Does the adoption of emerging technologies improve technical efficiency? Evidence from Korean manufacturing SMEs

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Abstract Despite the proliferation of innovative technologies during the Fourth Industrial Revolution (4IR), there is a severe lack of quantitative and empirical studies that deal with the effectiveness of recently emerging technologies. This study examines the impact of employing core technologies of the 4IR on small and medium enterprises (SMEs). We used the firm-level cross-sectional data on Korean manufacturing SMEs, including the information on technology utilization. The stochastic production frontier estimation with selectivity correction is employed, besides matching technique to obtain unbiased estimates on technology efficiency. The empirical analysis finds that adopting emerging technologies enhances the productivity of SMEs. After observed and unobserved factors are controlled, the technical efficiency of adopters is higher by more than 26% on average, compared to non-adopters. Moreover, if the gap among production frontiers is considered, the difference in productivity would rise further. Additionally,

a strategic alliance is a crucial route for SMEs to accept new technologies.

Plain English Summary Adopting emerging technologies in the Fourth Industrial Revolution makes production process more efficient by more than 26% on average. This research using the data on Korean manufacturing small and medium enterprises (SMEs) revealed that new digital technologies have a significantly positive impact on the productivity improvement. More specifically, SMEs adopting emerging technologies like “AI,” “Big Data,” and “Robotics” in the production process have remarkably higher productivity by more than 26%, compared to non-adopters. This result suggests that digital transformation is an unparalleled opportunity for SMEs suffering from lower productivity attributed to some reasons like the outbreak of COVID-19 pandemic. Additionally, the government needs to establish a pan-government control tower and consider a variety of policy measures to promote SMEs to utilize advanced technologies in their production.

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1 Introduction

Enormous transition stemming from digital technologies referred to as the Fourth Industrial Revolution (4IR) (Schwab, 2016) is expected to transform production processes in more efficient ways and lead to considerable productivity increase by diffusing and adopting technology at scale. According to cooperative research by the World Economic Forum and McKinsey (WEF, 2018), the technological revolution would create up to \$3.7 trillion in value by 2025. A forecast analysis by PricewaterhouseCooper (PwC) (2018) demonstrated that artificial intelligence technology could boost global GDP up to 14% higher in 2030, the equivalent of an addition \$15.7 trillion, and about 40% of the impact is accounted for by the improvement in labor productivity.

Even though these tremendous impacts are anticipated, and Korea has been commonly nominated as the most innovative country globally (e.g., Bloomberg Innovation Index), the pace of innovative technologies adoption has remained very low, that is, below 5% in 2018 for Korean manufacturing small and medium enterprises (SMEs) (Statistics Research Institute, 2020). The Korean government has made various policy efforts to exploit this current opportunity to deploy emerging technologies in many industrial fields and reinforce industrial productivity. For example, the Korean government has provided financial support to lower SMEs' initial cost when implementing an automated and integrated system to transform traditional production plants into smart plants. However, as some surveys (McKinsey, 2017, 2018) demonstrated that most industrial companies are still unable to go beyond the pilot stage, the slow pace of adoption is a problem in Korea.

This study focuses on Korean SMEs, considering unbalanced industrial structure between large enterprises (LEs) and SMEs in Korea. Conglomerates, referred to as "chaebol," have led Korean economic growth for almost half a century. According to the Ministry of SMEs and Startups (2018), SMEs take up 99.9% of total firms in 2018 and 83.1% of total employees belong to SMEs. When it comes to manufacturing sectors, SMEs account for 97.9% and employees working in SMEs occupy 71.4%. However, SMEs have yielded only below 40% of total

value-added in the manufacturing sectors. OECD (2020) pointed out that Korea has the largest productivity gap between LEs and SMEs among the Organization for Economic Co-operation and Development (OECD) member countries. This implies that SMEs' low productivity is one of crucial obstacles for Korean economic growth. The 4IR technologies might be a good solution for the productivity improvement and the inclusive growth.

One of the important reasons many SMEs hesitate to adopt emerging technologies in the production process is that they still lack practical evidence on the benefits despite several bright prospects from reports and mass media. There is a severe lack of quantitative and empirical studies that deal with recently emerging technologies such as artificial intelligence, big data, and internet of things. Without a clear return on investment, it would be challenging for SMEs to accept unprecedented changes and make enormous digital transformation investments. This study aims to provide comprehensive evidence on the technical efficiency of SMEs adopting new technologies related to the 4IR. We used a large cross-sectional data that includes firms' characteristics and a questionnaire on utilizing the 4IR's core technologies to accomplish the research purpose. In addition to matching techniques, we used the stochastic production frontier estimation with selectivity correction proposed by Greene (2010) to obtain unbiased estimates on technology efficiency. According to this study's empirical results, employing emerging technologies helps to manufacture SMEs, enhancing technical efficiency in the production process.

The following Sect. 2 begins with a short literature review on the relationship between adopting new technologies, productivity, and efficiency at the firm level. Section 3 elaborates on the analytical methodology in the paper, and Sect. 4 shows empirical results. The final section concludes with a summary of the results and possible directions for further work.

2 Literature review

2.1 New technology-adoption, productivity, and technical efficiency

The Third Industrial Revolution began in the latter half of the twentieth century with rapid advances in

information and communication technologies (ICTs). The proliferation of digital computers and the invention of the internet brought fundamental changes in production. Since the well-known Solow Paradox (Solow, 1987), the relationship between productivity and ICT has attracted explosive attention from economic researchers. Thus, most previous literature on the relationship between technology-adoption and productivity have been associated with ICT. Many studies found the adoption of ICT enhances productivity (Greenan & Mairesse, 2000; Brynjolfsson & Hitt, 2003; Matteucci et al., 2005; Hempell, 2005; Maliranta & Rouvinen, 2006), though a small number of studies could not find any significant evidence on the relation (Colombo et al., 2013; Haller & Lyons, 2015).

