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Restaurant sector efficiency frontiers: a meta-analysis

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Abstract

In recent years, there has been a growing interest in assessing the level of performance and efficiency of the foodservice industry. As a result, an increasing number of studies applied efficiency frontiers methods to quantify firm (in)efficiency. Starting from the benchmarking studies on restaurant efficiency, this paper aims to develop a meta-analysis based on 77 observations from 25 studies published in scientific journals from 1998 to 2020. The estimated effect size in our meta-analysis is equal to 0.842 and it is statistically different from zero, while the Cochran's Q test for the heterogeneity in our sample hints at the absence of heterogeneity in the previous studies on restaurant efficiency. A meta-regression analysis partially supports this result but also highlights the importance of assuming appropriate return to scale, given the peculiarity of the sector.

JEL classification: D24, L83.

Keywords: Meta-analysis, foodservice, restaurant, DEA, efficiency.

1 Introduction

The relevant direct and total contributions to GDP lead to deeming the foodservice industry among the most important sectors at global and national levels. Until 2019 this industry has continued growing, and it registered positive performances in most countries in terms of values and volume of transactions (Deloitte 2021). In 2019, the foodservice industry recorded €2,603 billion at a global level.[1]

Full-service restaurants, quick-service restaurants, cafes, and street food vendors are among segments of the foodservice industry that often require alternative organizational strategies to obtain efficiency and are also likely to respond differently to exogenous shocks. The same

[1] Covid-19 has altered the foodservice landscape and millions of restaurants worldwide shut down during the pandemic. Forbes estimates that approximately 4% of GDP and 11 million jobs were lost in the US in the foodservice industry because of the pandemic (Lew 2020).

holds for other types of segmentation usually used in this industry: chains are distinguished from independent business units, like small businesses, as well as on-site services are differentiated from takeaway and delivery services. Foodservice is also a dynamic industry, strongly affected by innovations and contaminations from contiguous sectors (Baregheh et al. 2012, Vasconcelos & Oliveria 2018, Matricano et al. 2022). From a cultural perspective, cuisine can be seen as a cultural product (Waldfogel 2020) since it preserves, strengthens, and conveys local and national cultures, traditions, and identities over time and across countries. Foodservice is also strongly linked with the tourism industries, where food consumption can even be the main reason for traveling (Kivela & Crotts 2006, Ji et al. 2016). All this makes the foodservice industry a rather complex industry, where knowing if the restaurants are operating efficiently becomes even more important both for the firms and consumers.

Generally speaking, restaurants are risky businesses that often operate inefficiently (Assaf et al. 2011, Mhlanga 2018*b*). Restaurant capacity is not fixed (Mhlanga 2018*a*) with a highly volatile demand (Reynolds 2004) and is subject to seasonal fluctuations. Moreover, the foodservice sector is highly sensitive to rises in labour and production costs (Assaf et al. 2011), and its subsectors react differently to these changes.[2] The peculiarities of the foodservice industry and its subsectors and the large number of factors affecting restaurants' efficiency make it crucial to identify performance indicators. Thus, assessing restaurant performance is essential for determining the proper strategies to improve business efficiency and competitiveness.

A limited number of approaches have been used to assess restaurant efficiency and identify cost reduction strategies (Reynolds 2003, Assaf & Matawie 2008, Assaf et al. 2011). Performance assessment is crucial to improve and maintain market power by identifying firms' weaknesses and strengths, formulating proper strategies, and evaluating them (Assaf & Magnini 2012). The most common performance measures are simple ratios such as sales per labour hour, sales per number of seats, and meals per employee, reflecting specific operational performance aspects. However, these ratios may provide a partial picture of the real situation, limited information on benchmarking units, and, sometimes, inconsistent or inaccurate details that can lead to inappropriate strategic decisions. Moreover, partial productivity measures can hardly capture the complexity of restaurants' production system, which combine multiple inputs and multiple outputs. Similar conclusions can be drawn when simple regression approaches are used to analyse productivity since results based on single output and multiple inputs (or vice versa) specifications may lead to inaccurate results and may suggest misleading solutions or strategies (Assaf & Matawie 2008).

However, differently from simple-ratio and regression analyses, the complexity of the foodservice industry has been better captured by frontier methods that assess restaurants' performance by including multi-inputs and outputs settings. This approach proved to better identify benchmarks and the gaps of firms from the optimal frontier, based on restaurants characteristics. In the economic literature, frontier methods, such as Data Envelopment

[2]The Covid-19 outbreak put several small and large companies in the foodservice industry in the need to rethink their business models, possibly forcing them to innovate their business paradigm, organization, products, and processes.

