producer- and time-specific random error term. However, these models consider any producer-specific, time-invariant component as unobserved heterogeneity. Long-run inefficiency is confounded with latent heterogeneity.

$$y_{it} = \beta_o + X_{it}^t\beta + V_{it} - U_{it} + U_i - \tau_{it} \tag{15}$$

Estimation of the model can be undertaken in a single stage ML method based on distributional assumptions on the four components (Colombi *et al.*, 2011). This specification is estimated in three steps. First, the standard random-effect panel regression is used to estimate β. Second, the time-varying technical inefficiency U_{it} is estimated. This procedure gives prediction of the time-varying residual technical inefficiency components. Third, we estimated U_i following a similar procedure as in second above and obtained estimates of the persistent technical inefficiency components, using the Jondrow *et al.* (1982) procedure. Persistent TE can then be estimated from PTE = exp $(-U_i)$. The overall technical efficiency (OTE) is then obtained from the product of PTE and RTE, that is, OTE = PTE × RTE.

Costs were used to reflect the quantity of inputs used, hence a production function captured the cost of inputs. Output (y) represents total output costs incurred by the firms. The output is valued in Kenya shillings (KSh). The Cobb–Douglas function has the specification of four input variables of capital, energy, labor and manufacturing with the corresponding costs being: Natural log of the total cost of labor in tea production (KShs), natural log of the total cost of capital (KShs), natural log of the total cost of energy (KShs) and natural log of leaf manufacturing cost (KShs).

3. Methodology and data

The data used for the empirical analysis were firm-level balanced panel data for 2012–2016 with 270 observations from all the 54 KTDA managed small-scale tea-processing firms in Kenya. The data source was from the individual tea processors under the management of Kenya Tea Development Agency (KTDA). The factories were broadly grouped into two regional clusters; East of Rift Valley and West of Rift Valley. East of Rift Valley spans seven counties namely; Kiambu, Murang'a, Nyeri, Kirinyaga, Embu, Meru and Tharaka Nithi. West of Rift Valley covers eight counties namely; Bomet, Kericho, Nandi, Nakuru, Kisii Nyamira, Kakamega and Trans Nzoia Counties. The output, input and inefficiency variables are summarized in Table 1. The data used for this analysis contained one output variable and four input variables.

Table 1. Descriptive statistics for small-scale tea processors in Kenya for the period 2012–2016

	East of Rift Valley (N = 175)		West of Rift Valley (N = 95)		
Variables	Mean	Std dev	Mean	Std dev	Mean difference
Output cost	19.533	0.271	19.971	0.666	0.438***
Leaf costs	20.583	0.313	20.731	0.733	0.148**
Energy	18.100	0.285	18.512	0.718	0.411***
Capital	17.038	0.434	17.389	0.498	0.35***
Labor	17.803	0.269	18.211	0.639	0.407***
Size	19.919	0.723	19.977	0.997	0.057
Factory age	35.142	10.469	35.842	11.028	0.69
Finance cost	17.099	0.803	17.851	1.005	0.751***
No. of employees	116.74	23.753	178.242	80.122	61***
Distance to market	14.046	0.559	14.389	0.486	0.343***
Leverage	0.767	0.483	0.8223	0.516	0.073
Mgt compensation	16.124	0.472	16.299	0.590	0.175***
Total Ha(land)	69,674	0	158505	0	100629.4

Source(s): Author's own calculation

Results in Table 1 show the means and standard deviations of the variables used for the empirical analysis. Firms in the West of Rift Valley region have, on average, the highest level of cultivated land, transport costs, management benefits, finance cost, energy cost, labor expense and capital use. However, it is also worth noting that there is a significant difference in these variables within all the regions as observed from the *t*-test for differences in means.

