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Transformative Technology Adoption and Firm Productivity: Illusionary Revolution or Guaranteed Innovation?

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ABSTRACT

This study examines the impact of strategic technological innovations (e.g., adoption of fourth industrial revolution (4IR) technologies) on firms' productivity. To estimate the heterogeneous effects of innovation efforts on firms' labor productivity, this paper employs a quantile regression model and calculates higher moments of the empirical distributions. This study uses data from 11,654 Korean firms that responded to surveys in 2017 and 2018, comprising 23,308 observations. Our empirical results find that 4IR technology adoption has a significant impact on labor productivity for firms across all quantiles, while the estimates of 4IR technology adoption coefficient on labor productivity are much larger in upper quantiles. This estimated impact of adopting 4IR technology on labor productivity at the upper quantile differs compared to the estimated impact of another innovation strategy, or internal R&D. Notably, adopting 4IR technology increases the median labor productivity of firms and the kurtosis of its distribution. Thus, firms that adopted 4IR technology show labor productivity gains more consistently than those that did not, with few outliers.

Keywords: South Korean firms, The Fourth Industrial Revolution Technology, Internal R&D, External R&D, Quantile Regression, Labor Productivity

Ⅰ. Introduction

In recent years, the world has witnessed the emergence and development of new and transformative technologies. Rapid advances are being made in big data, cloud computing, mobile network, blockchain, and artificial intelligence with machine learning. Therefore, unprecedented technological convergence is expected, as automation and "smartization" continue to increase, expanding the digital revolution. For example, "machine vision," an artificial intelligence technology that provides image-based auto-

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matic inspection, process control, and robot guidance, can dramatically change traditional manufacturing.

This change, which Schwab (2016) first described as "the fourth industrial revolution (4IR)," is expected to reverse the downward trend in productivity growth in developed countries and to help achieve sustainable development in the global economy (Manyika et al., 2017). At the core of 4IR, there are various technological drivers such as internet of things (IoT), cloud computing, big data, mobile, artificial intelligence (AI), blockchain, 3D printing, robotics, and augmented reality/virtual reality (AR/VR).

Some believe that 4IR technology will provide a window of opportunity for developing countries to catch up to advanced economies (Lee et al., 2020). However, significant productivity growth from 4IR technology at the macro level has not been observed. Further, while innovation appears to be accelerating, economic growth has slowed (Gordon, 2018). Some argue that 4IR technology is only an extension of the third industrial digital revolution (3IR) and that it will have no truly revolutionary economic effect (Lee and Lee, 2020; Nuvolari, 2019).

Solow's productivity paradox (1987), expressed by the renowned statement, "you can see the computer age everywhere except in the productivity statistics" has prompted discussion about the relationship between digital technology and productivity (Draca et al., 2007). For these reasons, the relationship between new technology adoption and productivity has been receiving attention (Brynjolfsson et al., 2018). Recently, focusing on a specific type of 4IR technologies such as robotics (Alguacil et al., 2022), big data (Ghasemaghaei and Calic, 2020), and artificial intelligence (Yang, 2022), researchers explored its effects on productivity or employment.

In this regard, this study investigates the relationship between 4IR technologies adoption and labor productivity at the firm level, employing a quantile regression analysis with survey data from South Korean (hereafter "Korean") firms. In details, this research attempts to answer following questions: What is the current stage of the diffusion of 4IR technologies? Does adopting 4IR technologies affect firm productivity? More specifically, how does the productivity distribution of firms that have adopted 4IR technology differ from the productivity distribution of those that have not? In which industry does the adoption of 4IR technologies first lead to improved productivity? What differentiates 4IR technology adoption from other firms' innovation strategies, for example, R&D?

The remainder of this study is structured as follows. Section 2 provides a review of the existing literature on this topic and develops research hypotheses. In Section 3, we describe our empirical method and survey data. In Section 4, the analysis results are presented and discussed. Lastly, Section 5 presents the conclusion and describes the contributions of the study.

Ⅱ. Literature Review

2.1. General Purpose Technology and Economic Productivity Gains

Many experts and futurists have predicted that emerging technologies such as 4IR technologies will increase productivity and dramatically change people's lives around the world. However, it is never easy to measure or predict how much a particular technology has or will increase productivity for a given economy. For example, there have been conflicting views on the role of railroads in US economic development (Fogel, 1962) and the effects of steam engines on the UK economy (Nuvolari and Verspagen, 2009).

Despite these difficulties, scholars continue to investigate this topic. The most representative mainstream approach is the GPT perspective. Bresnahan and Trajtenberg (1995) first introduced the concept of GPT, explaining that revolutionary technological advances and economic growth have been driven by several GPTs, such as the steam engine, electric motor, and semiconductors. These GPTs share the characteristic of pervasiveness (they are used as inputs by many downstream sectors); inherent potential of the GPT itself for technical improvements; and presence of complementarities within sectors using the technology (arising in manufacturing or in R&D technology). Thus, as GPTs improve, they spread throughout the economy, bringing about generalized productivity gains.

Helpman and Trajtenberg (1998a) included GPT in their endogenous growth model to derive long-term patterns of productivity enhancement. They showed that productivity improvement over time comes in two phases (Helpman and Trajtenberg, 1998b) and that productivity gains are only significant in the second phase of technology adoption (time to reap). In the early days of technology adoption (time to sow), before the technology diffuses throughout the economy, productivity improvements are slow and may even decline. Following studies such as Aghion and Howitt (1998) and Carlaw and Lipsey (2006) present advanced endogenous growth models using the GPT approach.