Analysis (DEA) and Stochastic Frontier Analysis (SFA), have been increasingly adopted to measure restaurant efficiency, using different output and input measures and various statistical approaches. Still, a comprehensive review of the results of these benchmarking studies is lacking. However, since the sample characteristics and size and the adopted frontier techniques may lead to non-generalizable efficiency measures, a systematic analysis of the efficiency studies is needed to check for the possible existence of heterogeneity in the results and, in that case, the causes of that heterogeneity.
To bridge this gap, in this paper, we develop a systematic literature review on restaurant efficiency, analysing the relevant benchmarking studies and conducting a meta-analysis that reflects the efficiency results of studies on frontier methods in the foodservice industry. In particular, we conduct a meta-analysis on the empirical studies investigating restaurant efficiency, based on 77 observations from 25 studies published in scientific journals from 1998 to 2020. The meta-analysis allows us to test for possible heterogeneity in the results of the studies and to identify the effect of the type of frontier methods and the factors affecting efficiency estimates in the literature concerning the foodservice industry. We then test for heterogeneity, using a Q-test which suggests the studies analysed are homogeneous enough. To further check the result of the Q-test, we also developed a meta-regression analysis, as suggested by Stanley & Doucouliagos (2012), finding an impact of the method used (CRS vs. VRS) and of the size of the sample. This analysis suggests that, while the efficiency scores estimated in the restaurant sector seem to be sufficiently homogeneous, scholars should carefully consider which method to use concerning returns to scale, since the assumption of proportionality between inputs and outputs cannot be always made in the foodservice industry. Our paper also adds to the literature on meta-analysis of foodservice industry, tourism, and leisure industries (Sainaghi 2010, Assaf & Josiassen 2016). However, only Assaf & Josiassen (2016) adopt a meta-regression approach to the best of our knowledge. The different sectors analysed in our and in Assaf & Josiassen's meta-regressions justify the differences among results, since they find heterogeneity in the hotel industry studies that can be explained by various choices concerning the estimation methods used in the papers covering the topic.

The remainder of the paper is structured as follows. Section 2 presents the use of frontier analysis in the foodservice industry. Section 3 describes the data we collected from our literature review and presents the meta-analysis and meta-regression results. Finally, section 4 concludes the paper.

2 Frontier analysis in the foodservice industry

In this section, we present a brief review of the literature on efficiency measurement in the foodservice industry, with a focus on frontier analysis. Efficiency plays a central role in the economic studies of industries and sectors due to its strict relationship with profitability, so measuring the efficiency of a (sub)sector provides hints on how efficiency can be improved and hence increase profitability. Studies on foodservice, in general, and several investigations on restaurant performance analyse the efficiency of the production units along with

the industry and sector (Rodríguez-López et al. 2020).
Different statistical parametric and non-parametric techniques can be used to estimate efficient frontiers.[3] These methods assess the relative efficiency of the so-called Decision-Making Units (DMU) (firms, countries, etc.) by identifying an efficiency frontier where the most efficient units are located. The relative distance of DMUs from the efficient frontier measures their inefficiency: the closer the DMUs' positions to the frontier, the larger their efficiency; the further the DMUs from the frontier, the larger their inefficiency. A parametric frontier is estimated from the sample when the functional form of the efficient frontier is a priori imposed, while a non-parametric frontier does not require the specification of a functional form and also works with relatively small samples. Among non-parametric frontier approaches, DEA is a class of mathematical programming models to calculate the production frontiers and the efficiency scores using observed data. In these deterministic models, noise is included in the efficiency score, and all deviations from the efficient frontier are interpreted as a sub-optimal performance of production units. On the contrary, parametric frontier approaches can be distinguished into deterministic and stochastic models.[4] Among the latter, SFA are stochastic models with a double-sided random error for controllable and uncontrollable factors in the model and are among the most used efficiency analysis method, together with DEA (Parman & Featherstone 2019).
Albeit their flexibility, the main drawback of non-parametric approaches is their deterministic form. For example, being a non-statistical method, the DEA cannot distinguish between technical inefficiency and statistical error. In other words, the absence of a random error in the DEA estimation makes the estimates sensitive to the presence of noise in the data, outliers, and sample size. On the other hand, parametric approaches require the specification of a functional form for the technology and the inefficiency error term (Assaf & Josiassen 2016). Rodgers & Assaf (2006) suggested that, in analysing restaurant efficiency, the SFA approach should be preferred to the DEA, since the latter approach cannot consider the presence of measurement error. However, as Section 3 will underline, most of the studies on restaurant efficiencies adopted the DEA approach.[5]
Frontier analysis approaches have their origin in the work of Farrell (1957), who introduced a statistical method to decompose the overall efficiency of a DMU into its technical and allocative components: the former refers to the case where a production unit obtains less than the maximum output it should get from its inputs, and the latter to a production unit that does not use the best inputs given their prices and marginal productivities. Through this method, a DMU can find itself on the frontier or below it. In the former case, it can

[3]See Murillo-Zamorano (2004) for a comprehensive review of parametric and non-parametric frontier techniques to measure economic efficiency.

[4]Note that the stochastic frontiers can be estimated by econometric techniques only, while the deterministic frontier functions can also be calculated by using mathematical programming, such as linear programming.