Estimates for the preferred frontier models were obtained after testing various null hypotheses in order to evaluate suitability and significance of the adopted models using the generalized likelihood-ratio (LR) statistic (Equation 16–17)

$$1.\ H_o : \gamma = 0 \tag{16}$$

$$2.\ H_o : f\left(X_{ij}, \beta_j^{Pool}\right) = f\left(X_{ij}, \beta_j^{E}\right) = f\left(X_{ij}, \beta_j^{W}\right) \tag{17}$$

The first hypothesis, tested for the presence of technical inefficiencies in small-scale tea processors. The hypothesis assumed that technical inefficiency effects are not present in small-scale tea processors. The Kodde and Palm table showed the critical value. Its LR statistic of 41.32 exceeds the 1% critical value of 5.412 at one degree of freedom (Kodde and Palm, 1986). Hence, outright rejection of the null hypothesis of no technical inefficiency. The use of SFA is also justified as opposed to ordinary least square (OLS). The test confirms that technical inefficiency is present in the tea-processing firms. Traditional stochastic frontier models assume that firms share similar production possibilities and differ only with respect to their levels of inefficiency (Njuki and Bravo-ureta, 2018). To examine whether the two regions East and West of Rift Valley, share similar production possibilities, a LR test was calculated. The hypothesis implies that production technology assumed in the two regions and the pooled sample are similar and the stochastic frontier is the same for all three groups (see Table 2).

The null hypothesis of the test is that the stochastic production frontier models for the two regions are the same for all firms. To test the hypothesis, the stochastic frontiers for each region were first estimated. Then the stochastic frontier including firms from all the regions was estimated. Following Battese *et al.* (2004), the LR statistic is defined by $\lambda = -2$ [ln L(H0) –ln L(H1)], where ln L(H0) is the value of the log likelihood function for the stochastic frontier estimated by pooling the data for all regions. Ln L(H1) is the sum of the values of the log likelihood functions of the three regional production frontiers. The statistical value of the LR test was 387, which is significant as it is greater than the critical value of Chi-squared distribution with degrees of freedom given by the difference between the number of parameters estimated under H1 and H0 (i.e. 272–130 = 142). This hypothesis was rejected implying that the production environments are heterogeneous. Therefore, justifying the specification of different production frontiers for the two regions. This indicates that the environment variables had a significant effect on the parameters for each region across the period of analysis. It is from the aforementioned that we decided to do a metafrontier analysis in order to determine the region-specific frontiers. To do the metafrontier analysis, we followed the Huang *et al.* (2014a, b) model.

Table 2. Results of tests of hypotheses for small-scale tea processors in Kenya

Null hypothesis	Location	Chi-square	Critical value	Decision
There is no technical inefficiency				
	*East R/V	41.36	5.412	Reject H_0
	**West R/V	41.33	5.412	Reject H_0
There is no difference between the regional frontiers				
Pooled estimation		387	142	Reject H_0

Source(s): Author's own calculation
Note(s): *East R/V is East of the Rift Valley regions, **West R/V is West of the Rift Valley regions

4. Results and discussion

Seven variables representing environmental characteristics of the small-scale tea processors were included in the inefficiency effects model. These variables include factory age, size of factory (number of employees), firm's leverage, finance costs, management agent fees, management benefits and transportation costs.

The estimated parameters and standard errors for the different ecological regions are presented in Table 3. In all three frontiers, the estimated mean output elasticities of all the inputs have positive signs with all of them highly significant, indicating a positive and significant relationship between inputs and the output. Additionally, the sum of the estimated parameters associated with all the inputs is less than one in all the regional frontiers, implying decreasing returns to scale.

Size had a positive effect on TE. The findings support the evidence documented by Lundvall and Battese (2000), who reported a positive and significant effect of firm size on TE. Large firms are more efficient than small firms because they have market power and the benefits of scale economies Lundvall and Battese (2000). A positive correlation was observed between the firm leverage and TE. It was further observed that age had a negative correlation with TE. Worth noting, firm age and leverage had no significant effect on TE. Similarly, Lundvall and Battese (2000), reported no significant effect of firm age on TE. Overall, management benefits was found to have a positive effect on TE.

