The Impact of Twin Transition on Firms' Business Performance: Empirical Evidence from Korean Manufacturing Firms

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CHOI, Jihoon

THESIS

Submitted to

KDI School of Public Policy and Management

In Partial Fulfillment of the Requirements

For the Degree of

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All glory and honor to my Lord, Jesus Christ.

**This research used the Korean Innovation Survey (KIS) data provided by the Science and Technology Policy Institute (STEPI).*

Abstract

The Impact of Twin Transition on Firms' Business Performance: Empirical Evidence from Korean Manufacturing Firms

Driven by the critical global demand for twin transition, the simultaneous pursuit of decarbonization and digitalization, the objective of this study is to empirically examine the impact of the joint adoption of eco-innovation and digital technologies on sales performance in the Korean manufacturing sector and to identify the implications of this strategic response to both market pressures and environmental challenges. The analysis, which uses data from the Korea Innovation Survey 2022 and employs propensity score matching techniques, shows significant positive effects on sales for firms that adopt both eco-innovation and digital technology. Specifically, the average treatment effect on the treated, in terms of increases in sales for firms that adopted both an eco-innovation and a new digital technology, was estimated at 46.1% and 38.6%. The study also explores the impact of combining eco-innovation with specific digital technologies. The results show significant sales increases for firms that combined eco-innovation with big data, cloud computing, or 5G telecommunications. These findings highlight the strategic importance of the twin transition, suggesting that firms that integrate eco-innovation with such technologies can enhance their business performance. This research underscores the need for supportive policies and incentives that promote sustainable growth and a competitive advantage by supporting the joint adoption of eco-innovations and new digital technologies.

Keywords: *twin transition, eco-innovation, digital transformation, firm's performance*

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1 Introduction

In recent years, the global business landscape has been reshaped by two pivotal megatrends: decarbonization and digitalization. These trends, often referred to collectively as the twin transition, represent an irresistible force driving profound changes across industries and economies worldwide (Muench et al., 2022). Decarbonization, the shift toward low-carbon energy sources and processes, is not just an environmental goal but also an economic one, characterized by structural change and innovation (Ayres & van den Bergh, 2005). It reflects growing recognition of the need to address the urgent challenges posed by climate change (Fay et al., 2015). Simultaneously, digitalization—the integration of digital technologies into all aspects of business—is transforming how companies operate, compete, and deliver value to customers (Colli et al., 2021).

Specific cases underscore the importance of the twin transition. According to Muench et al. (2022) and Celeste & Dominioni (2023), this transition has become a key priority for European businesses, reflecting a broader global trend. Additionally, Faivre et al. (2023) have highlighted a surge in investments by EU and US firms in digital and green technologies, signaling a widespread corporate response to these megatrends. Moreover, external shocks such as the COVID-19 pandemic and escalating concern over climate change have accelerated this dual transition, compelling firms to adapt rapidly (Herrmann et al., 2014).

The urgent need to motivate firms toward long-term commitments to both decarbonization and digitalization is increasingly evident. Kraus et al. (2020) have argued that in recent decades, environmental concerns have increasingly influenced industrial practices. In addition, Rehman et al. (2023) have argued that the quest for technological advancement has driven the fourth industrial revolution, commonly known as Industry 4.0. This revolution is associated with several contemporary technological developments including the internet of things (IoT), cyber-physical systems, digitalization, cloud computing, artificial intelligence (AI), automation and robotics, as well as additive manufacturing techniques. This leads me to two key questions: 1) How can stakeholders motivate firms to engage in eco-innovation and digital transformation? 2) What benefits can firms reap from pursuing both types of innovation? This study examines how a joint focus on eco-innovation and digital transformation can influence a company's business performance, a strong internal driver of change.

Despite the recognized importance of the twin transition, there is a scarcity of research on the joint adoption of these trends and its impact on firm performance. The literature has predominantly focused on the drivers of such change, its measurement, and the effects of the adoption of the two respective trends on firm performance, while acknowledging the mutual impact of eco-innovation and digitalization (Hojnik, 2017). However, the effects of the simultaneous pursuit of eco-innovation and digitalization, particularly on sales, remain underexplored. To address this gap, this study proposes an empirical test using propensity score matching to examine the causal effect of the twin transition on firms' business performance. It aims to provide a comprehensive understanding of the effect of the joint adoption of eco-innovation and digitalization by comparing two types of firms: adopters of both trends and those who adopted neither.

Furthermore, the response of South Korean manufacturing firms to eco-innovation and digitalization, framed within the country's Green New Deal and overarching digital strategy, provides a distinctive context in which to examine the impacts of the twin transition. In 2008, Korea became the first OECD country to produce a comprehensive green growth strategy (Kamal-Chaoui et al., 2011), and its Green New Deal and the Digital New Deal it adopted in July

2020 aim to address climate change and to promote recovery from the COVID-19 pandemic, similarly to the EU's Green Deal (Kamal-Chaoui et al., 2011). Manufacturing firms are not only foundational to the nation's status as a global power (Herrmann et al., 2014), but also major contributors to climate change (Zailani et al., 2012). The COVID-19 pandemic further accelerated this trend, motivating this research on the effects of the twin transition on Korean manufacturing firms.

Thus, the objective of this study is to address an empirical gap by examining the impact of the joint adoption of eco-innovation and new digital technologies on sales performance in the Korean manufacturing sector and to identify the implications of this strategic response to both market pressures and environmental challenges.

The remainder of this study is structured as follows. Section 2 reviews the relevant literature, which laid the groundwork for the research. Section 3 and 4, respectively, describe the data and the methods used to investigate the impact of the twin transition on firm performance. Section 5 presents the results of the empirical analysis. Lastly, Section 6 discusses the findings in context and their implications for practice and concludes the study, summarizing its key insights and suggesting directions for future research.

2 Literature Review

2.1. Twin Transition

The concept of the twin transition is defined as an integrated process of decarbonization and digitalization. As highlighted by Fouquet & Hippe (2022), European economies have embraced this structural transformation brought about by the coevolution of energy and communication technologies, which in turn has led to the development of the high-tech and Information Communication Technology (ICT) sectors. In addition, Celeste & Dominioni (2023) have outlined the concept of a twin transition where digital technologies and policies aimed at reducing greenhouse gas emissions mutually support each other. Digital technologies can enhance the efficiency of energy management systems in both domestic and industrial settings, leading to reduced energy consumption and lower emissions. Also, policies to mitigate greenhouse gas emissions can drive businesses to adopt more energy-efficient digital technologies.

Furthermore, the importance of the twin transition extends beyond national frameworks to individual business strategies (Uhrenholt et al., 2022). Adopting both green initiatives and technological innovations is becoming a cornerstone for business success as well as the public welfare. This has been further underscored by Rehman et al. (2023), who noted that the COVID-19 pandemic emphasized the need for technology and environmental sustainability within the modern corporate landscape, pushing firms to make efforts toward achieving these dual goals.

While the trend toward twin transition has accelerated, research exploring the combined impact of eco-innovation and digitalization on business performance has remained scarce. Antonioli et al. (2018) have examined the impact of the combined adoption of ICT and environmental innovation on firms' labor productivity. Van Der Krogt et al. (2023) have also investigated the impact of the twin transition on the business performance of small and medium-sized enterprises (SMEs) in the construction sector. While these studies have provided important insights, the current examination of the twin transition as a resilience strategy in the South Korean manufacturing industry during and after the COVID-19 pandemic provides a new context for research in this area.

2.2. Eco-innovation

Eco-innovation, defined as the development, production, application, or utilization of a new product, service, or process that reduces environmental risks, pollution, or resource use throughout its lifecycle (Arundel & Kemp, 2009; Ron Kemp & Kemp, 2010), is central to sustainable growth. Eco-innovation can refer to innovations to products or business processes that mitigate environmental impacts by conserving energy or by minimizing waste, climate change, water usage, air pollution, or coal, oil, or electricity usage (Favot et al., 2023). OECD (2009) has defined eco-innovation as follows: “It is innovation that reflects the concept’s explicit emphasis on a reduction of environmental impact, whether such an effect is intended or not. Additionally, it is not limited to innovation in products, processes, marketing methods and organisational methods, but also includes innovation in social and institutional structures.”

Additionally, various empirical studies have highlighted the significance of demand-pull factors within the eco-innovation framework, illustrating that demand factors are crucial for fostering eco-innovation (Horbach, 2008; Wagner, 2007). Specifically, Horbach (2008) demonstrated that among German manufacturing firms, demand, particularly a firm’s expectation of increased turnover, serves as a key driver of eco-innovations. Similarly, Wagner (2007) suggested that “collaboration with predominantly environmentally concerned stakeholders—partly reflecting the activities of consumer protection associations—plays an important role for the generation of eco-innovative products." Overall, these findings underscore the idea that demand factors, calls for corporate responsibility, and consumer preferences for environmentally friendly products and processes significantly influence firms' decisions to invest in eco-innovation.

