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The efficiency analysis of media companies: An application of DEA and Malmquist indices

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ABSTRACT

As the global entertainment and media market is expected to multiply, media companies, such as streaming services, television networks, and broadcasting companies, play critical roles in providing TV and movie content, the industry's fuel. Almost all players of small and large sizes in the industry spend enormous resources on content and expand their investment to retain global and regional content to win the battle of viewership. However, the efficiency of investments varies for media companies. Measuring efficiency has been crucial as all firms strive to achieve better productivity. In particular, estimating the efficiencies and productivities of firms producing and offering intangible assets, such as TV and movie content, and valuing the content on firm performance are challenging. With our longitudinal data about local and global media companies from 2019 to 2022, we first used a Data Envelopment Analysis (DEA) to answer which firms in the media industry have effectively exploited their resources to achieve better firm performance. In addition, with the Malmquist analysis, we show how the efficiencies and productivity of content providers change along with the dynamics of the media industry that the media industry has recently faced. Our understanding of the global media companies' efficiencies from diverse perspectives offers several theoretical and practical implications for the streams of efficiencies and competition in the media industry.

1. Introduction

The media industry has faced a dramatic transformation with new players. For example, over-the-top (OTT) media services, also referred to as video streaming, have changed the competitive landscape of the media and entertainment industry. Consumers can access a variety of content from global production studios and publishers in one place more quickly with OTT media services, such as Netflix and Amazon Prime Video. OTT services provide more personalized content with recommendation functions and better viewing time and location flexibility than traditional networks. Also, in general, the subscription fees of OTT services are lower than those of conventional networks, and OTTs offer diverse pricing options for subscriptions (e.g., Netflix Ad-supported Plans). With these advantages of OTT over traditional media players (e.g., cable firms and TV networks), more and more traditional TV viewing users have switched to OTT services. According to a report from Statista (Statista, 2023), the market share of OTT firms in the media industry has increased at a fast pace, is projected to reach $ 294.9 billion, is expected to surpass traditional TV companies' aggregated market shares in 2025 and be $397.2 billion by 2027. In addition, households subscribing to the conventional liner (wired) cable are below 40%

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(from 59.8%) for the first time in almost 20 years (Nielsen, 2023b).

The competition in the media industry has gotten stiffer and more severe for several reasons. First, the existing firms in the media industry have transformed their business models to respond to the threats from OTT firms. For example, traditional players, such as media companies, media production, and news channels in the media industry (e.g., Discovery, HBO, CNN), have launched their own OTT services by themselves or through partnerships. In addition, new entrants from diverse areas, such as Amazon, offer OTT to enter the market and provide OTT service. To achieve a better competitive advantage over competitors in the market, firms implement aggressive strategic actions with diverse patterns (Grimm, Lee, & Smith, 2006).

Also, both new and established players execute diverse strategies, for instance, mergers and acquisitions, releasing new products, and partnerships. Of course, the objective of implementing all these strategic actions must be achieving competitive advantages over competitors, thereby surviving in the market. However, in terms of detailed plans, most firms in the media industry heavily invest in content to win the battle of viewership. For example, Amazon in 2022 acquired MGM movie studio to strengthen its' OTT service, with MGM's more than 4000 films and 17,000 TV series. In 2018, just right before Disney launched its OTT service, Disney +, Netflix spent more than $12 billion on content proactively to deal with the challenges caused by new entrants with their own content (Statista, 2020).

Content providers, among other media companies, provide customers with content, such as TV, movies, sports games, and news. Content providers continue spending resources to create or buy content, and almost all players of small and large sizes seem to expand their investment to retain global and regional content. However, the effectiveness of investments varies for the firms in the media industry. The huge investment pays back for some firms but does not work for others. For instance, according to a report from Nielsen in 2023, Netflix dominated the top 15 streaming rankings (for both 15 streaming programs and 15 streaming original programs) in Nielsen's year-end rankings, while Amazon only put two of its original series (Nielsen, 2023a). In addition, although 'Lord of the Rings: The Rings of Power,' a streaming program from Amazon Prime, has surpassed 'Stranger Things,' the most streamed program for 2022, to become the most expensive TV show, spending $58.1 million per episode, the viewership of the Amazon streaming program is much lower than Netflix's original series in Nielsen's year-end rankings. Meanwhile, according to an article from Bloomberg, the case of Squid Game, one of the most-watched Netflix content of all time, generated $891.1 million in impact value. The show costs only $21.4 million per episode, or $2.4 million[1].