The minimum, maximum, mean and standard deviation of TE scores for small- scale tea firms for the ecological zones considered in this study were presented in Table 4. Mean TE estimates vary between the regional frontiers. Results indicate that the tea processors are technically inefficient. Similarly, Ngui-Muchai and Muniu (2012), reported that firms in the food subsector are relatively inefficient. Further, Ndicu (2015) observed a 60% TE for firms in the beverage subsector. Specifically, the mean TE were 82% for the region East of Rift Valley and 79% for the region West of Rift Valley. Overall TE was 76% for the pooled sample. With TE scores estimated as input-oriented measures, the results imply that the inputs of tea

	East of Rift Valley		West of Rift Valley		Pooled	
	Coefficient	Std	Coefficient	Std	Coefficient	Std
Production frontier						
Labor	0.414***	0.020	0.430***	0.027	0.431***	0.015755
Energy	0.408***	0.021	0.438***	0.031	0.423***	0.014913
Capital	0.103***	0.015	0.096***	0.018	0.097***	0.009997
Material	0.145***	0.016	0.111***	0.023	0.122***	0.010857
Environmental variables						
Experience	0.009	0.018	0.021	0.020	0.004	0.011
Size	−0.3501	0.474346	0.077814	0.202143	0.011	0.190
No. Employees	−0.05754***	0.013587	−0.03552***	0.00728	−0.036**	0.006
Finance cost	3.877802***	0.78439	1.769759***	0.376991	2.342***	0.327
Management benefits	−1.46351***	0.451514	0.292658	0.36099	−0.674***	0.206
Distance to market	−0.13345	0.330403	−0.15056	0.552021	−0.323	0.273
Leverage	−0.45478	0.598387	−0.27305	0.325947	−0.279	0.262
Constant	−34.6796***	12.59143	−35.5831***	10.11708	−28.610***	6.281
V sigma	−6.80375	0.175195	−7.05854	0.413062	−6.873	0.159
Log(likelihood)	308.58		146		443	

Source(s): Author's own calculation
Note(s): The asterisks indicate levels of significance. *** Significant at 1%. ** Significant at 5%. * Significant at 10%

Table 3. MLE Regional stochastic frontiers estimates for East and West of Rift Valley, small-scale tea processors in Kenya, 2012–2016

Table 4. Technical efficiency derived from the region-specific frontiers for the small-scale tea processors in Kenya, 2012–2016

	East of Rift Valley			West of Rift Valley			Pooled		
	Residual	Persistent	Overall	Residual	Persistent	Overall	Residual	Persistent	Overall
Mean	0.963	0.850	0.821	0.948	0.844	0.786	0.952	0.804	0.764
Std Dev	0.047	0.040	0.042	0.048	0.055	0.035	0.048	0.050	0.041
Min	0.607	0.773	0.491	0.619	0.747	0.689	0.630	0.726	0.477
Max	0.991	1	0.993	0.999	1	0.862	0.999	1	0.906

Source(s): Author's own calculation

processors in the East and West of Rift Valley regions can be reduced by 18 and 21% respectively if they are able to use the resources available to them more efficiently, without compromising output. More so, 24% technical potentiality exists for the pooled sample. Persistent inefficiency for the East and West regions was 15 and 16% respectively. The persistent inefficiency for the pooled sample was 18%. This calls for immediate policy ramifications at both regional and national level.

For the region East of Rift Valley, most of the tea firms (65%) had their technical efficiencies in the 81–100% range. In addition, 25% had their technical efficiencies in the 61–80% range, indicating that, at least 20% of their potential output is lost to inefficiency. The region West of Rift This implies that at least 20% of the regions firms' potential output is lost to factors that the tea firms cannot control. In addition, the distribution of technical efficiencies for the pooled sample revealed that 84% of the tea firms had their technical efficiencies in the 61–80% range, while only 16% obtained the highest technical efficiencies in the range of 80–100%. The implication is that small-scale tea firms have at least 20% of their potential inputs lost to inefficiency (see Figure 1).