However, empirical studies, such as those reviewed by Hojnik (2017), have produced mixed findings regarding the impact of eco-innovation on firms' performance. While some have suggested that environmental efforts may impose financial burdens (Ghisetti & Rennings, 2014; Zeng et al., 2011), others have indicated that sustainable practices can lead to enhanced efficiency, new growth opportunities, higher profits, and a competitive advantage (Farza et al., 2021; Kim & Brown, 2019). These contradictions emphasize the complexity of eco-innovation's economic effects and the need for deeper investigation, particularly in the context of the strong version of the Porter hypothesis, which suggests that more stringent environmental regulations lead firms to adopt eco-innovation (Cleff & Rennings, 1999; Porter & Van der Linde, 1995).

2.3. Digitalization

Technology has been considered the main factor in economic growth, as mechanized production can be substituted for labor (Mokyr et al., 2015). Digitalization refers to the process by which business operations are transformed through the integration of digital technologies, a process that impacts organizational efficiency and market dynamics. It encompasses the use of cutting-edge technologies, such as big data, cloud computing, IoT, 5G telecommunications, AI, 3D printing, robotics, and blockchain, to improve production processes and supply chain management (Jung & Gómez-Bengoechea, 2022). These technological integrations may not only optimize current processes but also open up new business models or opportunities for growth and innovation. For instance, utilizing big data analytics allows companies to make better informed decisions by analyzing vast amounts of data to identify trends and patterns. This can lead to improved customer insights, product development, and market trend forecasting. Cloud computing enables businesses to access and utilize computing resources over the internet on demand. 5G networks provide faster data transmission rates, which improve the connectivity and responsiveness of IoT devices and mobile services that are essential for real-time operations. These technologies can be regarded as a form of process innovation that is driven by the pursuit of efficiency and cost minimization (Klepper, 1996; Utterback & Abernathy, 1975). According to Santoalha et al. (2021), who investigated relatedness to find a key driver of new specializations in the domain of green technology, a region's e-skills endowment is a positive predictor of its ability to specialize in new technological domains, especially green technology.

The drive toward technological advancement has fueled the Industry 4.0 revolution, which is associated with a spectrum of cutting-edge technical developments (Benassi et al., 2022; Martinelli et al., 2021). These include IoT, the fusion of computational and physical systems, the digitization of processes, cloud-based computing services, the application of AI, the rise of automated and robotic systems, and the growth of 3D printing technologies. As a consequence of these innovations becoming more commercialized and widespread, businesses have had to undergo significant transformations in their operational approaches (Rojko, 2017).

The applied literature on the impact of ICT has shown that facilitating such technologies provides novel opportunities for firm-level actions that result in higher productivity. Niebel et al. (2019) have examined the relationship between the firm's use of big data and product innovation. Rammer et al. (2022) investigated the relationship between AI and industrial innovation, suggesting that the use of AI technologies is associated with better results in terms of product and process innovation. Antonioli et al. (2024) have investigated the relationship between robot adoption and product innovation. Although some studies have examined the relationship between digitalization and business performance (Jardak & Ben Hamad, 2022; Li et al., 2022; Ren & Li, 2023), the scope of digitalization examined in research models of managerial strategies has not often extended to advanced technologies like AI, big data, or cloud computing.

2.4. Identification of Gaps & Research Question

The literature on the integration of eco-innovation and digitalization within the manufacturing sector, particularly in South Korea, underscores a critical intersection of environmental and technological advancements shaping the future of industry. While the twin transition is increasingly recognized as a transformative strategy for sustainable and technological advancement, empirical research, particularly within the Korean context, is lacking. Studies such as those by Antonioli et al. (2018) and Van Der Krogt et al. (2023) provide foundational insights on the impact of these transitions on labor productivity and business performance in various sectors. However, to date there has been no targeted research on the twin transition among Korean manufacturing firms. Furthermore, the literature points to the pivotal role of demand factors in catalyzing eco-innovation, as evidenced by Horbach (2008) and Wagner (2007). These studies suggest that market dynamics and consumer expectations play a crucial role in shaping firms' investments in green technologies. Digitalization, encompassing IoT, AI, and blockchain, has been found to transform business operations by improving efficiency and minimizing costs (Jung & Gómez-Bengoechea, 2022). The Industry 4.0

revolution, galvanized by advancements in IoT, AI, automation, and 3D printing, has significantly altered business operations (Benassi et al., 2022; Martinelli et al., 2021; Rojko, 2017). Additionally, the discourse on the economic impact of these innovations remains mixed, suggesting a complex relationship between sustainable practices and financial performance that requires deeper examination within specific industrial contexts.

There is a clear gap in the literature regarding the combined effects of eco-innovation and digitalization. Understanding the joint adoption of these innovations is crucial for comprehensively assessing their impact on business performance. Despite the separate strands of research on eco-innovation and digitalization, there is a conspicuous gap in terms of studies that explore their joint impact on firm performance, particularly sales. This gap is particularly notable in the context of Korean manufacturing firms, where the synergy between eco-innovation and digital transformation remains unexplored.

This study investigates whether firm performance is improved through the complementary adoption of both types of innovation, in the context of Korean manufacturing. Ballot et al. (2015) has examined complementarities in performance among product, process, and organizational innovations, and analyzed conditional complementarities in French and UK manufacturing firms. The findings suggest that the presence of complementarities depends on the national context as well as firms' size and capabilities. Similarly, the complementarity of eco-innovation and digital technology adoption may depend on the national context, firm size, and firm capabilities. In fact, national policies and regulations can influence the extent of the complementarity between eco-innovation and digital technology adoption. Hullova et al. (2016) have also addressed the complementarity of process and product innovation, which are likely to emerge in process industries, where it is appropriate to hypothesize a progression from process to product. A similar complementarity can be observed in the adoption of eco-innovation and digital technology. For instance, eco-innovation (e.g., energy-efficient production processes) can be enhanced through the adoption of digital technologies (e.g., real-time energy monitoring via IoT sensors). Digital technologies can act as tools that maximize the effects of eco-innovation.

The review of the extant literature suggests a critical research question: How does the joint adoption of eco-innovation and digitalization impact the business performance of Korean manufacturing firms? Drawing on the literature to offer a new perspective on the benefits of twin transition, the study hypothesizes that dual adoption of eco-innovation and digitalization positively affects firms' sales and operational efficiency. The reviewed literature highlights the evolving significance of the twin transition and underscores the need for integrated strategies that encompass both eco-innovation and digitalization. This literature review sets the stage for the empirical investigation of the impact of twin transition on firm performance in Korean manufacturing, which is intended to address the identified research gaps and contribute valuable insights into sustainable and technologically advanced business practices.

3 Data

3.1. Data

The Korea Innovation Survey (KIS) is the main source of data for this empirical study. This survey follows the guidelines of the OECD Oslo Manual and the Community Innovation Survey (CIS), which assesses innovation in European countries. The KIS is conducted nationwide by the Science and Technology Policy Institute (STEPI), and it aims to provide comprehensive insights into the innovation activities of manufacturing firms and includes information such as firm size, age, and sales over the past three years.

The KIS 2022 is of particular interest for this study as it provides a unique opportunity to explore the joint adoption of eco-innovation and advanced digital technology and its effects on sales. This version of the KIS introduced new sections on "Environment and Business Innovation" and "Digital Transformation and Business Innovation," covering firms' respective environmental and digital innovation initiatives. These sections include questions about whether the surveyed firms have introduced environmental innovations or new digital technologies. The survey did not collect detailed information as to the timing of each firm's introduction of an eco-innovation or new digital technology within the three-year period it examines, thus the innovations might have been introduced at any time between 2019 and 2021.

Table 1. The key questions and answers from KIS 2022

	Questions	Answers (Adopt/Non-Adopt)
1	Has your firm adopted any innovations with environmental benefits[1] in the past three years (2019–2021)?	Material or water use reduction per unit of production
		Energy consumption reduction or carbon footprint (CO_2 emissions) reduction
		Reduction of air pollution, water pollution, soil pollution, or noise pollution
		Replacement of materials with substitutes that pollute less or are less harmful to the environment
		Partial substitution of fossil energy with renewable energy sources
		Recycling of waste, water, or materials for own use or for sale
		Reduction in energy use or carbon footprint (CO_2 emissions) for the final user
		Reduction of air pollution, water pollution, soil pollution, or noise pollution for the final user
		Promotion of recycling after product use
		Extension of product life through durable goods
2	Has your firm introduced any new digital technologies in the past three years (2019–2021)?	Big data
		AI
		IoT
		Cloud computing
		Robotics
		3D printing
		Mobile (5G) technology
		Augmented or Virtual Reality (AR/VR)
		Blockchain

Source: Korea Innovation Survey 2022

The KIS consists of a nationally representative sample of 4,000 manufacturing firms across all sectors, providing an overview of the Korean manufacturing industry. The sampled population for the KIS 2022 consisted of a total of 52,460 manufacturing enterprises classified under Section C (Manufacturing) in the 10th edition of the Korean Standard Industrial

[1] Innovations with environmental benefits: Innovations in products or business processes that have a positive or less negative impact on the environment. Environmental benefits could be a primary goal of the innovation or a byproduct of other goals. The environmental benefits of the innovation could occur during the production of goods (products/services) or while the goods are consumed/used by the end user. The end user could be individuals, other businesses, or the government.

