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Impact of COVID-19 on the Operational Efficiency and Competitiveness of Financial Holding Companies in Taiwan: A DEA and GRA Analysis

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Abstract. This study analyzes the impact of the COVID-19 pandemic on the competitiveness of financial holding companies (FHCs) in Taiwan and uses Data Envelopment Analysis (DEA) to assess their operational efficiency from 2019 to 2022. Furthermore, the study applies the Grey Relational Analysis (GRA) model to deeply analyze the input factors affecting operational efficiency. The findings show that both Technical Efficiency (TE) and Pure Technical Efficiency (PTE) values exceeded 0.9, indicating that the increase in production factors had limited impact on total output. Scale Efficiency (SE) values consistently exceeded 0.95, emphasizing the importance of capital and labor inputs. In 2021, operational efficiency declined by 4% due to the pandemic; however, by 2022, FHCs regained competitiveness and achieved a 6% growth. Key factors influencing efficiency include total assets, workforce size, and operating costs. The study suggests that FHCs should focus on resource allocation, human resource management, and cost control to enhance operational effectiveness in the post-pandemic era.

Keywords: COVID-19, Grey relational analysis, Operational efficiency, Pure technical efficiency, Scale efficiency, Technical efficiency.
JEL Classification: C45, G10.

1. INTRODUCTION

With the rapid changes in Taiwan's financial market, financial holding companies (FHCs) are playing an increasingly critical role in economic development. According to data from the Directorate-General of Budget, Accounting and Statistics, the total output of the financial services industry in Taiwan is estimated to reach NT$1,323 billion, accounting for 6.74% of the Gross Domestic Product (GDP). In 2021, due to a significant increase in investment income, the pre-tax profits of the three major financial sectors—banking, insurance, and securities—reached NT$936.597 billion, setting a historical record.

According to statistics from the Financial Supervisory Commission (FSC, 2022), in 2021, the insurance industry topped the pre-tax surplus among the three sectors with an annual income of NT$411.1 billion, reflecting an annual increase of 84.3%. The banking sector followed with an income of NT$385.61 billion, approaching the NT$400 billion mark, representing a 4% annual increase; while the securities and futures industry exceeded NT$100 billion for the first time, with an annual increase of 71.97%

In contrast, in 2022, as the world entered a cycle of interest rate hikes and faced volatile international financial conditions, the profitability of Taiwan's FHCs was put to the test. According to the FSC (2022), the earnings of Taiwan's 16 financial holding companies, such as bank holding companies, experienced difficulties in securities issuance, insurance underwriting, and other related services. Among them, Shin Kong Financial Holding Co., Ltd. saw its profits shrink the most, by 80%, while SinoPac Financial Holdings Co., Ltd. was the only profitable bank in Taiwan.

Furthermore, according to the FSC (2022) report, the financial holding industry faced frequent challenges in domestic and foreign investments in the first half of the year. By the end of June, the total domestic and foreign investment exposure of financial holding groups reached NT$34.91 trillion, with unrealized losses amounting to NT$827.76 billion, marking the worst record in history. Financial holding companies are closely linked to the economic development of their respective countries, which has led to an increasing emphasis on analyzing their operational performance as the economy continues to grow (Lin et al., 2022; Ahn et al., 2020; Liu, 2021; Lin et al., 2019). Previous studies have utilized Data Envelopment Analysis (DEA) model to measure operational efficiency in the financial industry, emphasizing the impact of efficiency in terms of inputs and outputs (Chang et al., 2019; Seiford & Zhu, 1999; Wagner & Shimshak, 2007).

As a non-parametric method, DEA possesses several unique features that distinguish it from traditional parametric approaches, including the ability to handle multiple inputs and outputs, the use of relative efficiency measures, the identification of peer groups for inefficient Decision-Making Units (DMUs), and the incorporation of Variable Returns to Scale (VRS) into the analysis. Financial holding companies leverage their expanded range of financial services, including securities dealing, insurance underwriting, and investment advisory services, to diversify their income streams beyond the capabilities of traditional banks. Therefore, this study will analyze the competitive changes in Taiwan's FHCs during the pandemic.

Grey relational analysis (GRA) is a method based on grey system theory, used to evaluate the degree of association between variables, particularly suitable for scenarios involving small samples or incomplete information. Its application process typically includes standardizing the original data to eliminate differences in

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scale among indicators, calculating the grey relational coefficients between input factors and the target variable (such as efficiency) to measure their relevance, and ranking the input factors based on the magnitude of their relational degrees. This approach helps researchers focus on the key influencing factors and provides a basis for optimizing strategies （Deng, 1989）.

The specific research objectives of this study are as follows:

1. To analyze the impact of the COVID-19 pandemic on the competitiveness of Taiwan's FHCs.
2. To apply the DEA model to evaluate the operational efficiency of FHCs.
3. Which input factors influence the efficiency of FHC during the pandemic?

The rest of this article is organized as follows: Section 2 reviews financial policy in Taiwan; Section 3 presents a literature review of FHCs; Section 4 briefly reviews the DEA method; Section 5 presents the empirical models and describes the results; finally, conclusions and future research directions are reported in the last section.

2. CURRENT SITUATION OF BANK HOLDING COMPANY DEVELOPMENT IN TAIWAN

In recent years, financial regulation and supervision have undergone significant transformations globally, particularly in the aftermath of the 2008 global financial crisis. These reforms aim to enhance the resilience of financial systems and mitigate the likelihood and severity of future crises. In Taiwan, similar initiatives have been undertaken to ensure the robust development of its financial framework. The introduction of the Financial Institution Merger Act and the Financial Holding Company Act in 2001 marked a pivotal moment, encouraging domestic financial institutions to consolidate into financial holding companies (FHCs). This strategic shift was designed to improve competitiveness, increase scale, enhance comprehensive management capabilities, and bolster international competitiveness (Chang et al., 2019; Yen et al., 2021).

The implementation of these reforms has yielded significant benefits for the Taiwanese financial industry. For instance, prominent financial holding companies such as Cathay Financial Holding Co. and Fubon Financial Holding Co. have successfully leveraged their diverse business models to achieve sustainable revenue growth. By offering comprehensive financial services, they have attracted both domestic and international clients, with Cathay Financial Holding reporting a net profit of NT$130 billion in 2021, placing it among the top-performing FHCs in Asia. Meanwhile, Fubon Financial Holding has aggressively expanded its overseas operations, enhancing its global competitive position. These achievements highlight the value of the FHC model in consolidating resources and maximizing operational synergies.

