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Machine Learning Augmented Propensity Score Matching Quasi-Experimental Evidence on the Role of New Fourth Industrial Revolution Technologies in Corporate Economic Performance

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Abstract: The paper evaluates the impact of adopting emerging technologies associated with the Fourth Industrial Revolution on the financial performance of companies in an empirical way. This study addresses the endogeneity issue commonly encountered in the traditional regression approach used in previous studies by applying propensity score matching based on the prospective outcomes approach. RandomForest machine learning technique was used to further edit the propensity score calculation. In addition, to augment the generalisability of the outcomes, the investigation scrutinises data from the Bangladesh Bureau of Statistics (BBS) that includes the whole demographic of relevant companies. The findings show that companies that have adopted Fourth Industrial Revolution technologies gain more than 40% of their revenue per year compared to those that do not. The impact varies from firm to firm depending on their size it is approximately 43% for small and medium sized enterprises (SMEs) and 77% for larger firms. This implies that major businesses hold a competitive edge over SMEs in their proficiency to adeptly employ recently accepted technologies. The importance of this investigation is that it applies advanced methodologies to do an accurate estimation of the economic impacts of the introduction of the Fourth Industrial Revolution technology, while giving policy implications based on the results.

Keyword: *Industrial Revolution, Economic Performance, Propensity Score Matching, Potential Outcomes Framework, Machine Learning.*

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I. INTRODUCTION

The advent of the Fourth Industrial Revolution is bringing about fundamental and systematic changes to our lives. At the core of these shifts lie the digital transformation of society as a whole and the widespread adoption of new, intelligence-based technologies. The industrial sector is also adapting to these developments by integrating the new technologies of the Fourth Industrial Revolution into various management functions including production management, marketing, organizational structure, human resources, and finance (Aithal and Aithal, 2018; Garrett, 2014; Howard, 2019). These emerging technologies serve as new engines of growth for enterprises and are exerting a profound impact on the industry.

Before the Fourth Industrial Revolution, humanity had already experienced three instances of disruptive innovation: the First Industrial Revolution in the 18th century, driven by the steam engine; the Second Industrial Revolution in the 19th century, based on electrical energy; and the Third Industrial Revolution in the latter half of the 20th century, brought about by the computer. Much like steam, electricity, and the computer in previous industrial revolutions (Bresnahan and Trajtenberg, 1995), the new technologies of the Fourth Industrial Revolution function as general-purpose technologies that exert a profound impact on society and the economy (Martinelli et al., 2021). Specifically, technologies such as the Internet of Things (IoT), cloud computing, big data, and mobile collectively referred to by the acronym "ICBM" due to their extensive reach (Lee et al., 2018) have been joined more recently by artificial intelligence (AI),

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including machine learning and deep learning, which has rapidly emerged as a significant new technological force (Cockburn et al., 2018; Crafts, 2021).

The emergence of new technologies associated with the Fourth Industrial Revolution presents both opportunities and challenges (Li et al., 2020). As seen in previous industrial revolutions, these technologies can enhance a firm's economic performance through the development of new products, increased production efficiency, and improved customer service (Neuhofer et al., 2015); however, they may also intensify competition within the business environment, thereby increasing the financial burden on firms (Kiel et al., 2017). Furthermore, the impact of these new technologies may vary depending on a firm's specific characteristics. For instance, larger firms tend to accumulate greater technical knowledge and capabilities (Damanpour, 1992), which can lead to disparities in performance among companies.

There has been ongoing research into the impact of the Third Industrial Revolution specifically, computerization on firm performance (e.g., Ettlie, 1998; Frey and Osborne, 2017; Greenan and Mairesse, 2000; Lehr and Lichtenberg, 1999; Lichtenberg, 1995; Ng and Chang, 2003). However, evidence regarding the economic effects of new technologies associated with the Fourth Industrial Revolution remains scarce. This is largely because only about eight years have passed since announced the advent of the Fourth Industrial Revolution at the 2016 World Economic Forum (WEF). Consequently, this study empirically examines the impact of new Fourth Industrial Revolution technologies on the economic performance of firms. To address endogeneity a significant limitation in prior studies that relied on standard regression analysis this research employs propensity score matching (PSM) based on the potential outcome framework. This approach helps mitigate the risk of underestimating or overestimating the effects of these new technologies due to selection bias. Furthermore, machine learning algorithms were incorporated to enhance the performance of the methodology.

II. LITERATURE REVIEW

The impact of technological progress driven by the Fourth Industrial Revolution on industries as a whole has been a subject of ongoing research. However, most existing studies focus primarily on changes within the labor market and employment. Specifically, (Acemoglu and Restrepo 2020) demonstrated, through a multidimensional empirical analysis, that the adoption of industrial robots can have a significantly negative impact on local employment and wages. Similarly, (Frank et al. 2019) found that while the rapid advancement of artificial intelligence and automation technologies can enhance worker productivity, it also carries the potential to displace workers from their jobs. While these studies have deepened our understanding of how the Fourth Industrial Revolution affects industries and employment, they do not focus on firms the primary agents responsible for the adoption and utilization of these new technologies which presents certain limitations in interpreting the outcomes of technological progress.

Some studies have empirically examined the outcomes of the Fourth Industrial Revolution and the impact of new technologies at the firm level has provided insights into corporate technological innovation activities by examining how firms utilize new technologies associated with the Fourth Industrial Revolution. Furthermore, utilized data from the "Survey on Business Activities" to analyze the correlation between the adoption of these new technologies and corporate employment, revealing that such technologies have a significant positive effect on employment growth. However, these studies are limited in the insights they offer, as they do not address the ultimate outcomes for firms namely, their economic and financial performance.

There have, of course, been studies that directly examined the relationship between the adoption of new technologies associated with the Fourth Industrial Revolution and corporate performance. Used quantile regression to investigate the link between a firm's adoption of Fourth Industrial Revolution technologies and its productivity, finding that the adoption of such technologies has a positive impact on a firm's absolute level of productivity. Similarly, (McAfee, 2011) analyzed the correlation between core Fourth Industrial Revolution technologies and economic performance, confirming that firms that adopted these technologies exhibited better performance. While the findings of these studies are straightforward to interpret, questions remain regarding the rigor of their analysis. As Noh points out, highly productive and larger firms tend to be more proactive in adopting Fourth Industrial Revolution technologies; this suggests that the aforementioned studies may not have sufficiently accounted for reverse causality in their methodology. However, their analysis was limited to small and medium-sized enterprises (SMEs) in the manufacturing sector, which constrains the generalizability of their results. The same limitation applies to a study by (Trento et al. 2018), which focused exclusively on large corporations. In reality, the impact of technological advancement is pervasive, extending across all types of industries and firm sizes Therefore, it is necessary to empirically verify the economic effects typically associated with new technologies of the Fourth Industrial Revolution. Accordingly, this study establishes the following research hypotheses.

Research Hypothesis H_a: "The utilization of new technologies from the Fourth Industrial Revolution has a positive effect on a firm's economic performance."

This study is distinguished by its use of a quasi-experimental approach and machine learning to derive rigorous estimates while minimizing endogeneity, furthermore, it seeks to provide results with high generalizability by accounting for the impacts of increasingly widespread digitalization and automation.

III. STATISTICAL MODELS

- *Potential Outcomes Framework*

The gold standard for causal inference is the randomized controlled trial (West et al., 2008), as random

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assignment can largely eliminate selection bias. However, since it is not practically feasible to randomly assign firms based on their adoption of new technologies associated with the Fourth Industrial Revolution, this study must rely on observational data. Consequently, to ensure the most rigorous possible inference within an observational framework, a quasi-experimental design approach is employed.

The theoretical foundation for the propensity score matching method used in this study lies in the potential outcomes framework. In general, a causal effect can be identified by comparing two potential states, states that manifest depending on the presence or absence of a cause.

However, the principle of causality dictates that a single entity can exist in only one state at any given time. The state that actually occurs is referred to as the factual outcome, while the state that does not occur is called the counterfactual outcome; collectively, these are known as potential outcomes. The potential outcomes framework is an approach that seeks to estimate causal effects by first estimating these counterfactual outcomes.

Specifically, in this study is whether or not firm i utilizes new technologies associated with the Fourth Industrial Revolution (D_i), and the potential outcomes resulting from this are two measures of the firm's economic performance (Y_{0i}, Y_{1i}). This can be expressed as shown in Equation (1).

$$Y_i = D_i Y_i + (1 - D_i) Y_{0i} \quad (1)$$

To test the research hypothesis established earlier, it is necessary to estimate the treatment effect that is, the effect T of utilizing new technologies associated with the Fourth Industrial Revolution which represents the relationship between D_i and Y_i as shown in Equation (2).

$$T = E(Y_1|D = 1) - E(Y_0|D = 0) \quad (2)$$

To this end, one would ideally need to know both economic outcomes, Y_{1i} and Y_{0i} , for each firm i however, a fundamental problem arises in practice: depending on the value of D_i only one of these two outcomes can be observed (Holland, 1986). Consequently, one must estimate the counterfactual outcomes Y_{1i} as the counterfactual for Y_{0i} , and Y_{0i} as the counterfactual for Y_{1i} .