Likewise, media companies spend a lot of resources, especially on content, but the investment outputs seem inconsistent. This situation leads us to question the effectiveness of media companies' investment. Thus, in this study, our primary objective is to answer the question: *which content providers in the media industry have effectively exploited their resources to achieve better productivity, and how does it change along with the industry dynamics (i.e., before and after the pandemic)?* We are mainly interested in the content providers' efficiency among other media companies since the content is the critical resource to win the battle of viewership, and all players heavily invest in the content.

With the recent data about local and global content providers from 2019 to 2022, we use a DEA-based methodology and the Malmquist method to measure firms' productivity and efficiencies from diverse perspectives. Our work differs from earlier research on the efficiency of media companies because the prior studies in the stream could not consider the significant change in the TV-watching behavior of consumers and the change in the productivity of content providers caused by the COVID-19 pandemic. The pandemic has changed every aspect of our lives, especially how consumers consume entertainment and media. Global streaming consumption soared after the pandemic. The safety restrictions made people stay home, and consumers turned to online video streaming services to fill their void. In the fourth quarter of 2020, Americans watched streaming programs 44% longer than they did in the fourth quarter of 2019, according to a report from Conviva, a streaming media intelligence company. Parallel to the pandemic, many new players, such as Disney+, Hulu, and Warner Bros, launched the streaming video service in the market (Vlassis, 2021). Streaming companies heavily invested in the content to lure increasing subscribers globally. For example, Disney + spent $27.8 billion in 2019, $28.6 billion in 202, and $25 billion in 2021 on content. Especially in 2022, Disney + spent $33 billion on content investment, almost double Neflix's $17 billion spending (Statista, 2022).

In addition, the performances of the media companies were different before and after the pandemic. Although the global OTT market size has dramatically expanded during the pandemic, more people are now cutting their streaming services. People are tired of watching TV and movies too much since the world entered the endemic era, and they answered that they are planning to spend less time watching TV or videos. Netflix, the biggest video streaming service, has curbed its content spending growth in 2023 and raised prices. Other streaming companies, such as Warner Bros. Discovery and Disney+, announced thousands of layoffs, cutting billions of dollars in content spending in 2023.

Likewise, the prior objective of content providers in the media industry is an effective use of resources for better profitability, not just simply the growth of subscribers and revenue. Thus, we believe that studying content provider firms' efficiency, especially the productivity change within the time window (i.e., from 2019 to 2022), is needed to understand the recent transformation in the industry's competitive landscape. We can learn which strategy content providers use to achieve better efficiency, given their position in the market and what they possess. This study will contribute to the extant literature on competition in media companies and provide several practical implications.

[1] https://www.bloomberg.com/news/articles/2021-10-17/squid-game-season-2-series-worth-900-million-to-netflix-so-far?embedded-checkout=true.

2. Research methodology

2.1. Data and measurement

We chose the global media industry as the research context, where the competition has recently gotten stiffer and more severe after the COVID-19 pandemic. Our sample includes 25 prominent local and global content providers in the industry available from 2019 to 2022. Data from multiple sources were employed, and Statista and S&P Global offered financial data of content providers.

There are many prior studies estimating efficiency in the media industry. For example, one paper (Rahman, Rodríguez-Serrano, & Hughes, 2021) estimated firms' advertising productivity levels and demonstrated the positive impact of advertising productivity on performance. In addition, Cheong et al. (Cheong et al, 2014; De Gregorio, & Kim, 2014) also found that US advertisers overspend advertising costs, contributing to lower profit margins and sales loss. Hababou et al. (Hababou, Amrouche, & Jedidi, 2016) measured economic efficiency in the motion picture industry. They uncovered the drivers of movie efficiency (e.g., genre, sequels, Academy Awards, etc.). Also, one recent study in the social media sector estimated the efficiency rankings of selected brands' marketing activities on a social media platform and the impact of social media marketing activities on firm performance (Kongar & Adebayo, 2021).