However, the GPT approach has been criticized in several respects. The most essential problem is that a given period of economic development does not depend solely on a single technology, and the adoption and diffusion of technology in an economy does not occur through simple patterns limited to the substitution of technologies. From the perspective of evolutionary economics, which is critical of the neoclassical economics underlying the GPT approach, in reality, technological advances and economic growth show a much more complex relationship for the following reasons.

First, in the real world, because their information is bounded, firms adopt new technologies through trial and error using local search, imitation, and probability tests (Nelson et al., 1976). The economic consequences of these firms' behaviors are extremely uncertain. Second, the emergence of new technologies appears to occur in clusters, which further amplifies the innovations' potential as they interact with each other. Therefore, Nelson et al. (1976) argue that it is more realistic to understand the adoption of new transformative technologies and productivity gains from the perspective of a "technology system." Several technological innovations are technically and organically interrelated, like a constellation, to form a system.

Structural change within a techno-economic paradigm is not a process in which a technological system is substituted but one in which emerging technological innovation spreads through the "installation and deployment" processes and is assimilated by institutions and society (Freeman and Perez, 2008). Adopting new technologies will enhance the overall productivity of the economy only when firms and institutions change the way they relate to or the practice of internal governance. From this evolutionary perspective, discussing the industrial revolution by highlighting the impact of one or two technologies, such as the steam engine or the semiconductor (Verspagen, 2005), is like discussing an unverifiable myth (Freeman, 2008).

2.2. Transformative Technology Adoption and Firm Productivity

The relationship between adopting new transformative technologies and firms' productivity enhancements is not easy to identify. According to studies on the productivity impact of adopting modern-day transformative technologies (Barua et al., 1995), no significant productivity enhancements were observed until the early 1990s, although computers started to achieve widespread use in firms by the 1980s. Productivity gains were first observed in studies on Forbes 500 firms in 1987-1991 (Brynjolfsson and Hitt, 1996), but those were already some of the most productive firms in the world. In the United States, where information technology (IT) was introduced the fastest, productivity at the macro level has been steadily declining except for IT-driven growth that accelerated from 1995 to 2004 (Gordon, 2014).

Many studies of this period show productivity enhancements due to the adoption of IT; however, despite the continued expansion of firms' IT investments through the 1990s and 2000s, adoption and absorption of new transformative technologies and productivity enhancement do not always take place simultaneously. There are many explanations for this finding. First, it takes time for a new transformative technology to function as a GPT and generate productivity enhancements throughout the economy (Brynjolfsson et al., 2021). In the early days of IT development, the proportion of IT investment to total fixed capital investment was very small. However, by the mid-2000s, firms' IT investment accounted for about 35% of total fixed asset investment, which has had a significant impact on firms' productivity.

Second, the impact of adopting new technologies is usually concentrated in a few industries. Given that adoption is not evenly distributed, overall productivity enhancement throughout the entire economy is fairly low. In industries where new technologies are embraced, fierce competition creates loser firms. Thus, firm productivity gains are not consistently observed even within a given industry. Third, the mismeasurement hypothesis may explain why the relationship between new technologies' adoption and productivity enhancement has not always been positive. For example, corporate financial indicators that typically represent firms' performance are not designed to show the impact of IT investments. Extant research shows that the impact is observed only through intermediate indicators in the production process.

Even when new technologies are adopted, not all firms enjoy productivity gains from those technologies. New technologies require an organizational component to achieve productivity gains. Productivity enhancement occurs only when accompanied by other efforts within the firm, such as employing high-quality human resources, improving corporate practices, and restructuring the organization to take advantage of the new technology (Bresnahan et al., 2002). Therefore, plants with higher employment and those that belong to multi-unit firms are typically more active in adopting new technologies (Brynjolfsson and McElheran, 2016).

Research also shows that firms with greater human capital and advanced management practices are more likely to adopt new technology and show better performance (Benhabib and Spiegel, 2005). Firms that adopt new transformative technologies enjoy higher productivity gains relatively quickly. That is, firms that expect greater benefits from technology (Jensen, 1982) and that are better positioned to cope with future uncertainties (Davies, 1979) adopt new technology more rapidly and achieve productivity gains faster than other firms, creating gaps among firms in terms of technology-related productivity gains.

2.3. R&D Activities and Firm Productivity

Regarding ways to enhance firm productivity, it is worth discussing the impact of adopting new technologies in relation to the impact of firms' other main approach to innovation, namely R&D. Although firms have heterogeneous innovation capabilities and means of obtaining gains from R&D activities (Pavitt, 1984), R&D-intensive firms exhibit higher productivity than firms with low R&D intensity (Coad, 2019; Cohen and Klepper, 1992). R&D activities increase firms' absorption capabilities (Cohen and Levinthal, 1989), and when combined with firms' managerial capabilities, they are a source of productivity enhancement (Bloom et al., 2019; Sadun et al., 2017). R&D investment has a sizable and significant impact on productivity beyond the physical capital involved, as seen in firm-level estimates of the production function under certain circumstances (Griliches and Mairesse, 1984).

While our understanding of the impact of R&D activities on productivity is evolving, fundamental changes in firms' innovation strategies are also being actively discussed. According to Bloom et al. (2017), the productivity associated with R&D activities continues to decline, primarily because the number of new discoveries is limited while the amount of resources committed to R&D globally is increasing rapidly. As R&D capabilities have increased across firms, the level of "red queen competition"—that is, the pressure to run faster than others—is intensifying. In addition, as value chains are increasingly segmented, R&D activity is no longer the most essential component of value creation in some industries. Firms are making a greater effort to secure irreplaceable complementary assets, such as marketing channels, consumer databases, or physical facilities.

