科学学研究
STUDIES IN SCIENCE OF SCIENCE
中国科学学与科技政策研究会
中国科学院科技战略咨询研究院
清华大学科学技术与社会研究中心
ISSN 1003-2053 CN 11-1805/G3

Does Efficiency Matter in M&A? Evidence from Indonesia's Industrial Estate Group Companies

并购中的效率是否重要？来自印度尼西亚工业园区控股公司的证据

Sulistyandari [1 3], Ali Akbar Anggara [2 *], Chih-Liang Liu [1]

[1] Department of Finance, College of Management, National Yunlin University of Science and Technology, Yunlin 64002, Taiwan
[2] Department of Management, Faculty of Economics and Business, Universitas Muhammadiyah Purwokerto, Central Java, Indonesia 53182
[3] Faculty of Economics and Business, Universitas Jenderal Soedirman, Purwokerto 53182, Indonesia

[*] Corresponding Author: Ali Akbar Anggara, aliakbarang@ump.ac.id

Abstract. The consolidation of Industrial Estate companies in Indonesia into a single holding company is reshaping the structure, behavior and business models of key actors in the country's industrial development landscape. This study examines whether there is a relationship between the efficiency levels achieved by Industrial Estate companies and their degree of involvement and strategic role in mergers, acquisitions and consolidation processes within the holding. Because this relationship may operate in different directions, both highly efficient and poorly performing parks may be targeted for integration. The issue is relevant for a wide range of stakeholders, from policy-makers and the holding's management to investors and regulators. We measure efficiency using two Stochastic Data Envelopment Analysis (SDEA) models. Based on a hand-collected data set of 113 Indonesian Industrial Estates, belonging to 48 corporate groups over the period 2022–2024, the results indicate that consolidation and M&A decisions essentially involve parks located at both ends of the efficiency spectrum, characterized by either relatively high or relatively low efficiency levels.

Keywords: Industrial Estate, efficiency, stochastic data envelopment analysis, M&A

摘要： 印尼工业园区企业整合为单一控股公司，正在重塑该国工业发展格局中关键参与者的结构、行为和商业模式。本研究考察工业园区企业所达到的效率水平，与其在控股公司内部并购与整合过程中的参与程度及战略角色之间是否存在关系。由于这种关系可能呈现不同方向，高效园区和绩效较差的园区都可能成为整合对象。该问题与广泛的利益相关者密切相关，包括政策制定者、控股公司管理层、投资者以及监管机构。我们采用两种随机数据包络分析（Stochastic Data Envelopment Analysis，SDEA）模型来衡量效率。基于一套手工收集的印尼 173 个工业园区的数据（分属于 48 个企业集团，时间范围为 2022–2024 年），研究结果表明，整合与并购决策主要涉及分布在效率谱两端的园区，即那些效率水平相对较高或相对较低的园区。

关键词: 工业园区; 效率; 随机数据包络分析; 并购

Received:	8 October 2025	Revised:	02 November 2025	Accepted:	24 December 2025	Published:	13 January 2026

Citation: Sulistyandari, S., Anggara, A. A., & Liu, C.-L. (2026). Does Efficiency Matter in M&A? Evidence from Indonesia's Industrial Estate Group Companies: 并购中的效率是否重要？来自印度尼西亚工业园区控股公司的证据. *Studies in Science of Science*, 44(1), 1-17.

1. Introduction

The recent emergence and expansion of Industrial Estates as strategic investment platforms in Indonesia is progressively and significantly reshaping the structure, behaviour and business models of the various actors involved in industrial development. Developers, operators, infrastructure providers and related service firms are under growing pressure to upgrade their capabilities in order to keep pace with new technologies, sustainability requirements and increasingly demanding tenants (Sulistyaningsih and Kulsum, 2023). There are three main approaches available to Industrial Estate developers and other relevant players to respond effectively to the rising demand for innovation in products, services and governance models, especially in the face of intensifying competition among locations. They may invest directly in more advanced infrastructure and utilities, establish targeted partnerships and strategic alliances, or engage in mergers and acquisitions (M&A) and broader consolidation processes involving existing Industrial Estate companies (Pandey et al., 2024).

This contribution focuses on the latter strategy for several reasons. Recent evidence suggests that M&A and consolidation deals in infrastructure-related and real-estate-based industries, including Industrial Estates, have been increasing and are expected to remain an important instrument for restructuring and growth in the near future. Despite the well-known challenges related to valuing Industrial Estate enterprises given their long-term assets, land banks and complex regulatory setting. The preference for strategic acquisitions can be seen as the outcome of multiple factors (KPMG, 2018). Among these are the potentially lower costs of acquiring an existing platform compared with building new capabilities entirely in-house, as well as important advantages in terms of exclusivity over key locations, rapid access to tenants and markets, and control of critical infrastructure and data (Kwon et al., 2024).

The aim of this study is to examine whether there is any relationship between the achievement of specific efficiency levels by Industrial Estate companies and their greater or lesser involvement in M&A transactions. This topic is relevant for a wide range of stakeholders, from individual and institutional investors to major market participants such as Industrial Estate developers and operators, market analysts and financial advisers as well as regulators and policy-makers. For all of these actors, it is crucial to understand whether M&A deals tend to focus mainly on the most efficient Industrial Estates or, on the contrary, on the less efficient ones, in order to benefit respectively from their superior managerial capabilities or from attractive acquisition prices (Calipha et al., 2010; Nguyen et al., 2012; Harjoto et al., 2012; Malik et al., 2014).

In more detail, the motives for acquiring or merging with a given target may be twofold. A company may be selected because it appears to be an "ideal" target; among the requirements for such a status, efficiency is inevitably central, as it is directly linked to the search for operational synergies capable of increasing revenues and/or reducing costs (Zhao and Ma, 2025). A target may be chosen primarily because its price is convenient relative to its current condition. In this latter case, even a poorly performing Industrial Estate may be attractive if its land bank, location or infrastructure offers substantial upside potential once integrated and restructured (Fidrmuc and Xia, 2019).

Accordingly, the direction of the relationship between efficiency and involvement in M&A is ambiguous. Under the first motive, the relationship would be positive: greater efficiency would tend to be associated with greater participation in M&A transactions (Onorato et al., 2024). Under the second motive, takeover or merger decisions would be driven mainly by the expected value of the acquisition premium rather than by the target's existing efficiency level, which could be high, medium or even very low. In such situations, the relationship between efficiency and involvement in M&A may be weak or non-existent, or may even be stronger at the lower end of the efficiency spectrum (Malik et al., 2014; Fidrmuc and Xia, 2019, Collevecchio et al., 2024).