Based on previous studies in the stream (e.g., Cheong et al., 2014; Hababou et al., 2016; Kim & Heshmati, 2009, pp. 315–339; Kongar & Adebayo, 2021; Li, Sun, Agyeman, Su, & Hu, 2022), the input and output factors of productivity measurement were determined. Table 1 summarizes previous studies estimating efficiency in the media industry.

The input factors include total assets, total expenses, and labor. These reflect the three factors of production in economics: land, capital, and labor. Total Revenue, EBITDA Margin before taxes, interest, and depreciation were set as output factors. EBITDA Margin indicates how much cash is generated through operating activities. EBITDA contains some negative numbers, but it is used because it is not much compared to operating profit or net profit. Table 2 shows the basic statistics.

2.2. Model of DEA and MPI analysis

We used DEA to derive the relative efficiencies of DMUs and identify the most efficient frontier using the selected input and output variables. Charnes et al. (Charnes, Cooper, & Rhodes, 1978) developed a way to measure relative efficiencies, titled data envelopment analysis (DEA), using multi-input and multi-output for comparable decision-making units (DMU), building on those ideas of Farrell's work. Farrell (1957) proposed an efficiency measurement method based on the idea that efficiency can be assumed to be constant returns to scale (CRS), and the efficiency of a company (an element of a production set) can be measured at a distance away from the production frontier. Behind the notion of DEA was that efficient firms can produce a given amount of or more outputs (i.e., input-oriented DEA) while spending a certain amount of inputs or using the same amount of or less inputs to create a given amount of outputs (i.e., output-oriented DEA), as compared with other firms in the test groups (Charnes et al., 1978). In general, the most commonly used models among DEA models are the CCR (Charnes, Cooper, Rhodes) model and the BCC (Banker, Charnes, Cooper) of Banker et al. (Banker, Charnes, & Cooper, 1984). The CCR model is used under Constant Returns to Scale, and the BCC model is used under the assumption of Variable Returns to Scale. Since the introduction of DEA and MPI analysis, the methods have significantly been employed both in social and natural science sectors (e.g., Bielov, Mitomo, Hämmäinen, & 2022; Oredegbe & Zhang, 2020; Wang, Wang, & Yao., 2021). In general, it is common for media companies to utilize given resources to maximize output actively. Therefore, this study estimated annual productivity fluctuations through an output-oriented approach. We also examined the scale efficiency through VRS.

In addition to the DEA model, DEA-based MPI analysis was used to measure the change in productivity between different periods, especially analyzing the movement of the efficient frontier and DMUs by period in the form of an index. MPI provides a better understanding of the meaning of total factor productivity. MPI can decompose total factor productivity (TFPI) into the *Technology Change Index* (TCI) and *Technology Efficiency Change Index* (TECI). TECI is classified again into the *Pure Efficiency Change Index* (PECI) and *Scale Efficiency Change Index* (SECI). Using MPI analysis, we measured these four dimensions of the productivity of 25 content providers. The detailed process of the output-oriented MPI decomposition follows below.

Table 1
Summary of previous studies estimating efficiency in the media industry.

Year	Authors	Inputs	Outputs	Research Context
2022	Li et al.	Total Capital Investment, Total Cost of Labor	Sales	Creative Cultural Enterprise in China
2016	Hababou et al.	Production-Related Costs, Costs for Advertising and Print, Distribution and Exhibition	Total Admission, Revenue from Ticket Sales	Motion Picture Industry
2014	Cheong et al.	6 Inputs about Expenditure: Magazines, Newspapers, TV, Radio, Outdoor, Internet	Sales	Advertising Industry
2021	Kongar & Adebayo	Number of Employees, Total Assets, Tweets	Sales, Likes, Followers, Friends, List Counts	Social Media Marketing
2009	Kim & Heshmati	Number of Employees, Capital, and Material Costs	Subscription Fee, Internet Fee, Other Fee	Korean Cable TV Industry

Table 2
Summary of basic statistics.