However, the technology-adoption might reduce firms' productivity. Huggett and Ospina (2001) argued that large equipment investments cause a decrease in total factor productivity by 3–9% annually. Sakellaris (2004) found that total factor productivity drops sharply after adopting new technologies due to the adjustment cost, but it starts to recover afterwards. Nakamura and Ohashi (2008) investigated the effects of new technology adoption in the steel industry's productivity. They found an initial productivity slowdown due to the loss of vintage-specific experience, but the productivity increased remarkably because of the high efficiency of new technology.

A firm's technical efficiency (TE) is defined as its success in producing a large output from a given set of inputs (Farrell, 1957). Technical efficiency measures how far a firm's production is positioned from the production frontier, referring to maximum possible output (or minimum possible input) using a given set of inputs (or outputs). As a relative concept of productivity, the efficiency can be measured as each firm's distance from the "best practice" frontier. According to the empirical results on productivity, significantly positive effects of ICT adoption on technical efficiency have been generally observed in the previous literature (Becchetti et al., 2003; Mouelhi, 2009; Castiglione, 2012).

Currently, a new round of the Solow paradox has begun in the era of the 4IR. Schwab (2016) emphasized that the 4IR is fundamentally different from the Third Industrial Revolution regarding speed,

scope, and depth. The 4IR has been triggered by more advanced, disruptive, and integrated technologies such as artificial intelligence (AI), the Internet of Things (IoT), and cloud computing. People are currently utilizing IoT-embedded systems, transmitting a large scale of data by 5G network, storing such big data in the cloud computing, and simultaneously processing the data by AI. The current breakthroughs are witnessed everywhere, but it is not easy to find economic research or statistics that evaluate returns on emerging technologies. Müller et al. (2018) showed that the firm's assets related to big data and analytics are associated with an average increase in productivity by about 4.1%. Additionally, their results indicated that such assets are associated with higher productivity for firms in highly competitive industries than firms in non-competitive industries. Graetz and Michaels (2018) provided an analysis of the economic contributions of modern industrial robots for the first time. According to their results, increased robot use contributed approximately 0.36 percentage points to annual labor productivity growth, accounting for 15% of aggregate economy-wide growth. Damioli et al. (2021) investigated the productivity growth for firms that have filed at least one patent related to the field of AI. Their results indicate AI patent applications generate a positive effect on firms' labor productivity. These studies analyzed the impact of independent technology. However, new technologies in the 4IR have highly integrated and connected characteristics, meaning they operate systematically rather than in isolation. This is why a comprehensive approach encompassing adjacent technologies is necessary to analyze impacts of emerging technologies.

2.2 Endogeneity in the estimation

A critical issue on the relationship between technology-adoption and productivity is an endogeneity problem in the estimation model that has been ignored in several previous studies. As Majumdar et al. (2009) highlighted, one example of a possibly correlated variable is managerial ability. Even though it is hard to measure the variable, a considerable fraction of the unexplained variation in productivity is due to such unobserved variables in the model. Besides endogeneity by omitted factors, Hempell (2005) and Müller et al. (2018) were also concerned about reverse causality. For example, highly productive firms with

Fig. 1 Analytical framework

skilled and flexible management are likely to be so productive that these firms tend to invest more in new technologies than others.

An estimation procedure with an instrument variable (IV) is commonly used to address potential endogeneity. Atrostic and Nguyen (2005) reported that the two-stage estimate was nearly twice as large as the ordinary least squares (OLS) estimate when examining the impact of a computer network on labor productivity. Matteucci et al. (2005) showed that the IV estimate on the productivity impact of ICT investments increased for manufacturing firms, and decreased for service firms, compared to the OLS estimate. While analyzing the productivity effects of ICT, Hempell (2005) also found a non-negligible difference between pooled OLS estimates and system GMM (generalized method of moments) estimates.

Furthermore, stochastic production frontier (SPF) models with correction of sample selection bias have been developed. If propensity score matching (PSM) before estimating an SPF model is used, observable variables that affect sample selection are controlled, while unobservable variables remain uncontrolled, causing sample selection bias. Several SPF models (Greene, 2010; Kumbhakar et al., 2009; Lai, 2015) have been developed to control the selection bias. These models have differences in assumption about the terms are correlated in the estimation model due to the unobserved variables. In this study, the SPF

model by Greene (2010), an extension of Heckman (1979)'s two-step procedure to the nonlinear estimation, is applied to obtain unbiased estimates. This methodology has been widely used to investigate the impact of technology adoption accounting for selectivity bias (Bravo-Ureta et al., 2012; González-Flores et al., 2014; Ma et al., 2018). Moreover, Lai (2015)'s approach based on the maximum likelihood function generally yields the same results as Greene (2010)'s methodology (Greene, 2016).

3 Analytical framework

An overall analytical framework is illustrated in Fig. 1. Following sequential processes of Bravo-Ureta et al. (2012), we incorporated PSM into the efficiency estimation. As a pre-process of the stochastic production frontier (SPF) estimation, the PSM method controls observed covariates in the production function. Thus, samples are divided into matched sample by PSM and unmatched sample. After the matching process of the first step, an untreated control group of each sample, referred to as "non-adopters" is found for comparison with a treated group, referred to as "adopters." As the second step for sample selection, probit equations are estimated. When it comes to the estimation of TEs, it is necessary to apply conventional and selectivity-corrected SPF models to

Fig. 2 Description of the stochastic production frontier model

unmatched and matched samples to verify the selection bias due to the unobserved factors. It is notable that the selectivity-corrected SPF models use the parameters estimated in the second step to take into account the selection bias. Finally, controlling the bias for both observed and unobserved variables using these estimation processes, unbiased and consistent effects of emerging technologies are obtained.