One of the primary advantages of FHCs is their authorization to provide a diverse array of financial services, including securities dealing, insurance underwriting, investment advisory services, and merchant banking. This diversification extends beyond the traditional offerings of ordinary banks, enabling FHCs to create multiple revenue streams. Notably, the ability to cross-sell products—such as combining insurance with wealth management services—has provided an efficient means of maximizing client lifetime value. Such diversification not only enhances their resilience to financial shocks but also facilitates greater income stability compared to conventional banks.

However, the development of FHCs is not without challenges. The increasing competition in the financial sector, driven by both local and international players, necessitates continuous innovation and adaptation. The rapid advancement of financial technology (fintech) presents both opportunities and threats. For example, many FHCs are incorporating artificial intelligence (AI), data analytics, and blockchain technology to optimize their operations and enhance client experiences. Cathay Financial, for instance, has implemented AI-driven customer service systems that improve response time and efficiency in claims processing. Additionally, the integration of blockchain has enabled FHCs to enhance transparency and security in transactions, building greater trust in their services.

Moreover, regulatory compliance and risk management have become increasingly complex as financial products grow more sophisticated. The global push toward environmental, social, and governance (ESG) investing represents another critical area where FHCs must adapt. Investors are now demanding greater transparency and accountability, compelling FHCs to integrate ESG principles into their operational and investment strategies to maintain their appeal in a rapidly evolving market.

Thus, while FHCs have made significant strides in enhancing their operational capabilities and market presence, ongoing vigilance and strategic planning are essential for navigating the complexities of the modern financial landscape. Future success will depend on their ability to harness fintech advancements, align with global ESG standards, and respond flexibly to an increasingly interconnected and competitive global economy.

3. LITERATURE REVIEW

Banks are strategic and highly regulated industries. They not only promote economic growth and industrial development but also serve as essential platforms for corporate finance and public savings. Their financial stability and operational efficiency are critical to national security and societal well-being, making the improvement of bank performance an important policy goal for many countries (Ho & Lin, 2012). In Taiwan, banking institutions have historically been at the core of economic development strategies, supporting industries, businesses, and individual households through varying stages of growth.

Taiwan's FHCs were formally established in 2001, with fourteen founded by the following year. These entities play a pivotal role in Taiwan's financial system by consolidating resources and providing a wide range of financial services under one organizational umbrella. The competitiveness of financial institutions is critical to economic progress and can support industrial growth at different stages. To achieve the vision of becoming a regional financial hub and a player in the international financial arena, it is imperative to continue enhancing the competitiveness and operational efficiency of FHCs and other banking institutions (Chen & Yeh, 2000; Ho, Chan & Chu, 2008).

Competitiveness, in essence, refers to the ability of an institution or company to excel in a given market through comparison with its peers. For banks, competitiveness also touches on their capacity to integrate corporate finance and achieve sustainable competitive advantages by effectively managing financial resources. This involves not only productivity but also the strategic alignment of internal processes to meet external demands. Over time, research has highlighted the importance of operational efficiency in determining competitiveness, particularly when measured through empirical methodologies.

Historically, the examination of bank efficiency has revolved around financial variables used by rating agencies such as Moody's and Standard & Poor's (S&P). These variables help construct models for evaluating efficiency, often incorporating measures of risk and credit assessment. For example, Morgan (2002) highlighted the potential opacity in banks' lending practices, especially when banks lend to borrowers with unclear repayment capabilities. Similarly, Carletti (2008) and Gao et al. (2019) emphasized the risks associated with monitoring opaque borrowers and the likelihood of banks concealing asset quality information, which ultimately links poor asset quality to broader financial risks. Issues of bank transparency are critical to evaluating competitiveness and understanding performance gaps in the industry.

Empirical studies on Taiwanese banks' competitiveness and operational efficiency provide additional insights. Kao and Liu (2014) introduced a relational network model that measured bank performance more effectively than previous models. Their approach differentiated the contributions of individual components to overall performance. Juo et al. (2016) expanded this analysis by using four distinct components—technical efficiency change, allocative efficiency change, technological shift, and output-input price effects—to capture productivity changes more comprehensively in Taiwanese banks. In another example, Chao et al. (2018) employed a meta-frontier network data envelopment analysis (DEA) model to examine efficiency differences between financial holding companies and standalone banks, concluding that banks affiliated with FHCs benefit from cost savings and operational advantages compared to non-FHC-affiliated entities.

The outbreak of COVID-19 has intensified global challenges for the banking industry. The pandemic severely disrupted financial markets worldwide, prompting a wave of research into its impacts. Globally, Ahmed et al. (2021) reviewed the impacts of the pandemic on financial markets and suggested various mitigation strategies. For example, Du and Hu (2021) and Gao and Zhu (2021) studied COVID-19's specific effects on China's financial system and highlighted measures adopted by Chinese banks to mitigate financial turbulence. Zhu et al. (2020) conducted a detailed analysis of the pandemic's impact on the Chinese banking sector's financial performance, while Hussain and Hussain (2020) investigated its implications for financial systems in both developed and developing countries.

In Taiwan, the banking sector has not been immune to the effects of COVID-19. Although FHCs have diversified their services by offering securities trading, insurance underwriting, and investment advisory services, the pandemic posed significant challenges, including heightened market volatility, declining credit quality, and operational disruptions. Despite the resilience demonstrated by FHCs and banks, operational inefficiencies and gaps remain underexplored, particularly in relation to how the pandemic has reshaped the dynamics of Taiwanese financial institutions.

The DEA method is uniquely suited to analyzing these changes, offering distinct advantages over traditional parametric approaches. By handling multiple inputs and outputs simultaneously, DEA can provide nuanced insights into relative efficiency, identify peer groups for inefficient decision-making units (DMUs), and account for variable scale returns (VRS). Its application in the context of Taiwanese banking allows for a detailed evaluation of how FHCs and traditional banks have adapted to the challenges of COVID-19.

On the other hand, Grey System Theory provides a reliable framework for solving systems characterized by uncertainty or incomplete information, effectively addressing issues of ambiguity, multi-input scenarios, and discrete data (Huang & Liao, 2003). Within this framework, Grey Relational Analysis (GRA) serves as a versatile tool, widely used for decision-making, prediction, and performance evaluation, particularly in complex systems with limited data (Ertugrul et al., 2016; Hweju & Abou-El-Hossein, 2021; Li et al., 1997).