Once the potential outcomes y_0 and y_1 corresponding to the treatment status d have been appropriately estimated for a given sample, the estimate of the treatment effect, $\hat{\tau}$ can be calculated as shown in Equation (3).

$$\hat{\tau} = E(\hat{y}_1|d = 1) - E(\hat{y}_0|d = 0) \quad (3)$$

Applying this framework requires two key assumptions: the ignorable treatment assignment assumption and the stable unit treatment value assumption (SUTVA). The former implies that, given a set of covariates, an individual's treatment status is independent of their potential outcomes (Wooldridge, 2005), while the latter requires that there be no interference between units and no alternative forms of treatment that could lead to different potential outcomes (Heckman, 2005; Keele, 2015).

➢ *Machine Learning-Augmented Propensity Scores*

A propensity score refers to the conditional probability that an individual is assigned to a particular treatment, given a specific vector of covariates (Rosenbaum and Rubin, 1973). In simpler terms, it is a single numerical value that summarizes a set of covariates through statistical techniques. This dimensionality reduction offers several statistical advantages, such as helping to circumvent the curse of dimensionality (Bellman, 1957). Furthermore, under the assumption of random treatment assignment, an individual's treatment status can be considered independent of their potential outcomes when conditioned on the propensity score, rather than on the individual covariates themselves.

In observational studies, since the functional form of the propensity score is unknown, it must be estimated for each individual. While various methods can be used for this estimation, most prior research has employed logit or probit models types of generalized linear models (Cuong, 2013; Weitzen et al., 2004; Wu et al., 2010) However, as recent studies have increasingly demonstrated the superior performance of machine learning-augmented propensity scores (Pirracchio et al., 2012; Zhao et al., 2021), there has been a growing effort to apply these methods in empirical analyses (e.g., Goller et al., 2020; Lee et al., 2010; Westreich et al., 2010).

In this study, we employ the Random Forest algorithm (Breiman, 2001). Random Forest is a type of ensemble-based classifier that uses classification trees as its building blocks. The rationale for using this approach is twofold. First, the classification trees that form the foundation of Random Forest can readily handle qualitative variables without the need for dummy variables; they are also capable of detecting high-dimensional interaction effects and identifying non-linear correlations (James et al., 2013; Sutton, 2005). In these respects, Random Forest often outperforms generalized linear models, such as logit or probit models. Second, as a form of ensemble learning, it offers significant advantages over other machine learning techniques for instance, by mitigating correlations between individual trees (Kuhn and Johnson, 2013). Furthermore, an extensive review of empirical studies utilizing machine learning-augmented propensity scores (Westreich et al., 2010) has shown that Random Forest can yield superior results while presenting fewer limitations compared to other machine learning algorithms, such as support vector machines or boosting.

➢ *Propensity Score Matching*

Propensity score matching is a technique that pairs individual subjects from a treatment group with those from a control group using a propensity score a summary measure derived from covariates. Its primary objective is to reduce bias in the estimation of treatment effects caused by confounding variables (Cochran and Rubin, 1973; Rubin, 1973). By condensing a vector of covariates into a single scalar, this method ensures covariate balance; consequently, it is widely employed in observational studies where random

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assignment of treatments is not feasible (Bai, 2011; Dehejia and Wahba, 2002).

For the matching procedure, this study employs full matching (Hansen and Klopfer, 2006). Although full matching is less widely used than greedy matching the default method provided by many statistical software packages (Hansen, 2004) it offers the advantage of incorporating all subjects from both the treatment and control groups into the analysis (Rosenbaum, 1991). This helps mitigate bias stemming from incomplete matching and improves covariate balance (Gu and Rosenbaum, 1993; Rosenbaum and Rubin, 1985; Stuart and Green, 2008). Furthermore, compared to optimal matching, full matching is particularly useful for this study because it allows for the estimation of the average treatment effect (ATE) for the entire population (Austin and Stuart, 2017a; Szafara et al., 2012). Additionally, full matching is a rational approach in that it does not require arbitrary judgment when configuring specific parameters, such as matching ratios or calipers.

Based on the process described above, this study estimates the effect of utilizing new technologies associated with the Fourth Industrial Revolution on the economic performance of firms. Since there are currently no non-parametric statistical tools available for estimating treatment effects when using machine learning-augmented propensity scores for matching, a parametric approach is employed. To ensure rigorous estimation, however, we also apply matching weights (Austin and Stuart, 2017b) which function similarly to inverse probability weights used in propensity score weighting. Furthermore, following the estimation of treatment effects, we conduct a Rosenbaum sensitivity analysis (Rosenbaum, 2015) to assess the extent of hidden bias (Rosenbaum, 2002) potentially arising from covariates not included in the propensity score estimation, and to examine the robustness of the findings. R 4.2.0 was used for the empirical analysis, and the specific R packages employed throughout the analytical process are noted where relevant.

IV. DATA AND VARIABLES

➢ *Data*

This study utilizes data from the Bangladesh Bureau of Statistics (BBS). The BBS is designed to provide a comprehensive overview of the various business activities of firms, thereby offering foundational data for the government to formulate economic policies and for businesses to develop management strategies and understand shifts in industrial structure. As the survey includes questions regarding the adoption of new technologies associated with the Fourth Industrial Revolution, it is well-suited for addressing the research hypotheses established in this study. The survey covers approximately 13,000 enterprises across all industries specifically, incorporated companies operating in Bangladesh that have 50 or more regular employees and a capital of at least 300 million BDT. Since the survey is a complete enumeration of the target population, no discussion regarding sampling or sample characteristics is provided.

Although this study employs a cross-sectional analysis, it incorporates data from 2015 and 2022 into the dataset to account for financial characteristics which reflect a firm's prior-year financial position and performance as well as variables related to innovation activities, the effects of which often manifest with a time lag. Incorporating the longitudinal characteristics of firms provides a richer dataset than single-year data alone, which in turn enhances the performance of propensity score estimation. The merging process resulted in an unbalanced panel dataset, as the firms participating in the Bangladesh Bureau of Statistics (BBS) vary from year to year. However, given that the non-response rate is relatively low and that firms failing to participate in the survey have no recorded values for any of the items rendering the imputation of missing values impossible the dataset was balanced using list wise deletion. Following this data preprocessing, 10,821 responses out of the 12,579 firms surveyed in the 2022 Bangladesh Bureau of Statistics (BBS) were deemed suitable for empirical analysis.

➢ *Variable Definition and Measurement*

- *Outcome Variable: Annual Sales Revenue*

In this study, economic performance is defined in terms of annual sales revenue specifically, the annual sales revenue of each firm as of December 31, 2022, for the relevant fiscal year. Sales revenue, which represents the income a firm generates through its business operations, serves as the primary and most essential indicator of a firm's economic performance. It should be noted that for the finance and insurance sector, operating sales are examined due to the distinct nature of their revenue-generating activities Bangladesh Bureau of Statistics (BBS 2022); however, in this study, this figure is also collectively referred to as sales revenue in a broad sense. Consequently, regardless of the industry, the revenue recorded at the very top of each firm's 2022 income statement was used as the measure for the sales revenue variable.

- *Treatment Variable: Whether or Not New Technologies of the Fourth Industrial Revolution are Utilized*

The new technologies of the Fourth Industrial Revolution specifically include the Internet of Things (IoT), cloud computing, big data, mobile technology, artificial intelligence, blockchain, 3D printing, robotics, and augmented and virtual reality. In this study, the treatment variable is defined as (yes=1) if a firm utilizes one or more of these new technologies in its business operations regardless of the specific purpose and (no=0) if it utilizes none of them. This operational definition is consistent with the approach used in previous studies, (Cho et al. (2022).

- *Covariate*

Approximately 20 covariates were used to estimate the propensity scores. Since a propensity score serves as a balancing score that corrects for imbalances between the treatment and control groups, it is crucial to maximize its performance through the careful selection of covariates and the specification of an appropriate estimation model (Guo and Fraser, 2014). According to simulations by (Brookhart et al. 2006), provided the sample size is sufficient, it is advisable to

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select covariates based on the following criteria First, a variable should be included as a covariate if it is correlated with either the treatment variable or the outcome variable. Second, if a variable is correlated with both, it must be included. However, a covariate should not function as a mediator between the treatment variable and the outcome variable. Given that such empirical correlations influence the performance of propensity score estimation, some approaches such as those proposed by (Stürmer et al. 2006) or methods like stepwise selection aim to enhance predictive power through data-driven selection. In this study, however, the covariates were selected based on prior research. This approach was adopted to derive various implications regarding the economic outcomes of new technologies associated with the Fourth Industrial Revolution. The covariates used in this study can be broadly categorized into three groups; the rationale for the selection of each covariate is as follows.

✓ Financial characteristics of a firm

✓ Structural characteristics of the firm

✓ Innovative characteristics of the firm

V. RESULTS

➢ *Results of Descriptive Statistical Analysis*

- *Descriptive Statistics*

Table 1 presents the descriptive statistics for the outcome variables and certain covariates measured as continuous variables. Variables related to firm size such as annual sales and the number of intellectual property rights were log-transformed. As of 2022, the average annual sales of the firms amounted to approximately 41.4 billion BDT. Furthermore, the firms exhibited an average return on total assets of 3.27%, return on equity of 4.76%, operating profit margin of 1.01%, total asset turnover of 141.04%, and a debt-to-equity ratio of 234.56%.