The SPF proposed by Aigner et al. (1977) and Meeusen and Broeck (1977) is based on the idea that observed outputs consist of the deterministic production frontier and stochastic terms; the stochastic terms, meaning deviations from the frontier consist of a random error term (v_i) and an inefficiency term (u_i). Using the logarithmic transformation, the stochastic production frontier is formulated as

$$\ln(y_i) = \ln f(x_i; \beta) + v_i - u_i \quad (1)$$

where y_i , x_i and β denote an output for the i th firm and a vector of production inputs, and a vector of coefficients to be estimated, respectively. The first term on the right side presents the deterministic production frontier, meaning the maximum feasible output from a given bundle of inputs. The random error term is assumed to be $N(0, \sigma_v^2)$, which is independent with the non-negative inefficiency term. The combination of the deterministic production frontier and the random error term presents the stochastic production frontier. The unobserved u_i (e.g., u_A and u_B in Fig. 2) is estimated by the distance from the stochastic production frontier. In general, the output-oriented technical efficiency is measured as an exponential form

of u_i , $\exp(-u_i)$. A simple SPF model with one input and one output is described in Fig. 2. The observed outputs are dispersed from the deterministic production frontier due to the noise effect of v_i and the inefficiency effect of u_i .

Greene (2010) incorporated self-selection specification of Heckman (1979) in the SPF estimation. The SPF model with correction for sample selection assumes that the sample selection model's unobserved factors are correlated with the random error term in the SPF model. Combining the sample selection and SPF models, the selectivity-corrected SPF model can be written as

$$\begin{aligned} \text{Sample selection : } d_i &= 1[\alpha'z_i + w_i], \quad w_i \sim N(0, 1) \\ \text{SPF model : } \ln(y_i) &= \ln f(x_i; \beta) + \varepsilon_i, \quad \varepsilon_i \sim N(0, \sigma_\varepsilon^2) \\ (y_i, x_i) &\text{ observed only when } d_i = 1 \end{aligned} \quad (2)$$

$$\text{Error structure: } \varepsilon_i = v_i - u_i$$

$$u_i = |\sigma_u U_i| = \sigma_u |U_i|, \text{ where } U_i \sim N(0, 1)$$

$$v_i = \sigma_v V_i, \text{ where } V_i \sim N(0, 1)$$

$$(w_i, v_i) \sim N_2[(0, 1), (1, \rho\sigma_v, \sigma_v^2)]$$

After assorting the sample into treated and control groups with or without matching, the next step is to estimate a sample selection probit model. The binary choice, d_i , represents whether a certain firm adopted emerging technologies ($d_i = 1$) or not ($d_i = 0$). A vector of variables that affect the adoption is denoted by z_i , including the firm's various characteristics. α and w_i present a vector of unknown coefficients to be estimated and a random error term, respectively. Given

the estimates of α , the following step is to estimate the SPF model jointly using maximum likelihood estimator (MLE). In contrast, the conventional SPF model is estimated regardless of the estimates from the sample selection model. The key parameter is ρ which captures selectivity bias. For instance, if both the selection model and the SPF model are simultaneously affected by unobserved factors, sample selection bias arises due to the correlation between error terms of each model. Thus, the statistical significance of ρ indicates the presence or the absence of selectivity bias.

The conditional density function on the unobserved $|U_i|$ of conventional SPF and selectivity-corrected SPF with the correlation parameter is specified as.

- Convention SPF:

$$f(y_i|x_i, |U_i|) = \frac{\exp\left[-\frac{1}{2} \frac{(\ln(y_i) - \ln f(x_i; \beta) + \sigma_u |U_i|)^2}{\sigma_v^2}\right]}{\sigma_v \sqrt{2\pi}} \quad (3)$$

- Selectivity-corrected SPF:

$$f(y_i|x_i, |U_i|, z_i, d_i) = \left[d_i \left\{ \frac{\exp\left(-\frac{1}{2} \frac{(\ln(y_i) - \ln f(x_i; \beta) + \sigma_u |U_i|)^2}{\sigma_v^2}\right)}{\sigma_v \sqrt{2\pi}} \Phi\left(\frac{\rho(\ln(y_i) - \ln f(x_i; \beta) + \sigma_u |U_i|) + \alpha' z_i}{\sqrt{1-\rho^2}}\right) \right\} + (1 - d_i) \Phi(-\alpha' z_i) \right] \quad (4)$$

where $\Phi(\bullet)$ is the cumulative distribution function of the standard normal distribution. The estimates of the previous sample selection model, $\alpha' z_i$, and the correlation parameter, ρ , are considered in the following selectivity-corrected SPF estimation, different from the estimation of the conventional SPF model. It is necessary to integrate the conditional density function concerning $|U_i|$ to obtain the unconditional log-likelihood function as:

$$\ln L(\beta, \sigma_u, \sigma_v, \rho) = \sum_{i=1}^N \ln \int_{|U_i|} f(y_i|x_i, z_i, d_i, |U_i|) p(|U_i|) d|U_i| \quad (5)$$

where $p(|U_i|) = \sqrt{2/\pi} \cdot \exp(-\frac{1}{2}|U_i|^2)$. In case integrating the unobserved random variable, $|U_i|$, does not yield a close form of the log-likelihood function, the maximum simulated likelihood estimator

is used regarding the unobserved $|U_i|$. Consistent with Greene (2010), parameters of the SPF model are estimated through a conventional gradient-based approach, the Broyden-Fletcher-Goldfarb-Shanno (BFGS) method, and asymptotic standard errors are estimated through the Berndt-Hall-Hall-Hausman (BHHH) estimator. After fitting the frontier to the data, an individual random term, ϵ_i , is estimated and then the individual inefficiency, u_i , or technical efficiency, $\exp(-u_i)$, is computed by the conditional means, $E[u_i|\epsilon_i]$, as presented by Jondrow et al. (1982). These estimation procedures are conducted with NLOGIT (version 6) and open-source software R (version 4.0.2).