Developed by Julong Deng (Deng, 1989), GRA is a key component of Grey System Theory and has extensive applications (Pathak & Agrawal, 2023). The method involves calculating the correlation between reference and comparison sequences to determine rankings or identify key influencing factors (Ertugrul et al., 2016; Pathak & Agrawal, 2023). For example, GRA has been applied in university performance comparison (Ertugrul et al., 2016), ERP system analysis (Pathak & Agrawal, 2023), prediction of surface roughness in diamond turning (Hweju & Abou-El-Hossein, 2021), and analysis of the environmental factors influencing atmospheric corrosion of Q235 carbon steel (Cao et al., 2015).

While numerous studies have provided valuable insights into the broad impacts of the pandemic on global financial systems, there remains a critical research gap regarding its specific effects on the competitiveness of Taiwanese banks. This study aims to fill this gap by applying the DEA model to assess the impact of COVID-19 on the financial performance of Taiwanese banks. As mentioned earlier, the advantage of GRA lies in its ability to effectively handle uncertainty and partial information, providing efficient solutions in scenarios where traditional statistical methods are limited, thereby identifying key influencing factors (Ertugrul et al., 2016; Li et al., 1997; Cao et al., 2015). Such analysis is crucial not only for identifying performance issues but also for developing targeted financial strategies to enhance resilience during future crises. By bridging this knowledge gap, this research intends to contribute to strengthening Taiwan's financial sector in facing both global uncertainties and local challenges.

4. METHODOLOGY

In the explanation of the research methodology, this study will be divided into two parts. First, the DEA model technique was initially developed in the 1980s and has since become a popular method for evaluating the efficiency of comparable units. This method assesses the relative efficiency of units by considering multiple inputs and outputs and has been widely applied in various studies within the banking and financial sectors. This section aims to provide an overview of the basic principles and applications of the DEA model.

Second, GRA model is used to identify the key factors influencing efficiency. This method calculates the correlation between reference sequences and comparison sequences to identify the factors that most significantly impact efficiency. The advantage of GRA lies in its ability to handle uncertainty and partial information, providing efficient solutions in situations where traditional statistical methods are limited. These two methods complement each other, with DEA being used to assess the overall efficiency of units, while GRA helps identify the key factors influencing efficiency, providing guidance for subsequent strategy formulation.

4.1. Data Envelopment Analysis (DEA)

4.1.1. Characteristics of the DEA Model

DEA, as a nonparametric method, has several unique features that distinguish it from traditional parametric approaches. These features include the ability to handle multiple inputs and outputs, the use of relative efficiency measures, the identification of peer groups for inefficient decision-making units (DMUs), and the incorporation of variable returns to scale (VRS) into the analysis.

First, DEA allows for the analysis of multiple inputs and outputs simultaneously, making it well suited for evaluating the efficiency of complex systems with multiple performance criteria (Lewin, 1986). Second, DEA calculates relative efficiency measures, which provide information on the efficiency of a DMU relative to its peers. This allows for comparisons of DMUs with different sizes and capacities (Lewin, 1982).

Third, DEA identifies peer groups for inefficient DMUs, which can help managers identify areas for improvement and adopt best practices from more efficient peers (Lewin, 1986). Finally, DEA incorporates variable returns to scale (VRS) into the analysis, allowing for the identification of increasing, decreasing, or constant returns to scale for a given set of inputs and outputs (Lewin, 1982).

Overall, these features make DEA a powerful tool for assessing the efficiency of DMUs in a variety of contexts, including healthcare, education, and finance.).

4.1.2. A formula for the Solution of DEA Models

The initial DEA model was introduced by Charmes et al. (1978) and was named the Charnes, Cooper and Rhodes model (called the CCR model). This model assumes that the decision-making units (DMUs) being evaluated operate under a production technology that exhibits constant returns to scale (CRS). The CRS property means that a proportional increase in all inputs results in a proportional increase in all outputs. The CCR model is based on Equation (1):

$$\text{Max} h_k = \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \quad (1)$$

$$s.t \quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1 \quad , \quad j = 1,\ldots,n$$

$$u_r, v_i \geq \varepsilon > 0, \quad r = 1,\ldots\ldots, s, \quad i = 1,\ldots\ldots, m$$

where x_{ij} represents the amount of the i-th input to DMU j, C represents the amount of the r-th output to DMU j, u_r , v_i represents the virtual multiplier output and i represents the virtual input multiplier, the value of h_k obtained is termed the relative efficiency and is called the CCR efficiency, ε represents a non-Archimedean positive element smaller than any real number (10^{-6}), and the CCR model is called the non-Archimedean small number.

The DEA model was further improved by Banker et al. (1984) to evaluate the productive efficiency of DMUs that operate with variable returns to scale (VRS) technology. This enhanced model is known as the Banker, Chames, and Cooper Model (called the BCC model).

This VRS model, also known as BCC, includes a convexity constraint in the previous formulation. The constraint is expressed as the summation of the product of the inputs and their respective weights to be equal to one ($\sum_{i=1}^{m} v_i x_{ik} = 1$) Thus, the following equation can be obtained for computing efficiencies via Equation (2): Technical Efficiency = Pure Technical Efficiency × Scale Efficiency…………………….... (2)

- Technical efficiency: This refers to the ability of a business or organization to produce the required product or service at the lowest cost possible, using fixed resources (CRS). The efficiency score is called the technical efficiency score (TE).
- Pure Technical Efficiency: Refers to the ability of a business or organization to produce the required product or service at the lowest cost possible, using variable resources (VRSs). The efficiency score is called the pure technical efficiency score (PTE).
- Scale Efficiency: This is an indicator that measures whether a business or organization is using the most effective production methods according to scale. The efficiency score obtained under variable returns (VRSs) to scale is called the scale efficiency score (SE).

In the field of banking, the DEA model is widely utilized to measure bank efficiency. However, it is essential to note that the relative efficiency values obtained by the traditional DEA model, particularly technical efficiency (TE), do not necessarily reflect absolute efficiency. While DEA has some distinct advantages over parameter estimation methods, it may result in efficiency evaluation deviations in small sample sizes and overlook the issue of statistical testing.

4.1.3. DEA Model Measurement

In the DEA model, the production frontier is represented economically as an envelope, which serves as a boundary created by the optimal solution among all feasible solutions. By taking into account the input and output items of all DMUs, the DEA model calculates the relative efficiency of individual producers by dividing the weighted output by the weighted input, with any unit achieving a relative efficiency value of 1 (located on the production boundary) deemed efficient, whereas any unit with a relative efficiency value less than 1 (located off the production boundary) is deemed inefficient.