	Min	Max	Mean	s.d
1. Total Asset	0.012041	203.6	18.31316	38.01177
2. Total Expense	0.142462	79.17	7.538814	13.37743
3. Employee	287	223000	14460.15	40095.9
4. Revenue	0.179773	82.72	8.259541	14.38247
5. RevenuePerEmployee	0.000142	0.00266	0.000904	0.000519
6. EBITDA	−0.0307	20	2.174576	3.979502
7. EBITDAMargin	−9.24104	64.28	23.93466	16.49488

Assuming that the time series of data to be analyzed is t = 1,2, …T, Färe et al. (Färe, Grosskopf, Norris, & Zhang, 1994) can define s^t all of the following technology components and technology elements that are produced by inputting input elements $x^t \in R_t^m, x^t = (x_1, x_2, \cdots, x_m)$ for $y^t = (y_1, y_{2,} \cdots, y_s)$ time point t.

$$s^t = (x^t, y^t) : x^t \ yields \ y^t \tag{1}$$

According to Sephard 1970, the calculation distance function for the time point t is defined as follows.

$$D_o^t(x^t, y^t) = \infty\theta : \left(x^t, \frac{y^t}{\theta}\right) \in s^t = \left[SUP\ \theta : \left(x^t, \theta_y^t\right) \in s^t\right]^{-1} \tag{2}$$

The calculated distance function defined above is the reciprocal of a value capable of maximally extending y^t using x^t. In particular, if $(x^t, y^t) \in S^t$, it is $D_o^t(x^t, y^t) \leq 1$, and if (x^t, y^t) exists in the technology change, it is $D_o^t(x^t, y^t) = 1$. This means $\theta = 1$. According to Farrell's definition (Farrell, 1957), it occurs when production is technically efficient. Malmquist productivity (MPI) can be calculated as follows through a combination of input and output of t, t+1, assuming production technology at the time t (Caves, Christensen, & Diewert, 1982).

$$M^t = \frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \tag{3}$$

Assuming the production technology of the t+1 stage, the MPI can be calculated by combining the two different time points t and t+1 stage.

$$M^{t+1} = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^t, y^t)} \tag{4}$$

As follows, the output-oriented Malmquist production change index is defined using the geometric average of the two MPI indexes to avoid the random selection of the base year for production technology.

$$M_o\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \bullet \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^{t+1}}\right]^{\frac{1}{2}} \tag{5}$$

If $M_o(x^{t+1}, y^{t+1}, x^t, y^t) > 1$, that productivity increased in the (t+1) group compared to the t group, and $M_o(x^{t+1}, y^{t+1}, x^t, y^t) < 1$ means that there is no productivity change when $M_o(x^{t+1}, y^{t+1}, x^t, y^t) = 1$. Equation (5) can be expressed as follows.

$$M_o\left(x^{t+1}, y^{t+1}, x^t, y^t\right) = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \bullet \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \bullet \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}} = TECI \cdot TCI \tag{6}$$

In equation (6), the formula outside the parentheses represents the ratio of the distance function at the two points in time (t, t+1). This is called the Technical Efficiency Change Index (TECI). It can be said to be a measure of evaluating changes in technical efficiency from these two points of view. The geometric mean in parentheses is called the Technical Change Index (TCI) between two points of view (t, t+1). It measures how changes in production technology, that is, movement to efficient boundaries, contribute to productivity changes (Charnes et al., 1978). The TECI is again classified into the Pure Efficiency Change Index (PECI).

$$\mathrm{M_o}\left(\mathrm{x^{t+1}, y^{t+1}, x^t, y^t}\right) = \frac{\mathrm{V_o^{t+1}(x^{t+1}, y^{t+1})}}{\mathrm{V_o^t(x^t, y^t)}} \bullet \left[\frac{\mathrm{V_o^t(x^t, y^t)}}{\mathrm{D_o^t(x^t, y^t)}} \bullet \frac{\mathrm{V_o^{t+1}(x^{t+1}, y^{t+1})}}{\mathrm{D_o^{t+1}(x^{t+1}, y^{t+1})}}\right] \left[\frac{\mathrm{D_o^t(x^{t+1}, y^{t+1})}}{\mathrm{D_o^{t+1}(x^{t+1}, y^{t+1})}} \bullet \frac{\mathrm{D_o^t(x^t, y^t)}}{\mathrm{D_o^{t+1}(x^t, y^t)}}\right]^{\frac{1}{2}} = \mathrm{PECI} \bullet \mathrm{SECI} \bullet \mathrm{TCI} \tag{7}$$

As shown in equation (7), MPI can be calculated by decomposing into three parts: the Pure Efficiency Index (PECI), the Scale Efficiency Change Index (SECI), and the Technology Change Index (TCI). In the above equation, $V_o^t(x^t, y^t)$ represents the calculated distance function under the magnitude of the revenue change of the t group and $\frac{V_o^{t+1}(x^{t+1}, y^{t+1})}{V_o^t(x^t, y^t)}$ is a measure of the change in net efficiency at the time of t. $\frac{V_o^t(x^t, y^t)}{D_o^t(x^t, y^t)}$ represents the ratio of the scale revenue variable technology calculation distance function to the scale revenue constant technology at the time t and defines the scale efficiency change index.