Table 1 Descriptive Statistics

Variable		N	M	SD	Min	Max
Annual sales revenue	REVE	10,821	10.63	1.55	0	18.90
Return on Total Assets	ROA	10,821	3.27	19.78	-842.17	714.41
Return on Equity (ROE)	ROE	10,821	4.76	151.37	-7255.06	2542.26
Operating profit margin on sales	OPM	10,821	1.010	50.51	-3087.38	93.27
Total Asset Turnover	ASTU	10,821	141.04	179.36	0	11,006.31
Debt-to-equity ratio	DEEQ	10,821	234.56	3798.59	-37524.6	325,250
Proportion of foreign capital	FOEQ	10,821	10.07	27.81	0	100
Proportion of regular employees	PERM	10,821	95.06	14.46	1.09	100
Proportion of male employees	MALE	10,821	72.96	21.10	0	100
Number of Intellectual Property	lag_INTE	10,821	1.90	1.81	0	10.73
R&D expenditure ratio	lag_REDE	10,821	1.50	7.09	0	418.18

This study explores the treatment effect of utilizing new technologies associated with the Fourth Industrial Revolution on a firm's economic performance; therefore, it is first necessary to investigate whether such a difference actually exists. A comparison of annual sales revenue reveals that firms utilizing these new technologies have an average annual revenue of approximately 87.5 billion BDT (log 11.38 million BDT), whereas those that do not have an average of approximately 38.6 billion BDT (log 10.56 million BDT). This difference is statistically highly significant $= 0.82$, $t = 11.70$, $p < 0.001$.

Since the covariates used for propensity score estimation are only useful if they vary in relation to the treatment variable in this case, the adoption of new technologies associated with the Fourth Industrial Revolution we examined the differences in these covariates based on whether or not such technologies were adopted Figure 1. Statistically significant differences were observed in total asset turnover $d = -1.02$, $t = -5.16$, $p < 0.001$, the number of intellectual property rights $d = 0.74$, $t = 15.60$, $p < 0.001$, and the ratio of R&D expenditures $d = 2.28$, $t = 5.93$, $p < 0.001$. Although some variables did not show statistically significant differences, they are nonetheless included in the propensity score estimation because they were selected based on a review of prior research.

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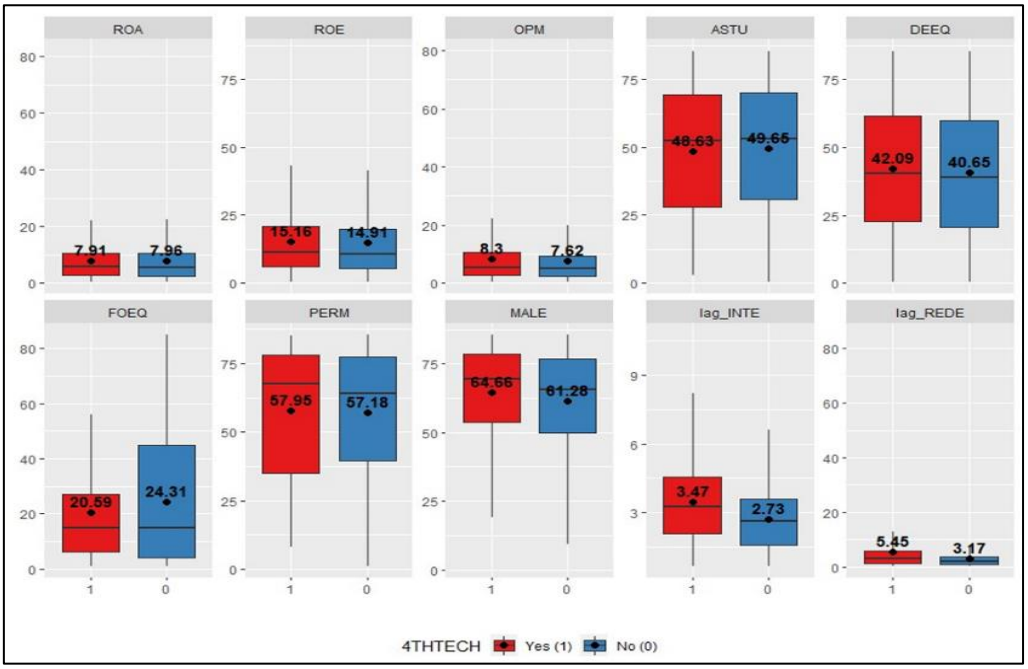


Fig 1 Differences in Covariates Based on the Utilization of New Technologies from the Fourth Industrial Revolution

Table 2 Results of Frequency Analysis

Variable		Category (Value)	Frequency	Composition ratio (%)	Cumulative percentage (%)
Whether new technologies of the Fourth Industrial Revolution are utilized	4THTECH	Yes(1)	850	7.85	7.85
		No (0)	9,971	92.14	100.00
Whether engaged in manufacturing	MANU	Yes(1)	5,260	48.61	48.61
		No (0)	5,561	51.39	100.00
Whether it is a service industry	SERV	Yes(1)	5,040	46.58	46.58
		No (0)	5,781	53.42	100.00
Whether it is an advanced manufacturing industry	MAHI	Yes(1)	3,054	28.22	28.22
		No (0)	7,767	71.78	100.00
Whether it is a high-tech service industry	SEHI	Yes(1)	2,178	20.13	20.13
		No (0)	8,643	79.87	100.00
Presence of subsidiaries	SUBS	Yes(1)	4,898	45.26	45.26
		No (0)	5,923	54.74	100.00
Presence of a parent company	PARE	Yes(1)	2,706	25.01	25.01
		No (0)	8,115	74.99	100.00
Whether an enterprise is a small or medium-sized enterprise (SME)	SMSE	Yes(1)	10,110	93.34	93.34
		No (0)	721	6.66	100.00
Listing status	LIST	Yes(1)	1,722	15.91	15.91
		No (0)	9,099	84.09	100.00
Whether a strategic alliance exists	lag_STRA	Yes(1)	552	5.10	5.10
		No (0)	10,269	94.90	100.00

A frequency analysis was conducted for the treatment variable measured as a discrete variable and the remaining covariates Table 2. Among all the firms, 7.85% were found to utilize new technologies associated with the Fourth Industrial Revolution. Furthermore, the manufacturing and service sectors combined accounted for 95.46% of all industries, while high-tech manufacturing and high-tech services together represented 48.35%. Meanwhile, the proportion of small and medium-sized enterprises was calculated at 93.34% a figure that deviates somewhat from official statistics, which typically report this proportion to be over 99%.

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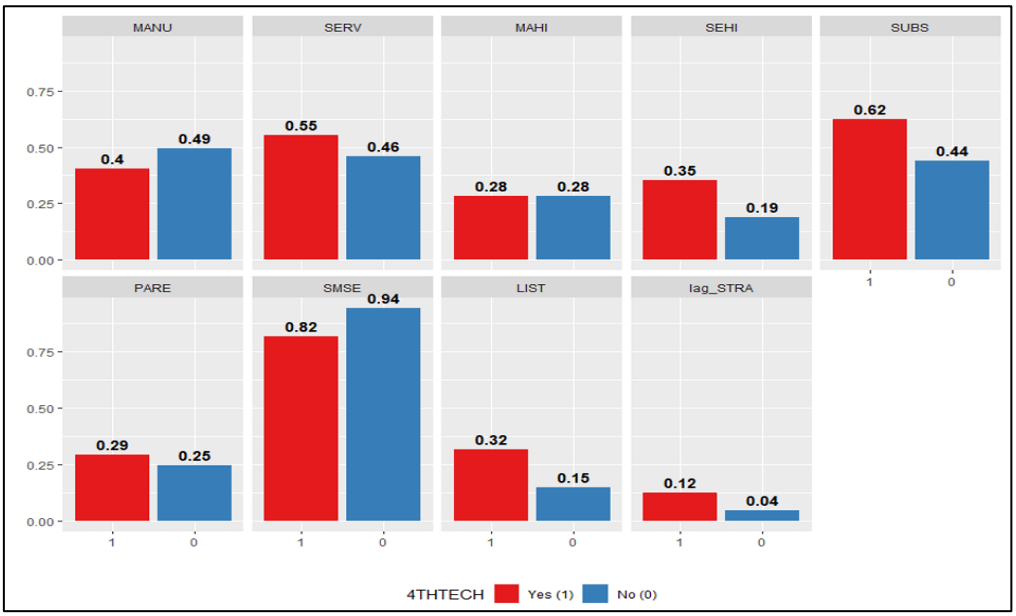


Fig 2 Differences in Covariates Based on the Utilization of New Technologies from the Fourth Industrial Revolution

We examined whether these variables differed based on the adoption of new technologies associated with the Fourth Industrial Revolution Figure 2 and conducted statistical tests to verify these differences. The results indicate that, with the exception of whether a firm belongs to the advanced manufacturing sector $\chi^2 = 0.00$, $p < .980$, most covariates including whether a firm operates in the manufacturing sector $\chi^2 = 24.81$, $p < .001$, the service sector $\chi^2 = 28.56$, $p < .001$, or the advanced service sector $\chi^2 = 130.97$, $p < .001$, the presence of a subsidiary $\chi^2 = 107.99$, $p < .001$, or a parent company $\chi^2 = 8.79$, $p < .01$, whether a firm is an SME $\chi^2 = 188.67$, $p < .001$ whether it is publicly listed $\chi^2 = 166.84$, $p < .001$, and whether it has entered into strategic alliances $\chi^2 = 98.59$, $p < .001$, showed statistically significant differences at conventional levels.

