Financial Innovation

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

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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

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 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 2021[1] (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 longstanding 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 Ghiasvand (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; Brockett 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; Nourani 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

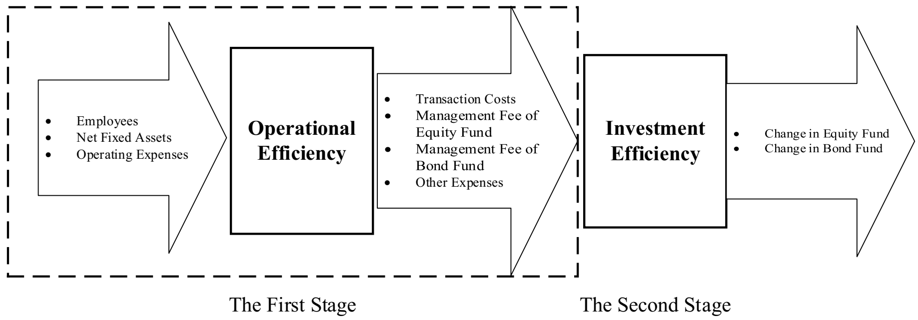


Fig. 1 The two-stage production process of investment trust companies

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.[2] Our sample included ITCs for

[2] https://emops.twse.com.tw/server-java/t58query.

Table 1 Variables definitions

Variables	Definitions
Inputs	
Employees	Individual who works part time or full time under a contract of employment, whether oral or written, express or implied, and has recognized rights and duties, measured in person
Net fixed assets	(Purchase price of all fixed assets + Leasehold improvements) – (Accumulated depreciation + Total liabilities), measured in NT$ thousand
Operating expenses	Those incurred in carrying out a firm's day-to-day activities but not directly associated with production, measured in NT$ thousand
Intermediates	
Transaction costs	The expenses when funds buy and sell securities (or "turns over" its portfolio), measured in NT$ million
Management fee of equity fund	Cost of running an equity fund or unit trust, charged against its income, measured in NT$ million
Management fee of bond fund	Cost of running a bond fund or unit trust, charged against its income, measured in NT$ million
Other expenses	Included in this category are expenses not included in the categories of "Management Fees," measured in NT$ million
Outputs	
Change in equity fund	It is computed once a day based on the closing market prices of the securities in the equity fund's portfolio, measured in NT$ million
Change in bond fund	It is computed once a day based on the closing market prices of the securities in the bond fund's portfolio, measured in NT$ million

Table 2 ITCs type

ITC type	ITCs
Foreign capital	Mirae Asset (MA), Allianz (AGI), Manulife (HL), Blackrock (BR), Prudential Financial, Inc. (PRU), Schroders (SC), PineBridge (PB), Nomura (NOM), Franklin Templeton (FTH), Invesco (GIN), Paradigm (HD), HSBC (HSBC), UBS (UBS), Deutsche Far Eastern (DWS), JPMorgan (JP), Alliance Bernstein (AB), Eastspring (ES)
Domestic capital	CTBC (CTBC), Yuan Ta (YT), Jih Sun (JS), Tai Shin (TS), Sino Pac (YF), Mega (MG), Cathay (CA), First Securities (FS), Uni-President (EZ), KGI (KGI), Fubon (FB), Fuh Hwa (FH), Hua Nan (HN), Shin Kong (SK), Capital (CAP), Reliance (RS), Union (UN)

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.[3] 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

[3] https://eng.stat.gov.tw/point.asp?index=2.