4 Empirical results

4.1 Data

The most important obstacle to find evidence on the economic impacts of emerging technologies in the era of 4IR is that there are little data available to use. Seamans and Raj (2018) emphasized: “There are no public datasets on the utilization or adoption of AI at

either the macro or micro level. Systematic data on the adoption and use of robots and AI, particularly at the establishment level, is necessary to understand the efforts of these technologies on the economy and society as a whole.”

Fortunately, the relevant firm-level information on which firms adopt emerging technologies and in which stage of the supply chain these technologies are being utilized is obtained from “The Survey of Business Activities,” annually published by the Statistics Korea.¹ The survey’s target includes all the firms across Korea’s industries with more than 50 fully employed workers and more than 0.3 billion

¹ If you want to download the latest version of the microdata, please refer to the website of the Statistics Korea (<https://mdis.kostat.go.kr/eng/index.do>).

Table 1 Ratio of firms using and developing 4IR technologies by business function (%)

	Manufacturing			Service		
	LEs	SMEs	All firms	LEs	SMEs	All firms
Research and development	15.84 (32)	5.39 (321)	5.73 (353)	13.84 (62)	7.82 (481)	8.23 (543)
Production process	9.41 (19)	2.67 (159)	2.89 (178)	2.01 (9)	0.63 (39)	0.73 (48)
Organization management	3.96 (8)	1.48 (88)	1.56 (96)	4.02 (18)	1.63 (100)	1.79 (118)
Marketing	4.46 (9)	0.79 (47)	0.91 (56)	8.93 (40)	2.24 (138)	2.70 (178)
Total firms	202	5960	6162	448	6151	6599

Note: Figures in parentheses represent the number of firms.

Fig. 3 Number of SMEs by adopting technology

KRW as capital. That is, it is based on complete enumeration for all firms over a certain size and the firms are compelled to respond to the national survey by the Statistics Korea since it is one of designated statistics. Besides, the large micro-survey also includes financial information, characteristics, and management strategies for 13,144 firms across industry. Table 1 shows the ratio of firms using and developing 4IR technologies by business functions. It is based on multiple selections. The ratio is different from the adoption rate in that it includes firms developing 4IR technologies as well as adopting them. The ratio is relatively low for SMEs in the either sector of manufacturing and service, compared to LEs.²

Using the survey of 2018, we abstracted 5598 SMEs in the manufacturing sector, excepting LEs. The firms that do not have any missing data for indispensable information for SPF estimation are

² If total assets of a firm are valued over 10 trillion KRW, it is classified as a large enterprise (LE). Moreover, the relevant subsidiaries are also regarded as LEs. Otherwise, the firm is classified as a small and medium enterprise (SME).

abstracted from the original dataset. The “adopters” do not mean SMEs that develop emerging technologies but employ such technologies in their production process. Only 2.68% (150 firms) of the total sample SMEs have utilized new technologies classified into nine categories: “IoT,” “Cloud Computing,” “Big Data,” “5G mobile network,” “AI,” “Block Chain,” “3D printing,” “Robotics,” and “Virtual/Augmented Reality (VAR).”

Figure 3 shows the number of adopting firms by technology. The most prevalent for the production process is industrial robotics which occupies 65% of adopting firms, followed by IoT (24.7%), and Big Data (24%). Twenty-three firms of the 150 SMEs had adopted two technologies, while 14 firms utilized three or more technologies. This presents that about one-fourth of total adopting firms are deploying more than one emerging technologies simultaneously and are systematically integrated into the production plants.

Table 2 lists the definition and summary statistics of variables used in the empirical analysis. Some

Table 2 Variable definition and summary statistics

Variable	Definition	Mean	S.D	Min	Max
Stochastic production frontier model					
VAD	Value added (million KRW)	19,730.01	54,745.63	12	1,873,281
CAP	The total amount of fixed asset (million KRW)	62,494.70	187,105.55	2	4,190,242
LAB	Number of employees	220.99	597.07	50	21,756
ICD _{<i>i</i>}	Dummy variable for industrial classification	-	-	0	1
ADP	One if the firm adopted emerging technologies, 0 otherwise	0.03	0.16	0	1
Sample selection probit model					
GEND	One if the owner is male, 0 otherwise	0.95	0.22	0	1
RRND	Research and development expenditure to total sales	0.02	0.04	0	0.99
RPRF	Net profit before tax to total sales	0.05	0.13	-0.67	4.50
NPAT	Number of patents	18.22	88.06	0	2779
NBIZ	One if the firm is starting a business in the new area, 0 otherwise	0.03	0.16	0	1
ALLI	One if the firm is in strategic alliances with others, 0 otherwise	0.07	0.25	0	1
SMK1	One if the type of stock market listing is KOSPI, 0 otherwise	0.07	0.25	0	1
SMK2	One if the type of stock market listing is KOSDAQ, 0 otherwise	0.11	0.31	0	1

Table 3 Adoption rate by manufacturing industry

Manufacturing industry	Adopters	Non-adopters	Adoption rate (%)
(1) Food products, beverages, and tobacco	10	404	2.41
(2) Textiles, wearing apparel, and leather	6	334	1.76
(3) Refined petroleum and chemical products	20	787	2.48
(4) Pharmaceuticals	3	165	1.79
(5) Non-metallic mineral products	6	160	3.61
(6) Basic metals and fabricated metal products	28	717	3.76
(7) Electronic components, computer, and communication equipment	18	780	2.26
(8) Electrical and machinery equipment	25	1055	2.31
(9) Transport equipment	26	767	3.28
(10) Other manufacturing	8	279	2.79

variables related to value-added, labor, and capital are used in the stochastic production function, while others are used in the probit model for sample selection. Data on the firm's value-added, capital, and labor are spread in a wide range, which indicates the variety of firm size. To consider differences in the production process attributed to industrial heterogeneity, a dummy variable (ICD_{*i*}) is added in the production

function. The manufacturing sector is classified into 10 industries and adoption rates in each industry are shown in Table 3. The adoption rates for manufacturers of "basic metals and fabricated metal products" and "non-metallic mineral products" amount to more than 3.5%.

