Operational and investment efficiency of investment trust companies: Do foreign firms outperform domestic firms?

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Introduction
Among the various tools available in the field, including stochastic frontier analysis (SFA), financial statement ratio analysis, and data envelopment analysis (DEA), DEA is the preferred method because it can produce numerous outputs using multiple inputs with no assumptions concerning the measurement of best-practice technology (Sherman and Gold 1985). Since Charnes et al. (1978), the field of measuring efficiency has evolved in its applications in several areas, ranging from productivity assessment in various institutions to the performance of countries and refinements or complements made to the initial model. As summarized in Cooper et al. (2000), the use of DEA has helped to illuminate areas, such as sources of inefficiencies among companies, that were previously used as benchmarks. However, these companies operate using heterogeneous technologies. Therefore, evaluating the effect of the difference on efficiency measurements will provide a clearer picture of more accurate efficiency scores. Our study does not depart from the use of DEA but complements it with other models, with the main objective

Abstract
This study examines the efficiency of investment trust companies (ITCs) from 2011 to 2020 using a meta-frontier two-stage network data envelopment analysis (DEA) based on the directional distance function (DDF). We improved the accuracy of the efficiency measurement and added a network-based ranking component to rank the top-performing entities. In the group-specific technology assessment, foreign ITCs excel in investment efficiency. Meanwhile, in the meta-technology assessment, domestic ITCs outperform foreign ITCs in terms of both investment and operational efficiencies. Group-specific technology efficiency scores were found to be lower than or equal to the meta-technology efficiency scores for both the operational and investment stages. Based on the network-based ranking approach, Yuan Ta, a domestic ITC that ranked fourth in the operational stage and first in the investment stage, can be used as a reliable benchmark. This study will enable practitioners to gain a better understanding of the performance of ITCs operating under heterogeneous technologies.

Keywords: Data envelopment analysis, Metafrontier two-stage network, Network-based ranking, Directional distance function, Investment trust companies

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being to determine better benchmarks among investment trust companies (ITC), which are led mostly by mutual funds with heterogeneous characteristics. The resulting efficiency evaluation may not be accurate, thus becoming less meaningful due to the lack of a common frontier or benchmark. To overcome the different production types of ITCs, we proposed a metafrontier framework that analyzes ITCs based on a global frontier, which is the best possible efficiency with the top available technology and cluster frontiers formed by the most efficient ITCs in their respective operating technologies.

The financial sector has faced various challenges, including the lack of control over new financial institutions entering the financial arena, low-interest rates, which can potentially affect areas such as savings and loan defaults, and the role of ITCs in the financial markets. To avoid future contagious events such as that of Lehman Brothers, which filed for bankruptcy and disrupted the global financial markets on September 15, 2008, researchers must assess how ITCs are performing and, more importantly, which ITCs can be used as benchmarks. To this end, performance measures can be used to evaluate the efficiency of ITCs and identify potential areas of inefficiency.

After allowing foreign investors to engage in the mutual fund business for the first time in 1983, the value of mutual funds grew exponentially from NT$54 billion to NT$2.3 trillion; in addition, the number of ITCs increased from four to 39 organizations as of 2021¹ (Lin et al. 2021). Investors from other countries may now purchase or partner with the businesses to access the investment trust market. Consequently, the number of foreign-owned ITCs has increased. Apart from these foreign companies, the two local ITCs compete in the market. As a result of the Financial Holding Company Act of 2001, ITCs became subsidiaries of Financial Holding Companies (FHCs). The second category comprises local ITCs with 100% local stockholders. Given the differences in ownership arrangements, such as foreign versus local ownership, the market has evolved into a battleground for various management systems, resulting in distinct performance outcomes for ITCs.

On the one hand, foreign ITCs have the benefit of integrating global resources, thanks to the assistance of their parent firms. On the other hand, domestic ITCs have no trouble communicating in the local market and have amassed significant expertise in the underwriting business because they began earlier. These local companies have a better understanding of the characteristics of the stock markets. As a result, they have a long-standing reputation and adaptable marketing strategies, along with advantages in recognizing market conditions, cultivating retail investors, and completing product lines (Lu et al. 2016). Foreign versus domestic ITC success and performance in the market would be fascinating to compare, given the advantages and disadvantages of each. Establishing a benchmark business or firm can help other market participants improve their performance and, in the long run, promote healthier competition.

Compared with other financial hubs in the region, the province has the ideal demographics for mutual funds with a middle-class population, which mostly comprises middle-aged individuals with a relatively high savings rate, a high average income with modest pension schemes, and a high motivation to invest and manage their money.

¹ https://www.yesfund.com.tw/w/wp/wp00.djhtm.
actively (Aldcroft 2012). A study on the efficiencies and rankings of ITCs is warranted. The motivation for such research is backed by the following factors: a market capitalization to GDP ratio consistently above 130% over the last 10 years, stable real GDP growth of approximately 2% since 2017, a GDP per capita that has been continuously trending upward since the latest global financial crisis, unemployment rates that have been trending downwards since 2010, stabilizing at approximately 3.5%, and a more than threefold increase in the number of finance and insurance companies (CEIC 2019).

Moreover, the literature on network DEA and meta-frontier analysis of ITCs require further exploration, particularly because network DEA usually yields several efficient DMUs. To our knowledge, this is the first study to explore this issue within the context of a meta-frontier analysis based on directional distance function (DDF). While evidence on the use of DEA in ITCs is scarce, Basso and Funari (2016) provided a good summary of DEA studies that evaluated mutual funds and other managed funds. In addition, Galagedera (2019) evaluated mutual fund performance by decomposing the total management process of mutual funds into a connected two-stage process, where operational management and portfolio management were used as the first- and second-stage processes, respectively. More recent innovative DEA applications on ITCs include Lin et al. (2021), who proposed a trend analysis technique to forecast the future efficiency scores of each ITC. Lin et al. (2021), Chuweni et al. (2021) and Chuweni (2019) examined the efficiency scores of Malaysian real estate investment trusts. Meanwhile, Lin and Liu (2021) applied a DEA model based on a directional distance function to mutual funds in the U.S. and found good practical value for mutual fund portfolio selection. Consistent with Galagedera et al. (2018), Premachandra et al. (2012), and Galagedera et al. (2016), our study also looked at operational efficiency and investment efficiency but diverged slightly in terms of which variables are used as inputs, intermediates, and outputs, and particularly the DEA methodologies that are used to gauge the efficiencies of ITCs better. Specifically, we assessed the efficiencies of ITCs regarding their heterogeneous technologies and ranked the most efficient ones in 2011–2020. Yuan Ta, a domestic ITC, ranked first during the operational stage and third during the investment stage. Given these rankings, the company can be used as a reliable benchmark. Meanwhile, the top-performing foreign ITC was UBS, which ranked third and second in the first and second stages of the meta-frontier DEA, respectively.

While we initially adopted the metafrontier framework set by Chiu et al. (2016), our study differs in three distinct ways. First, in addition to the assessment of metafrontier efficiencies and inefficiencies of ITCs using network DEA, we incorporated the DDF-based technique to estimate the relative efficiency of ITCs along a predetermined direction vector that is not restricted by a radial direction (Yang et al. 2018) and can handle negative values (Lin and Liu 2021). We also followed Liu and Lu (2010) and Liu et al. (2015) to complement the DEA model with a network-based ranking approach and identify the most valuable input and output factors. As postulated by Lu et al. (2016), who also implemented the network-based ranking approach over the management and investment efficiencies for ITCs, this approach can rank efficient institutions at various stages and illuminate each institution’s weaknesses and strengths. We departed slightly from these authors in that they adopted an additive efficiency approach, and Lu et al. (2021) adopted a slacks-based measure DEA model, whereas our study consists
predominantly of a meta-frontier analysis complemented with a network-based ranking approach. In other words, the use of the metafrontier two-stage DEA model with network-based ranking allows us to identify ITC firms that can ultimately serve as more reliable benchmarks. Second, we do not restrict our scope of study to undesirable output, as in Chiu et al. (2016), because an ITC’s underlying capital investment base is relatively stable, with managers investing and selling assets when they feel the time is right and not act when investors move in and out of the fund. Compared with other institutions, such as fund management companies, ITCs’ managers need only to match buyers with sellers who want to liquidate their positions, rather than be forced to liquidate investments in, for instance, a falling market. Furthermore, ITCs typically have lower operating costs than open-ended funds.

Thus, we contribute to the literature on two-stage network efficiency. Specifically, we demonstrated the need to consider heterogeneity in ITCs’ technologies. Furthermore, we estimated efficiencies in an accurate and meaningful way after addressing the potential issue of the lack of a common frontier or benchmark. Our DEA approach simultaneously incorporates various performance indicators while evaluating the performance of ITCs operating under different technologies. Moreover, we enrich related studies using a network-based ranking approach. In this method, the envelopment variable return-to-scale DEA model, which is based on the concept of the production possibility set (Tone and Tsutsui 2009), is combined with a network-based approach to identify the most valuable input and output factors and to determine ITC companies that can be treated as benchmarks. Overall, by deriving more accurate efficiency scores and rankings of ITCs, we revealed that, although foreign ITCs excel in terms of investment efficiency in the group technology evaluation, domestic ITCs outperform foreign ITCs in investment and operational efficiencies in the metafrontier evaluation.

The remainder of the paper provides a breakdown of the literature review on network DEA and the metafrontier framework in financial institutions, and the research methodology and data section follow. We then present the empirical results. Finally, we present the concluding remarks.