The production input elasticities for the various agro ecological regions are presented in Table 5. For instance, the results showed that a 1% rise in the levels of labor, energy, capital and material costs in the East of Rift Valley region has the effect of increasing output costs by 43%, 47%, 6.4% and 10.4% respectively. Similarly, a 1% rise in the levels of labor, energy, capital and material costs in the West of Rift Valley region has the effect of increasing output costs by 41%, 44%, 14% and 8% respectively.

The coefficients and standard error of the estimated parameters for the metafrontier are presented in Table 6. All the input coefficients are significant and have the expected signs. This signifies the role that the input variable play in affecting TGR in tea production. Regarding environmental variables, the higher the finance cost, the further apart is the production frontier from the metafrontier. In particular, finance cost had a negative effect on efficiency of small-scale tea processors in all regions. High finance costs discourages technical innovation and increases monetary constraints on production. Facilitating timely monetary liquidity as needed for production reduces inefficiency (Sardaro *et al.*, 2017). This is an indication of the importance of finance access in reducing the technology gap faced by some tea firms and regions. Other environmental variables show the expected signs for the different regions. Transport costs and management agent fee had a negative association with

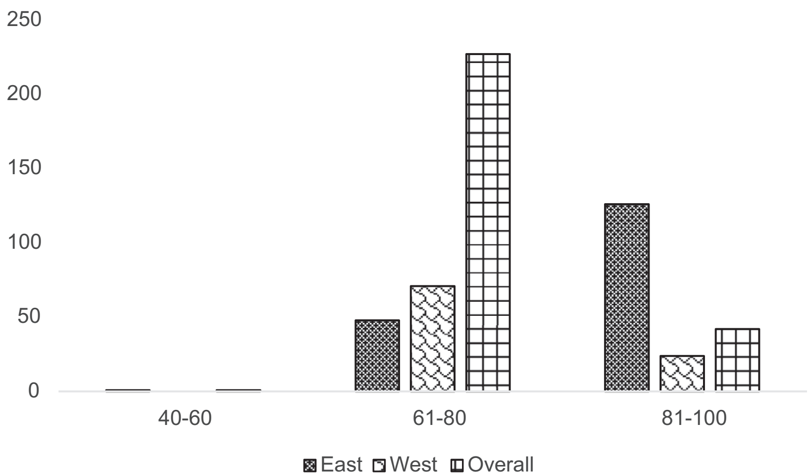

Figure 1.
Frequency distribution of technical efficiency of the small-scale tea processors in Kenya (2012–2016)

TE, though insignificant. High transport and agency fees may lead to temporary coordination problems within the firm, resulting in lower efficiency.

Presented in Table 7 are the means and standard deviations of the TGR, MTE and the TE measures. TGR is the distance from the respective region-specific frontiers to the

Variable	East of Rift Valley	Elasticity West of Rift Valley	Pooled sample
Labor	0.43306	0.409631	0.446272
Energy	0.471283	0.44617	0.444967
Capital	0.064514	0.142121	0.103164
Leaf cost	0.10399	0.082076	0.083195

Source(s): Author's own calculation

Table 5. Input elasticities of the small-scale tea processors in Kenya, 2012–2016

Variables	Coefficient	Standard errors
Labor	0.4205297***	0.0096135
Energy	0.5028959***	0.0096938
Capital	0.0622338***	0.0046796
Leaf cost	0.0495603***	0.0066809
_cons	0.8930605***	0.0812615
Second step environmental variables		
Finance cost	0.4354155**	0.1725658
Transport cost	0.3106676	0.1959522
Management agent fees	0.1897783	0.2798058
Constant	−12.77646***	5.152583
Sigma2	−5.085686***	0.0244114
Gamma	1.987961***	0.1064378
log likelihood	587.61	

