African Journal of Hospitality, Tourism and Leisure. ISSN: 2223-814X

August 2023, Vol 12, 3, pp. 834-847

A Re-examination of Factors that Influence Restaurant Efficiency in South Africa: A Bootstrapped Meta-Frontier Approach

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How to cite this article: Mhlanga, O. (2023). A Re-examination of Factors that Influence Restaurant Efficiency in South Africa: A Bootstrapped Meta-Frontier Approach. African Journal of Hospitality, Tourism and Leisure, 12(3):834-847. DOI: **https://doi.org/10.46222/ajhtl.19770720.402**

Abstract

A persistent paradox in restaurant literature reveals that most studies tend to combine different restaurants in one data sample prior to the estimation of efficiency which blurs efficiency. Therefore, the purpose of this study was to provide further validation on the factors influencing restaurant efficiency using a meta-frontier approach. This study endeavour applied the meta-frontier concept to account for the different environmental and technological factors by ensuring that heterogeneous restaurants are compared based on one homogeneous technology. To test the model, the study used a panel data sample of 84 South African restaurants, which operated from 2015 to 2018. The findings revealed that uncontrollable factors, namely, location, size and restaurant type significantly and positively influence (p<0.05) restaurant efficiency. Empirical evidence supports the view that traditional efficiency techniques tend to underestimate efficiency scores resulting in biased efficiency comparisons between different restaurants. Although there are many other explanatory variables (e.g., restaurant ownership) that influence restaurant efficiency, however, these factors were not taken into account in this analysis due to lack of availability of data associated with those variables. The findings could enhance the service data and revenue management in the restaurant industry.

Keywords: Restaurant efficiency; bootstrapped meta-frontier approach; restaurant size; restaurant location; revenue management

Introduction

Efficiency evaluation has become an important improvement tool for restaurants to sustain in today's highly competitive environment (Mhlanga, 2015). However, because of the simultaneity and perishability of restaurant services, attaining efficiency is a challenging endeavour for restaurateurs (Reynolds, 2004). This is further exacerbated by the stochastic and unpredictable demand for restaurant services (Robson, 2013), both in terms of annual seasonal variations and within shorter time periods which make it difficult to attain operational efficiency (Mhlanga, 2018a). Consequently, because of a combination of macro-predictability and micro-uncertainty, attaining efficiency is a constant challenge for restaurateurs (Gimenez, 2004).

Just as important as measuring efficiency is knowing the factors that influence it, a review of the current literature however indicates that most studies on restaurant efficiency tend to suffer from one common limitation in terms of identifying factors influencing restaurant efficiency. For example, a persistent paradox in restaurant literature reveals that most studies tend to combine different restaurants (e.g. in terms of size or location) in one data sample prior to the estimation of efficiency which blurs efficiency (Assaf & Matawie, 2008). According to Battese et al. (2004), because of their divergent characteristics, different restaurants should not be treated as a homogeneous data sample. This is so because the efficiency frontiers for these restaurants might not be identical to provide an unbiased comparison. Therefore, there is a need for a holistic approach that provides a homogeneous boundary for all heterogeneous firms in the restaurant industry.

This drives the motivation of this study which aims at remedying the shortcomings of the existing approaches by re-examining factors influencing restaurant efficiency in South Africa using a meta-frontier approach. This study aims to extend existing literature on restaurant efficiency, making two important contributions: (a) measuring restaurant efficiency using a novel technique, which is, the meta-frontier approach; and (b) validating the results of previous studies that used parametric and non-parametric techniques, namely, DEA and stochastic frontier approach.

Due to the importance of restaurants to the tourism industry, research in this context is envisaged. The theoretical contribution relates to critically articulating factors influencing restaurant efficiency using a meta-frontier approach, where such findings could validate previous studies that traditionally used parametric and non-parametric approaches to measure restaurant efficiency. The findings may provide a clearer reflection on factors influencing restaurant efficiency and thereby inform restaurateurs of strategic implications which could be useful for management endeavours.

Theoretical background

Over the past decades, the tourism industry has been recognised as playing a significant role in global and national economies [WTTC (World Travel and Tourism Council), 2018]. According to Mhlanga (2018a), data from the World Travel and Tourism Council report that the tourism industry generated US$7.6 trillion [which is 10.2 percent of the global gross domestic product (GDP)] and 292 million jobs in 2016, equivalent to 1 in 10 jobs in the global economy. According to Statistics South Africa (SSA, 2018) the direct contribution of tourism to South Africa's gross domestic product (GDP) was ZAR412.5 billion, which is 8.9 percent of GDP in 2017. According to Statistics South Africa (SSA, 2018) one in every 22 working South Africans are employed in the tourism sector and the industry generated 32 000 net new jobs in 2017. Therefore, tourism is a key driver of South Africa's economy.

Restaurants are classified as one of the subsectors of the South African tourism industry [CATHSSETA (Culture, Arts, Tourism, Hospitality and Sports Sector Education and Training Authority), 2019]. The Tourism Satellite Account for 2017 (SSA, 2018) estimated that the subsector constituted 1.86 percent of the tourism industry's contribution towards the GDP of South Africa and directly supported 726 500 jobs, which is 4.5 percent of total employment. The restaurant subsector generated revenue of more than ZAR57.25 billion in 2017 [SSA (Statistics South Africa), 2018]. This is over 51 percent of total income generated in the food and beverages sector in 2017. The restaurant subsector is, therefore, a small segment of the tourism industry with an economic impact comparable to that of the sport, recreation, and fitness subsector (Mhlanga, 2018b).