**Literature review**

**Network DEA and metafrontier framework in financial institutions**

The study of financial institutions is one of the most extensively discoursed areas in the literature on efficiency (Liu et al. 2013). A comprehensive survey of frontier efficiency analysis in financial institutions by Berger and Humphrey (1997) shows that DEA is the most frequently used approach for efficiency evaluation. Izadikhah (2022) recently summarized 455 papers involving the use of different DEA approaches for financial evaluation from 1994 to 2021. Although DEA applications are observed in various industries, we focused on financial markets and institutions. For instance, Mohtashami and Ghiyasvand (2020) found that using a fuzzy DEA model could simultaneously evaluate the efficiency and effectiveness of companies, thus making the model more efficient. Lim et al. (2014) used DEA cross-efficiency evaluation to select portfolios and found that the selected portfolio yielded higher risk-adjusted returns than the other benchmark portfolios. More importantly, Goyal et al. (2019) applied a meta-frontier directional distance...
function DEA approach and determined different production functions across various ownership (foreign, private, and public) structures of the banking industry.

Two theoretical approaches can evaluate the efficiency of financial institutions, namely, the production approach (Chen et al. 2011; Kuo et al. 2015; Sherman and Gold 1985) and the intermediation approach (Haslem et al. 1999; Miller and Noulas 1996; Nourani et al., 2018). Building on financial portfolio theory (Biger and Kahane 1978; Doherty 1980), Nourani et al. (2018) mentioned that a financial institution (for example, an insurance company that acts as an intermediary operator) generates capital through the sale of diversified portfolios and invests the proceeds in balanced portfolios consisting of financial instruments. In addition to features such as shareholders’ rights, an independent board of directors, and competitive pricing, a major benefit of financial institutions, such as investment trust companies, is the ability to tap into gearing, where borrowing can be undertaken to take advantage of investment opportunities. While leverage increases the risk of being liable to creditors if investments fail, leveraged mutual funds can increase their potential returns faster than traditional mutual funds that use only equity capital to fund operations. Furthermore, the production approach is appropriate for assessing financial branches or subsidiaries, while the intermediation approach is suitable for evaluating the entire financial industry (Berger and Humphrey 1997; Brock-ett et al. 2004). Relying on the concept of intermediation, financial institutions are financial intermediaries that are viewed as investment operation entities. Hence, investment operations are an important part of financial institutions.

After the novel work of Charnes et al. (1978), who introduced the Charnes, Cooper, and Rhodes (CCR) model, the pioneering study of Sherman and Gold (1985) presented the first application of DEA research in financial institutions, where the authors estimated the operational efficiency of bank branches. This research was followed by many other studies that applied various traditional DEA models (Berg et al. 1993; Elyasiani and Mehdian 1990; Parkan 1987; Rangan et al. 1988; Sherman and Gold 1985). As traditional DEA methodologies often ignore the underlying functions of production processes (Färe and Grosskopf 1996), the concept of network DEA (two-stage/multiple-stage DEA) was eventually introduced, with the latter offering a solution by opening the so-called “black box” of production processes and assessing internal processes (Cook et al. 2010). Since then, several studies have explored network DEA techniques in various settings within the financial domain (for example, Avkiran 2014; Chiu et al. 2016; Kao and Hwang 2008, 2010; Kuo et al. 2015; Kweh et al. 2018; Lo and Lu 2006; Lu et al. 2016; Luo 2003; Nour-ani et al. 2018; Nourani et al. 2017; Pasiouras 2008; Premachandra et al. 2012; Seiford and Zhu 1999; Tone and Tsutsui 2009, 2014; Yang and Liu 2012).

Seiford and Zhu (1999) and Luo (2003) separated banking processes into profitability and marketability stages. In a study of U.S. commercial banks, Seiford and Zhu (1999) found that large banks outperform in the area of profitability while small banks exhibit better marketability. Consistent with the findings of Seiford and Zhu (1999), Luo (2003) concluded that large banks acquire higher profitability than marketability efficiency in a global context. In addition, Lo and Lu (2006) studied financial holding companies in a two-stage DEA setting, specifically profitability and marketability. In the insurance literature, Kao and Hwang (2008) divided the production process into premium acquisition and profit generation using relational and independent
two-stage models. They found that non-life insurers are more efficient in premium acquisitions. Similarly, using the dynamic network slacks-based measure DEA model, Nourani et al. (2018) revealed a lack of efficiency in investment capabilities among Malaysian local insurance companies compared with their foreign counterparts. Nourani et al. (2017) segregated insurance operations into managerial efficiency and value-creation efficiency, with the inclusion of risk management activities as exogenous factors, and found that Malaysian insurance companies’ efficiency was largely attributed to value-creation efficiency. Other applications include Premachandra et al. (2012), who decomposed the mutual fund performance of large U.S. family funds into operational and portfolio management functions, and Lu et al. (2016), who estimated the performance of ITCs in two stages and examined management and investment efficiencies. While network DEA has several advantages over traditional DEA, a two-stage analysis typically results in more than one efficient DMU, especially when the number of DMUs is not significantly higher than the total variables used in DEA (Liu and Lu 2010; Liu et al. 2015).

Another argument relates to the use of production technology in DEA. Traditional and network DEA models assume that all DMUs have common production technology and possess the best practice in measuring efficiency (Chiu et al. 2016). Therefore, an imprecise efficiency frontier may result in inaccurate benchmarking of the DMUs. To deal with this issue, Hayami (1969) originally proposed using a metafrontier approach to assess the differences in the productivity of agricultural firms between two distinct frontiers, namely, developed and developing countries. Hayami and Ruttan (1971) further pointed out that meta-frontier technology envelopes the production points of DMUs operating in different production possibility curves.

Metafrontier analysis has been used in various frontier-efficiency contexts. Battese and Rao (2002) and Battese et al. (2004) used SFA to estimate firm efficiencies using metafrontier production technology. In a comparative study using SFA and metafrontier as efficiency estimation techniques, Bos and Schmiedel (2007) concluded that conventional models underestimate cost and profit efficiency in a combined frontier compared with the metafrontier and group frontier. The benefit of adopting DEA over SFA is that no requirement is needed to define the functional relationship between inputs and outputs or determine the weights of inputs and outputs (Chandra et al. 1998). Consequently, SFA-based efficiency scores are partly dependent on the accuracy of the selected functional form that represents the true production function (Kumar and Arora 2011). Comparatively, DEA allows the simultaneous use of multiple inputs and outputs, calculates relative efficiency scores, and derives a quantifiable measure of firm performance. Furthermore, DEA enables an investigation of whether changes in efficiency are caused by pure technical efficiency (management practices) or scale efficiency (positive returns to scale) (Topuz et al. 2005).

To address the shortcomings of SFA, ODonnell et al. (2008) obtained the technical efficiencies of the meta-frontier and group frontier using DEA. Chen and Yang (2011) compared the scale of efficiencies of Chinese banks, and Chen (2012) used a metafrontier framework to compare public and private banks using the Malmquist productivity index. The results of both studies highlighted that distinct technological sets for various groups must be used to evaluate efficiency. Chiu et al. (2016) integrated
the meta-frontier approach with a two-stage DEA to estimate the efficiency and inefficiency of banks with desirable and undesirable outputs.

Although several recent studies have explored network DEA frameworks in various financial institutions, little attention has been paid to mutual fund operators and ITCs. Furthermore, the literature on network DEA and meta-frontiers in financial institutions require further exploration. Network DEA typically results in a number of efficient DMUs. We could not find any study that examined this issue through a metafrontier analysis. For a thorough analysis of the efficiencies across different ITC groups, we used a meta-frontier production function based on directional distance, which was effectively used by various authors, including Huang et al. (2015), Yao et al. (2015), Färe and Grosskopf (2000), and Chambers et al. (1998). In addition to investigating metafrontier efficiencies and inefficiencies of ITCs in using network DEA, we followed Liu and Lu (2010) and Liu et al. (2015) to combine the DEA model with a network-based ranking approach to identify the most valuable input and output factors. Therefore, we can accurately determine which ITC firms can eventually use as relatively better benchmarks.

Methodology
Framework, data description, and sample selection
Similar to Galagedera et al. (2018), Premachandra et al. (2012), and Galagedera et al. (2016), our study explores operational efficiency and investment efficiency. However, the present study diverges slightly regarding the variables used as inputs, intermediates, outputs, and DEA methods. Although Premachandra et al. (2012) and Galagedera et al. (2016) considered net asset value (NAV) as an intermediate variable, they also included other variables such as fund size, variability in returns, and expense ratio as inputs for the portfolio (investment) process. We included transaction costs and management fees as intermediates because more fixed assets result in higher transaction costs for firms. Furthermore, we incorporated NAV into our models as outputs, such as changes in bond and equity funds. While the production process of mutual funds remains the same in any setting, the types of efficiency under consideration within the “black box” and the nature of the firms in a particular market (Taiwan Province, People’s Republic of China, in our case) denote the inputs or outputs that must be used (Nourani et al. 2021). For example, Galagedera et al. (2018) proposed a three-stage network model to evaluate mutual funds, with the three stages being operational management, resource management, and portfolio management. Given the similar environmental conditions (low-risk undertakings) in both operational and resource management processes, these two processes are combined, resulting in a three-stage network model in which the first two stages function as an allied process. Another significant difference between the two-stage production process we devised for ITCs and that of Galagedera et al. (2018) is that the latter includes total risk, downside risk, systematic risk, and NAV as inputs for the portfolio management process, with the return included as the output of the investment stage.

