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# Evaluating the efficiency of Korean festival tourism and its determinants on efficiency change: Parametric and non-parametric approaches☆

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ABSTRACT

Local festivals may leverage local specialties and various historical, cultural, and artistic resources throughout their respective regions to attract tourists, inducing positive economic impacts. In this study, this paper is a first attempt to analyze the relative efficiency of local festival tourism by using parametric and non-parametric approaches with the data from local festivals held in Korea from 2015 to 2018. We also deal with the efficiency determinants of each typology of festivals by employing a truncated regression with double bootstrapping. Results showed that the leading sources of inefficiency were primarily embedded in pure technology inefficiency, while the principal operational drivers posed different effects depending on the typology of festivals. These insights have important practical implications for the local festival organizing committees and operators in Korea and are helpful in developing tailored operational strategies to maximize the efficiency among different typologies of festivals.

## 1. Introduction

Festival tourism, which refers to the attraction of visitors to local festivals by using a local region's tourism resources, is one of the fastest-growing fields in the tourism industry (O'Sullivan & Jackson, 2002; Getz & Page, 2016). Local festivals may leverage a variety of local specialties and the various historical, cultural, and artistic resources available in the region to attract tourists, inducing positive economic ripple effects, which can revitalize local economies, and creating new jobs (Getz, 2008; Lee et al., 2011; Mules & Dwyer, 2006, pp. 206–223). In particular, the representative local festivals have gained worldwide reputation such as *Oktoberfest*, *Edinburgh International Festival*, *Sapporo Snow Festival*, *Rio Carnival*, *Burning-man festival*, *Gilroy Garlic Festival*, *Menton Lemon Festival*, and *Arena di Verona Opera Festival*. These renowned events not only play a role in creating favorable national images but also draw millions of tourists from around the world, thereby creating enormous economic and social value to the individual nation (Alves, Cerro, & Martins, 2010; Zhang, Fong, & Li, 2019). For instance, *Oktoberfest*, which has become known as the world's largest beer event, drew approximately 7.2 million tourists to Munich in 2019, where they consumed 6.9 million liters of beer, 550,000 chickens, and 172 cows, thus amounting to an economic value of 1.2 billion euros (www.oktoberfest.net). In 2014, Japan's *Sapporo Snow Festival* generated direct and indirect economic effects estimated at 41.9 billion yen with 2.4 million tourists, which was 150 times greater than the 29 million yen investment made by the local government in order to host the festival (en.prothomalo.com/opinion/Sapporo's-snow-for-economic-benefits).

With the growing awareness that local festivals can improve regional images while boosting the local economy and further inducing the employment of local residents, festival events utilizing various regional arts and cultural resources are competitively held from around the world. As of 2019, there were approximately 1110 music festivals, 1093 film festivals, and 1930 festivals related to food and beverages in the United States alone (www.festforums.com). The numbers are even greater in China, where more than 5000 local festivals are held each year (Lu et al., 2009).

However, the recent surge in excessive competition among local festivals has been posing a serious threat to the overall sustainability of festival tourism (O'Sullivan & Jackson, 2002; Van Heerden & Saayman, 2018). According to Van Heerden and Saayman (2018), more than 600 festivals are held every year in South Africa, but despite the continually increasing number of events, the number of attendees has been

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plummeting. O'Sullivan and Jackson (2002) also empirically investigated that economic profits of the festivals decrease in proportion to the number of festivals.

In Korea, 884 local festivals were celebrated in 2019 (kto.visitkorea.or.kr), but a number of festivals, except a few successful local events, trigger relatively low economic effects compared to the investment made by their respective local government. This was mainly due to a lack of festival-specific visions or values and the poor operation management. Additionally, several local festivals resulted in low tourist satisfaction with poor festival programs, insufficient infrastructure, and service policies that did not meet the needs of tourists effectively. Accordingly, some controversies have recently been raised over whether or not to continue holding the local Korean festivals.

In this backdrop, study 1 employed parametric stochastic frontier analysis (SFA) to estimate the efficiency in four typologies of local festivals held in Korea from 2015 to 2018. Within the context of thin and short panel data, a simple and naive approach is to pool the data across different periods (Du et al., 2018). Accordingly, this study considered the period from 2015 to 2018 as a cross-sectional analysis, to pool the festivals of each typology for the period comparing them as a cross-section analysis and then compared the average festival groups. Local festivals can generally be categorized based on their materials, and the motivation of festival attendees; different festivals tend to set different goals and operational strategies, depending on the type of festival (Crompton & McKay, 1997; Getz & Page, 2016; Lee et al., 2004; Ma & Lew, 2012; Nicholson & Pearce, 2001; Scott, 1995). Previous studies investigated the different motivations of visitors attending various festivals with different characteristics. Scott (1995) compares visitors' motivation for visiting three festivals: *the holiday lights festival, the bug fest,* and *the maple sugaring festival*. They categorized motivational factors into six dimensions: event excitement, nature appreciation, curiosity, sociability, family togetherness, and escape from routine. Nicholson and Pearce (2001) highlight the diversity in motivation to attend different events using a comparative analysis of the visitors' motivations to events such as food and beverage festivals, a country and music festival, and an air show. Ma and Lew (2012) argue that different festival types have different challenges. They classified Chinese festivals into four categories—*local heritage*, *local modern*, *national heritage*, and *global modern*—according to historical and geographic dimensions of the events. Local identity, uniqueness, fun/liminality, and authenticity were mentioned as important concerns that affected the dimensions. They further state that for event managers to plan the festival successfully, it is necessary to focus on these issues, which are related to the different types of festival. In Korea, regional festivals are classified into four different typologies based on the main themes and contents of the festival, including *culture and art* (e.g., music, dance, opera, theater), *local specialty products* (e.g., beer, lemon, garlic, rice wine, tulip), *ecological and/or nature-related* (e.g., snow, purple butterflies, cherry blossom, whale), and *historical and/or cultural heritage* (e.g., shamanism, Confucianism). In study 1, we estimated the festival performance of four different typologies, based on the translog output distance function, and compared the results using two approaches: parametric SFA and non-parametric DEA (data envelopment analysis).

In study 2, we measured metafrontier technical efficiency (TE*), technical efficiency (TE), and technology gap ratio (TGR) by using metafrontier DEA methodology to compare the efficiencies among different festival groups with heterogeneous production technologies. We also analyzed the causes of inefficiency, returns to scale, and fluctuation patterns of metafrontier index values, thereby providing subsequent insights for festival organizers and operators. Furthermore, we demonstrated the efficiency determinants of each typology of festivals by employing truncated regression with double bootstrapping, as suggested by Simar and Wilson (2000, 2007a), for identifying the key drivers of efficiency variation. Accordingly, we attempted to figure out major operational variables that affected efficiency change in each typology of local festivals, while addressing strategic operational initiatives tailored to individual festival groups in order to improve contemporaneous efficiency. The research issues of interest in this study are:

(1) Are there any differences in technical efficiency estimates using parametric and non-parametric approaches among the different typologies of local festivals in Korea?
(2) What are the major sources of inefficiency observed among different local festivals group?
(3) What are the fluctuation patterns of TE*, TE, and TGR among different local festival groups?
(4) What are the festival-specific determinants that affect technical efficiency of each festival group?

Through studies 1 and 2, we thus offer three theoretical and managerial contributions:

• While the vast amount of previous studies have measured the efficiency for specific aspects of tourism, such as restaurants (Alberca & Parte, 2018; Reynolds & Thompson, 2007), airlines (Choi, 2017; Merkert & Hensher, 2011; Yu et al., 2019) and hotels (Assaf et al., 2010; Barros, 2005; Lado-Sestayo & Fernández-Castro, 2019; Oukil et al., 2016), previous applications of SFA and DEA models in the field of festival tourism have been scarce. In particular, this paper is a first attempt to analyze the efficiency of festival tourism via parametric and non-parametric approaches.

• According to the results of the metafrontier analysis, there were significant mean differences in metafrontier technical efficiency among festival groups. The average TE* in the *local specialty product festivals* group was the highest, while the TE* of the *ecological and/or natural-related* group was the lowest. Furthermore, the main driver of inefficiency in local Korean festivals was mostly stated to be pure technology inefficiency, which was further negatively affected by operational inefficiency. In particular, most *ecological and/or natural-related* festivals showed pure technology inefficiency, having the lowest TE* values. Thus, this group requires innovative operating policies and strategic benchmarking initiatives to improve its operational efficiency.

• Lots of festivals in the *local specialty product festivals* group have relatively longer histories and offer well-known local food traditions that imprint stronger images upon potential tourists. This widespread recognition produces a more stable festival operation, compared with those in other groups, and ultimately leads to more consistent metafrontier index values.

• This study empirically identified which operational factors affected the efficiencies for four typologies of the local festival. Our results showed the efficiencies of the categorized festival groups are influenced by different explanatory factors, thus suggesting that festival organizing committees and operators require tailored operational strategies to maximize their efficiency.

The rest of this research is structured as follows. The previous literature on festivals is presented in section 2. The research model and empirical data used in this study are presented in Section 3. Section 4 estimates the parametric efficiency for four local festival parties. In section 5, we performed the metafrontier analysis and compared results to those of SFA. Using the Simar and Wilson approach, we evaluated the impact of contextual variables on efficiency for the festival group in section 6. Section 7 discusses the theoretical and practical implications as well as study limitations.

## 2. Literature review for festival

From the cultural and anthropological perspective, festivals are sacred and/or religious celebrations. However, there are various wordings for this in the literature. For example, according to Pieper (1965), a festival is composed of *religious rituals and celebration*, while Falassi (1987, pp. 1–10) explained it as *a sacred or profane time of celebration*. Nevertheless, festivals have become more diverse in form and theme over time, in which case the various definitions have also evolved. Indeed, they are no longer confined to the realm of the sacred, with many having transformed into *themed, public events* (Getz, 2005) that are generally visited by individuals in search of cultural enrichment, education, novelty remainder and socialization (Crompton & McKay, 1997). As festivals have recently become more extensively available and diverse in nature around the world, attendees have begun to desire more purposeful events with differentiated contents. Under these changing demands, festival tourism has become one of the core research area in the field of tourism management.

Most studies on festivals have focused on factors such as political and socio-cultural meaning (Crespi-Vallbona & Richards, 2007; Derrett, 2003; Jamal & Kim, 2005; Jeong & Santos, 2004; Reid, 2006; Sharpe, 2008), the motivations of attendees (Crompton, 2003; Dewar et al., 2001; Kim et al., 2010; Matheson et al., 2014), and economic impacts. However, due to a growing interest in the satisfaction levels and behaviors of festival attendees, many recent studies have highlighted issues related to festival operations, including their social impacts (Capocchi et al., 2020; Koizumi, 2016; Pavlukovic et al., 2017), branding (Garay & Morales Perez, 2020; Masiello et al., 2020), and stakeholder interests (Adongo et al., 2019; Weber & Hsu, 2021).

Table 1 shows a tabulation of previous studies on festivals based on the festival groups established in this study. Among the local specialty product type, most studies were focused on wine-themed festivals, while the culture and art festival type was associated with many studies on music festivals (e.g., folk and jazz). In Korea, previous studies have focused on the *Rice Cake* Festival (Kim et al., 2010), *Strawberry* Festival (Choo et al., 2016), *Ginseng* Festival (Yoon et al., 2010), and *Mud* Festival (Lee et al., 2011; Song et al., 2014).

As mentioned earlier, most festival studies have focused on satisfaction and behavioral intentions from the tourist's perspective (Getz, 2010). In this regard, few studies have analyzed operational efficiency or the strategic benchmarking policies used at festivals from the practitioner's perspective. While Van Heerden and Saayman (2018) measured the efficiency of the Inobos National Art Festival based on visitor satisfaction and perceptions of spending, their approach was limited in that it was impossible to conduct efficiency comparisons between groups with different production functions. In addition, most previous studies have concentrated on specific festivals, thus failing to offer tailored operational strategies that reflect the unique characteristics of various festivals and types. This study addressed this gap in the literature by categorizing 35 local Korean festivals held from 2015 to 2018 into four groups based on their themes and characteristics. We then conducted an SFA and metafrontier analysis to estimate the efficiency of these local festivals, with a particular focus on operating efficiency and best industry practices.

**Table 1**
Previous studies on four typologies of local festivals.

| Authors | Research | Target Festival | Category |
|---|---|---|---|
| Zhang et al. (2019) | Place attachment and festival satisfaction | International Parade (Macau) | Culture and Art Festivals |
| Pavluković et al. (2017) | Social and cultural impact | Exit (Serbia) & Sziget (Hungary) | |
| Yolal et al. (2016) | Impact on well-being of residents | Golden Boll Film (Turkey) | |
| Lee (2016) | Government policy and satisfaction/ loyalty | Music festivals (Taiwan) | |
| Rota and Salone (2014) | Neighborhood effect of festival | Paratissima (Italy Turin) | |
| Yan et al. (2012) | Programming quality determinants | Cultural and Tourism Festival (Beijing) | |
| Lau and Li (2019) | Effect of an urban festival: place theory approach | Wine & Dine Festival (Hong Kong) | Local Specialty Product Festivals |
| Velikova et al. (2017) | Festival satisfaction drivers | Wine festivals (southwestern US) | |
| Akhoondnejad (2016) | Tourist loyalty | Turkmen Handicrafts festival | |
| Choo et al. (2016) | Satisfaction and revisit intentions | Strawberry festival (Korea) | |
| Kim et al. (2010) | Determinants of festival participants' expenditures | Traditional Drink and Rice Cake (Korea) | |
| Yoon et al. (2010) | Measuring festival quality, satisfaction and loyalty | Ginseng festival (Korea) | |
| Gannon et al. (2019) | Festival quality, self-connection, and bragging | Cappadox festival (Turkey) | Ecological/ Nature-related Festivals |
| Lee et al. (2011) | Role of emotional and functional values in festival evaluation | Boryeong Mud Festival (Korea) | |
| Lawton and Weaver (2010) | Normative and innovative sustainable resource management | Birding festivals (US) | |
| Lawton (2009) | Sustainability and ecotourism | Birding festivals (US) | |
| Lee et al. (2007) | Role of quality and attendees' behavioral intention | Cajun Catfish Festival (US) | |
| Matheson et al. (2014) | Spiritual attitudes and visitor motivations | Beltane Fire Festival (Scotland) | Historical/ Cultural Heritage Festivals |
| Song et al. (2014) | Behavioral intention of visitors | Sancheong Herbal Festival (Korea) | |
| Lee et al. (2012) | Benefits of visiting a multicultural festival | The Global Village/ Colourful Multicultural Festival (US) | |
| Ryan and Gu (2010) | Constructionism and culture in Buddhist festival | Wutaishan Buddihist festival (China) | |
| Litvin and Fetter (2006) | Festival-driven benefits and local hotels | Spoleto festival (US) | |

## 3. Research model and empirical setting

### 3.1. Research model

The individual local festivals were set as decision-making units (DMUs), then chosen based on the following criteria: (1) held by local residents, local organizations, or local governments in Korea, (2) held for more than three days, and (3) open to the public. See Appendix A for the names of these festival groups, their locations, and DMU codes.