4.2. GRA Method for Data Normalization

The GRA methodology involves translating alternative performances into comparability sequences through gray relational generation. Deng (1989) applied GRA for analyzing systems with unclear or incomplete information, such as energy system modeling, and evaluating the degree of association in sequences of discrete data. Its description is as follows:

- Problems and response variables or quality characteristics are defined.
- Data collection.
- The data are normalized such that the better or larger the value is, the better the quality characteristics.
- Find the gray relation coefficient for the normalized data.
- The gray relation grade is calculated.
- The optimum level is selected on the basis of the grade value.

Finally, in a multiple attribute decision-making (MADM) problem that includes m alternatives and n attributes, y_i denotes the performance value of attribute j on a specific attribute. In this stage, y_i is translated into a comparability sequence x_i. Normalization can be performed via two different approaches as follows:

For better quality characteristics, in a multiple attribute decision-making (MADM) problem, we use y_i to represent the performance value of alternative i on a specific attribute. Next, we convert y_i into a comparability sequence x_i, which involves normalizing the data (Equation (1)).

$$x_i = \frac{y_i - Min\,(y_i)}{Max\,(y_i) - Min\,(y_i)} \quad for\ i = 1,2,,\ldots,m \tag{1}$$

Where:

- $Max\,(y_i)$: the maximum value of attribute i;
- $Min\,(y_i)$: is the minimum value of attribute i;
- x_i: is the normalized value, which ranges between [0, 1].

Another for smaller the better-quality characteristic, normalized value, i.e., Equations (2).

$$x_i = \frac{Max\ (y_i) - y_i}{Max\ (y_i) - Min\ (y_i)}\ for\ i = 1,2,,\dots,m \tag{2}$$

4.2.1. Gray Relational Grade Calculation for Weights

The gray relational coefficient is calculated based on the set target value and is standardized through formulas (1, 2). The calculation of the gray relational coefficient for each criterion typically involves the following formula (3):

$$\Gamma_i = \frac{\Delta_{min} + \sigma\Delta_{max}}{\Delta_{ij} + \sigma\Delta_{max}} \tag{3}$$

where:

- where Δ_{min}, and Δ_{max} are the minimum and maximum differences, respectively.
- σ is the distinguishing coefficient (usually between 0 and 1 or set 0.5)

By substituting Γ_i into the calculation, the gray relational degree for each option can be calculated, typically taking the average of all the relational coefficients and being calculated via Equation (4):

$$G_i = \frac{1}{n}\sum_{i=1}^{n}\Gamma_i \tag{4}$$

After the gray relational coefficients G_i are calculated, they can be substituted into Formula (5) to estimate the weights of each criterion. This process typically involves the following steps:

$$w_i = \frac{G_i}{\sum_{i=1}^{n} G_i} \tag{5}$$

where:

- where w_i is the GRA weight of the i-th option.
- G_i is the gray relational degree of the i-th option, and m is the total number of options.

The final w_i GRA weights reflect the relative importance of each criterion in the overall decision-making process, with larger values indicating a more significant influence of that criterion in the analysis.

4.2.2. Explanation of GRA Weights

In Equation (5), G_i is the gray relational grade, which indicates the degree of similarity between the comparison sequence and the reference sequence. Therefore, the general guidelines for interpreting gray relational grade results are as follows: 0 to 0.20 is considered negligible, 0.21 to 0.35 is categorized as weak, 0.36 to 0.67 is considered moderate, 0.68--0.90 is classified as strong, and 0.91 to 1.00 is deemed very strong (Taylor, 1990). These categories apply to the rank of the gray relational coefficient results, as presented in Table 1.

Table 1: Ranks of the GRA calculated.

No	GRA value	Variable correlation degree
1	0.91-1.00	Very strong
2	0.68-0.90	Strong
3	0.36-0.67	Moderate
4	0.21-0.35	Weak
5	0-0.20	Negligible

5. EMPIRICAL RESULTS AND ANALYSIS

The efficiency analysis conducted in this study can be broken down into three primary sections. The first section outlines the study's subjects and identifies the variables used for inputs and outputs. In the second section, a data description and correlation analysis between inputs and outputs are presented. Finally, the third section evaluates the impact of COVID-19 on FHC efficiency analysis.

5.1. Study Objects and Variables for Inputs and Outputs in This Study

The study objects and variable selection for inputs and outputs in this study are described as follows:

5.1.1. Study Objects

The main purpose of this study is to investigate whether there has been any change in the operational efficiency of financial holding companies during the COVID-19 pandemic. Therefore, 16 financial holding companies were selected for analysis in this study, including Taiwan Financial Holdings Co., Ltd., which was established on January 1, 2008, and is one of the financial holding companies established jointly by public financial institutions with the Taiwan Bank as the main body. It is the only nonlisted public financial holding company. In addition, Jih Sun Financial Holding Co., Ltd., which was incorporated on February 5, 2002, and was merged with Fubon Financial Holding Co., Ltd., on November 11, 2022, was excluded from the analysis. Finally, the data of these 14 financial holding companies were aggregated in this study, and the specific results of the data aggregation can be found in Table 2.

Table 2: Names of FHCs in Taiwan.

No.	Company initials
1.	Hua Nan Financial Holdings Co., Ltd. (HNFHC)
2.	Fubon Financial Holding Co., Ltd. (Fubon FHC)
3.	China Development Financial Holding Corporation (CDFHC)
4.	Cathay Financial Holding Co., Ltd. (Cathay FHC)
5.	CTBC Financial Holding Co., Ltd. (CTBC FHC)
6.	SinoPac Financial Holding Group Co., Ltd. (SinoPac FHC)
7.	E.SUN Financial Holding Co., Ltd. (E. SUN FHC)
8.	Yuanta Financial Holding Co., Ltd. (Yuanta FHC)
9.	Taishin Financial Holdings Co., Ltd. (Taishin FHC)
10.	Shin Kong Financial Holding Co., Ltd. (SKFH)
11.	Mega Financial Holding Co., Ltd. (Mega FHC)
12.	First Financial Holding Co., Ltd. (First FHC)
13.	Taiwan Cooperative Financial Holding Co., Ltd. (TCFHC)
14.	IBF Financial Holdings Co., Ltd. (IBF FHC)

5.1.2. Variables for Inputs and Outputs in This Study

The objective of this research is to evaluate how COVID-19 has affected financial holding companies. To achieve this goal, the study employs four years of cross-sectional data covering the period from 2019--2022. The primary source of data is publicly available financial statements from companies and the Taiwan Stock Exchange. A total of six variables are used in this study, consisting of three input and three output variables. Please refer to Table 3 for variable definitions.