In comparison, for inputs, we used employees, net fixed assets, and operating expenses; for intermediates, we used transaction costs and management fees; and for outputs, we used increases in the net asset values of bond and equity funds. The proposed efficiency model represents the operational mechanism of the ITCs while remaining in line with the literature on mutual funds. Based on the rationale provided above
for our choice of variables used in DEA, we outlined the production process of ITCs proposed in this study.

To assess complex production processes, an adequate number of inputs and outputs must be considered. These indicators produce a series of network structures that are linked through intermediate measures. Breaking down the production process into several divisions and subsequently opening the black box allows the respective decision-makers to act in the shareholders’ best interests. Based on the intermediation approach, this study divides the production process of ITCs into two stages: operational efficiency and investment efficiency. In the operational efficiency stage, ITCs invest in human and financial capital, specifically, employees, net fixed assets, and operating expenses, to generate the intermediates, that is, the transaction costs, management fee of the equity fund, management fee of the bond fund, and other expenses, which can be aptly used as the inputs for investment efficiency. However, it is important to note that employees, net fixed assets, and operating expenses do not produce the costs and fees for transactions and management. Instead, as ITCs grow, their inputs on employees, fixed assets, and operating expenses increase. In other words, with a higher amount of these inputs, which come from more business, ITCs are expected to also have higher amounts spent on transaction costs, the management fee of the equity fund, the management fee of the bond fund, and other expenses.

Next, in the investment efficiency stage, these intermediates are used to generate two outputs, that is, the change in equity funds and the change in bond funds. Figure 1 shows the network framework of ITCs, with their performance divided into two connected stages. In the first stage, we measured operational efficiency. We also assessed ITCs’ investment efficiency in the second stage. Table 1 presents the definitions of the input, intermediate, and output indicators and provides the relevant references used in the two-stage production process.

To conduct an efficiency analysis, firm-level data from the ITCs are required. Therefore, we compiled the financial data presented in the Taiwan Economic Journal (TEJ) database to collect necessary information regarding active ITCs. In addition, to ensure the availability of data, we checked the data published by the Taiwan Province Stock Exchange Market Observation Post System. Our sample included ITCs for

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2 https://emops.twse.com.tw/server-java/t58query.
which data were available from 2011 to 2020. Since the variables of inputs, intermediates, and outputs are intertemporal price variables, we deflated all variables according to the 2011 Consumer Price Index in Taiwan Province, PRC. In addition, we ensured that all companies in the sample had the necessary data for the specified sample period. We excluded ITCs that lacked sufficient data for the sample period. The final

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3 https://eng.stat.gov.tw/point.asp?index=2.
sample comprised 34 ITCs that was divided equally between domestic and foreign operators in the industry. Table 2 presents a list of the ITCs evaluated in this study.

In Table 3, the weighted averages of inputs, intermediates, and outputs for 340 observations for the sample period are segregated into two distinct panels, which correspond to domestic and foreign samples with 170 observations each. On average, the results demonstrated that domestic ITCs hired a greater number of employees than foreign ITCs. In addition, domestic ITCs have more net fixed assets and lower operating expenses than foreign ITCs. Domestic ITCs incurred higher transaction costs and other expenses during the sample period. In contrast, domestic ITCs tended to spend less on bond funds but more on equity funds than foreign ITCs with the same indicators. This comparison emphasizes that domestic ITCs are more prudent regarding their management fee spending and tend to spend less on risky assets. Meanwhile, foreign ITCs’ higher median management fees for bond funds compared to domestic ITCs indicate that a greater number of domestic ITCs have high spending on bond funds. In addition, the output values of domestic ITCs are significantly better than those of foreign ones. The change in the equity fund is nearly 50%, while the change in the bond fund is more than double that in foreign outputs. These findings were as
anticipated, with more values placed on certain inputs and intermediate quantities. Table 3 demonstrates that all values are normally distributed across the two panels. Golany and Roll (1989) stated that for DEA, an isotonicity assumption is required. This assumption states that the input and output factors must have a positive correlation, showing that a proportional increase in the input indicator produces a proportional increase in the output indicator. To ensure that this assumption was met, we performed a Spearman's rho correlation test, as shown in Table 4, which yielded satisfactory results. All values indicated positive correlations between the variables used in the DEA, except for net fixed assets (X2) and other expenses (Z4). The trivial correlation coefficient of $-0.035$ obtained was negligible and unsurprising, as more fixed assets resulted in fewer additional expenses. Hence, in general, the results indicate positive correlations between the variables. Furthermore, Golany and Roll (1989) suggested that the number of DMUs should at least double the number of input and output factors. Our sample satisfied this requirement, with $34 > 2 \times (3 + 4 + 2)$. Cooper et al. (2006) established a more restricted rule for the minimum number of DMUs; they recommended that DMUs be at least three times more than the input and output factors. This constraint was also satisfied by our sample: $34 > 3 \times (3 + 4 + 2)$. Finally, as our ITCs operate in the same environment, our sample fulfills the homogeneity assumption. Thus, the affirmative results for the isotonicity assumption, minimum number of DMUs, and homogeneity assumption all indicated that our model had a

### Table 4 Correlation matrix

|          | X1  | X2  | X3  | Z1  | Z2  | Z3  | Z4  | Y1  |
|----------|-----|-----|-----|-----|-----|-----|-----|-----|
| Employees (X1) | 1   |     |     |     |     |     |     |     |
| Net fixed assets (X2) | 0.208 | 1   |     |     |     |     |     |     |
| Operating expenses (X3) | 0.541 | 0.436 | 1   |     |     |     |     |     |
| Transaction costs (Z1) | 0.792 | 0.111 | 0.460 | 1   |     |     |     |     |
| Management fee of equity fund (Z2) | 0.792 | 0.383 | 0.683 | 0.851 | 1   |     |     |     |
| Management fee of bond fund (Z3) | 0.423 | 0.277 | 0.691 | 0.374 | 0.488 | 1   |     |     |
| Other expenses (Z4) | 0.768 | -0.035 | 0.483 | 0.828 | 0.735 | 0.530 | 1   |     |
| Change in equity fund (Y1) | 0.795 | 0.373 | 0.698 | 0.843 | 0.984 | 0.517 | 0.751 | 1   |
| Change in bond fund (Y2) | 0.503 | 0.121 | 0.478 | 0.536 | 0.548 | 0.808 | 0.701 | 0.567 |

### Table 5 Kolmogorov–Smirnov test of differences between foreign and domestic capitals

|          | Domestic mean | Foreign mean | Domestic SD | Foreign SD | p level |
|----------|---------------|--------------|-------------|------------|---------|
| Employees | 121           | 98           | 65          | 63         | <0.01   |
| Net fixed assets | 222,118       | 147,610      | 350,646     | 219,603    | <0.05   |
| Operating expenses | 484,107       | 893,198      | 441,490     | 731,507    | <0.01   |
| Transaction costs | 423,093,259   | 310,740,146  | 513,557,355 | 473,357,382 | <0.01   |
| Management fee of equity fund | 379,278,032   | 319,087,913  | 439,182,008 | 359,730,111 | <0.01   |
| Management fee of bond fund | 163,732,391   | 221,673,376  | 178,496,288 | 263,952,641 | >0.10   |
| Other expenses | 64,613,412    | 53,048,272   | 63,730,930  | 65,276,265 | <0.01   |
| Change in equity fund | 32,037,712,379 | 19,863,046,537 | 54,128,905,799 | 22,162,088,306 | <0.01   |
| Change in bond fund | 53,087,172,554 | 22,610,043,340 | 55,570,832,573 | 21,287,392,559 | <0.01   |
high level of construct validity regarding the selection of the input, intermediate, and output variables.

Table 5 displays the results of the Kolmogorov–Smirnov test of the differences between foreign and domestic capital regarding the inputs, intermediates, and outputs used in the DEA. The use of this test is in line with prior studies such as Nataraja and Johnson (2011). The findings showed significant differences between all input and output quantities when comparing domestic and foreign ITCs. Compared with foreign ITCs, domestic ITCs had a significantly higher number of net fixed assets and employees but lower operating expenses. In addition, domestic ITCs showed a greater increase in equity funds and an increase of more than double in bond funds. Regarding intermediate factors, domestic ITCs showed significantly higher transaction costs and management fees for equity funds than for other expenses. Although domestic operators had lower management fees for bond funds than foreign operators, the statistical test of differences demonstrated that it was not significant at the 10% level. Overall, these results indicate that domestic and foreign ITCs have noticeable differences in their technologies.

The DDF-based metafrontier and group frontiers
Following ODonnell et al. (2008) to measure the impact of technological heterogeneity, we grouped N ITCs into two groups \( G_g, g = 1, 2 \). The sample of the \( G_g \) group is \( N_g \), where \( N_1 + N_2 = N \). These ITCs used \( m \) inputs to generate \( d \) intermediates (first stage), which are ultimately transformed into \( s \) outputs (second stage). In our study, in the first stage, we input \( x \in R^m_+ \), intermediate outputs (first stage), input (second stage) \( z \in R^d_+ \), and final outputs \( y \in R^s_+ \). We assumed a convex\(^4\) production possibility set and defined the DDF-based two-stage network framework, both metafrontier \((M)\) and group-specific \((G)\), using the following equations:

\[
\begin{align*}
D^M_{\mathbf{x}, \mathbf{z}, \mathbf{y}; \mathbf{g}_x, \mathbf{g}_y} &= \text{Max} \{ \alpha + \beta : (x - \alpha g_x, z, y + \beta g_y) \in T^M_{\mathbf{x}, \mathbf{z}, \mathbf{y}} \}.
\end{align*}
\]

\[
\begin{align*}
D^G_{\mathbf{x}, \mathbf{z}, \mathbf{y}; \mathbf{g}_x, \mathbf{g}_y} &= \text{Max} \{ \gamma + \tau : (x - \gamma g_x, z, y + \tau g_y) \in T^G_{\mathbf{x}, \mathbf{z}, \mathbf{y}} \}, \quad G = G_1, G_2.
\end{align*}
\]

The respective technology sets are thus detailed as follows:

The ITCs used \( T^M_{\mathbf{x}, \mathbf{y}, \mathbf{z}} \mathbf{x} \in R^m_+ \) to generate the intermediate outputs \( z \in R^d_+ \) in the first stage. Meanwhile, they used \( z \in R^d_+ \) to make the final outputs \( y \in R^s_+ \) in the second stage.