Festivals require a variety of human and/or material resources. Generally, central or local governments provide subsidies for this purpose (Frey, 2019, pp. 63–70). In this regard, the festival budget is a critical input variable for measuring relative efficiency. The number of days the festival is held is also an important input variable (Bracalente et al., 2011), since tourists can only visit the festival when it is open. Tentatively, this means there is a higher potential for tourist visitation the longer the festival is held. Accordingly, festival budgets and durations were used as the input variables. On the other hand, it is critical for these festivals to induce local economic effects, either directly or indirectly, by maximizing the total number of tourists (Alberca-Oliver et al., 2015; Andersson & Getz, 2009; Fuentes, 2011). Thus, the total number of festival visitors and its economic impacts were used as the output variables. The economic impacts of individual festivals are calculated using quantitative indicators from the annual *Comprehensive Evaluation of Local Festivals* survey published by the Korean Ministry of Culture, Sports, and Tourism. According to this annual report, the economic impacts of the festivals is divided into two categories: direct revenue and indirect estimated economic impact. First, direct revenue is annually measured by multiplying the total number of festival attendees by the average tourist consumption expenditure calculated by *travel cost* method. Second, indirect economic effects of regional festivals are theoretically projected using the associated industrial inducement coefficients from the *regional input-output* statistics, which are divided into production, value-added, imports, and labor. However, indirect economic effects cannot be accurately calculated due to the practical difficulty of festivals-related industrial classification. As a result, the economic impacts of festivals employed as an output variable of this study primarily include the direct festival revenue. Fig. 1 shows the input/output variables of SFA and meta-efficiency and the potential efficiency determinants.

### 3.2. Empirical data

This study obtained data on festival budgets from the annual public reports on local festivals published by the Ministry of Culture, Sports and Tourism (www.mcst.go.kr), while data on festival durations were collected based on the festival dates announced for each local festival. The total number of festival visitors and economic impacts of the individual festivals were extracted from the annual report released by the Korean Ministry of Culture, Sports and Tourism. Generally, most festivals strive to trigger socio-economic benefits for their respective regions by maximizing the number of festival tourists, which ultimately ensures sustainable festival growth. As such, this study adopted output-oriented model to estimate efficiency scores of local Korean festivals held from 2015 to 2018 using the SFA and DEA. Table 2 summarizes the descriptive statistics related to the input and output variables for each typology of local Korean festivals from 2015 to 2018. In this study, we employed the LIMDEP 11 and MaxDEA 8.9 software to measure the SFA and metafrontier DEA estimations, and conducted the Simar and Wilson's truncated regression with bootstrapping using the STATA 16 software.

To confirm the strength and direction of association that exists between input and output variables, this study used Pearson correlation coefficients (0.01 significant level, two-tailed). As seen in Fig. 2, there was a moderate positive correlation between inputs and outputs. For instance, the number of festival visitors was found to have the lowest ($r = .3852$, $p < .000$) correlation coefficient with the festival budget and the highest ($r = .8052$, $p < .000$) with the economic impacts of festival.

## 4. Study 1: measurement of Korean festival efficiency using stochastic frontier analysis

### 4.1. Stochastic frontier analysis (SFA)

The SFA, originally developed by Aigner et al. (1977), has been adopted in many existing literatures for the purpose of an economic modeling such as production, cost, revenue, profit, and other models of goal attainment. The canonical formulation that serves as the foundation for other variations is as following.

$$lny_{it} = x_{it}\beta + v_{it} - u_{it} \ (i = 1, \ldots, I, \ t = i, \ldots, T) \tag{1}$$

where $y_{it}$ is the vector representing produced quantities by the unit of production $i$ in period $t$; $x_{it}$ is a $K+1$ vector containing the logarithms of inputs used by the unit of production in period $t$; $\beta$ is the vector to be estimated; and $v_{it}$ and $u_{it}$ are vectors that represent distinct error components. Further, $v_{it}$ is the noise or random part of error with independent and identically distributed (*iid*) normal distribution, and truncated in zero and variance $\sigma_v^2[v_{it} \sim iid\, N(0, \sigma_v^2)]$; $v_{it}$ is assumed to have constant variance (homoskedasticity). Additionally, $u_{it}$ is a non-negative random variable related to technical inefficiency and it constitutes a deviation in relation to the production frontier; $u_{it}$ is a non-negative random variable with variance $\sigma_u^2[u_{it} \sim iid\, N^+(0, \sigma_u^2)]$ under the assumptions of a half-normal distribution. The parameters of the stochastic frontier function are estimated by the maximum likelihood (ML) method. Estimation of the stochastic frontier is facilitated by the use of the reparameterization, as proposed by Battese and Coelli (1992) and Kumbhakar and Lovell (2000), $\sigma^2 = \sigma_u^2 + \sigma_v^2$, $\gamma = \sigma_u^2/\sigma^2 (0 \le \gamma \le 1)$. This study tailored the translog output distance approach to evaluate festival efficiency by considering multiple inputs and outputs. The translog distance function with $m$ inputs and $s$ outputs is expressed as follows:

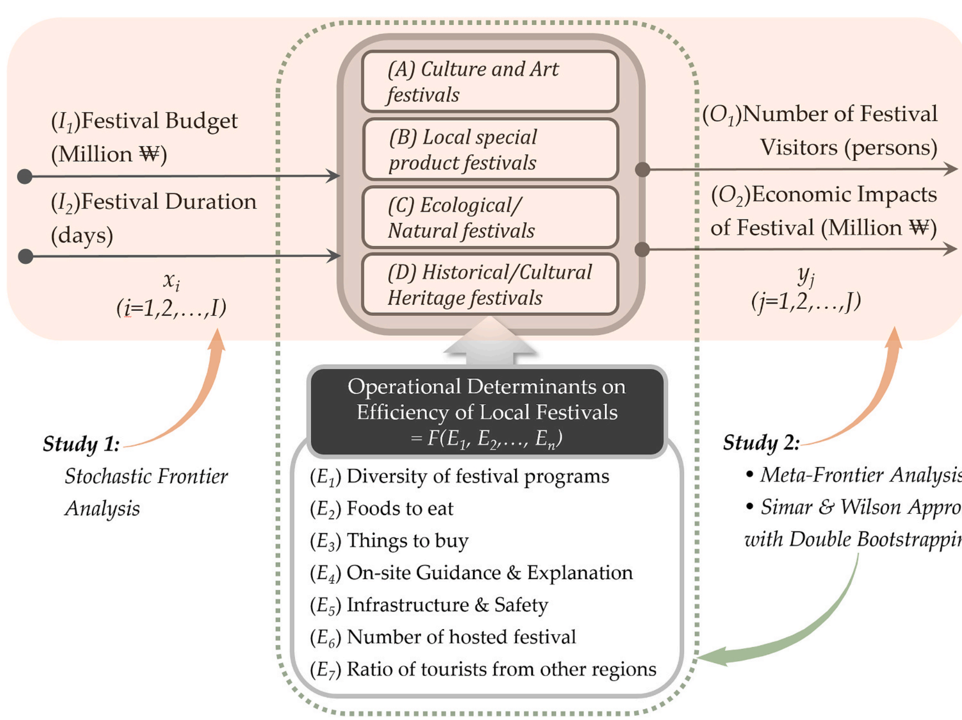



**Fig. 1.** Research model for festival efficiency.

**Table 2**
Input-output variables for local Korean festivals.

| Year | | | | Input Variables | | Output Variables | |
|---|---|---|---|---|---|---|---|
| | | | | ($I_1$) Festival Budget (Million ₩) | ($I_2$) Festival Duration (Days) | ($O_1$) Number of Festival Visitors (Person) | ($O_2$) Economic Impacts of Festival (Million ₩) |
| (A) | N = | Max/Min | | 3009/567 | 23/3 | 2,142,649/71,415 | 129,850/7000 |
| Culture and Art Festivals | 40 | Mean(S.D.) | | 1301.4(643.2) | 8.0(5.7) | 528,402.3(591,062.9) | 27,968.2(28,159.5) |
| | | Skewness/kurtosis | | 1.436/1.608 | 1.852/2.939 | 1.666/1.489 | 2.334/4.941 |
| | | Quantile | (25%) | 870.00 | 4.00 | 194,555.25 | 13,349.50 |
| | | | (50%) | 1211.50 | 6.50 | 274,483.50 | 17,118.50 |
| | | | (75%) | 1504.00 | 9.75 | 535,513.50 | 25,776.50 |
| (B) | N = | Max/Min | | 2052/624 | 11/3 | 830,000/51,053 | 25,500/2190 |
| Local Special Product Festivals | 35 | Mean(S.D.) | | 850.1(300.8) | 5.0(2.3) | 274,304.3(162,143.5) | 13,840.2(7920.7) |
| | | Skewness/kurtosis | | 2.533/7.134 | 1.716/2.418 | 1.170/2.493 | .087/-1.488 |
| | | Quantile | (25%) | 688.00 | 3.00 | 148,064.00 | 7043.00 |
| | | | (50%) | 740.00 | 5.00 | 265,306.00 | 12,083.00 |
| | | | (75%) | 854.00 | 5.00 | 405,032.00 | 21,689.00 |
| (C) | N = | Max/Min | | 1884/595 | 10/4 | 1,102,358/120,746 | 57,000/8029 |
| Ecological/Natural Festivals | 20 | Mean(S.D.) | | 1157.0(423.0) | 7.6(2.1) | 368,217.9(285,377.2) | 19,945.4(14,347.9) |
| | | Skewness/kurtosis | | .208/-1.465 | -.750/-.563 | 1.532/1.858 | 1.390/1.274 |
| | | Quantile | (25%) | 750.00 | 7.00 | 142,693.00 | 9181.25 |
| | | | (50%) | 1170.00 | 8.00 | 265,993.00 | 12,999.00 |
| | | | (75%) | 1584.75 | 9.00 | 456,216.00 | 12,654.25 |
| (D) | N = | Max/Min | | 1980/400 | 5/3 | 672,031/54,433 | 31,426/1876 |
| Historical/Cultural Heritage Festivals | 36 | Mean(S.D.) | | 904.6(408.5) | 4.1(0.9) | 25,4242.9(142,058.6) | 12,099.1(7785.9) |
| | | Skewness/kurtosis | | 1.254/1.262 | -.168/-1.701 | .963/1.251 | .747/-.359 |
| | | Quantile | (25%) | 603.00 | 3.00 | 125,233.25 | 5831.00 |
| | | | (50%) | 815.00 | 4.00 | 239,064.50 | 10,191.00 |
| | | | (75%) | 1098.75 | 5.00 | 329,398.75 | 16,698.25 |

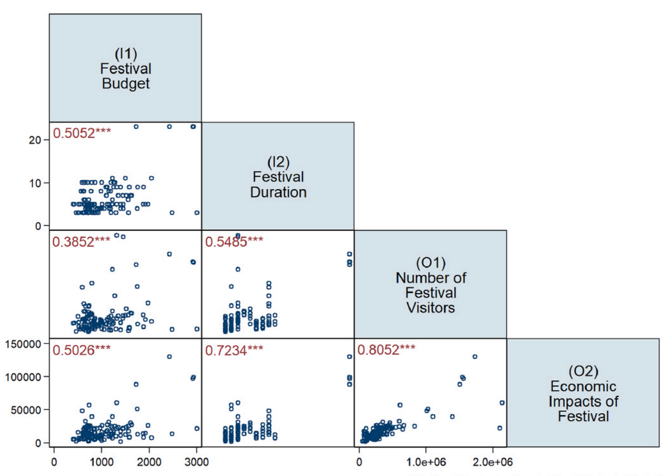



**Fig. 2.** Correlation matrix between input and output variables.

$$\ln D_{okt} = \alpha_0 + \sum_{r=1}^{s}\alpha_r \ln y_{rkt} + \tfrac{1}{2}\sum_{q=1}^{s}\sum_{r=1}^{s}\alpha_{qr}\ln y_{qkt}y_{rkt} + \sum_{i=1}^{m}\beta_i \ln x_{ikt} + \frac{1}{2}\sum_{h=1}^{m}\sum_{i=1}^{m}\beta_{hi}\ln x_{hkt}\ln x_{ikt} + \sum_{i=1}^{m}\sum_{r=1}^{s}\delta_{ir}\ln x_{ikt}\ln y_{rkt} + v_{kt} \tag{2}$$

To maintain the homogeneity conditions, certain restrictions need to be imposed. These conditions require the constraints $\sum_{r=1}^{s}\alpha_r = 1$, $\sum_{r=1}^{s}\alpha_{qr} = 1$, and $\sum_{r=1}^{s}\delta_{ir} = 1$, while symmetry restrictions require $\alpha_{qr} = \alpha_{rq}$ and $\beta_{hi} = \beta_{ih}$. The homogeneity restrictions can be imposed by normalizing the function by one of the outputs (for a more detailed illustration, see Coelli & Perelman, 1999; Coelli et al., 2005; and Kumbhakar et al., 2015). In this study, the stochastic frontier distance function is estimated in the translog function with $m$ inputs and $s$ outputs, as follows:

$$\ln y_{skt} = \alpha_0 + \sum_{r=1}^{s-1}\alpha_r \ln y^*_{rkt} + \tfrac{1}{2}\sum_{q=1}^{s-1}\sum_{r=1}^{s-1}\alpha_{qr}\ln y^*_{qkt}\ln y^*_{rkt} + \sum_{i=1}^{m}\beta_i \ln x_{ikt} + \frac{1}{2}\sum_{h=1}^{m}\sum_{i=1}^{m}\beta_{hi}\ln x_{hkt}\ln x_{ikt} + \sum_{i=1}^{m}\sum_{r=1}^{s-1}\delta_{ir}\ln x_{ikt}\ln y^*_{rkt} + v_{kt} - u_{kt} \quad (k=1,2,\cdots,n,\ t=1,2,\ldots,T) \tag{3}$$

where $y^*_{rkt} = y_{qkt}/y_{skt}$. We need to impose symmetry restrictions in the translog output function, *i.e.*, $\alpha_{hi} = \alpha_{ih}$ and $\beta_{qr} = \beta_{rq}$. $v_{kt}$ is the statistical noise, which is assumed to be an independent normally-distributed random error term. Moreover, $u_{kt}$ is an unobserved technical inefficiency component that follows a nonnegative random one-sided error term, assuming a half-normal distribution, and $v_{kt} - u_{kt}$ constitutes a compound error term of a stochastic production frontier (Battese & Coelli, 1992). This study derives an answer by applying a stochastic translog output distance function, with inefficiency effects to pooled data for the local Korean festivals from 2015 to 2018 as follows:

$$\ln y_{2kt} = \alpha_0 + \alpha_1 \ln\left(\frac{y_{1kt}}{y_{2kt}}\right) + \tfrac{1}{2}\alpha_{11}\left(\ln\left(\frac{y_{1kt}}{y_{2kt}}\right)\right)^2 + \beta_1 \ln x_{1kt} + \beta_2 \ln x_{2kt} + \frac{1}{2}\beta_{11}(\ln x_{1kt})^2 + \frac{1}{2}\beta_{22}(\ln x_{2kt})^2 + \beta_{12}\ln x_{1kt}\ln x_{2kt} + \delta_{11}\ln x_{1kt}\ln\left(\frac{y_{1kt}}{y_{2kt}}\right) + \delta_{21}\ln x_{2kt}\ln\left(\frac{y_{1kt}}{y_{2kt}}\right) + v_{kt} - u_{kt} \tag{4}$$

where $k$ and $t$ are the subscripts denoting the local Korean festival and the year, respectively. Two inputs were employed in the production frontier: festival budgets ($x_{1kt}$), festival durations ($x_{2kt}$), while two output measures are included in the production function: total number of festival visitors ($y_{1kt}$) and economic impacts of the individual festivals ($y_{2kt}$). The technical efficiency of a festival is defined as the ratio of the measured output to the maximum possible output, defined by a particular level of inputs used by the festival. Thus, the technical efficiency of festival $k$ at time $t$ can be expressed as follows:

$$\begin{aligned} TE_{kt} &= \exp(-u_{kt}) \\ &= E\left[\exp(-u_{kt})/(v_{it}-u_{kt})\right] \\ &\quad (0 \le TE_{it} \le 1) \end{aligned} \tag{5}$$

### *4.2. Empirical results of SFA*

The estimated parameters for the translog output distance function are reported in Table 3. According to Table 3, when the model is correctly specified, the frontier parameters are appropriately estimated. However, we observed the presence of a strongly positive skewness of group (A)'s finite sample data in this case. While the SFA theory predicts that the least squares residuals will be negatively skewed in production frontiers, the estimated residuals may display positive skewness (Bonanno et al., 2017). The stability of the ML estimator and the *wrong skew* results are derived or simulated for common parametric assumptions on the inefficiency distribution (Kumbhakar et al., 2015; Hafner et al., 2018). Waldman (1982) demonstrates that if ordinary least square (OLS) residuals are skewed in the wrong direction, a solution for the ML estimator in the stochastic frontier model equals the OLS estimators for the slopes and for $\sigma_v^2$, and 0.0 for $\sigma_u^2$. This generally indicates that there is no evidence of inefficiency in the observation or measurement data (Greene, 2016). In this study, due to a huge standard error and estimate of $\sigma_u^2$, which is 0.00007, the estimate of $\lambda$ for group (A) has to be zero. The remaining estimates are the same as OLS estimators. The kernel density estimator for the OLS residuals is skewed in the positive (Fig. 3), the wrong direction (Greene, 1993; Hafner et al., 2018). This indicates a failure of the data conforming to the SFA model. The wrong skewness phenomenon seen in group (A) data implies an overall wrong skewness problem, as—according to the classical SFA—the technical inefficiency null hypothesis of positive skewness of the composed error would indicate that there are no inefficiencies and that all festivals in the sample are "*super*" efficient and should be rejected. Thus, the estimator of stochastic frontier modeling for group (A) is not provided in this study.