- *Current Status of the Use of New Technologies from the Fourth Industrial Revolution*

The treatment variable and the core variable in this study is whether or not a firm utilizes new technologies associated with the Fourth Industrial Revolution. We examined the specific technologies employed by the 850 firms previously identified as users of such Fourth Industrial Revolution technologies. As shown in Figure 3, these technologies are utilized by the following number of firms: 242 (2.24%) for the Internet of Things (IoT), 275 (2.54%) for cloud computing, 289 (2.67%) for big data, 362 (3.35%) for mobile technologies, 147 (1.36%) for artificial intelligence, 81 (0.75%) for blockchain, 97 (0.90%) for 3D printing, 87 (0.80%) for robotics, and 86 (0.79%) for virtual and augmented reality. These findings indicate a relatively higher adoption rate for the Internet of Things, cloud computing, big data, and mobile technologies collectively referred to as ICBM compared to other new technologies.

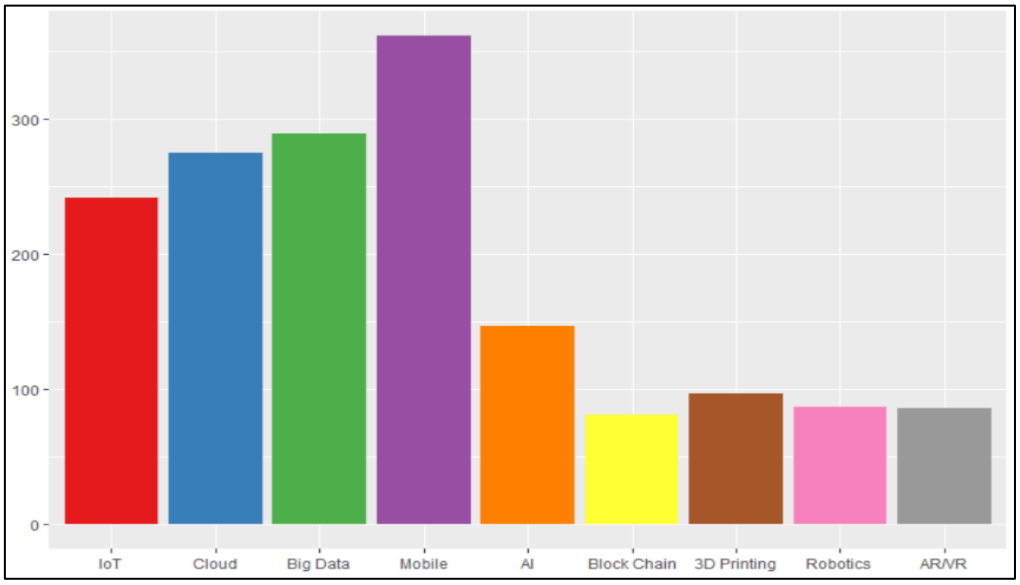


Fig 3 Number of Companies Utilizing New Technologies of the Fourth Industrial Revolution

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➢ *Preliminary Analysis: The Relationship between Treatment Variables and Covariates*

- *Correlation Analysis Results*

A Pearson correlation analysis was conducted to examine the relationships between the treatment variable and the covariates Figure 4. The results indicated significant correlations between the use of new technologies associated with the Fourth Industrial Revolution and the following variables: total asset turnover $r = -0.03$, $p < .001$, manufacturing sector status $r = -0.05$, $p < .001$, service sector status $r = 0.05$, $p < .001$, advanced service sector status $r = 0.11$, $p < .001$, presence of a subsidiary $r = 0.10$, $p < .001$, presence of a parent company $r = 0.03$, $p < .001$, small and medium-sized enterprise status $r = -0.13$, $p < .001$, publicly listed status $r = 0.12$, $p < .001$, engagement in strategic alliances $r = 0.10$, $p < .001$, number of intellectual property rights $r = 0.17$, $p < .001$, and the ratio of R&D expenditure $r = 0.07$, $p < .001$.

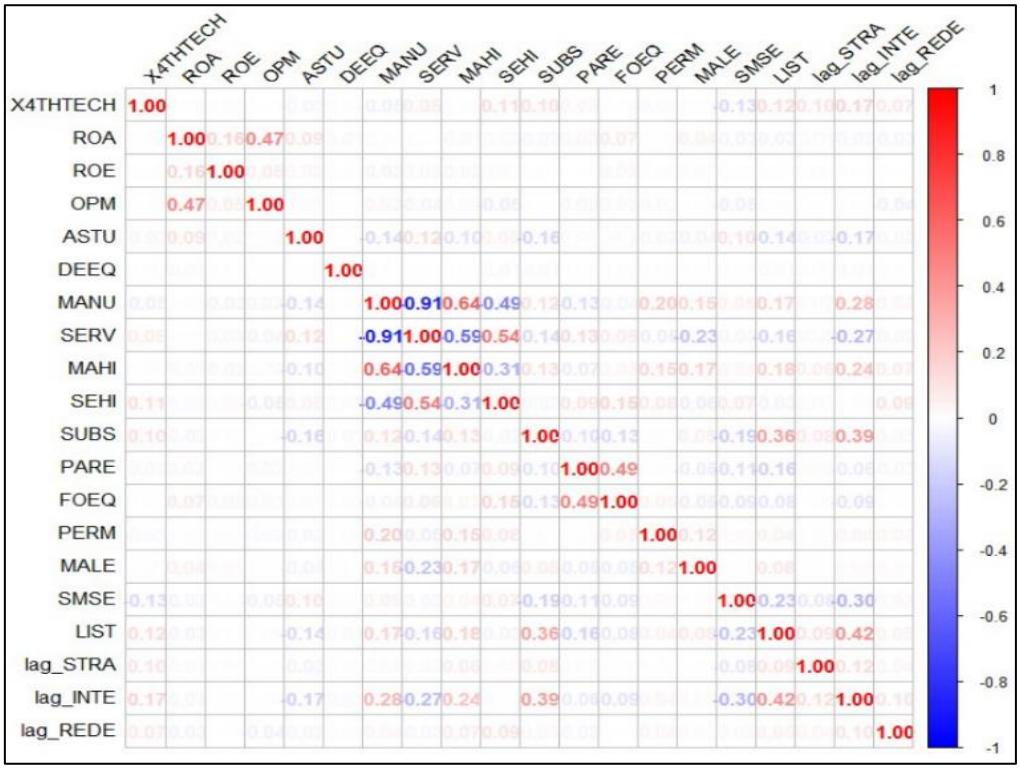


Fig 4 Correlation between Treatment Variables and Covariates

- *Probit Regression Analysis Results*

A probit regression analysis was conducted to examine how the previously observed correlations manifest when the influence of each variable is controlled for Table 3. The results indicate that firms utilizing new technologies associated with the Fourth Industrial Revolution differ from those that do not across various characteristics. Specifically, the adoption of such technologies shows a statistically significant positive correlation with structural firm characteristics such as whether the firm belongs to the advanced manufacturing sector $b = 0.18$, $p < .01$ or the advanced service sector $b = 0.44$, $p < .001$, the presence of subsidiaries $b = 0.12$, $p < .01$ or a parent company $b = 0.17$, $p < .001$, and whether the firm is publicly listed $b = 0.23$, $p < .001$. Conversely, it shows a statistically significant negative correlation with the proportion of regular employees $b = -0.00$, $p < .01$ and whether the firm is a small or medium-sized enterprise $b = -0.37$, $p < .001$. Furthermore, there is a highly significant positive correlation with variables representing a firm's innovative characteristics, including the number of intellectual property rights $b = 0.37$, $p < .001$, the ratio of R&D expenditure $b = 0.11$, $p < .001$, and the existence of strategic alliances $b = 0.01$, $p < .001$.

Table 3 Probit Regression Analysis Results Regarding the Relationship between the Treatment Variable and Covariates

Dependent variable: Whether or not new technologies of the Fourth Industrial Revolution are utilized					
Variable		**Coef. (SE)**	**Variable**		**Coef. (SE)**
Return on Total Assets	ROA	0.00 (0.00)	Presence of a parent company	PARE	0.17*** (0.05)
Return on Equity	ROE	-0.00 (0.00)	Proportion of foreign capital	FOEQ	-0.00 (0.00)
Operating profit margin	OPM	0.00 (0.00)	Proportion of regular employees	PERM	-0.00 (0.00)

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Total Asset Turnover	ASTU	0.00 (0.00)	Proportion of male employees	MALE	-0.00 (0.00)
Debt-to-equity ratio	DEEQ	-0.00 (0.00)	Small or medium-sized enterprise	SMSE	-0.37*** (0.07)
Manufacturing	MANU	-0.08 (0.11)	Listing status	LIST	0.23*** (0.05)
Service of industry	SERV	0.13 (0.11)	Number of Intellectual Property Rights	lag _INTE	0.37*** (0.07)
Manufacturing industry	MAHI	0.18** (0.06)	R&D expenditure ratio	lag _REDE	0.11*** (0.01)
High-tech service industry	SEHI	0.44*** (0.06)	Strategic alliance exists	lag _STRA	0.01*** (0.00)
Presence of subsidiaries	SUBS	0.12** (0.04)	constant term		-1.29*** (0.17)

Note: *p < .05, **p < .01, ***p < .001

This discrepancy demonstrates that, as in standard regression analysis, simply including these covariates as control variables is insufficient to accurately estimate the economic impact of utilizing new technologies associated with the Fourth Industrial Revolution. Consequently, it is evident that a quasi-experimental approach such as propensity score matching, which allows for the appropriate definition of treatment and control groups is necessary.