To the best of our knowledge, no study has directly examined how the achievement of efficiency is related to the degree of involvement of Industrial Estate firms in M&A activity (Balak et al., 2021; Mourad, 2022). This paper therefore seeks to open this line of inquiry and fill a relevant gap in the literature. It does so by analysing M&A deals involving Indonesian Industrial Estate companies over the period 2022–2024. The choice of this observation window is largely driven by data availability, but it also coincides with a phase of intense restructuring and heightened policy attention to industrial estate development in the country (Onorato et al., 2024).

With regard to the measurement of efficiency, the study takes into account the well-documented limitations of the Stochastic Frontier Approach (SFA) and of deterministic Data Envelopment Analysis (DEA), the two most widely used techniques for this purpose (Onorato et al., 2024). Industrial Estate efficiency is instead assessed using Stochastic Data Envelopment Analysis (SDEA), which constitutes another element of originality of the paper. Specifically, two models within the SDEA framework are employed, both of which replace the point data used in standard DEA with input and output value distributions for each statistical unit (in this case, each Industrial Estate firm). More precisely, we implement (i) a general SDEA model that incorporates slack variables (Khodabakhshi et al., 2010) and (ii) a model belonging to the family of Stochastic Input-Oriented Data Envelopment Analysis (Demerdash et al., 2013; Balak et al., 2021; Mourad, 2022).

2. Theoretical Framework

Mergers and acquisitions (M&A) involving Industrial Estate developers and operators are attracting growing interest in both academic work and industry practice, mirroring the dynamic evolution of the industrial development and infrastructure sectors. Numerous literature now examines consolidation and strategic alliances in capital-intensive, real-estate based industries from multiple perspectives. Existing studies suggest that M&A activity in such sectors often triggered by the need for innovation, better infrastructure, and more advanced management models can create substantial benefits in terms of profitability, efficiency, and competitive positioning, but also brings a series of challenges that must be carefully managed. Traditional Industrial Estate companies and related infrastructure firms pursue M&A to upgrade utilities, technological capabilities, modernise service offerings, and preserve or strengthen their competitive advantage in attracting tenants and investors (Akhtar & Nosheen, 2022; Chiu et al., 2022; Zheng & Mao, 2024; Li, 2024), consolidation enables acquirers to integrate new solutions without having to develop them entirely in-house. Klus et al. (2019) emphasize that acquirers often seek rapid access to innovation and new markets, while targets look for resources and organisational capabilities to grow in highly regulated environments.

Studies such as Bellardini et al. (2022) highlight that target characteristics are shaped by the acquirer's risk–return profile and financing constraints. Regulatory settings, even if not fully decisive, can influence the choice of financing structures and the appetite for deals. Insights from alliance research (Hornuf et al., 2021) on who collaborates with whom, and how intensely, likewise offer useful analogies for understanding partnership and consolidation patterns among Industrial Estate firms. Evidence from property and real estate sectors indicates that successful integration through M&A can improve profitability and operational efficiency (Alhenawi & Stilwell, 2017; Bianconi & Tan, 2019). Systematic reviews such as Suryono et al. (2020) stress that integration frequently leads to better customer experiences and more streamlined processes, but also point to recurring obstacles including cultural clashes, regulatory compliance burdens, and the need for strong risk-management capabilities. Recent work (Wang & Nor, 2022; Dasilas & Karanović, 2023; Tarawneh et al., 2024) further highlights that the performance gains from M&A are conditional on careful deal design and post-merger integration.

Li et al. (2023) find that superior post-deal performance is associated with investments in targets that are "core-related" to the acquirer's main business, echoing corporate venture capital findings. Acquirers not only select such targets more effectively but also participate more actively in governance. In Industrial Estate consolidation: value creation is more likely when the acquired park's profile (location, tenant mix, infrastructure) fits the acquirer's strategic focus, and when the new owner is deeply involved in governance and operational oversight. The broader M&A landscape in infrastructure and development-oriented sectors is also shaped by rapid growth, evolving regulatory frameworks, and the diversification of business models (Gomber et al., 2018). Yet, persistent challenges remain: aligning the cultures and routines of different park operators, dealing with land-use and environmental regulations, and managing complex financial and operational risks. Suryono et al. (2020) stress the importance of strategic fit and thorough due diligence, while Collevecchio et al. (2024) show that M&A create value only under specific conditions for example, when a sustainable acquirer takes a minority stake in a target operating in a markedly different institutional setting such as when Industrial Estates with heterogeneous governance and regulatory environments are consolidated.

Understanding how specific efficiency levels relate to an Industrial Estate company's involvement in M&A is relevant for a broad set of stakeholders. First, Industrial Estate developers and operators may wish to know whether achieving high operational and overall efficiency actually makes them more competitive and attractive as M&A partners (Hay & Guy, 1997; Herbert & Reimann, 2005; Appadu et al., 2016). Second, such information is useful for market analysts and financial advisers when screening investment opportunities in the industrial estate sector, either for proprietary investment or on behalf of clients (Oberholzer, 2010; Santosuosso, 2014). Third, tenants and potential investors in Industrial Estates may be concerned with whether the park in which they operate could become more efficient following a merger or acquisition (Eisenmann et al., 2009; Ryu, 2018). If consolidation is expected to deliver better infrastructure, more reliable services and stronger governance, this may reinforce trust in the park's brand and support tenants' decisions to expand or remain (Nangin et al., 2020; Pramaswari et al., 2021; Kini et al., 2024).

Clarifying how efficiency influences consolidation via M&A in the Industrial Estate sector can also inform regulatory and industrial policy. It may guide adjustments to competition rules, licensing procedures, environmental and social safeguards, risk-management standards and investor-protection measures, with the broader aim of fostering innovation and sustainable development while preserving market integrity and protecting tenants and investors (Cummins & Xiaoying, 2008; Rezaee, 2011; Restoy, 2019). Despite these considerations, to the best of our knowledge no study has explicitly investigated the relationship between efficiency and the extent of firms' involvement in M&A in the Industrial Estate domain. This study therefore seeks to open this line of inquiry and address this gap by examining M&A transactions involving Indonesian Industrial Estate companies and analysing how their efficiency profiles relate to consolidation outcomes.