Note(s): *** Significant at 1%. ** Significant at 5%. * Significant at 10%
Source(s): Author's own calculation

Table 6. Estimated parameters for the metafrontier of the small-scale tea processors in Kenya, 2012–2016

	Obs	Mean	SD	Min	Max
East of Rift Valley					
TGR	175	0.983996	0.016395	0.893018	0.998365
TE	175	0.820732	0.041666	0.491103	0.992768
MTE	175	0.807559	0.042677	0.490201	0.989024
West of Rift Valley					
TGR	95	0.984799	0.020878	0.892041	0.998414
TE	95	0.785596	0.035248	0.688844	0.862169
MTE	95	0.773896	0.042704	0.658831	0.859266
Overall					
TGR	270	0.970356	0.022458	0.871254	0.996757
TE	270	0.763604	0.040897	0.477134	0.906497
MTE	270	0.740676	0.038062	0.468875	0.893848

Note(s): Obs is observation, TGR-Technology Gap Ratio, TE-Technical Efficiency, MTE-Meta-Technical Efficiency
Source(s): Author's own calculation

Table 7. Summary statistics of regional efficiency measures for the small-scale tea processors, 2012–2016

metafrontier. MTE measures the distance from the *i*th factory to the metafrontier. TE is the region-specific production frontiers. The significance of measuring MTE is that it allows us to make efficiency comparisons of firm units across ecological regions (O'Donnell *et al.*, 2008). Results show that the average TE, MTE and TGR are 76%, 74 and 97% respectively. The TE measures indicate that firm units could achieve TE if they operate at the most optimal levels within the region. The results of MTE and TGR indicate that there is scope for improving the performance of the small-scale tea industry as a whole. As indicated earlier, this could be achieved by reducing the cost of finance. In general, East of Rift Valley is more technically efficient in operation with respect to the overall small-scale tea industry (80.7%) followed by West of Rift Valley (77.3%). This implies that the overall efficiency of firms in East of Rift Valley is superior to that West of Rift Valley. This may be attributed to the differences in geographical, cultural, soils, quality of raw material, altitude, resource endowments and to climatic factors between the two ecological regions. In general, TE values computed relative to the meta-frontier function across the regions are substantially lower than their mean TEs.

5. Conclusion and implication

This paper estimates and compares the TE of efficiency of small-scale tea processors in the regions East and West of the Rift Valley of Kenya. The empirical analysis is carried out by employing the stochastic meta- frontier approach. This approach allows us to compare TE under different technological condition. On average, the TE derived from the regional frontier was 76%; TE from the metafrontier was 74%, and the technological gap ratio was 97%. To this end, the study provides empirical evidence comparison on how environmental variables determine TE in East and West of Rift regional clusters to cater for spatial heterogeneity. Findings from this study could be important in suggesting policy options as well as scenarios to optimize firm performance for firm managers. The study found that the mean technical efficiencies for small-scale tea processors in the East and West regions of Kenya were 82 and 79%, respectively. The implication is that observed tea processors in each of the aforementioned regions could have further increased their outputs by about 18 and 21% respectively if they had operated at an optimal scale. The study concludes that small-scale tea processors in both regions are technically inefficient. The inefficiencies were observed to have emanated from small-scale tea processors exhibiting decreasing returns to scale. Hence, resulting into higher average costs per unit. Optimal scales will therefore be achieved if these processors employ less production inputs.

Results showed presence of persistent technical inefficiency in all regions. The implication is that a greater percentage of total inefficiency among these processors might be caused by factors beyond their control. These factors require immediate and radical policy reforms to save the ailing industry. Therefore, the room for improving technical efficiencies in the various agro ecological zones is huge vis-à-vis the margin due to residual inefficiencies.