➢ *Propensity Score Estimation and Matching Results*

- *Estimation of Propensity Scores and Assessment of the Common Support Region*

✓ *Propensity Score Estimation*

It was previously established that imbalances in certain covariates influence the probability of a firm adopting new technologies associated with the Fourth Industrial Revolution. Consequently, the probability of adopting such technologies that is, the probability of each observation being assigned to the treatment group was defined as the propensity score. These propensity scores were estimated using the RandomForest, which implements the random forest algorithm. In general, machine learning models are trained by partitioning data into training, testing, and validation sets to maximize predictive performance. However, in this study, such a partition is not employed, given that machine learning is used solely to calculate balancing scores, and because the random forest algorithm inherently stabilizes error estimates by utilizing OOB samples (Hastie et al., 2009).

The simulation results for the out-of-bag error rate are presented in Figure 5. To maximize classification accuracy, only 3 out of the 19 total covariates were used for each tree in the random forest. Furthermore, the number of trees was set to 5,000, following the recommendation of (Hastie et al. 2009). The resulting model achieved a classification accuracy of 92.16%.

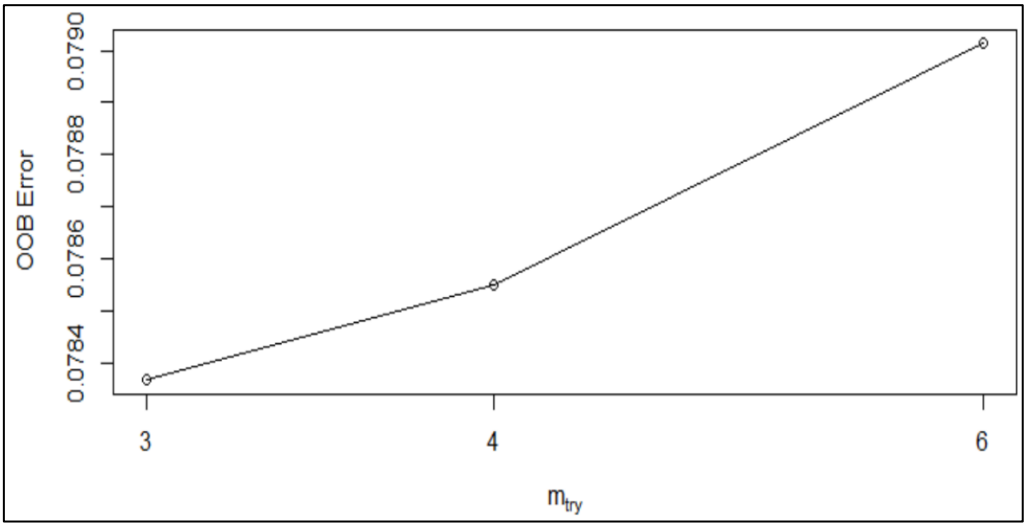


Fig 5 Out-of-Bag (OOB) Error Rate of the Model Based on Variable Parameters

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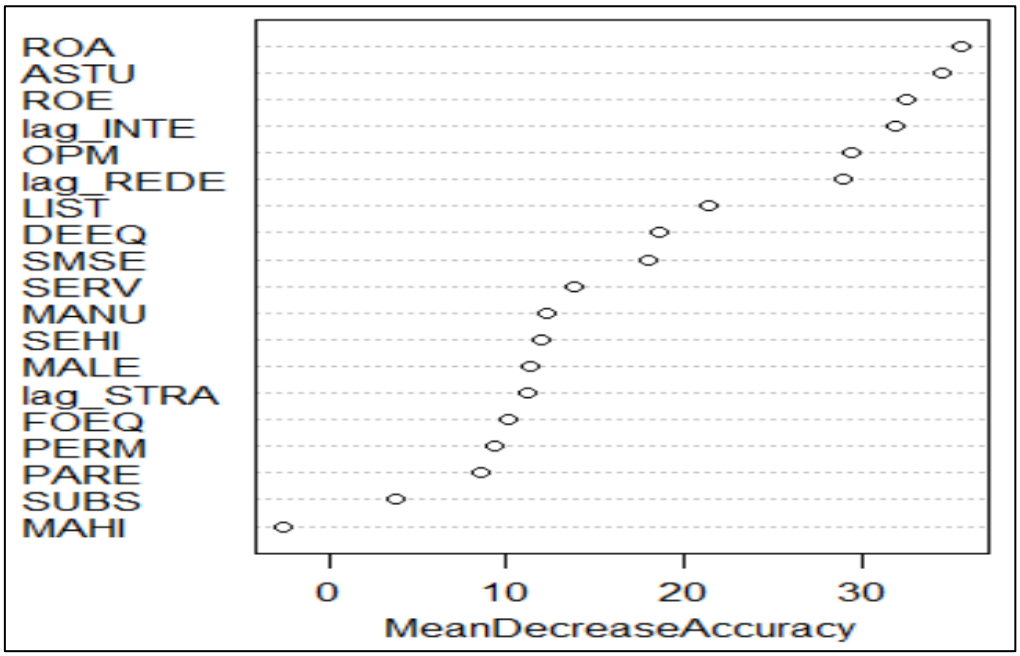


Fig 6 Importance of the Covariates Used in Model Construction

The random forest algorithm provides information on the importance of variables used in tree-based classification (James et al., 2013). In this study, mean decrease in accuracy was employed as a metric for variable importance; it represents the average extent to which the splitting of nodes based on a given covariate reduces the model's accuracy. An examination of covariate importance using this metric Figure 6 reveals that factors such as return on total assets, total asset turnover, return on equity, the number of intellectual property rights, the operating profit margin on sales, and the ratio of R&D expenditures are highly influential in distinguishing whether or not a firm adopts new technologies associated with the Fourth Industrial Revolution. This result differs significantly from that of the preceding probit regression analysis, demonstrating that an ensemble-based machine learning approach to augmented propensity scores which is robust to interaction effects and non-linear correlations is exceptionally well-suited for achieving the objectives of this study.

✓ *Inspection of Common Support Areas*

To assess how effectively propensity scores estimated via Random Forest can be used to estimate treatment effects, we examined the extent of the common support region shared between the treatment and control groups Figure 7. Most observations from the treatment group fall within the common support region alongside observations from the control group, confirming that there are no significant issues regarding the estimation of treatment effects.

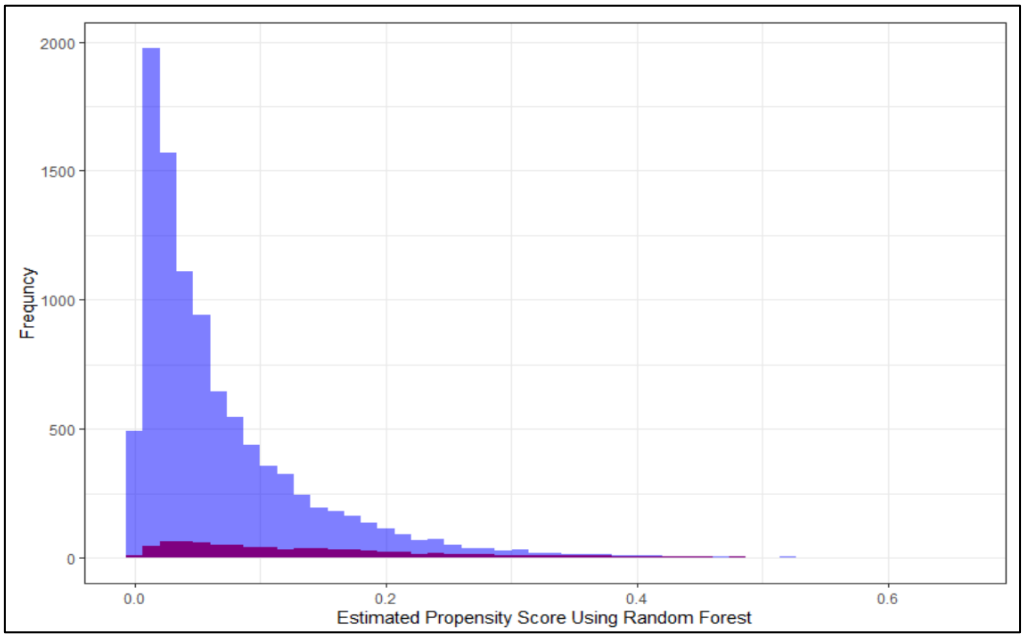


Fig 7 Estimated Propensity Scores and the Region of Common Support for the Treatment and Control Groups

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- *Propensity Score Matching and Assessment of Covariate Balance*

Matching was performed using the estimated propensity scores. The (MatchIt v4.4.0) package was used for the matching process, while the (cobalt v4.3.2) package was employed to assess and visualize covariate balance. As this study estimates the Average Treatment Effect effect for the entire population propensity score matching was conducted to estimate both the Average Treatment Effect on the Treated and the Average Treatment Effect on the Untreated. A comparison of the propensity score distributions between the treatment and control groups before and after matching Figures 8 and 10 confirms that balance in propensity scores was effectively achieved. Furthermore, plots were generated to examine the balance of individual covariates. Through these plots, the differences in the means and variance ratios of the standardized covariates were assessed before and after propensity score matching Figures 9 and 11. According to established rules of thumb, a mean difference of 0.1 or 0.25 is considered an acceptable threshold (Stuart et al., 2013), while a variance ratio of 1 is considered ideal, and a value of 2 or less is generally deemed acceptable (Zhang et al., 2019). Based on these criteria, it can be concluded that covariate balance was successfully maintained in both the propensity score matching for the ATT and the matching for the ATU.