3. Results

3.1. Productivity changes of the total sample from 2019 to 2022

Table 3 and Fig. 1 below show the productivity changes in the total sample from 2019 to 2022. Productivity from 2019 to 2020 shows a decreasing trend overall, rebounding sharply in 2021 and then falling again in 2022. Technological change rose modestly from 2019 to 2021 but decreased rapidly between 2021 and 2022. Conversely, the change in pure efficiency is similar to technological change, but it appears more rapid. The change in scale efficiency shows the opposite pattern of the change in pure efficiency.

Although the factors of productivity change vary, most media companies seem to have experienced the growth of productivity caused by COVID-19 between 2020 and 2021. In addition, from 2019 to 2020, as many new video streaming service firms (e.g., Hulu, Disney+, and Warner Bros. Discovery) entered the market, competition appeared, centered on the United States. It can be seen that the productivity of media companies was decreased due to increased production costs and stagnation of subscribers. Production activities became difficult due to severe COVID-19 restrictions and the economic downturn, significantly impacting productivity. It caused the effect of lowering the overall production frontier, which is believed to have led to changes in pure efficiency and technology. In addition, the promotion of M&A to reduce competition in the production factor market and create synergy is an effort to lead to changes in scale efficiency.

3.2. Results of productivity analysis of individual content companies

Table 4 below shows the productivity of individual media companies. The productivity average from 2019 to 2022 for the rest of the companies did not exceed 1. In the order of the productivity index, also called the Malmquist index (MI), Television Francaise 1 showed the highest productivity (MI = 1.0053), and Warner Bros. Discovery, Inc. led the lowest productivity (MI = 0.932). While Television Francaise 1 has a relatively low technological change index (TCITelevision Francaise1 = 0.978), the pure efficiency change (PECITTelevision Francaise1 = 1.050) contributes to high productivity. On the other hand, in the case of Lions Gate, its technological change index (TCILions Gate = 1.034) influences productivity. At the same time, its scale efficiency is lower than 1, indicating that productivity (MI = 0.995) is decreasing on average. In the case of Netflix, technological change (TCINetflix = 1.021) is leading the change in MI. Netflix is the only firm having the technology change index, the pure efficiency change index, and the scale efficiency change index, all exceeding 1.

3.3. Malmquist productivity analysis of individual companies

Table 5 presents the results of analyzing the MPI values by year. The average overall productivity index also called the Malmquis index (MI), from 2019 to 2022 was high in Television Francaise 1. Still, when decomposed by each year, Paramount Global in 2019 showed the highest productivity index (MI = 1.239). As elaborated in section 2.2, the productivity index is calculated as a *Technology Change Index* × *Pure Efficiency Change Index* × *Scale Efficiency Change Index*. Each company has different reasons for the cause of productivity. Paramount Global in 2019–2020 and Channel A in 2020–2021 have improved productivity through high-scale efficiency changes, and Television Francaise 1 in 2021–2022 has a pure efficiency change index (PECI) of 1.234, driving productivity. We assume most media companies increased investments to improve scale efficiency and the efficiency of the investment just before COVID-19, thereby enhancing productivity as demand for media content soared during the pandemic.

4. Discussion

This study estimated productivity changes through four-year data from 2019 to 2022 for 25 major content provider companies, including OTT firms and major broadcasters. To measure the productivity changes, we ran DEA and MPI. This study offers several theoretical contributions and practical implications, as listed below.

First, utilizing the recent data set, this study allows us to compare several productivity index changes for firms in the media industry before and after the COVID-19 pandemic. The prior studies depended on limited countries' surveys of a specific time or employing data with a long publication period. Thus, the efficiency and productivity of media companies, especially comparing them during and after the pandemic, were missed. This study differentiates itself from the prior studies by showing the efficiency measures of media companies when the pandemic began and how their productivity changed during and after the pandemic. We can link the results to the change in consumers' watching behavior of video streaming and content providers' firm performance during and after the pandemic.