Table 3 includes an estimate of standard deviations of the two error components, $\sigma_u$, $\sigma_v$, and the estimates of the total error variance ($\sigma^2 = \sigma_u^2 + \sigma_v^2$) and the estimate of the ratio of the standard deviation of the

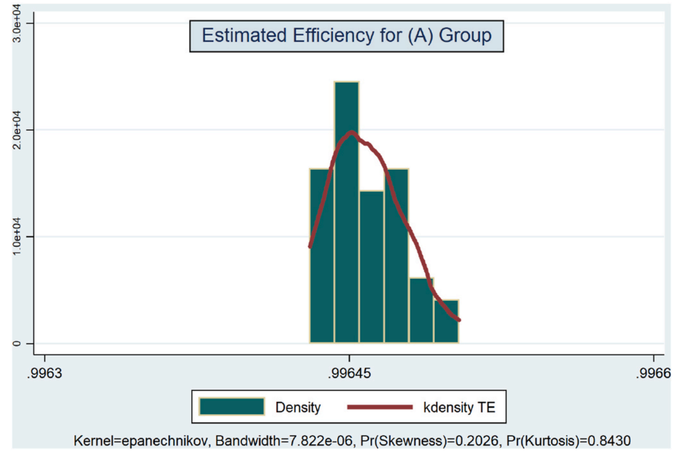



**Fig. 3.** Wrong skew problem of estimated efficiency for (A) group.

inefficiency to the total error component ($\gamma = \sigma_u^2/\sigma^2$) respectively. We also note that, $\gamma$ is close to one ($\gamma = 1$) for groups (B), (C), and (D), which indicates that the deviations from the average production frontier are due mostly to the one-sided technical inefficiency effect ($\sigma_u$). In particular, $\gamma$for group (A) is close to zero ($\gamma = 0.0000$), indicating that the variance of the technical inefficiency effect is equal to zero and therefore, the model is simplified to the traditional mean response function with parameters that can be consistently estimated by OLS.

Furthermore, the LogL (Log Likelihood Ratio) statistic compares the values of likelihood functions under null hypothesis $H_0 : \sigma_u^2 = 0$ ($H_1 : \sigma_u^2 \succ 0$). If the null hypothesis is true, the stochastic frontier model is simplified into an OLS model. As shown in Table 3, $\chi_q^2$ equals 10.251 (B), 12.763 (C), and 15.733 (D) for half-normal, with a relatively low AIC (Akaike Information Standard)/N of 0.584, 0.694, and 1.397, respectively. Therefore, the null hypothesis of groups (B), (C), and (D)—that there is no technical inefficiency, i.e. $\sigma_u = 0$—is strongly rejected at a 1% statistical significance level. However, $\chi_q^2$ of group (A) equals 0.000; therefore, the null hypothesis is retained. Finally, in three groups shown in Table 3, the generalized log likelihood shows that variables

**Table 3**
Stochastic frontier maximum likelihood estimates using LIMDEP 11 software.

| Para-meter | Variable | (A) Group | (B) Group | | | (C) Group | | | (D) Group | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Coef. | S.E. | z | Coef. | S.E. | z | Coef. | S.E. | z |
| $\alpha_0$ | Constant | N/A | −6.324 | 20.571 | −0.31 | −61.044 | 51.846 | −1.18 | −33.275[a] | 18.263 | −1.82 |
| $\alpha_1$ | $\ln(y_1/y_2)$ | : Wrong Skew | 25.764 | 20.915 | 1.23 | 29.583** | 13.333 | 2.22 | −10.367*** | 3.768 | −2.75 |
| $\alpha_{11}$ | $0.5\ln(y_1/y_2)^2$ | | 6.233*** | 2.300 | 2.71 | −2.997 | 4.179 | −0.72 | −1.573*** | 0.230 | −6.85 |
| $\beta_1$ | $\ln x_1$ | | 10.068 | 12.423 | 0.81 | 23.615[a] | 12.465 | 1.89 | 14.051** | 6.857 | 2.05 |
| $\beta_2$ | $\ln x_2$ | | 26.827*** | 8.486 | 3.16 | 31.958*** | 9.068 | 3.52 | −28.119** | 12.182 | −2.31 |
| $\beta_{11}$ | $0.5\ln {x_1}^2$ | | −0.901 | 2.748 | −0.33 | −1.869 | 1.558 | −1.20 | −2.317** | 1.019 | −2.28 |
| $\beta_{22}$ | $0.5\ln {x_2}^2$ | | −4.309*** | 2.142 | −2.01 | 1.283 | 1.396 | 0.92 | 2.450 | 5.426 | 0.45 |
| $\beta_{12}$ | $\ln x_1 \ln x_2$ | | −3.614*** | 1.263 | −2.86 | −8.644*** | 0.997 | −8.67 | 3.471*** | 1.223 | 2.84 |
| $\delta_{11}$ | $\ln x_1 \ln(y_1/y_2)$ | | −0.682 | 2.312 | −0.29 | −2.551 | 1.680 | −1.52 | 0.952* | 0.541 | 1.76 |
| $\delta_{12}$ | $\ln x_2 \ln(y_1/y_2)$ | | −1.863 | 1.217 | −1.53 | −9.552*** | 2.737 | −3.49 | −0.873 | 1.310 | −0.67 |
| $\sigma_v$ | | 0.95097 | 0.00002 | | | 0.00006 | | | 0.00020 | | |
| $\sigma_u$ | | 0.00007 | 0.45961 | | | 0.37565 | | | 0.69821 | | |
| $\sigma^2 = \sigma_u^2 + \sigma_v^2$ | | 0.90434 | 0.21124 | | | 0.14111 | | | 0.48750 | | |
| $\gamma = \sigma_u^2/\sigma^2$ | | 0.00000 | 1.00000 | | | 1.00000 | | | 1.00000 | | |
| Log Likelihood | | −54.74649 | 1.78676 | | | 5.06445 | | | −13.14292 | | |
| AIC/N | | 2.887 | 0.584 | | | 0.694 | | | 1.397 | | |
| LogL when sigma(u) = 0 | | −54.74649 | −3.33859 | | | −1.31726 | | | −21.00963 | | |
| $\chi_q^2$[a] = 2[LogL(SF)-LogL(LS)] | | 0.000 | 10.251 | | | 12.763 | | | 15.733 | | |

[a] Note: The likelihood-ratio test statistic has approximately $\chi_q^2$ distribution with $q$ equal to the number of parameters assumed to be zero in the null hypothesis. Critical values for the hypotheses are taken from Kodde-Palm (1986): 95%(2.706), 99%(5.412).

incorporated in the production function are all highly significant. This indicates that the null hypothesis are rejected at a 1% statistical significance level. The estimated SFA efficiencies for each local Korean festival type are presented in Appendix B.

## 5. Study 2: measurement of Korean festival efficiency using metafrontier analysis

### 5.1. Metafrontier analysis

Conventional DEA models is based on homogeneity assumption that the decision making units (DMUs) selected for analysis share the same production technology, and encounter single piecewise linear surfaces (Yu & Chen, 2020a). However, DMUs may have different environmental characteristics, in which case their production technologies may not be identical, potentially even belonging to different groups (O'Donnell et al., 2008). For instance, the local festivals investigated in this study may be heterogeneous depending on the unique characteristics of the group to which they belong. To account for the problem of bias in efficiency evaluation results stemming from heterogeneity between DMUs, Battese and Rao (2002), and O'Donnell et al. (2008) introduced a metafrontier model for different groups with different technologies. This model analyzes the technology gaps between different production groups and their efficiency levels by way of a decomposition result. The metafrontier technique consists of enveloping the groups of frontiers estimated through another frontier, which is referred to as metatechnology. This technique entails the estimation of the metatechnology and frontiers of relatively homogenous groups (O'Donnell et al., 2008; Yu & Chen, 2020b).

Suppose there are $J$ local festivals ($j = 1, \cdots, J$). Each of them produces outputs $y_{mj}$ ($m = 1, \cdots, M$), using inputs $x_{sj}$ ($s = 1, \cdots, S$). The local festivals can be categorized into $K$ groups, which employ different operating technologies, $T^k (k = 1, \cdots, K)$. The number of festivals belong to the $K$th group is $J^k$ and is subject to $\sum_{k=1}^{K} J^k = J$. In order to set up DEA model based on the linear programming formulation, we must include intensity variables $\lambda_j$ and $\mu_j$, which is non-negative, for the group frontier and metafrontier technologies. $\lambda_j$ and $\mu_j$ represent the degree to which local festivals, that achieve best practices and efficiency, are referred from certain inefficient DMU under evaluation (Yu & Chen, 2020b).

The frontier technology of $K$th group is defined as follows:

$$T^k = \left\{ (x,\ y) : \sum_{j \in J^k} \lambda_j y_{mj} \geq y_m, \sum_{j \in J^k} \lambda_j x_{sj} \geq x_s, \lambda_j \geq 0 \right\} \quad (m = 1, \cdots, M, s = 1, \cdots, S, j = 1, \cdots, J^k) \tag{6}$$

The group technology efficiency of festival $i$, $\theta_i^{Group}$, can be estimated from group frontier technology, to which the festival belongs, by solving the fractional problem of output-oriented model. The formulations are as follows:

$$\begin{aligned} &\left\{ D_i^G (x_s,\ y_m) \right\}^{-1} = \max \theta_i^{Group} \\ s.t. &\sum_{j \in J^k} \lambda_j \cdot y_{mj} \geq \theta_i^{Group} \cdot y_{mi},\ m = 1,\ \cdots, M \\ &\sum_{j \in J^k} \lambda_j \cdot x_{sj} \leq x_{si},\ s = 1,\ \cdots,\ S \\ &\lambda_j \geq 0,\ j = 1,\ \cdots,\ J^k \end{aligned} \tag{7}$$

In the optimization problem above, the objective function requires to maximize the output improvement potential $\theta_i^{Group}$ across all outputs. If $\theta_i^{Group} = 1$, which means the reciprocal $1/\theta_i^{Group}$ is also equal to 1, then festival $i$ operates on the frontier of group $K$. If $\theta_i^{Group} > 1$, then the value of reciprocal $1/\theta_i^{Group}$ is less than 1, and festival $i$ operates inside the frontier of $K$th group, which shows that festival $i$ is relatively less efficient than other festivals in the group. However, a metatechnology merges the entire set of measurements across all groups to form a single production set. Hence, the metatechnology can be defined as follows:

$$\begin{aligned} T &= \text{Convex Hull } \left\{ T^1 \cup \cdots \cup T^K \right\} \\ &= \left\{ (x,\ y) : \sum_{k=1}^{K} \sum_{j \in J^k} \mu_j^k \cdot y_{mj} \geq y_m,\ \sum_{k=1}^{K} \sum_{j \in J^k} \mu_j^k \cdot x_{sj} \geq x_s, \mu_j^k \geq 0 \right\} \\ &\quad \left( m = 1, \cdots M,\ s = 1, \cdots, S,\ k = 1, \cdots, K,\ j = 1, \cdots, J^k \right) \end{aligned} \tag{8}$$

The model for estimating the metatechnology efficiency of festival $i$, $\theta_i^{Meta}$, can be formulated as follows:

$$\begin{aligned} &\left\{ D^* (x_s,\ y_m) \right\}^{-1} = \max \theta_i^{Meta} \\ s.t. &\sum_{k=1}^{K} \sum_{j \in J^k} \mu_j^k \cdot y_{mj} \geq \theta_i^{Meta} \cdot y_{mi},\ m = 1,\ \cdots, M \\ &\sum_{k=1}^{K} \sum_{j \in J^k} \mu_j^k \cdot x_{sj} \leq x_{si},\ s = 1,\ \cdots,\ S \\ &\mu_j^k \geq 0,\ k = 1,\ \cdots,\ K,\ j = 1,\ \cdots,\ J \end{aligned} \tag{9}$$

If $\theta_i^{Meta} = 1$, then festival $i$ operates on the metafrontier. If $\theta_i^{Meta} > 1$, then festival $i$ operates inside the metafrontier and is inefficient in its frontier. $\theta_i^{Group*}$ and $\theta_i^{Meta*}$ denote the optimal objective values of group technology efficiency and metatechnology efficiency, respectively.

Further, a measure of how close a group-specific frontier is to the metafrontier can be obtained by comparing the output distance functions for the metafrontier and group frontiers (Battese et al., 2004; O'Donnell et al., 2008). Thus, TGR of festival $i$ was obtained by dividing the $\theta_i^{Meta*}$ by $\theta_i^{Group*}$ as equation (10). $\theta_i^{Meta*}$ and $\theta_i^{Group*}$ are the efficiency scores obtained under the metafrontier and the group frontier, respectively.

$$TGR_i = \frac{\theta_i^{Meta*}}{\theta_i^{Group*}} \tag{10}$$

The metafrontier envelops the group frontiers; therefore, $TGR_i \leq 1$. If the TGR gets close to 1, it means the $K$th group frontier and the metafrontier get closer, so that the gap between them decreases. Conversely, if the TGR gets smaller, it indicates that the gap between the $K$th group frontier and the metafrontier gets bigger. Thus, as noted by O'Donnell et al. (2008), meta-efficiency ($\theta_i^{Meta*}$), a technical efficiency measured according to the metafrontier can be broken down into group efficiency ($\theta_i^{Group*}$), technical efficiency measured according to the $K$th group frontier, and TGR, as follows:

$$\theta_i^{Meta*} = TGR_i \times \theta_i^{Group*} \tag{11}$$

Among other things, the group efficiency captures the existing state of knowledge and economic environment characterizing group $K$, while the TGR measures the distance between the $K$th group frontier and the metafrontier. The estimated DEA efficiencies for each local Korean festival group are presented in Appendix C.

### 5.2. Empirical metafrontier results

The 35 local festivals shared the homogeneous characteristic of being held for certain periods of time with budgets that were subsidized by central or local governments in order to attract tourists while creating economic impacts. However, their festival-seeking values and operational strategies appear to be somewhat different, according to their respective main themes and characteristics (Scott, 1995). In study 2, we first measured meta-efficiency for all 35 homogeneous local festivals held in Korea from 2015 to 2018, then categorized the festivals into four heterogeneous groups based on their themes and characteristics to measure their efficiency (TE) and then calculated the technology gap ratio (TGR).

#### 5.2.1. Changes in average TE*, TE, and TGR

Figs. 4–6 show the changes in TE, TE*, and TGR averages for all local festival groups. As shown in the figures, there were different patterns for average TE and TGR, based on the unique characteristics of individual festival groups.