Firms with core competencies often outsource R&D activities to lower their fixed costs and improve productivity. According to Narula (2001), growing technological complexity and uncertainty regarding the rate and success of technological development facilitates R&D outsourcing and segmentation of R&D activities. No firm can handle the entire R&D process internally because of the need for a broad scientific knowledge base (Odagiri, 2003); therefore, more firms attempt to hedge against the risk of knowledge depreciation by externalizing R&D activities, especially in the field of emerging technologies (Leiponen, 2005). Because of recent advances in information and communications technology, innovation activities have evolved from a linear model of internal R&D toward a more agile, interactive, cooperative model of exploiting external R&D resources (Belderbos et al., 2004). The problem that these studies highlight is consistent with Jones's (1995) critique; he found that total factor productivity growth was declining despite an increase in R&D in the United States and European Union.

While internal R&D may fail to generate productivity growth, external R&D strategy does not always bring about a productivity gain. R&D outsourcing cannot be free from the cost of complexity, uncertainty, and imperfect information. The contracting counterparty may engage in opportunistic behavior and may appropriate innovation output (Oxley and Sampson, 2004). Managing these uncertainties, risks, and imperfections involves transaction costs, and firms that cannot afford them cannot benefit from an external R&D strategy. Aghion and Tirole (1994) show that only R&D project sponsors with sufficient financial resources can appropriate innovation outcomes and, therefore, have the incentive to invest in such R&D projects. Firms implementing both internal R&D and external R&D can achieve higher productivity than those operating only external R&D. This is because by implementing their own internal R&D, the learning capability of firms can be increased, and they are less exposed to asymmetrical information problems (Beneito, 2006; Lokshin et al., 2008).

2.4. Hypothesis Development

In this context, this study verifies whether the 4IR technology has been introduced and diffused to Korean firms enough to be considered GPT. Specifically, investigating descriptive statistics, this study verifies how many Korean firms have adopted the 4IR technology, and which industries have been adopting the 4IR technology faster.

To the next, employing quantile regression, this study investigates the relationship between new technology adoption and individual firms' productivity enhancement. Specifically, the following hypotheses are tested.

H1: The adoption of 4IR technology is positively related to the improvement of the Korean firms' labor productivity.

H2: The relationship between 4IR technology adoption and firm's labor productivity enhancement is different by Korean firms' productivity quantile.

In addition, this study comparatively analyzes the impacts of various innovation strategies (4IR technology adoption, internal R&D and external R&D) on Korean firms' labor productivity enhancement. Specifically, the following hypotheses are tested.

H3: The impacts of various innovation strategies on Korean firms' labor productivity enhancement are differentiated from each other.

H4: The impact of 4IR technology adoption on the distribution of Korean firms' labor productivity is differentiated from the impact of other innovation strategies.

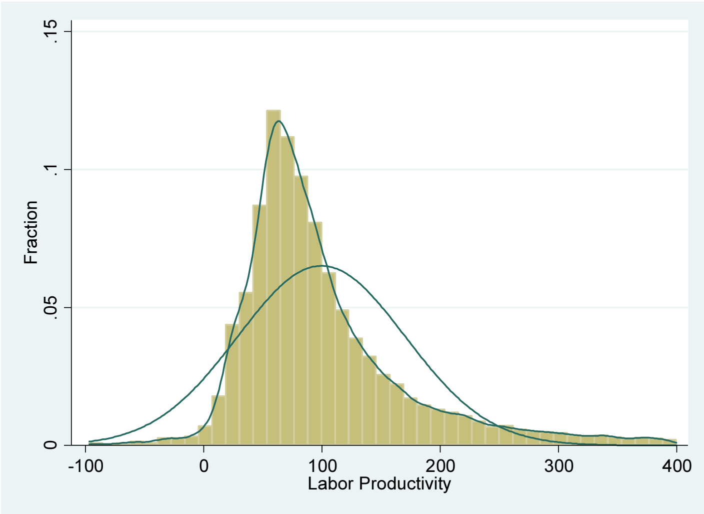
Ⅲ. Methodology

3.1. Research Strategy

This study employs quantile regression to investigate the impact of firms' innovation efforts—namely, 4IR technology adoption and internal and external R&D—on labor productivity. While related studies like Coad and Rao (2008) and Mata and Woerter (2013) advocate for the usefulness of the quantile regression method, it is advantageous in analyzing the data used in this study for the following reasons.

First, quantile regression is useful when analyzing a dependent variable that has a leptokurtic, asymmetric (in this case, right-tailed and positively skewed) distribution. When measuring labor productivity based on the value added, firms' labor productivity is rarely negative, and there are many firms with higher than average values (Yang et al., 2019). Likewise, the distribution of labor productivity among Korean firms cannot be accurately estimated by assuming a normal distribution; rather, it can be estimated better by a Levy alpha-stable distribution, as in Yang et al. (2019)'s work <Figure 1>. Standard regression methods are not appropriate for analyzing data that does not follow a Gaussian distribution; quantile regression can be a good alternative.