In addition, expanding the analysis from a particular region to the global market helps our understanding of the efficiency of the

Table 3
Productivity changes of content providers from 2019 to 2022.

Period	Productivity Index	Technology Change Index	Pure Efficiency Change Index	Scale Efficiency Change Index
2019	0.990842	0.974881	0.976737	1.04058
2020	0.965894	1.018436	1.049871	0.903357
2021	1.047278	1.02722	0.999319	1.020221
2022	0.985071	0.937687	0.971855	1.080957

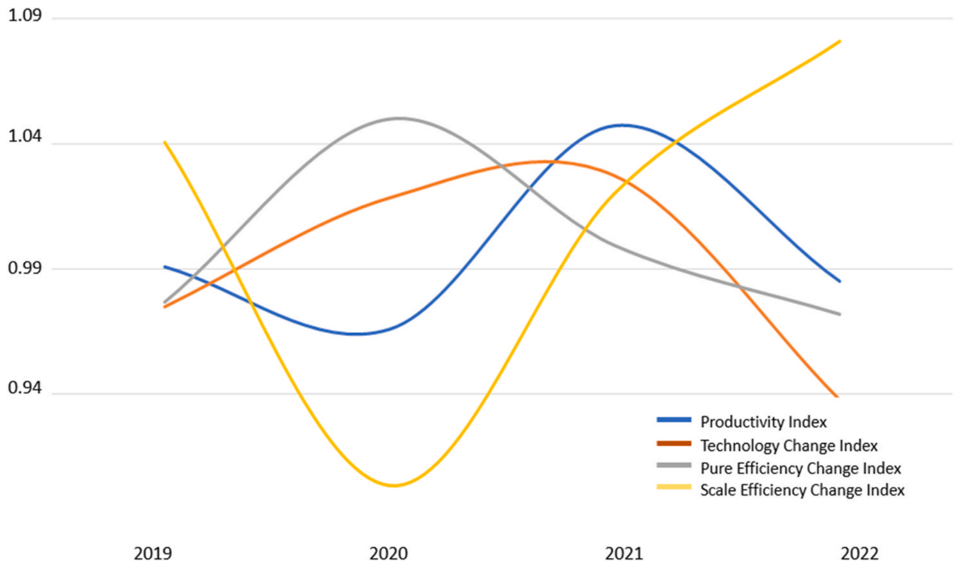

Fig. 1. Productivity changes of content providers from 2019 to 2022.

Table 4
The productivity of individual content providers.

MU.	Productivity Index	Technology Change Index	Pure Efficiency Change Index	Scale Efficiency Change Index
AMC Networks	0.993	0.993	0.982	1.018
Channel A	1.039	0.992	1.000	1.048
CJENM	0.992	0.998	0.992	1.002
Fox Corporation	0.970	0.992	0.982	0.995
Fuji Media Holdings	0.952	0.952	1.000	1.000
Gray Television	0.979	0.992	0.972	1.015
JTBC	0.964	0.964	1.000	1.000
Lions Gate Entertainment	0.995	1.034	0.971	0.991
MBN	1.020	0.990	1.006	1.023
Mediaset Espana Comunicacion	0.972	0.977	0.995	0.999
Mfe-Mediaforeurope	1.040	0.978	1.058	1.006
Netflix	1.021	1.021	1.000	1.000
Nexstar Media Group	1.015	0.992	1.011	1.012
Nippon Television Holdings	0.998	0.989	0.991	1.018
Paramount Global	0.995	0.983	0.980	1.033
Prosiebensat1 Media	1.003	0.977	1.023	1.004
Seoul Broadcasting System	1.042	0.981	1.056	1.005
Sinclair Broadcast Group	0.961	1.003	0.953	1.006
TBS	1.007	0.988	0.991	1.028
Telekom Austria	1.023	0.986	1.034	1.003
Television Francaise 1	1.053	0.978	1.050	1.025
Toho	0.986	0.984	0.978	1.024
TVCHOSUN	1.037	1.000	1.000	1.037
Walt Disney	0.944	0.985	1.000	0.958
Warner Bros. Discovery, Inc	0.932	0.994	1.003	0.934

media industry. Content providers compete globally, not in the US or some specific market. Also, big OTT firms, such as Netflix, Amazon, and Disney+, work hard to secure content with good quality from diverse areas, including the Asia market. Given the situation, this study helps us better understand how the industry works today.