Classification (KSIC) that conducted normal business activities during the three-year period from 2019 to 2021 and had at least 10 regular employees. STEPI used a stratified sample design for the KIS 2022. The sample size for the analyses was reduced from 4,000 to a final sample of 2,185 firms due to missing values.

3.2. Treatment variables

In line with Antonioli et al. (2018), my study empirically examines how complementarity in innovation adoption affects firms' business performance. The treatment variable used in this study is the joint adoption of an eco-innovation and a new digital technology, with each type of adoption represented as a binary variable. Eco-innovation adoption is coded 1 if a firm adopted an eco-innovation and 0 if it did not. Similarly, the adoption of a new digital technology is coded 1 if a firm adopted a new digital technology and 0 if it did not. Then, the joint adoption of eco-innovation and digital technology is operationalized using a binary treatment variable where 1 indicates the adoption of both types of innovation and 0 represents all other cases. This binary approach facilitates the examination of the synergistic effects of eco-innovation and digitalization on sales, distinguishing firms that engage in both from those that do not.

3.3. Outcome variables

In this study, sales performance is operationalized as the primary outcome variable, measured in terms of millions of won. This approach is grounded in the notion that sales performance, a direct indicator of business success, effectively reflects the economic consequences of innovation activities. The transformation of sales data into a logarithmic form is a standard practice aimed at addressing issues associated with skewed distributions, which are often caused by outliers or a few exceptionally high values in the dataset. The rationale for using a logarithmic transformation lies in its ability to render the data more amenable to normal distribution assumptions, thereby enabling more accurate and reliable statistical analyses. Additionally, this transformation stabilizes variance across the dataset, ensuring that the spread of sales figures is more uniform across different levels of the independent variables, which in this context include the adoption of eco-innovations and digital technologies. To correct for the skewedness inherent in sales data, these figures are converted to a logarithmic scale.

3.4. Summary statistics

Table 2. Summary Statistics

Variable	(1) Full sample	(2) Only Eco-innovation	(3) Only Digital Technology	(4) Both	(5) Neither
$\log(sales)_{2021}$	10.41	10.11	9.47	11.18	10.03
	(1.900)	(1.717)	(1.711)	(1.811)	(1.842)
$\log(R\&D\ expenditure)_{2021}$	6.45	6.40	5.56	7.17	5.97
	(1.696)	(1.565)	(1.387)	(1.806)	(1.374)
R&D Staff Ratio	10.52	10.34	11.78	11.17	9.38
	(9.457)	(8.668)	(10.61)	(10.40)	(8.022)
Firm's age	24.45	22.67	20.18	27.81	23.09
	(14.42)	(13.72)	(11.79)	(15.46)	(13.65)
Observations	2,185	362	273	829	721

Notes: The analysis covers a total sample of 2,185 firms, segmented into four categories: (2) Firms that adopted only an eco-innovation (362 firms), (3) Firms that adopted only a new digital technology (273 firms), (4) Firms that adopted a new eco-innovation and a new digital technology (829 firms), and (5) Firms that adopted neither an eco-innovation nor a new digital technology (721 firms). The reported values represent the mean (average) values for each variable across the different firm categories, and standard deviations are presented in parentheses.

Table 2 presents a comprehensive overview of how the firms in the sample are categorized based on their adoption of eco-innovation and digital technology. The detailed breakdown by category offers a multifaceted view of the current business landscape. The categorization creates five distinct groups: the full sample (all firms), firms with eco-innovation only, firms with digital innovation only, firms with both, and firms with neither. This classification allows for a detailed analysis of each group's characteristics and how they relate to the adoption of eco-innovation and new digital technologies.

Notably, firms that adopted both an eco-innovation and a new digital technology (both) exhibited the highest average log sales in 2021, suggesting that integrating both eco-friendly innovation and digital advancements might be associated with better sales performance. The $log(R\&D\ expenditure)_{2021}$ and R&D staff ratio metrics provide insight into the firms' investments in innovation and development. In particular, firms in the 'both' category have higher averages on both metrics, suggesting that a significant commitment to research and development could be driving these firms' superior sales figures. The investment in R&D is not only monetary but also human, as indicated by the R&D staff ratio. It is interesting that firms that adopted only a new digital technology have the highest average R&D staff ratio, suggesting a labor-intensive approach to their digital initiatives.

The firms' age distribution reveals variation in the propensity to adopt new technologies and sustainable practices, with older and more established firms more likely to embrace both eco-innovation and digital technology. This reflects maturity in their resource allocation and organizational structure that seems to be conducive to technological and sustainable advancements. The distribution of firm size and the technological intensity of their industries is presented in Appendix Figures A.1 and A.2.

4 Methods

4.1. Ordinary Least Squares (OLS)

I start off the analysis using OLS. I investigate the relationship between a firm's sales and the combined implementation of eco-innovation and digital technology through an OLS estimator. The model is expressed as equation (1):

$$Y_i = \alpha \times (Eco_i \times Digi_i) + \beta \times Eco_i + \gamma \times Digi_i + X'_i + \epsilon_i \tag{1}$$

where Y_i is the outcome variable, the log of a firm i's sales in 2021. Eco_i is coded 1 if the firm *i* has adopted an eco-innovation and 0 if it has not. $Digi_i$ is coded 1 if the firm *i* has adopted a new digital technology and 0 if it has not. The primary variable of interest is the interaction term $Eco_i \times Digi_i$, which represents the combined effect of adopting an eco-innovation (Eco_i) and a new digital technology ($Digi_i$). The main coefficient of interest, α, captures the impact of this joint adoption on the sales of the firm. Additionally, to account for the individual contributions of each type of innovation, both Eco_i and $Digi_i$ are also included separately in the model. The model also incorporates a set of control variables, X_i', which capture a variety of firm-specific characteristics such as the firm's age, R&D expenditures, R&D staff ratio, the firm's size, its technological intensity, and the location of the firm's headquarters, allowing for heterogeneity and controlling for fixed effects across different firm characteristics. The classification for technological intensity follows the OECD taxonomy (Galindo-Rueda & Verger, 2016). The error term ϵ_i addresses unobserved factors that might affect sales.

Despite the utility of the OLS method, there is the possibility of endogeneity in the interaction term, $Eco_i \times Digi_i$, especially if it is correlated with the error term ϵ_i, potentially leading to biased estimates. This correlation implies that the impact of joint adoption might be over- or under-estimated if determined solely through OLS, due to selection bias.

4.2. Identification strategy

To determine the causal impact of the joint adoption of the two types of innovation on sales performance, it is essential to address the potential endogeneity arising from unobserved variables that may influence both adoption of these innovations and sales outcomes. This study employs a propensity score matching (PSM) approach to mitigate these biases. Using PSM, the study aims to match firms that have adopted both an eco-innovation and a new digital technology (the treatment group) with similar firms that have not done so (the control group), based on observable characteristics before the adoption. This method helps to reduce sample selection bias and simulate a randomized controlled trial environment, although it may reduce the sample size after matching.

4.3. Propensity Score Matching

PSM is utilized to estimate the causal impact of the joint adoption of eco-innovation and digital technologies on sales by creating a comparable control group in a non-experimental setting. The process involves two main stages: estimating the probability of adopting both innovations through a binary choice model and second, matching firms based on the estimated propensity scores. This method enhances the estimation of causal effects by ensuring comparability between the treated and control groups based on observed characteristics. It is crucial to ensure that the common support condition is met, meaning that each firm in the treatment group has a comparable firm in the control group with a similar propensity score, which makes the matching process and the estimates of the reliability of the treatment effect valid.