ITCs used \( T^G_{\mathbf{x}, \mathbf{y}, \mathbf{z}} \mathbf{x} \in R^m_+ \) in Group \( G_g \) in the first stage to yield \( z \in R^d_+ \). They used \( z \in R^d_+ \) to produce \( y \in R^s_+ \) in the second stage.

Furthermore, the meta-technology set consists of the G-group-specific technology set \( T^M_{\mathbf{x}, \mathbf{y}, \mathbf{z}} = \{ T^{G_1}_{\mathbf{x}, \mathbf{y}, \mathbf{z}} \cup T^{G_2}_{\mathbf{x}, \mathbf{y}, \mathbf{z}} \} \). Fried et al. (2008) claimed that the direction vector \( g = (g_x, g_y) \) should be selected before the DDF can be evaluated. In the present study, we considered the direction to be \( g = (g_x = x, g_y = y) \) (Chiu et al. 2012). In this

\(^4\) Readers are encouraged to refer to Chiu et al. (2013) about the technical assumption of convexity that reasonably holds when the meta-frontiers of the production process envelop all of the group-frontiers of the production process. The envelopment concept implies that the meta-frontier is a convex piecewise frontier. Moreover, the union of two convex sets need not be convex, but the convex hull of the union is the smallest convex set that contains both groups.
case, the inefficiency measure of the \( ITCo \) of meta-technology and group-specific technology sets under convex constraints can be represented by the following two linear programs:

\[
\begin{align*}
\tilde{D}^M &= \text{Max } \alpha^M_o + \beta^M_o \\
\sum_{g=1}^{G_o} \sum_{j=1}^{N_j} \delta_j^g x_{ij}^g &\leq x_{io} - \alpha^M_o g_{iox}, \quad i = 1, \ldots, m, \\
\sum_{g=1}^{G_o} \sum_{j=1}^{N_j} \delta_j^g x_{ij}^g &\geq \delta_{ho}^g, \quad h = 1, \ldots, d, \\
\sum_{g=1}^{G_o} \sum_{j=1}^{N_j} \delta_j^g x_{ij}^g &\geq \delta_{ho}^g, \quad h = 1, \ldots, d, \\
\sum_{g=1}^{G_o} \sum_{j=1}^{N_j} \delta_j^g y_{ij}^g &\geq y_{io} + \beta^M_o g_{roy}, \quad r = 1, \ldots, s, \\
\sum_{g=1}^{G_o} \sum_{j=1}^{N_j} \delta_j^g y_{ij}^g &\leq 1, \\
\sum_{g=1}^{G_o} \sum_{j=1}^{N_j} \delta_j^g y_{ij}^g &\leq 1, \\
\delta_j^g, \eta_j^g &\geq 0, g = 1, \ldots, G_o.
\end{align*}
\]

(1)

\[
\begin{align*}
\tilde{D}^g &= \text{Max } \gamma_o^g + \tau_o^g \\
\sum_{j=1}^{N_j} \delta_j^g x_{ij}^g &\leq x_{io} - \gamma_o^g g_{iox}, \quad i = 1, \ldots, m, \\
\sum_{j=1}^{N_j} \delta_j^g x_{ij}^g &\geq \delta_{ho}^g, \quad h = 1, \ldots, d, \\
\sum_{j=1}^{N_j} \delta_j^g x_{ij}^g &\geq \delta_{ho}^g, \quad h = 1, \ldots, d, \\
\sum_{j=1}^{N_j} \eta_j^g y_{ij}^g &\geq y_{io} + \tau_o^g g_{roy}, \quad r = 1, \ldots, s, \\
\sum_{j=1}^{N_j} \delta_j^g y_{ij}^g &\leq 1, \\
\sum_{j=1}^{N_j} \delta_j^g y_{ij}^g &\geq 1, \\
\delta_j^g, \eta_j^g &\geq 0,
\end{align*}
\]

(2)

where \( \delta_j^g \) and \( \eta_j^g \) represent the intensity variables corresponding to the first and second processes, respectively, and \( N_1 + N_2 = N \).

Consequently, the operational efficiency of the first stage in the meta-technology and group-specific technology sets is defined as \( OE_o^M = 1 - \alpha_o^M \) and \( OE_o^g = 1 - \gamma_o^g \), respectively, which is the operational efficiency with values between 0 and 1. The efficiency of the second stage in these sets is defined as \( IE_o^M = 1 / (1 + \beta_o^M) \) and \( IE_o^g = 1 / (1 + \tau_o^g) \), or investment efficiency. To make the efficiency measure consistent, investment efficiency takes a derivative between 0 and 1. The target \( ITCo \) is regarded as efficient in both stages if \( OE_o^M, OE_o^g, IE_o^M, \) and \( IE_o^g \) have a value of 1. \( TE_o^M = OE_o^M / IE_o^M \) denotes the technical efficiency of the overall stage in a metafrontier setting.

**Decompositions of metafrontier inefficiency**

The frontier of metafrontier operational efficiency (\( MOE_o \)) is smaller than that of group-specific operational efficiency (\( GOE_o \)). However, the frontier of meta-frontier investment efficiency (\( MIE_o \)) is larger than that of group-specific investment efficiency (\( GIE_o \)). Mathematically, we have
The ratio between \( MOE_o \) and \( GOE_o \) is known as the operational technology gap ratio (OTGR), whereas that between \( MIE_o \) and \( GIE_o \) is known as the investment technology gap ratio (ITGR). In equations, we have:

\[
\begin{align*}
\frac{MOE_o(x, z, y)}{GOE_o(x, z, y)} & \leq 1 \\
\frac{MIE_o(x, z, y)}{GIE_o(x, z, y)} & \leq 1.
\end{align*}
\] (4)

\( GOE_o \) (\( GIE_o \)) is closer to \( MOE_o \) (\( MIE_o \)) if the values of OTGR and ITGR are closer to one.

Given that the ratios of the two frontiers are unable to explore the source of meta-frontier inefficiency (Chiu et al. 2012, 2013), we obtained the operational technology gap inefficiency (OTGI) and operational technical inefficiency (OTI) of the operational stage, and the investment technology gap inefficiency (ITGI) and investment technical inefficiency (ITI) of the investment stage as follows:

\[
\begin{align*}
OTGI(x, z, y) & = GOE(x, z, y) \times (1 - OTGR(x, z, y)) \\
ITGI(x, z, y) & = GIE(x, z, y) \times (1 - ITGR(x, z, y)).
\end{align*}
\] (5)

Furthermore, we have ITI and OTI as the managerial inefficiency of \( ITC_o \) in group-specific best practices based on the input excess in the operational stage or output shortfall in the investment stage as follows:

\[
\begin{align*}
OTI(x, z, y) & = 1 - GOE(x, z, y) \\
ITI(x, z, y) & = 1 - GIE(x, z, y).
\end{align*}
\] (6)

Therefore, we have the metafrontier operational and investment inefficiencies as follows:

\[
\begin{align*}
MOI(x, z, y) & = OTGI^g(x, z, y) + OTI^g(x, z, y) \\
MII(x, z, y) & = ITGI^g(x, z, y) + ITI^g(x, z, y).
\end{align*}
\] (7)

**Network-based ranking approach**

Following Liu and Lu (2010), the two-stage network DDF and radial network-based approaches were combined to rank the sample ITCs and the most important inputs or outputs for benchmarking purposes. The related steps are discussed in the following paragraphs.

**Step 1.** Under the assumption of variable returns to scale, the efficiency scores of all ITCs are estimated, considering all possible sets of inputs, intermediates, and outputs. Each specification \( k \) represents one possible set. The linear programming for each two-stage network DDF specification \( k \) is as follows:
The solution to \( \eta^g_{ij} \) indicates whether ITC \( j \) is a benchmark for the observed ITC in the first stage for each DEA specification \( k \). The solution of \( \eta^g_{ij} \) has the same definition as that in the second stage.

**Step 2.** The two-stage network DDF results are transformed into a network structure using the solution of \( \lambda^g_{ij} \) in the first stage. Each ITC was regarded as a network node. The corresponding \( \lambda^g_{ij} \) is taken as the weight of the endorsement; if ITC \( j \) is a paragon of the observed ITC \( o \) and has the corresponding \( \lambda^g_{ij} \), then a directed link of weight \( \lambda^g_{ij} \) pointing from node \( o \) to node \( j \) can be created. \( \eta^g_{ij} \) uses the same definition as in the second stage.