Second, the distribution of labor productivity in Korean firms has many outliers. Quantile regression



<Figure 1> Labor Productivity Distribution of Korean Survey Firms

not only reflects such outliers in detail but also provides robust estimators. According to Buchinsky (1998), the quantile regression solution is invariant to outliers of the dependent variable that tend to $\pm\infty$. A more complete estimate of covariate effects can be obtained by estimating a family of conditional quantile functions with less information loss due to outliers (Koenker and Hallock, 2001). To obtain estimates of the conditional quantile function, θth-quantile regression minimizes the sum of the weighted absolute values of the error terms as follows. Note that the weighted value depends on the value of θ:

$$min_{\beta}[\sum_{\{i:y_i \geq x_i'\beta\}} \theta|y_i - x_i'\beta| + \sum_{\{i:y_i < x_i'\beta\}} (1-\theta)|y_i - x_i'\beta|],$$
$$0 < \theta < 1.$$

Third, the quantile regression method allows us to obtain a more complete picture of the relationship between transformative technology adoption and firm productivity. The ordinary least square regression method provides only summary point estimates that mean the average impact of the independent regressor on the average firm. However, as can be seen from previous studies (Coad and Rao, 2008; Mata and Woerter, 2013), various innovation strategies of a firm have different effects on performance enhancement for firms in different quantiles. Employing quantile regression analysis, this study can estimate the impact of innovation strategies on productivity for Korean firms with different productivity levels. Therefore, we can get a more complete understanding of the relationship between new transformative technology adoption and productivity enhancement. The coefficients estimated by quantile regression can be interpreted as the partial derivative of the conditional quantile of y with respect to particular regressors, $\frac{\partial Q_\theta(ln\, y_{it}/x_{it})}{\partial x}$. The derivative is interpreted as the marginal change in y at the θth conditional quantile due to marginal change in a particular regressor (Yasar et al., 2006).

Further, we can ask and obtain answers to interesting questions using quantile regression, computing higher order moments of the distribution, such as dispersion, skewness, and kurtosis, based on quantile regression estimates. Specifically, we can analyze the stability of primary statistics through secondary statistics, such as skewness and kurtosis (Oja, 1981). These statistics can be compared to the impacts of internal versus external R&D strategies. Although there may be different views on measuring and accurately interpreting kurtosis (Ruppert, 1987), following Mata and Woerter (2013), we define statistics of scale, skewness, and kurtosis based on quantiles as follows.

$$Scale = \frac{Q\{0.75\} - Q\{0.25\}}{Q\{0.75\} + Q\{0.25\}}$$

$$Skewness = \frac{Q\{0.75\} + Q\{0.25\} - 2Q\{0.5\}}{Q\{0.75\} - Q\{0.25\}}$$

$$Kurtosis = \frac{Q\{0.90\} - Q\{0.10\}}{Q\{0.75\} - Q\{0.25\}}$$

3.2. Data

This paper uses the "Survey of Business Activities" dataset from the National Statistical Office of Korea (a state-designed statistic; Approval No. 10166), which discloses in-depth business management activities of Korean firms with more than 50 regular employees and over KRW 300 million (around US$ 3 million) in capital. The survey was conducted via a self-administered questionnaire, for which a surveyor visited the firm in person, explained the survey's purpose and instructions, and asked the respondents to complete the survey. The survey results provide financial data, such as sales, cost of goods sold, and operating expenses. Additionally, it includes data on firms' innovation activities, such as R&D spending. R&D is surveyed separately with respect to spending on internal and outsourced activities.

Beginning in 2017, the survey has included data on 4IR-related emerging technologies, allowing us to compare the productivity impact of 4IR technology adoption strategies with the impacts of internal and external R&D efforts. It is possible to determine whether a firm is using a given technology.

We conduct empirical analysis to examine the hypotheses constructed using dataset of 11,654 firms that responded to the survey for 2 years (2017 and 2018); therefore, there are a total of 23,308 observations. The dataset includes variables, such as labor productivity, a 4IR technology adoption dummy, in-house R&D expenditures, outsourced R&D expenditures, and permanent employees. The dataset also includes an industry classification for each firm.

<Table 1> shows the proportion and industry distribution of firms that use 4IR technology. Individual 4IR technologies have not yet evolved into GPTs widely used across industries. In some industries, the number of firms that have adopted 4IR technology decreased in 2018 compared to 2017 (Accommodation and food service activities; Human health and social work activities; and Arts, sports, and recreational services). Excluding a few industries (Information and communication; Financial and insurance activities; and Professional, scientific and technical activities, and Manufacturing), the proportion of firms employing 4IR technology in most industries is less than 10%. 4IR technologies are not yet pervasive; that is, they are not affecting a wide range of activities (Lee and Lee, 2020).

3.3. Empirical Specification

This study employs following regression model.

$$\begin{aligned} LaborProduct = {} & \alpha_0 + \alpha_1 * 4IR\ tech\ adoption + \alpha_2 * Internal\ R\&D \\ & + \alpha_3 * External\ R\&D + \alpha_4 * Tangible\ capital \\ & + \alpha_5 * Intangible\ capital + \varepsilon \end{aligned}$$

The dependent variable is average labor pro-

<Table 1> 4IR Technology Adoption by Industry

(Unit: No. of Adopting Firms / No. of Total Firms)

	2017	2018		2017	2018
All Industries	961/ 11,654	1,347/ 11,654	Information and communication	252/977	377/975
Agriculture, Forestry, and Fishing	0/20	1/20	Financial and insurance activities	47/305	65/307
Mining and Quarrying	0/3	0/3	Real estate activities	3/228	6/228
Manufacturing	390/5,684	570/5,695	Professional, scientific, and technical activities	45/500	55/498
Electricity, Gas, Steam, and Air Conditioning Supply	7/46	10/46	Business facilities management and business support services; rental and leasing activities	25/568	28/566
Water Supply; Sewage, Waste Management, and Materials Recovery	1/111	4/112	Public administration and defense; compulsory social security	6/73	12/72
Construction	28/491	44/493	Education	0/15	0/15
Wholesale and Retail Trade	92/1,334	117/1,323	Human health and social work activities	23/267	13/266
Transportation and Storage	19/670	27/670	Arts, sports, and recreation related services	4/64	3/65
Accommodation and food service activities	19/279	15/300			

Note: There are no observations for the following four industry categories: Membership organizations, repair, and other personal services; Activities of households as employers; Undifferentiated goods-and services-producing activities of households for own use; and Activities of extraterritorial organizations and bodies.

ductivity, defined as the ratio of value added to number of permanent employees in the firm. The inputs used to calculate the value added, are described in <Table 2>.