Table 3 Descriptive statistics of inputs, intermediates, and outputs (n = 340)

	Mean	Median	SD	Normality test
Domestic capital				
Inputs				(p-value)
Employees	121	111	65	< 0.01
Net fixed assets	222,118	50,900	350,646	< 0.01
Operating expenses	484,107	340,448	441,490	< 0.01
Intermediates				
Transaction costs	423,093,259	230,237,707	513,557,355	< 0.01
Management fee of equity fund	379,278,032	162,800,644	439,182,008	< 0.01
Management fee of bond fund	163,732,391	110,517,318	178,496,288	< 0.01
Other expenses	64,613,412	49,577,523	63,730,930	< 0.01
Outputs				
Change in equity fund	32,037,712,379	9,710,464,158	54,128,905,799	< 0.01
Change in bond fund	53,087,172,554	37,105,351,993	55,570,832,573	< 0.01
Foreign capital				
Inputs	98	75	63	< 0.01
Employees	147,610	58,735	219,603	< 0.01
Net fixed assets	893,198	702,719	731,507	< 0.01
Operating expenses				
Intermediates	310,740,146	113,036,783	473,357,382	< 0.01
Transaction costs	319,087,913	146,764,953	359,730,111	< 0.01
Management fee of equity fund	221,673,376	140,596,260	263,952,641	< 0.01
Management fee of bond fund	53,048,272	15,343,565	65,276,265	< 0.01
Other expenses				
Outputs	19,863,046,537	10,641,690,207	22,162,088,306	< 0.01
Change in equity fund	22,610,043,340	14,987,395,244	21,287,392,559	< 0.01
Change in bond fund	98	75	63	< 0.01

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

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

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 affirmatory results for the isotonicity assumption, minimum number of DMUs, and homogeneity assumption all indicated that our model had a 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 $\mathbf{x} \in R_+^m$, intermediate outputs (the first stage), input (the second stage) $\mathbf{z} \in R_+^d$, and final outputs $\mathbf{y} \in R_+^s$. 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:

$$\vec{D}^{M}\left(\mathbf{x},\mathbf{z},\mathbf{y};\mathbf{g_x},\mathbf{g_y}\right) = Max\left\{\alpha+\beta : \left(\mathbf{x}-\alpha\mathbf{g_x},\mathbf{z},\mathbf{y}+\beta\mathbf{g_y}\right) \in T^M\left(\mathbf{x},\mathbf{z},\mathbf{y}\right)\right\}.$$
$$\vec{D}^{G}\left(\mathbf{x},\mathbf{z},\mathbf{y};\mathbf{g_x},\mathbf{g_y}\right) = Max\left\{\gamma+\tau : \left(\mathbf{x}-\gamma\mathbf{g_x},\mathbf{z},\mathbf{y}+\tau\mathbf{g_y}\right) \in T^G\left(\mathbf{x},\mathbf{z},\mathbf{y}\right)\right\}, G=G_1,G_2.$$

The respective technology sets are thus detailed as follows:

The ITCs used $T^M\left(\mathbf{x},\mathbf{y},\mathbf{z}\right)$:$\mathbf{x} \in R_+^m$ to generate the intermediate outputs $\mathbf{z} \in R_+^d$ in the first stage. Meanwhile, they used $\mathbf{z} \in R_+^d$ to make the final outputs $\mathbf{y} \in R_+^s$ in the second stage.

ITCs used $T^G\left(\mathbf{x},,\mathbf{y},\mathbf{z}\right)$:$\mathbf{x} \in R_+^m$ in Group G_g in the first stage to yield $\mathbf{z} \in R_+^d$. They used $\mathbf{z} \in R_+^d$ to produce $\mathbf{y} \in R_+^s$ in the second stage.

Furthermore, the meta-technology set consists of the G-group-specific technology set $T^M\left(\mathbf{x},\mathbf{y},\mathbf{z}\right) = \left\{T^{G1}\left(\mathbf{x},\mathbf{y},\mathbf{z}\right) \cup T^{G2}\left(\mathbf{x},\mathbf{y},\mathbf{z}\right)\right\}$. Fried et al. (2008) claimed that the direction vector $\mathbf{g} = \left(\mathbf{g_x},\mathbf{g_y}\right)$ should be selected before the DDF can be evaluated. In the present study, we considered the direction to be $\mathbf{g} = \left(\mathbf{g_x}=\mathbf{x},\mathbf{g_y}=\mathbf{y}\right)$ (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 ITC_o of meta-technology and group-specific technology sets under convex constraints can be represented by the following two linear programs:

$$\begin{aligned}
&\vec{D}^{M} = Max\,\alpha_o^M + \beta_o^M \\
&\textstyle\sum_{g=1}^{G_g}\sum_{j=1}^{N_g}\lambda_j^g x_{ij}^g \le x_{io}^g - \alpha_o^M g_{iox}, \ i = 1,\ldots,m, \\
&\textstyle\sum_{g=1}^{G_g}\sum_{j=1}^{N_g}\lambda_j^g z_{hj}^g \ge z_{ho}^g, \qquad h = 1,\ldots,d, \\
&\textstyle\sum_{g=1}^{G_g}\sum_{j=1}^{N_g}\eta_j^g z_{hj}^g \le z_{ho}^g, \qquad h = 1,\ldots,d, \\
&\textstyle\sum_{g=1}^{G_g}\sum_{j=1}^{N_g}\eta_j^g y_{rj}^g \ge y_{ro}^g + \beta_o^M g_{roy}, \ r = 1,\ldots,s, \\
&\textstyle\sum_{g=1}^{G_g}\sum_{j=1}^{N_g}\lambda_j^g = 1, \\
&\textstyle\sum_{g=1}^{G_g}\sum_{j=1}^{N_g}\eta_j^g = 1, \\
&\lambda_j^g, \eta_j^g \ge 0, g = 1,\ldots,G_g.
\end{aligned} \tag{1}$$

$$\begin{aligned}
&\vec{D}^{g} = Max\,\gamma_o^g + \tau_o^g \\
&\textstyle\sum_{j=1}^{N_g}\lambda_j^g x_{ij}^g \le x_{io}^g - \gamma_o^g g_{iox}, \ i = 1,\ldots,m, \\
&\textstyle\sum_{j=1}^{N_g}\lambda_j^g z_{hj}^g \ge z_{ho}^g, \qquad h = 1,\ldots,d, \\
&\textstyle\sum_{j=1}^{N_g}\eta_j^g z_{hj}^g \le z_{ho}^g, \qquad h = 1,\ldots,d, \\
&\textstyle\sum_{j=1}^{N_g}\eta_j^g y_{rj}^g \ge y_{ro}^g + \tau_o^g g_{roy}, \ r = 1,\ldots,s, \\
&\textstyle\sum_{j=1}^{N_g}\lambda_j^g = 1, \\
&\textstyle\sum_{j=1}^{N_g}\eta_j^g = 1, \\
&\lambda_j^g, \eta_j^g \ge 0,
\end{aligned} \tag{2}$$

where λ_j^g and η_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 $IE_o^M = 1/\left(1 + \beta_o^M\right)$ and $IE_o^g = 1\Big/\left(1 + \tau_o^g\right)$, or investment efficiency. To make the efficiency measure consistent, investment efficiency takes a derivative between 0 and 1. The target ITC_o 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

$$\begin{aligned} &MOE_o\left(\mathbf{x},\mathbf{z},\mathbf{y}\right) \leq GOE_o\left(\mathbf{x},\mathbf{z},\mathbf{y}\right) \\ &MIE_o\left(\mathbf{x},\mathbf{z},\mathbf{y}\right) \leq GIE_o\left(\mathbf{x},\mathbf{z},\mathbf{y}\right). \end{aligned} \tag{3}$$

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:

$$\begin{aligned} &OTGR(\mathbf{x},\mathbf{z},\mathbf{y}) = MOE(\mathbf{x},\mathbf{z},\mathbf{y})\big/GOE(\mathbf{x},\mathbf{z},\mathbf{y}) \leq 1 \\ &ITGR(\mathbf{x},\mathbf{z},\mathbf{y}) = MIE(\mathbf{x},\mathbf{z},\mathbf{y})\big/GIE(\mathbf{x},\mathbf{z},\mathbf{y}) \leq 1. \end{aligned} \tag{4}$$