The TE is an indicator for each festival's relative efficiency, compared with the maximum group efficiency; an increase in the average TE value implies that the efficiency of the festivals in a certain group has increased. Conversely, a rapid decline in average TE is because of the following two reasons: First, only a few festivals maximized their efficiency through operational innovations and ultimately facilitated the upward movement of the production frontier. An increased production function resulting from innovative festivals temporarily lowered the relative efficiency scores of the other festivals, thereby reducing the average TE. Second, the overall festival efficiency within a group simply declined due to the external risk factors, regardless of variations in the production frontier.

The average TE value of groups (A) and (D) showed the greatest fluctuation during the study period (Fig. 4). In 2016, the sharp decline in these groups' average TE was mainly due to external environmental factors, such as the outbreak of the *Middle East Respiratory Syndrome* (as called *MERS*), regardless of the change in TGR value. In particular, the *International Fireworks Festival* of group (A) and the *Horizon Festival* and *Dongnae Eupseong History Festival* of group (D) show very low TE scores in 2016, compared with 2015. Nonetheless, the average TE score recovered quickly in 2017, as the other festivals that are far from frontier production also benchmarked efficient festivals while gradually improving their overall operational efficiencies, thus causing an overall increase in average TE. This result indicates that the increase in average TE is caused by incremental innovation among festivals while maintaining the production frontier at a certain level. Group (B)'s TE shows relatively little variation, due to its festival-specific characteristics and the significant effects of economies of scale on efficiency. Most of the festivals in group (B) have very similar production functions during the study period (Fig. 4). Moreover, the average TE in group (C) was stable, showing no significant changes until 2017, when group (C)'s scores started increasing rapidly.

Meanwhile, TGR compares the maximum efficiencies of the different groups; it is expressed as the ratio of the metafrontier (maximum efficiency of all festivals) to the group frontier (maximum efficiency within the festival group; Battese et al., 2004). TGR indicates the potential input reduction of copying best practice metatechnology (Lin & Zhao, 2016).

The results of the TGR evaluation showed that group (B) achieved an average of 96.90% for potential payoffs, greater than other technology groups. In particular, group (B)'s average TGR continued to increase slowly, approaching 1. This implies that the technology of group (B) was

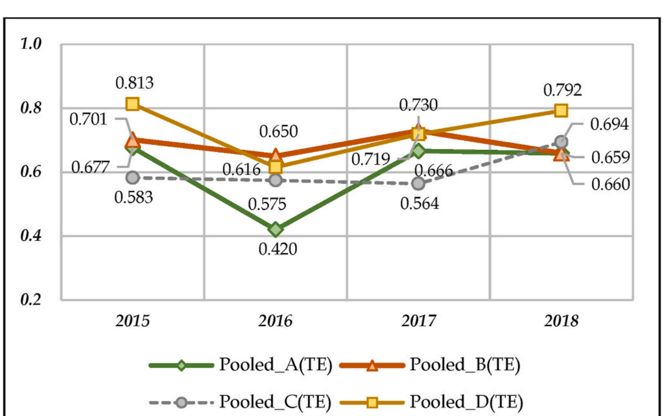



**Fig. 4.** Change in TE for pooled festival groups.

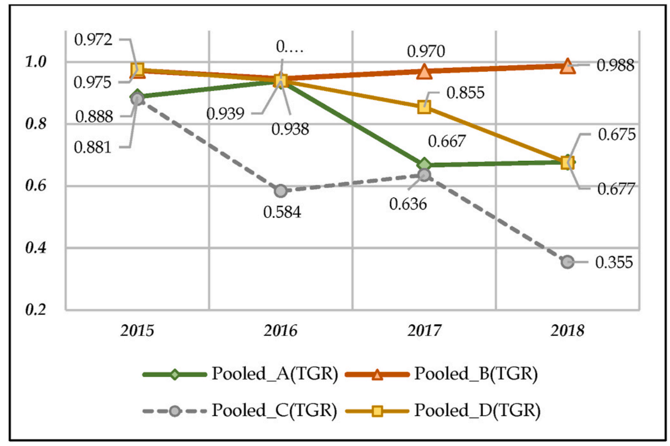



**Fig. 5.** The change of TGR for pooled festival groups.

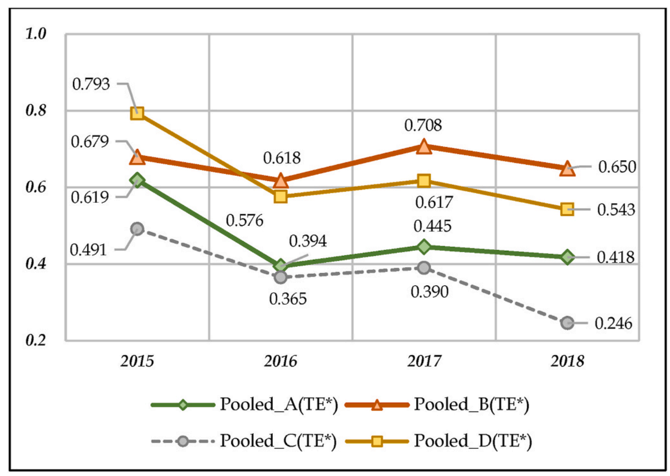



**Fig. 6.** The change of TE* for pooled festival groups.

the best among all festivals tested, as it produced the most outputs under the given input level. Notably, numerous festivals in group (B) have relatively long histories (e.g., *B1, Salted seafood festival* and *B4, Green tea festival*) and well-known local food traditions (e.g., *B2, Chili pepper festival*, and *B6, Gochujang festival*), resulting in more stability in the operation of the festival, compared with those in other groups. This stability ultimately leads to a more steadfastly average TE and TE* values.

Another important feature is the apparent decrease in the TGR for groups (A) and (C) during the study period. This means that some highly efficient festivals in their groups (e.g., *A11, Sancheoneo ice festival,* and *C3, Seodong lotus festival*) have consistently maintained their dominance. The low TGR value implies that there is a lot of room for improvement, compared with the potential optimal production technology.

As mentioned above, TE* of all Korean festival groups in 2016 plummeted suddenly, due to uncontrollable risk factors such as the *MERS* outbreak. However, the overall TE* has been recovering since 2017. In particular, for group (C), the average TGR and TE* remained relatively low, compared with other festival groups, and declined along a similar trend. This decline may be due to the stagnant operation practices of *ecological/nature-related* festivals or their failure to implement innovations or knowledge transfers within the group.

#### 5.2.2. The returns-to-scale (RTS) and the main cause of inefficiency

This study examined both the returns-to-scale (RTS) and the main cause of inefficiency (see Appendix C). To figure out the main cause of inefficiency, technological efficiency can be broken down into pure technical efficiency (PTE) and scale efficiency (SE). In terms of efficiency for individual DMUs, the ratio of constant returns-to-scale was 10.69% out of 131 overall DMUs. Moreover, a major sources of inefficiency in local Korean festivals reveals that their inefficiencies could be attributed to pure technical inefficiency (PTE < SE, 79.67%) rather than scale inefficiency (PTE > SE, 20.33%). Pure technical inefficiency was also relatively higher than scale efficiency in terms of the inefficiencies found in individual festival groups (A group: 64.9%, B group: 80.6%, C group: 94.1%, D group: 87.5%). In particular, most festivals in the (C) group had comparatively higher pure technical inefficiencies with PTE < SE, which implies that they failed to efficiently allocate festival resources such as human and physical environments, which was further problematized by poor input utilization. Thus, the pure technical inefficient DMUs require innovative initiatives to improve their managerial inefficiency (Choi, 2017; Kumar, 2011).

By contrast, festivals in the (A) group showed relatively higher scale inefficiencies, thus indicating that they achieved higher efficiencies by expanding or reducing their economic scales. Scale inefficiency occurs when a company is operating at a scale that is either larger or smaller than the optimal scale. From an RTS perspective, approximately 62.8% of all DMUs were in the region of increasing returns-to-scale, which indicates that the DMUs require size expansions if they are aiming for dramatically improved festival efficiency. Conversely, 25.6% of all DMUs were in the region of decreasing returns-to-scale. In general, a DRS occurs when the proportion of output is less than the desired increased input (Choi, 2017). Particularly, 61.9% of (C) group were in the DRS regions. This is a form of managerial inefficiency that is primarily caused by complexities in the communication and decision-making systems within the festival committee. Thus, group (C) can improve their efficiency by adjusting their festival sizes, such as eliminating overcapacities and overlapping employees (Choi, 2020).

#### 5.2.3. Comparison among typologies of local Korean festival

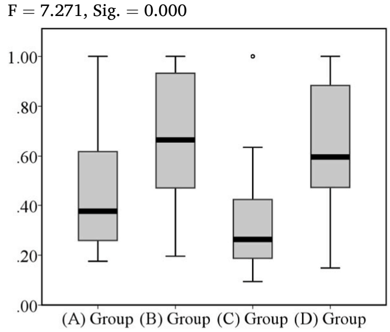
This study conducted the ANOVA test to verify whether there are statistically significant differences among the average TE* in each typology of local Korean festival based on parametric and non-parametric approaches. For comparison, the null hypothesis is defined as '*the four samples are drawn from identical populations*'. The results of the ANOVA test in Table 4 showed that the mean differences in average TE* based on the parametric approach between groups were not statistically significant difference (*F = 2.011, p-value = .140 > 0.05*), whereas the mean differences in CRS- and VRS-based TE* were a statistically significant at the 0.05% level [*F = 7.271(CRS) and 3.558(VRS), Sig = 0.000(CRS) and 0.016(VRS) < 0.05*]. The CRS-based average TE* was the highest in the (B) group at 0.667, followed by the (D) group at 0.631, the (A) group at 0.469, and the (C) group at 0.373. The mean VRS-based TE* rank was revealed in the following order: (B) group at 0.716; (D) group at 0.682; (A) group at 0.632; (C) group at 0.473. We also performed Scheffe's multiple comparisons to determine differences between festival groups. Table 4 shows the results of the multiple comparisons for each group, which clearly show significant differences in average TE* between the (A)–(B), (A)–(D), (B)–(C), and (C)-(D) groups (CRS-based) and (B)–(C) and (C)–(D) groups (VRS-based). However, there were no significant differences between the groups based on the SFA.

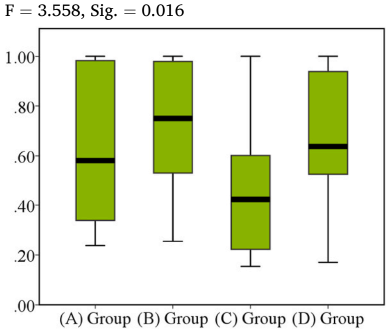
#### 5.2.4. Comparison between SFA and DEA results

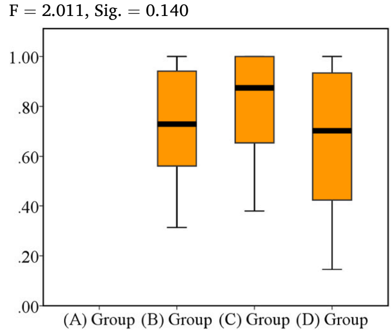
SFA is a parametric approach for econometrically estimating unknown parameters using input-output data by hypothesizing specific function forms. While SFA has the advantage of testing the significance of estimates and separating random noise from efficiency, it is necessary to specify function forms such as *Cobb-Douglas* and *Translog*, and

**Table 4**
Results of the ANOVA test in typologies of local Korean festival.

| Group | DEA: Non-parametric | | | | | | SFA: Parametric | | |
|---|---|---|---|---|---|---|---|---|---|
| | CRS | | | VRS | | | | | |
| | Mean | S.D. | S.E. | Mean | S.D. | S.E. | Mean | S.D. | S.E. |
| •Pooled_(A) (n = 40) | 0.469 | 0.259 | 0.041 | 0.632 | 0.296 | 0.047 | N/A | | |
| •Pooled_(B) (n = 35) | 0.662 | 0.268 | 0.045 | 0.716 | 0.252 | 0.043 | 0.737 | 0.207 | 0.035 |
| •Pooled_(C) (n = 20) | 0.373 | 0.299 | 0.067 | 0.473 | 0.305 | 0.068 | 0.808 | 0.205 | 0.046 |
| •Pooled_(D) (n = 36) | 0.631 | 0.259 | 0.043 | 0.682 | 0.263 | 0.044 | 0.679 | 0.267 | 0.045 |
| | F = 7.271, Sig. = 0.000 | | | F = 3.558, Sig. = 0.016 | | | F = 2.011, Sig. = 0.140 | | |




| •Multiple Comparisons: Pooled_(I)-Pooled_(J) | Mean Diff. (I)-(J) | S.E. | Sig. | Mean Diff. (I)-(J) | S.E. | Sig. | Mean Diff. (I)-(J) | S.E. | Sig. |
|---|---|---|---|---|---|---|---|---|---|
| (A)-(B) | −0.193** | 0.062 | 0.024 | −0.084 | 0.064 | 0.639 | N/A | | |
| (A)-(C) | 0.096 | 0.073 | 0.636 | 0.159 | 0.076 | 0.230 | N/A | | |
| (A)-(D) | −0.162* | 0.062 | 0.080 | −0.050 | 0.064 | 0.891 | N/A | | |
| (B)-(C) | 0.289*** | 0.075 | 0.003 | 0.242** | 0.078 | 0.024 | −0.072 | 0.065 | 0.548 |
| (B)-(D) | 0.032 | 0.064 | 0.970 | 0.033 | 0.066 | 0.968 | 0.057 | 0.055 | 0.584 |
| (C)-(D) | −0.258*** | 0.075 | 0.010 | −0.209* | 0.077 | 0.068 | 0.129 | 0.065 | 0.143 |

estimates may react sensitively to underperforming outliers depending on the probability distributions of inefficient errors chosen. Meanwhile, DEA is a linear programming methodology that calculates a nonparametric frontier using given data and estimates efficiency by comparing the calculated frontier to the actual data. DEA does not require a specific function form and can accommodate multiple outputs and inputs, but it fails to distinguish between technical efficiency and statistical errors, and cannot test the significance test of estimates. As a result, SFA and DEA should be used in tandem (Hjalmarsson et al., 1996).

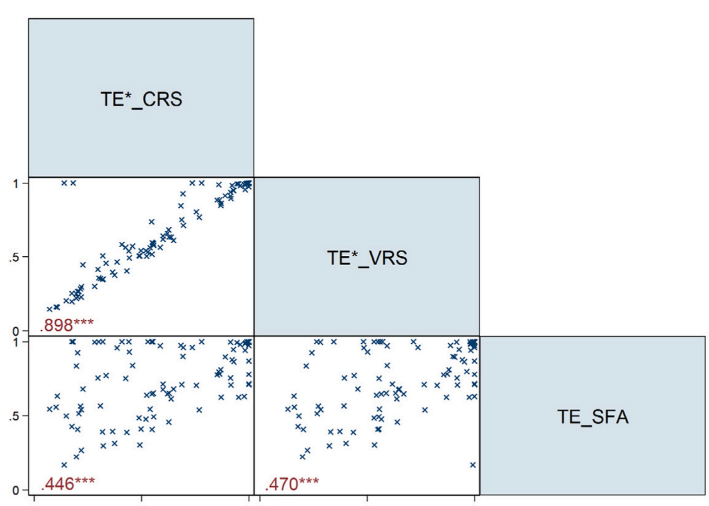
In this study, we investigate the consistency of technical efficiency measures derived with two different methodologies: SFA and DEA. The correlation coefficients matrix between the technical efficiency measures obtained from the SFA and the corresponding DEA are depicted below (A) of Fig. 7. Correlation coefficients of efficiency in the three models are positive and significant. The strongest correlation is obtained between the efficiency scores estimated from the VRS-DEA and CRS-DEA model ($r = .898$, $p < .000$). The weakest correlation is achieved between the TE_SFA and the TE*_CRS model ($r = .446$, $p < .000$). This result is similar to the result of Reinhard et al. (2000), and Wadud and White (2000). As seen in (B) of Fig. 7, the results of the ANOVA test revealed that the mean differences in average TE scores among CRS-DEA, VRS-DEA, and SFA were the statistically significant differences at the 0.05% level ($F = 6.415$, $p\text{-value} = .002 < 0.05$). The TE of SFA was the highest at 0.730, followed by the TE* of VRS-DEA at 0.649, and the TE* of CRS-DEA at 0.586. Moreover, the results of Games-Howell's multiple comparisons (*Levene statistics* = *4.025, P* = *.019* < *0.05*) show significant differences in average TE scores between the CRS-DEA and SFA (*p-value* = *.001*) and the VRS-DEA and SFA (*p-value* = *.094*), but there were no significant differences between the CRS- and VRS-DEA.