To examine the impact of joint adoption of eco-innovation and digital technologies on firms' sales, a sales outcome equation for Y_i is specified in equation (2):

$$Y_i = X'_i + \delta \times T_i + \epsilon_i \tag{2}$$

where Y_i represents the log of a firm i's sales in 2021, X'_i denotes the firm i's characteristics, T_i is a binary indicator of the joint adoption. δ measures the effect of the treatment on the outcome variable. However, since the joint adoption variable is endogenous in the outcome equation because of its potential correlation with the unobservable covariates, ϵ_i, using the OLS estimator to assess the impact of joint adoption of these innovations on firms' sales may result in inconsistent estimates and misleading conclusions. For a more rigorous analysis, firms that have adopted both an eco-innovation and a new digital technology are designated as the treatment group, whereas firms that have adopted neither are assigned as the control group in this matching process. This approach ensures clarity in assessing the joint impact on sales, avoiding the ambiguity that might arise from comparing firms that adopted only one of these innovations to those that adopted both or neither. There are two steps to the PSM approach: first, estimating the propensity (p-score) of adoption using a binary choice model (logit or probit), and second, matching treated and control firms based on the predicted p-scores. The average treatment effect on the treated (ATET) was given as follows in equation (3):

$$ATET = E(Y_{1i} - Y_{0i}|P(X_i)) = E(Y_{1i}|P(X_i), T_i = 1) - E(Y_{0i}|P(X_i), T_i = 0) \tag{3}$$

where Y_{1i} and Y_{0i} are the potential outcomes for the firm *i* if it is treated and untreated, respectively. $P(X_i)$ represents the propensity score, the probability of firm *i* receiving treatment given its covariates. The ATET is defined as the expected difference in outcomes between treated and untreated firms, conditional on propensity scores. This method assumes common support across treated and untreated firms, ensuring a valid comparison by maintaining overlap in their propensity scores.

5 Empirical Results

5.1. OLS results

Despite these methodological challenges, the regression analysis yielded significant results, as shown in Table 3. The coefficient for the main regressor, α, is statistically significant at the 5% significance level, with a value of 0.134 in Model (3). This indicates a significant impact of the joint adoption of an eco-innovation and a new digital technology on firm sales, suggesting that there is a statistically significant difference in logarithmic sales between firms that have adopted both types of innovations and those that have not. The coefficient of 0.134 implies that firms adopting both types of innovation experienced an approximate 13.4% increase in sales. Model adjustments and the evaluation of various model specifications (as shown in Table 3) led to the determination that Models (2) and (3) provide a more accurate estimation of the relationship than Model (1).

Table 3. Multiple Regression using OLS

Variable	(1)	(2)	(3)
		$\log(sales)_{2021}$	
Eco-innovation×Digital Transformation	1.623***	0.427***	0.134**
	(0.166)	(0.104)	(0.0647)
Eco-innovation	0.0808	-0.211***	-0.0169
	(0.113)	(0.0705)	(0.0439)
Digital Transformation	-0.552***	-0.0468	-0.0673
	(0.124)	(0.0754)	(0.0489)
$\log(R\&DExpenditure)_{2021}$		0.799***	0.310***
		(0.0203)	(0.0173)
R&D Staff Ratio		-0.0452***	-0.0155***
		(0.00201)	(0.00182)
Firm's Age		0.0224***	0.00518***
		(0.00201)	(0.00129)
Fixed effects			
Firm's size	No	No	Yes
Firm's technological intensity	No	No	Yes
Firm's region	No	No	Yes
Observations	2,185	2,185	2,185
Adjusted R-squared	0.109	0.678	0.868

Notes: This table presents the estimated coefficients from three regression models. The main regressor of interest, the interaction term between Eco-innovation and Digital Transformation, is noteworthy. Control variables accounted for in the models are as follows: firm size, technological intensity, and the location of a firm's headquarters. Robust standard errors are reported in parentheses below each coefficient. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

5.2. Estimation of Propensity Scores

The sample was divided into two groups to estimate the propensity scores of adopting both an eco-innovation and a new digital technology: one group that includes firms that have adopted both, and another group that includes firms that adopted neither.

p-scores are estimated utilizing the observed characteristics of the firms in the first stage. The firm characteristics included in the analysis are as follows: R&D expenditures, R&D staff ratio, firm size, firm's age, technological intensity of a firm's industry, and the location of the firm's headquarters. These characteristics are chosen because they are likely to influence both the decision to adopt the relevant innovations and the firms' sales performance. Secondly, firms in the treatment group are matched with firms in the control group that have similar propensity scores, ensuring that the matched groups are comparable on the observed characteristics. To ensure a robust matching process, I included all 15 administrative regions as locations of firms' headquarters in the matching methods. This allowed me to control for unobserved region-level characteristics and region-specific economic conditions.

Table 4. Coefficients and standard errors in the logistic regression of propensity score matching

Variable	Coefficient	Robust Std. Error
$\log(R\&D\ expenditures)_{2021}$	0.182***	0.058
R&D Staff Ratio	0.008	0.008
Firm's Age	0.008*	0.005
Small Firm	-0.639*	0.343
Medium Firm	-0.162	0.288
Medium Large Firm	0.29	0.268
Low Tech	2.828***	0.249
Medium Low Tech	1.237***	0.182
Medium High Tech	-0.144	0.215
Seoul	0.203	0.318
Busan	-0.478	0.356
Daegu	0.191	0.41
Gwangju	0.253	0.57
Daejeon	0.074	0.493
Ulsan	1.17**	0.531
Sejong	-0.569	0.819
Gyeonggi	-0.333	0.27
Gangwon	-0.76	0.52
Chungbuk	-0.497	0.348
Chungnam	-0.126	0.336
Jeonbuk	-0.599	0.437
Jeonnam	-0.815	0.502
Gyeongbuk	-0.18	0.346
Gyeongnam	-0.603*	0.312
Constant	-1.94***	0.601
Pseudo R-squared	0.240	
Wald Chi-squared	353.74***	
Log pseudo likelihood	-814.1	
Number of observations	1,550	

Notes: The table shows the results of a logistic regression to estimate propensity score. The covariates included are $\log(R\&D\ expenditure)_{2021}$, R&D staff ratio, firm size (categorized as small, medium, medium large, and large), firm's age, technological intensity of the firm's industry (categorized as low, medium low, medium high, and high). Additionally, the location of the firm's headquarters in one of the 15 Korean administrative regions (Seoul, Busan, Daegu, Ulsan, Sejong, Gyeonggi, Gangwon, Chungbuk, Chungnam, Jeonbuk, Jeonnam, Gyeongbuk, and Gyeongnam) is also included as a covariate. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Logit model results are presented in Table 4. This model produces propensity scores for each observational unit. The significant determinants of joint adoption of both types of innovation are $\log(R\&D\ expenditure)_{2021}$, firm's age, being a small firm, being in a low or medium-low technology industry, and having a headquarters in Ulsan or Gyeongnam regions. The logistic regression model used to estimate the propensity scores reveals several key determinants of the joint adoption of eco-innovation and digital technologies. For instance, firms with higher R&D expenditures and those located in certain regions may be more likely to adopt these innovations. This step is crucial for understanding the characteristics that predispose firms to pursue eco-innovation and digital transformation, providing insights into the underlying drivers of innovation adoption in the Korean manufacturing sector. A graph of the propensity scores, which compares adopters with non-adopters, is presented in Appendix Figure A.3. The upper section of the graph displays the p-scores for adopters, while the lower section shows the p-scores for non-adopters.

Table 5. Comparative analysis of the characteristics of firms with and without joint adoption of eco-innovation and new digital technology after matching

Variable	Treated	Control	Difference	p-value
$\log(R\&D\ expenditure)_{2021}$	6.923	6.776	0.147*	0.073
R&D Staff Ratio	10.504	11.176	-0.672	0.178
Firm's Age	27	26.251	0.749	0.308
Small Firm	0.179	0.221	-0.042**	0.04
Medium Firm	0.423	0.481	-0.058**	0.023
Medium Large Firm	0.309	0.21	0.099***	0
Large Firm	0.089	0.088	0.001	0.928
Low Tech	0.252	0.29	-0.038*	0.093
Medium Low Tech	0.545	0.501	0.044*	0.089
Medium High Tech	0.109	0.106	0.003	0.868
High Tech	0.094	0.102	-0.008	0.604
Seoul	0.127	0.149	-0.022	0.232
Busan	0.046	0.04	0.006	0.526
Daegu	0.042	0.046	-0.004	0.708
Gwangju	0.023	0.025	-0.002	0.736
Daejeon	0.023	0.009	0.014**	0.04
Ulsan	0.038	0.045	-0.007	0.52
Sejong	0.005	0.003	0.002	0.414
Gyeonggi	0.322	0.285	0.037	0.117
Gangwon	0.015	0.008	0.007	0.223
Chungbuk	0.052	0.041	0.011	0.328
Chungnam	0.08	0.076	0.004	0.773
Jeonbuk	0.017	0.011	0.006	0.272
Jeonnam	0.012	0.013	-0.001	0.818
Gyeongbuk	0.052	0.06	-0.008	0.501
Gyeongnam	0.078	0.086	-0.008	0.574
Observations	754	721		

Notes: The covariates included are $\log(R\&D\ expenditure)_{2021}$, R&D staff ratio, firm size (categorized as small, medium, medium large, and large), firm's age, technological intensity of a firm's industry (categorized as low, medium low, medium high, and high. Additionally, the location of the firm's headquarters in one of the 15 Korean administrative regions (Seoul, Busan, Daegu, Ulsan, Sejong, Gyeonggi, Gangwon, Chungbuk, Chungnam, Jeonbuk, Jeonnam, Gyeongbuk, and Gyeongnam) is also included as a covariate. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5 shows the paired t-test results after matching, indicating that the propensity score matching process was effective in balancing the observed covariates between the treated and control groups. Before matching, there were significant differences between the groups in terms of $\log(R\&D\ expenditure)_{2021}$, R&D staff ratio, firm's age, firm size, technological intensity, and location, which could bias the treatment effect estimation. The result of the comparative analysis of characteristics between the treated and control groups before matching is presented in Appendix Table A.1.