[5]To exploit the advantages of the two approaches, new classes of models have recently been introduced in the literature: stochastic DEA and Bayesian SFA. Indeed, stochastic DEA is a statistical model that allows for the determination of statistical properties of the non-parametric frontier estimators. The main advantage of the Bayesian SFA is to include prior information about parameters of the functional form in the inference (Van den Broeck et al. 1994). Furthermore, bootstrap techniques have been used in several applications to improve the accuracy of the DEA efficiency analysis (Simar & Wilson 1998).

be called efficient.[6] However, the shortage of data on (input and output) prices and specific costs makes difficult the assessment of the allocative efficiency. Nevertheless, while, in general, frontier methods can estimate the overall efficiency, some DEA approaches assuming variable rather than constant returns to scale (VRS vs. CRS) allow to decompose it into technical and scale efficiency.[7]
Since efficiency can be defined either as "the level of performance that uses the least amount of inputs to achieve a given amount of outputs" or "the level of performances that obtains the highest amount of outputs by using a given amount of inputs," in the literature two possible orientations of the frontier models can occur. In the output-oriented model, the weighted sums of outputs are maximized, holding inputs constant. In the input-oriented model, the weighted sums of inputs are minimized, keeping outputs constant. The choice of orientation does not affect the technical efficiency results when constant return to scale is assumed, while it differentiates technical efficiency estimates when increasing or decreasing return to scale occur (Färe & Knox Lovell 1978, Kopp 1981). Thus, researchers must choose the orientation and the return-to-scale type that better fit the conditions and characteristics of the industry analysed (Barros 2005, Assaf & Josiassen 2016).

Looking at the efficiency measurement studies about restaurants, the previous literature focuses primarily on general-public restaurants, fast-food restaurants, and other types of restaurants and food services located in specific contexts, such as hospitals and airports. Aside from the analysis of restaurant efficiency per se, the DEA method has also been implemented on the efficiency of the characteristics of restaurants, such as the efficiency of menus (Reynolds & Taylor 2011, Fang & Hsu 2012, Fang et al. 2013, Chou & Fang 2013) and recipes (Chiang & Sheu 2020), and of the management of time slots (Joo et al. 2012). Since restaurants are heterogeneous in terms of organization structure, size, and location, using such a measurement method could lead to heterogeneous results with potential issues in generalizing the efficiency claims for the sector. For this reason, a meta-analysis study should be developed to check for potential heterogeneity in the estimated effect sizes.

3 Meta-analysis

In this section, we describe our data on empirical literature used in the meta-analysis, and then we perform this analysis and discuss the main results.

3.1 Data description

We collected our data through an empirical literature review on the studies using DEA and SFA methods in the foodservice industry. In particular, we searched on Scopus and Web

[6] The direct estimation of the economic efficiency of DMUs by a production function, or the indirect estimation through a cost function, is the duality econometric problem (Murillo-Zamorano 2004). The duality theory allows for the use of the production or cost function for the joint investigation of both technical and allocative efficiency.

[7] VRS is based on the BCC model (Banker et al. 1984), whereas CRS is based on the CCR approach (Charnes et al. 1978).

of Science websites, as well as working papers and preprints repositories (SSRN, SocArxiv, Mendeley, Arxiv) and EBSCO Hospitality and Tourism Complete database. Keywords used in our search were: restaurant, foodservice, and gastronomy together with SFA, stochastic frontier analysis, DEA, data envelopment analysis, for a total of 12 combinations. We also considered the references in the papers obtained from the first search.[8] After the search, jointly performed by the authors in November 2020, each of the authors independently read and coded all the papers.[9] We obtained 152 papers from the search and dropped 34 of them because they were out of our research fields that include cultural, tourism, and service economics studies, or because they were papers in which DEA and/or SFA were not used to assess restaurant efficiency, so they were not in line with the aim of our study.[10] Among the remaining, 54 papers were related to the hospitality and foodservice industry, but they used DMUs other than restaurants (such as hotels, healthcare foodservice, coffee stores, menus, worked hours, etc.), 15 did not use actual data but either a theoretical approach or simulations, 4 were related to restaurants but did not use the methodologies we focused on (DEA and SFA), 1 was not written in English but in Korean (a language the authors are not able to read), 3 had been republished (namely, both the published version and the working paper version are part of the search results and have the same coefficients and results), 1 used data from another paper present in our dataset, 6 did not report at all the coefficients for the single DMUs or reported the list of coefficients for only some of the DMUs nor they reported the average efficiency coefficient and a measure of dispersion, 2 considered hotels and restaurants together in the analysis, 2 used regions as DMUs, and 2 had too few DMUs used in the analysis (3 and 7). So, we only consider 28 papers, all published in international research journals, listed in Table 1, which reports the author names and publication year (from 1998 to 2020) of each study. In the final sample, 20 papers have 1 period of analysis, while the others have more than 1 period and/or use time subsamples. The total number of DMUs ranges from 10 to 48,900, with 82 models, and so 82 efficiency scores. 26 studies are based on the DEA method while 2 are based on the SFA method. The range of the estimated average efficiency scores goes from 0.222 to 0.940. Among the papers whose data covers more than 1 year, 2 use pooled data for different years, while 3 do not, and 5 studies use both pooled and non-pooled data. 2 analyses used the bootstrap DEA method and 2 use panel DEA method. Finally, 10 studies in the sample are internal benchmarking analyses.

To limit the sample heterogeneity and maintain the comparability of the approaches applied in the papers reported in Table 1, we did not include in the meta-analysis the two papers that applied the SFA method (IDs 16 and 22).[11] We also did not consider the paper with

[8] In statistics, this procedure is noted as snowball sampling, which is a non-probability sampling technique.

[9] The information resulting from the coding obtained by each of the authors was compared and deemed to be aligned.