However, the restaurant subsector in South Africa exhibits a dichotomy (Mhlanga et al., 2013). Although the rising income of the black middle class has increased restaurant demand in South Africa, restaurants have been recording narrow profit margins with most struggling to survive (Mhlanga et al., 2015). Mhlanga (2015) cites restaurateurs' inability to ascertain the influence of uncontrollable factors on restaurant efficiency as the main source of failure. Therefore, a better understanding of the factors influencing restaurant efficiency might provide important practical implications for restaurateurs.

Theoretical framework

Reynolds and Thompson (2007) proposed a model that allows restaurateurs to compare efficiency at different restaurants and assess the management decisions that enhance, or interfere with, efficiency. These researchers demonstrated their model in a study of the relative efficiency of restaurants in a 60-unit dinner house chain. According to these authors, a restaurants' efficiency depends on controllable and uncontrollable variables in an environment. "Controllable (discretionary) variables", are within management's purview and control and are determined by managerial ability, whilst "uncontrollable (non-discretionary) variables", are beyond management's control (Assaf & Matawie, 2008). Controllable variables include labour hours, number of servers during a given shift, or wages paid to employees whilst uncontrollable variables include restaurant location, restaurant size and restaurant type (service). Figure 1 summarises the model.

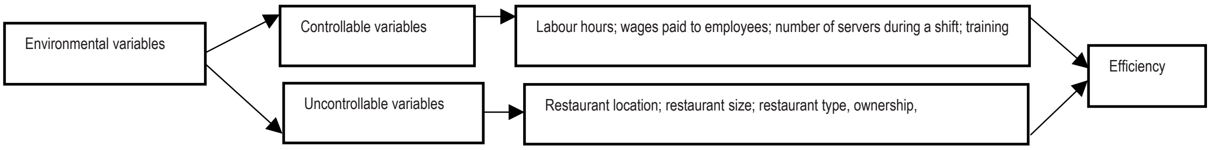

Figure 1: Theoretical model of factors influencing restaurant efficiency

The model identifies and connects controllable and uncontrollable factors that influence restaurant efficiency. However, studies that account for uncontrollable variables are more vital than a mixed analysis, because uncontrollable variables are more influential in establishing an efficiency frontier (Reynolds & Thompson, 2007). Moreover, when uncontrollable factors are accounted for, restaurant performance becomes a function of management decisions. If uncontrollable factors turn out to have a statistically significant influence on the efficiency scores, this may show what percentage of a restaurant's efficiency is beyond the management's control. Therefore, this study focuses on the influence of uncontrollable factors on restaurant efficiency.

Literature review

Although the debate on the factors influencing restaurant efficiency is on-going, most scholars on restaurant efficiency have based their arguments on parametric and non-parametric techniques, (namely, DEA and stochastic frontier approach DEA) to estimate efficiency. However, as previously stated, parametric and non-parametric techniques fail to address the heterogeneity problem which blurs efficiency. For instance, Donthu and Yoo (1998) used a DEA to identify factors influencing the efficiency of 24 fast-food chain restaurants in a major metropolitan city. To measure efficiency, these researchers used four inputs: (1) restaurant size, (2) the experience of managers in years, (3) promotion/give-away expenses in dollars and (4) location. However, only two outputs were used: (1) total restaurant sales and (2) the results of customer satisfaction surveys. Their findings revealed that uncontrollable factors, namely, restaurant size, promotion and location significantly influence restaurant efficiency.

Reynolds and Thompson (2007) used DEA to analyse the efficiency of 62 midscale, fine dining restaurants in the USA. These authors employed three input (server wage, number of seats and stand-alone facility) and two output (daily sales, tip percentage) variables in the model. The behavioural output variable, tip percentage, was used as a surrogate for customer satisfaction. Their results found one uncontrollable factor, namely, location to be a significant determinant of efficiency. Reynolds (2004) explored the relationship between restaurant location and efficiency and concluded that location significantly influences restaurant efficiency. He then concluded that restaurants located in, or near, metropolitan areas are more efficient than those in remote locations.

Mhlanga (2018a) adopted DEA to identify factors influencing efficiency in 16 restaurants in South Africa. The author estimated efficiency by using Tobit regression models on inputs and outputs against various factors of restaurant efficiency. Four inputs were chosen: (1) the staff strength, (2) the number of seats, (3) operational expenses and (4) staff expenses. However, only two outputs were considered: (1) total restaurant sales per month and (2) total covers per month. His results found two uncontrollable factors, namely, restaurant type and location to be significant determinants of efficiency. However, restaurant size did not have any influence on efficiency.

According to Mhlanga (2018a) since demand plays a role in restaurant efficiency, restaurants located in, or near, metropolitan areas tend to be more efficient than those in remote locations. A rationale for this result is that demand plays a role in restaurant efficiency, and metropolitan areas tend to be accessible, have high foot or vehicular traffic counts and proximal demand generators which increases revenue per available seat hour (RevPASH). Hadad et al. (2007) used a DEA approach to study the efficiency of 30 restaurants in Israel. The four inputs used were: (1) the number of seats, (2) the average number of waiters in a shift, (3) the average number of general employees and (4) the area of the restaurant in square metres. The two outputs used were: (1) the number of customers in a day and (2) the price of an average meal. Their results found one uncontrollable factor, namely, restaurant type to be the factor highly influencing efficiency. These researchers concluded that fast food restaurants tend to be more efficient than fine dining restaurants.