3. Methodology

The main objective is to investigate whether there is a relationship between the attainment of specific efficiency levels by Industrial Estate firms and their involvement in M&A transactions. As discussed in introduction, there are two fundamental motives for acquiring or merging with a target company. First, a target may be perceived as an "ideal" asset, often because it operates efficiently and is expected to generate strong operational synergies, such as higher revenues or lower costs once integrated. Second, a target may be attractive primarily because its acquisition price is low relative to its current condition and future potential. In the former case, one would expect a positive association between efficiency and participation in M&A deals (Hypothesis 1). In the latter, acquisition decisions are driven mainly by the anticipated takeover premium rather than by the target's existing efficiency level. As a result, targets may be highly efficient, moderately efficient or clearly underperforming. Under this scenario, the relationship between efficiency and M&A activity may be weak or absent, or even concentrated at the lower end of the efficiency spectrum (Hypothesis 2).

The empirical analysis must begin with a robust measurement of the efficiency levels achieved by Industrial Estate companies. This raises an immediate methodological question: how should efficiency be quantified, given that the literature has widely documented the limitations of two benchmark approaches, namely the Stochastic Frontier Approach (SFA) (Aigner et al., 1977; Battese & Coelli, 1995; Coelli et al., 2005; Pampurini & Quaranta, 2018; Pagano, 2021) and Data Envelopment Analysis (DEA)(Charnes et al., 1978; Ray, 2004; Thanassoulis et al., 2004; Feng et al., 2024).

In the case of SFA, the main difficulties concern, on the one hand, specifying a production function that adequately captures the relationship between inputs and outputs for the units under study and, on the other hand, defining plausible distributional assumptions for the two components of the regression error term (Quaranta et al., 2018; Onorato et al., 2024). This is particularly challenging for Industrial Estates, whose "production process" combines land development, infrastructure provision, utilities and a range of services, and is therefore not easily represented by a single functional form. DEA, as a non-parametric alternative, avoids the need to specify a production function but also has well-known drawbacks (Olesen & Petersen, 2016). Difficulties arise when inputs and outputs are measured in heterogeneous units or when the number of observations is small, especially if it is lower than the number of variables, as this may lead to an excessive number of units appearing fully efficient. DEA is also sensitive to outliers, treats data as deterministic because they may contain measurement errors or because they capture management outcomes that fluctuate over time but are only observed at the end of the accounting period.

For Industrial Estate firms, defining a realistic production function for SFA is particularly problematic, given the complex and project-based nature of their activities. DEA thus emerges as the more feasible starting point, since it does not require an a priori specification of the input–output relationship. The first three limitations of DEA can be mitigated by (i) standardising the values of variables used as input and output proxies, (ii) ensuring an adequate number of observations, and (iii) identifying and removing outliers using conventional statistical and econometric procedures. However, the fourth limitation (treating data as deterministic) remains critical. Even though the variables are drawn from firms' financial statements, it is reasonable to treat them as stochastic (Kao & Liu, 2004, 2009; Wong et al., 2014), both because recording errors cannot be ruled out a priori and because they represent managerial outcomes that vary over time while being observed at a single reference date.

A suitable way to incorporate the random nature of these input and output vectors is Stochastic Data Envelopment Analysis (SDEA) (Khodabakhshi et al., 2010; Wanke & Kalam Azad, 2018), which extends deterministic DEA by allowing for random variability in the variables. Two main strategies can be adopted when applying SDEA. The first aims to estimate the true efficiency frontier consistently by introducing specific statistical assumptions and constructing a modified DEA model based on a sampling process (Olesen & Petersen, 2016). The second strategy replaces the point data of standard DEA with distributions of input and output values for each decision-making unit (DMU), each Industrial Estate firm explicitly incorporating random noise into the variable vectors (Huang & Li, 2001). Both strategies lead to hybrid models that largely eliminate the original drawbacks of SFA and DEA while retaining their strengths. In this study, we follow the second strategy. Two models within this SDEA framework are implemented: a general SDEA model that includes slack variables (Khodabakhshi et al., 2010), and a model belonging to the Stochastic Input-

Oriented Data Envelopment Analysis (SIODEA) family (Demerdash et al., 2013; Balak et al., 2021; Mourad, 2022).

A further methodological challenge concerns the definition and measurement of the inputs and outputs that characterise the "operating process" of Industrial Estate firms. The companies analysed differ markedly in terms of size, location, tenant mix, and business model. It is therefore necessary to identify variables that, while abstracting from these differences, can still represent the key features of each firm's activity and allow efficiency scores to be compared meaningfully across units. An in-depth examination of the financial statements of the Industrial Estate companies considered reveals a highly heterogeneous landscape, making the choice of common proxies particularly demanding.

A workable solution, consistent with the widely used intermediation approach (Berger & Humphrey, 1997; Fethi & Pasiouras, 2010), is to treat Industrial Estate firms as intermediaries that transform capital, land, infrastructure and labour into revenue-generating industrial and commercial space. Accordingly, the following variables are adopted:

- Output (O): total operating revenue, as a synthetic measure of the value created through land lease, service charges and utilities;
- F1 (human capital): staff expenses divided by total operating revenue;
- F2 (operational and infrastructure costs): utilities, maintenance and other operating expenses divided by total assets;
- F3 (administrative and marketing effort): selling, general and administrative expenses divided by total fixed assets;
- F4 (netput): total equity, capturing the long-term capital committed to the Industrial Estate.

These variables are used as inputs and output in the implementation of both SDEA models.

For each year in the observation period, the resulting efficiency scores are then used to classify all DMUs into three homogeneous clusters. Cluster 1 includes Industrial Estate companies with the lowest efficiency levels, Cluster 2 comprises firms with medium levels of efficiency, and Cluster 3 groups the most efficient ones. To define these clusters appropriately, the skewness of the distribution of efficiency scores is assessed for each year. In the case of skewed distributions, the usual three ranges are applied:

[minimum value; (median − standard deviation)]