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 metafrontier 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:

$$\begin{aligned} &OTGI\left(\mathbf{x},\mathbf{z},\mathbf{y}\right) = GOE\left(\mathbf{x},\mathbf{z},\mathbf{y}\right) \times \left(1 - OTGR(\mathbf{x},\mathbf{z},\mathbf{y})\right) \\ &ITGI\left(\mathbf{x},\mathbf{z},\mathbf{y}\right) = GIE\left(\mathbf{x},\mathbf{z},\mathbf{y}\right) \times \left(1 - ITGR(\mathbf{x},\mathbf{z},\mathbf{y})\right). \end{aligned} \tag{5}$$

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:

$$\begin{aligned} &OTI\left(\mathbf{x},\mathbf{z},\mathbf{y}\right) = 1 - GOE(\mathbf{x},\mathbf{z},\mathbf{y}) \\ &ITI\left(\mathbf{x},\mathbf{z},\mathbf{y}\right) = 1 - GIE(\mathbf{x},\mathbf{z},\mathbf{y}). \end{aligned} \tag{6}$$

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

$$\begin{aligned} &MOI\left(\mathbf{x},\mathbf{z},\mathbf{y}\right) = OTGI^g(\mathbf{x},\mathbf{z},\mathbf{y}) + OTI^g(\mathbf{x},\mathbf{z},\mathbf{y}) \\ &MII\left(\mathbf{x},\mathbf{z},\mathbf{y}\right) = ITGI^g(\mathbf{x},\mathbf{z},\mathbf{y}) + ITI^g(\mathbf{x},\mathbf{z},\mathbf{y}). \end{aligned} \tag{7}$$

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:

$$
\begin{aligned}
&\overrightarrow{DDF}^{M} = Max\ \alpha_o^{M,k} + \beta_o^{M,k} \\
&\sum_{g=1}^{G_g}\sum_{j=1}^{N_g}\lambda_j^{g,k}x_{ij}^{g,k} \le x_{io}^{g,k} - \alpha_o^{M,k}x_{io}^{g,k}, i=1,\dots,m, \\
&\sum_{g=1}^{G_g}\sum_{j=1}^{N_g}\lambda_j^{g,k}z_{hj}^{g,k} \le z_{ho}^{g,k}, \qquad h=1,\dots,d, \\
&\sum_{g=1}^{G_g}\sum_{j=1}^{N_g}\eta_j^{g,k}z_{hj}^{g,k} \ge z_{ho}^{g,k}, \qquad h=1,\dots,d, \\
&\sum_{g=1}^{G_g}\sum_{j=1}^{N_g}\eta_j^{g,k}y_{rj}^{g,k} \ge y_{ro}^{g,k} + \beta_o^{M,k}y_{ro}^{g,k}, r=1,\dots,s, \\
&\sum_{g=1}^{G_g}\sum_{j=1}^{N_g}\lambda_j^{g,k} = 1, \\
&\sum_{g=1}^{G_g}\sum_{j=1}^{N_g}\eta_j^{g,k} = 1, \\
&\lambda_j^g, \eta_j^g \ge 0, g=1,\dots,G_g.
\end{aligned}
\tag{8}
$$

The solution to λ_j^{g,k^*} indicates whether ITC j is a benchmark for the observed ITC in the first stage for each DEA specification k. The solution of η_j^{g,k^*} 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 λ_j^{g,k^*} in the first stage. Each ITC was regarded as a network node. The corresponding λ_j^{g,k^*} is taken as the weight of the endorsement; if ITC j is a paragon of the observed ITC o and has the corresponding λ_j^{g,k^*}, then a directed link of weight λ_j^{g,k^*} pointing from node o to node j can be created. η_j^{g,k^*} uses the same definition as in the second stage.