[10] The papers we did not consider were either study on restaurants, not focused on the efficiency, such as analyses of the effect of laws on restaurants, menu translations, experience in robotic restaurants, or papers that studied food but they were not related to restaurants, such as analyses of food chemistry and nutrition science. Several papers also studied the efficiency of non-restaurant DMUs (such as recycling centres and layer supply chains). The complete list of papers resulting from our search is available upon request.

[11] These two papers account for 3 data points over the total 82 data points.

ID 27 (Sveum & Sykuta 2019) since the two samples used in this analysis are much larger than those used in all the other papers (40,000 and 8,900) and they may bias our results. In this way, we have 77 final observations coming from 25 papers: several papers have more than one data point, as in the case of studies with ID 10, 19, 20, 23, 24, and 27, in which the authors used some variables to split the sample of observations such as brand, time periods, sample characteristics, etc., and applied the DEA methodology also to these subsamples.
The papers used in the meta-analysis were published between 1998 and 2020 in international research journals and used a DEA approach to measure the efficiency of restaurants in 10 countries (Australia, China, Greece, Iran, Israel, Italy, Slovenia, South Africa, Spain, and the USA). We included several types of restaurants in our sample, such as coffee-restaurants, street food-restaurants, and airport restaurants, but we explicitly excluded hotel-restaurants since they adopt a production technology that also considers the accommodation side of their offer.

We extract a series of variables from the information present in the papers or, when not present, we received the information from direct contact with the authors.[12] Collected information refers to the mean and the standard deviation of efficiency scores, respectively `Mean` and `SD`, the restaurant-specific characteristics recorded as dummy variables for inputs and outputs, that we summarise in the variables `Inputs` and `Outputs`, respectively representing the sum of inputs and outputs used in each paper's analysis, and the dimension of the sample of restaurants used in the estimation in each model, `SampleSize`. We also built two dummy variables, one for the orientation used in the estimation (`InputOrientation`, equal to 1 when input orientation is used) and one for the method used (`CRSMethod`, equal to 1 when the CSR method is used).[13] We also collected from Web of Science the number of citations per article, reported in the variable `WeightedCitations`, which has been weighted for the number of years from the paper publication. Descriptive statistics for these variables are reported in Table 2.

We are aware that publication bias may distort the assessment under investigation.[14] Published studies may indeed systematically differ from unpublished analyses and meta-analyses should include unpublished studies (such as government reports, dissertations, working papers, etc.) to avoid misleading conclusions and control for potential publication bias but, despite our meticulous search, no unpublished study emerged. Moreover, we do not expect any truncation due to publication selection, given that benchmarking of efficiency analysis identifies the optimal frontier for a sample of DMUs and measures the relative firms' efficiency based on the distance between firms and the efficiency frontier. Thus, a low (high) average measure of firms' efficiency only means that, in the analysed sample, a large

[12] We want to thank the authors who sent us the information that was not available in the published version of their papers.

[13] `InputOrientation` for the paper with ID 4 (Donthu et al. 2005) is equal to 0 since the paper does not use either input-oriented or output-oriented approach.

[14] Publication bias (or the "file drawer problem") occurs when the results of a scientific study influence the decision by the scientist on how to publish it (that is whether, where, when to publish the result). A series of methods, among which we find the meta-significance test and the precision-effect test (Roberts 2005, Stanley 2005), have been developed to test for the presence of this bias.

Table 1: **Papers collected**

The table reports, for each paper, the authors' names, the publication year, the number of periods (and time subsamples, if any) and the total number of DMUs (and models or efficiency scores), the adoption of DEA (or SFA) method, the average efficiency score of the models in each paper (AES), if it is an internal benchmarking analysis (for example, when all the DMUs are part of the same restaurant chain), the use of pooled data (in case of multiple years), the use of bootstrap methods or panel methods, and the inclusion of the paper in the meta-analysis developed in Section 3.2. The average efficiency score is rounded to the third digit. All studies are published in international research journals. Since some of the studies provide more than 1 average efficiency score, we have 82 observations from 28 papers.