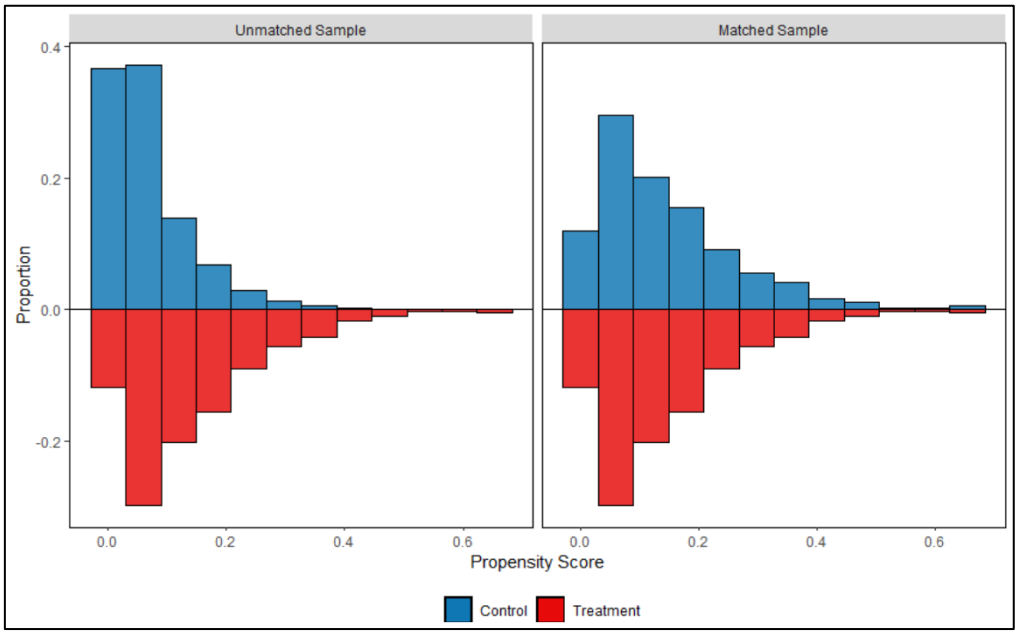
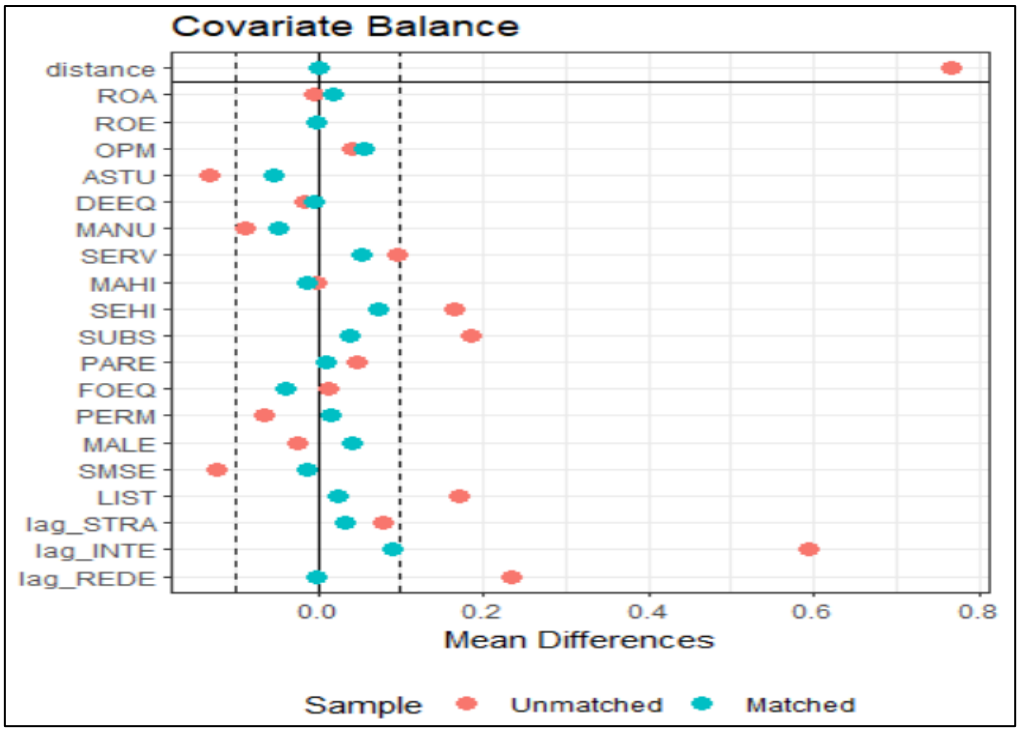


Fig 8 Comparison of Propensity Score Distributions between the Treatment and Control Groups Before and After Propensity Score Matching, Conducted to Estimate the Average Treatment Effect on the Treated (ATT)



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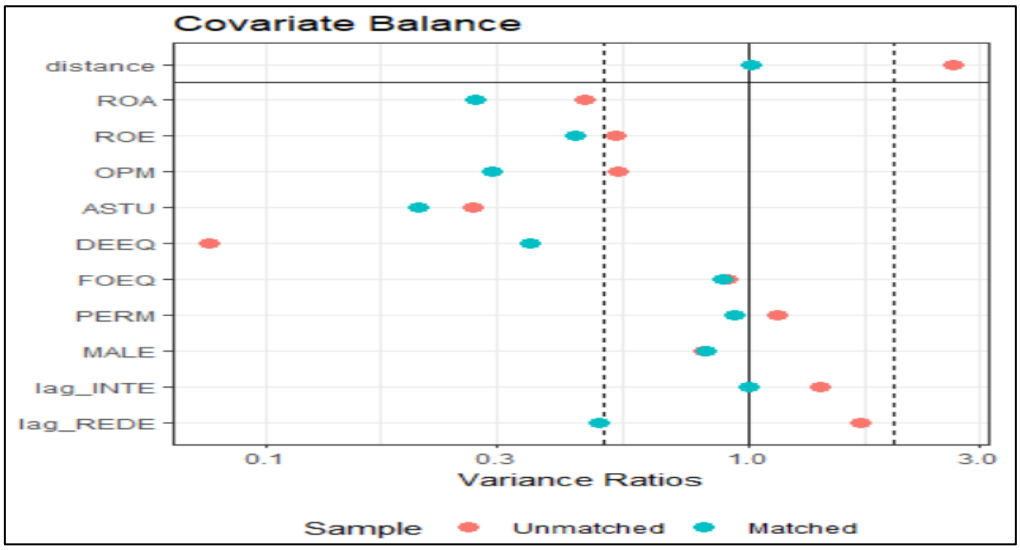


Fig 9 Examination of Differences in the Means and Variance Ratios of Standardized Covariates Before and After Propensity Score Matching for the Estimation of the Average Treatment Effect on the Treated (ATT)

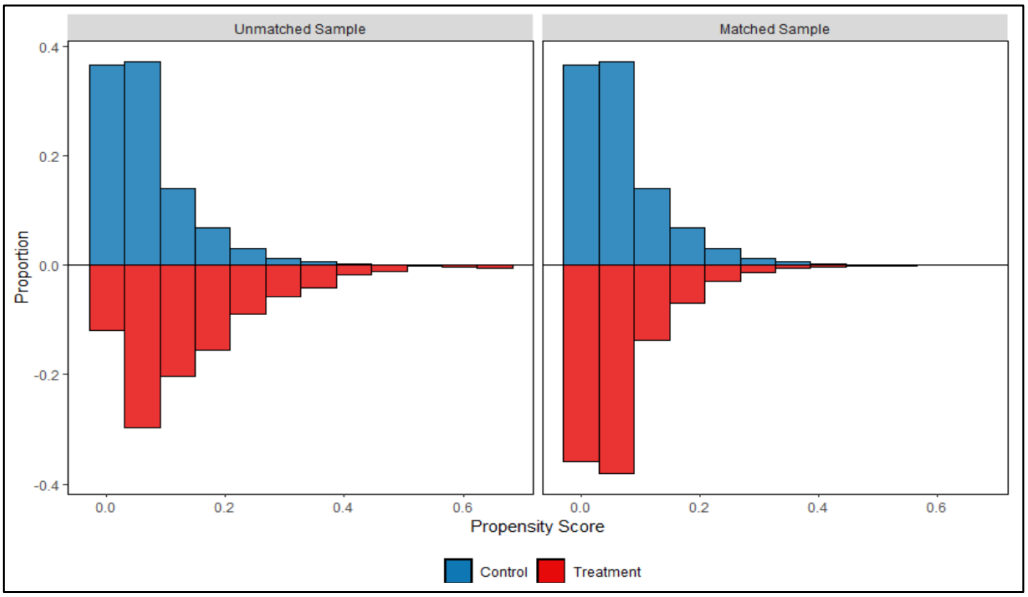
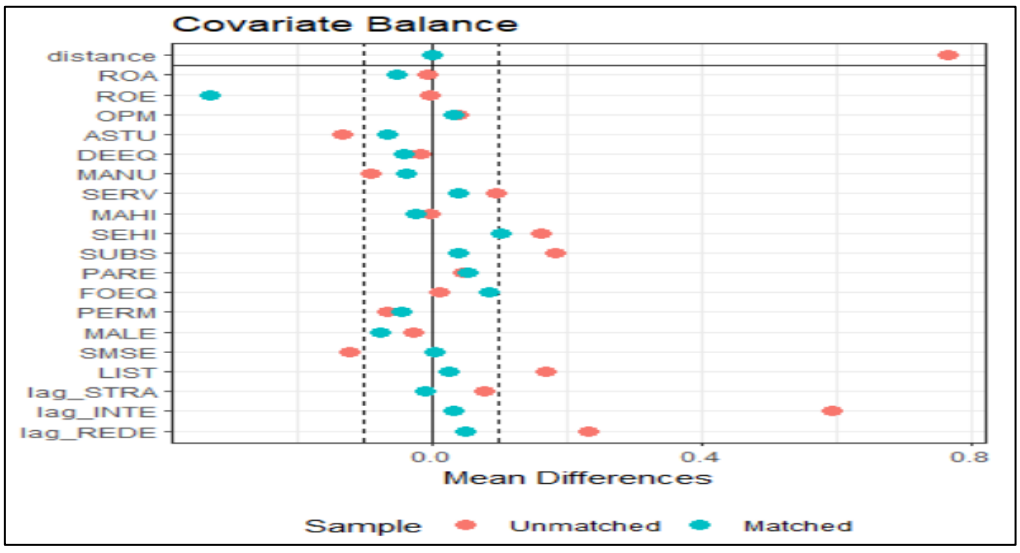