**Step 3.** \( \lambda^g_{ij} \) is normalized to solve scale effects. \( E_k \) denotes the index set for the reference set of the observed ITC. The contribution of the \( i \)-th input of the \( o \)-th ITC to the \( j \)-th ITC in the reference set under DEA specification \( k \) is defined as:

\[
I_{ij}^g = \lambda^g_{ij} x_{ij}^g x_{ij}^g / \sum_{j \in E_k} \lambda^g_{ij} x_{ij}^g x_{ij}^g, \quad 0 < I_{ij}^g \leq 1, \quad i = 1, \ldots, m. \tag{9}
\]

Similarly, the contribution of the \( h \)-th intermediate of the observed ITC to the \( j \)-th ITC in the reference set under DEA specification \( k \) is defined as:

\[
M_{ij}^g = \lambda^g_{ij} z_{ij}^g z_{ij}^g / \sum_{j \in E_k} \lambda^g_{ij} z_{ij}^g z_{ij}^g, \quad 0 < M_{ij}^g \leq 1, \quad h = 1, \ldots, d. \tag{10}
\]

The contribution of the \( h \)-th inputs of the second stage of the observed ITC to the \( j \)-th ITC in the reference set under DEA specification \( k \) is defined as:

\[
MO_{ij}^g = \eta^g_{ij} x_{ij}^g x_{ij}^g / \sum_{j \in E_k} \eta^g_{ij} x_{ij}^g x_{ij}^g, \quad 0 < MO_{ij}^g \leq 1, \quad h = 1, \ldots, d. \tag{11}
\]

Similarly, the contribution of the \( r \)-th output of the observed ITC to the \( j \)-th ITC in the reference set under the DEA specification \( k \) is defined as
**Step 4.** A relationship network was established. Efficiency analysis was run numerous times to enrich the network in terms of different specifications. The results from all DEA specifications are aggregated into one network for all ITCs. The adjacency matrix of the network is developed as follows:

\[
R_{ij} = \sum_{j \in E_k} y^{R,k}_{ij}, \quad 0 < Oy^{R,k}_{ij} \leq 1, \quad r = 1, \ldots, s.
\]  

where \( R \) is a squared matrix of order \( n \) and \( K \) is the total number of DEA specifications. All possible input, intermediate, and output combinations were \( K = (2^m - 1)(2^d - 1)(2^s - 1) \). Each element \( R_{ij} \) is the aggregated weight for the link directed from the observed node \( i \) to node \( j \). The principal diagonal elements of the matrix \( R \) were all 0.

**Step 5.** Eigenvector centrality (Liu et al. 2015) was computed to rank each ITC. The scores to measure the importance of each ITC, represented as a column vector \( I \), can help understand how the eigenvector centrality value can be used to rank the importance of a network ITC. The rank score for each ITC should be proportional to the importance of all nodes referencing it but weighted by the link weights:

\[
c \cdot I = R \cdot I,
\]

where \( c \) is the proportionality constant. In its matrix notation, Eq. (14) is an eigenvector system with \( n \) solutions. The largest eigenvalue and its corresponding eigenvector provide the most meaningful outcomes. Each element in this eigenvector is a measure of the importance of the corresponding node. In the research area of social networks, this method, which is usually called Bonacich centrality, offers two additional conditions: the endorsing weight and the importance of the endorsing peer. Readers can refer to “Appendix” for the abbreviations of the DEA-related terms and their expositions in this study.

**Empirical results**

**Efficiency analysis of investment trust companies**

Tables 6 and 7 present the average efficiency scores for the ITCs for 2011–2020. Table 6 reports the results of the first stage, operational efficiency, while Table 7 reports those of the second stage, investment efficiency. The second column in the two tables presents the operational and investment efficiencies of all ITCs in the meta-technology set, namely, MOE and MIE. The third column in the two tables represents the operational and investment efficiencies of domestic and foreign ITCs in the group-specific technology set, namely GOE and GIE. Using Eq. 4, we can calculate the technology gap ratio for the operational and investment stages, as shown in the fourth column of the two tables: OTGR and ITGR. Based on the technology gap ratio and group-specific efficiencies, the inefficiencies in group-specific frontiers are
calculated, which are represented by the OTGI and ITGI, as outlined in Eq. 5. Additionally, managerial inefficiencies in group-specific frontiers, namely OTI and ITI, were obtained using Eq. 6. The metafrontier operational and investment inefficiencies are shown in the last columns of Tables 6 and 7. They are presented as the MOI and

| Firms                      | MOE | GOE | OTGR | OTGI | OTI | MOI |
|----------------------------|-----|-----|------|------|-----|-----|
| Domestic ITCs              |     |     |      |      |     |     |
| Capital (CAP)              | 0.941| 0.957| 0.983| 0.016| 0.043| 0.059|
| Cathay (CA)                | 0.808| 0.865| 0.941| 0.057| 0.135| 0.192|
| CTBC (CTBC)                | 0.663| 0.727| 0.915| 0.065| 0.273| 0.337|
| First securities (FS)      | 0.909| 0.940| 0.966| 0.032| 0.060| 0.091|
| Fubon (FB)                 | 0.712| 0.720| 0.990| 0.008| 0.280| 0.288|
| Fuh Hwa (FH)               | 0.750| 0.857| 0.881| 0.107| 0.143| 0.250|
| Hua Nan (HN)               | 0.702| 0.723| 0.972| 0.022| 0.277| 0.298|
| Jih Sun (JS)               | 0.713| 0.713| 1.000| 0.000| 0.287| 0.287|
| KGI (KGI)                  | 0.916| 0.954| 0.961| 0.039| 0.046| 0.084|
| Mega (MG)                  | 0.966| 0.968| 0.998| 0.002| 0.032| 0.034|
| Reliance (RS)              | 0.903| 0.904| 0.999| 0.001| 0.096| 0.097|
| Shin Kong (SK)             | 0.632| 0.638| 0.988| 0.006| 0.362| 0.368|
| Sino Pac (YP)              | 0.640| 0.722| 0.905| 0.081| 0.278| 0.360|
| Tai Shin (TS)              | 0.808| 0.836| 0.951| 0.029| 0.164| 0.192|
| Uni-President (EZ)         | 0.671| 0.671| 1.000| 0.000| 0.329| 0.329|
| Union (UN)                 | 0.941| 0.995| 0.945| 0.055| 0.005| 0.059|
| Yuan Ta (YT)               | 0.971| 0.973| 0.998| 0.002| 0.027| 0.029|
| Average Domestic           |     |     |      |      |     |     |
|                           | 0.803|      |      |      |     |     |
| Foreign ITCs               |     |     |      |      |     |     |
| Alliance Bernstein (AB)    | 0.567| 0.584| 0.965| 0.017| 0.416| 0.433|
| Allianz (AGI)              | 0.755| 0.878| 0.849| 0.123| 0.122| 0.245|
| BlackRock (BR)             | 0.473| 0.478| 0.988| 0.005| 0.522| 0.527|
| Deutsche Far Eastern (DWS) | 0.936| 0.990| 0.945| 0.054| 0.010| 0.064|
| Eastspring (ES)            | 0.626| 0.758| 0.832| 0.132| 0.242| 0.374|
| Franklin Templeton (FTH)   | 0.819| 0.906| 0.897| 0.087| 0.094| 0.181|
| HSBC (HSBC)                | 0.658| 0.826| 0.795| 0.168| 0.174| 0.342|
| Invesco (GIN)              | 0.624| 0.695| 0.885| 0.071| 0.305| 0.376|
| JPMorgan (JP)              | 0.732| 0.928| 0.797| 0.196| 0.072| 0.268|
| Manulife (HL)              | 0.618| 0.753| 0.818| 0.135| 0.247| 0.382|
| Mirae Asset (MA)           | 0.781| 0.836| 0.939| 0.054| 0.164| 0.219|
| Nomura (NOM)               | 0.618| 0.732| 0.843| 0.115| 0.268| 0.382|
| Paradigm (HD)              | 0.572| 0.806| 0.723| 0.234| 0.194| 0.428|
| PineBridge (PB)            | 0.928| 0.951| 0.973| 0.023| 0.049| 0.072|
| Prudential Financial, Inc. (PRU) | 0.788| 0.960| 0.821| 0.172| 0.040| 0.212|
| Schroders (SC)             | 0.632| 0.638| 0.988| 0.005| 0.362| 0.368|
| UBS (UBS)                  | 0.982| 0.984| 0.998| 0.002| 0.016| 0.018|
| Average                    | 0.757| 0.820| 0.925| 0.062| 0.180| 0.243|
| Average Domestic           |     |     |      |      |     |     |
|                           | 0.803|      |      |      |     |     |
| Average Foreign            |     |     |      |      |     |     |
|                           | 0.712|      |      |      |     |     |

MOE: metafrontier operational efficiency, GOE: group-specific operational efficiency, OTGR: operational technology gap ratio, OTGI: operational technology gap inefficiency, OTI: operational technical inefficiency, MOI: metafrontier operational inefficiency
The empirical results in Tables 6 and 7 reveal that none of the ITCs from 2011 to 2020 achieve an efficiency score of 1 in the meta-technology and group-specific technology sets. The lack of an efficient unit in the ITC market indicates that there is room for improvement for all operating firms in the industry, regardless of their ownership.