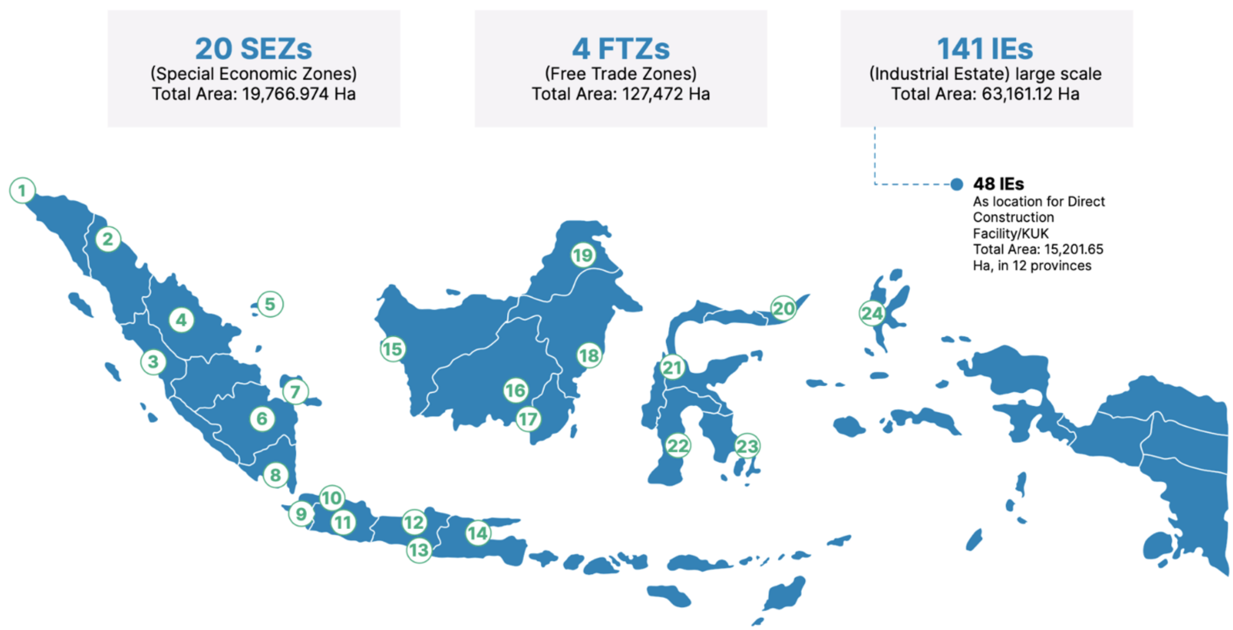
[(median − standard deviation); (median + standard deviation)]

[(median + standard deviation); maximum value]

In the case of a symmetric distribution, the median coincides with the mean.

The next step is to describe, for each year, the profile of the DMUs in each cluster in order to identify the common traits of Industrial Estate companies belonging to the same group. To this end, in addition to qualitative characteristics such as geographical corridor (Sumatra, Java, Bali-Nusa, Kalimantan, Sulawesi, and Papua) and park type (manufacturing-oriented estate, logistics/warehousing park, resource-based/processing cluster, SEZ-linked park, mixed-use industrial township), the following quantitative variables drawn from firms' financial statements are used: land bank, developed land, occupied land, fixed assets, total assets, operating revenue, number of tenants, number of employees, cash and liquid assets, leverage (debt/equity), ROA and ROE. To mitigate size effects, all variables except leverage, ROA and ROE are scaled by total assets or total land area. Finally, the relationship between the efficiency levels achieved by Industrial Estate firms and their degree of involvement in M&A transactions is assessed through standard statistical association analysis, using chi-square tests and Cramer's V. This allows us to test whether firms in different efficiency clusters exhibit systematically different patterns of participation in M&A deals, in line with Hypotheses 1 and 2.

Before presenting the hand-collected dataset used in this study, it is important to highlight a preliminary difficulty: identifying a list of Industrial Estate firms that have been active for at least the last three years. This challenge arises for at least two reasons. First, it is not straightforward to determine, in an objective way, which companies should actually be classified as Industrial Estate (Giglio, 2021). Consequently, no universally accepted and comprehensive list of such firms exists. In this regard, we are particularly indebted to Industrial Estate sector, which provided an updated list of its member firms as of early 2024 and also indicated which of them had been involved in M&A transactions over the preceding three years. To obtain the financial statement data required for the analysis currently available only up to 2024 we relied on the BKPM (Ministery of Investment) and Industrial Estate Association in Indonesia database. Starting from the initial list of 141 firms supplied by Industrial Estate sector, we first excluded all entities not operating under group, leaving 113 firms (Operated by 48 firm groups). For each year in the 2022–2024 period, we then removed those firms that had not yet been established or had ceased operations, ultimately arriving at the sample of Industrial Estate reported in Figure 1.



Source: BKPM Indonesia, 2024

Figure 1. Industrial Estate Development Firms in Indonesia

Table 1 shows, the number of firms operating in each specific area which prevents a robust. We opted for the set of common proxies described there to represent the output and input variables in the Industrial Estate operating process.

Table 1. List of Industrial Estate In Indonesia

No	Province	Industrial Estates
1	Nanggroe Aceh Darussalam	• Aceh Ladong Industrial Estate
2	North Sumatera	• Medanstar Industrial Estate • Medan Industrial Estate • Sei Mangkei (KEK) Industrial Estate
3	West Sumatera	• Padang Industrial Park
4	Riau	• Tanjung Buton Industrial Estate • Dumai Industrial Estate • Tenayan Industrial Estate
5	Riau Islands	• Bintan Inti Industrial Estate • Karimun Maritime Industrial Complex • Batamindo Industrial Park • Panbil Industrial Estate • Bintang Industrial Park • Puri Industrial Park 2000 • Tunas Industrial Estate • Union Industrial Park • Kabil Integrated Industrial Park • Executive Industrial Park • Sarana Industrial Park • Sekupang Makmur Abadi Industrial Estate • Hijrah Industrial Park • Indah Industrial Park • Kabil Integrated Industrial Park
6	South Sumatera	• Tanjung Enim Industrial Estate
7	Bangka Belitung	• Sadul Industrial Estate
8	Lampung	• Lampung Industrial Estate • Waylaga Bizpark
9	Banten	• Modern Cikande Industrial Estate • Modern Cilegon Industrial Estate • Nikomas Gemilang Industrial Estate • Surya Balaraja Industrial Estate • SBS Industrial Estate • Wilmar Integrated Industrial Estate • Millenium Industrial Estate • Pasar Kemis Industrial Estate • Cikupa Mas Industrial Estate and Warehouse • Roda Mas Industrial Estate • Kosambi Permai Industrial Estate and Warehouse • Griya Idola Industrial Park • Sumber Berkat Industrial Estate • Laksana Business Park • Krakatau Industrial Estate Cilegon • Pancapuri Industrial Estate