ID	Authors (Pub. Year)	Periods (Subs.)	DMUs (Models)	AES	DEA	Int. Bench.	Pooled	Bootstrap	Panel	In Meta-an.?
1	Donthu & Yoo (1998)	3 (1)	24 (2)	0.864	Y	Y	Y/N	N	N	Y
2	Reynolds (2004)	1	38 (1)	0.844	Y	Y	–	N	N	Y
3	Giménez-García (2004)	1	16 (1)	0.921	Y	Y	–	N	N	Y
4	Donthu et al. (2005)	1	26 (6)	0.881	Y	Y	–	N	N	Y
5	Lan et al. (2006)	1	27 (1)	0.956	Y	Y	–	N	N	Y
6	Giménez-García et al. (2007)	1	54 (1)	0.765	Y	Y	–	N	N	Y
7	Reynolds & Biel (2007)	1	36 (1)	0.859	Y	Y	–	Y	N	Y
8	Hadad et al. (2007)	1	30 (2)	0.771	Y	N	–	N	N	Y
9	Du et al. (2010)	1	20 (1)	0.940	Y	Y	–	N	N	Y
10	Roh & Choi (2010)	1 (3)	136 (8)	0.759	Y	N	Y/N	N	N	Y
11	Hadad et al. (2011)	1	20 (3)	0.937	Y	Y	–	N	Y	Y
12	Assaf et al. (2011)	1	105 (2)	0.535	Y	N	–	Y	N	Y
13	Chang et al. (2012)	1	14 (3)	0.881	Y	N	–	Y	N	Y
14	Gharakhani et al. (2012)	1	15 (1)	0.583	Y	N	–	N	N	Y
15	Hadad et al. (2013)	2	10 (2)	0.806	Y	Y	N	N	N	Y
16	Lai & Huang (2013)	5 (1)	250 (2)	0.810	N	N	Y	N	N	N
17	Dokas et al. (2014)	2	24 (5)	0.769	Y	N	Y/N	N	N	Y
18	Giokas et al. (2015)	3	21 (6)	0.740	Y	N	N	N	Y	Y
19	Alfiero et al. (2017)	1 (3)	41 (3)	0.800	Y	N	–	N	N	Y
20	Planinc et al. (2018)	1 (2)	137 (3)	0.850	Y	N	Y/N	N	N	Y
21	Kukanja & Planinc (2018)	1	142 (1)	0.850	Y	N	–	N	N	Y
22	Mhlanga (2018*a*)	1	42 (1)	0.767	N	N	–	N	N	N
23	Mhlanga (2018*b*)	4	16 (2)	0.798	Y	N	Y	N	N	Y
24	Alberca & Parte (2018)	4 (3)	863 (19)	0.659	Y	N	Y/N	N	N	Y
25	Kukanja & Planinc (2019)	1	371 (1)	0.830	Y	N	–	N	N	Y
26	Planinc & Kukanja (2019)	1	52 (1)	0.670	Y	N	–	N	N	Y
27	Sveum & Sykuta (2019)	1 (2)	48900 (2)	0.222	Y	N	N	N	N	N
28	Kukanja & Planinc (2020)	1	371 (1)	0.850	Y	N	–	N	N	Y

Table 2: **Descriptive statistics of meta-analysis observations**

The table reports number of observations (N), means, standard deviations (SD), minima (Min), and maxima (Max) for continuous variables and relative frequencies for dummy variables. The values are rounded to the second digit.

Continuous variables	N	Mean	SD	Min	Max
`Mean`	77	0.77	0.11	0.46	0.97
`SD`	77	0.16	0.05	0.04	0.26
`Inputs`	77	3.56	2.81	0	11
`Outputs`	77	1.91	1.28	1	5
`SampleSize`	77	74.30	82.89	10	371
`WeightedCitations`	77	4.72	4.57	0	17.57
Dummy-variables	N	Rel. Freq.			
`InputOrientation`	77	0.69			
`CRSMethod`	77	0.52			

(small) number of firms is relatively inefficient (efficient). Differently from other investigated subjects, there are not expected signs or results. These are the reasons why we do not control for publication bias.

3.2 Empirical methodology and results

A meta-analysis is a statistical method used to analyse the empirical literature on a certain phenomenon. It investigates the parameters and methodologies that emerge as the most important in explaining the empirical results found in the literature. The main goal of a meta-analysis is to make the empirical results of specific studies comparable and suitable by controlling for the effect size. The effect size is a standard measure of the empirical effect, which can be assumed as a constant across the literature sample. Given this assumption, the meta-analysis approach uses empirical results as data to study their generating process (Stanley & Jarrell 2005).

The goal of the meta-analysis is then to combine the estimates of true and unknown effect size with its standard error to infer the population parameter of interest. Three models are commonly used for a meta-analysis: the common-effect model, the fixed-effect model, and the random-effect model. These models make different assumptions on the distribution of the effect size. A common-effect model assumes that all study effect sizes are the same and equal to the true effect size. A fixed-effects (FE) model assumes that the studies share a common effect, while a random-effects (RE) model assumes that each study estimates a different underlying impact. The main difference among FE and RE model assumptions involves the characteristics of the studies: in the first case, studies should represent the entire population of interest, while in the second case, they should represent a random sample from a population of interest and the inference target is to extend the results from the sample to the entire population of interest. Since our research question concerns only the study-specific effect sizes included in the meta-analysis and we recovered all the available studies in public repositories concerning restaurant efficiency estimated with DEA, we perform a fixed-effects (FE) meta-analysis model.

In particular, we estimate the weighted average of true study-specific effect sizes, $\mathbb{E}[\theta_j]$, using the estimated weights of true and unknown weights, ω_j, which depend on the estimates of the variance of the sampling errors, $Var[\epsilon_j] = \sigma_j^2$; in other words, the standard errors as estimates of the effect sizes variance in the sample are generally used to estimate the effect size of the population of interest:

$$\mathbb{E}[\theta_j] = \frac{\sum_j \omega_j \theta_j}{\sum_j \omega_j}$$

where $\omega_j = 1/\sigma_j^2$.