### Table 7  Average investment efficiencies and metafrontier inefficiencies from 2011 to 2020

| Firms               | MIE | GIE | ITGR | ITGI | ITI | MII |
|---------------------|-----|-----|------|------|-----|-----|
| **Domestic ITCs**   |     |     |      |      |     |     |
| Capital (CAP)       | 0.698 | 0.698 | 1.000 | 0.000 | 0.302 | 0.302 |
| Cathay (CA)         | 0.630 | 0.633 | 0.995 | 0.003 | 0.367 | 0.370 |
| CTBC (CTBC)         | 0.633 | 0.812 | 0.788 | 0.179 | 0.188 | 0.367 |
| First Securities (FS)| 0.574 | 0.632 | 0.932 | 0.058 | 0.368 | 0.426 |
| Fubon (FB)          | 0.734 | 0.741 | 0.990 | 0.007 | 0.259 | 0.266 |
| Fuh Hwa (FH)        | 0.509 | 0.522 | 0.983 | 0.012 | 0.478 | 0.491 |
| Hua Nan (HN)        | 0.586 | 0.602 | 0.973 | 0.016 | 0.398 | 0.414 |
| Jh Sun (JS)         | 0.735 | 0.758 | 0.970 | 0.024 | 0.242 | 0.265 |
| KGI (KGI)           | 0.602 | 0.639 | 0.943 | 0.037 | 0.361 | 0.398 |
| Mega (MG)           | 0.753 | 0.763 | 0.988 | 0.010 | 0.237 | 0.247 |
| Reliance (RS)       | 0.739 | 0.867 | 0.851 | 0.128 | 0.133 | 0.261 |
| Shin Kong (SK)      | 0.661 | 0.691 | 0.952 | 0.030 | 0.309 | 0.339 |
| Sino Pac (YF)       | 0.411 | 0.428 | 0.960 | 0.018 | 0.572 | 0.589 |
| Tai Shin (TS)       | 0.591 | 0.615 | 0.950 | 0.025 | 0.385 | 0.409 |
| Uni-President (EZ)  | 0.677 | 0.683 | 0.991 | 0.006 | 0.317 | 0.323 |
| Union (UN)          | 0.650 | 0.787 | 0.833 | 0.137 | 0.213 | 0.350 |
| Yuan Ta (YT)        | 0.941 | 0.943 | 0.998 | 0.002 | 0.057 | 0.059 |
| **Foreign ITCs**    |     |     |      |      |     |     |
| Alliance Bernstein (AB) | 0.639 | 0.788 | 0.813 | 0.149 | 0.212 | 0.361 |
| Allianz (AGI)       | 0.503 | 0.840 | 0.584 | 0.337 | 0.160 | 0.497 |
| Blackrock (BR)      | 0.823 | 0.838 | 0.968 | 0.015 | 0.162 | 0.177 |
| Deutsche Far Eastern (DWS) | 0.366 | 0.440 | 0.838 | 0.074 | 0.560 | 0.634 |
| Eastspring (ES)     | 0.526 | 0.895 | 0.607 | 0.370 | 0.105 | 0.474 |
| Franklin Templeton (FTH) | 0.525 | 0.823 | 0.647 | 0.298 | 0.177 | 0.475 |
| HSBC (HSBC)         | 0.443 | 0.734 | 0.612 | 0.291 | 0.266 | 0.557 |
| Invesco (GIN)       | 0.746 | 0.831 | 0.858 | 0.085 | 0.169 | 0.254 |
| JPMorgan (JP)       | 0.589 | 0.969 | 0.609 | 0.381 | 0.031 | 0.411 |
| Manulife (HL)       | 0.426 | 0.628 | 0.683 | 0.202 | 0.372 | 0.574 |
| Mirae Asset (MA)    | 0.672 | 0.682 | 0.975 | 0.011 | 0.318 | 0.328 |
| Nomura (NOM)        | 0.489 | 0.825 | 0.583 | 0.337 | 0.175 | 0.511 |
| Paradigm (HD)       | 0.577 | 0.648 | 0.872 | 0.070 | 0.352 | 0.423 |
| PineBridge (PB)     | 0.612 | 0.873 | 0.695 | 0.261 | 0.127 | 0.388 |
| Prudential Financial, Inc. (PRU) | 0.610 | 0.927 | 0.646 | 0.317 | 0.073 | 0.390 |
| Schroders (SC)      | 0.641 | 0.719 | 0.853 | 0.079 | 0.281 | 0.359 |
| UBS (UBS)           | 0.424 | 0.445 | 0.934 | 0.021 | 0.555 | 0.576 |
| Average             | 0.610 | 0.727 | 0.849 | 0.117 | 0.273 | 0.390 |
| Average Domestic    | 0.654 |     |      |      |     |     |
| Average Foreign     | 0.565 |     |      |      |     |     |

MII, respectively, which are the summations of the fifth and sixth columns in their respective tables.

The empirical results in Tables 6 and 7 reveal that none of the ITCs from 2011 to 2020 achieve an efficiency score of 1 in the meta-technology and group-specific technology sets. The lack of an efficient unit in the ITC market indicates that there is room for improvement for all operating firms in the industry, regardless of their ownership.

MIE metafrontier investment efficiency, GIE group-specific investment efficiency, ITGR investment technology gap ratio, ITGI investment technology gap inefficiency, ITI investment technical inefficiency, MII metafrontier investment inefficiency
status. When both operational and investment stages are considered, Yuan Ta consistently maintains a high ranking among both domestic and foreign ITCs. This finding demonstrates that this firm could be a benchmark for the entire industry, irrespective of the frontier technology being evaluated. At the operational efficiency stage, Yuan Ta and Union from the domestic group, Deutsche Far Eastern, and UBS from the foreign group ranked highest among the ITCs. The much stronger output creation capabilities of these domestic enterprises, on average, compared to those of foreign firms, explain the significantly higher number of domestic ITCs that scored higher than their overseas counterparts. In the meta-technology evaluation, domestic ITCs outperform their foreign counterparts in both operational and investment efficiencies ($MOE_d = 0.803 > MOE_f = 0.712$ and $MIE_d = 0.654 > MIE_f = 0.565$) on average.

MOI and MII are the meta-frontier inefficiencies for stages 1 and 2, respectively. The sources of meta-frontier inefficiency are OTGI and OTI for the operational stage and ITGI and ITI for the investment stage. For example, the paradigm’s metafrontier efficiency ($MOE$) was 0.572. Hence, its inefficiency is equal to $1 - 0.572 = 0.428$ ($MOI$). This value can be broken down into $OTGI = 0.234$ and $OTI = 0.194$. For this paradigm, the main source of metafrontier inefficiency in the operational stage is technology gap inefficiency (OTGI) and not technical inefficiency (OTI). When the technology gap inefficiency (OTGI or ITGI) is 0, metafrontier efficiency and group-specific efficiency must be equal. Similarly, a figure close to 0 indicates that the two technology efficiencies should not differ significantly (e.g., Reliance, Mega, Yuan Ta, and UBS in the first stage and Cathay, Yuan Ta, Uni-President, and Fubon in the second stage). These results highlight that when the source of inefficiency is technical inefficiency (OTI and ITI), and the technology gap inefficiency is 0 or close to 0; neither resource is used. Moreover, the production process involves input excesses, output shortfalls, or both. For example, Uni-President’s OTGI is 0, which means that the metafrontier and group-specific technology estimate the same level of efficiency. In addition, its OTI is 0.329, which means that technical inefficiency lowers efficiency at the operational stage, either through input excesses or output shortfalls or both at that stage of production. This is a significant finding that identifies the primary reason for an ITC company’s lack of efficiency; as a result, it enables ITC firms’ managers to accurately implement strategies that improve their companies’ levels of efficiency.

Looking at the average operational inefficiency ($MOI$) and average investment inefficiency ($MII$), ITCs underperform in the second stage when the meta-technology set is assumed. This result is consistent for both foreign and domestic ITCs. The average technology gap inefficiency was lower in the operational stage than in the investment stage ($OTGI = 0.062$ vs. $ITGI = 0.117$). Hence, ITCs possess a wider technology gap between the metafrontier and the group-specific frontier in the investment stage. On average, the main source of inefficiency originated from technical inefficiency in the operational stage ($OTI = 0.180$). This case is the same for the investment stage, where technical inefficiency has a higher value ($ITI = 0.273$) than the technology gap inefficiency. Interestingly, the main source of inefficiency for both domestic and foreign ITCs in these two stages is technical inefficiency. This finding suggests that ITCs’ inefficiencies of ITCs originate from their inability to use inputs and produce outputs efficiently. Therefore, regardless of the ownership status of an ITC company,
the technical inefficiency in both stages is greater than the inefficiency caused by the technology gap, and ITC managers should pay more attention to input excesses or output shortfalls. On the one hand, it is recommended that domestic ITCs focus more on technical inefficiency because their technology gap inefficiency is relatively lower than that of their foreign counterparts. On the other hand, foreign ITCs are advised to simultaneously try to minimize both inefficiency components, as the technology gap inefficiency is relatively higher than that of their counterparts.

Figures 2 and 3 display the yearly average efficiencies and inefficiencies of ITCs from 2011 to 2020 to observe chronological changes. The results show inconsistent variations in the meta-frontier and group-specific efficiencies at the two stages. In the operational stage, 2017 had the highest MOE and GOE, whereas 2020 had the highest MIE and GIE in the investment stage. During 2011–2018, the MOE was higher than the MIE. However, ITCs became more efficient in the investment stage in 2019 and 2020. A similar finding was observed when comparing GOE and GIE. Consistent with the lowest efficiencies of ITCs in 2017 and 2018 for the operation stage and 2019 and 2020 for the investment stage, the MOI and MII show high inefficiencies in these years. In both stages, the source of inefficiency is more concentrated in the OTI and ITI than in the OTGI and ITGI. In the operational stage, technological gap inefficiency shows a decreasing trend over the years, while technical inefficiency shows fluctuations with a sharp decline in 2017. However, during the investment stage, dissimilar observations were recorded. Both sources of inefficiency demonstrate declining trends with a few slight increases. From 2017 onwards, the ITGI and ITI delineate
steeper downward slopes, thus suggesting that technological gaps and technical inefficiencies are improving at the investment stage.