Fig 10 Comparison of Propensity Score Distributions for the Treatment and Control Groups Before and After Propensity Score Matching for the Estimation of the Average Treatment Effect on the Controls (ATC)



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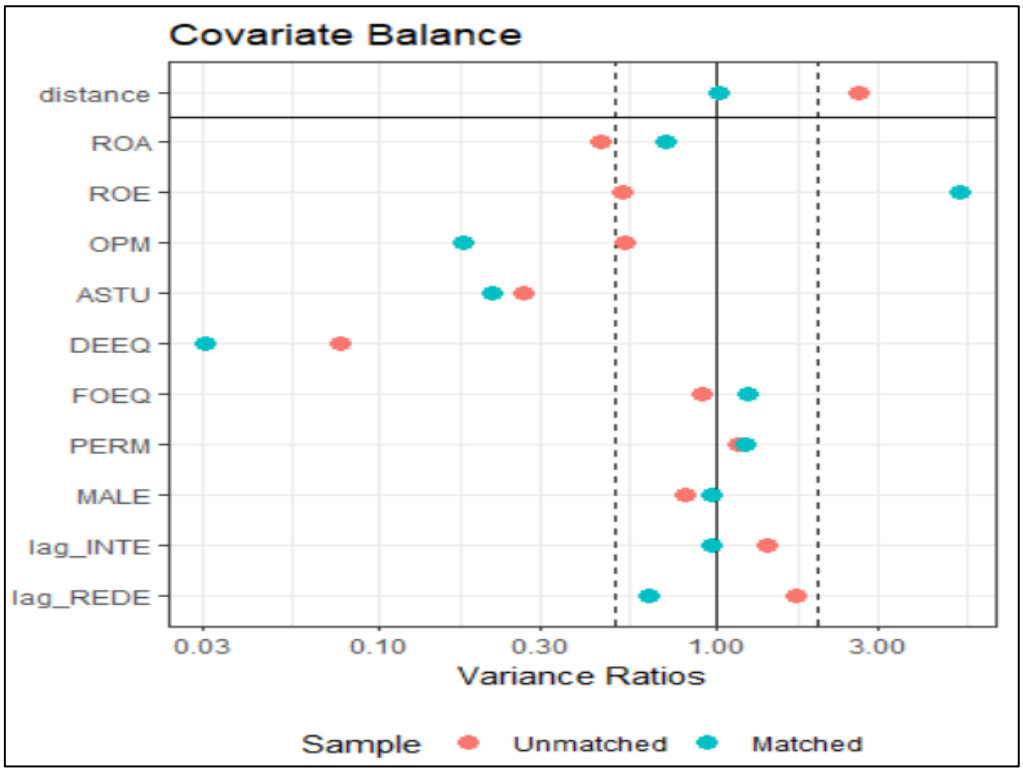


Fig 11 Examination of Differences in the Means and Variance Ratios of Standardized Covariates Before and After Propensity Score Matching for the Estimation of the Average Treatment Effect on the Controls (ATC)

➢ *Estimation Results of Treatment Effects and Sensitivity Analysis*

- *Results of Treatment Effect Estimation*

We estimated the treatment effect of utilizing new technologies associated with the Fourth Industrial Revolution on the economic performance of firms. The (MatchIt v4.4.0) package was used for this estimation, consistent with the approach taken during the matching process. A summary of the analysis results is presented in Table 4. The primary finding the Average Treatment Effect was estimated at 0.3289 $p < .001$. This indicates that firms utilizing new technologies from the Fourth Industrial Revolution exhibit an annual revenue approximately 39% higher ($(= e^{0.3289} - 1) \times 100$) than those that do not. Meanwhile, the Average Treatment Effect on the Treated was estimated at 0.2570 ($p < .001$), and the Average Treatment Effect on the Untreated (ATU) was calculated at 0.4629 $p < .001$. Furthermore, an estimate derived from a standard regression analysis was 0.1287 $p < .001$, confirming the presence of a significant negative bias resulting from selection bias. These figures are compared in Figure 12.

Table 4 Treatment Effects of the Adoption of New Technologies from the Fourth Industrial Revolution on Firm Economic Performance

Analysis Method		**Estimate (SE)**	**95% CI**
Method	**Estimand**		
Propensity score matching	Average Treatment Treated (ATT)	0.2570*** (0.0757)	[0.1086, 0.4055]
	Average Treatment (ATC)	0.4629*** (0.1235)	[0.2208, 0.7050]
	Average Treatment Effect (ATE)	0.3289*** (0.0656)	[0.2003, 0.4575]
General regression analysis		0.1287*** (0.0384)	[0.2039, 0.2791]

Note: 1) Estimates from the general regression analysis were obtained using ordinary least squares (OLS) with covariates included as control variables. 2) For propensity score matching, cluster-robust standard errors (Zeger and Liang, 1986) calculated using the (sandwich v3.0-2) package were applied. 3) *p < .05, **p < .01, ***p < .001.

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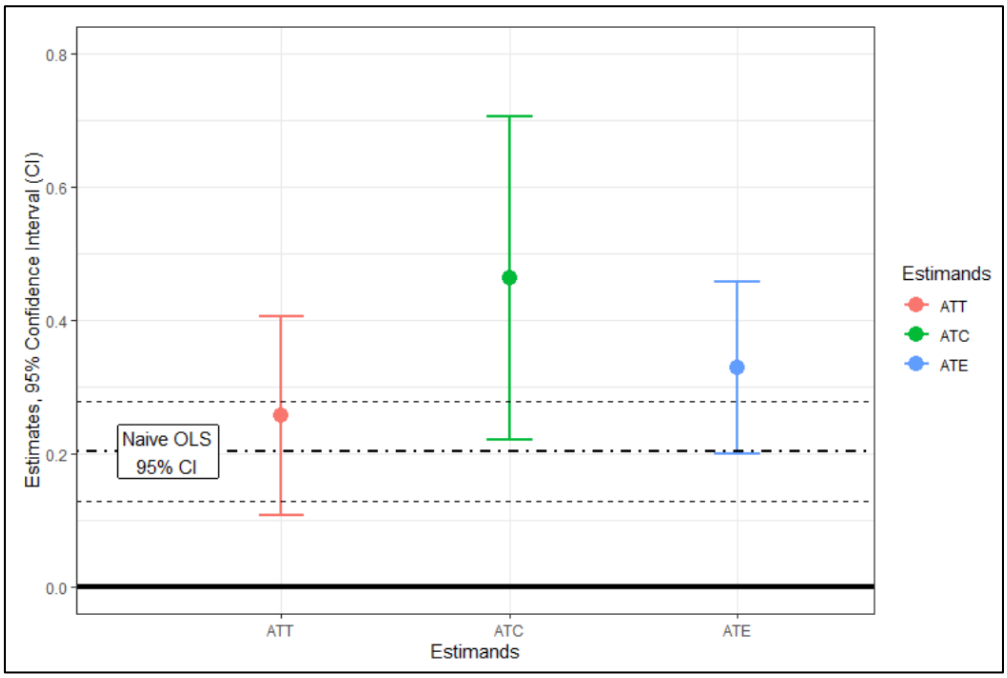


Fig 12 Comparison of Treatment Effect Estimates

- *Results of Sensitivity Analysis*

To examine the robustness of the previously estimated treatment effects against omitted variable bias, a Rosenbaum sensitivity analysis (Rosenbaum, 2015) was conducted. Among the three previously estimated treatment effects, the average treatment effect for the entire population is a weighted average of the average treatment effect for the treated group and the average treatment effect for the control group therefore, the analysis was performed only for the estimates of the average treatment effect for the treated group and the average treatment effect for the control group. The (sensitivityfull v1.5.6) package was used for this purpose.