Furthermore, for small- scale tea processors in Kenya to operate at an optimal scale, there is the need for reduce finance costs. For TE to be improved, scale tea processors in the various agro ecological regions of Kenya are encouraged to employ less of the production inputs available to them. For the small-scale tea processors to be able to employ less of these inputs, cost of production inputs could be subsidized and credit could be given to them by government. Results revealed that energy costs account for a big portion of production costs. Policy measures such as shifting production time to off- peak time could help the firms reduce their huge energy costs by almost half. In summary, we found that firm units in the two ecological regions of Kenya's small-scale tea industry do not share the same production frontier. This can be attributed to differences in economic environments, regional resource endowments, weather, traditional settings and regulations, climate and tastes and preferences. While it was not possible to determine the many reasons for variations in TEs, TGRs and MTEs across regions, thus this limitation is for future.

References

Akamin, A., Bidogeza, J., Minkoua-N, J.R. and Afari-sefa, V. (2017), "Efficiency and productivity analysis of vegetable farming within root and tuber-based systems in the humid tropics of Cameroon", *Journal of Integrative Agriculture*, Vol. 16 No. 8, pp. 1865-1873, doi: 10.1016/S2095-3119(17)61662-9.

Alem, H., Lien, G., Hardaker, J.B. and Guttormsen, A. (2017), "Regional differences in technical efficiency and technological gap of Norwegian dairy farms: a stochastic metafrontier model", *XV EAAE Congress, Towards Sustainable Agri-food Systems: Balancing Between Markets of the International Conference Proceedings in Palma*, Italy 2017, Universita Di Parma and Society, pp. 1-15.

Amornkitvikai, Y. and Harvie, C. (2011), "Finance, ownership, executive remuneration, and technical efficiency: a stochastic frontier analysis (SFA) of Thai listed manufacturing enterprises", *Australasian Accounting Business and Finance Journal*, Vol. 5 No. 1, pp. 35-55.

Basnayake, K. and Gunaratne, P. (2002), "Estimation of technical efficiency and its determinants in the tea small holding sector in the mid country wet zone of Sri Lanka", *Srilankan Journal of Agricultural Economics*, Vol. 4 No. 1, p. 15.

Battese, G.E. and Coelli, T.J. (1995), "A model for technical inefficiency effects in a stochastic frontier production function for panel data", *Empirical Economics*, Vol. 20, pp. 325-32.

Battese, G.E., Rao, D.S.P. and O'Donnell, C. (2004), "A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies", *Journal of Productivity Analysis*, Vol. 21, pp. 91-103.

Chen, Y.-Y., Schmidt, P. and Wang, H.-J. (2014), "Consistent estimation of the fixed effects stochastic frontier model", *Journal of Econometrics*, Vol. 18 No. 2, pp. 65-76.

Colombi, R., Martini, G. and Vittadini, G. (2011), "A stochastic frontier model with short-run and long-run inefficiency random effects", Working Papers Series No. 1101, Department of Economics and Technology Management, Universita di Bergamo, Bergamo.

Danquah, M. and Ouattara, B. (2015), "What drives national efficiency in Sub-Saharan Africa", *Economic Modelling*, Vol. 44, pp. 171-179.

Danquah, M. and Quartey, P. (2015), "Examining the determinants of efficiency using a latent class stochastic Frontier model", *Cogent Economics and Finance*, Vol. 3 No. 1, p. 1124741.

Donkor, E., Matthews, N. and Ogundeji, A.A. (2018), "Efficiency of rice farming in Ghana: policy implications for rice sector development", *African Development Review*, Vol. 30 No. 2, pp. 149-161, doi: 10.1111/1467-8268.12320.

Gatimbu, K.K., Ogada, M.J., Budambula, N. and Kariuki, S. (2018), "Environmental sustainability and financial performance of the small - scale tea processors in Kenya", *Business Strategy and the Environment*, Vols 1–7, doi: 10.1002/bse.2243.