**Network-based ranking of companies**

After obtaining the efficiencies and inefficiencies using the two-stage network DEA with meta-frontier analysis, we further ranked the efficient ITCs using the network-based ranking approach. This approach allows the benchmarking of DMUs that were found to score unity in efficiency analysis.⁵ Subsequently, we can distinguish the

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⁵ For brevity’s sake, the individual efficiency scores for each year are not reported in this study. Tables 6 and 7 show the average efficiency score for each firm.
best-performing DMUs among top performers. The network-based ranking approach uses the $\alpha$-centrality concept developed in the social network analysis domain. This approach classifies benchmarks according to different stages.

Table 8 depicts the ranking and $\alpha$ centrality values for ITCs that were found to be efficient in terms of operational efficiency and investment efficiency. In the operational efficiency stage, Union, a domestic ITC, ranked first among the five other ranked ITCs, followed by the two foreign ITCs, which ranked second and third, respectively, in the list with centrality values above 100. In the investment efficiency stage, the domestic ITC (Yuan Ta) ranked first. Notably, this company ranked fourth in the first stage. In second place for the second stage was Blackrock, a foreign ITC. If one ITC is to be selected as a benchmark in the entire production process, Yuan Ta can be nominated, as it ranked fourth in the operational stage and first in the investment stage. Another outstanding ITC is the UBS, which ranks fifth in both stages. These two companies stand out among the top five ITCs for both operational and investment efficiency. Hence, they can be regarded as references for other types of ITCs. Overall, this study comports with prior studies such as Lu et al. (2016) and Lu et al. (2021).

Conclusion
As an emerging market, Taiwan Province has evolved significantly over the last 10 years in terms of various financial and economic indicators. One of the main drivers of this achievement can be attributed to financial institutions’ activities. While various studies worldwide have looked at specific sectors, such as banking, very few studies exist regarding the performance of the financial institutions and, more specifically, ITCs. Although some empirical studies have focused on mutual funds at the individual level, they have mostly failed to provide key information on the performance of the fund companies to which the individual fund belongs. This knowledge is critical for investors who want to invest in mutual fund companies rather than across multiple companies. In other words, information on how a given mutual fund company as a whole has performed compared with other mutual fund companies is important.

Although prior studies, such as Premachandra et al. (2012) and Lu et al. (2016) have examined ITCs’ efficiencies using DEA, they overlook the different technologies between foreign and domestic entities. Because the resulting efficiency evaluation using only a common frontier may not be accurate; this study fills the gap in our emerging market by using the metafrontier two-stage network DEA proposed initially by Chiu et al. (2016) to decompose the efficiency of ITCs and suggest domestic or foreign entities that can be used as benchmarks. The adopted two-stage DEA model helps shed light on the performance of ITCs by decomposing the overall efficiency into two components: operational and investment efficiencies. This crucial information can help investors make better decisions and allow fund administrators to conduct a more thorough evaluation of how well their portfolio managers perform in comparison to competitors. We also complement the study with a network-based ranking approach to rank the top performing ITCs based on their relative efficiencies. This ranking tool introduces the possibility of ranking
efficient institutions at various stages and provides insights into the weaknesses and strengths of each institution.

The findings of the metafrontier-based DEA model for 2011–2020 suggest that domestic ITCs outperform foreign ITCs in both operational and investment efficiencies compared with the outcomes of group-specific technology evaluation, where foreign ITCs led in the area of investment efficiency. The group-specific technology efficiency scores are equal to or larger than the meta-technology efficiency scores for both operational and investment stages. Using a network-based ranking approach to rank ITCs, the domestic entity Yuan Ta can be used as a reliable benchmark, as it was ranked fourth in the operational stage and first in the investment stage. Furthermore, UBS, a foreign ITC, maintained its fifth rank in both stages. Hence, it can be a suitable benchmark for foreign ITCs, given its consistent efficiency scores in the entire production process. The meta-frontier two-stage network DEA, coupled with the ranking approach, can also be applied to other financial institutions, such as credit unions, insurance, and banks, to break down different areas of efficiency and propose more reliable benchmarks among financial institutions. Another potential future research avenue is to analyze and compare the results of efficiency among different groups of countries, which are clustered as developed, emerging, and developing nations, by considering corporate strategies such as carbon emission strategies (Kou et al. 2022) or fintech investments (Kou et al. 2021).

Appendix
See Table 9.

| Variables | Expositions |
|-----------|-------------|
| ITC       | Investment trust companies |
| DDF       | Directional distance function |
| DEA       | Data envelopment analysis |
| DMU       | Decision-making unit |
| MOE       | Metafrontier operational efficiency |
| GOE       | Group-specific operational efficiency |
| MIE       | Metafrontier investment efficiency |
| GIE       | Group-specific investment efficiency |
| OTGR      | Operational technology gap ratio |
| ITGR      | Investment technology gap ratio |
| OTGI      | Operational technology gap inefficiency of the operational stage |
| OTI       | Operational technical inefficiency of the operational stage |
| ITGI      | Investment technology gap inefficiency of the investment stage |
| ITI       | Investment technical inefficiency of the investment stage |
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Authors’ contributions

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Availability of data and materials

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Declarations

Competing interests

The authors have no financial and non-financial competing interests.