In Table 3, we report the estimated effect sizes for all our data points, together with their weights. The estimated $\mathbb{E}[\theta_j]$ in our meta-analysis is equal to 0.842 (with a 95% confidence interval between 0.814 and 0.870) and is statistically different from zero. We also carried out a Cochran's Q test for the heterogeneity which occurs when the variation between the study effect sizes cannot be explained by sampling variability alone. Given that, in our case, it is distributed as a $\chi^2(76)$ and our test statistic Q is equal to 57.04 (p-value = 0.9487), we fail to reject the null hypothesis of absence of heterogeneity. However, since the Q-test has low power, results may suggest homogeneity in the data when there is indeed heterogeneity. To take this into account, following Stanley & Doucouliagos (2012), we perform a meta-regression analysis to investigate the effect of the study characteristics on the efficiency result. A meta-regression analysis can explicitly estimate regression coefficients and their magnitudes and enlighten whether estimated coefficients are statistically different from zero. The variation among the empirical results may depend on the data (sample selection bias) and statistical methods or model specifications (misspecification bias).[15]

Table 4 reports the estimated meta-regression by using the variables listed in Table 2.[16] The results suggest that the only sources of heterogeneity are the sample size and the CRS method, the former having a negative coefficient and the latter having a positive one.[17] A larger sample size seems to strongly affect the estimated efficiency of the restaurants in the sample, reducing the average score. In a larger sample, it is possible to identify benchmark restaurants that significantly outperform less efficient restaurants. Moreover, in

[15] Since the studies in literature may use different datasets with different sample sizes and independent variables, meta-regression errors are likely to be heteroskedastic. Meta-regression analysis allows controlling for sample selection and misspecification bias by identifying the statistical structures underlying the empirical effect (Stanley & Jarrell 2005).

[16] The variable `SampleSize` has been transformed in the logarithmic form to account for its high variability.

[17] Notice that considering the sample size impact in the meta-regression allows us to check for the presence of a possible bias due to the small size of the sample. Moreover, our results are robust to different model specifications. Given that the average efficiency score (the dependent variable) ranges between 0 (full inefficiency) and 1 (full efficiency), we also estimated two different model specifications: a tobit model (in line with Assaf & Josiassen (2016)) and a beta regression model (which specifically accommodates dependent variables greater than 0 and lower than 1). The resulting outputs are analogous to meta-regression results both in terms of sign and significance level. For this reason, those results are not reported in this paper but are available upon request.

Table 3: **Effect sizes of the studies part of the meta-analysis**

The table reports the effect sizes of the 77 model estimations considered in our meta-analysis, as presented in Table 1. The effects are computed considering a fixed-effect model to account for heterogeneity, using the inverse of the variance as the weight. All values are rounded to the third digit, but the weight is rounded to the second digit.

Study	Effect Size	95% Interval	Weight
Donthu & Yoo (1998)	0.856	[0.654, 1.057]	1.94
Donthu & Yoo (1998)	0.872	[0.667, 1.077]	1.87
Reynolds (2004)	0.844	[0.608, 1.080]	1.41
Giménez-García (2004)	0.921	[0.695, 1.147]	1.54
Donthu et al. (2005)	0.896	[0.696, 1.097]	1.96
Donthu et al. (2005)	0.936	[0.757, 1.115]	2.46
Donthu et al. (2005)	0.908	[0.683, 1.133]	1.55
Donthu et al. (2005)	0.935	[0.786, 1.084]	3.53
Donthu et al. (2005)	0.693	[0.283, 1.104]	0.47
Donthu et al. (2005)	0.919	[0.751, 1.087]	2.79
Lan et al. (2006)	0.956	[0.881, 1.031]	14.03
Giménez-García et al. (2007)	0.765	[0.635, 0.895]	4.69
Reynolds & Biel (2007)	0.859	[0.649, 1.069]	1.79
Hadad et al. (2007)	0.713	[0.291, 1.135]	0.44
Hadad et al. (2007)	0.829	[0.453, 1.205]	0.56
Du et al. (2010)	0.940	[0.854, 1.025]	10.72
Roh & Choi (2010)	0.774	[0.460, 1.089]	0.80
Roh & Choi (2010)	0.823	[0.527, 1.120]	0.89
Roh & Choi (2010)	0.687	[0.435, 0.940]	1.23
Roh & Choi (2010)	0.734	[0.470, 0.998]	1.12
Roh & Choi (2010)	0.754	[0.452, 1.055]	0.86
Roh & Choi (2010)	0.787	[0.488, 1.087]	0.88
Roh & Choi (2010)	0.733	[0.438, 1.028]	0.90
Roh & Choi (2010)	0.776	[0.484, 1.068]	0.92
Hadad et al. (2011)	0.924	[0.748, 1.101]	2.52
Hadad et al. (2011)	0.921	[0.561, 1.281]	0.61
Hadad et al. (2011)	0.967	[0.571, 1.363]	0.50
Assaf et al. (2011)	0.606	[0.133, 1.080]	0.35
Assaf et al. (2011)	0.463	[0.077, 0.848]	0.53
Chang et al. (2012)	0.824	[0.481, 1.167]	0.67
Chang et al. (2012)	0.930	[0.712, 1.149]	1.65
Chang et al. (2012)	0.890	[0.569, 1.211]	0.77
Gharakhani et al. (2012)	0.583	[0.151, 1.015]	0.42
Hadad et al. (2013)	0.831	[0.665, 0.998]	2.84
Hadad et al. (2013)	0.780	[0.373, 1.188]	0.47
Dokas et al. (2014)	0.717	[0.314, 1.119]	0.48
Dokas et al. (2014)	0.800	[0.354, 1.246]	0.40
Dokas et al. (2014)	0.810	[0.410, 1.210]	0.49
Dokas et al. (2014)	0.750	[0.276, 1.224]	0.35