No	Province	Industrial Estates
		• Kawasan Industri dan Pergudangan Taman Tekno BSD
10	DKI Jakarta	• Jakarta Industrial Estate Pulogadung • Berikat Nusantara Industrial Estate
11	West Java	• Jababeka Industrial Estate • Hacaca Business Park • Indonesia China Integrated Industrial Estate • Bekasi International Industrial Estate • MM2100 Industrial Town BFIE • MM2100 Industrial Town MMID • Jababeka Industrial Estate • East Jakarta Industrial Estate • Delta Silicon Industrial Estate • Greenland International Industrial Center (GIIC) • Greenland Industrial Estate • Karawang International Industrial City • KIIC • MM2100 Industrial Town BFIE • Greenland International Industrial Center 2 (GIIC 2) • Cimareme Industrial Estate • Suryacipta City of Industry • Cibitung Industrial Estate • Cikarang Barat Industrial Estate • Cikarang Industrial Estate • Kota Bukit Indah Industrial City • Cikopo Industrial Estate • SNI Industrial Estate • Jatiluhur Industrial Smart City • Suryacipta Subang Smartpolitan • Tala Tadruse Industrial Estate • Cikempur Industrial Estate • Dwipapuri Abadi Industrial Estate
12	Central Java	• Batang Industrial Park • Java Integrated Industrial Park Sayung • Kendal Industrial Estate • Wijayakusuma Industrial Estate • Awyana Industrial Estate • BSB Industrial Park • Terboyo Semarang Industrial Estate
13	Special Region of Yogyakarta	• Piyungan Creative Economy Park Industrial Estate
14	East Java	• Gresik Industrial Estate • Maspion Industrial Estate • Java Integrated Industrial and Port Estate • Ngoro Industrial Park (S) • Ngoro Industrial Park (KII) • Pasuruan Industrial Estate Rembang • Sidoarjo Industrial Estate Berbek

No	Province	Industrial Estates
		• Safe N Lock Industrial Estate • SIER Industrial Estate • Tuban Industrial Estate • Surabaya Industrial Estate Rungkut
15	West Kalimantan	• Ketapang Ecology and Agriculture Forestry Industrial Park • KBS Industrial Estate • Landak Industrial Estate
16	Central Kalimantan	• Surya Borneo Industrial Estate
17	South Kalimantan	• Batulicin Industrial Estate (TSB) • Batulicin Industrial Estate (WSC) • Batulicin Industrial Estate (SCL)• Batulicin Industrial Estate (APP) • Batulicin Industrial Estate (BCK)
18	East Kalimantan	• Batuta Industrial Estate (BCIP) • Kariangau Industrial Estate • Kalim Industrial Estate
19	North Kalimantan	• KIPI
20	North Sulawesi	• Bolaang Mongondow (KIMONG) Industrial Estate
21	Central Sulawesi	• Morowali Industrial Estate • ATI Industrial Estate • Qingdao Indonesia Industrial Park • ESKI (Eram Sembilan Kawasan Industri) • Palu Industrial Estate
22	South Sulawesi	• Makassar Industrial Estate
23	Southeast Sulawesi	• Konawe Industrial Estate • Motui Industrial Estate
24	North Maluku	• Pulau Obi Industrial Estate • Teluk Weda Industrial Estate • EFI Industrial Estate

4. Result and Discussion

From the efficiency scores obtained for each Industrial Estate firm using the two SDEA models, we were able to derive, for each of the three years under review, largely consistent rankings of decision-making units (DMUs). On the basis of these scores, every DMU was then assigned to a specific efficiency cluster. For each year, Tables 2 and 3 report, respectively, the composition of the clusters and the average values of the variables used to describe the profile of the DMUs in each efficiency group. Industrial Estate firms were classified annually into three distinct clusters according to their efficiency levels. In Table 2, Cluster 1 gathers the least efficient DMUs, Cluster 2 includes firms with intermediate efficiency, and Cluster 3 comprises the most efficient Industrial Estates. To ensure that this classification was appropriate, the skewness of the annual distributions of efficiency values was examined for each year.

Table 2. Industrial Estate groups by year with respect to efficiency.

Cluster	2022	2023	2024
1 – low efficiency	52	54	60
2 – medium efficiency	46	48	51
3 – high efficiency	28	27	30
Total	**126**	**129**	**141**

Regarding geographic location, the evidence in Table 3 shows that, across all three years, the highest concentration of firms is found in the main industrial corridor (in particular on the island of Java), which is consistent with the fact that the country's core manufacturing and logistics hubs are located there. Given this clear pattern, location alone cannot be considered a factor that discriminates between different efficiency levels. This conclusion is supported by the association measures (chi-square and Cramer's V), which indicate no statistically significant link between efficiency and the region in which the firms are based.

Table 3. Average values of the characteristics describing the Industrial Estate profile by efficiency groups and year.

Variable	Cluster	2021	2022	2023
Geographic area	1	Java Corridor	Makassar Corridor	Makassar Corridor
	2	Java Corridor	Java Corridor	Bali–Nusa Corridor
	3	Java Corridor	Java Corridor	Java Corridor
Core business	1	Industrial land	Property land lot	Property land lot
	2	Industrial land	Industrial land	Utilities
	3	Industrial land	Industrial land	Industrial township
Financial assets	1	0.50	0.70	1.00
(% of total assets)	2	0.30	0.40	0.50
	3	1.20	1.50	2.00
Receivables	1	22.00	24.00	26.00
(% of total assets)	2	30.00	35.00	32.00
	3	28.00	26.00	29.00
Financial fixed assets	1	2.00	2.50	3.00
(% of total assets)	2	1.50	2.00	2.20
	3	2.80	3.00	3.50
Tangible assets	1	45.00	47.00	48.00
(% of total assets)	2	40.00	42.00	44.00
	3	35.00	38.00	40.00
Intangibles	1	18.00	17.00	16.00
(% of total assets)	2	20.00	19.00	18.00
	3	22.00	21.00	20.00
Total fixed assets	1	65.00	66.00	67.00
(% of total assets)	2	60.00	61.00	62.00
	3	58.00	59.00	60.00

Variable	Cluster	2021	2022	2023
Sales	1	16.00	18.00	19.00
(% of total assets or	2	12.00	14.00	16.00
index)	3	20.00	22.00	24.00
Number of employees	1	0.70	0.68	0.66
(per revenue unit –	2	0.60	0.58	0.55
index)	3	0.50	0.48	0.45
Leverage	1	1.00	1.10	1.00
(Debt/Equity, ×)	2	0.80	0.90	0.80
	3	0.40	0.50	0.50
Liquidity ratio	1	25.00	24.00	23.00
(Current ratio, %)	2	28.00	27.00	26.00
	3	30.00	32.00	33.00
ROA **(%)**	1	2.50	3.00	3.50
	2	3.50	4.00	4.50
	3	5.00	6.00	6.50
ROE **(%)**	1	6.00	7.00	8.00
	2	8.00	9.00	10.00
	3	10.00	12.00	14.00