The analysis presented in the table focuses on assessing the differences in key variables between firms that have adopted both an eco-innovation and a new digital technology (treated) and those that have not done so (control) after the application of PSM. This method is used to ensure that the two groups are comparable on various characteristics, allowing for a more accurate estimation of the impact of adopting these innovations. After applying PSM, the differences between the treated and control groups were significantly reduced or eliminated across all measured variables, indicating that the matching process effectively created comparable groups. This outcome is crucial for the validity of the subsequent analyses assessing the impact of eco-innovation and digital transformation on firm performance, as it minimizes the risk that the observed effects are due to factors other than the treatment itself.

Notably, the reduction in the difference between the two groups was not complete for all variables; for instance, log R&D expenditures and firm size still showed some differences between the groups after matching, though these were reduced. This indicates that while PSM can significantly improve the balance between groups, it does not always perfectly equalize all characteristics. The successful reduction in differences for most variables, however, supports moving forward to analyze the impact of eco-innovation and digital transformation on firms' sales performance, with increased confidence that any observed effects are likely due to the innovations themselves rather than other confounding factors.

5.3. Covariate balancing test

It is essential to perform a covariate balancing test after matching to ensure that the matching process successfully balanced the observed characteristics across the treatment and control groups. The results indicate significant improvement in balance post-matching, with the mean absolute standardized bias (MASB) for most covariates falling below the 20% threshold. This improvement suggests that the matched samples are comparable, allowing for a more accurate estimation of the treatment effect.

To address the covariate differences used in estimating the propensity scores, a covariate balancing test was performed. This test aims to ensure that the matched samples of adopters and non-adopters are similar in their observable characteristics, except for their adoption of the relevant innovations. The MASB proposed by Rosenbaum & Rubin (1983) was used to evaluate covariate balance. After the MASB was computed for each variable both before and after matching, the average MASB across all variables was calculated. A valid matching process is indicated by an MASB of less than 20% between the treated and untreated groups after matching. If the standardized difference exceeds 20% after matching, it suggests the matching process was ineffective, resulting in poor matches.

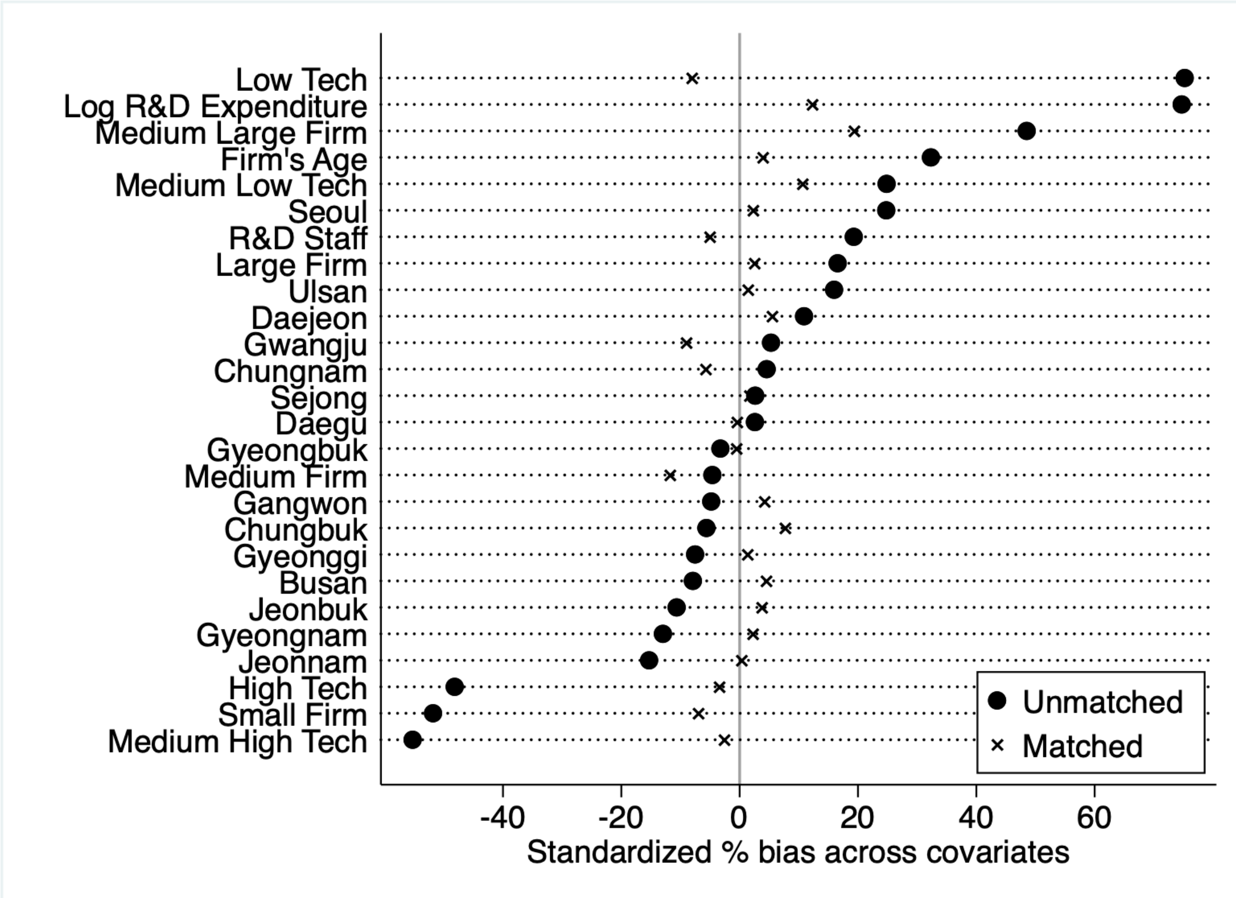

Figure 1. Individual covariate balancing test

Figure 1 shows the results of the covariate balancing test for each firm covariate, comparing the matched and unmatched samples. The figure demonstrates that the absolute bias for all variables is lower in the matched sample.

5.4. The estimation of the average treatment effect on the treated (ATET)

Table 6. Impact of the joint adoption of eco-innovation and digital technology on firm's sales with NNM and KBM

Matching Algorithm	Nearest Neighbor Matching (NNM)	Kernel-Based Matching (KBM) (bandwidth=0.08)
Panel A		
Matched Treated	754	754
Matched Controls	721	721
Treated	11.038	11.038
Controls	10.577	10.652
ATET	0.461**	0.386***
SE	0.192	0.146
t-statistic	2.4	2.64
Panel B		
Matched Treated	754	754
Matched Controls	721	721
ATET	0.461***	0.386***
SE	0.167	0.132
z-statistic	2.77	2.92

Notes: This table presents the impact of the joint adoption of eco-innovation and digital technology on $\log(sales)_{2021}$, using two different matching algorithms: NNM and KBM. The results are reported in two panels: Panel A and Panel B. Both panels report the number of matched treated firms (754) and controls (721). Panel A provides the t-statistic, which helps assess the reliability of the ATET estimate, while Panel B uses a z-statistic derived from the standard errors bootstrapped with 150 replications to provide a more robust estimate. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$

As detailed in Section 4.3, the treatment variable in this analysis is the joint adoption of an eco-innovation and a new digital technology. Firms that adopted only one of these were excluded to focus exclusively on comparing the treatment effect, which is a combined and synergistic effect. Table 6 shows the respective ATETs of the joint adoption of an eco-innovation and a new digital technology when NNM and KBM are used. These are commonly applied matching algorithms in the impact evaluation literature. For NNM, a treated firm is matched with its nearest neighbor, that is, the most similar firm among the untreated group, with replacements. Normal densities with bandwidths of 0.08 were used for the KBM, and standard errors were bootstrapped 150 times in Panel B.