Many available information of each firm is used in the sample selection equation to reflect current

Table 4 Descriptive statistics of variables used in the stochastic frontier model

Variable	Pooled		Adopters		Non-adopters		Test of means
	Mean	S.D	Mean	S.D	Mean	S.D	
Before matching							
VAD	19,730.01	54,745.63	46,523.84	119,531.84	18,992.29	51,657.20	−2.814***
CAP	62,494.70	187,105.55	178,405.75	525,906.67	59,303.31	167,411.86	−2.77***
LAB	220.99	597.07	439.46	905.55	214.98	585.26	−3.019***
Obs	5598		150		5448		
After matching							
VAD	45,384.35	153,161.20	46,523.84	119,531.84	44,244.86	181,062.62	−0.127
CAP	168,666.22	512,299.79	178,405.75	525,906.67	158,926.69	499,894.73	−0.332
LAB	490.807	1656.06	439.46	905.55	542.15	2162.90	0.532
Obs	300		150		150		

Note: *t*-test is used to determine if the mean values of samples between adopters and non-adopters are significantly different.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

circumstances from various perspectives. The gender of firm's owner is considered as a control variable, because entrepreneurs' gender could have an impact on the innovative activities of a firm (Chen et al., 2018; Torchia et al., 2018). Its mean value of owner's gender (GEND) is 0.95, which indicates firm's owners in the sample firms are mostly male. Since firm's technological capacity and financial status might be associated with an investment in innovative technologies (Wang et al., 2008; Yam et al., 2004), variables related to research and development (RRND), net profit (RPRF), and patents (NPAT) are considered in the probit model. Table 2 shows that the average portion of R&D expenditure in total sales is around 2%. The net profit ratio to total sales varies largely across firms and some firms make a negative profit. In case of the number of patents, more than 30% of total sample firms do not have patents, whereas its maximum is 2779. This implies that a small number of innovative firms increased the average number of patents dramatically. The variable, "NBIZ," is added to consider the possibility that a firm allows the adoption of new equipment if it has been in the initial phase of a new business area. The strategic alliance for technology development, market or other purposes, and cooperation and openness can affect innovative technologies' acceptance. However, the ratio of firms engaging in strategically alliance is low, just around 7%. Additionally, the stock market in which a firm is listed is considered one measure of its characteristics. The

Korean stock markets, "KOSPI" and "KOSDAQ," correspond to the "NYSE" and "NASDAQ," in the United States (U.S.), respectively.

Table 4 shows the mean differences of the variable used in the production function before and after applying PSM. Before matching, adopters and non-adopters are significantly different groups in terms of primary inputs and output. Firms that belong to the adopters' group create a larger amount of value-added on average, putting in more labor and capital in the production. This implies that firms with a relatively large scale tend to adopt emerging technologies. Since most firms in total sample firms belong to non-adopters group, the mean and standard deviation of each variable between pooled sample and non-adopters are fairly similar. It is not reasonable to assume the production function to have constant returns to scale without evidence. However, if the production function has increasing or decreasing returns to scale, it is necessary to adjust inputs and output in the control group (non-adopters) to the same level with the treatment group (adopters) to rule out the effect from economies or diseconomies of scale.

Using the nearest neighbor matching with probit distance measure, the values of all variables get balanced between the two groups, representing mean differences are statistically insignificant. Compared to other matching techniques such as radius and kernel matching, the nearest neighbor matching shows better

balancing performance in this sample. Since the “one to one” matching process is used without replacement, the non-adopters group consist of the same number of firms as in the adopters’ group. The matching procedure is applied to observed variables in the production function. If the matching is applied to variables even in the sample selection probit model, the null hypothesis that all coefficients in the model are simultaneously zero is not rejected. This is because probit regressions are duplicated to the same variables in the selection model as well as in the matching process.

4.2 Decision on the adoption of emerging technologies

Manufacturing SMEs can decide to make use of new technologies in their production process. Postulating that the decision of the i th firm is a function of firms’ characteristics (z_{ji}) listed in Table 2 for the selection model, the selection criterion function is described as:

$$d_i^* = \alpha' z_i = \alpha_0 + \sum_{j=1}^8 \alpha_j z_{ji} + w_i \quad (6)$$

where d_i^* is an unobserved latent variable. The observed d_i indicates whether or not to decide adoption depending on the latent variable.

$$d_i = \begin{cases} 1, & \text{iff } d_i^* \geq 0 \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

Therefore, this probit model is based on the selection probability of $\Pr(d_i = 1|z_i) = \Pr(d_i^* > 0) = \Phi(\alpha' z_i)$.