In another study, Gharakani et al. (2012) used a DEA approach to evaluate the efficiency of 15 restaurants in Iran. The inputs used were: (1) monthly working hours, (2) branch area and (3) managers' experiences, while the outputs used were: (1) monthly number of customers and (2) monthly sales. Their results found restaurant size to be the highly significant factor influencing efficiency with large restaurants being the highly efficient. According to these authors large restaurants tend to be more efficient then small restaurants because of economies of scale. Robson (2013) investigated the influence of uncontrollable factors on restaurant efficiency and found restaurant size to be a significant factor influencing efficiency with small restaurants being more efficient than large restaurants. According to this author, as small restaurants require fewer covers per hour, they are much more likely to be financially feasible than a large restaurant. However, Sanjeev (2007) explored the relationship between restaurant size and efficiency and found no clear link.

Gimenez (2004) found that fine dining restaurants had a positive correlation with efficiency and concluded that restaurant type significantly influences efficiency. According to Mhlanga et al. (2013), high service quality in fine dining restaurants ensures high menu prices, thereby contributing to the efficiency of fine dining restaurants. Therefore, there is a positive relationship between varied table service menus offered in fine dining restaurants and profitable high-class clientele, whilst limited low priced menus in fast food restaurants tend to be associated with unprofitable budget customers (Mhlanga et al., 2015).

However, none of the aforementioned studies used a meta-frontier analysis to measure efficiency in the restaurant industry. To remedy the shortcomings of the existing approaches this study re-examines factors influencing restaurant efficiency using a meta-frontier approach to ensure that all heterogeneous restaurants are assessed based on their distance from a common and identical frontier. The results may provide a clearer reflection on factors influencing restaurant efficiency, given that it also controls for the heterogeneity between restaurants that belong to different environmental characteristics.

The meta-frontier model

The meta-frontier model is a complex academic model able to calculate comparable efficiencies for companies operating under different technologies. Hayami and Ruttan (1971) developed the meta-frontier concept using production function as a neoclassical concept. Thereafter, Assaf et al. (2012) used the meta-frontier to calculate Taiwanese hotel and company efficiency. Specifically, the study builds on advances by Assaf et al. (2012) in enveloping restaurant frontiers. However, as previously stated, the meta-frontier analysis has rarely been used in the restaurant industry.

To introduce the meta-frontier model, let y and x, respectively, denote non-negative output and input vectors of dimensions (N×1) and (M×1) respectively. The researcher considers the case where there are $K(>1)$ groups and each group operates under a specific technology, $K^k (k = 1, 2, . . ., K)$. Battese et al. (2004) argued that since technology is a state of knowledge related to the transformation of N input into M outputs, it is possible to conceptualise the existence of an over-arching technology or meta-technology, which they represented by T^*.

The technology of a given group, called technology set, is defined as the set of all feasible input-output vectors that are technologically feasible.

$$T= \{(x, y) \in R_+^{\,p+q} \mid x \text{ can produce } y\} \qquad (1)$$

which describes the amount of some p inputs x that can produce q outputs y. As in Assafs' et al. (2012) study, the researcher defines the input and output sets associated with the production technology set T, which provides an equivalent representation of production technology. The input set defined for a specific output vector y is the set of all input vectors x which can produce y.

$$X(y) = \{ x : (x,y) \in T \} \qquad (2)$$

The boundaries for the input sets determine the 'isoquants'. The output meta-frontier is the limited territory of this output set. The output set is assumed that it can reach the standard regularity properties listed in Battese et al. (2004). Since the main focus of this research is to measure efficiency, the output set is defined for a specific vector of input x as the set of all output vectors y which can be produced using x:

$$P(y) = \{y: (x,y) \in T \} \qquad (3)$$

The boundary of the output set is the production possibility frontier and represents and represents technically efficient production. The meta-frontier can be described as a function that envelops separate group frontiers, each having their specific state of technology and environmental factors. As such, the meta-frontier model is considered as an envelope of all the possible group technologies. For example, if a particular output, y, can be produced using input vector, x, in one of the groups, then (x,y) are considered as part of the meta-technology, T^*, which is defined by O'Donnell et al. (2007) as:

$$T^* = \{(x,y): x \geq 0 \text{ and } y \geq 0,$$

such that x can produce y in at least

$$T^{1,} T^2,\ldots,T^k\} \qquad (4)$$

The convexity property of this meta-technology was ensured by O'Donnell et al. (2007) by defining the meta-technology as the convex hull of the union of group specific technologies, denoted by:

$$T^* \equiv \text{Convex Hull } \{T^1 \cup T^2 \cup \ldots \cup T^k\} \qquad (5)$$

African Journal of Hospitality, Tourism and Leisure, Volume 12 (3) - (2023) ISSN: 2223-814X

By letting $D^{*}_{0}(x,y)$ and $D^{*}_{i}(x,y)$ denote the output and input distance function defined using the meta-technology T^{*}, where for a given group k, an output distance function is defined as:

$$D^{k}_{0}(x,y) = \inf_{\theta} \{\theta > 0 : (y/\theta) \in P^{k} (x)\} \qquad (6)$$

And it shows the maximum degree to which a given output vector can be increased and still within the production feasibility set, while an input distance function is defined as:

$$D^{k}_{i}(x,y) = \sup/\lambda \ \{\lambda > 0:(x/\lambda \in X^{k} (y)\} \qquad (7)$$

and it shows the maximum degree to which a given input vector can be radically contracted and yet produce the same level of output, y. From the definition of meta-technology it can be easily shown that the input "$D^{*}_{i}(x,y)$" and output distance functions "$D^{*}_{0}(x,y)$" defined using the meta-technology T^{*}, satisfy the following requirements:

Requirement 1: For any given group k, $D^{k}_{0} (x,y) \geq D^{*}_{0} (x,y)$,
$k = 1,2,\ldots,k$ (8)