The efficiency scores of SFA and DEA produce different results because of their theoretical differences in the estimation process. The TE score of the SFA show higher efficiency estimates with less variability than those of the DEA, although the characteristics of the two production frontiers are so similar. This difference is consistent with previous studies because of the separation of the error term (Reinhard et al., 2000; Wadud & White, 2000). In the case of SFA, the efficiency is estimated by separating random errors and inefficiencies, whereas, in the DEA approach, all errors in the estimation process are regarded as inefficient factors (Hjalmarsson et al., 1996). Thus, any efficiency differences between DEA and SFA can be attributed to the different assumptions implied by these two approaches (Weill, 2004). However, as shown in Table 3, $\gamma$, which represents the ratio of inefficiency to the total error, has a value of almost 1. It can be interpreted that there is no random noise in the measurement data, so other causes such as the influence of outliers can be considered. DEA, which estimates the frontier based on the relative comparison, is more sensitive to the presence of outlier DMU in the group than SFA that assumes the production function of the frontier. If there is an overwhelming DMU, the efficiency of the remaining DMUs is underestimated (Fiorentino et al., 2006; Reinhard et al., 2000; Weill, 2004). Although SFA and DEA generate somewhat different mean efficiency scores (as seen in (B) of Fig. 7), the two techniques generate similar efficiency scores of individual festivals based on the various efficiency criteria. Overall, both SFA and DEA methodologies are appropriate for estimating the efficiency of the local Korean festival, and they are generally consistent and can support each other.

## 6. Determinants of festivals' meta-efficiency

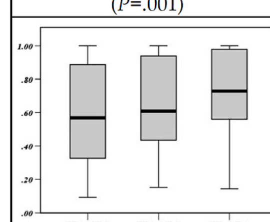
In the first stage, we estimate the efficiency scores using metafrontier DEA. In the second stage, we regress the TE* estimates using operational factors, while considering their influence on the efficiency level of each typology of local Korean festivals. Using parametric SFA, Battese and Coelli (1995) argues that two-stage procedure can be biased because of the misspecification of the first stage. Wang and Schmidt (2002) also commented that, regardless of correlations between input/output variables and exogenous variables, the results of second stage are likely to be biased (Kumbhakar et al., 2015). However, this may occur when no a *priori* knowledge exists, and in that case, non-parametric DEA which makes the problem less acute than parametric approach, is required using a two-stage procedure (Banker & Natarajan, 2008).

As mentioned in the DEA methodology, the dependent variable, consisting of DEA scores, is bound to the interval 0 and 1 ($0 < TE^* \leq 1$). This limited dependent variable represents a variable with a range of possible values that are constrained in some ways. In a vast quantity of existing literature, the use of censored and truncated regressions is recommended when the dependent variable is restrained in the second stage (Greene, 2005). However, according to Simar and Wilson (2007b, pp. 421–521), Banker and Natarajan (2008), and McDonald (2009), the Tobit regression was considered inappropriate in the second stage of DEA, as efficiency scores are fractional data and not generated by a censoring process, thereby yielding biased and inconsistent estimators.




(A) Correlation between the DEA and SFA

| Groups | Mean | S.D. | S.E. |
|---|---|---|---|
| TE*_CRS | 0.586 | .292 | .031 |
| TE*_VRS | 0.649 | .282 | .030 |
| TE_SFA | 0.730 | .235 | .025 |
| | Welch's *Statistics*=6.876 (*P*=.001) | | |




| Multiple Comparisons: | Mean Diff. (I)-(J) | S.E. | Sig. |
|---|---|---|---|
| CRS - VRS | -0.063 | .0426 | .305 |
| CRS - SFA | -0.143*** | .0393 | .001 |
| VRS - SFA | -0.081* | .0385 | .094 |

Note: * Significant at p < 0.10, ** is p < 0.05, and *** is p < 0.01.

(B) ANOVA test between the DEA and SFA

**Fig. 7.** DEA vs. SFA efficiency measures (excluded (A) group).

Furthermore, the truncated regression results are extremely sensitive to the point of truncation. This means that the truncated estimation is only available for models in which the truncation points are well-known, as the likelihood function is otherwise undefined. A solution to these problems was proposed by Simar and Wilson (2000, 2007b, pp. 421–521). Their work introduced the semi-parametric bootstrap, thus correcting bias estimation efficiency and giving the confidence interval of efficiency. Simar and Wilson (2007a; 2007b, pp. 421–521) introduced a truncated regression with double bootstrapping in the second stage to adjust for the downward bias inherent in conventional DEA and to test for the significance of factors impacting efficiency (Du et al., 2018). This study therefore employed Simar and Wilson's approach with double bootstrapping to reveal the impact of operational determinants on TE* estimates in a two-stage procedure, explaining the sources of efficiency variability (Appendix D). For more mathematical details concerning the smoothed bootstrap procedures for computing efficiency, readers are advised to refer to Simar and Wilson (2000; 2007a; 2007b, pp. 421–521; 2011) and Badunenko and Tauchmann (2019).

### 6.1. Research model for truncated regression with double bootstrapping

The efficiency scores were set as dependent variables, while the factors that determined the efficiency scores were set as independent variables. The truncated regression with double bootstrapping was designed as follows:

$$\widehat{\theta}_i = \beta_0 + \beta_1 Div_i + \beta_2 Food_i + \beta_3 Buy_i + \beta_4 Exp_i + \beta_5 Inf_i + \beta_6 Host_i + \beta_7 Reg_i + \varepsilon_i \tag{12}$$

where $\widehat{\theta}_i$ is the bootstrapped bias-corrected TE* score of individual festival group *i*. $\beta_0$ is a constant term, $\beta_1 \cdots \beta_8$ are coefficients of TE* determinants in local Korean festival, and $\varepsilon_i$ is the error term (statistical noise). To empirically analyze the effects of external operational factors on the efficiency of individual festival groups, specifically, we tested eight operational factors, including *diversity of festival programs* ($Div_i$), *foods to eat* ($Food_i$), *things to buy* ($Buy_i$), *on-site guidance & explanation* ($Exp_i$), *infrastructure & safety* ($Inf_i$), *number of hosted festivals* ($Host_i$), and *the ratio of tourists from other regions* ($Reg_i$).

The influential environmental factors listed above were taken from the questionnaires used in the annual survey conducted by the Korea Tourism Organization, which has been implemented since 2015 (kto.visitkorea.or.kr). Items are designed to obtain information from tourists concerning their awareness and perceived satisfaction in the individual festival context (e.g., PR and marketing, programs, food and souvenirs, and convenience). The main goal of this survey is to establish objective and empirical measurement items that can generally be used to assess the effectiveness of local festivals. The questionnaire consists of 10 items and is distributed to 200 randomly-chosen festival tourists each at 40 festivals. In this study, we extracted six items related to perceived festival satisfaction, and excluded four items related to the consumption patterns of festival tourists, but added the number of hosted festivals (i.

**Table 5**
A comparison among *Tobit*, *Truncated Regression*, and *Simar & Wilson approach* measuring the determinants on efficiency change.

| Group | Factors | Tobit Regression | | | | Conventional Truncated Regression | | | | Simar & Wilson Approach with Double Bootstrapping | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Coef. | S.E. | t | P>\|t\| | Coef. | S.E. | z | P>\|z\| | Coef. | S.E. | z | P>\|z\| |
| (A) | $\beta_0$ | 4.893** | 2.020 | 2.42 | 0.021 | 1.920 | 2.161 | 0.89 | 0.374 | 2.020 | 2.240 | 0.90 | 0.367 |
| | $\beta_1$ | -.313 | 1.232 | −0.25 | 0.800 | 2.464** | 1.048 | 2.35 | 0.019 | 2.515** | 1.122 | 2.24 | 0.025 |
| | $\beta_2$ | -.148 | 1.108 | −0.13 | 0.894 | −1.741* | .975 | −1.78 | 0.074 | −1.800* | 1.022 | −1.76 | 0.078 |
| | $\beta_3$ | −3.272*** | 1.149 | −2.85 | 0.008 | −1.911** | .868 | −2.20 | 0.028 | −1.983** | .936 | −2.12 | 0.034 |
| | $\beta_4$ | 3.355* | 1.720 | 1.95 | 0.060 | 3.240*** | 1.237 | 2.62 | 0.009 | 3.345*** | 1.304 | 2.57 | 0.010 |
| | $\beta_5$ | −1.208 | 1.701 | −0.71 | 0.482 | −2.725** | 1.381 | −1.97 | 0.049 | −2.793** | 1.419 | −1.97 | 0.049 |
| | $\beta_6$ | -.107 | .142 | −0.76 | 0.454 | .049 | .103 | 0.47 | 0.635 | .049 | .107 | 0.46 | 0.646 |
| | $\beta_7$ | -.346** | .149 | −2.31 | 0.027 | -.142 | .136 | −1.04 | 0.298 | -.150 | .144 | −1.05 | 0.296 |
| | Sigma | .249 | .033 | | | .154 | .021 | 7.12 | 0.000 | .159*** | .023 | 6.82 | 0.000 |
| | | *LR $\chi^2$=25.56, Prob>$\chi^2$=0.0006* | | | | *Wald $\chi^2$=39.19, Prob>$\chi^2$=0.0000* | | | | *Wald $\chi^2$=34.21, Prob>$\chi^2$=0.0000* | | | |
| (B) | $\beta_0$ | -.475 | 3.092 | −0.15 | 0.879 | −2.741 | 2.343 | −1.17 | 0.242 | −2.773 | 2.343 | −1.18 | 0.237 |
| | $\beta_1$ | .017 | 2.030 | 0.01 | 0.993 | -.174 | 1.501 | −0.12 | 0.907 | -.197 | 1.491 | −0.13 | 0.895 |
| | $\beta_2$ | 2.837 | 2.043 | 1.39 | 0.176 | 3.248** | 1.506 | 2.16 | 0.031 | 3.290** | 1.452 | 2.27 | 0.023 |
| | $\beta_3$ | −3.206 | 2.006 | −1.60 | 0.121 | −1.390 | 1.515 | −0.92 | 0.359 | −1.406 | 1.474 | −0.95 | 0.340 |
| | $\beta_4$ | -.218 | 2.247 | −0.10 | 0.923 | -.843 | 1.662 | −0.51 | 0.612 | -.858 | 1.690 | −0.51 | 0.611 |
| | $\beta_5$ | .645 | 1.654 | 0.39 | 0.699 | -.890 | 1.252 | −0.71 | 0.477 | -.876 | 1.311 | −0.67 | 0.504 |
| | $\beta_6$ | .477*** | .120 | 3.98 | 0.000 | .451*** | .095 | 4.72 | 0.000 | .457*** | .093 | 4.88 | 0.000 |
| | $\beta_7$ | -.069 | .449 | −0.16 | 0.878 | .500 | .373 | 1.34 | 0.181 | .502 | .381 | 1.32 | 0.188 |
| | Sigma | .228 | .033 | | | .147*** | .023 | 6.26 | 0.000 | .148*** | .022 | 6.58 | 0.000 |
| | | *LR $\chi^2$=18.62, Prob>$\chi^2$=0.0095* | | | | *Wald $\chi^2$=26.48, Prob>$\chi^2$=0.0004* | | | | *Wald $\chi^2$=28.05, Prob>$\chi^2$=0.0002* | | | |
| (C) | $\beta_0$ | −21.877** | 9.921 | −2.21 | 0.046 | .867 | 4.321 | 0.20 | 0.841 | .850 | 4.462 | 0.19 | 0.849 |
| | $\beta_1$ | 2.185 | 3.017 | 0.72 | 0.482 | 2.193* | 1.147 | 1.91 | 0.056 | 2.198* | 1.167 | 1.88 | 0.060 |
| | $\beta_2$ | −4.110 | 3.927 | −1.05 | 0.314 | −2.089 | 1.513 | −1.38 | 0.168 | −2.113 | 1.566 | −1.35 | 0.177 |
| | $\beta_3$ | 7.591*** | 2.403 | 3.16 | 0.008 | 2.244** | 1.053 | 2.13 | 0.033 | 2.280** | 1.095 | 2.08 | 0.037 |
| | $\beta_4$ | -.630 | 3.079 | −0.20 | 0.841 | -.926 | 1.170 | −0.79 | 0.429 | -.942 | 1.205 | −0.78 | 0.434 |
| | $\beta_5$ | −1.619 | 3.785 | −0.43 | 0.676 | −1.486 | 1.497 | −0.99 | 0.321 | −1.485 | 1.548 | −0.96 | 0.338 |
| | $\beta_6$ | .248 | .184 | 1.35 | 0.200 | -.082 | .084 | −0.98 | 0.326 | -.083 | .085 | −0.98 | 0.327 |
| | $\beta_7$ | 3.613* | 1.704 | 2.12 | 0.054 | -.039 | .740 | −0.05 | 0.958 | -.035 | .761 | −0.05 | 0.963 |
| | Sigma | .252 | .047 | | | .093*** | .016 | 5.66 | 0.000 | .095*** | .017 | 5.57 | 0.000 |
| | | *LR $\chi^2$=14.30, Prob>$\chi^2$=0.0461* | | | | *Wald $\chi^2$=27.68, Prob>$\chi^2$=0.0003* | | | | *Wald $\chi^2$=28.09, Prob>$\chi^2$=0.0002* | | | |

*p < .10, **p < .05, ***p < .01.
(*Note:* $\beta_1$ :*diversity of festival programs*, $\beta_2$ : *foods to eat*, $\beta_3$ : *things to buy*, $\beta_4$ : *on-site guidance & explanation*, $\beta_5$ : *infrastructure & safety*, $\beta_6$ : *number of hosted festivals*, and $\beta_7$ : *the ratio of tourists from other regions*).

e., the number of years since the festival was first held) as determinants of festival TE*.

### 6.2. Simar & Wilson approach measuring the determinants on efficiency change

Table 5 tabulates the regression results of the second stage for each typology of the local Korean festival, using (1) *Tobit Regression,* (2) Conventional *Truncated Regression*, and (3) Simar & Wilson's *truncated regression with double bootstrapping,* respectively. As seen in Table 5, for all the regression method, (A), (B), and (C) groups rejected the null hypothesis stating that the parameters in the regression equation were jointly equal to zero, whereas the result of the (D) group showed no significant relationships between the external operational factors and technical efficiency (*Tobit: LR* $\chi^2 = 8.37$, *Prob* $> \chi^2 = 0.3012$, *Truncated Regression: Wald* $\chi^2 = 11.38$, *Prob* $> \chi^2 = 0.1227$, *Simar & Wilson: Wald* $\chi^2 = 6.60$, *Prob* $> \chi^2 = 0.4713$). Thus, the results of the (D) group were excluded from Table 5. To figure out the cause of poor fit in group (D), this study additionally conducted the *Pearson* correlation coefficient of the group (D) between environmental variables and technical efficiency. The results revealed that there was no correlation between contextual variables and efficiency scores for group (D). Based on these results, it is reasonable to exclude the results of the (D) group from Table 5.