The joint adoption of an eco-innovation and a new digital technology had significant positive effects on firms' sales. Using NNM, the treated group (the firms that adopted both an eco-innovation and a new digital technology) consisted of 754 firms, and they were matched with 721 control firms (firms that adopted neither innovation). The ATET is calculated to be 0.461, with a standard error of 0.192, resulting in a t-statistic of 2.4, which indicates statistical significance at the 5% significance level. This suggests that the adoption of both an eco-innovation and a new digital technology had a positive and statistically significant effect on the treated firms compared with the control group. The KBM results also show a positive ATET of 0.386 with a smaller standard error of 0.146, resulting in a higher t-statistic of 2.64, which provides stronger evidence of statistical significance. In this case, the bandwidth parameter set at 0.08 indicates the range used to average the outcomes of the treated and control units, providing a smoother and potentially more generalized estimate of the treatment effect.

The results from the two matching algorithms (NNM and KBM) are consistent in demonstrating a positive impact of the treatment on the treated firms. These coefficients correspond to increases in sales of approximately 46.1% and 38.6%, respectively. The fact that both methods yield statistically significant ATET values reinforces the robustness of the findings. In Panel (B), it is noteworthy that the standard errors were bootstrapped with 150 replications, enhancing the reliability of these estimates by accounting for the variability in the sampling process. This bootstrapping procedure is essential in non-parametric methods like matching, where assumptions about the distribution of the estimator are not made.

Table 7. Impact of the joint adoption of eco-innovation and specific digital technologies on firms' sales with NNM and KBM

	Treatment Variable								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent variable: $\log(sales)_{2021}$	Eco× AI	Eco× Big data	Eco× Block chain	Eco× IoT	Eco× Cloud	Eco× Robotics	Eco× 3D Printing	Eco× 5G	Eco × AR
ATET									
NNM	0.511* (0.296)	0.586*** (0.189)	0.480 (1.630)	0.515*** (0.124)	0.780*** (0.139)	0.657*** (0.176)	0.359* (0.185)	0.493*** (0.144)	-
KBM	0.421* (0.243)	0.343** (0.138)	1.052 (1.225)	0.252* (0.143)	0.349*** (0.124)	0.030 (0.142)	0.343* (0.190)	0.452*** (0.137)	-
Matched Treated	62	289	5	488	577	249	184	288	-
Matched Controls	718	721	188	721	721	721	721	721	-

Notes: This table presents the impact of the joint adoption of eco-innovation and specific digital technologies on $\log(sales)_{2021}$, using two different matching algorithms: NNM and KBM. The treatment variables include combinations of eco-innovation with various digital technologies (AI, big data, blockchain, IoT, cloud computing, robotics, 3D printing, 5G, and AR). In this analysis, standard errors were bootstrapped with 150 replications. Column (9) Eco×AR, the combination of eco-innovation and AR, does not have coefficients due to an insufficient number of observations. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 7 analyzes the ATET of combining eco-innovation with specific digital technologies, measured in terms of the logarithm of a firm's sales in 2021, employing two matching methods, NNM and KBM with a bandwidth of 0.08. The technologies examined include AI, big data, blockchain, IoT, cloud computing, robotics, 3D printing, 5G, and AR. This detailed breakdown demonstrates the varying impacts of combining eco-innovation with different digital technologies on firm sales. The absence of data for AR based on an insufficient number of observations suggests the need for further research in this area.

Notably, the combination of eco-innovation and big data, cloud computing, and 5G shows a positive impact on sales at the 5% significance level. In particular, a coefficient of 0.586 in column (2) corresponds to an approximate 58.6% increase in sales, and a coefficient of 0.343

in column (2) corresponds to an approximate 34.3% increase in sales. Likewise, each treatment increases the sales by 78.0% and 34.9% for column (5), and by 49.3% and 45.2% for column (8), respectively. Other combinations do not produce a consistent significant impact at the 5% significance level. This suggests that the combination of an eco-innovation with AI, blockchain, IoT, robotics, or 3D printing is not likely to be associated with an increase in sales. Due to missing observations, data on firms that adopted both an eco-innovation and AR are not available.

6 Discussion & Conclusion

This study substantiates the synergy created by the twin transition, in which firms pursue decarbonization and digitalization simultaneously, as a compelling lever for enhanced firm performance. The empirical analysis reveals a significant increase in sales among Korean manufacturing firms that embraced both types of innovation during the period from 2019 to 2021. The OLS models (Table 3) and ATET calculations drawn from PSM (Table 6 and Table 7) further validate the finding. These provide a strong argument that firms should engage in joint adoption of these two types of innovation. The significant increase in sales among firms that did so suggests that this transition is more than an environmental or technological effort; it is a valuable business strategy and an indication of a new operational paradigm that harmonizes profitability with sustainability.

Real-world examples illuminate these findings. According to Ren & Li (2023), digital transformation has significantly improved the financial performance of renewable energy companies in China. Their study revealed that green technology innovation fully mediates the effect of digital transformation on financial performance, suggesting that digital advancements lead to more effective green technology innovations, which in turn boost financial outcomes. Moreover, according to Betti et al. (2020), digital transformation is revolutionizing all aspects of manufacturing, including reducing environmental impacts, such as by lowering emissions, reducing waste, and increasing the efficiency of energy, water, and raw materials consumption. Industry 4.0 can unlock significant value across multiple areas of a factory network in terms of 1) computational data connectivity based on blockchain and IoT, 2) advanced production methods involving renewable energy technology and 3D printing, 3) analytics and intelligence based on big data and AI, and 4) human-machine interaction with robotic processes and automation using virtual and augmented reality, resulting in labor-productivity increases and improvements in forecasting accuracy.

However, the impact of the joint adoption of eco-innovation and digital technologies varies across the specific technologies adopted. The combination of eco-innovation with big data, cloud computing, or 5G telecommunications had a significant positive impact on Korean manufacturing firms' sales across both NNM and KBM methods of PSM at the 5% significance level. This indicates that integrating these advanced technologies with eco-innovative practices can further enhance firms' sales performance.

The significance of the results when eco-innovation is combined with these three specific technologies may be because these technologies are immediately applicable and can be integrated seamlessly into current business operations. This quick integration may allow firms to see immediate benefits in terms of enhanced data management and connectivity, directly impacting their sales performance. Kusiak (2017) and Manyika et al. (2011) have discussed firms' use of big data to enhance operational efficiency and competitiveness, obtaining real-time data on defects and adjusting their production processes immediately. Marston et al. (2011) has pointed out that cloud computing supports business operations, emphasizing its ability to reduce costs and enhance flexibility. Hashem et al. (2015) have highlighted that pairing cloud computing and big data has reduced the cost of automation and computerization for both individuals and enterprises, and also offers benefits like lower infrastructure maintenance expenses, improved management efficiency, and enhanced user accessibility. Fosso Wamba et al. (2015) have emphasized big data's ability to optimize real-time resource management by analyzing workers' skills and qualifications to improve decision making. In addition, 5G technology can support increased connectivity and faster data transfer rates, which are essential for deploying advanced eco-innovative technologies such as smart grids. This enhances operational efficiency and supports real-time decision-making in the area of environmental management.

On the other hand, technologies such as AI, blockchain, and robotics may have longer implementation and learning curves. The complexity and initial cost of implementing technologies like AI or robotics might not immediately translate into significant economic returns, making their short-term impact on sales less apparent. The time it takes to effectively integrate these technologies into business processes can delay their impact on sales. While AI can be used to improve quality management, standardization and maintenance through predictive analysis of machinery functions in the manufacturing process, the time required to train models and adapt business processes to fully leverage AI may delay tangible sales results due to identified barriers such as data quality, machine-to-machine variation, cybersecurity and operational regimes (Javaid et al., 2022). Blockchain also faces significant regulatory uncertainties and technical challenges related to scalability and security. These challenges can hinder its widespread adoption and thus delay its impact on sales. Similarly, the integration of robotics and IoT devices can raise concerns about cybersecurity, data privacy, and compliance with existing regulations, which can slow down their deployment and sales impact.

Some technologies like IoT and 3D Printing may have more niche applications that may not directly contribute to immediate sales increases. Their benefits might be more pronounced when used to enhance long-term operational efficiency or when deployed in specific industries. It takes time to contribute to sales increases since additive manufacturing techniques such as 3D printing require training skilled labor and rely heavily on experience (Weller et al., 2015).

Therefore, firms should be strategic to maximize the impact of such innovations. The findings underscore the importance of selecting and implementing tailored digital technologies that align closely with a firm's operational needs and immediate goals. Technologies that offer rapid integration and immediate applicability to existing business models, such as big data, cloud computing, and 5G telecommunications, are more likely to drive significant increases in sales than technologies with longer time horizons. While the immediate impact of AI, blockchain, and other complex technologies on sales may be less significant, they hold potential to provide strategic benefits in the long term. Firms should consider phased implementations of these technologies that align with their long-term goals such as operational efficiency and innovation.