Requirement 2: For any given group k, $D^{k}_{i} (x,y) \leq D^{*}_{i} (x,y)$,
$k = 1,2,\ldots,k$ (9)

Using the conditions in (8) and (9) the researcher obtains measures of the gap between the group k technology and the meta-technology. For example, Battese et al. (2004) formulated a technology gap ratio that takes a value between zero and one and measures the ratio of the output for the frontier production function for the *k-th* group relative the potential output defined by the meta-frontier function, given the observed inputs. To illustrate, the output oriented technology gap ratio can be defined using the output distances functions from technologies T^{k} and T^{*} as:

$$TGR_i^k(x,y) = \frac{D_i^k(x,y)}{D_i^*(x,y)} = \frac{TE_i^*(x,y)}{GTE_i^k(x,y)} \qquad (10)$$

Where TE^{*}_{i}; denotes the technical efficiency with respect to meta-frontier and GTE_{i}^{k}; the technical efficiency with respect to a group k. This implies that the technical efficiency of a restaurant relative to the meta-frontier is simple the product of the technical efficiency of that restaurant relative to the frontier for a particular group and the technology gap for that group. As it is clear from above, the first step in estimating these different efficiency measures is to estimate the meta-frontier technology and the group frontier technology. These are then constructed using data envelopment analysis (DEA) since DEA easily accommodates multiple inputs and outputs.

Research methodology

In order to maintain the homogeneity of the restaurants for equitable comparisons, a list of local registered restaurants was obtained from the Restaurant Association of South Africa (RASA, 2014) website (restaurant.org.za) through desktop research in 2019. There were more than 800 registered restaurants by the Restaurant Association of South Africa at the time of the study, however, only restaurants with complete data and that operated from 2015 to 2018 were chosen to be samples in this research. A total of 100 restaurants were randomly selected. However, nine restaurants had incomplete information whilst seven of the restaurants ceased operations during the year in 2017. As a result, the final sample included the balanced data of 84 restaurants with complete information.

The sample size was calculated based on Leedy and Ormrod's (2013) formulae on sample size calculation. According to Leedy and Ormrod (2013) to determine the sample size, from a given finite population, the following formulae should be used:

$$n = \frac{\left(z1 - \frac{a}{2}\right)^2 \times P(q) \times N}{(d)^2 \times (N-1) + \left(z1 - \frac{a}{2}\right)^2 \times P(q)^2}$$

Where:

n = sample size (number of restaurants)

N = size of population (reference number of population)

$z1 - a/2$ = normal standard value which depends on a; if a = 0.05, then z= 1.960, and if a = 0.01, then z =2.576

d = amount of tolerable deviation; the smaller the value, the more accurate the research – example values are d = 1% or d = 5%

P = population proportion estimator (if P = 0.05, the sample size n will be maximized)

q = 1 – p or (1 – 0.5) = 0.5

$$ni = \frac{Ni}{N} \times n_{sector}$$

Where:

ni = total sample of sector i

Ni = total population of sector i

N = total reference population

n_{sector} = total sample of a sector

Using the above formulae, a sample size of 84 restaurants was deemed appropriate and consequently used for the study. However, the names of the restaurants be kept anonymous and confidential. Therefore, abbreviations were used to name restaurants.

Data for this study consisted of several input/output variable related to the operational characteristics of restaurant operations. In line with previous studies (Assaf et al., 2011; Hadad et al., 2007; Mhlanga, 2018a), total food and beverage sales and total covers generated were used as output measures. The inputs used to generate the above output were the number of full-time employees, staff expenses, food and beverage expenses and the number of seats. All these variables were selected based on an extensive review of available studies in the restaurant industry.

To obtain data for the input and the output variables to be used in the meta-frontier model, the researcher requested financial statements from each participating restaurant. The following information was requested, namely, total customers (to be used as a proxy for total covers), total food and beverage sales, the number of full-time employees, and food and beverage expenses. The researcher also requested the total wages and salaries (to be used as a proxy for staff expenses) and restaurant capacity (to be used as a proxy for the number of seats). The selection of the variables was performed taking into account the availability of data and the previous literature for the sector. In total, data on the above variables were collected from 84 restaurants, during the study period from January 2015 to December 2018. Consequently, the study managed to create an unbalanced panel with 336 total observations (84x4=336) over 4 years, containing efficiency scores as the dependant variable and various other environmental parameters as independent explanatory variables recorded over the said time period.

To estimate the meta-frontier model, restaurants were categorised into different groups based on the uncontrollable environmental differences amongst the restaurants in the sample. As such, to categorise restaurants, the following uncontrollable variables were used, namely, location, size and type. These variables were selected based on an extensive review of available studies in the restaurant industry. The influence of size creates heterogeneity between restaurants hence some research endeavours (Donthu & Yoo, 1998; Gharakani et al., 2012; Robson, 2013) have also tested the influence of restaurant size on efficiency. To test the influence of restaurant size on efficiency, restaurants were classified into small and large restaurants. Robson's (2013) definition of small and large restaurants was used. According to Robson (2013), a small restaurant is one with fewer than 50 seats and fewer than 20 employees whilst a large restaurant is one with more than 50 seats and more than 20 employees.

To test the influence of location on restaurant efficiency, location was classified into two, namely metropolitan and non-metropolitan. This is comparable to previous studies (Reynolds & Thompson, 2007; Mhlanga, 2018a) that also tested the influence of location on restaurant efficiency. Finally, the influence of restaurant type on efficiency was also tested since literature review revealed some scholars (Gimenez, 2004; Hadad et al., 2007) that tested the influence of restaurant type on efficiency. To test the influence of restaurant type on efficiency, restaurants were classified into fine dining and fast food restaurants. Consequently, Figure 2 provides a graphical representation of each group.