Table 5 shows the results of the selection model for both the unmatched and matched samples. The chi-square test statistics of the two cases verify that the selection model is statistically significant at the 5% confidence level, rejecting the hypothesis that all coefficients of the model are zero. Estimates report that patents (NPAT), new business plans (NBIZ), strategic alliances (ALLI), and stock market listing (SMK1) significantly influence the technology adoption for the unmatched sample. The estimated coefficients for the new business plans (NBIZ) and the strategic alliance (ALLI) remain significantly positive even for the matched. It is not surprising that firms getting ready for new business decide to adopt new

Table 5 Parameter estimates of the selection model

Variables	Unmatched sample	Matched sample
Constant	−1.991*** (0.163)	−0.335 (0.316)
GEND	−0.030 (0.166)	0.217 (0.321)
RRND	−2.083 (1.369)	−0.687 (3.227)
RPRF	0.123 (0.258)	0.385 (0.720)
NPAT	0.001* (0.000)	−0.000 (0.000)
NBIZ	0.518*** (0.158)	0.602* (0.353)
ALLI	0.507*** (0.105)	0.722*** (0.238)
SMK1	0.283** (0.118)	0.162 (0.249)
SMK2	0.018 (0.118)	−0.057 (0.241)
L -Likelihood	−664.191	−199.730
$\chi^2(8)$	53.422***	16.429**
Pseudo R^2	0.039	0.040
N	5598	300

Note: Standard errors are presented in parentheses.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

technologies. They need innovative technologies to step into and compete in new business areas. When it comes to strategic alliance, previous studies emphasize its importance as a source of innovation (Ahuja, 2000; Baum et al., 2000). Alliances also positively influence technological diversity, providing an opportunity to learn more quickly from their partners than isolated firms. Therefore, our result reveals that strategic alliances with other firms work as an effective driver for the knowledge transfer and technology diffusion in the era of the 4IR.

4.3 Stochastic frontier analysis

The production frontier is postulated to be a flexible translog functional form without restriction except for symmetry as:

Table 6 Parameter estimates for the SPF models with unmatched samples

Variables	Conventional SPF			Selectivity-corrected SPF	
	Pooled (Model 1)	Adopters (Model 2)	Non-adopters (Model 3)	Adopters (Model 4)	Non-adopters (Model 5)
Constant	0.650*** (0.039)	0.273 (0.172)	0.656*** (0.040)	0.388 (0.579)	0.563*** (0.053)
lnCAP	0.222*** (0.010)	0.268*** (0.052)	0.222*** (0.010)	0.235*** (0.070)	0.195*** (0.009)
lnLAB	0.890*** (0.018)	0.778*** (0.080)	0.891*** (0.018)	0.805*** (0.098)	0.918*** (0.019)
(lnCAP) ²	0.106*** (0.009)	0.202** (0.082)	0.106*** (0.009)	0.205** (0.094)	0.085*** (0.007)
(lnLAB) ²	−0.040 (0.030)	0.377** (0.155)	−0.049 (0.031)	0.369** (0.194)	−0.120*** (0.013)
lnCAP × lnLAB	−0.058*** (0.015)	−0.266*** (0.102)	−0.054*** (0.015)	−0.269** (0.119)	−0.011 (0.009)
ICD ₁	−0.145*** (0.050)	−0.093 (0.211)	−0.148*** (0.051)	0.046 (0.276)	−0.155** (0.061)
ICD ₂	−0.115** (0.052)	0.413* (0.235)	−0.125** (0.053)	0.562** (0.252)	−0.161*** (0.058)
ICD ₃	0.089**				
(0.044)	0.029				
(0.188)	0.091**				
(0.045)	0.186				
(0.197)	0.080				
(0.053)					
ICD ₄	0.054 (0.062)	0.219 (0.298)	0.051 (0.063)	0.410 (2.237)	0.015 (0.069)
ICD ₅	0.064 (0.063)	0.100 (0.239)	0.067 (0.064)	0.240 (0.264)	0.063 (0.072)
ICD ₆	−0.062 (0.045)	0.068 (0.178)	−0.064 (0.046)	0.209 (0.131)	−0.062 (0.055)
ICD ₇	−0.098** (0.044)	0.096 (0.188)	−0.101** (0.045)	0.208 (0.174)	−0.143*** (0.053)
ICD ₈	−0.020 (0.043)	0.339* (0.181)	0.013 (0.044)	0.482*** (0.156)	−0.011 (0.052)
ICD ₉	−0.190*** (0.044)	−0.097 (0.183)	−0.189*** (0.045)	0.047 (0.173)	−0.186*** (0.056)
ADP	0.014 (0.053)				
L.Likelihood	−5582.829	−86.204	−5470.717	−604.539	−5782.412
λ	1.866*** (0.045)	1.536*** (0.276)	1.870*** (0.046)		
σ	0.942*** (0.000)	0.584*** (0.003)	0.949*** (0.000)		
σ _u				0.369*** (0.207)	0.696*** (0.021)
σ _v				0.396*** (0.094)	0.562*** (0.009)
ρ _(w,v)				−0.365 (0.486)	0.112 (0.369)
N	5598	150	5448	150	5448

Note: Standard errors are presented in parentheses. $\lambda = \sigma_u / \sigma_v$ and $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

$$\ln(\gamma_i) = \beta_0 + \sum_{j=1}^2 \beta_j \ln(x_{ji}) + \frac{1}{2} \sum_{k=1}^2 \sum_{j=1}^2 \beta_{jk} \ln(x_{ki}) \ln(x_{ji}) + \sum_{j=1}^{10} \delta_j ICD_{ji} + v_i - u_i, \beta_{jk} = \beta_{kj} \quad (8)$$

where y_i denotes the value-added of the i th firm and x_i is the primary inputs (i.e., capital and labor). The industrial dummy, ICD_{ji} , is 1 when the firm belongs to the j th industry. When pooled samples are used for estimation, one dummy variable, ADP_i , indicating

whether or not to adopt emerging technologies is added. The MLE results for the SPF model are presented in Tables 6 and 7. Table 6 presents the empirical results of the unmatched sample, while Table 7 presents the matched. For all cases, a likelihood ratio test of the one-sided error, in which the critical values are given by Kodde and Palm (1986), indicates that the inefficiency is significant. Additionally, the estimates of λ which denotes the ratio of standard deviations, σ_u and σ_v , are greater than one in all the models, indicating that the inefficiency effect is greater than the noise effect.