The significance of coefficient estimators based on Tobit regression are different from those based on conventional truncated regression and Simar & Wilson's approach. The differences in results might be due to the different production process characterizations such as underlying data-generating process and separability condition. There is some discussion between the Tobit and SW approach about which is the best approach for evaluating the impact of contextual variables on efficiency in a second stage analysis (Banker et al., 2019; Du et al., 2018; McDonald, 2009; Simar and Wilson, 2007a, 2007b, pp. 421–521). In this study, the influence of environmental variables on the efficiency of each typology of the festival was mainly explained based on the Simar and Wilson approach with double bootstrapping (2007).

The operating factors affecting the efficiency of each festival types were as follows: First, festival operating attributes with a significantly positive effect on the ME* in group (A) is the diversity of festival programs ($\beta_1 = 2.515$) and on-site guidance & explanation ($\beta_4 = 3.345$); conversely, foods to eat ($\beta_2 - 1.800$), things to buy ($\beta_3 = -1.983$), and infrastructure & safety ($\beta_5 = -2.793$), have a negative effect on TE* (Table 5). In *culture and art* festivals—such as music, dance, opera, and theater—festival organizers and operators should plan various performances and presentation line-ups representing different genres, sizes, foci, and target groups to meet the expectations of festival attendees and ensure a more successful festival, as suggested by Leenders et al. (2005). Professional explanations and on-site guidance should also be provided to increase tourists' satisfaction with the festival and performances. These operating determinants are crucial strategies for enhancing the efficiency of the *culture and art* festival group.

It should be noted that some researchers are concerned about the unprecedented commercialization and corporatization of the *culture and art* festivals in particular (Szmigin et al., 2017). Increasing commercialization and touristification of festivals have led to the erosion of the values and significance of festivals. In the current modern age, we often witness the meaning of a festival gradually deteriorating into a commercial gimmick. Some local festivals have been converted into festival-themed shopping malls with a variety of specialty items or into huge restaurants full of discarded food packets, containers, and shade papers. This commercialization and touristification may bring great pleasure to the festival tourists—with more foods to eat and things to buy at the festival—thereby increasing local economic potential. However, the over-commercialization of local festivals tarnishes their original meaning and has a negative effect on festival efficiency (Choi et al., 2020). Focusing on art festivals, Finkel (2010) argue that an emphasis on garnering corporate support and providing corporate entertainment can have an exclusionary effect on the local population and arts enthusiasts. Festival organizers and managers should therefore implement strategic initiatives to utilize both positive and negative aspects of commercialization, touristification, or festivalization.

Second, food to eat ($\beta_2 = 3.290$) and the number of hosted festivals ($\beta_6 = 0.457$) had significant positive effects on TE in the (B) group. Most festivals in this group use their specific local foods or products as mediums of attraction. Indeed, Chang and Yuan (2011) suggested that attendees primarily visit food festivals for the wine and food itself. Similarly, Lee and Arcodia (2011) illustrated the key components of food tourism, which especially include specialty restaurants and locally or regionally produced food products. To ensure sustainability, it is thus important to increase tourist satisfaction by developing new recipes that reflect the main festival themes, such as garlic in the case of the Gilroy Garlic Festival, and preparing various food items that highlight local specialty products. Moreover, festivals in the (B) group require considerable amounts of time to build appealing images (Jago et al., 2003; Lee & Arcodia, 2011; McCartney, 2005) and thus attract tourists from other regions. For example, *Oktoberfest* has been held 210 times since 1811, while the *Menton Lemon Festival* has been held 87 times since 1928, thus demonstrating that longer festival histories are associated with stronger images for potential tourists. This increases the likelihood of participation for potential festival attendees. In particular, foreign visitors to the *Oktoberfest* constitute 14% of total attendees, and 240,000 tourists from France and abroad visit the *Menton Lemon Festival* every year. Strategically, festivals in group (B) should offer various unique local foods and products, which create lasting memories of the festival to draw tourists from various other regions; these items should serve as a showcase of local specialties.

Third, from the perspective of TE of the (C) group, the diversity of festival programs ($\beta_1 = 1.9388$) and things to buy ($\beta_3 = 2.8753$) are positively and significantly related with the TE score for the (C) group. Dewar et al. (2001) attributed the success of the *Harbin Ice Lantern and Snow Festival* to its 23 different activities, including snow and ice sculpting competitions, ice and snow sculpture parks, parades, a book show, and much more. Further, the world-renowned *Sapporo Snow Festival* not only exhibits hundreds of ice sculptures, but also operates 23 snow-related fun activities for visitors to experience at its three main sites, including *Odori Park*, *Susukino Ice World*, and *Tsudome Site* (snowfes.com). Another example is the *Bonghwa Sweet Fish Festival (C_02)*, which is a popular ecological event held in Korea. It offers 30 to 40 hands-on activities that reflect the main festival theme (bonghwafestival.or.kr).

In particular, there are contradictory results among several studies that analyzed the relationship between festival tourism and event-specific products, souvenirs. Lee et al. (2011) asserted that festival products do not contribute to festival attendee's satisfaction and festival values in the case of *Boyeong Mud* Festival in Korea. Grappi and Montanari (2011) demonstrated that souvenir availability in the Italian festival has a negative influence on attendees' perceptions and emotion. On the contrary, some of literature argued that the potential benefits of souvenir sales have a positive impact on the festival values and financial performance of the festival host community in many positive ways (De Rojas & Camarero, 2008; Kong & Chang, 2012; Tanford & Jung, 2017; Yoon et al., 2010). Tanford and Jung (2017) implemented Meta-analysis on 66 festival or event papers published from 2000 to 2016 to figure out the relationship between festival attributes and festival attendee satisfaction and post-experience behavior. The results of analysis confirmed that tangible festival attributes such as festival activities and souvenirs outlets are strongly related to festival attendee's satisfaction and value. In particular, De Rojas and Camarero (2008) examined that higher tourist satisfaction contributed to an improvement in their purchasing power on events or venue souvenirs. Moreover, Kong and Chang (2012) investigated that memorable festival signature souvenirs generate the favorability of the tourist perception and contribute to the local economy development. Based on these prior studies, the relationship between *things to buy* and *festival efficiency* reveals different aspects according to the theme and nature of festival such as group (A) and (C).

As illustrated, the principal operational drivers for changing the TE of various festival groups differed depending on preferred operational strategies and unique group characteristics. Thus, differentiated operating initiatives tailored to the specific characteristics of each typology of local festival is required to maximize their efficiency.

## 7. Discussion and conclusions

### 7.1. Implications for theoretical and managerial practices

This study employed the parametric and non-parametric model to measure the relative efficiencies of local festivals held in Korea from 2015 to 2018 and identified the main determinants of their efficiencies at the group level by using a truncated regression with double bootstrapping. Based on these empirical results, we herein offer several theoretical and managerial contributions to festival tourism literature and practices.

First, this paper contributed to the literature concerning the efficiency of festival tourism. In festival tourism literature, most previous studies have mainly focused on attendee satisfaction, visitor motivations, and the economic effects of festivals (Hudson et al., 2015; Kendall et al., 2020; Lau & Li, 2019; Ma & Lew, 2012; Oh & Yi, 2016; Quinn, 2006), whereas there were few studies on festivals' efficiency, except a recent study of Van Heerden and Saayman (2018). In particular, this paper is an unprecedented attempt to analyze the technical efficiency of festival tourism using the parametric and non-parametric methodology. By employing the stochastic frontier and metafrontier analysis, this study measured the parametric technical efficiency and the nonparametric metafrontier index values (e.g., ME, GE, and TGR) of 35 local Korean festivals, identified notable sources of inefficiency, and provided an elaborated framework for achieving their optimal economy of scale to improve technical efficiency.

Second, it is impossible to compare the relative efficiencies between groups with different production functions using a conventional DEA method. However, a metafrontier approach can be used to measure the comparable efficiency of DMUs operating under distinctive and heterogeneous technologies. associated with distinctive and heterogeneous technologies. This study considered the study period of 2015–2018 as a cross-sectional analysis to pool the festivals of each typology across the periods, after we estimated the frontier in the first stage. Next, we compared the group efficiency among four distinct groups, each of which operated under different technical conditions.

Third, most previous metafrontier studies have overlooked the causes of fluctuation in TE and TGR. However, Hafeez et al. (2020) analyzed the causal relationship between the fluctuation of TE and TGR values and the shift of the production frontier based on the innovation and imitation processes used by some DMUs within groups. In this study, we analyzed how efficiency changes in local festivals shifted the production function and altered average TE and TGR values. We also tracked the fluctuation patterns of the metafrontier, group frontiers, and TGR of local festivals over time in order to establish strategic benchmarking insights.

Fourth, this study demonstrated that the efficiencies of individual festival groups were affected by different operational factors, depending on the characteristic of each festival group, and suggested that a differentiated operational strategy for the individual local festival groups is required to maximize their efficiency. Accordingly, festival organizing committees and operators should implement tailored operational strategies, which will provide them with a competitive edge. Strategically, festival organizers and operators of events in group (B) require a strategy for developing unique foods and beverages utilizing local-specific ingredients and specialty products to draw tourists from other countries and regions. Further, festivals in groups (A) and (C) should plan a variety of tourist participation programs that enable them to experience *"culture and art"* and *"ecology and nature"* (Dewar et al., 2001; Getz, 2010) and develop thematic branding strategies designed to convert these enjoyable experiences into positive festival images.

The notable findings of this research could be highlighted as follows:

- Although SFA and DEA generate few differences in the distribution characteristics of technical efficiency caused by different assumptions in the two approaches, these differences are not too serious; it is merely a matter of deciding which method to use. Overall, both methods are appropriate for estimating the efficiency of local Korean festivals. They are both fairly consistent and can support each other.
- The TGR of group (B) achieved an average 96.90% of the potential payoffs, as it produced the most outputs under its given input level. In particular, numerous festivals in group (B) have relatively long histories and well-known local food traditions, rendering them more stable from an operation perspective and ultimately leading to more higher and more consistent TE and TE* values.
- The major sources of inefficiency in local Korean festivals are mostly attributed to pure technology inefficiency. In particular, most of the festivals in the (C) group show pure technology inefficiency. Therefore, these DMUs require innovative operating policies and strategic benchmarking initiatives to improve managerial efficiency.
- Different principal operational drivers affected TE* depending on the festival group. These operational variables have practical implications for the organizing committee and operators of local Korean festivals and are helpful in developing sophisticated marketing and operation plans that reflect their unique themes and characteristics of festivals to maximize efficiency.

### 7.2. Limitations and directions for future research

While this study provides meaningful insights for local Korean festivals from the perspective of operational theory and practice, there were also some limitations. First, the two input and two output variables employed in this study were used to measure the efficiency of local Korean festivals from the perspectives of organizers and operators. However, we excluded certain qualitative information from our model, including festival quality, fame and attractiveness as perceived by visitors. This was due to limited data accessibility. As such, future research should verify not only the *efficiency* aspect of local festivals but also the *effectiveness* aspect. Future analyses should expand on our model by including qualitative factors reported by festival tourists, such as festival images and/or attractiveness. Moreover, in areas where festival tourism occurs, tourism also exists during non-festival periods and even becomes the most important local industry. Tourism output is influenced by a variety of factors, not just festivals. Nonetheless, there is a limitation on this study in that we cannot account for these various external factors. Thus, future research could adopt more diverse environmental variables, such as quality of area and facilities (Lade & Jackson, 2004), amenities and convenience of place and time (Taylor & Shanka, 2008), and brand image (Leenders, 2010). This will allow improved managerial insight for subsequent studies. Second, this study investigated efficiency changes in local Korean festivals from 2015 to 2018. However, four-years may be considered too short to measure yearly fluctuation patterns. Hence, future studies should accumulate longitudinal data that can be used to accurately track efficiency changes while figuring out the key drivers of efficiency fluctuation. Third, this study compared and analyzed the relative efficiencies only for local festivals held in Korea. However, it is inevitable to compare the local Korean festivals with representative festivals held in other countries to enhance the global competitive advantage of local Korean festivals and to explore new ways to operate more innovative festivals. This will require an accumulation of data related to festivals held in other countries, thereby enabling efficiency comparisons at the global level.

## Credit author statement

Kanghwa Choi: Conceptualization, Methodology, Software, Writing-Reviewing and Editing, Hee Jay Kang: Writing – original draft preparation, Writing-Reviewing and Editing, Changhee Kim: Data curation, Visualization, writing-Reviewing and Editing

## Impact statement

Korea's festivals are rising as a new cultural competitiveness, unleashing a second Korean wave. Local festivals in Korea have evolved into global events, combining international trends and peculiar regional characteristics. In order to further promote and support the development of local Korean festivals, this study empirically examines the efficiency determinants of heterogeneous festival groups to figure out the key drivers of efficiency variation. Moreover, we argue that developing a sophisticated marketing and operation initiatives for the each festival groups is required to maximize their efficiency.

## Contribution

The corresponding author, Hee Jay Kang, and the third author, Changhee Kim, contributed equally to this work.

## Declarations of competing interest

None.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## Appendix A. The definition, names, and codes of the decision making units (DMUs)

| Category | Region or City | Festival Names | DMU_Code |
|---|---|---|---|
| (A) Culture and Art Festivals | Gapyeong | *Jarasum Jazz Festival* | A(yr.)_01 |
| | Gangjin | *Celadon Festival* | A(yr.)_02 |
| | Gwangju | *Chungjang Festival* | A(yr.)_03 |
| | Mungyeong | *Chasabal Festival* | A(yr.)_04 |
| | Anseong | *Namsadang Baudeogi Festival* | A(yr.)_05 |
| | Yeongam | *Wangin Culture Festival* | A(yr.)_06 |
| | Incheon | *Pentaport Rock Festival* | A(yr.)_07 |
| | Chuncheon | *International Mime Festival* | A(yr.)_08 |
| | Pyeongchang | *Hyoseok Culture Festival* | A(yr.)_09 |
| | Pohang | *International Fireworks Festival* | A(yr.)_10 |
| | Hwacheon | *Sancheoneo Ice Festival* | A(yr.)_11 |
| (B) Local Specialty Product Festivals | Ganggyeong | *Salted Seafood Festival* | B(yr.)_01 |
| | Goesan | *Red Pepper Festival* | B(yr.)_02 |
| | Damyang | *Bamboo Festival* | B(yr.)_03 |
| | Boseong | *Green Tea Festival* | B(yr.)_04 |
| | Sancheong | *Medicinal Herb Festival* | B(yr.)_05 |
| | Sunchang | *Fermented Food Festival* | B(yr.)_06 |
| | Yeoju | *Ogok Naru Festival* | B(yr.)_07 |
| | Wanju | *Wild Food Festival* | B(yr.)_08 |
| | Icheon | *Rice Cultural Festival* | B(yr.)_09 |
| (C) Ecological/Nature-related Festivals | Muju | *Firefly Festival* | C(yr.)_01 |
| | Bonghwa | *Sweet Fish Festival* | C(yr.)_02 |
| | Buyeo | *Seodong Lotus Festival* | C(yr.)_03 |
| | Jangheung | *Jeongnamjin Water Festival* | C(yr.)_04 |
| | Jindo | *Miracle Sea Road Festival* | C(yr.)_05 |
| (D) Historical/Cultural Heritage Festivals | Goryeong | *Daegaya Experience Festival* | D(yr.)_01 |
| | Gochang | *Moyang Fortress Festival* | D(yr.)_02 |
| | Gimje | *Horizon Festival* | D(yr.)_03 |
| | Yangnyeongsi | *Herb Medicine Festival* | D(yr.)_04 |
| | Daejeon | *Hyo Culture Ppuri Festival* | D(yr.)_05 |
| | Mokpo | *Harbor Festival* | D(yr.)_06 |
| | Busan | *Dongnae Eupseong History Festival* | D(yr.)_07 |
| | Seosan | *Haemieupseong Fortress Festival* | D(yr.)_08 |
| | Jeju | *Fire Festival* | D(yr.)_09 |
| | Tongyeong | *Hansan Battle Festival* | D(yr.)_10 |