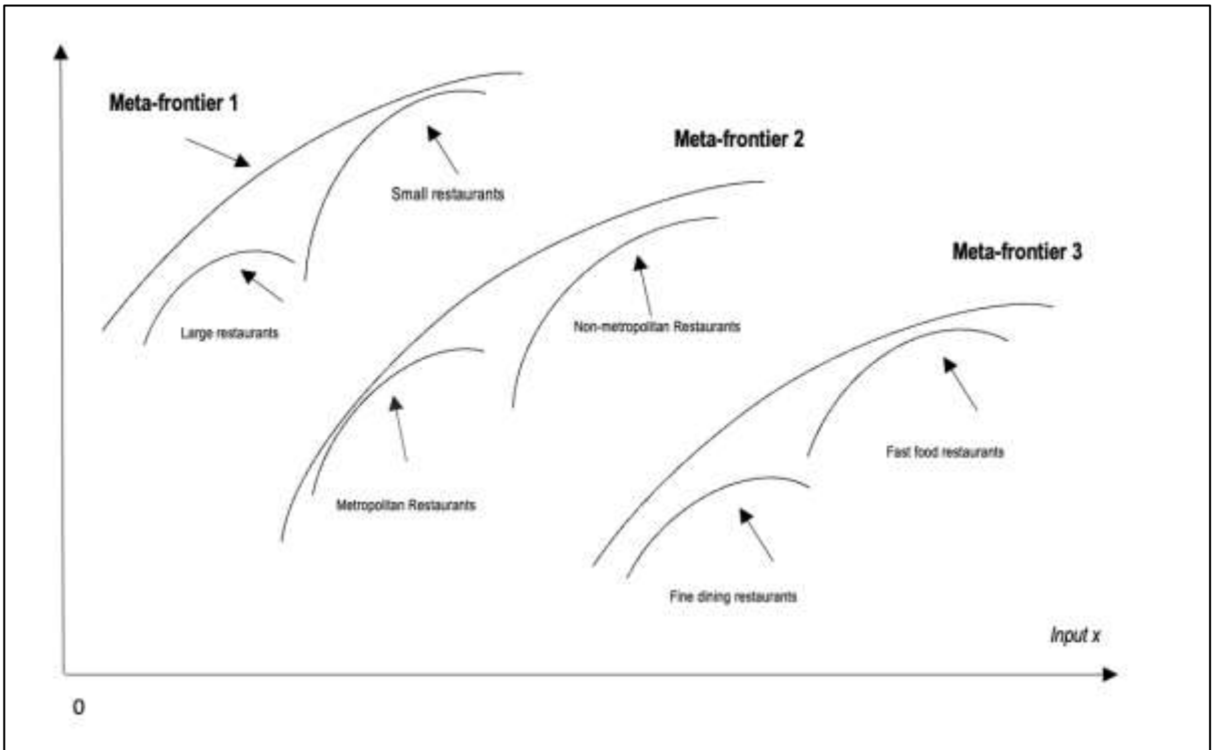

Figure 2: Graphical representations of different restaurant categories

From Figure 2 it is clear that the meta-frontier envelops each group frontier and thus provides a more consistent and homogeneous efficiency comparison. According to Assaf et al. (2012) the group frontier may touch the meta-frontier if a restaurant is equally efficient with respect to both the groups and meta-frontier model. In this study, the researcher estimates three separates meta-frontier models, and six group frontiers, one for each environmental category.

Results

The technical efficiency estimates associated with the group and meta-frontier models were obtained using 2000 bootstrap iterations. Simar and Wilson (2007) recommended the use of 2000 bootstrap iterations to obtain reliable bootstrap estimates. The sample size of each group as well as the descriptive statistics of the data are reported in Table 1 whilst the results of selected restaurants in South Africa are presented in Table 2.

Table 1: Descriptive statistics of the data

Parameters	Categories	Food & beverage expenses		Total covers		Number of seats		FTE in restaurant		Operational expenses		Staff expenses	
		M	SD	M	SD	M	SD	M	SD	M	SD	M	SD
Size	Small	9470829	0.87	4429	0.73	3774	1.28	389	1.36	3906120	0.86	3089207	1.51
	Large	16719635	0.64	7957	0.99	5792	1.07	703	1.11	6275140	0.70	7633982	1.63
Location	Metropolitan	15962591	1.73	8154	0.89	5986	0.96	685	1.50	5842675	1.36	7002974	0.86
	Non-metropolitan	9655643	0.77	4365	1.36	3656	0.61	454	0.83	4072944	0.91	3299526	0.70
Type	Fine dining restaurant	15826959	1.52	7863	0.69	5450	0.79	692	1.03	6691098	1.89	7465287	1.99
	Fast food restaurant	9507089	1.46	4761	1.37	3809	1.79	392	0.64	3615104	0.65	3490133	0.81

*FTE is the number of full-time equivalent employees

The individual efficiency results of selected restaurants will be presented in the subsection below, and the subsequent section will present the one-way ANOVA test results and the findings thereof.