Government of Kenya (2013), Kenya Vision 2030 Progress Report, available at: http://www.vision2030.go.ke/cms/vds/Vision_2030-_score_booklet.pdf (accessed 25 July 2013).

Greene, W.H. (2005a), "Fixed and random effects in stochastic frontier models", *Journal of Productivity Analysis*, Vol. 23, pp. 7-32.

Greene, W.H. (2005b), "Reconsidering heterogeneity in panel data estimators of the stochastic frontier model", *Journal of Econometrics*, Vol. 126, pp. 269-303.

Haron, M. and Chellakumar, J.A. (2012), "Efficiency performance of manufacturing companies in Kenya: evaluation and policies", *International Journal of Management and Business Research*, Vol. 2 No. 3, pp. 233-242.

Hong, N.B. and Yabe, M. (2015), "Technical efficiency analysis of tea production in the northern mountainous region of Vietnam", *Global Journal of Science Frontier Research*, Vol. 15 No. 1, p. 13.

Huang, C.J., Huang, T.-H. and Liu, N.-H. (2014a), "A new approach to estimating the metafrontier production function based on a stochastic frontier framework", *Journal of Productivity Analysis*, Vol. 42 No. 3, pp. 241-254, doi: 10.1007/s11123-014-0402-2.

Huang, Y., Wong, Y. and Yang, M. (2014b), "Proactive environmental management and performance", *Management Research Review*, Vol. 37 No. 3, pp. 210-240, doi: 10.1108/MRR-09-2012-%090196.

Jondrow, J., Lovell, C.A.K., Materov, I.S. and Schmidt, P. (1982), "On the estimation of technical inefficiency in the stochastic frontier production function model", *Journal of Econometrics*, Vol. 19, pp. 233-8.

Kagira, E.K., Kimani, S.W. and Githii, K.S. (2012), "Sustainable methods of addressing challenges facing small holder tea sector in Kenya: a supply chain management approach", *Journal of Management and Sustainability*, Vol. 2 No. 2, p. 75, doi: 10.5539/jms.v2n2p75.

Kaimba, G.K. and Nkari, I.M. (2014), "Impact of cost reduction strategies on performance of tea factories in Embu county, Kenya", *European Journal of Business and Social Sciences*, Vol. 3 No. 9, pp. 26-48.

Kamande, M. (2010), "Technical and environmental efficiency of Kenya' s manufacturing sector: a stochastic frontier analysis", *the thirteen annual conference on Global Economic Analysis*, United Nations Conference Centre , Bangkok, Thailand 2010, p. 33.

Kibaara, B. (2005), "technical efficiency in Kenya's maize production: an application of the stochastic frontier approach", Unpublished thesis, Colorado State University, CO.

Kenya National Bureau of Statistics (KNBS), (2015), Economic Survey, Government [Data File], Online Database, available at: http://www.knbs.or.ke.

Kenya National Bureau of Statistics (KNBS), (2017), Economic Survey, Government [Data File], Online Database, available at: http://www.knbs.or.ke.

Kodde, D.A. and Palm, F.C. (1986), "Wald criteria for jointly testing equality and inequality restrictions", *Econometrica*, Vol. 54, pp. 1243-1248.

Kumbhakar, S.C. and Wang, H.-J. (2005), "Estimation of growth convergence using a stochastic production frontier approach", *Economics Letters*, Vol. 88, pp. 300-5.

Kumbhakar, S.C., Wang, H. and Horncastle, A. (2015), *A Practitioner's Guide to Stochastic Frontier Analysis Using Stata*, Cambridge University Press, New York.

Le, V., Vu, X.-B.(Benjamin) and Nghiem, S. (2018), "Technical efficiency of small and medium manufacturing firms in Vietnam: a stochastic meta-frontier analysis", *Economic Analysis and Policy*. doi: 10.1016/j.eap.2018.03.001.