Study	Effect Size	95% Interval	Weight
Dokas et al. (2014)	0.770	[0.265, 1.275]	0.31
Giokas et al. (2015)	0.850	[0.493, 1.207]	0.62
Giokas et al. (2015)	0.800	[0.377, 1.223]	0.44
Giokas et al. (2015)	0.800	[0.426, 1.174]	0.56
Giokas et al. (2015)	0.710	[0.293, 1.127]	0.45
Giokas et al. (2015)	0.640	[0.168, 1.112]	0.35
Giokas et al. (2015)	0.640	[0.174, 1.106]	0.36
Alfiero et al. (2017)	0.800	[0.467, 1.133]	0.71
Alfiero et al. (2017)	0.850	[0.556, 1.144]	0.91
Alfiero et al. (2017)	0.750	[0.378, 1.122]	0.57
Planinc et al. (2018)	0.850	[0.608, 1.092]	1.34
Planinc et al. (2018)	0.830	[0.588, 1.072]	1.34
Planinc et al. (2018)	0.870	[0.628, 1.112]	1.34
Kukanja & Planinc (2018)	0.850	[0.640, 1.060]	1.79
Mhlanga (2018*b*)	0.821	[0.537, 1.105]	0.98
Mhlanga (2018*b*)	0.774	[0.489, 1.060]	0.97
Alberca & Parte (2018)	0.611	[0.213, 1.009]	0.50
Alberca & Parte (2018)	0.543	[0.222, 0.864]	0.76
Alberca & Parte (2018)	0.663	[0.273, 1.053]	0.52
Alberca & Parte (2018)	0.690	[0.374, 1.006]	0.79
Alberca & Parte (2018)	0.728	[0.409, 1.047]	0.77
Alberca & Parte (2018)	0.655	[0.236, 1.074]	0.45
Alberca & Parte (2018)	0.704	[0.400, 1.008]	0.85
Alberca & Parte (2018)	0.734	[0.424, 1.044]	0.82
Alberca & Parte (2018)	0.658	[0.244, 1.072]	0.46
Alberca & Parte (2018)	0.730	[0.422, 1.038]	0.83
Alberca & Parte (2018)	0.721	[0.400, 1.042]	0.76
Alberca & Parte (2018)	0.632	[0.260, 1.004]	0.57
Alberca & Parte (2018)	0.596	[0.237, 0.955]	0.61
Alberca & Parte (2018)	0.592	[0.216, 0.968]	0.56
Alberca & Parte (2018)	0.595	[0.219, 0.971]	0.56
Alberca & Parte (2018)	0.607	[0.227, 0.987]	0.54
Alberca & Parte (2018)	0.686	[0.306, 1.066]	0.54
Alberca & Parte (2018)	0.685	[0.397, 0.973]	0.95
Alberca & Parte (2018)	0.686	[0.306, 1.066]	0.54
Kukanja & Planinc (2019)	0.830	[0.531, 1.129]	0.88
Planinc & Kukanja (2019)	0.670	[0.232, 1.108]	0.41
Kukanja & Planinc (2020)	0.850	[0.561, 1.139]	0.94

many contexts, it is more common to find data of only more efficient DMUs. In our results, the use of CRS positively affects average efficiency scores. In the literature, it is clear that the VRS specification is a safer alternative when there are relevant omitted variables or when the model specification includes unnecessary variables (Galagedera & Silvapulle 2003). When non-necessary variables are included in the specification, estimating a DEA which assumes CRS overestimates efficiency with respect to the case where increasing return to scale is assumed. However, sample size does not present a strong significance, since the logarithm of `SampleSize` coefficient is significant at 5%.

Table 4: **Meta-regression results**

The table reports the results of the fixed-effects meta-regression implemented using the inverse-variance method. Standard errors are reported in parentheses. All values are rounded to the third digit. *** p<0.01, ** p<0.05, * p<0.1

Variable	Coefficient
`CRSMethod`	0.097***
	(0.036)
log(`SampleSize`)	-0.050**
	(0.024)
`InputOrientation`	0.008
	(0.041)
`Outputs`	0.016
	(0.013)
`Inputs`	-0.001
	(0.006)
`WeightedCitations`	-0.000
	(0.003)
Observations	77

Figure 1 reports the forest plot considering the two subgroups given by CRS and VRS models and the two subgroups of small and large sample size, built so that around 50% of observations are in each subgroup (small sample size subgroup contains models estimated with less than 46 observations, accounting for 51.95% of the total observations).[18] The figure and the tests confirm the results reported in Table 4. In general, there seems to exist some heterogeneity in the studies covering the efficiency of restaurants, but the Q-test does not capture it since it is not very impacting on the average coefficients. From our analysis, a suggestion to the scholars who use DEA to study restaurant efficiency is to carefully impose the proper assumption concerning the return to scale used in the model, since this has an impact on the estimated efficiency. CRS should be used only when one can assume full

[18]The `LargeSample` dummy used in Figure 1 is equal to 1 if `SampleSize` is higher than 45. Recall that the theoretical range within which θ can fall (i.e., $[0, 1]$) should be considered when interpreting the meta-significance test reported in the figure (where $H_0 : \theta = 0$).

proportionality between inputs and outputs. Still, this assumption cannot be always made in the restaurant industry, where the production function uses both physical and intangible inputs. The latter, such as creativity, cultural features, marketing strategies, etc., could likely have a nonproportional impact on outputs.