Step 3. λ_j^{g,k^*} 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:

$$
Ix_{ij}^{g,k} = \lambda_j^{g,k^*}x_{ij}^{g,k} \Big/ \sum_{j\in E_k}\lambda_j^{g,k^*}x_{ij}^{g,k}, \quad 0 < Ix_{ij}^{g,k} \le 1, \quad i=1,\dots,m. \tag{9}
$$

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:

$$
MIz_{hj}^{g,k} = \lambda_j^{g,k^*}z_{hj}^{g,k} \Big/ \sum_{j\in E_k}\lambda_j^{g,k^*}z_{hj}^{g,k}, \quad 0 < MIz_{hj}^{g,k} \le 1, \quad h=1,\dots,d. \tag{10}
$$

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:

$$
MOz_{hj}^{g,k} = \eta_j^{g,k^*}z_{hj}^{g,k} \Big/ \sum_{j\in E_k}\eta_j^{g,k^*}z_{hj}^{g,k}, \quad 0 < MOz_{hj}^{g,k} \le 1, \quad h=1,\dots,d. \tag{11}
$$

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

$$Oy_{rj}^{g,k} = \eta_j^{g,k^*} y_{rj}^{g,k} \Big/ \sum_{j \in E_k} \eta_j^{g,k^*} y_{rj}^{g,k}, \quad 0 < Oy_{rj}^{g,k} \le 1, \quad r = 1, \ldots, s. \tag{12}$$

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:

$$\mathbf{R} = \left[\sum_{k=1}^{K} \left(\sum\nolimits_{i=1}^{m} Ix_{ij}^{g,k} + \sum\nolimits_{h=1}^{d} MIz_{hj}^{g,k} + \sum\nolimits_{h=1}^{d} MOz_{hj}^{g,k} + \sum\nolimits_{r=1}^{s} Oy_{rj}^{k} \right) \right]_{n \times n} \tag{13}$$

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

$$c \cdot \mathbf{I} = \mathbf{R} \cdot \mathbf{I}, \tag{14}$$

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

Table 6 Average operational efficiencies and metafrontier inefficiencies from 2011 to 2020

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 (YF)	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
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

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

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
Jih 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					

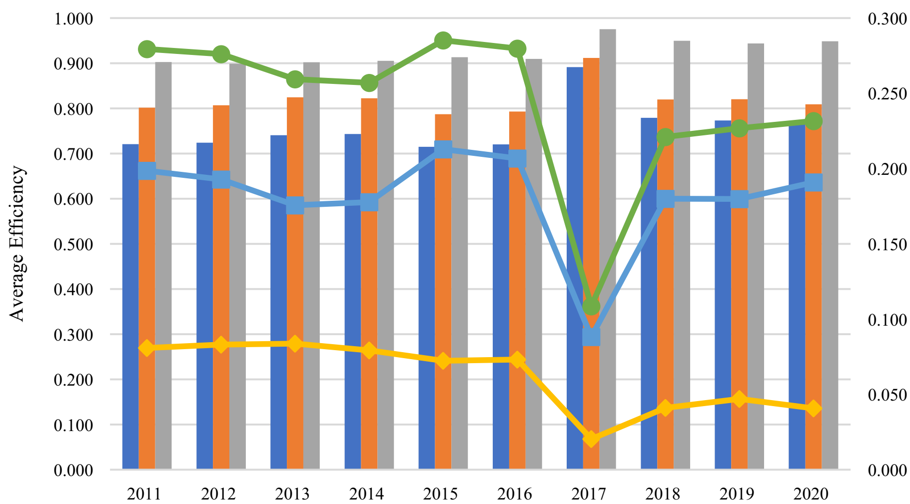
MIE metafrontier investment efficiency, *GIE* group-specific investment efficiency, *ITGR* investment technology gap ratio, *ITGI* investment technology gap inefficiency, *ITI* investment technical inefficiency, *MII* metafrontier investment inefficiency

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 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–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,