By contrast, there appears to be a weak but statistically significant relationship between park type and efficiency. The results in Table 3 suggest that: (i) multi-purpose or "industrial land" estates function more as a common business model shared by many firms, rather than as a distinguishing feature across clusters; (ii) parks that focus on relatively basic or low-value-added activities (for example, legacy industrial zones with limited service offerings) tend to be over-represented among the least efficient firms; and (iii) at least in the most recent year, parks with a stronger emphasis on higher-value segments such as industrial township clusters or SEZ-linked estates are more frequently found in the intermediate and high-efficiency clusters. For each year and across the three groups, the average values of receivables, fixed assets (both tangible and intangible) and total fixed assets do not differ significantly, indicating that these variables are not particularly informative in distinguishing the profiles of the efficiency clusters. In contrast, the average values of financial assets, sales, number of employees, leverage, liquidity ratio, ROA and ROE differ meaningfully across clusters. These variables clearly show that the management dimensions they capture are systematically stronger over the three years for the most efficient firms, and generally weaker for firms in Cluster 1.

Turning to the core question of the study whether it is actually possible to identify a relationship between the efficiency level achieved by Industrial Estate firms and their involvement in M&A transactions. Table 4 summarises the relevant results by cluster and by year. The total number of firms reported in Table 4 refers to the previous year's sample, rather than to the contemporaneous totals shown in Table 2. The underlying assumption is that M&A decisions are taken (and subsequently completed) based on the economic, financial and managerial characteristics observed in the year prior to the deal, including the efficiency level. Accordingly, the association measures test whether being involved in an M&A transaction is linked to the efficiency cluster to which the firm belonged in the preceding year. While the total number of M&A deals recorded over the period is relatively small thus limiting the possibility of drawing fully conclusive inferences. Table 4 nonetheless reveals a clear pattern: none of the medium-efficiency firms (Cluster 2) were involved in M&A; all completed deals concerned firms in either Cluster 1 (low efficiency) or Cluster 3 (high efficiency). The chi-square statistics and Cramer's V values confirm the absence of a statistically significant relationship between efficiency clusters and M&A participation.

Table 4. Analysis of the relationship between the level of efficiency achieved by Industrial Estate firms and their involvement in M&A transactions

M&A	Cluster 1	Cluster 2	Cluster 3	Total Number of Industrial Estate
2022	2	0	1	3
2023	2	0	2	4
2024	9	0	3	12

$\chi^2 = 4.23$
Cramer's V = 0.15
p-value = 0.22

The chi-square test ($\chi^2 = 4.23$; p = 0.22) and the associated effect size (Cramer's V = 0.15) indicate that there is no statistically significant association between the efficiency clusters and the occurrence of M&A transactions. In practical terms, the data do not support the existence of a strong systematic pattern linking a firm's efficiency level to whether it is involved in a merger or an acquisition. At a descriptive level, mergers appear more frequently among Industrial Estates that already exhibit relatively strong performance and solid management, suggesting that these transactions are used to integrate healthy and efficient partners into a larger group. By contrast, acquisitions tend to involve parks with attractive land or locational potential but weaker current performance, which may create opportunities to purchase assets at favourable prices and attempt a turnaround. A similar, weak tendency emerges when park type is considered: low-efficiency targets are more often traditional or lower-value industrial estates, whereas highly efficient firms involved in deals are more frequently advanced parks (e.g., Industrial land, Industrial township, logistics-intensive, or SEZ-linked). However, given the limited number of M&A cases and the lack of statistical significance, these patterns should be regarded as indicative rather than conclusive.

5. Conclusion

This study set out to explore whether the efficiency level of Industrial Estate firms is systematically related to their involvement in M&A transactions. The empirical evidence based on cluster analysis and chi-square tests does not reveal a statistically significant association between efficiency clusters and M&A activity. In other words, more or less efficient firms are not demonstrably more likely to appear as acquirers or targets in the sample period. Any apparent differences across clusters should therefore be interpreted as descriptive patterns rather than as robust causal regularities.

Nonetheless, the descriptive results offer some suggestive insights into deal rationales. Transactions classified as mergers tend to involve Industrial Estates that already display relatively sound financial conditions and high efficiency, whereas acquisitions more frequently concern parks with attractive land banks or locations but weaker current performance and governance. This configuration is consistent with a pragmatic strategy in which healthy parks are integrated as strong partners, while underperforming parks are acquired at relatively favourable prices in the expectation of a turnaround within a larger group. A similar, though weak, tendency emerges when park type is considered: low-efficiency targets are more often traditional or lower-value estates, whereas several highly efficient firms involved in deals belong to more advanced categories such as export-oriented, logistics-intensive or SEZ-linked parks.

From a regulatory and supervisory perspective, these indications, while preliminary, suggest that the progressive consolidation of Industrial Estates through M&A could contribute to the emergence of larger park platforms with greater systemic relevance. Competition and financial authorities may therefore need to monitor how such consolidation affects market structure, bargaining power vis-à-vis tenants, and regional development outcomes. Given that the statistical tests do not support strong claims, however, any policy interpretation should be cautious and framed as hypothesis-generating rather than prescriptive.

For practitioners, the results imply that efficiency should be seen not only as an internal operational objective but also as a potential signal in capital and control markets. Efficient parks may be better positioned to attract strategic partners, negotiate from a position of strength in M&A, and use transactions to access new markets or regulatory regimes. Conversely, parks with good locational fundamentals but weak current performance may still be attractive to investors pursuing turnaround or land-bank strategies.

Finally, this research remains exploratory. The number of M&A deals in the observation window is limited, and the analysis focuses on a single national context. Future work should extend the dataset to a larger pool of countries, park types and time periods, and integrate richer information on deal structure, ownership changes and post-transaction performance. Such extensions would allow a more powerful test of whether the tentative patterns identified here. Particularly the role of efficiency and park type in shaping M&A strategies, hold across different institutional and developmental settings.

References

Aigner, D., Lovell, C. K., & Schmidt, P. (1977). Formulation and estimation of stochastic frontier production function models. *J. Econ., 6*(1), 21–37.