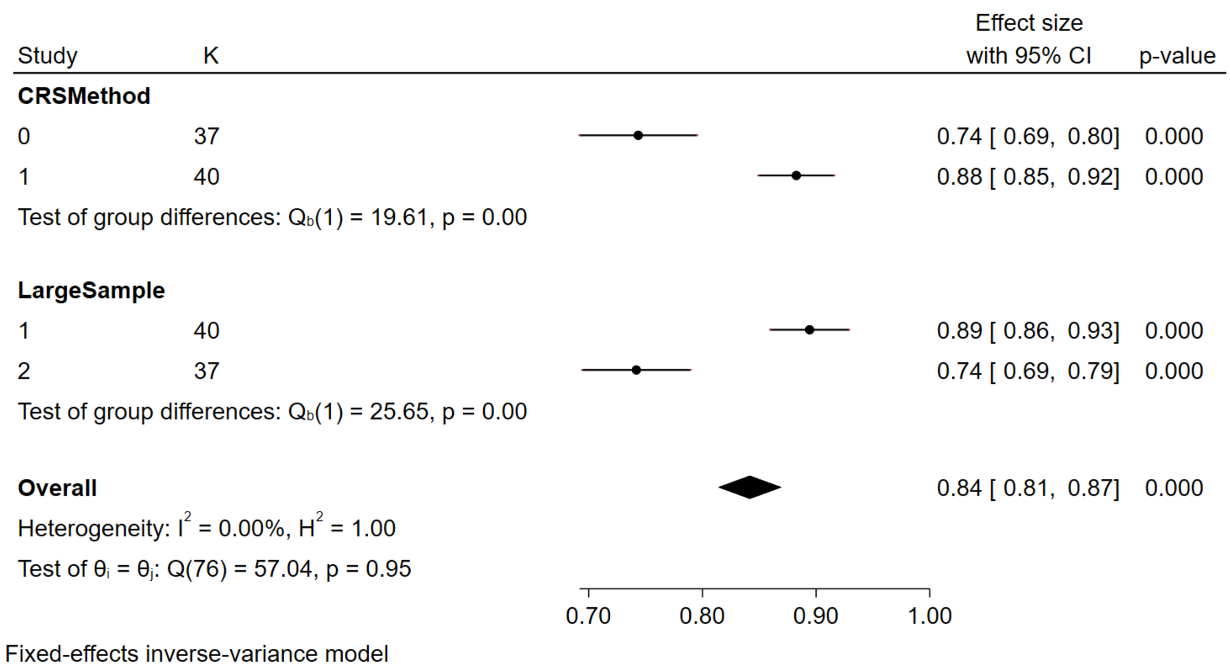

Figure 1: Forest plot on subgroups built on `CRS` and `LargeSample`

4 Conclusions

The focal role of the foodservice sector concerns its economic contribution to GDP and its spillover effects on other contiguous sectors. Moreover, its innate propensity to convey local and national cultures, traditions, and identities thrusts the sector into the public and academic spotlight. Efficiency studies in the foodservice industry can be used as a tool to enhance competitiveness in the restaurant sector and to understand whether the economic decisions and the organizational strategies adopted by restaurants are efficient. Moreover, efficiency enhancement in the foodservice industry spills over and positively affects contiguous and linked sectors such as the tourism industry. In the last 20 years, the academic interest in restaurants efficiency assessment has grown, and a large number of studies on this topic allows us to compare the efficiency of several types of restaurants and to check for the presence of heterogeneity in the results of the studies and, if present, which are its sources. Starting from an overview of the frontier analyses about restaurant efficiency (Section 2), we analysed the benchmarking studies of restaurant efficiency in the economic literature up to November 2020, collecting studies from the two most used approaches for frontier analyses, SFA and DEA. Despite Rodgers & Assaf (2006) having recommended adopting the SFA approach in restaurant efficiency analysis to take measurement errors into account, most of the studies on restaurant efficiency made use of DEA, so we focused only on this approach for our meta-analysis (Section 3). Our analysis is based on 77 observations from 25 studies published in scientific journals between 1998 and 2020. The estimated effect size in our meta-analysis is equal to 0.842 (with a 95% confidence interval ranging between 0.814 and 0.870) and it is statistically different from zero. The Cochran's Q test for the heterogeneity in our sample hints at the absence of heterogeneity in the previous studies on restaurant efficiency. However, we also developed a meta-regression to check for possible misleading results of the Q-test given its low power, and we found that both the method used (CRS vs. VRS) and the sample size have an impact on the average efficiency score, suggesting that a source of heterogeneity exists within the models in our sample. Our results also suggest carefully considering the choice between CRS and VRS when performing a DEA on efficiency in the restaurant sector, given that the assumption on proportional inputs and outputs needed to apply the CRS method is not always appropriate in the restaurant sector.

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