Table 7 Parameter estimates for the SPF models with matched samples

Variables	Conventional SPF			Selectivity-corrected SPF	
	Pooled (Model 1)	Adopters (Model 2)	Non-adopters (Model 3)	Adopters (Model 4)	Non-adopters (Model 5)
Constant	0.477*** (0.152)	0.273 (0.172)	0.510** (0.225)	0.283 (0.288)	0.243 (0.427)
lnCAP	0.197*** (0.039)	0.268*** (0.052)	0.094 (0.061)	0.283*** (0.059)	0.040 (0.075)
lnLAB	0.807*** (0.065)	0.778*** (0.080)	0.806*** (0.109)	0.756*** (0.088)	0.877*** (0.141)
(lnCAP) ²	0.235*** (0.063)	0.202** (0.082)	0.307*** (0.090)	0.217** (0.089)	0.258*** (0.098)
(lnLAB) ²	0.253** (0.109)	0.377** (0.155)	0.258* (0.148)	0.413** (0.186)	0.217 (0.180)
lnCAP × lnLAB	−0.230*** (0.074)	−0.266*** (0.102)	−0.247** (0.105)	−0.289** (0.114)	−0.208 (0.128)
ICD ₁	−0.224 (0.197)	−0.093 (0.211)	−0.341 (0.326)	−0.084 (0.258)	−0.391 (0.828)
ICD ₂	−0.112 (0.212)	0.413* (0.235)	−0.934*** (0.349)	0.489** (0.243)	−1.220*** (0.353)
ICD ₃	0.095 (0.169)	0.029 (0.188)	0.316 (0.274)	0.068 (0.190)	0.251 (0.303)
ICD ₄	0.326 (0.288)	0.219 (0.298)	0.629 (0.486)	0.277 (1.433)	0.679 (0.926)
ICD ₅	0.053 (0.220)	0.100 (0.239)	0.120 (0.352)	0.140 (0.240)	0.186 (0.829)
ICD ₆	0.002 (0.157)	0.068 (0.178)	0.012 (0.241)	0.114 (0.135)	−0.012 (0.293)
ICD ₇	−0.098 (0.162)	0.096 (0.188)	−0.212 (0.247)	0.119 (0.182)	−0.209 (0.327)
ICD ₈	0.126 (0.162)	0.339* (0.181)	−0.126 (0.257)	0.373** (0.163)	−0.196 (0.308)
ICD ₉	−0.141 (0.161)	−0.097 (0.183)	−0.108 (0.251)	−0.050 (0.176)	−0.107 (0.314)
ADP	0.043 (0.068)				
L.Likelihood	−260.096	−86.204	−146.263	−186.881	−248.701
λ	2.064*** (0.235)	1.536*** (0.276)	2.261*** (0.377)		
σ	0.849*** (0.002)	0.584*** (0.003)	0.967*** (0.005)		
σ_u				0.469*** (0.125)	0.841*** (0.226)
σ_v				0.349*** (0.081)	0.558** (0.229)
$\rho_{(w,v)}$				−0.321 (0.662)	0.661 (0.731)
N	300	150	150	150	150

Note: Standard errors are presented in parentheses. $\lambda = \sigma_u / \sigma_v$ and $\sigma = \sqrt{\sigma_u^2 + \sigma_v^2}$

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The coefficients of ADP_i are not significant in both matched and unmatched samples. A log-likelihood ratio (LR) is used to conduct a more reliable test for the homogeneity in the production technology among adopters and non-adopters. The test statistic (Greene, 2007) is calculated as:

$$LR = 2 * [\ln L_P - (\ln L_A + \ln L_N)] \quad (9)$$

where L_P , L_A , and L_N denote the values of the log-likelihood function derived from the conventional SPF estimation for pooled sample, adopters, and non-adopters subsamples, respectively. In both unmatched ($\chi^2=51.815$, p -value < 0.01) and matched ($\chi^2=55.258$, p -value < 0.01) cases, the LR test rejects

the null hypothesis that there are no significant differences between adopters and non-adopters at 1% confidence level. The production technology (or frontier) differs across adopters and non-adopters, supporting separate estimations for the production frontier of the two groups.

The primary inputs positively impact the output, and their interaction has a negatively significant impact in most models. That is, two input factors work as substitutes in production. As expected, output elasticities of labor in all models are larger than those of the capital. But it is notable that output elasticities of capital are relatively larger for adopters, which implies production equipment with advanced technologies has an important role in production. Thus, replacement and automation of obsolete production

Table 8 Technical efficiency levels across SPF models

SPF model	Pooled		Adopters		Non-adopters		Test of means
	Mean	S.D	Mean	S.D	Mean	S.D	
Unmatched							
Conventional SPF(pooled)	0.560	0.152	0.573	0.123	0.560	0.153	1.044
Conventional SPF(separate)			0.694	0.122	0.558	0.153	10.780***
Selectivity-corrected SPF			0.749	0.082	0.603	0.118	15.082***
Matched							
Conventional SPF(pooled)	0.588	0.155	0.595	0.137	0.580	0.171	0.874
Conventional SPF(separate)			0.694	0.122	0.547	0.170	8.590***
Selectivity-corrected SPF			0.705	0.111	0.557	0.148	9.824***

Note: *t*-test is used to determine if the mean values of samples between adopters and non-adopters are significantly different.
 $*p < 0.10$, $**p < 0.05$,
 $***p < 0.01$

equipment would lead to labor productivity improvement. The selectivity-corrected SPF model is estimated for adopters and non-adopters. Applying the model to non-adopters, the indicator for adoption, d_i , is reversed to be one for non-adopters. The correlation parameter, $\rho_{(w,v)}$, is insignificant in the estimation with unmatched samples as well as with matched samples, not identifying any selectivity bias in the estimated models. This also indicates that the estimates of the conventional SPF model with the matched sample are unbiased. If the parameters of the production frontier are biased, derived TEs are also affected.