Akhtar, Q., & Nosheen, S. (2022). The impact of fintech and banks M&A on acquirer's performance: A strategic win or loss? *Borsa Istanbul Review, 22*(6), 1195–1208.

Alhenawi, Y., & Stilwell, M. (2017). Value creation and the probability of success in merger and acquisition transactions. *Review of Quantitative Finance and Accounting, 49*, 1041–1085.

Anggara, A. A., Aryoko, Y. P., Dewandaru, R. O., Kharismasyah, A. Y., & Fatchan, I. N. (2025). Does maintaining resources, diversification, and internationalization matter for achieving high firm performance? A sustainable competitiveness strategy for China Taipei firms. *Sustainability*, 17(4), 1576. https://doi.org/10.3390/su17041576

Anggara, A. A., Kaukab, M. E., & Randikaparsa, I. (2024). Optimizing halal supply chains in the food industry: Enhancing sales management through ERP system integration. *Asian Journal of Economics, Business and Accounting*, 24(2), 52–63.

Appadu, N., Faelten, A., Moeller, S. D., & Vitkova, V. (2016). Assessing market attractiveness for mergers and acquisitions: The M&A Attractiveness Index Score. *European Journal of Finance, 22*(8–9), 732–755.

Balak, S., Behzadi, M. H., & Nazari, A. (2021). Stochastic copula-DEA model based on the dependence structure of stochastic variables: An application to twenty bank branches. *Economic Analysis and Policy, 72*, 326–341, 487–499.

Battese, G. E., & Coelli, T. J. (1995). A model for technical inefficiency effects in a stochastic frontier production function for panel data. *Empirical Economics, 20*, 325–332.

Bellardini, L., Del Gaudio, B. L., Previtali, D., & Verdoliva, V. (2022). How do banks invest in FinTechs? Evidence from advanced economies. *Journal of International Financial Markets, Institutions and Money, 77*, 101498.

Berger, A. N., & Humphrey, D. B. (1997). Efficiency of financial institutions: International survey and directions for future research. *European Journal of Operational Research, 98*, 175–212.

Bianconi, M., & Tan, C. M. (2019). Evaluating the instantaneous and medium-run impact of mergers and acquisitions on firm values. *International Review of Economics and Finance, 59*, 71–87.

Calipha, R., Tarba, S., & Brock, D. (2010). Mergers and acquisitions: A review of phases, motives, and success factors. *Advances in Mergers and Acquisitions, 9*, 1–24.

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research, 2*(6), 429–444.

Chiu, W. H., Shih, Y. S., Chu, L. S., & Chen, S. L. (2022). Merger and acquisitions integration implementation as an innovative approach toward sustainable competitive advantage: A case analysis from Chinese sports brands. *Frontiers in Psychology, 13*, 869836.

Coelli, T. J., Rao, D. S. P., O'Donnell, C. J., & Battese, G. E. (2005). *An introduction to efficiency and productivity analysis*. Springer.

Collevecchio, F., Cappa, F., Peruffo, E., & Oriani, R. (2024). When do M&As with FinTech firms benefit traditional banks? *British Journal of Management, 35*(1), 192–209.

Cummins, J. D., & Xiaoying, X. (2008). Mergers and acquisitions in the US property-liability insurance industry: Productivity and efficiency effects. *Journal of Banking and Finance, 32*(1), 30–55.

Dasilas, A., & Karanović, G. (2023). The impact of FinTech firms on bank performance: Evidence from the UK. *Eur. J. Bus.*

Demerdash, B. E., Khodary, I. A., & Tharwat, A. A. (2013). Developing a stochastic input oriented data envelopment analysis (SIODEA) model. *International Journal of Advanced Computer Science and Applications, 4*(4), 40–44.

Eisenmann, T. R., Parker, G., & Van Alstyne, M. (2009). Opening platforms: How, when and why. In *Platforms, markets and innovation* (pp. 131–162).

Feng, C., Zhong, S., & Wang, M. (2024). How can green finance promote the transformation of China's economic growth momentum? A perspective from internal structures of green total-factor productivity. *Research in International Business and Finance, 70*, 102356.

Fethi, M. D., & Pasiouras, F. (2010). Assessing bank efficiency and performance with operational research and artificial intelligence techniques: A survey. *European Journal of Operational Research, 204*, 189–198.

Fidrmuc, J. P., & Xia, C. (2019). M&A deal initiation and managerial motivation. *Journal of Corporate Finance, 59*, 320–343.

Giglio, F. (2021). Fintech: A literature review. *European Research Studies Journal, 24*(2B), 600–627.

Gomber, P., Kauffman, R. J., Parker, C., & Weber, B. W. (2018). On the FinTech revolution: Interpreting the forces of innovation, disruption, and transformation in financial services. *Journal of Management Information Systems, 35*(1), 220–265.

Handayani, E., Anggara, A. A., Ira, H., & Lin, C.-T. (2024). Developing an instrument and assessing SDGs implementation in Indonesian higher education. *International Journal of Sustainable Development and Planning*, 19(2), 577–590.

Harjoto, M. A., Yi, H. C., & Chotigeat, T. (2012). Why do banks acquire non-banks? *Journal of Economics and Finance, 36*(3), 587–612.

Hay, D. A., & Guy, S. L. (1997). The efficiency of firms: What difference does competition make? *Economic Journal, 107*(442), 597–617.

Herbert, D., & Reimann, M. (2005). Evaluating market attractiveness: Individual incentives versus industry profitability. *Computational Economics, 24*, 321–355.

Hornuf, L., Klus, M. F., Lohwasser, T. S., & Schwienbacher, A. (2021). How do banks interact with FinTech startups? *Small Business Economics, 57*(3), 1505–1526.

Huang, Z., & Li, S. X. (2001). Stochastic DEA models with different types of input-output disturbances. *Journal of Productivity Analysis, 15*, 95–113.

Kao, C., & Liu, S. T. (2004). Predicting bank performance with financial forecasts: A case of Taiwan commercial banks. *Journal of Banking and Finance, 28*, 2353–2368.

Kao, C., & Liu, S. T. (2009). Stochastic Data Envelopment Analysis in measuring the efficiency of Taiwan commercial banks. *European Journal of Operational Research, 196*(1), 312–322.

Kaukab, M. E., Anggara, A. A., & Imron, A. (2025). Business process transformation to maintain high performance: Driving an AI-based business value project. *Current Perspective on Business Operations*, 1(1), 1–20.