This study suggests that a holistic approach that integrates immediately useful technologies with eco-innovations can provide a dual benefit of enhancing firm sustainability while boosting economic performance. In order to maximize the advantages of digital transformation in conjunction with eco-innovation, firms should make strategic choices about the technologies they adopt, considering both their immediate impact and their potential long-term benefits. This expanded discussion provides a deeper insight of how different technologies may influence sales performance when combined with eco-innovation. It suggests that firms should align their technological capabilities with their strategic business objectives to maximize the benefits of the synergy with eco-innovation. In the meantime, global challenges such as the COVID-19 pandemic have brought the principles of the twin transition into sharp focus. Firms that have proactively embraced these strategies have demonstrated remarkable resilience and agility, mitigating the pandemic's disruptive impact. This resilience underscores the twin transition's vital role in ensuring business continuity and preparing firms for future adversity.

The implications of this study stretch into the realm of policy-making. Policymakers have the opportunity to craft incentives that propel firms toward the twin transition. Incentives such as tax relief, subsidies, or R&D support could ease the initial financial burden of such changes and spotlight the long-term profitability of sustainable practices. Governments can also encourage the twin transition by cultivating an ecosystem that fosters both eco-innovation and digital transformation, including a comprehensive regulatory framework that offers clarity and predictability to businesses embarking on these transformations.

A robust policy framework would offer not only encouragement, but systemic support, including for infrastructure development and public-private partnerships. Governments have the potential to catalyze the twin transition by creating an environment where eco-innovations and digital transformation can be piloted, scaled, and integrated into the broader economy. The establishment of a regulatory framework is also paramount. Policymakers should provide necessary guidelines and regulations to navigate the eco-digital transition. This framework could offer direction, establish technological and environmental standards, and enhance market predictability, thereby facilitating a smoother transition for firms.

While this study analyzed the impact of the twin transition on sales performance in the Korean manufacturing sector, however, several limitations should be acknowledged. Although PSM is useful for reducing selection bias, it cannot account for unobservable variables that may influence both the adoption of innovations and sales outcomes, potentially leading to residual confounding. Additionally, the findings are specific to the Korean manufacturing sector and may not be generalizable to other sectors or countries, given the unique economic, cultural, and regulatory environment in Korea. The study period, spanning from 2019 to 2021, includes the impact of the COVID-19 pandemic, which may not represent normal conditions and could limit the applicability of the results to other time periods. Finally, while the study found varied impacts of different digital technologies on sales, it did not deeply explore the mechanisms through which these technologies influence firm performance. These limitations highlight the need for caution in interpreting the findings and suggest areas for future research to address these gaps.

In conclusion, the twin transition is more than a trend; it is a directive for the future of business and policy-making. This study reaffirms the need for firms to embrace this transition, avoiding a binary choice between sustainability and profitability and instead formulating an integrated strategy that leverages the symbiotic potential of eco-innovation and digital transformation to achieve business success. The future holds the promise of transformation, and a collective effort from businesses and policymakers alike is needed to harness the momentum of the twin transition to create a greener, more technologically integrated future.

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Appendix

In Figure A.1, the firm size distribution across the five categories demonstrates the diversity in the scale of these companies, with significant representation in each size category, indicating a broad range of firm sizes within the industry as a whole. In Figure A.2, the variability of the industry distribution across the five categories suggests the comprehensive involvement of various industries in the current market landscape. Figure A.3 illustrates the distribution of propensity scores for two groups: those who were treated (shown in red) and those who were untreated (shown in blue).

Table A.1 provides the pre-matching comparative analysis of firms that adopted both eco-innovation and a new digital technology and those that did not. It reveals significant differences in R&D expenditures, R&D staff ratios, firm age, and the technological intensity of the firms' industries. Notably, after matching, the differences are reduced, indicating the effectiveness of the matching process at creating comparable groups for further analysis. The p-values suggest that these differences have varying levels of statistical significance.