Table 2: Individual efficiency results of selected restaurants in South Africa

DMUs	Parameters			GTE	MTE	TGR	DMUs	Parameters			GTE	MTE	TGR
	Size	Location	Type					Size	Location	Type			
A1	Small	Metropolitan	Fast food	0.73	0.56	0.69	L3	Large	Metropolitan	Fine dining	0.86	0.63	0.94
A2	Large	Non-Metropolitan	Fine dining	0.71	0.63	0.66	L4	Large	Non-Metropolitan	Fast food	0.65	0.41	0.81
A3	Large	Non-Metropolitan	Fast food	0.66	0.47	0.86	M1	Small	Metropolitan	Fine dining	0.78	0.66	0.86
A4	Small	Metropolitan	Fine dining	0.79	0.62	0.76	M2	Small	Non-Metropolitan	Fast food	0.63	0.42	0.70
B1	Large	Metropolitan	Fine dining	0.94	0.74	0.98	M3	Small	Metropolitan	Fine dining	0.79	0.50	0.87
B2	Small	Non-Metropolitan	Fast food	0.63	0.46	0.87	M4	Large	Non-Metropolitan	Fine dining	0.72	0.69	0.85
B3	Small	Metropolitan	Fine dining	0.74	0.59	0.83	N1	Large	Non-Metropolitan	Fast food	0.69	0.57	0.74
B4	Small	Non-Metropolitan	Fast food	0.68	0.47	0.82	N2	Large	Metropolitan	Fine dining	0.89	0.65	0.93
C1	Large	Metropolitan	Fine dining	0.91	0.83	0.95	N3	Small	Non-Metropolitan	Fine dining	0.82	0.65	0.91
C2	Large	Metropolitan	Fine dining	0.93	0.72	0.97	N4	Small	Metropolitan	Fast food	0.85	0.64	0.89
C3	Small	Non-Metropolitan	Fast food	0.66	0.40	0.74	O1	Small	Non-Metropolitan	Fast food	0.55	0.36	0.72
C4	Large	Non-Metropolitan	Fine dining	0.75	0.41	0.82	O2	Large	Metropolitan	Fast food	0.77	0.55	0.85
D1	Small	Non-Metropolitan	Fine dining	0.71	0.52	0.83	O3	Large	Non-Metropolitan	Fine dining	0.69	0.59	0.78
D2	Small	Non-Metropolitan	Fine dining	0.67	0.49	0.59	O4	Small	Non-Metropolitan	Fast food	0.63	0.48	0.76
D3	Small	Metropolitan	Fast food	0.82	0.62	0.89	P1	Small	Non-Metropolitan	Fine dining	0.59	0.49	0.72
D4	Large	Non-Metropolitan	Fine dining	0.63	0.44	0.78	P2	Small	Metropolitan	Fast food	0.76	0.53	0.86
F1	Large	Metropolitan	Fast food	0.87	0.60	0.90	P3	Large	Metropolitan	Fine dining	0.95	0.80	0.97
F2	Small	Metropolitan	Fine dining	0.72	0.53	0.86	P4	Large	Non-Metropolitan	Fine dining	0.71	0.59	0.83
F3	Small	Metropolitan	Fast food	0.66	0.42	0.84	Q1	Large	Metropolitan	Fast food	0.76	0.50	0.86
F4	Large	Metropolitan	Fast food	0.80	0.67	0.86	Q2	Small	Non-Metropolitan	Fast food	0.65	0.47	0.84
G1	Small	Non-Metropolitan	Fine dining	0.69	0.46	0.70	Q3	Large	Metropolitan	Fast food	0.73	0.52	0.87
G2	Large	Metropolitan	Fine dining	0.86	0.65	0.89	Q4	Small	Metropolitan	Fine dining	0.78	0.55	0.84
G3	Large	Non-Metropolitan	Fast food	0.79	0.50	0.81	R1	Small	Non-Metropolitan	Fine dining	0.66	0.43	0.81
G4	Small	Non-Metropolitan	Fast food	0.56	0.38	0.73	R2	Large	Metropolitan	Fast food	0.79	0.56	0.88
H1	Large	Metropolitan	Fine dining	0.90	0.83	0.97	R3	Large	Metropolitan	Fine dining	0.87	0.61	0.92
H2	Large	Metropolitan	Fast food	0.83	0.67	0.92	R4	Small	Non-Metropolitan	Fine dining	0.69	0.44	0.84
H3	Large	Metropolitan	Fine dining	0.88	0.62	0.90	S1	Large	Metropolitan	Fine dining	0.86	0.66	0.94
H4	Small	Non-Metropolitan	Fast food	0.59	0.40	0.74	S2	Small	Metropolitan	Fast food	0.85	0.62	0.96
I1	Large	Metropolitan	Fine dining	0.90	0.79	0.95	S3	Large	Non-Metropolitan	Fine dining	0.73	0.56	0.81

I2	Large	Metropolitan	Fast food	0.76	0.58	0.89	S4	Small	Metropolitan	Fast food	0.79	0.47	0.84
I3	Small	Metropolitan	Fine dining	0.74	0.55	0.87	T1	Small	Non-Metropolitan	Fine dining	0.63	0.45	0.85
I4	Small	Non-Metropolitan	Fast food	0.57	0.43	0.65	T2	Large	Metropolitan	Fast food	0.78	0.57	0.81
J1	Large	Non-Metropolitan	Fast food	0.68	0.48	0.71	T3	Large	Non-Metropolitan	Fast food	0.70	0.59	0.84
J2	Small	Non-Metropolitan	Fast food	0.57	0.39	0.66	T4	Small	Non-Metropolitan	Fast food	0.64	0.44	0.82
J3	Large	Non-Metropolitan	Fast food	0.70	0.52	0.88	U1	Large	Non-Metropolitan	Fine dining	0.81	0.76	0.93
J4	Small	Metropolitan	Fine dining	0.76	0.58	0.90	U2	Large	Non-Metropolitan	Fast food	0.72	0.56	0.79
K1	Large	Non-Metropolitan	Fast food	0.67	0.42	0.64	U3	Small	Metropolitan	Fine dining	0.79	0.54	0.67
K2	Large	Non-Metropolitan	Fast food	0.64	0.44	0.72	U4	Small	Metropolitan	Fast food	0.70	0.57	0.83
K3	Small	Metropolitan	Fine dining	0.71	0.58	0.77	V1	Large	Metropolitan	Fast food	0.83	0.67	0.91
K4	Small	Non-Metropolitan	Fast food	0.61	0.43	0.70	V2	Small	Metropolitan	Fine dining	0.76	0.59	0.84
L1	Small	Non-Metropolitan	Fast food	0.55	0.46	0.84	V3	Large	Non-Metropolitan	Fast food	0.68	0.42	0.78
L2	Large	Metropolitan	Fine dining	0.85	0.69	0.95	V4	Small	Non-Metropolitan	Fast food	0.53	0.41	0.73
Mean efficiency											0.74	0.55	0.83