We measure 4IR technology as a dummy variable; firms that reported utilizing 4IR technology are assigned a value of 1 and those that did not are given a value of 0. We consider 4IR technology in terms of nine technology domains: internet of things (IoT), cloud computing, big data, mobile, artificial intelligence (AI), blockchain, 3D printing, robotics, and augmented reality/virtual reality (AR/VR). If even one of these technologies was adopted, the firm is classified as having adopted 4IR technology. Next, we define internal and external R&D as two independent variables representing different innovation strategies. As with 4IR technology, these are dummy variables, which make it easy to compare the impacts of these different innovation strategies.

There are various opinions regarding specific technological drivers of 4IR. For instance, across the physical, digital and biological domains, Schwab (2016) exampled nine key technologies of 4IR such as autonomous vehicles, 3D printing, advanced robotics, new materials (graphene), IoT, blockchain, genetics, synthetic biology, and genetic editing. PricewaterhouseCoopers (2021) identified 4IR technologies as AI, VR, AR, blockchain, drones, IoT, robotics, and 3D printing. Meanwhile, the National Statistical Office of Korea outlined AI, IoT, cloud

<Table 2> Variable Definitions

Variable	Description
Labor Productivity	{Revenue - (Cost of sales + Selling and administrative expense - Personnel expense – Rent - Depreciation cost - Taxes and dues - Bad debt expense)} / Number of Permanent Employees
4IR Technology Adoption	Dummy variable: 1 for firms using one or more 4IR technologies; 0 otherwise (4IR technologies: IoT, cloud computing, Big Data, mobile, AI, blockchain, 3D printing, robotics, AR / VR)
Internal R&D	Dummy variable: 1 for firms conducting in-house R&D; 0 otherwise
External R&D	Dummy variable: 1 for firms that outsourced R&D; 0 otherwise;
Tangible Capital Formation	Increase in tangible assets in the current year / Number of permanent employees
Intangible Capital Formation	Increase in intangible assets in the current year / Number of permanent employees

computing, big data, mobile, blockchain, 3D printing, robotics, and AR/VR as the core of 4IR technologies in its state-designed survey.

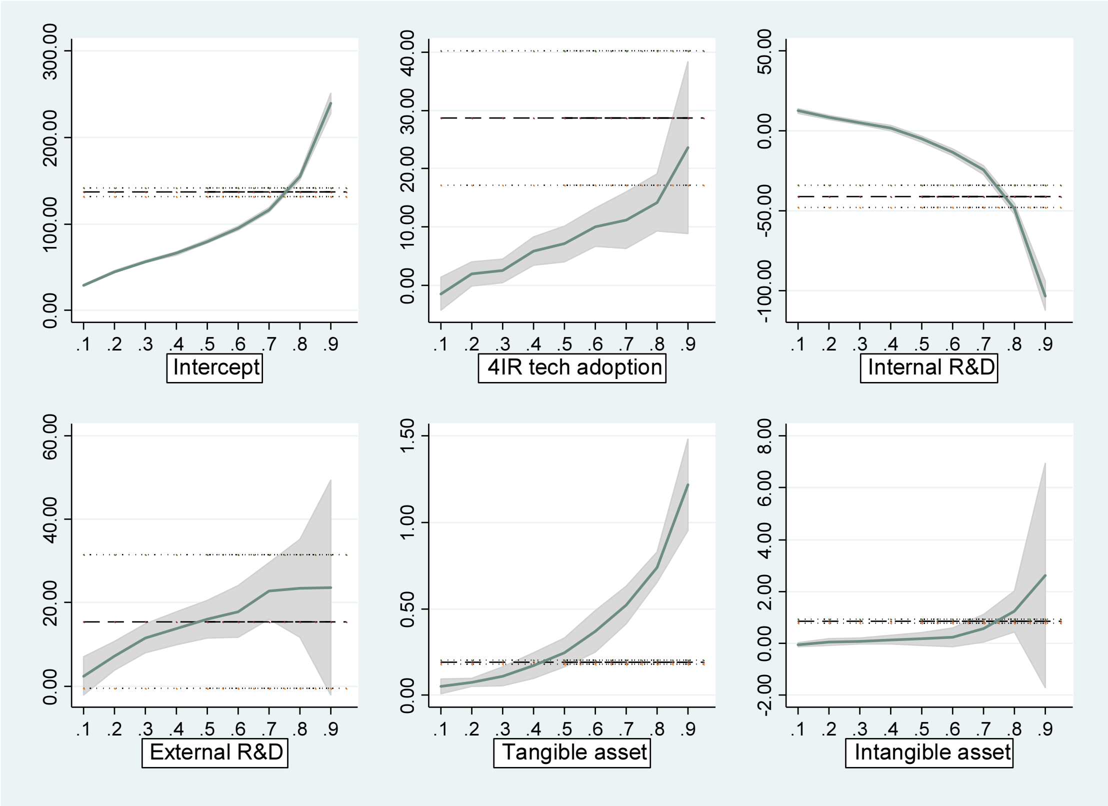
Internal R&D is measured as a dummy variable; firms that reported inhouse R&D are assigned a value of 1, and those that did not are given a value of 0. External R&D also is measured as a dummy variable; firms that reported contracted-out R&D are assigned a value of 1, and those that did not are given a value of 0.