## Appendix B. Meta efficiency (TE*) and SFA estimation in four typologies of the local Korean festival

| (A) Culture and Art Festivals | | | | (B) Local Specialty Product Festivals | | | | (C) Ecological/Nature-related Festivals | | | | (D) Historical/Cultural Heritage Festivals | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DMU | DEA | | SFA | DMU | DEA | | SFA | DMU | DEA | | SFA | DMU | DEA | | SFA |
| | CRS | VRS | | | CRS | VRS | | | CRS | VRS | | | CRS | VRS | |
| A(15)_01 | 0.590 | 1 | N/A | B(15)_01 | 0.581 | 0.581 | 0.494 | C(15)_01 | 0.155 | 0.245 | 0.999 | D(15)_01 | 0.586 | 0.593 | 0.999 |
| A(15)_02 | 0.288 | 0.300 | | B(15)_02 | 0.475 | 0.517 | 0.313 | C(15)_02 | 0.300 | 0.301 | 0.999 | D(15)_03 | 1 | 1 | 0.999 |
| A(15)_03 | 0.984 | 0.984 | | B(15)_03 | 0.673 | 0.750 | 0.708 | C(15)_03 | 0.635 | 0.635 | 0.705 | D(15)_04 | 0.718 | 1 | 0.954 |
| A(15)_04 | 0.241 | 0.253 | | B(15)_04 | 0.758 | 0.830 | 0.729 | C(15)_04 | 0.366 | 0.466 | 0.960 | D(15)_05 | 0.914 | 0.937 | 0.854 |
| A(15)_06 | 0.349 | 0.482 | | B(15)_05 | 0.978 | 1 | 0.999 | C(15)_05 | 1 | 1 | 0.999 | D(15)_06 | 0.873 | 0.877 | 0.770 |

(continued on next page)

(*continued*)

| (A) Culture and Art Festivals | | | | (B) Local Specialty Product Festivals | | | | (C) Ecological/Nature-related Festivals | | | | (D) Historical/Cultural Heritage Festivals | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DMU | DEA | | SFA | DMU | DEA | | SFA | DMU | DEA | | SFA | DMU | DEA | | SFA |
| | CRS | VRS | | | CRS | VRS | | | CRS | VRS | | | CRS | VRS | |
| A(15)_07 | 0.566 | 1 | | B(15)_06 | 0.510 | 0.556 | 0.489 | C(16)_01 | 0.094 | 0.154 | 0.554 | D(15)_07 | 1 | 1 | 0.999 |
| A(15)_08 | 0.241 | 1 | | B(15)_07 | 0.782 | 1 | 0.999 | C(16)_02 | 0.218 | 0.238 | 0.827 | D(15)_08 | 0.592 | 0.609 | 0.702 |
| A(15)_09 | 0.955 | 1 | | B(15)_08 | 0.357 | 0.461 | 0.775 | C(16)_03 | 1 | 1 | 0.999 | D(15)_09 | 0.519 | 0.522 | 0.999 |
| A(15)_10 | 1 | 1 | | B(15)_09 | 1 | 1 | 0.999 | C(16)_04 | 0.314 | 0.411 | 0.752 | D(15)_10 | 0.931 | 0.952 | 0.847 |
| A(15)_11 | 0.977 | 0.981 | | B(16)_01 | 0.616 | 0.616 | 0.597 | C(16)_05 | 0.201 | 1 | 0.999 | D(16)_01 | 0.223 | 0.225 | 0.262 |
| A(16)_01 | 0.259 | 0.507 | | B(16)_02 | 0.477 | 0.533 | 0.401 | C(17)_01 | 0.102 | 0.162 | 0.561 | D(16)_02 | 0.327 | 0.338 | 0.381 |
| A(16)_02 | 0.324 | 0.334 | | B(16)_03 | 1 | 1 | 0.783 | C(17)_02 | 0.225 | 0.266 | 0.923 | D(16)_03 | 0.536 | 0.536 | 0.427 |
| A(16)_03 | 1 | 1 | | B(16)_04 | 0.954 | 1 | 0.640 | C(17)_03 | 1 | 1 | 0.714 | D(16)_04 | 0.706 | 0.914 | 0.884 |
| A(16)_04 | 0.221 | 0.238 | | B(16)_05 | 0.434 | 0.493 | 0.931 | C(17)_04 | 0.419 | 0.539 | 0.999 | D(16)_05 | 0.864 | 0.875 | 0.840 |
| A(16)_05 | 0.250 | 0.259 | | B(16)_06 | 0.485 | 0.529 | 0.507 | C(17)_05 | 0.204 | 0.434 | 0.668 | D(16)_06 | 1 | 1 | 0.999 |
| A(16)_06 | 0.176 | 0.259 | | B(16)_07 | 0.464 | 0.597 | 0.866 | C(18)_01 | 0.115 | 0.165 | 0.640 | D(16)_07 | 0.149 | 1 | 0.145 |
| A(16)_07 | 0.345 | 0.610 | | B(16)_08 | 0.196 | 0.255 | 0.502 | C(18)_02 | 0.174 | 0.207 | 0.502 | D(16)_08 | 0.512 | 0.530 | 0.665 |
| A(16)_08 | 0.228 | 1 | | B(16)_09 | 0.936 | 0.936 | 0.936 | C(18)_03 | 0.311 | 0.473 | 0.999 | D(16)_09 | 0.547 | 0.581 | 0.647 |
| A(16)_09 | 0.475 | 0.517 | | B(17)_01 | 0.787 | 0.787 | 0.558 | C(18)_04 | 0.428 | 0.568 | 0.991 | D(16)_10 | 0.894 | 0.898 | 0.711 |
| A(16)_10 | 0.401 | 1 | | B(17)_02 | 0.919 | 1 | 0.999 | C(18)_05 | 0.203 | 0.203 | 0.379 | D(17)_01 | 0.210 | 0.211 | 0.213 |
| A(16)_11 | 0.658 | 0.853 | | B(17)_03 | 1 | 1 | 0.863 | | | | | D(17)_02 | 0.376 | 0.382 | 0.379 |
| A(17)_01 | 0.450 | 0.797 | | B(17)_04 | 0.977 | 1 | 0.631 | | | | | D(17)_03 | 0.620 | 0.622 | 0.640 |
| A(17)_02 | 0.471 | 0.502 | | B(17)_05 | 0.226 | 0.283 | 0.564 | | | | | D(17)_04 | 0.580 | 0.626 | 0.662 |
| A(17)_03 | 0.700 | 0.743 | | B(17)_06 | 0.568 | 0.738 | 0.999 | | | | | D(17)_05 | 0.913 | 0.929 | 0.914 |
| A(17)_04 | 0.248 | 0.252 | | B(17)_08 | 0.225 | 0.291 | 0.537 | | | | | D(17)_08 | 0.564 | 0.583 | 0.999 |
| A(17)_05 | 0.327 | 0.343 | | B(17)_09 | 0.959 | 0.959 | 0.947 | | | | | D(17)_09 | 0.675 | 0.718 | 0.965 |
| A(17)_06 | 0.199 | 0.305 | | B(18)_01 | 0.849 | 0.849 | 0.613 | | | | | D(17)_10 | 1 | 1 | 0.703 |
| A(17)_07 | 0.316 | 0.552 | | B(18)_02 | 0.531 | 0.549 | 0.528 | | | | | D(18)_01 | 0.168 | 0.170 | 0.400 |
| A(17)_08 | 0.416 | 0.919 | | B(18)_03 | 0.928 | 0.931 | 0.774 | | | | | D(18)_02 | 0.326 | 0.329 | 0.277 |
| A(17)_09 | 0.686 | 0.746 | | B(18)_04 | 0.880 | 0.889 | 0.787 | | | | | D(18)_04 | 0.601 | 0.649 | 0.637 |
| A(17)_10 | 0.436 | 0.743 | | B(18)_05 | 0.290 | 0.334 | 0.999 | | | | | D(18)_05 | 0.568 | 0.586 | 0.636 |
| A(17)_11 | 0.646 | 0.855 | | B(18)_06 | 0.413 | 0.540 | 0.728 | | | | | D(18)_06 | 0.364 | 0.390 | 0.326 |
| A(18)_02 | 0.315 | 0.332 | | B(18)_07 | 0.665 | 0.869 | 0.999 | | | | | D(18)_07 | 0.431 | 0.435 | 0.421 |
| A(18)_03 | 0.409 | 0.432 | | B(18)_08 | 0.291 | 0.376 | 0.591 | | | | | D(18)_08 | 0.852 | 0.957 | 0.767 |
| A(18)_04 | 0.231 | 0.248 | | B(18)_09 | 1 | 1 | 0.999 | | | | | D(18)_09 | 0.939 | 0.941 | 0.999 |
| A(18)_05 | 0.346 | 0.386 | | | | | | | | | | D(18)_10 | 0.635 | 0.649 | 0.425 |
| A(18)_06 | 0.258 | 0.370 | | | | | | | | | | | | | |
| A(18)_08 | 0.434 | 0.820 | | | | | | | | | | | | | |
| A(18)_09 | 0.351 | 0.361 | | | | | | | | | | | | | |
| A(18)_11 | 1 | 1 | | | | | | | | | | | | | |

## Appendix C. Meta-frontier index values (TE*, TE, and TGR) of local Korean festivals

| DMU | CRS-based | | | VRS-based | | | SE | RTS | Main Cause of Inefficiency | |
|---|---|---|---|---|---|---|---|---|---|---|
| | TE* | TE | TGR | TE* (PTE) | TE | TGR | | | PTE | SE |
| A(15)_01 | 0.590 | 0.769 | 0.767 | 1 | 1 | 1 | 0.590 | IRS | | ✓ |
| A(15)_02 | 0.288 | 0.374 | 0.770 | 0.300 | 0.386 | 0.777 | 0.959 | IRS | ✓ | |
| A(15)_03 | 0.984 | 1 | 0.984 | 0.984 | 1 | 0.984 | 1 | CRS | ✓ | |
| A(15)_04 | 0.241 | 0.306 | 0.785 | 0.253 | 0.316 | 0.799 | 0.952 | IRS | ✓ | |
| A(15)_05 | N/A | | | | | | | | | |
| A(15)_06 | 0.349 | 0.494 | 0.707 | 0.482 | 0.602 | 0.800 | 0.724 | IRS | ✓ | |
| A(15)_07 | 0.566 | 0.566 | 1 | 1 | 1 | 1 | 0.566 | IRS | | ✓ |
| A(15)_08 | 0.241 | 0.258 | 0.933 | 1 | 1 | 1 | 0.241 | IRS | | ✓ |
| A(15)_09 | 0.955 | 1 | 0.955 | 1 | 1 | 1 | 0.955 | IRS | | ✓ |
| A(15)_10 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| A(15)_11 | 0.977 | 1 | 0.977 | 0.981 | 1 | 0.981 | 0.996 | IRS | ✓ | |
| A(16)_01 | 0.259 | 0.274 | 0.947 | 0.507 | 1 | 0.507 | 0.512 | IRS | ✓ | |
| A(16)_02 | 0.324 | 0.353 | 0.918 | 0.334 | 0.353 | 0.945 | 0.969 | IRS | ✓ | |
| A(16)_03 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| A(16)_04 | 0.221 | 0.250 | 0.884 | 0.238 | 0.276 | 0.860 | 0.931 | IRS | ✓ | |
| A(16)_05 | 0.250 | 0.250 | 1 | 0.259 | 0.266 | 0.971 | 0.966 | IRS | ✓ | |
| A(16)_06 | 0.176 | 0.178 | 0.988 | 0.259 | 0.349 | 0.742 | 0.679 | IRS | ✓ | |
| A(16)_07 | 0.345 | 0.365 | 0.945 | 0.610 | 1 | 0.610 | 0.565 | IRS | | ✓ |
| A(16)_08 | 0.228 | 0.243 | 0.937 | 1 | 1 | 1 | 0.228 | IRS | | ✓ |
| A(16)_09 | 0.475 | 0.554 | 0.857 | 0.517 | 1 | 0.517 | 0.919 | IRS | ✓ | |
| A(16)_10 | 0.401 | 0.422 | 0.951 | 1 | 1 | 1.000 | 0.401 | IRS | | ✓ |
| A(16)_11 | 0.658 | 0.736 | 0.894 | 0.853 | 1 | 0.853 | 0.771 | DRA | | ✓ |
| A(17)_01 | 0.450 | 0.730 | 0.617 | 0.797 | 1 | 0.797 | 0.565 | IRS | | ✓ |
| A(17)_02 | 0.471 | 0.715 | 0.658 | 0.502 | 0.718 | 0.699 | 0.937 | IRS | ✓ | |
| A(17)_03 | 0.700 | 1 | 0.700 | 0.743 | 1 | 0.743 | 0.942 | IRS | ✓ | |
| A(17)_04 | 0.248 | 0.369 | 0.672 | 0.252 | 0.371 | 0.680 | 0.981 | IRS | ✓ | |
| A(17)_05 | 0.327 | 0.475 | 0.689 | 0.343 | 0.510 | 0.672 | 0.955 | DRA | ✓ | |
| A(17)_06 | 0.199 | 0.291 | 0.685 | 0.305 | 1 | 0.305 | 0.652 | IRS | ✓ | |

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(*continued*)