* '1' is the efficiency frontier

An input-oriented meta-frontier model for computation of GTE, MTE and TGR scores for individual restaurants was used. According to the inputs and outputs used in the meta-frontier model, the technical efficiency of a restaurant relative to the meta-frontier is simple the product of the technical efficiency of that restaurant relative to the frontier for a particular group and the technology gap for that group. Consequently, restaurants that make the most efficient use of their seats (operating expenses) and staff (employee expenses) in generating maximum revenue are the most efficient. As shown in Table 2, most large, fine dining restaurants located in metropolitan areas had high efficiency scores than small, fast-food restaurants located in non-metropolitan areas. The simultaneous and triple influence of restaurant type, location, and size suggests the strong influence of uncontrollable factors on restaurant efficiency. To understand the dynamics underlying these efficiency scores and the factors influencing them, the results are discussed below.

ANOVA results

To investigate the relationship between the three uncontrollable factors (independent variable) and restaurant efficiency (dependant variable) a one-way Analysis of Variance (ANOVA) test was conducted. Table 3 presents the one-way Analysis of Variance (ANOVA) test on factors influencing restaurant efficiency in South Africa.

Table 3: Factors influencing restaurant efficiency in South Africa

PARAMETERS	AVERAGE GTE	AVERAGE MTE	AVERAGE TGR
Fine dining restaurants	0.8045	0.6660	0.8369
Fast food restaurants	0.7619	0.6273	0.7190
Difference test	5.6137*	4.2902*	4.6147*
Large restaurants	0.7912	0.7461	0.7286
Small restaurants	0.6580	0.6294	0.6444
Difference test	5.9201*	5.3609*	6.9305*
Metropolitan restaurants	0.7768	0.8967	0.8968
Non-metropolitan restaurants	0.6486	0.8145	0.8042
Difference test	3.0074	4.1213*	4.7481**

* Significance at 5% level; **significance at 1% level. One-way ANOVA test with *F*-statistic employed

It is clear from the ANOVA results (Table 3) that fine dining restaurants had higher average efficiency scores than fast food restaurants both in terms of the group and meta-frontier models. For example, the average group efficiency for fine dining restaurants is 80.45%, whereas the average group efficiency for fast food restaurants is 76.19%. The meta-frontier comparison is however expected to be more accurate as it is based on one common homogeneous technology. For instance, according to the meta-frontier results, fine dining restaurants are only operating at 66.60% efficiency level, but are still higher than fast food restaurants which are operating at an efficiency level of 62.73%, which contradicts results from Hadad et al. (2007) who found fast food restaurants to be more efficient than fine dining restaurants. An interesting measure is also the technology gap ratio (TGR) which indicates that fast food restaurants have achieved only 71.90% of their potential outputs while fine dining restaurants have achieved 83.69% of their potential output.

From Table 3 it is also clear that large restaurants had higher average efficiency scores than small restaurants both in terms of the group and meta-frontier models, validating previous research in the area (Assaf et al., 2011; Gharakani et al., 2012). For instance, large restaurants had an average group efficiency of 79.12% and average meta-frontier efficiency of 74.61%, while the average efficiency of small restaurants is 65.80% and 62.94% for the group and meta-frontier models respectively. The TGR measures also illustrate the advantage of size, with large restaurants achieving around 7% higher of their potential outputs than small restaurants. The table further shows that restaurants located in metropolitan areas were operating at a similar group efficiency level in comparison to restaurants located in non-metropolitan areas. However, their average meta-frontier efficiency was slightly higher (close to 4%). The average technology gap ratio is also in line with the efficiency results and is close to 5% higher for restaurants located in metropolitan areas. To understand the dynamics underlying these average efficiency scores and the influencing factors, the results from the meta-frontier approach are discussed below.

Discussion

The purpose of this research endeavour was to re-examine factors influencing restaurant efficiency and thereby validate previous findings. The use of the meta-frontier model is in line with the bootstrapped meta-frontier approach used by Assaf et al. (2012) in Taiwanese hotels which justifies that hotels are heterogeneous in terms of the capabilities on which they base their managerial practices, and thus heterogeneity is expected to interfere with efficiency. Since there is a paucity on the use of this methodology in the restaurant literature, it is possible to debate whether previous studies on restaurant efficiency (that used the homogeneous stochastic frontier model and the data envelopment analysis) have converged to similar conclusions in terms of the factors influencing restaurant efficiency. The results show that restaurant size significantly and positively influences (p<0.05) (at 5 percent level) efficiency. The results further reveal that, large restaurants had higher efficiency scores in terms of the group and the meta-frontier models, as well as a higher TGR. However, the results deviate from the findings by Sanjeev (2007) who found no clear link in efficiency between large and small restaurants. Mhlanga (2018a) also concluded that restaurant size did not have any influence on efficiency. A possible reason for the differences in results might lie in differences in methodologies and data. This study uses a meta-frontier model whilst Sanjeev (2007) and Mhlanga (2018a) used a simple data envelopment analysis. Nevertheless, the results are consistent with the findings by Gharakani et al. (2012) who found restaurant size to be a highly significant factor influencing efficiency because of economies of scale. Therefore, the relationship between size and efficiency is not easily discerned in the restaurant literature.