Control variables representing fixed capital formation in the current year are defined as the net increase in tangible and intangible capital for the current year divided by the number of permanent employees. These represent “capital deepening” and are, therefore, a proxy for the capital-to-labor ratio. Tangible assets are physical assets, such as property, plant, and equipment. Intangible assets are non-physical assets, such as intellectual property rights and software licenses. Both are expected to generate value for the firm. These two control variables vary depending on the number of employees, which can be a good proxy for the size of the firm. The increase in property, plant, and equipment can also function as a control variable representing firm size.

Ⅳ. Results

The results of the quantile regression are presented in <Figure 2> and <Table 3>. Ordinary least squares regression estimates are shown as a horizontal line. Each coefficient curve shows that the value of the estimated coefficient of the variable changes over the conditional labor productivity distribution. The estimated impact is significant at almost all quantiles of the productivity distribution (excluding the 10th quantile for 4IR technology adoption and outsourced R&D; <Table 3>) (Hypothesis 1). With respect to the variable of 4IR technology adoption, which is of particular interest in this study, the coefficient rises sharply for high labor productivity firms in the upper quantiles. Thus, the higher a firm’s labor productivity, the greater the estimated impact of adopting 4IR technology on differences in labor productivity (Hypothesis 2).

This result is also seen in the estimated coefficients on the outsourced R&D variable. However, the estimated coefficients related to internal R&D show the opposite result. The estimated impact of internal R&D on labor productivity has a positive coefficient at low labor productivity quantiles and becomes negative at the 50th quantile (the median). The negative estimated impact of



Note: Between the 10th and 90th percentiles, the confidence interval is 90%. The X-axis is labor productivity by quantile, and the Y-axis shows the estimated coefficients.

<Figure 2> Marginal Effects of Independent Variables on Firms' Labor Productivity

internal R&D on labor productivity increases sharply for firms in the upper quantiles of labor productivity (Hypothesis 3).

The marginal impacts of the tangible and intangible assets control variables also have interesting implications. As predicted by the definition of labor productivity, an increase in capital equipment has a significant impact on labor productivity for firms at all quantiles. The magnitude of the estimates of the impact is much greater as firms' labor productivity moves from the lower to upper quantiles. While capital-intensive firms are expected to have high labor productivity, the estimated impact of intangible assets on labor productivity show interesting results because the estimates are exceptionally high at the upper quantile. The results may be interpreted as indicating that intangible assets have a decisive impact on labor productivity for highly productive firms.

Next, we examine the impact of the independent variables that are related to firms' innovation strategies on measures of the distribution of labor productivity. <Table 4> shows statistics from the quantile regression. 4IR technology adoption and external R&D have positive estimates of impact on location, which means that the median marginal impact (50th quantile) is positive. Internal R&D, how-

<Table 3> Results of Quantile Regression

	Dependent Variable: Labor Productivity								
	q10	q20	q30	q40	q50	q60	q70	q80	q90
4IR Tech	−1.486 −1.48	1.92 2.20*	2.48 2.80**	5.90 4.06**	7.09 4.45**	10.00 5.09**	11.17 4.55**	14.20 3.09**	23.65 2.52*
R&D In	12.391 19.14**	8.35 16.84**	4.83 8.85**	1.66 2.08*	−5.28 −5.77**	−13.56 −13.43**	−24.62 −17.55**	−48.90 −15.73**	−103.44 −19.44**
R&D Out	2.403 0.93	7.21 4.60**	11.50 7.90**	13.85 10.50**	16.10 11.72**	17.88 11.68**	22.83 10.92**	23.44 4.88**	23.58 1.98*
Tangible Assets	0.051 2.92**	0.077 5.38**	0.109 4.19**	0.171 5.13**	0.246 7.08**	0.371 7.16**	0.523 9.53**	0.740 8.73**	1.217 11.43**
Intangible Assets	−0.044 −0.75	0.055 0.75	0.091 1.68*	0.145 2.26*	0.180 1.33	0.243 1.14	0.581 2.19*	1.239 1.85*	2.622 0.81
Cons	28.81 42.57**	44.90 66.78**	56.46 78.90**	66.05 63.75**	79.69 75.86**	94.98 64.01**	116.28 66.36**	154.82 59.55**	239.52 47.19**

Note: Coefficients are marginal effects (t-values) and their p-values. * $p < 0.1$, ** $p < 0.01$.

ever, shows a negative location (Hypothesis 4).