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References

Aldcroft S (2012) Taiwan – Asia’s Mutual Funds Giant. Retrieved from Citi Investor Services: https://www.citibank.com/mss/doc/1188840_taiwan_asias Mutual_funds_giant_sspdf
Avkiran NK (2014) An illustration of dynamic network DEA in commercial banking including robustness tests. OMEGA Int J Manag Sci. https://doi.org/10.1016/j.omega.2014.07.002
Basso A, Funari S (2016) DEA performance assessment of mutual funds. In: Zhu J (ed) Data envelopment analysis: a handbook of empirical studies and applications. Springer, Boston, pp 229–287
Battese GE, Rao DP (2002) Technology gap, efficiency, and a stochastic metafrontier function. Int J Bus Econ 1(2):87
Battese GE, Rao DP, O’Donnell CJ (2004) A metafrontier production function for estimation of technical efficiencies and technology gaps for firms operating under different technologies. J Prod Anal 21(1):91–103
Berg SA, Farsund FR, Hjalmarsson L, Suominen M (1993) Banking efficiency in the Nordic countries. J Bank Finance 17(2):371–388
Berger AN, Humphrey DB (1997) Efficiency of financial institutions: International survey and directions for future research. Eur J Oper Res 98(2):175–212
Biger N, Kahane Y (1978) Risk considerations in insurance ratemaking. J Risk Insur 45(1):121–132. https://doi.org/10.2307/251812
Box JW, Schwedel H (2007) Is there a single frontier in a single European banking market? J Bank Finance 31(7):2081–2102
Brockett PL, Cooper WW, Golden LL, Rousseau JJ, Wang Y (2004) Evaluating solvency versus efficiency performance and different forms of organization and marketing in US property—liability insurance companies. Eur J Oper Res 154(2):492–514
CEIC. (2019). Taiwan Indicators. CEIC’s Data Global Database. Retrieved from https://www.ceicdata.com/en/country/taiwan
Chambers RG, Chung Y, Färe R (1998) Profit, directional distance functions, and nerlovian efficiency. J Optim Theory Appl 98(2):351–364. https://doi.org/10.1023/A:1022637501082
Chandra P, Cooper WW, Li S, Rahman A (1998) Using DEA to evaluate 29 Canadian textile companies—considering returns to scale. Int J Prod Econ 54(2):129–141. https://doi.org/10.1016/S0925-5273(97)00135-7
Charnes A, Cooper WW, Rhodes E (1978) Measuring the efficiency of decision making units. Eur J Oper Res 2(6):429–444
Chen K-H (2012) Incorporating risk input into the analysis of bank productivity: application to the Taiwanese banking industry. J Bank Finance 36(7):1911–1927
Chen K-H, Yang H-Y (2011) A cross-country comparison of productivity growth using the generalised metafrontier Malmquist productivity index: with application to banking industries in Taiwan and China. J Prod Anal 35(3):197–212
Chen L-R, Lai GC, Wang JL (2011) Conversion and efficiency performance changes: evidence from the US property-liability insurance industry. Geneva Risk Insur Rev 36(1):1–35
Chiu C-R, Lou J-L, Wu P-L, Fang C-L (2012) Decomposition of the environmental inefficiency of the meta-frontier with undesirable output. Energy Econ 34(5):1392–1399
Chiu CR, Lu KH, Tsang SS, Chen YF (2013) Decomposition of meta-frontier inefficiency in the two-stage network directional distance function with quasi-fixed inputs. Int Trans Oper Res 20(4):595–611
Chiu C-R, Chu Y-H, Chen Y-C, Fang C-L (2016) Exploring the source of metafrontier inefficiency for various bank types in the two-stage network system with undesirable output. Pac Basin Financ J 36:1–13. https://doi.org/10.1016/j.pacfin.2015.11.003
Chuweni NN, Ali SN, Faizi NS, Shukor NB (2021) Technical, scale and managerial efficiencies in malaysian reits: a non-parametric approach. Plann Malays 19
Chuweni NN (2019) Measuring technical efficiency of Malaysian real estate investment trusts: a data envelopment analysis approach. Plan Malays 17(1)
Cook WD, Liang L, Zhu J (2010) Measuring performance of two-stage network structures by DEA: a review and future perspective. Omega 38(6):423–430
Cooper WW, Seiford LM, Tone K (2000). Data envelopment analysis. Handbook on data envelopment analysis. In: Cooper WW, Seiford LM, Tone K (eds), 1st ed, pp 1–40
Cooper WW, Seiford LM, Tone K (2006) Introduction to data envelopment analysis and its uses: with DEA-solver software and references. Springer, Berlin
Doherty NA (1980) A portfolio theory of insurance capacity. J Risk Insur 47(3):405–420. https://doi.org/10.2307/252630
Elyasiani E, Mehdi SN (1990) A nonparametric approach to measurement of efficiency and technological change: The case of large US commercial banks. J Financ Serv Res 4(2):157–168
Färe R, Grosskopf S (1996) Intertemporal production frontiers: with dynamic DEA. Kluwer Academic Publishers, Boston
Färe R, Grosskopf S (2000) Network DEA. Socioecon Plann Sci 49:34–35
Fried HO, Lovell CK, Schmidt SS, Schmidt SS (2008) The measurement of productive efficiency and productivity growth. Oxford University Press, Oxford
Galagedera DUA (2019) Modelling social responsibility in mutual fund performance appraisal: a two-stage data envelopment analysis model with non-discretionary first stage output. Eur J Oper Res 273(1):376–389. https://doi.org/10.1016/j.ejor.2018.08.011
Galagedera DUA, Watson J, Premachandra IM, Chen Y (2016) Modeling leakage in two-stage DEAs models: an application to US mutual fund families. Omega 61:62–77. https://doi.org/10.1016/j.omega.2015.07.007
Galagedera DUA, Rashid I, Fukuyama H, Zhu J (2018) A new network DEA model for mutual fund performance appraisal: An application to U.S. equity mutual funds. Omega 77:168–179. https://doi.org/10.1016/j.omega.2017.06.006
Galony B, Roll Y (1989) An application procedure for DEA. Omega 17(3):237–250
Goyal J, Singh M, Singh R, Aggarwal A (2019) Efficiency and technology gaps in Indian banking sector: application of meta-frontier directional distance function DEA approach. J Finance Data Sci 5(3):156–172. https://doi.org/10.1016/j.jfds.2018.08.002
Haslem JA, Scheraga CA, Bed singh JP (1999) DEA efficiency profiles of US banks operating internationally. Int Rev Econ Finance 8(2):165–182
Hayami Y (1969) Sources of agricultural productivity gap among selected countries. Am J Agric Econ 51(3):564–575
Hayami Y, Ruttan VW (1971) Agricultural development: an international perspective. The Johns Hopkins Press, London
Huang T-H, Chiang D-L, Tsai C-M (2015) Applying the new metafrontier directional distance function to compare banking efficiencies in central and eastern European counties. Econ Model 44:188–199. https://doi.org/10.1016/j.econmod.2014.10.029
Izadi Khah M (2022) DEA approaches for financial evaluation—a literature review. Adv Math Finance Appl 7(1):1–36. https://doi.org/10.22034/amfa.2021.194209.1639
Kao C, Hwang S-N (2008) Efficiency decomposition in two-stage data envelopment analysis: An application to non-life insurance companies in Taiwan. Eur J Oper Res 185(1):418–429. https://doi.org/10.1016/j.ejor.2006.11.041
Kao C, Hwang S-N (2010) Efficiency measurement for network systems: IT impact on firm performance. Decis Support Syst 48(3):437–446
Kou G, Olgu Akdeniz O, Dinçer H, Yüksel S (2021) Fintech investments in European banks: a hybrid IT2 fuzzy multidimensional decision-making approach. Financial Innovation 7(1):1–28
Kou G, Yüksel S, Dinçer H (2022) Inventive problem-solving map of innovative carbon emission strategies for solar energy-based transportation investment projects. Appl Energy 311:118680
Kumar S, Arora N (2011) Assessing technical efficiency of sugar industry in uttar pradesh: an application of data envelopment analysis. Indian Econ Rev 46(2):323–335
Kuo K-C, Kweh QL, Ting WK, Azizan NA (2015) Dynamic network performance evaluation of general insurance companies: an insight into risk management committee structure. Total Qual Manag Bus Excell. https://doi.org/10.1080/14783634.2015.1100516
Kweh QL, Lu W-M, Nourani M, Ghazali MH (2018) Risk management and dynamic network performance: an illustration using a dual banking system. Appl Econ 50(30):3285–3299. https://doi.org/10.1080/00036846.2017.1420889
Lim S, Oh KW, Zhu J (2014) Use of DEA cross-efficiency evaluation in portfolio selection: an application to Korean stock market. Eur J Oper Res 236(1):361–368. https://doi.org/10.1016/j.ejor.2013.12.002
Lin R, Liu Q (2021) Multitier dynamic data envelopment analysis based on directional distance function: an application to mutual funds. Eur J Oper Res 293(3):1043–1057. https://doi.org/10.1016/j.ejor.2021.01.005
Lin S-W, Lu W-M, Lin F (2021) Entrusting decisions to the public service pension fund: an integrated predictive model with additive network DEA approach. J Oper Res Soc 72(5):1015–1032
Liu JS, Lu W-M (2010) DEA and ranking with the network-based approach: a case of R&D performance. Omega 38(6):453–464. https://doi.org/10.1016/j.omega.2009.12.002
Liu JS, Lu W-M, Lin BJ (2013) A survey of DEA applications. OMEGA Int J Manag Sci 41(5):893–902
Liu JS, Lu W-M, Ho MH-C (2015) National characteristics: innovation systems from the process efficiency perspective. R&D Management 45(4):317–338. https://doi.org/10.1111/radm.12067
Lo S-F, Lu W-M (2006) Does size matter? Finding the profitability and marketability benchmark of financial holding companies. Asia-Pacific J Oper Res 23(02):229–246
Lu W-M, Liu JS, Kweh QL, Wang C-W (2016) Exploring the benchmarks of the Taiwanese investment trust corporations: Management and investment efficiency perspectives. Eur J Oper Res 248(2):607–618
Lu W-M, Kweh QL, Wang C-W (2021) Integration and application of rough sets and data envelopment analysis for assessment of the investment trusts industry. Ann Oper Res 296(1):163–194. https://doi.org/10.1007/s10479-019-03233-y
Luo X (2003) Evaluating the profitability and marketability efficiency of large banks: an application of data envelopment analysis. J Bus Res 56(8):627–635
Miller SM, Noulas AG (1996) The technical efficiency of large bank production. J Bank Finance 20(3):495–509
Mohtashami A, Ghiasvand BM (2020) Z-ERM DEA integrated approach for evaluation of banks & financial institutes in stock exchange. Expert Syst Appl 147:113218. https://doi.org/10.1016/j.eswa.2020.113218
Nataraja NR, Johnson AL (2011) Guidelines for using variable selection techniques in data envelopment analysis. Eur J Oper Res 215(3):662–669
Nourani M, Devadason ES, Kweh QL, Lu W‑M (2017) Business excellence: the managerial and value‑creation efficiencies of the insurance companies. Total Qual Manag Bus Excell 28(7–8):879–896. https://doi.org/10.1080/14783363.2015.1133244
Nourani M, Devadason ES, Chandran V (2018) Measuring technical efficiency of insurance companies using dynamic network DEA: an intermediation approach. Technol Econ Dev Econ 24(5):1909–1940
Nourani M, Kweh QL, Ting IW, Lu WM, Strutt A (2021) Evaluating traditional, dynamic and network business models: an efficiency‑based study of Chinese insurance companies. The Geneva Papers on Risk and Insurance ‑ Issues and Practice, 1–39.
O'Donnell CJ, Rao DP, Battese GE (2008) Metafrontier Frameworks for the study of firm‑level efficiencies and technology ratios. Empir Econ 34(2):231–255
Parkan C (1987) Measuring the efficiency of service operations: an application to bank branches. Eng Costs Prod Econ 12(1):237–242
Pasiouras F (2008) International evidence on the impact of regulations and supervision on banks' technical efficiency: an application of two‑stage data envelopment analysis. Rev Quant Financ Acc 30(2):187–223. https://doi.org/10.1007/s11156‑007‑0046‑7
Premachandra I, Zhu J, Watson J, Galagedera DU (2012) Best‑performing US mutual fund families from 1993 to 2008: Evidence from a novel two‑stage DEA model for efficiency decomposition. J Bank Finance 36(12):3302–3317
Rangan N, Grabowski R, Aly HY, Pasurka C (1988) The technical efficiency of US banks. Econ Lett 28(2):169–175
Seiford LM, Zhu J (1999) Profitability and marketability of the top 55 US commercial banks. Manage Sci 45(9):1270–1288
Sherman HD, Gold F (1985) Bank branch operating efficiency: evaluation with data envelopment analysis. J Bank Finance 9(2):297–315
Tone K, Tsutsui M (2009) Network DEA: a slacks‑based measure approach. Eur J Oper Res 197(1):243–252
Tone K, Tsutsui M (2014) Dynamic DEA with network structure: A slacks‑based measure approach. OMEGA Int J Manag Sci 42(1):124–131. https://doi.org/10.1016/j.omega.2013.04.002
Topuz JC, Darrat AF, Shelor RM (2005) Technical, allocative and scale efficiencies of REITs: an empirical inquiry. J Bus Financ Acc 32(9‑10):1961–1994. https://doi.org/10.1111/j.0306‑686X.2005.00653.x
Yang C, Liu H‑M (2012) Managerial efficiency in Taiwan bank branches: a network DEA. Econ Model 29(2):450–461
Yang F, Wei F, Li Y, Huang Y, Chen Y (2018) Expected efficiency based on directional distance function in data envelopment analysis. Comput Ind Eng 125:33–45. https://doi.org/10.1016/j.cie.2018.08.010
Yao X, Zhou H, Zhang A, Li A (2015) Regional energy efficiency, carbon emission performance and technology gaps in China: a meta‑frontier non‑radial directional distance function analysis. Energy Policy 84:142–154. https://doi.org/10.1016/j.enpol.2015.05.001

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