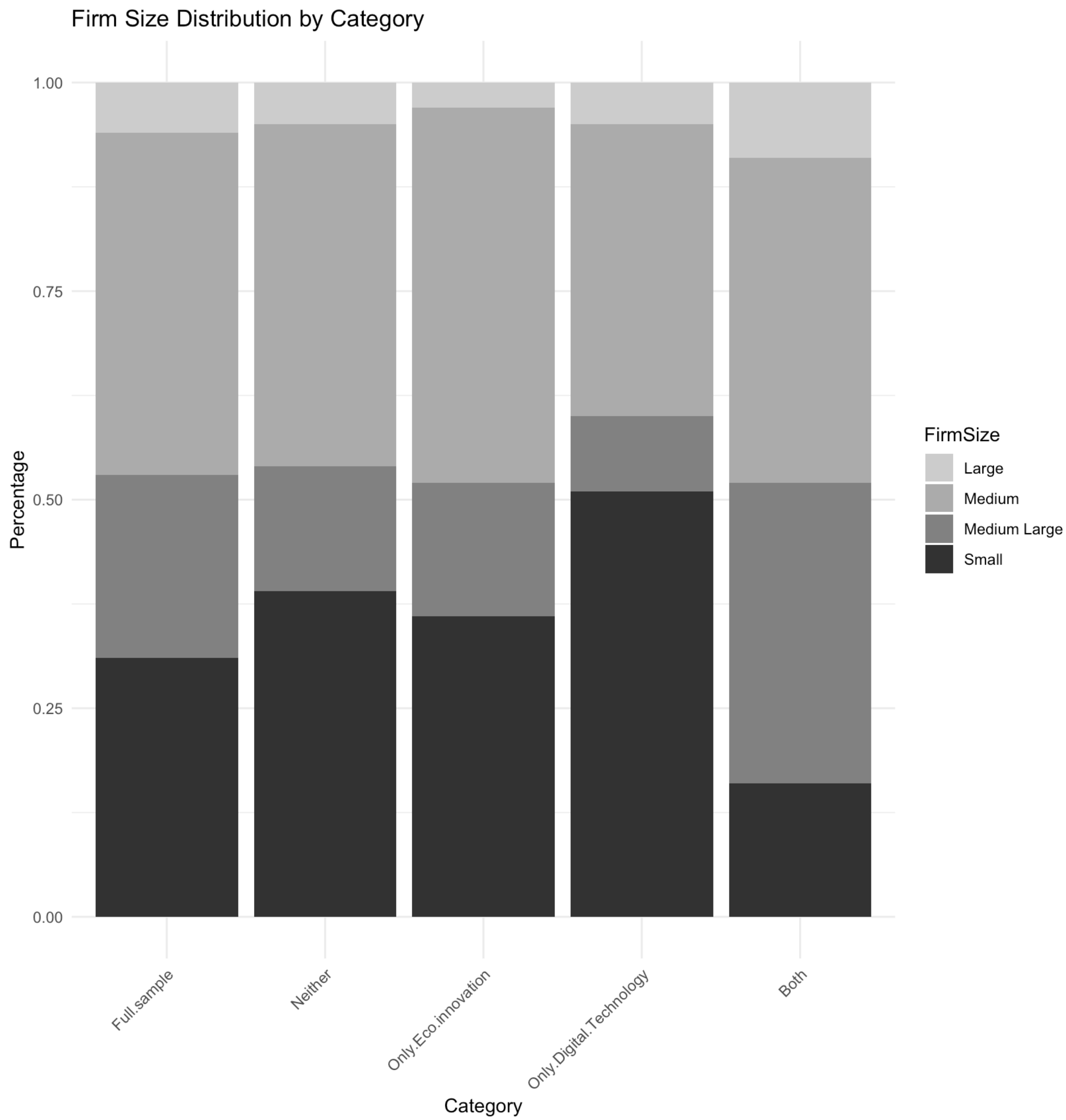

Figure A.1. Firm size distribution across the five categories

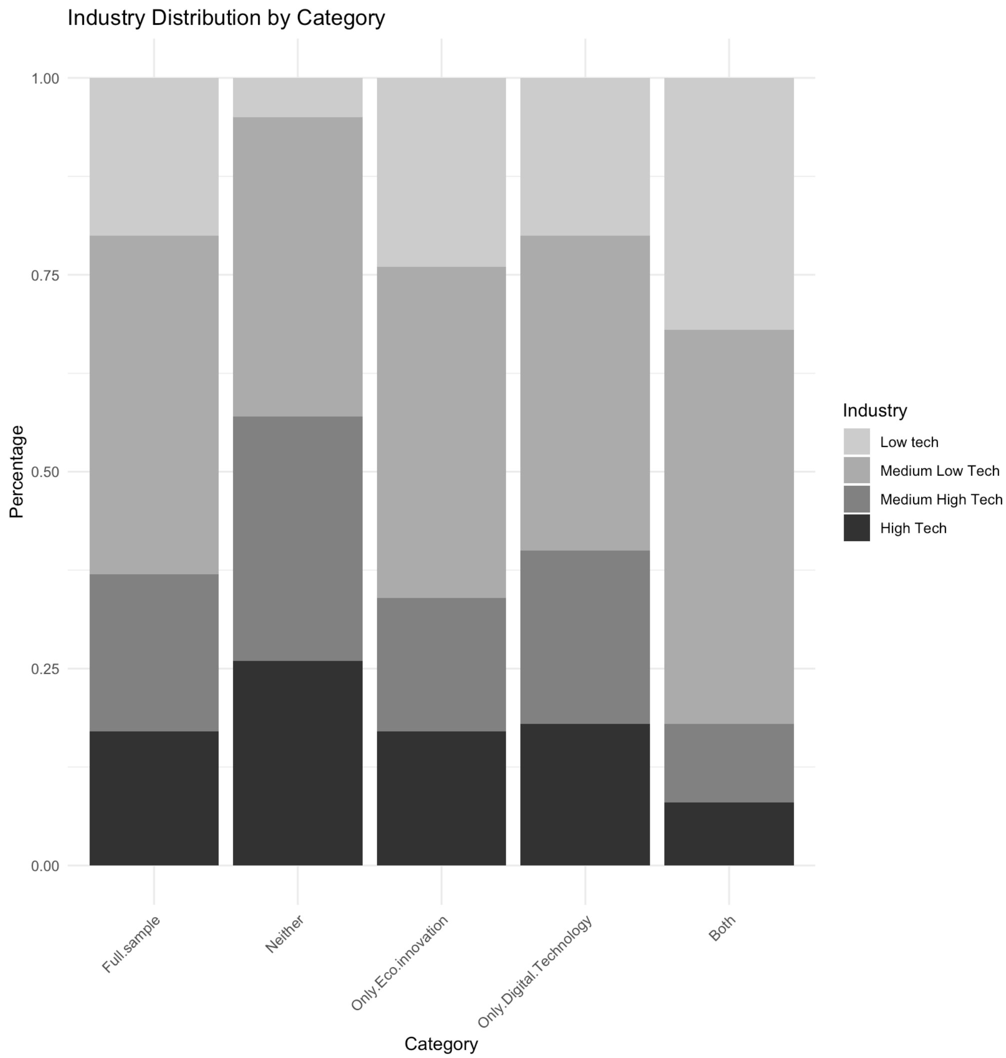

Figure A.2. Industry distribution across the five categories

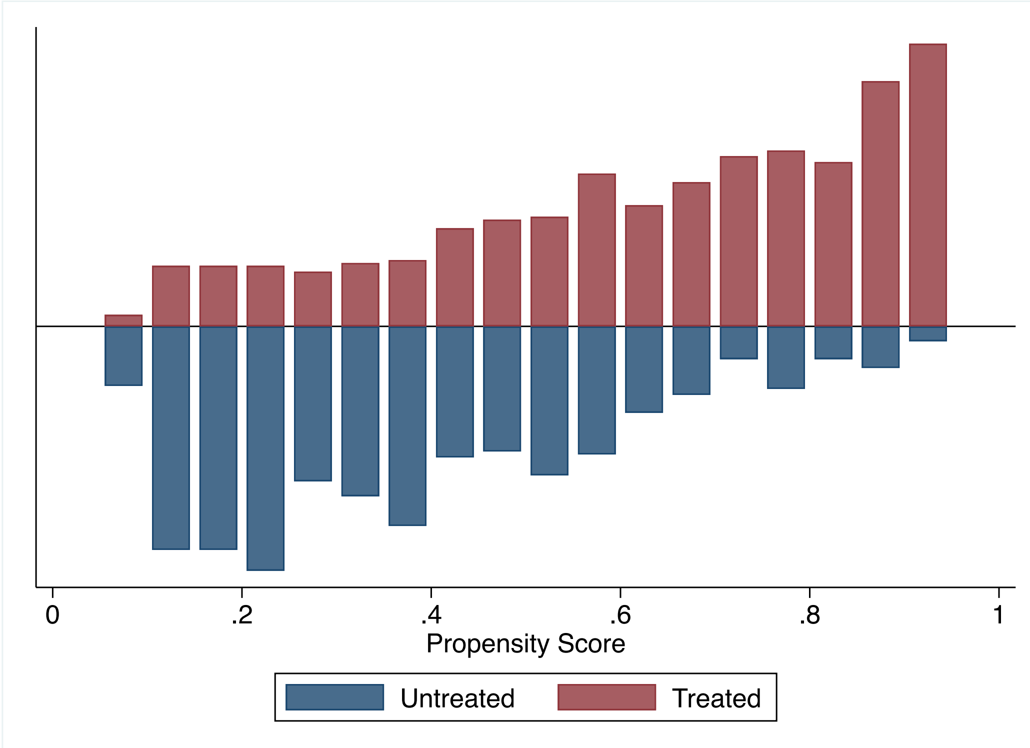

Figure A.3. Distribution of propensity scores by treatment and common support

Table A.1. Pre-matching comparative analysis of firms that adopted both eco-innovation and a new digital technology and those that did not

Variable	Matching status (Unmatched/Matched)	Treated	Control	Difference	p-value
Log R&D	U	7.170	5.972	1.198***	0.000
Expenditure	M	6.923	6.776	0.147*	0.073
R&D Staff	U	11.166	9.376	1.79***	0.000
	M	10.504	11.176	-0.672	0.178
Firm's Age	U	27.806	23.094	4.712***	0.000
	M	27	26.251	0.749	0.308
Small Firm	U	0.163	0.387	-0.224***	0.000
	M	0.179	0.221	-0.042**	0.040
Medium Firm	U	0.392	0.415	-0.023	0.364
	M	0.423	0.481	-0.058**	0.023
Medium Large Firm	U	0.358	0.153	0.205***	0.000
	M	0.309	0.210	0.099***	0.000
Large Firm	U	0.087	0.046	0.041***	0.001
	M	0.089	0.088	0.001	0.928
Low Tech	U	0.317	0.046	0.271***	0.000
	M	0.252	0.290	-0.038*	0.093
Medium Low Tech	U	0.498	0.376	0.122***	0.000
	M	0.545	0.501	0.044*	0.089
Medium High Tech	U	0.099	0.315	-0.216***	0.000
	M	0.109	0.106	0.003	0.868
High Tech	U	0.086	0.264	-0.178***	0.000
	M	0.094	0.102	-0.008	0.604
Seoul	U	0.157	0.078	0.079***	0.000
	M	0.127	0.149	-0.022	0.232
Busan	U	0.043	0.061	-0.018	0.118
	M	0.046	0.040	0.006	0.526
Daegu	U	0.041	0.036	0.005	0.614
	M	0.042	0.046	-0.004	0.708
Gwangju	U	0.024	0.017	0.007	0.302
	M	0.023	0.025	-0.002	0.736
Daejeon	U	0.028	0.012	0.016**	0.035
	M	0.023	0.009	0.014**	0.040
Ulsan	U	0.035	0.011	0.024***	0.002
	M	0.038	0.045	-0.007	0.520
Sejong	U	0.006	0.004	0.002	0.609
	M	0.005	0.003	0.002	0.414
Gyeonggi	U	0.310	0.345	-0.035	0.139
	M	0.322	0.285	0.037	0.117
Gangwon	U	0.014	0.021	-0.007	0.342
	M	0.015	0.008	0.007	0.223
Chungbuk	U	0.048	0.061	-0.013	0.268
	M	0.052	0.041	0.011	0.328
Chungnam	U	0.078	0.067	0.011	0.372
	M	0.080	0.076	0.004	0.773
Jeonbuk	U	0.016	0.032	-0.016**	0.034
	M	0.017	0.011	0.006	0.272
Jeonnam	U	0.011	0.033	-0.022***	0.002
	M	0.012	0.013	-0.001	0.818
Gyeongbuk	U	0.048	0.055	-0.007	0.522
	M	0.052	0.060	-0.008	0.501
Gyeongnam	U	0.071	0.108	-0.037***	0.010
	M	0.078	0.086	-0.008	0.574

Notes: This table provides a comparative analysis before and after matching firms based on their adoption of eco-innovation and digital technologies across different regions in Korea. Although Korea has 17 administrative regions including Seoul, Busan, Daegu, Gwangju, Daejeon, Ulsan, Incheon, Sejong, and various provinces such as Gyeonggi, Gangwon, Chungbuk, Chungnam, Jeonbuk, Jeonnam, Gyeongbuk, Gyeongnam, and Jeju, the analysis for ATET estimation used only 15, excluding Incheon and Jeju. Incheon was excluded due to significantly increased discrepancies between the treated and control groups after matching, which could bias the treatment effect estimates and disrupt the balance of the matching results. Jeju was also excluded due to missing values, affecting the completeness and accuracy of the analysis. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$