Lundvall, K. and Battese, G.E. (2000), "Firm size, age and efficiency: evidence from Kenyan manufacturing firms", *Journal of Development Studies*, Vol. 36 No. 3, pp. 146-163, doi: 10.1080/00220380008422632.

O'Donnell, C.J., Prasada Rao, D.S. and Battese, G.E. (2008), "Metafrontier frameworks for the study of firm-level efficiencies and technology ratios", *Empirical Economics*, Vol. 34 No. 2, pp. 231-255.

Ogundari, K. (2008), "Resource-productivity, allocative efficiency and determinants of technical efficiency of rain-fed rice farmers: a guide for food security policy in Nigeria", *Agricultural Economics*, Vol. 54 No. 5, pp. 224-233.

Ndicu, S. (2015), "efficiency analysis of the agro-processing industry in Kenya", Unpublished thesis, Kenyatta University, Nairobi.

Ng'ang'a, S.I. (2011), "The PESTLE dynamics in tea trade: effects on return to the farmer and sustainability of the smallholder tea enterprise", *In The First International Conference Proceedings of on Tea Science and Development*, Karatina University, Nyeri 2015, pp. 162-181.

Ngenoh, E., Mutai, B.K., Chelang'a, P.K. and Koech, W. (2015), "Evaluation of technical efficiency ofSweet corn production among smallholder farmers in njoro district, Kenya", *Journal of Economics and Sustainable Development*, Vol. 6 No. 17, pp. 183-193.

Ngui-Muchai, D.M. and Muniu, J.M. (2012), "Firm efficiency differences and distribution in the kenyan manufacturing sector", *African Development Review*, Vol. 24 No. 1, pp. 52-66.

Njuki, E. and Bravo-ureta, B.E. (2018), "Irrigation water use and technical efficiencies: accounting for technological and environmental heterogeneity in U.S. agriculture using random parameters", *Water Resources and Economics*, Vols 1–12, doi: 10.1016/j.wre.2018.02.004.

Pitt, M.M. and Lee, L.-F. (1981), "The measurement and sources of technical inefficiency in the Indonesian weaving industry", *Journal of Development Economics*, Vol. 9, pp. 43-64.

Sardaro, R., Pieragostini, E., Rubino, G. and Petazzi, F. (2017), "Impact of *Mycobacterium avium* subspecies paratuberculosis on profit efficiency in semi-extensive dairy sheep and goat farms of Apulia, southern Italy", *Preventive Veterinary Medicine*, Vol. 136, pp. 56-64, doi: 10.1016/j.prevetmed.2016.11.013.

Shavgulidze, R., Bedoshvili, D. and Aurbacher, J. (2017), "Annals of Agrarian Science Technical efficiency of potato and dairy farming in mountainous Kazbegi district, Georgia", *Annals of Agrarian Sciences*, Vol. 15 No. 1, pp. 55-60, doi: 10.1016/j.aasci.2016.11.002.

Tea Board of Kenya (2010), "Opening emerging markets for Kenyan Tea.Translog SFA model", *Journal of Agricultural Science*, Vol. 7 No. 9, pp. 160-172, doi: 10.5539/jas.v7n9p160.

Trujillo, J.C. and Iglesias, W.J. (2013), "Measurement of the technical efficiency of small pineapple farmers in Santander, Colombia: a stochastic Frontier approach", *Revista de Economia e Sociologia Rural*, Vol. 51 No. 1, pp. s049-s062, doi: 10.1590/S0103-20032013000600003.

Wang, H.-J. and Ho, C.-W. (2010), "Estimating fixed-effect panel stochastic frontier models by model transformation", *Journal of Econometrics*, Vol. 157, pp. 286-296.

Corresponding author
Karambu Kiende Gatimbu can be contacted at: kiendegatts@gmail.com