The results of the analysis are presented in Table 5. The parameter γ, derived from Rosenbaum's sensitivity analysis, serves as a sensitivity parameter related to hidden bias stemming from covariates not included in the estimation of propensity scores. A value of $\gamma = 1$ corresponds to the assumption of random treatment assignment, whereas $\gamma = 2$ implies that, even with identical observed covariates, the presence of an omitted covariate could make the probability of treatment assignment twice as high (Rosenbaum, 2007). Consequently, if a scenario exists where $\gamma = 2$, the treatment effect estimated via propensity score matching could be considered invalid. Although there is no absolute standard, a higher threshold value for Γ indicates that the estimate is more robust against bias caused by omitted variables.

Table 5 Results of Rosenbaum Sensitivity Analysis

Estimand	γ	p-vale
Average Treatment Treated (ATT)	1.0	0.0000
	1.1	0.0014
	1.2	0.0254
	1.3	0.1592
Average Treatment Controls (ATC)	1.0	0.0000
	1.1	0.0001
	1.2	0.0196
	1.3	0.1316

Note: Results are based on a one-sided test with a significance level of 0.05.

In this study, the γ threshold for the estimated average treatment effect on the treated group was 1.2 $p = 0.0254$, while the γ threshold for the average treatment effect on the control group was 1.3 $p = 0.1316$ values that are nearly identical. This suggests that if there were an unobserved covariate one that influences a firm's adoption of new technologies related to the Fourth Industrial Revolution but was not included in this study that increased the probability of treatment assignment by a factor of approximately 1.3, then the previously estimated treatment effect might no longer be statistically distinguishable from zero. However, it is important to interpret this result with caution, as it is based on a hypothetical scenario (DiPrete and Gangl, 2004)

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essentially a sensitivity analysis that considers a worst-case scenario.

➢ *Supplementary Analysis: Comparison of Small and Medium-sized Enterprises and Large Enterprises*

The impact of utilizing new technologies associated with the Fourth Industrial Revolution on corporate performance may vary depending on firm size. Consequently, an additional analysis was conducted to examine the differences in estimated treatment effects between small and medium-sized enterprises (SMEs) and large enterprises Table 6 and Figure 13. The estimated average treatment effect for the entire sample indicates that the economic impact of utilizing new Fourth Industrial Revolution technologies is 0.3587 $p < .001$ for SMEs and 0.5714 $p < .001$ for large enterprises. This suggests that, among SMEs, firms that utilize these new technologies have an annual revenue approximately 43% $((e^{0.3587} - 1) \times 100)$ higher than those that do not; for large enterprises, this figure is approximately 77% $((e^{0.5714} - 1) \times 100)$. Thus, there is a 34% difference in the revenue-enhancing effect between SMEs and large enterprises.

Table 6 Estimation Results of Treatment Effects for Small and Medium-sized Enterprises (SMEs) and Large Enterprises

Estimand	Small and medium-sized enterprises (SMEs)	Large corporation
	Estimate (SE)	Estimate (SE)
Average Treatment Treated (ATT)	0.1748*** (0.0638)	0.6334*** (0.1392)
Average Treatment Controls (ATC)	0.4242*** (0.1092)	0.5055*** (0.1216)
Average Treatment Effect (ATE)	0.3587*** (0.1088)	0.5714*** (0.1155)

Note: 1) For propensity score matching, cluster-robust standard errors (Zeger and Liang, 1986) calculated using the (sandwich v3.0-2) package were applied. 2) *p < .05, **p < .01, ***p < .001

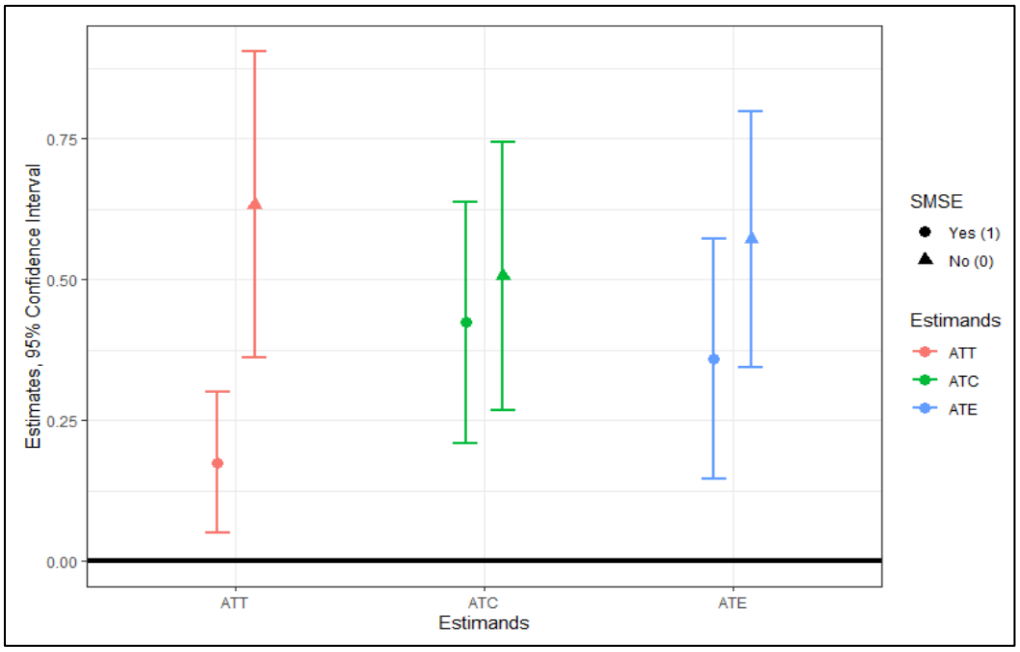


Fig 13 Comparison of Treatment Effect Estimates for Small and Medium-Sized Enterprises Versus Large Enterprises

VI. DISCUSSIONS AND CONCLUSION

This study empirically examines the impact of utilizing new technologies associated with the Fourth Industrial Revolution on the economic performance of firms. To mitigate endogeneity issues a common challenge in prior research we employed propensity score matching based on the potential outcomes framework for causal inference. Furthermore, we utilized a random forest algorithm a type of machine learning technique to maximize the accuracy of propensity score estimation. The key findings of this study and their policy implications are presented below.

There were systematic differences between firms that utilize new technologies associated with the Fourth Industrial Revolution and those that do not. While variations appeared across various corporate characteristics, the most significant differences were found in the firms innovative attributes. Companies leveraging these new technologies exhibited a statistically significant higher number of intellectual property rights and a greater ratio of R&D expenditure compared to their counterparts; they were also more likely to have formed strategic alliances with other firms. This suggests that the adoption of new technologies may, in a broad sense, be a component of the technological innovation process or a form of diversification in technology management.

An examination of the differences in propensity scores among firms based on their adoption of new technologies associated with the Fourth Industrial Revolution reveals a

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significant disparity. This indicates that the adoption of these new technologies is unevenly distributed across firms, depending on their specific characteristics. If the adoption of such technologies is both influenced by a firm's unique attributes and, in turn, affects its economic performance, the performance gap between firms could widen over time potentially leading to high market concentration among a few large corporations. Consequently, continuous monitoring is essential.

The adoption of new technologies associated with the Fourth Industrial Revolution has been shown to increase a firm's annual revenue by approximately 40%. This finding is significant because it provides a rigorous estimate derived through a quasi-experimental approach and machine learning that effectively controls for endogeneity, a step that distinguishes it from figures reported in previous studies. In essence, it quantifies the contribution of these Fourth Industrial Revolution technologies a novel form of business activity to a firm's economic performance. Furthermore, the analysis is highly meaningful as it is not restricted to any specific industry or firm size. Therefore, to consistently enhance the economic performance of domestic firms, it is essential to establish and implement a national-level roadmap aimed at the systematic development and dissemination of new technologies related to the Fourth Industrial Revolution.

Furthermore, this study examined whether the economic impact of utilizing new technologies associated with the Fourth Industrial Revolution varies by firm size. The findings indicate that, among small and medium-sized enterprises, those that utilize these new technologies exhibit approximately 43% higher annual revenue, whereas for large enterprises, the figure is about 77% higher. This suggests that, within the context of the Fourth Industrial Revolution, larger firms possess a greater capacity to leverage newly adopted technologies compared to smaller ones. Consequently, if one views the adoption of Fourth Industrial Revolution technologies as a component of the technological innovation process, it becomes imperative for SMEs to cultivate mutually interdependent relationships with large enterprises. This is supported by the earlier finding that strategic alliances with other firms significantly influence a company's decision to adopt new technologies related to the Fourth Industrial Revolution. Meanwhile, to prevent this disparity from exacerbating polarization between firms or slowing the growth of SMEs, it is essential to strengthen the capabilities of SMEs and establish support systems tailored to their specific stages of growth. Expanding the adoption of new technologies such as those integrated with smart factory initiatives (Chung and Chung, 2021) is also a strategy worth considering.

While this study offers various significant contributions, it also has clear limitations. First, Bangladesh Bureau of Statistics (BBS) data provides industry classifications only up to the medium-category level, making it impossible to account for more granular classifications. Consequently, the scope of the knowledge-based service industry used to construct the covariates could not be defined with absolute precision. This is an aspect that warrants improvement in future iterations of the BBS data. Second, although propensity score matching was employed to control for endogeneity, concerns remain regarding potential bias from omitted variables, as well as the possibility that the stable unit treatment value assumption may have been violated due to spillover effects such as those arising from strategic alliances with external firms. Therefore, future research should aim to address these limitations, ideally by conducting longitudinal studies that incorporate BBS data from 2024 onwards.

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