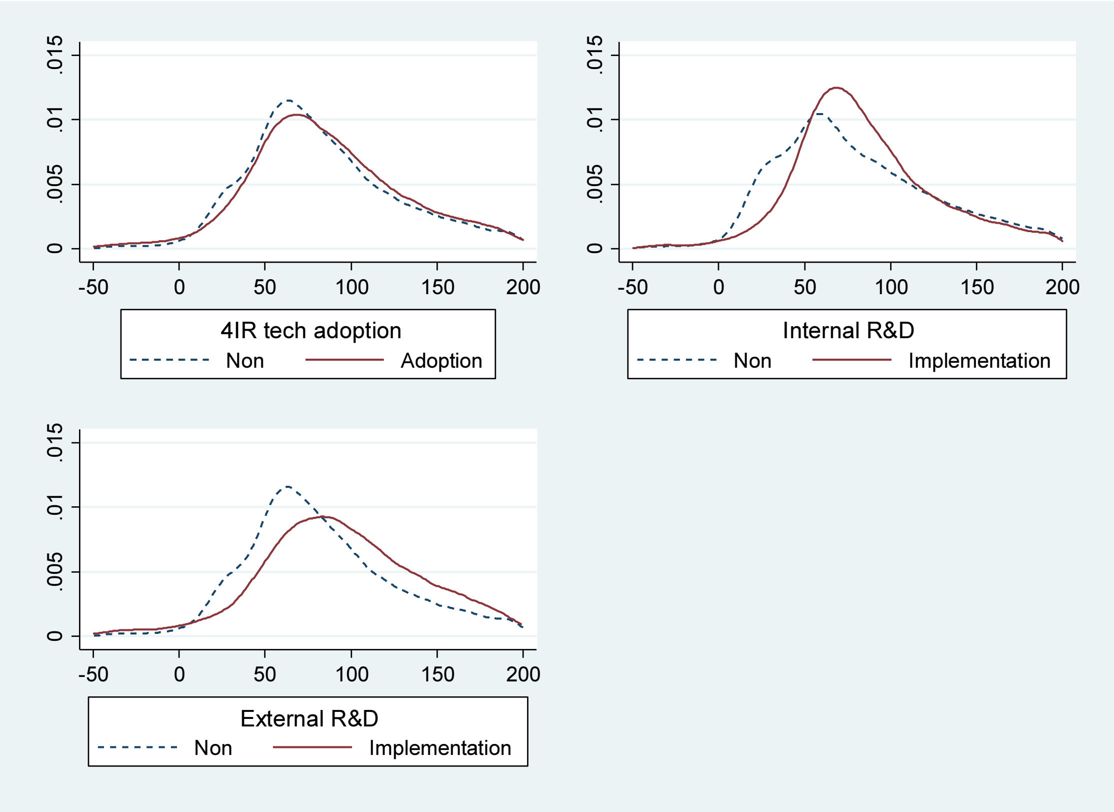
The scale statistics indicate how spread out the distribution is and determines the overall shape of the distribution along with kurtosis. For the 4IR technology adoption variable, the scale of the distribution is moderate and kurtosis is relatively high. A distribution with high kurtosis (leptokurtic) is concentrated on the mean and produces fewer outliers. This result can be interpreted as indicating that 4IR technology adoption has a uniform impact on labor productivity improvement with few outliers. For internal R&D, the scale of the distribution is very high and kurtosis is moderate. This means that the labor productivity of firms that conduct internal R&D is widespread.

For firms that use outsourced external R&D, the scale of the distribution is very low and kurtosis is also very low. These two statistics represent different aspects of a distribution. A low scale means that the average dispersion of the distribution is small and that R&D outsourcing has a relatively predictable impact on labor productivity improvement. In contrast, low kurtosis indicates more outliers relative to the median. This second characteristic is consistent with the high-risk, high-returns impact of an external R&D strategy found by Mata and Woerter (2013). The distribution of the impact of outsourced R&D on labor productivity has exceptionally negative

<Table 4> Distribution Statistics from Quantile Regression

	Location	Scale	Skewness	Kurtosis
4IR Technology	7.133736	0.609791	0.51879	4.72173
R&D In-House	−2.837868	1.631543	0.46561	3.03395
R&D Outsourcing	17.504020	0.256395	−0.53366	1.22742

Note: Measures are defined as location (q50), scale (([q75] − [q25]) / ([q75] + [q25])), skewness (([q75] + [q25]−2*[q50]) / ([q75] − [q25])), and kurtosis (([q90] − [q10]) / ([q75] − [q25])).

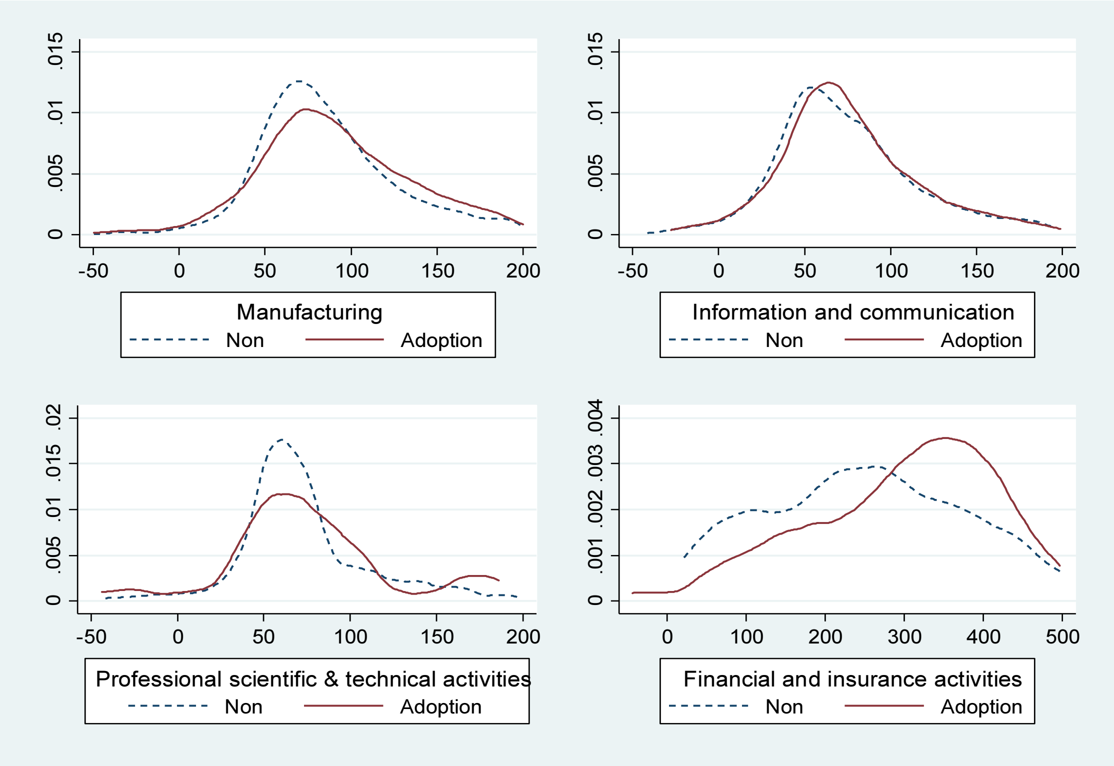


<Figure 3> Conditional Distribution of Firms' Labor Productivity by Three Innovation Strategies

skewness. <Figure 3> shows these results graphically.