Also, although each dimension of efficiency represents a different or unique aspect, the prior studies failed to reflect and consider it. Most existing studies analyzed only the *Technology Efficiency Change Index* and *Technology Change Index*. Unlike the previous studies, this study decomposes the *Technology Efficiency Change Index* into the *Pure Efficiency Change Index* and *Scale Efficiency Index* to better understand the causes of total factor productivity change in more detail. Our study provides a new case of achieving better productivity through a *Pure Efficiency Change*. For example, in the case of Television Francaise 1, which shows the highest productivity among 25 other DMUs, its pure efficiency change (PECITTelevision Francaise1 = 1.050) contributes to increased productivity.

This paper also offers some practical implications from analyzing the study's results. The result advises industry practitioners to highlight the growth engines of media companies derived from the study's results. It is necessary to expand the size and scope of media

Table 5
Malmquist productivity index values for individual firms by year.

Period	DMU	Productivity Index	Technology Change Index	Pure Efficiency Change Index	Scale Efficiency Change Index
2019	AMC Networks	1.000	0.980	0.957	1.067
2020		1.006	0.978	1.058	0.972
2021		1.038	1.059	0.964	1.017
2022		0.932	0.959	0.954	1.019
2019	Channel A	0.956	0.959	1.000	0.997
2020		1.038	1.135	1.000	0.915
2021		1.236	0.980	1.000	1.262
2022		0.950	0.907	1.000	1.047
2019	CJENM	1.024	0.970	1.051	1.004
2020		0.949	1.004	0.991	0.954
2021		1.047	1.058	0.988	1.001
2022		0.952	0.964	0.942	1.049
2019	Fox Corporation	0.907	0.965	0.929	1.011
2020		0.966	0.997	1.036	0.936
2021		1.063	1.057	1.031	0.975
2022		0.949	0.952	0.938	1.063
2019	Fuji Media Holdings	1.004	1.004	1.000	1.000
2020		0.856	0.856	1.000	1.000
2021		1.042	1.042	1.000	1.000
2022		0.915	0.915	1.000	1.000
2019	Gray Television	0.880	1.012	0.821	1.059
2020		1.106	1.123	1.301	0.757
2021		0.860	0.935	0.851	1.081
2022		1.099	0.913	0.983	1.224
2019	JTBC	0.799	0.845	1.000	0.945
2020		0.985	0.998	0.993	0.994
2021		1.056	1.059	1.007	0.991
2022		1.041	0.969	1.000	1.075
2019	Lions Gate Entertainment	1.013	1.054	1.000	0.961
2020		0.976	1.060	0.859	1.071
2021		0.971	1.065	1.009	0.903
2022		1.023	0.961	1.026	1.037
2019	MBN	1.002	1.002	1.026	0.974
2020		1.036	0.973	1.000	1.064
2021		1.070	1.051	1.000	1.018
2022		0.973	0.937	1.000	1.039
2019	Mediaset Espana Comunicacion	0.946	0.948	1.000	0.998
2020		0.936	0.969	1.000	0.966
2021		0.991	1.047	1.000	0.947
2022		1.017	0.948	0.981	1.093
2019	Mfe-Mediaforeurope	1.007	0.966	1.024	1.018
2020		0.955	0.943	1.145	0.885
2021		1.062	1.051	1.007	1.004
2022		1.146	0.955	1.061	1.131
2019	Netflix	1.029	1.029	1.000	1.000
2020		1.081	1.081	1.000	1.000
2021		1.026	1.026	1.000	1.000
2022		0.953	0.953	1.000	1.000
2019	Nexstar Media Group	0.921	1.012	0.825	1.103
2020		1.131	1.123	1.391	0.724
2021		1.011	0.935	0.977	1.107
2022		1.009	0.913	0.931	1.187
2019	Nippon Television Holdings	0.976	1.020	0.886	1.080
2020		0.985	0.930	1.205	0.879
2021		1.041	1.048	1.022	0.971
2022		0.992	0.965	0.882	1.165
2019	Paramount Global	1.239	0.992	1.021	1.224
2020		0.836	0.929	1.000	0.899
2021		1.034	1.056	0.963	1.017
2022		0.916	0.959	0.938	1.019
2019	Prosiebensat1 Media	1.023	0.935	1.003	1.091
2020		0.930	0.981	1.085	0.874
2021		1.087	1.063	1.030	0.994
2022		0.979	0.934	0.979	1.070
2019	Seoul Broadcasting System	0.937	0.917	1.017	1.005
2020		1.005	0.988	1.031	0.987
2021		1.195	1.057	1.096	1.032
2022		1.048	0.968	1.085	0.998