A. Description of the input variables

- Total assets: refers to the economic resources that a company owns or controls and can be measured in monetary terms, including various properties, claims, and other rights.
- Operating expense: the basic operating expense of a company and includes expenses related to the sale of goods or services, such as office expenses, personnel expenses, advertising and marketing expenses, and research and development expenses.
- Number of employees: refers to the number of employees who received salaries at the end of the year and were employed.

B. Description of the output variables

- Interest income refers to the interest income generated from financing credits, various deposits, debt instruments measured at fair value through other comprehensive income, and debt instruments measured at amortized cost.
- Earnings per share: a financial indicator that represents the net income attributable to each outstanding common share of a company.
- Net operating revenue: calculated as the amount of revenue generated in a given year minus various costs, losses, and taxes to arrive at the net income.

Table 3: Definitions of inputs and outputs

No.	Indicators	Code	Definition
1.	Total assets	x_1	Inputs variable
2.	Operating expense	x_2	Inputs variable
3.	Number of employees	x_3	Inputs variable
4.	Interest income	y_1	Outputs variable
5.	Earnings per share	y_2	Outputs variable
6.	Net operating revenue	y_3	Outputs variable

5.2. Data Descriptions and Correlation Analysis

As the focus of this study is to investigate the changes in the operational efficiency of FHCs during the pandemic period, we first conducted basic statistical analysis and correlation analysis on the sample.

5.2.1. Data Descriptions

We collected data on multiple variables from 15 financial holding companies over a period of four years and calculated descriptive statistics. The data are organized in Table 4, which includes a variable list and its summary statistics. The following is an explanation of the variables and their statistical data in Table 3. These statistics describe six indicators: x_1, x_2, x_3, y_1, y_2, and y_3. Here, each statistical description is as follows:

- x_1: This indicator ranges from 2.92E+08 to 1.16E+10, with a mean of 4.24E+09 and a standard deviation of 2.80E+09. The variance of this indicator is 7.83E+18.
- x_2: This indicator ranges from 1.47E+06 to 4.28E+07, with a mean of 1.80E+07 and a standard deviation

of 1.05E+07. The variance of this indicator is 1.10E+14.

- x_3: This indicator ranges from 1.52E+03 to 5.74E+04, with a mean of 1.68E+04 and a standard deviation of 1.48E+04. The variance of this indicator is 2.19E+08.
- y_1: This indicator ranges from 1.68E+06 to 1.13E+08, with a mean of 3.79E+07 and a standard deviation of 2.98E+07. The variance of this indicator is 8.90E+14.
- y_2: This indicator ranges from 1.10E-01 to 8.34E+00, with a mean of 1.27E+00 and a standard deviation of 1.53E+00. The variance of this indicator is 2.34E+00.
- y_3: This indicator ranges from 2.96E+06 to 1.21E+08, with a mean of 4.32E+07 and a standard deviation of 2.91E+07. The variance of this indicator is 8.47E+14.

Table 4: Descriptive statistics.

Indicators	Minimum	Maximum	Mean	SD	Variance
x_1	2.92E+08	1.16E+10	4.24E+09	2.80E+09	7.83E+18
x_2	1.47E+06	4.28E+07	1.80E+07	1.05E+07	1.10E+14
x_3	1.52E+03	5.74E+04	1.68E+04	1.48E+04	2.19E+08
y_1	1.68E+06	1.13E+08	3.79E+07	2.98E+07	8.90E+14
y_2	1.10E-01	8.34E+00	1.27E+00	1.53E+00	2.34E+00
y_3	2.96E+06	1.21E+08	4.32E+07	2.91E+07	8.47E+14

5.2.2. Correlation Analysis

As this study utilizes DEA models for analysis, it is necessary to ensure that there is a positive correlation between the input and output variables before they can be used. According to the results, all the variables are positively correlated, and a detailed summary of the results is presented in Table 5.

Table 5: Correlation analysis results.

	x1	x2	x3	y1	y2	y3
x1	1					
x2	.859**	1				
x3	.958**	.847**	1			
y1	.964**	.835**	.949**	1		
y2	.880**	.736**	.931**	.838**	1	
y3	.955**	.913**	.945**	.984**	.820**	1

5.3. Efficiency Analysis

5.3.1. Annual Efficiency Analysis

Because the epidemic broke out at the end of 2019 and did not gradually ease until 2022, this study compares each year (2020--2022) with 2019 (before the outbreak) to explore the impact of the epidemic on the competitiveness of financial holding companies, and its analysis includes four parts: TE, PTE, SE, and RTS. Finally, this study collates the data in Table 6 (2019--2022) and conducts the following related efficiency analysis.

A. 2019 Efficiency Analysis

Based on the data provided for 2019, we can analyze the efficiency scores of the 14 Taiwanese banks.

The highest TE (under CRS conditions) score is achieved by IBF, SKFH, Mega, and CTBC, with a score of 1.000, indicating that they are operating at their maximum efficiency level and that any increase in inputs will lead to a proportionate increase in outputs.

The highest PTE (under VRS conditions) score is achieved by Fubon, Taishin, SinoPac, E. SUN, and Yuanta, with a score of 1.000, indicating that they have achieved PTE and are operating at their best possible level given their current input levels.

The highest SE score is achieved by Taishin, with a score of 0.996, indicating that they have achieved a high level of scale efficiency in utilizing their resources.

In terms of RTS, some banks operate at increasing returns to scale, indicating that they can further expand their operations to improve efficiency (e.g., first, TCFHC, CDFHC, and SinoPac), whereas others operate at decreasing returns to scale, indicating that they need to optimize their resource utilization to improve efficiency (e.g., Fubon, Cathay, HNFHC, Taishin, E. SUN, and Yuanta).

B. 2020 Efficiency Analysis

In 2020, most banks had a decreasing trend in their TE efficiency scores, indicating a decline in their ability to efficiently use their inputs to generate outputs at the same rate. However, there were two exceptions: TCFHC and Taishin, which both showed increasing trends in TE efficiency (under CRS conditions).

For PTE efficiency (under VRS conditions), most banks also had a decreasing trend, except for four banks: TCFHC, CDFHC, Taishin, and SinoPac. This suggests that those banks were able to adjust their input mix and scale to become more efficient in using their resources to generate outputs.