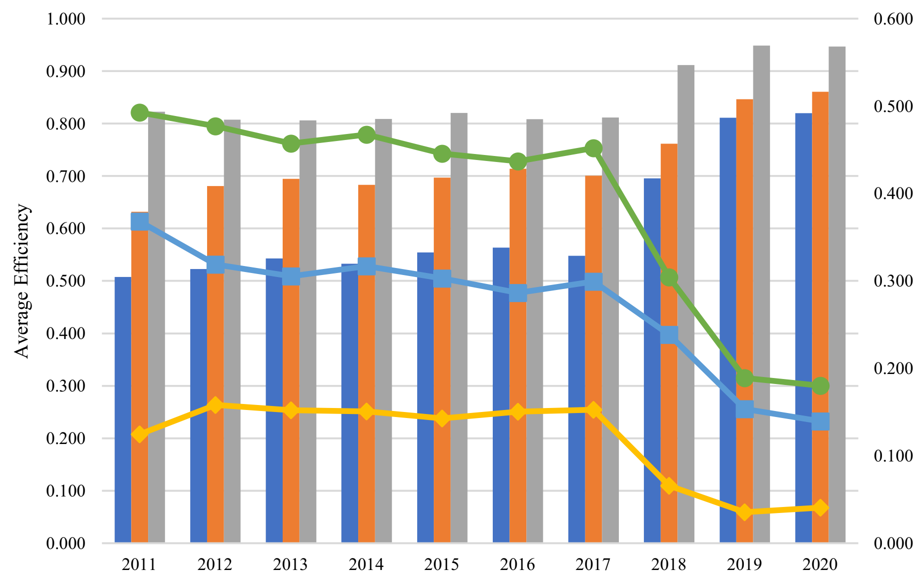


	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
MOE	0.721	0.724	0.741	0.743	0.715	0.720	0.891	0.779	0.773	0.768
GOE	0.801	0.807	0.824	0.822	0.787	0.793	0.912	0.820	0.820	0.809
OTGR	0.903	0.899	0.902	0.905	0.913	0.910	0.976	0.950	0.944	0.949
OTGI	0.081	0.083	0.084	0.079	0.072	0.073	0.020	0.041	0.047	0.041
OTI	0.199	0.193	0.176	0.178	0.213	0.207	0.088	0.180	0.180	0.191
MOI	0.279	0.276	0.259	0.257	0.285	0.280	0.109	0.221	0.227	0.232

Fig. 2 The stack straight bar chart for average operational efficiencies and inefficiencies

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



	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
MIE	0.507	0.523	0.543	0.533	0.554	0.563	0.548	0.696	0.811	0.820
GIE	0.632	0.681	0.695	0.683	0.697	0.714	0.701	0.761	0.846	0.860
ITGR	0.823	0.808	0.806	0.809	0.820	0.808	0.811	0.912	0.948	0.947
ITGI	0.125	0.158	0.152	0.151	0.143	0.150	0.153	0.066	0.035	0.041
ITI	0.368	0.319	0.305	0.317	0.303	0.286	0.299	0.239	0.154	0.140
MII	0.493	0.477	0.457	0.467	0.446	0.437	0.452	0.304	0.189	0.180

Fig. 3 The stack straight bar chart for average investment efficiencies and inefficiencies

Table 8 Ranks of the efficient ITCs at two-stage production processes

Operational efficiency			Investment efficiency		
Rank	**ITCs**	**α centrality value**	**Rank**	**ITCs**	**α centrality value**
1	Union (UN)	352.647	1	Yuan Ta (YT)	318.948
2	PineBridge (PB)	223.839	2	Blackrock (BR)	278.134
3	Deutsche Far Eastern (DWS)	206.367	3	Reliance (RS)	239.006
4	Yuan Ta (YT)	174.666	4	Mirae Asset (MA)	200.209
5	UBS (UBS)	157.225	5	UBS (UBS)	108.485

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

[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 α-centrality concept developed in the social network analysis domain. This approach classifies benchmarks according to different stages.

Table 8 depicts the ranking and α 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.

Table 9 Abbreviations of DEA-related terms and their expositions

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

Acknowledgements
None.

Authors' contributions
All authors read and approved the final manuscript.

Funding
No funding was acquired for this study.

Availability of data and materials
The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

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

Received: 4 October 2021 Accepted: 12 August 2022
Published online: 25 August 2022

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