(*continued on next page*)

Table 5 (*continued*)

Period	DMU	Productivity Index	Technology Change Index	Pure Efficiency Change Index	Scale Efficiency Change Index
2019	Sinclair Broadcast Group	0.897	0.998	0.811	1.108
2020		0.828	1.049	0.905	0.872
2021		1.209	1.063	1.231	0.924
2022		0.950	0.908	0.913	1.146
2019	TBS	1.021	0.991	0.922	1.118
2020		0.984	1.058	1.200	0.775
2021		1.006	0.997	0.970	1.040
2022		1.017	0.913	0.897	1.242
2019	Telekom Austria	1.018	0.939	0.959	1.130
2020		1.014	1.147	1.205	0.733
2021		1.024	0.974	0.973	1.081
2022		1.036	0.902	1.016	1.129
2019	Television Francaise 1	1.133	0.915	1.118	1.107
2020		0.884	0.976	0.976	0.929
2021		1.012	1.059	0.905	1.056
2022		1.215	0.969	1.234	1.017
2019	Toho	1.030	0.976	0.959	1.101
2020		0.857	1.011	1.012	0.837
2021		1.117	1.033	1.078	1.002
2022		0.957	0.919	0.874	1.192
2019	TV CHOSUN	1.089	0.965	1.000	1.128
2020		1.192	1.163	1.000	1.025
2021		0.999	0.999	1.000	1.000
2022		0.893	0.893	1.000	1.000
2019	Walt Disney	0.900	0.984	1.000	0.915
2020		0.812	1.123	1.000	0.723
2021		1.078	0.935	1.000	1.152
2022		1.007	0.911	1.000	1.105
2019	Warner Bros. Discovery, Inc	1.121	1.020	1.047	1.050
2020		0.913	0.941	1.074	0.903
2021		0.978	1.055	0.918	1.009
2022		0.754	0.965	0.983	0.795

companies by achieving scale efficiency. Globalization and the composition of global supply chains with foreign countries are essential. Scale growth can be achieved through diverse ways, such as business diversification or M&A. The most representative example from our study is Netflix, which maximizes scale efficiency by entering more than 50 countries worldwide through large-scale investments and eventually increases productivity in the market by expanding technology efficiency.

However, "Going Global Strategy" and "Growth Strategy" do not work for all individual firms or all situations. By comparing productivity for local and global companies, entering other countries and bulking up through M&A or other interrelationships will be beneficial to increase firms' efficiency, whereas some small firms would have instead focused their market and sectors conversely to improve operational efficiency by focusing locally rather than clumsy internationalization. For instance, in the case of TV Chosun and Channel A in South Korea, they maximize productivity by concentrating on local investment, reducing production costs, and expanding distribution channels of production content so media companies can determine the size and scope of investment according to their size.

Along with these research results, this study has several limitations. First, although 25 DMUs that meet the DEA analysis criteria were analyzed, future research should consider employing more samples to secure more analysis targets. In addition, despite the need to investigate the causes of productivity and efficiency analysis of each DMU, the discussion's depth is insufficient due to the natural limitations of DEA. Second, the results of productivity changes are decomposed to explain the cause of the change to some extent. Analyzing the cause of the second stage productivity decision is needed by considering various variables for external effect analysis outside the company. Therefore, the external effects that affect these productivity causes through multiple methodologies and data need to be identified in future studies.

CRediT authorship contribution statement

Yonghee Kim: Project administration, Methodology, Formal analysis, Data curation. **Sungjin Yoo:** Writing – original draft, Methodology, Funding acquisition, Conceptualization.

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