In the same vein, studies which have compared small and large restaurants have not converged to the same conclusion. For example, Robson (2013) found small restaurants to more efficient than large restaurants because they require fewer covers per hour hence they are much more likely to be financially feasible than large restaurants. However, Donthu and Yoo

(1998) found contradictory results when he noted that large restaurants were more efficient than small restaurants. The same conclusion was also reached by Reynolds and Thompson (2007) in their study on US restaurants. Outside the restaurant sector, many authors in sectors such as hotels, manufacturing and banking have also converged to the conclusion that large size significantly and positively influences an organisation's performance (Gimenez, 2004). Consequently, the results of this study should provide a clearer reflection on the influence of restaurant size on efficiency, given that it also controls for the heterogeneity between small and large restaurant groups. The results further show that restaurant type significantly and positively influences ($p<0.05$) (at 5 per cent level) restaurant efficiency with fine dining restaurants attaining higher efficiency scores than fast food restaurants in terms of the group and the meta-frontier models, as well as a higher TGR. The findings corroborate previous research scholars (Gimenez, 2004; Mhlanga, 2018a) who also found the same results. However, the results contradict previous research findings by Hadad et al. (2007) who found fast food restaurants to be more efficient than fine dining restaurants.

In terms of the influence of location on restaurant efficiency, the matter appears to be less contradictory with restaurants located in metropolitan areas attaining higher efficiency scores than restaurants located in non-metropolitan areas. This is in line with most scholars (Donthu & Yoo, 1998; Reynolds & Thompson, 2007; Reynolds, 2004) who also found location to significantly and positively influence restaurant efficiency. Such agreement in the literature might be attributed to the fact that restaurants located in metropolitan areas tend to be easily accessible, have high foot or vehicular traffic counts and proximal demand generators which increases revenue per available seat hour (RevPASH) (Mhlanga, 2018a). Therefore, this conclusion may not be excitingly revealing, but it is consistent with intuitive logic and the common industry knowledge that restaurants located in, or near, metropolitan areas are more efficient than those in non-metropolitan areas (Reynolds, 2004). The empirical results corroborate the practical situation in the South African restaurant industry where most small, fast-food restaurants in non-metropolitan areas, particularly in townships, have a high failure rate compared to large, fine dining restaurants in metropolitan areas which have a high survival rate. It is therefore no surprise that five out of seven new restaurants in townships fail within their first year of operation and 81 percent fail within five years of operation (Mhlanga, 2019). The results derived from this study suggest that it is not feasible to open a restaurant in non-metropolitan areas in South Africa because the demand for restaurants tend to be high in metropolitan areas where most of the households have higher disposable incomes which increases revenue per available seat hour.

Conclusion

This study endeavour re-examined factors influencing restaurant efficiency by applying the meta-frontier approach to account for the heterogeneity of DMUs (i.e., restaurants that are different in size, location, and service) and further validate previous findings. The meta-frontier framework revealed that restaurant efficiency with respect to group frontiers and the meta-frontier is significantly and positively influenced ($p<0.05$) by uncontrollable factors, in particular, restaurant size, location and type. The findings contradicts some previous studies that suggest that restaurant size has no influence on efficiency and or that small restaurants are more efficient that large restaurants. In doing so, the study shows that the methodology choices have an important impact on the estimated efficiency scores, supporting the view that traditional efficiency techniques tend to underestimate efficiency scores resulting in biased efficiency comparisons between different restaurants.

The results have potential policy implications. Firstly, since it is not feasible to open a restaurant in non-metropolitan areas, entrepreneurs who intend to open restaurants in non-

metropolitan areas in South Africa should first identify niche markets where they can have customer monopoly, such as Kentucky Fried Chicken (KFC). Secondly, the findings could be of interest to the South African government, especially in formulating improvement strategies for the whole industry. Government officials can now formulate policies with a better understanding of the difference in efficiency between different types of restaurants.
Specifically, it is crucial that the South African government adopts different policies for restaurants with different sizes. For example, policies towards small restaurants might need to be different from large restaurants as these restaurants have traditional resource limitations and thus might need further assistance. Finally, the results reveal that fine dining restaurants are more efficient than fast food restaurants, hence some strategies of fine dining restaurants can be emulated by fast food restaurants for better operational efficiency. The need for higher service standards should be embedded in any strategy.

While interesting, this study has several limitations. Considering the important role played by uncontrollable factors in influencing restaurant efficiency, more extensive research needs to be done to find alternative methods for incorporating these uncontrollable factors in performance measurement. Moreover, there are many other explanatory variables (e.g., restaurant ownership, customer service) that influence efficiency. However, these factors have not been taken into account in this analysis due to lack of availability of data associated with those variables. Consequently, a more comprehensive analysis of factors influencing restaurant efficiency requires accounting for these factors in the analysis as well. Nonetheless, despite the data limitations, this study shows that the meta-frontier approach is a useful tool to identify factors influencing restaurant efficiency and could enhance the service data and revenue management in the restaurant industry.

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