With respect to SE, most banks had a decreasing trend in 2020, indicating that they were operating further from their optimal scale than they were in 2019. Only three banks, TCFHC, Taishin, and SinoPac, had an increasing trend in SE, suggesting that they were able to operate closer to their optimal scale in 2020 (better than 2019).

C. 2021 Efficiency Analysis

Since the data provided for 2021, we can see that Fubon, IBF, SKFH, and CTBC have maintained their efficiency levels, whereas some banks have improved their efficiency, such as the TCFHC, HNFHC, Mega, and SinoPac. However, some banks, such as Taishin and E. SUN, have experienced a decrease in efficiency since 2019.

The results of the analysis indicate that IBF, SKFH, and CTBC are the most efficient banks in terms of total efficiency (CRS), meaning that they have achieved the highest level of efficiency in utilizing their resources. However, all banks have achieved pure technical efficiency in terms of production efficiency (PTE), which means that they are operating at their best possible level given their current input levels.

In terms of scale efficiency (SE), SKFH and CTBC achieve the highest scores, indicating that they utilize their resources effectively to achieve a high level of scale efficiency. In contrast, Taishin and Cathay have lower scores in terms of scale efficiency.

With respect to returns to scale (RTS), TCFHC operates at increasing returns to scale, indicating that they are increasing their output more than proportionally to their input increase, whereas Taishin and Cathay are operating at decreasing returns to scale, indicating that they are not increasing their output as much as their input increases.

Overall, the analysis provides valuable insights into the efficiency levels of banks and highlights areas where improvements can be made to achieve higher levels of efficiency.

D. 2022 Efficiency Analysis

Because of the data provided for 2022, Fubon, IBF, SKFH, and CTBC maintain their efficiency levels, whereas some banks, such as TCFHC, CDFHC, Mega, and E. SUN, have improved their efficiency. However, some banks, such as Cathay, Taishin, and Yuanta, experienced a decrease in efficiency compared with 2019.

In terms of TE (under CRS conditions), IBF, SKFH, and CTBC achieve the highest scores, indicating that they are operating at their maximum efficiency levels.

In terms of PTE (under VRS conditions), all banks, except for SinoPac and Yuanta, have achieved their maximum level of efficiency and are operating at their optimal performance level when the current input levels are considered.

With respect to SE, SKFH and CTBC achieved the highest scores, indicating that they achieved a high level of scale efficiency in utilizing their resources. Finally, for RTS, the TCFHC is the only bank operating at increasing returns to scale, whereas some banks, such as Cathay, Taishin, E. SUN, and Yuanta, are operating at decreasing returns to scale.

Table 6: Efficiency scores of 14 Taiwanese FHCs from 2019 to 2022.

Year	DMU	CRS	VRS	SE	RTS
2019	First	0.867	0.880	0.986	Increasing
2019	Fubon	0.838	1.000	0.838	Decreasing
2019	IBF	1.000	1.000	1.000	Constant
2019	Cathay	0.856	1.000	0.856	Decreasing
2019	TCFHC	0.912	0.926	0.985	Increasing
2019	HNFHC	0.775	0.784	0.989	Decreasing
2019	CDFHC	0.853	0.878	0.971	Increasing
2019	Taishin	0.980	0.984	0.996	Decreasing
2019	SKFH	1.000	1.000	1.000	Constant
2019	SinoPac	0.942	0.947	0.994	Increasing
2019	E. SUN	0.947	1.000	0.947	Decreasing
2019	Yuanta	0.952	1.000	0.952	Decreasing
2019	Mega	1.000	1.000	1.000	Constant
2019	CTBC	1.000	1.000	1.000	Constant
2020	First	0.893	0.913	0.978	Decreasing
2020	Fubon	0.884	1.000	0.884	Decreasing
2020	IBF	1.000	1.000	1.000	Constant
2020	Cathay	0.861	1.000	0.861	Decreasing
2020	TCFHC	0.972	0.987	0.985	Increasing
2020	HNFHC	0.675	0.685	0.986	Increasing
2020	CDFHC	0.939	0.953	0.985	Increasing
2020	Taishin	0.975	0.977	0.998	Increasing
2020	SKFH	1.000	1.000	1.000	Constant
2020	SinoPac	0.971	0.975	0.996	Increasing
2020	E. SUN	0.880	0.961	0.915	Decreasing
2020	Yuanta	0.978	1.000	0.978	Decreasing

2020	Mega	0.989	1.000	0.989	Decreasing
2020	CTBC	1.000	1.000	1.000	Constant
2021	First	0.813	0.821	0.990	Increasing
2021	Fubon	1.000	1.000	1.000	Constant
2021	IBF	1.000	1.000	1.000	Constant
2021	Cathay	0.890	1.000	0.890	Decreasing
2021	TCFHC	0.894	0.925	0.967	Increasing
2021	HNFHC	0.661	0.674	0.980	Increasing
2021	CDFHC	0.938	0.951	0.986	Decreasing
2021	Taishin	0.783	0.803	0.975	Decreasing
2021	SKFH	1.000	1.000	1.000	Constant
2021	SinoPac	0.874	0.878	0.995	Increasing
2021	E. SUN	0.832	0.847	0.982	Increasing
2021	Yuanta	1.000	1.000	1.000	Constant
2021	Mega	0.819	0.827	0.990	Increasing
2021	CTBC	1.000	1.000	1.000	Constant
2022	First	0.990	0.992	0.997	Increasing
2022	Fubon	1.000	1.000	1.000	Constant
2022	IBF	1.000	1.000	1.000	Constant
2022	Cathay	0.961	1.000	0.961	Decreasing
2022	TCFHC	1.000	1.000	1.000	Constant
2022	HNFHC	0.778	0.781	0.996	Decreasing
2022	CDFHC	0.978	0.988	0.990	Increasing
2022	Taishin	0.801	0.803	0.997	Decreasing
2022	SKFH	1.000	1.000	1.000	Constant
2022	SinoPac	0.962	1.000	0.962	Decreasing
2022	E. SUN	0.966	0.990	0.976	Increasing
2022	Yuanta	0.990	1.000	0.990	Decreasing
2022	Mega	0.945	0.951	0.994	Increasing
2022	CTBC	1.000	1.000	1.000	Constant

5.3.2. Efficiency Scores and Changes during the Epidemic

A. Analysis of Efficiency Scores During the Epidemic

During the pandemic, changes have been observed in the average values of TE, PTE, and SE over the past four years. These data help us understand the impact of the pandemic on the operational efficiency of Taiwan's financial industry. According to the data in Table 6 and Figure 1, the annual impacts on the three indicators (TE, PTE, and SE) are not consistent. For example, TE increased by 3.2% from 2019--2022, whereas SE increased by 1.7% during the same period.