| DMU | CRS-based | | | VRS-based | | | SE | RTS | Main Cause of Inefficiency | |
|---|---|---|---|---|---|---|---|---|---|---|
| | TE* | TE | TGR | TE* (PTE) | TE | TGR | | | PTE | SE |
| A(17)_07 | 0.316 | 0.506 | 0.624 | 0.552 | 1 | 0.552 | 0.571 | IRS | ✓ | |
| A(17)_08 | 0.416 | 0.614 | 0.677 | 0.919 | 1 | 0.919 | 0.453 | IRS | | ✓ |
| A(17)_09 | 0.686 | 1 | 0.686 | 0.746 | 1 | 0.746 | 0.919 | IRS | ✓ | |
| A(17)_10 | 0.436 | 0.647 | 0.673 | 0.743 | 1 | 0.743 | 0.586 | IRS | | ✓ |
| A(17)_11 | 0.646 | 0.981 | 0.659 | 0.855 | 1 | 0.855 | 0.756 | DRA | | ✓ |
| A(18)_01 | N/A | | | | | | | | | |
| A(18)_02 | 0.315 | 0.433 | 0.728 | 0.332 | 0.635 | 0.523 | 0.948 | IRS | ✓ | |
| A(18)_03 | 0.409 | 0.821 | 0.498 | 0.432 | 1 | 0.432 | 0.947 | IRS | ✓ | |
| A(18)_04 | 0.231 | 0.267 | 0.865 | 0.248 | 0.445 | 0.557 | 0.934 | IRS | ✓ | |
| A(18)_05 | 0.346 | 0.906 | 0.382 | 0.386 | 1 | 0.386 | 0.897 | DRA | ✓ | |
| A(18)_06 | 0.258 | 0.867 | 0.298 | 0.370 | 1 | 0.370 | 0.697 | IRS | ✓ | |
| A(18)_07 | N/A | | | | | | | | | |
| A(18)_08 | 0.434 | 0.434 | 1 | 0.820 | 1 | 0.820 | 0.529 | IRS | | ✓ |
| A(18)_09 | 0.351 | 0.545 | 0.644 | 0.361 | 1 | 0.361 | 0.973 | IRS | ✓ | |
| A(18)_10 | N/A | | | | | | | | | |
| A(18)_11 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| B(15)_01 | 0.581 | 0.581 | 1.000 | 0.581 | 0.581 | 1.000 | 1 | CRS | ✓ | |
| B(15)_02 | 0.475 | 0.479 | 0.992 | 0.517 | 0.637 | 0.811 | 0.920 | IRS | ✓ | |
| B(15)_03 | 0.673 | 0.760 | 0.885 | 0.750 | 0.992 | 0.756 | 0.897 | IRS | ✓ | |
| B(15)_04 | 0.758 | 0.839 | 0.904 | 0.830 | 1 | 0.830 | 0.914 | IRS | ✓ | |
| B(15)_05 | 0.978 | 1 | 0.978 | 1 | 1 | 1 | 0.978 | DRS | | ✓ |
| B(15)_06 | 0.510 | 0.514 | 0.992 | 0.556 | 0.684 | 0.812 | 0.919 | IRS | ✓ | |
| B(15)_07 | 0.782 | 0.782 | 1 | 1 | 1 | 1 | 0.782 | IRS | | ✓ |
| B(15)_08 | 0.357 | 0.357 | 1 | 0.461 | 0.636 | 0.725 | 0.775 | IRS | ✓ | |
| B(15)_09 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| B(16)_01 | 0.616 | 0.659 | 0.934 | 0.616 | 0.659 | 0.934 | 1 | CRS | ✓ | |
| B(16)_02 | 0.477 | 0.512 | 0.932 | 0.533 | 0.741 | 0.720 | 0.894 | IRS | ✓ | |
| B(16)_03 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| B(16)_04 | 0.954 | 1 | 0.954 | 1 | 1 | 1 | 0.954 | IRS | | ✓ |
| B(16)_05 | 0.434 | 0.458 | 0.949 | 0.493 | 0.839 | 0.588 | 0.881 | DRS | ✓ | |
| B(16)_06 | 0.485 | 0.519 | 0.935 | 0.529 | 0.641 | 0.825 | 0.917 | IRS | ✓ | |
| B(16)_07 | 0.464 | 0.496 | 0.936 | 0.597 | 1.000 | 0.597 | 0.777 | IRS | ✓ | |
| B(16)_08 | 0.196 | 0.209 | 0.936 | 0.255 | 0.555 | 0.459 | 0.770 | IRS | ✓ | |
| B(16)_09 | 0.936 | 1 | 0.936 | 0.936 | 1 | 0.936 | 1 | CRS | ✓ | |
| B(17)_01 | 0.787 | 0.822 | 0.958 | 0.787 | 0.822 | 0.958 | 1 | CRS | ✓ | |
| B(17)_02 | 0.919 | 0.959 | 0.958 | 1 | 1 | 1 | 0.919 | IRS | | ✓ |
| B(17)_03 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| B(17)_04 | 0.977 | 1 | 0.977 | 1 | 1 | 1 | 0.977 | IRS | | ✓ |
| B(17)_05 | 0.226 | 0.227 | 0.996 | 0.283 | 0.415 | 0.681 | 0.797 | DRS | ✓ | |
| B(17)_06 | 0.568 | 0.595 | 0.956 | 0.738 | 0.756 | 0.976 | 0.770 | IRS | ✓ | |
| B(17)_07 | N/A | | | | | | | | | |
| B(17)_08 | 0.225 | 0.235 | 0.956 | 0.291 | 1 | 0.291 | 0.773 | IRS | ✓ | |
| B(17)_09 | 0.959 | 1 | 0.959 | 0.959 | 1 | 0.959 | 1 | CRS | ✓ | |
| B(18)_01 | 0.849 | 0.849 | 1 | 0.849 | 0.849 | 1 | 1 | CRS | ✓ | |
| B(18)_02 | 0.531 | 0.531 | 1 | 0.549 | 0.704 | 0.779 | 0.968 | IRS | ✓ | |
| B(18)_03 | 0.928 | 1 | 0.928 | 0.931 | 1 | 0.931 | 0.996 | DRS | ✓ | |
| B(18)_04 | 0.880 | 0.880 | 1 | 0.889 | 1 | 0.889 | 0.990 | IRS | ✓ | |
| B(18)_05 | 0.290 | 0.293 | 0.990 | 0.334 | 0.590 | 0.565 | 0.869 | DRS | ✓ | |
| B(18)_06 | 0.413 | 0.417 | 0.990 | 0.540 | 0.894 | 0.604 | 0.764 | IRS | ✓ | |
| B(18)_07 | 0.665 | 0.672 | 0.990 | 0.869 | 1 | 0.869 | 0.765 | IRS | | ✓ |
| B(18)_08 | 0.291 | 0.294 | 0.990 | 0.376 | 1 | 0.376 | 0.775 | IRS | ✓ | |
| B(18)_09 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| C(15)_01 | 0.155 | 0.155 | 1.000 | 0.245 | 0.338 | 0.726 | 0.634 | DRS | ✓ | |
| C(15)_02 | 0.300 | 0.391 | 0.768 | 0.301 | 0.442 | 0.681 | 0.999 | DRS | ✓ | |
| C(15)_03 | 0.635 | 1 | 0.635 | 0.635 | 1 | 0.635 | 1 | CRS | ✓ | |
| C(15)_04 | 0.366 | 0.366 | 1 | 0.466 | 0.621 | 0.750 | 0.787 | DRS | ✓ | |
| C(15)_05 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| C(16)_01 | 0.094 | 0.228 | 0.414 | 0.154 | 0.235 | 0.655 | 0.612 | DRS | ✓ | |
| C(16)_02 | 0.218 | 0.289 | 0.753 | 0.238 | 0.311 | 0.765 | 0.915 | DRS | ✓ | |
| C(16)_03 | 1 | 1 | 1 | 1 | 1 | 1 | 1.000 | CRS | | |
| C(16)_04 | 0.314 | 0.772 | 0.407 | 0.411 | 0.876 | 0.469 | 0.766 | DRS | ✓ | |
| C(16)_05 | 0.201 | 0.584 | 0.344 | 1 | 1 | 1 | 0.201 | IRS | | ✓ |
| C(17)_01 | 0.102 | 0.194 | 0.527 | 0.162 | 0.201 | 0.807 | 0.629 | DRS | ✓ | |
| C(17)_02 | 0.225 | 0.308 | 0.732 | 0.266 | 0.348 | 0.763 | 0.848 | DRS | ✓ | |
| C(17)_03 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| C(17)_04 | 0.419 | 0.807 | 0.519 | 0.539 | 0.938 | 0.575 | 0.777 | DRS | ✓ | |
| C(17)_05 | 0.204 | 0.511 | 0.400 | 0.434 | 1.000 | 0.434 | 0.471 | IRS | ✓ | |
| C(18)_01 | 0.115 | 0.290 | 0.396 | 0.165 | 0.345 | 0.479 | 0.695 | DRS | ✓ | |
| C(18)_02 | 0.174 | 0.527 | 0.330 | 0.207 | 0.573 | 0.361 | 0.842 | DRS | ✓ | |
| C(18)_03 | 0.311 | 1 | 0.311 | 0.473 | 1 | 0.473 | 0.657 | DRS | ✓ | |
| C(18)_04 | 0.428 | 1.000 | 0.428 | 0.568 | 1 | 0.568 | 0.753 | DRS | ✓ | |
| C(18)_05 | 0.203 | 0.654 | 0.311 | 0.203 | 1 | 0.203 | 1 | CRS | ✓ | |
| D(15)_01 | 0.586 | 0.586 | 1 | 0.593 | 1 | 0.934 | 0.989 | DRS | ✓ | |
| D(15)_02 | N/A | | | | | | | | | |

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(*continued*)

| DMU | CRS-based | | | VRS-based | | | SE | RTS | Main Cause of Inefficiency | |
|---|---|---|---|---|---|---|---|---|---|---|
| | TE* | TE | TGR | TE* (PTE) | TE | TGR | | | PTE | SE |
| D(15)_03 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| D(15)_04 | 0.718 | 0.783 | 0.918 | 1 | 1 | 1 | 0.718 | IRS | | ✓ |
| D(15)_05 | 0.914 | 0.926 | 0.987 | 0.937 | 0.937 | 1 | 0.976 | IRS | ✓ | |
| D(15)_06 | 0.873 | 0.896 | 0.973 | 0.877 | 1 | 0.877 | 0.995 | DRS | ✓ | |
| D(15)_07 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| D(15)_08 | 0.592 | 0.592 | 1 | 0.609 | 0.609 | 1 | 0.972 | IRS | ✓ | |
| D(15)_09 | 0.519 | 0.536 | 0.969 | 0.522 | 0.577 | 0.904 | 0.995 | DRS | ✓ | |
| D(15)_10 | 0.931 | 1 | 0.931 | 0.952 | 1 | 0.952 | 0.978 | IRS | ✓ | |
| D(16)_01 | 0.223 | 0.240 | 0.928 | 0.225 | 0.247 | 0.910 | 0.990 | DRS | ✓ | |
| D(16)_02 | 0.327 | 0.327 | 1 | 0.338 | 0.455 | 0.744 | 0.965 | IRS | ✓ | |
| D(16)_03 | 0.536 | 0.595 | 0.901 | 0.536 | 0.595 | 0.901 | 1 | CRS | ✓ | |
| D(16)_04 | 0.706 | 0.706 | 1 | 0.914 | 1 | 0.914 | 0.773 | IRS | | ✓ |
| D(16)_05 | 0.864 | 0.921 | 0.938 | 0.875 | 1.000 | 0.875 | 0.987 | IRS | ✓ | |
| D(16)_06 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| D(16)_07 | 0.149 | 0.152 | 0.980 | 1 | 1 | 1 | 0.149 | IRS | | ✓ |
| D(16)_08 | 0.512 | 0.558 | 0.917 | 0.530 | 0.606 | 0.875 | 0.965 | IRS | ✓ | |
| D(16)_09 | 0.547 | 0.656 | 0.833 | 0.581 | 0.697 | 0.834 | 0.940 | IRS | ✓ | |
| D(16)_10 | 0.894 | 1 | 0.894 | 0.898 | 1 | 0.898 | 0.995 | DRS | ✓ | |
| D(17)_01 | 0.210 | 0.241 | 0.871 | 0.211 | 0.274 | 0.769 | 0.994 | DRS | ✓ | |
| D(17)_02 | 0.376 | 0.577 | 0.651 | 0.382 | 0.792 | 0.482 | 0.983 | IRS | ✓ | |
| D(17)_03 | 0.620 | 0.708 | 0.875 | 0.622 | 1 | 0.622 | 0.996 | DRS | ✓ | |
| D(17)_04 | 0.580 | 0.922 | 0.629 | 0.626 | 1 | 0.626 | 0.927 | IRS | ✓ | |
| D(17)_05 | 0.913 | 1 | 0.913 | 0.929 | 1 | 0.929 | 0.983 | IRS | ✓ | |
| D(17)_06 | N/A | | | | | | | | | |
| D(17)_07 | N/A | | | | | | | | | |
| D(17)_08 | 0.564 | 0.628 | 0.898 | 0.583 | 0.628 | 0.929 | 0.967 | IRS | ✓ | |
| D(17)_09 | 0.675 | 0.675 | 1 | 0.718 | 0.776 | 0.926 | 0.940 | IRS | ✓ | |
| D(17)_10 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | CRS | | |
| D(18)_01 | 0.168 | 0.232 | 0.726 | 0.170 | 0.232 | 0.732 | 0.989 | IRS | ✓ | |
| D(18)_02 | 0.326 | 0.616 | 0.530 | 0.329 | 0.624 | 0.527 | 0.992 | DRS | ✓ | |
| D(18)_03 | N/A | | | | | | | | | |
| D(18)_04 | 0.601 | 1 | 0.601 | 0.649 | 1 | 0.649 | 0.925 | IRS | ✓ | |
| D(18)_05 | 0.568 | 0.891 | 0.638 | 0.586 | 0.970 | 0.604 | 0.970 | IRS | ✓ | |
| D(18)_06 | 0.364 | 0.593 | 0.614 | 0.390 | 0.673 | 0.580 | 0.933 | IRS | ✓ | |
| D(18)_07 | 0.431 | 0.850 | 0.507 | 0.435 | 1 | 0.435 | 0.990 | IRS | ✓ | |
| D(18)_08 | 0.852 | 1 | 0.852 | 0.957 | 1 | 0.957 | 0.890 | IRS | | ✓ |
| D(18)_09 | 0.939 | 1 | 0.939 | 0.941 | 1 | 0.941 | 0.998 | IRS | ✓ | |
| D(18)_10 | 0.635 | 0.947 | 0.670 | 0.649 | 1 | 0.649 | 0.978 | DRS | ✓ | |

## Appendix D. Simar & Wilson's truncated regression with double bootstrapping

Non-parametric approaches such as the DEA measure efficiency relative to a non-parametric, maximum likelihood estimate of an unobserved true frontier, which is conditional on observed data resulting from an underlying data-generating process (Simar & Wilson, 2011). Nonparametric approximations are primarily concerned with estimating a production-possibility frontier and measuring the efficiency scores of production units as a distance to the frontier with input-output combinations, based on a finite sample of observed production units. However, the DEA is not possible to apply to statistical inference due to its deterministic nature, and tends to generate biased estimates. Thus, a well-defined, coherent statistical model is necessary in order to know what is estimated.

To mitigate this limitation of non-parametric approaches, Simar & Wilson (2007) proposed the semi-parametric bootstrap, thus correcting the bias estimation efficiency and giving the confidence interval of efficiency. First, they described a *sensible* data generating process to generate artificial *i.i.d.* bootstrap samples from an artificial data generating process. Second, they developed a parametric bootstrap procedure that is consistent with the assumed data generating process in order to construct estimated standard errors and confidence intervals that do not suffer from bias due to the correlation of estimated efficiency scores.

The main assumption is that the original efficiency score is given by $\widehat{\theta}_i = \psi(\beta', z_i) + \varepsilon_i \geq 1$ and can be translated into the following regression specification:

$$\widehat{\theta}_i = \beta' z_i + \varepsilon_i \geq 1$$

where $\psi$ is a smooth continuous function, $z_i$ is a vector of the environmental variables, $\beta'$ is a vector of parameters estimated by maximum likelihood, and $\varepsilon_i \sim N(0, \sigma_\varepsilon^2)$ is a continuous *i.i.d* random variable independent of $z_i$.

The algorithm requires the following steps:

Step 1: Compute the efficiency score $\theta_i (i = 1, \ldots, \ \mathrm{N})$ using DEA.

Step 2: Fit the $\widehat{\theta}_i = \beta' z_i + \varepsilon_i \geq 1$ truncated regression by adopting the maximum likelihood (ML) method to obtain estimates $\widehat{\beta}$ of $\beta$ and $\widehat{\sigma}_\varepsilon$ of $\sigma_\varepsilon$.

- Efficient DMUs $j(\widehat{\theta}_j = 1, \ \mathrm{j} = 1, \ldots, \ \mathrm{M})$ excluded.
- $\widehat{\theta}_i^{in} \in (0, 1]$ (input-orient): right-truncation at 1.
- $\widehat{\theta}_i^{out} \in [0, \infty)$ (output-orient): left-truncation at 1.

Step 3: Loop over steps 3.1–3.3 $B$ times ($b = 1, \ldots, B$) to obtain a set of bootstrap estimates.

3.1 For each $i = 1, \ldots, N$, draw $\varepsilon_i^b \sim N(0, \widehat{\sigma}_\varepsilon^2)$ with left-truncation at. $(1 - \widehat{\beta}' z_i)$

3.2 For each $i = 1, \ldots, N$, compute. $\theta_i^b = \widehat{\beta}' z_i + \varepsilon_i^b$

3.3 Estimate $\widehat{\beta}^b$ and $\widehat{\sigma}_\varepsilon^b$ through the truncated regression model using the artificial efficiency scores $\theta_i^b$ as lhs-variable.

Step 4: Construct standard errors for $\widehat{\beta}$ and $\widehat{\sigma}_\varepsilon$ (confidence intervals for $\beta$ and $\sigma_\varepsilon$) from the simulated distribution of $\widehat{\beta}^b$ and $\widehat{\sigma}_\varepsilon^b$.

Following both Simar and Wilson (2007a; 2007b, pp. 421–521), and Badunenko and Tauchmann (2019), we employed a STATA 16 software program to obtain unbiased coefficients and confidence intervals with 2000 replications. A set of exogenous covariates affecting the TE* scores were developed for the second-stage regression analysis, which represents the operating environments of a local Korean festival.

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