<Figure 4> shows the conditional distribution of firms' labor productivity based on 4IR technology adoption in certain industries. The four industries are those with the highest proportion of 4IR technology adoption <Table 1>, namely manufacturing, information and communication, professional scientific and technical activities, and financial and insurance activities. For manufacturing and professional scientific and technical activities, the impact of 4IR technology adoption makes the distribution of firms' labor productivity more dispersed with less kurtosis. For the information and communication industry, adopting 4IR technology shifts the mean of the distribution of firms' labor productivity to the right without outliers. In the financial and insurance activities arena, a much more dramatic result is observed. The labor productivity distribution of firms that have adopted 4IR technology is clearly positively skewed with a higher mean compared to that of firms that did not adopt 4IR technology.

This indicates that firms in these industries that adopted 4IR technology show a significant labor productivity improvement. In the financial and insurance industries, 4IR technologies, such as AI, big data, blockchain, and cloud computing, are converging to form "fintech," which appears to improve firms' labor productivity. In these industries, 4IR technologies have an important feature of GPT: improvement and innovation spawning.



<Figure 4> Conditional Distribution of Firms' Labor Productivity based on Adoption of 4IR Technology in Specific Industries

Ⅴ. Conclusion

Our study reveals that as of 2018, 4IR technologies have not yet evolved into GPTs widely used across industries in Korea. 4IR technologies have been partially adopted by firms in some industries in Korea. The extent to which 4IR technology has penetrated individual industries differs for Korean firms, and technology adoption is relatively strong in four industries (manufacturing, information and communication, professional scientific and technical activities, and financial and insurance activities). The rapid adoption of 4IR technologies among professional scientific and technical activities is consistent with an important assumption of endogenous growth theory that proposes that individual innovations first increase the productivity of the R&D process itself (Romer, 1990). In the financial and insurance activities industries, the productivity enhancement of Korean firms that adopted 4IR technology is particularly notable.

However, despite this lack of pervasive adoption, we found that adopting 4IR technologies does lead to statistically significant productivity gains in Korean firms. And our quantile regression results reveal that the productivity gap between adopters and non-adopters is larger within high-productivity quantile firms. That is, compared to average-productivity firms, 4IR technology adoption is of great impact on high-productivity firms. These results are in line with the results of previous studies on firms with heterogeneous performance (Coad, 2019). In addition, the productivity distribution of 4IR technology-adopting firms is leptokurtic, meaning that firms that adopted 4IR technology show consistent labor productivity gains with fewer outliers.

Also, these estimated results are compared to the estimated impact of other innovation strategies, such as internal (in-house) and external (contracted-out) research and development (R&D), on firms' productivity. Regarding the impact of other innovation strategies, the higher a firm's labor productivity, the greater the estimated impact of external R&D on differences in productivity. By the way, the estimated impact of internal R&D on productivity has the opposite direction.

On the other hand, this study has limitations in terms of causality tests and robustness checks, and there is room for improvement. As the most important point, the conclusion that the 4IR technology adoption has a significant impact on productivity enhancement for high-productivity quantile firms cannot rule out the possibility of reverse causality. For example, the high labor productivity firm might have adopted 4IR technology more actively. Similarly, high-productivity firms can be active in uncertain innovation strategies such as external R&D. It is a crucial limitation that the important variable, 4IR technology adoption, is measured with a dummy variable. A tangible asset used as a control variable may be a significant factor that has a more decisive effect on Korean firms' productivity. Therefore, it would be safe to interpret the estimated coefficient from quantile regression as a significant correlation rather than a definite causal relationship. These limitations can be supplemented through various methods of causal inference such as the difference-in-difference (DID) analysis and instrumental variable quantile treatment effects (IV-QTE) method, and additional robustness checks in future studies.

Despite the limitations, the findings of this study are quite interesting. The high correlation between the new transformative technology adoption and the productivity of firms, especially in the high productivity quantile, means that the 4IR technology adoption has to bear a lot of uncertainty from the perspective of firms. The 4IR technology adoption is one of the newly emerging innovation strategies, and from the individual firm's point of view, investment in this innovation activity can be like playing the lottery (Coad and Rao, 2008; Mata and Woerter, 2013). There are some possibilities that the correlation is high in the high productivity quantile, but a firm that achieves great performance by adopting 4IR technology may be a 'Big Winning' in the game, and a firm with high productivity and financial capability may be running the lottery more.

Based on our analysis of Korean firms, we can conjecture that Korean firms are first trying to safely introduce 4IR technology that can have a reliable effect on productivity. Therefore, the adoption of 4IR technology can be said to be the pursuit of 'Guaranteed Innovation' for Korean firms. The productivity gap between firms that adopt new technology and those that do not will widen over time (Brynjolfsson and Hitt, 2003). Whether it is described as "time to sow" or the "installation stage," however, the impact of 4IR technologies on overall productivity in Korea is still modest. It takes time to reach the "time to reap" or "deployment stage." Still, it's certainly not at the stage where we would say 4IR technology is an 'Illusion'.

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