Khodabakhshi, M., Asgharian, M., & Gregoriou, G. N. (2010). An input-oriented super-efficiency measure in Stochastic Data Envelopment Analysis: Evaluating chief executive officers of US public banks and thrifts. *Expert Systems with Applications, 37*(3), 2092–2097.

Kini, A. N., Savitha, B., & Hawaldar, I. T. (2024). Brand loyalty in FinTech services: The role of self-concept, customer engagement behavior and self-brand connection. *Journal of Open Innovation: Technology, Market, and Complexity, 10*(1), 100240.

Klus, M. F., Lohwasser, T. S., Holotiuk, F., & Moormann, J. (2019). Strategic alliances between banks and FinTechs for digital innovation: Motives to collaborate and types of interaction. *Journal of Entrepreneurial Finance, 21*(1), 1–23.

KPMG. (2018). *Continuing to climb: Global banking M&A trends 2018*. KPMG.

Kwon, K. Y., Molyneux, P., Pancotto, L., & Reghezza, A. (2024). Banks and FinTech acquisitions. *Journal of Financial Services Research, 65*(1), 41–75.

Li, E., Mao, M. Q., Zhang, H. F., & Zheng, H. (2023). Banks' investments in FinTech ventures. *Journal of Banking and Finance, 149*, 106754.

Li, X. (2024). The impact of technology mergers and acquisitions on enterprise sustainable competitiveness. *Sustainability, 16*(6), 2291.

Malik, M. F., Anuar, M. A., Khan, S., & Khan, F. (2014). Mergers and acquisitions: A conceptual review. *International Journal of Accounting and Financial Reporting, 4*(2), 520.

Mourad, N. (2022). Second-order conic programming for data envelopment analysis models. *Periodicals of Engineering and Natural Sciences, 10*(2), 487–499.

Nangin, M. A., Barus, I. R. G., & Wahyoedi, S. (2020). The effects of perceived ease of use, security, and promotion on trust and its implications on FinTech adoption. *Journal of Consumer Sciences, 5*(2), 124–138.

Nguyen, H. T., Yung, K., & Sun, Q. (2012). Motives for mergers and acquisitions: Ex-post market evidence from the US. *Journal of Business Finance & Accounting, 39*(9–10), 1357–1375.

Oberholzer, M. (2010). A model to compare firms' efficiency in creating shareholders' value. *South African Journal of Accounting Research, 24*(1), 13–30.

Olesen, O. B., & Petersen, N. C. (2016). Stochastic data envelopment analysis: A review. *European Journal of Operational Research, 251*, 2–21.

Onorato, G., Pampurini, F., & Quaranta, A. G. (2024). Lending activity efficiency: A comparison between fintech firms and the banking sector. *Research in International Business and Finance, 68*, 102185.

Pagano, M. S. (2021). The shrinking role of foreign operations at global financial institutions and its impact on efficiency. *Finance Research Letters, 38*, 101419.

Pampurini, F., & Quaranta, A. G. (2018). Sustainability and efficiency of the European banking market after the global crisis: The impact of some strategic choices. *Sustainability, 10*(2237), 1–16.

Pandey, D. K., Hassan, M. K., Kumari, V., Zaied, Y. B., & Rai, V. K. (2024). Mapping the landscape of FinTech in banking and finance: A bibliometric review. *Research in International Business and Finance, 67*, 102116.

Pramaswari, F., Nasution, A. P., & Nasution, S. L. A. (2021). The effect of branding quality and service quality on customer satisfaction through financial technology (FinTech) at PT. WOM Finance

branch Rantauprapat. *Bp. International Research and Critics Institute (BIRCI Journal): Humanities and Social Sciences, 4*(2), 2995–3004.
Quaranta, A. G., Raffoni, A., & Visani, F. (2018). A multidimensional approach to measuring bank branch efficiency. *European Journal of Operational Research, 266*(2), 746–760.
Ray, S. C. (2004). *Data envelopment analysis: Theory and techniques for economics and operations research*. Cambridge University Press.
Restoy, F. (2019). Regulating FinTech: What is going on, and where are the challenges? *Bank for International Settlements*, 1–7.
Rezaee, Z. (2011). *Financial services firms: Governance, regulations, valuations, mergers, and acquisitions*. John Wiley & Sons.
Ryu, H. S. (2018). What makes users willing or hesitant to use FinTech? The moderating effect of user type. *Industrial Management & Data Systems, 118*(3), 541–569.
Santosuosso, P. (2014). Do efficiency ratios help investors to explore firm performances? Evidence from Italian listed firms. *International Business Research, 7*(12), 111.
Sulistyandari, Anggara, A. A., Liu, C.-L., Kaukab, M. E., & Alam, M. M. (2025). Evaluating firm value and eco-efficiency with environmental footprint model approach in the coal mining industry: Further evidence from G20 countries. *Modern Economic Science*, 47(5), 105–125.
Suryono, R. R., Budi, I., & Purwandari, B. (2020). Challenges and trends of financial technology (FinTech): A systematic literature review. *Information, 11*(12), 590.
Tarawneh, A., Abdul-Rahman, A., Mohd Amin, S. I., & Ghazali, M. F. (2024). A systematic review of fintech and banking profitability. *International Journal of Financial Studies, 12*(1), 3.
Thanassoulis, E., Portela, M., Allen, R., Cooper, W., Seiford, L., & Zhu, J. (2004). Handbook on data envelopment analysis. *International Series in Operations Research & Management Science, 71*, 99–138.
Wang, J., Yuan, X., Huang, X., Liu, C., & Zhang, P. (2024). Can digitalization facilitate cross-border M&A? Evidence from Chinese A-share listed companies. *Research in International Business and Finance, 67*, 102118.
Wang, Y., & Nor, E. (2022). The impact of FinTech on the profitability of traditional banks. *Global Business and Management Research, 14*.
Wanke, P., & Kalam Azad, M. A. (2018). Efficiency in Asian railways: A comparison between Data Envelopment Analysis approaches. *Transport Planning and Technology, 41*(6), 573–599.
Wong, W. P., Deng, Q., Tseng, M. L., Lee, L. H., & Hooy, C. W. (2014). A stochastic setting to bank financial performance for refining efficiency estimates. *Intelligent Systems in Accounting, Finance and Management, 21*(4), 225–245.
Zhao, Y., & Ma, F. (2025). Will fintech enhance financial regulation? *Research in International Business and Finance*, 103005.
Zheng, H., & Mao, M. Q. (2024). FinTech mergers and acquisitions. *Journal of International Money and Finance, 143*, 103076.