4.4 Technical efficiency

Table 8 shows the comparison of TE levels by the SPF model. The mean difference of TE levels is not statistically significant in the estimation with pooled samples in the matched and the unmatched, even though the average TE in the matched samples is a little higher than in the unmatched. Since it is known that the production frontier of each group is different through the likelihood ratio test, the comparison of separate estimations between the two groups is more reliable.

The results of all separate estimations suggest that the average TE of adopters is higher than that of non-adopters. Specifically, when the unmatched samples are used, the average TE of adopters is 0.694 in the conventional SPF model, higher by 24.4% than non-adopters and 0.749 in the selectivity-corrected SPF model, higher by 24.2%. The efficiency gap between adopters and non-adopters turns to be a little larger after controlling for scales of inputs and output in the production function by PSM. Using the matched

samples, the average TE of adopters is higher by 26.9% in the conventional SPF model and 26.6% in the selectivity-corrected SPF model. Since any significant selection bias is not found, the difference of the TE level between two groups does not change a lot by controlling for the unobserved factors. These results present that the adopters generally manufacture goods more efficiently with limited input resources under their production frontier.

Kernel density estimates of TE distribution are compared in Fig. 4 to visualize the differences between different SPF models. In all SPF models, the TEs of adopters are concentrated on the upper scores, skewed toward the right side. In contrast, the TEs of non-adopters are widely dispersed, centered on the lower scores than adopters. Especially after controlling for observed and unobserved factors in the selectivity-corrected SPF model with match samples, Fig. 4d shows TE scores between two groups.

When comparing TE scores between two or more groups, it is necessary to be more careful. A simple comparison of average levels and distribution of TE might lead to misunderstanding between relative and absolute differences since TE scores of two groups come from different production frontiers. If one group's production frontier is positioned below the production frontier of another group, higher TE scores of the former do not guarantee absolute higher productivity. The gap among production frontiers is referred to as "technology gap" (Battese & Rao, 2002). Figure 5 describes the range of predicted frontier values ($\hat{y}_i = f(x_i; \beta)$) after applying PSM and selection correction. This figure implies that adopters have a higher production frontier, supporting adopters to be more productive than non-adopters.

Fig. 4 a–d Kernel density estimate across SPF models

Fig. 5 Predicted frontier values of selectivity-corrected SPF model after matching

5 Concluding remarks

This study examines the impact of employing core technologies in the era of the 4IR on the SMEs' productivity. Therefore, we used the firm-level cross-sectional data on Korean manufacturing SMEs, including the technology utilization information. A stochastic frontier model with selectivity correction and propensity score matching was used to mitigate biases from unobserved factors and economies of

scale from observed inputs and output. The technical efficiency of SMEs that adopt and utilize emerging technologies in the production process is compared with that of non-adopters using sequential procedures.

This study's main findings can be summarized as follows: (1) Adopting emerging technologies enhances SMEs' productivity. In practice, a LR test indicates production technologies between adopters and non-adopters are significantly different. After

observed and unobserved factors are controlled, the adopters' technical efficiency is higher by more than 26% than non-adopters. Moreover, if the gap among production frontiers is considered, the difference in productivity would rise further. (2) A strategic alliance is a crucial route for SMEs to accept new technologies of the 4IR. The selection model results reveal that adopters are more likely to be involved in collaboration with other firms. These findings would be helpful for innovative entrepreneurs and owners running SMEs to plan a production strategy.

Some policy implications can be drawn from the findings of this study. Low productivity is one of the chronic problems in Korean manufacturing SMEs. Moreover, the polarization of productivity between SMEs and LEs has been worsening, and, the outbreak of COVID-19 pandemic has a negative influence on the productivity of the manufacturers. Digital transformation in the SMEs' plants would be a magnificent opportunity to enhance SMEs' productivity. Thus, it is necessary to promote SMEs to utilize advanced technologies in their production. To this end, the government is required to consider a variety of policy measures such as customized consulting services, tax benefits, or training. Additionally, it might be necessary to establish a pan-government control tower in order to enforce comprehensive and consistent measures. More importantly, policy-makers should strive to establish an innovative ecosystem to strengthen alliance networks among SMEs.

Even though this study focused on the manufacturing sector in Korea, the implications in this study can be extended to other industries as well as other countries. For example, emerging technologies can be used as even more innovative forms in a diversity of service industries such as smart healthcare (Hwang & Choi, 2019), marketing (Overgoor et al., 2019), and finance (Hasan et al., 2020). This also implies competent entrepreneurs have been facing various chances though digital transformation. In addition, as Aly (2020) argued, rapid technology advances and digital transformation could give massive benefits for the developing countries, increasing employment and enhancing labor productivity.

This study has some limitations. First, variables in the selection model are restricted because of data availability. If more data related to organizational culture, marketing, and human capital are available, it would be helpful to investigate various aspects that

affect firm's technology adoption. Moreover, even though the effects of these unobserved factors are controlled in the selectivity-corrected SPF model, it would be better to control them explicitly to prevent overestimation of results. Second, panel analysis would yield more abundant empirical results and implications. Since panel data include temporal variations for variables, it is possible to trace technical efficiency changes before and after technology adoption. Moreover, time-invariant unobserved heterogeneity is more easily controlled in panel analyses. In the near future, such panel analyses would be possible after the survey datasets are accumulated for years.

Data availability The Survey of Business Activities, available at <https://mdis.kostat.go.kr/eng/index.do>.

Code availability Not applicable.

Declarations

Conflict of interest The authors declare no competing interests.

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