Furthermore, throughout all the years, the values of TE and PTE are both greater than 0.9, indicating that the increase in production factors (such as funding and power) has a relatively small marginal effect on total output. Additionally, the value of PTE is usually greater than that of TE, suggesting the presence of changeable factors in the production process that would have a greater impact on total production.

On the other hand, SE values are greater than 0.95 in all years, indicating that an increase in capital and labor input leads to relatively smaller increases in output but is still necessary for overall performance. The 2021 data are comparatively lower in all years, possibly due to the impact of COVID-19 on production and economic activity.

In general, higher values of TE and VRS are desirable, as they indicate that the increase in input variables results in a greater increase in output. Conversely, lower values of SE are preferable, as they indicate a more efficient relationship between output and input. Finally, the data are organized in Table 7 and Figure 1.

Table 7: TE, PTE, and SE averages for 2019--2022.

Year	TE	PTE	SE
2019	0.923	0.957	0.965
2020	0.930	0.961	0.968
2021	0.893	0.909	0.983
2022	0.955	0.965	0.990

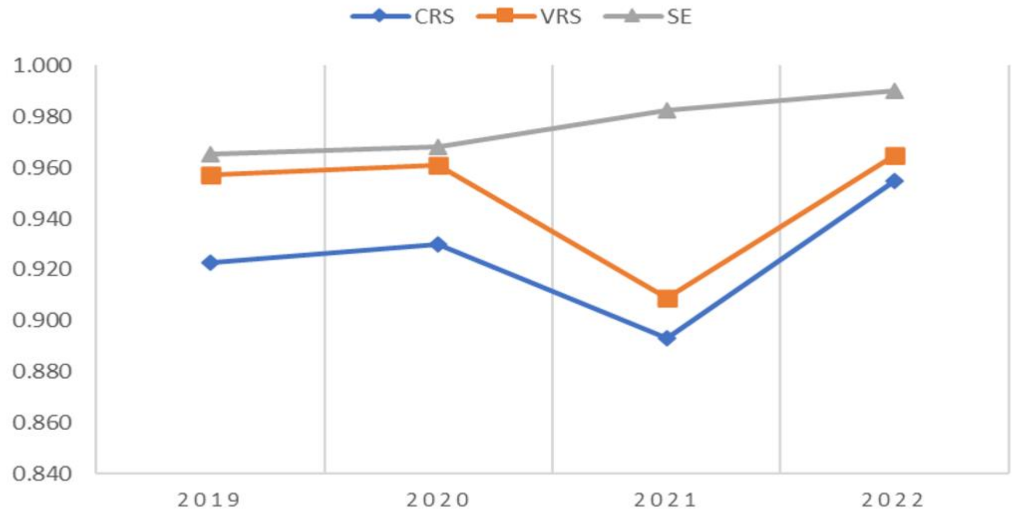

Figure 1: Four-year (2019--2022) trend chart of TE, PTE, and SE.

5.3.3. Overall Efficiency Changes During the Epidemic

According to the data presented in this study, which further analyzes the competitiveness of financial holding companies from 2019--2022, the impact of the pandemic on these companies was relatively minor in 2019. As a result, the overall competitiveness of financial holding companies increased by 1% in 2020 compared with 2019. However, by 2021, when the pandemic had become more severe, the overall competitiveness of financial holding companies had declined by approximately 4%. Fortunately, by 2022, as the pandemic began to ease, financial holding companies experienced growth of approximately 6%, returning to pracademic levels of competitiveness. Finally, the data are organized in Table 8 and Figure 2.

Table 8: FHCSs from 2019--2022.

Year	Competitiveness of Financial Holding Companies (%)
2019	100
2020	101
2021	97
2022	103

Note: The data presented in the table show the percentage change in the competitiveness of financial holding companies from 2019--2022. In 2019, the competitiveness of financial holding companies was considered the base level or 100%. Source: Authors' compilation.

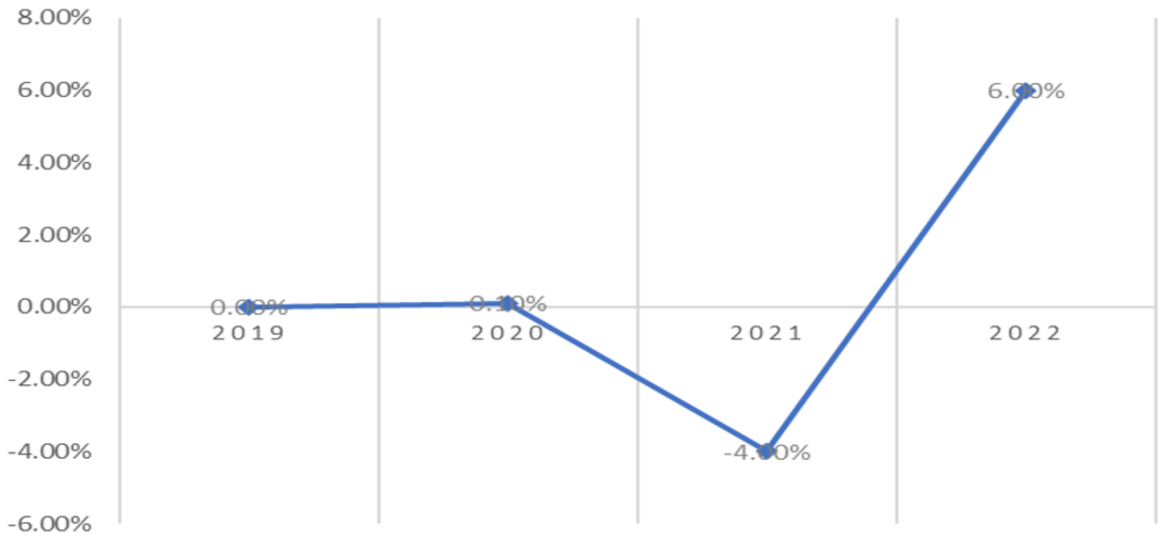

Figure 2: Overall efficiency changes during the epidemic.

5.4. The Results of the GRA Model

This study further applies the GRA model to conduct an in-depth analysis of the factors influencing operational efficiency, which include Total assets (x_1), Operating expenses (x_2), and Number of employees (x_3). Based on the results of the GRA model, the correlation degrees of the input variables are as follows:

1. Total assets (x_1) has a correlation degree of 0.719, indicating a "strong correlation." This highlights the significant impact of total assets on operational efficiency, suggesting that the scale of a company's resources plays a decisive role in its operational performance. A larger asset base likely contributes to greater production capacity and market competitiveness, thus enhancing overall operational efficiency.

2. Operating expenses (x_2) has a correlation degree of 0.623, indicating a "moderate correlation." This suggests that while operating expenses do influence operational efficiency, their effect is relatively moderate. Efficient cost management can reduce unnecessary expenditures and enhance resource utilization, but excessive operating expenses may still constrain overall performance.
3. Number of employees (x_3) has a correlation degree of 0.825, indicating a "strong correlation." This shows a high degree of correlation between the number of employees and operational efficiency, which may be related to workforce allocation and management. A larger workforce often enhances business execution and operational efficiency, but an excessive number of employees, if not effectively managed, can lead to organizational redundancy and negatively impact overall efficiency.

In summary, total assets and the number of employees have a strong impact on operational efficiency, while operating expenses have a moderate effect. This suggests that businesses should focus on resource allocation and human resource management to improve operational efficiency, while maintaining effective cost control. These conclusions not only help businesses identify key factors affecting operational efficiency but also provide a theoretical basis for future business strategies.

The detailed results of this analysis are summarized in Table 9, with specific data and explanations provided in the table.

Table 9: GRA model of GRC and the correlation degree of variables.

No	Indicators	Code	GRC	Variable Correlation Degree
1	Total assets	x_1	0.719	Strong
2	Operating expense	x_2	0.623	Moderate
3	Number of employees	x_3	0.825	Strong

6. CONCLUDING REMARKS

The main purpose of this study was to analyze the changes in the operational efficiency of FHCs in Taiwan during the COVID-19 pandemic. Utilizing a DEA model, this study selected 14 financial holding companies to evaluate their TE, PTE, and SE indicators over a four-year period. Based on the empirical results, the following conclusions and recommendations are provided:

6.1. Concluding

This study identified notable trends in the efficiency of Taiwan's financial industry through TE, PTE, and SE indicators. The results revealed varying degrees of change in these values over the past four years due to the impact of the pandemic, offering valuable insights into the operational challenges and adaptations of FHCs.

1. Impact of COVID-19 on Operational Efficiency: The analysis reveals that the TE and PTE values consistently exceeded 0.9, highlighting that marginal increases in total output for higher input were minimal but remained acceptable. The SE values remained consistently above 0.95, indicating that although capital and labor inputs yielded diminishing returns, such inputs were still crucial for overall performance improvement. These results suggest that financial holding companies (FHCs) showed resilience, maintaining satisfactory operational efficiency despite the disruptions caused by the pandemic.
2. Annual Insights on Efficiency Fluctuations: Specifically, the data for 2019 and 2020 show minimal impact on operational efficiency, with a 1% improvement in 2020 attributed to adjustments in operational practices due to the initial pandemic response. However, in 2021, operational efficiency declined by 4%, primarily due to disruptions in production and economic activities. By the end of 2022, FHCs achieved a 6% growth, returning operational efficiency to pre-pandemic levels. These fluctuations reflect both the challenges brought by COVID-19 and the adaptability of Taiwan's FHCs in managing these challenges.
3. Implications for the Post-Pandemic Era: The study highlights the importance of maintaining high TE and PTE values, as they reflect the efficient use of input variables in generating output. While lower SE values imply a need for improved relationships between inputs and outputs, the improvement over time indicates potential areas for strategic intervention. These findings suggest that FHCs should adopt targeted strategies, such as refining resource allocation and optimizing operational processes, to further strengthen Taiwan's financial sector competitiveness.
4. Strategies for Enhancing Operational Efficiency: In summary, total assets and the number of employees have a strong impact on operational efficiency, while operating expenses have a moderate effect. This indicates that FHCs should focus on resource allocation and human resource management to enhance operational efficiency while maintaining effective cost control. These conclusions not only help FHCs identify the key factors influencing operational efficiency but also provide a theoretical basis for future business strategies.

6.2. Recommendations for Future Research

Based on the findings and limitations of this study, several recommendations for future research are proposed:

1. Exploration of Specific Factors Influencing Efficiency: Future research should take a deeper dive into the factors influencing the efficiency of Taiwan's FHCs, particularly in the aftermath of the pandemic. This could include investigations into how advancements in technology and digitalization—such as the establishment of digital banks—impact operational efficiency. Moreover, exploring the role of evolving banking regulations on institutional performance would provide additional insights into the interplay between regulatory frameworks and competitiveness.
2. Longitudinal Studies on Pandemic Effects: As the pandemic's long-term impacts continue to unfold, future studies should monitor and analyze the sustained effects of COVID-19 on Taiwan's financial industry and beyond. Using longitudinal analysis, researchers could identify patterns in operational efficiency, along with examining the effectiveness of the strategies financial institutions employed to mitigate the pandemic's negative effects. Cross-country comparisons could further enhance our understanding of global best practices.
3. Incorporation of Risk and Market Dynamics: While this study focused on efficiency metrics, future research could integrate risk evaluation frameworks or market dynamic analyses to extend the scope of performance evaluation. Such studies could address broader dimensions of market stability, operational adaptability, and profitability, which are essential for comprehensive performance assessments.
4. Reflection on Methodological Limitations: It is important to note that this study's conclusions are limited by the scope of the selected sample, the time period observed, and the DEA model employed. Future research should consider expanding the sample size or incorporating alternative methodologies, such as stochastic frontier analysis (SFA), to compare and validate findings. Additionally, revisiting the analysis within the context of changing external factors—such as international financial trends or macroeconomic policies—would allow for more precise and globally applicable insights.

In conclusion, this study offers valuable insights into the operational efficiency of Taiwan's financial holding companies during the COVID-19 pandemic. While the pandemic undoubtedly disrupted economic activity, the findings reveal remarkable resilience within Taiwan's financial industry, coupled with opportunities for improvement. By addressing the limitations outlined and pursuing the recommendations proposed, future research can further support the development of robust strategies for enhancing the financial sector's efficiency and adaptability in both domestic and international contexts.

Finally, the conclusions and recommendations provided in this study are derived from the models developed, sample data gathered, and research methodologies utilized. Therefore, it is important to consider the evolving landscape of Taiwan's FSC environment and make necessary adjustments when applying our findings to ensure more precise conclusions.

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