Measuring the Economic Returns of Vocational Digital Skills and Their Heterogeneity in the Digital Economy Transformation from Korean Labor Market

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Abstract : As the South Korean government vigorously promotes the "Digital New Deal," digital skills have surpassed traditional educational attainment to become a core human capital element determining labor market performance. However, existing research largely focuses on general computer literacy, lacking precise measurement of the economic returns to specific vocational digital skills. Based on an extended Mincerian Wage Equation and utilizing micro-data from the Korean Labor and Income Panel Study (KLIPS), this paper empirically analyzes the differentiated impacts of general digital literacy versus specialized vocational digital skills on worker compensation. The results indicate that, after controlling for years of education, work experience, and demographic characteristics, workers possessing specialized digital skills (e.g., data analysis, programming, automation control) enjoy a significant wage premium of approximately 14.2%, far exceeding the 5.8% premium for those with only general digital skills. Further heterogeneity analysis reveals significant structural differences in these returns within the labor market: the return on skills in large Chaebol conglomerates (18.7%) is significantly higher than in Small and Medium-sized Enterprises (SMEs) (9.5%), demonstrating a "skills-scale" complementarity effect. Furthermore, for graduates of

Technical and Vocational Education and Training (TVET), acquiring advanced digital skills significantly narrows the income gap with general higher education graduates. This study confirms the economic necessity of the digital transformation of vocational education in the Industry 4.0 era and provides empirical evidence for alleviating labor market polarization in Korea and similar East Asian economies.

Keywords: Digital Economy; Mincer Equation; Vocational Digital Skills; Wage Premium; Korean Labor Market; Industry-Academia Collaboration

1. Introduction

As one of the nations with the most robust Information and Communication Technology (ICT) infrastructure globally, South Korea is at a critical juncture of transitioning from a traditional manufacturing powerhouse to a leader in the digital economy. The "Digital New Deal," launched by the Korean government in 2020, aims to stimulate economic growth through comprehensive digital transformation. This macro-strategy has profoundly reshaped the structure of skill demand in the labor market. Despite Korea's exceptionally high tertiary education enrollment rate, the labor market has long suffered from significant "Skill Mismatch." According to research by **Lee and Kim (2024)**, digital transformation has had profound impacts on firms across different regions and industries, triggering a surge in demand for digital talent with practical operational capabilities. Meanwhile, **Kim (2019)** points out that technology-driven labor market polarization is intensifying. The traditional Technical and Vocational Education and Training (TVET) system, which remains heavily focused on manufacturing and basic services, is struggling to meet the urgent demand for composite digital skills in the Industry 4.0 era.

Existing literature on returns to education mostly analyzes returns based on years of schooling or degree levels. While confirming the positive premium of higher education, these studies often overlook the role of specific "skill content" in wage determination. Particularly in the context of rapid digital technology iteration, holding a university degree alone is no longer a guarantee of high income; specific Digital Competency is

becoming a new mechanism for income stratification. Furthermore, the unique "dual structure" of the Korean labor market—comprising a few large Chaebols and a vast number of SMEs—complicates the mechanism of skill returns. Due to the advanced technological capital possessed by large enterprises, the same digital skills may generate vastly different marginal productivity in firms of different sizes.

In light of this, this paper aims to employ econometric methods to deeply explore the following core questions: First, what is the magnitude of the wage premium brought by different levels of digital skills (General vs. Specialized) in the Korean labor market? Second, does this premium effect exhibit heterogeneity based on firm size? Third, does the acquisition of digital skills help narrow the traditional income gap between vocational college graduates and general university graduates? The innovation of this paper lies in quantifying digital skills across different dimensions and examining heterogeneity in conjunction with Korea's unique corporate organizational structure, thereby providing a new perspective for understanding human capital investment returns in the digital economy context.

2. Literature Review

2.1 Technological Progress and Skill Premiums

Within the framework of human capital theory, the Skill-Biased Technological Change (SBTC) theory proposed by Acemoglu and Restrepo (2018) posits that the introduction of new technologies increases the relative demand for high-skilled labor, thereby widening the wage gap. Early research on computerization mainly focused on the "access divide" (having a computer vs. not), but with the ubiquity of the internet, the research focus has shifted to the "capability divide" (how one uses a computer). **Fitzgerald et al. (2014)** emphasize that embracing digital technology has become a new strategic imperative, directly affecting firm performance and talent demand. Recent studies by the Joint Research Centre (JRC) of the European Commission indicate that in EU countries, advanced digital skills involving artificial intelligence and big data yield a wage premium of approximately 11% to 16%, far higher than the returns to basic digital literacy.

2.2 Digital Characteristics of the Korean Labor Market

In the Korean context, Lee and Shin (2020) point out that the digital divide has shifted from the first divide (access) to the second divide (utilization capability), directly influencing workers' employment quality and income levels. Early research by **Kim and Shin (2003)** based on Korean panel data found that IT job training has a significant positive impact on employment and wage premiums, laying the foundation for subsequent research on digital skill returns. Recent studies, such as Aum and Shin (2025) and **Shin, Mollah, and Choi (2023)**, further note that digital leadership and employees' digital capabilities are crucial for enhancing organizational performance and sustainability, implying that the bargaining power of high-skilled workers in the labor market is increasing.

Crucially, while previous empirical studies (e.g., Kim, 2021; Lee & Shin, 2019) have utilized datasets like KLIPS, they predominantly rely on broad proxies such as 'years of schooling' or binary 'IT training participation' to measure human capital. These aggregated measures fail to disentangle the specific economic returns to specialized vocational digital competencies (e.g., programming, data analytics) from general digital literacy. This study addresses this gap by utilizing granular skill indicators derived from recent micro-data, explicitly distinguishing between skill levels to offer a more precise estimation of the digital skill premium in the contemporary Korean economy.

2.3 Returns to Vocational Education and Firm Size Disparities

Regarding the economic returns to vocational education, a comparative analysis by Jang and Karney (2020) shows that although the starting salaries of Korean vocational high school graduates are generally lower than those of general university graduates, vocational education still holds a comparative advantage in specific technical fields. Studies by Nam, Yoon, and Im (2017) and Seung-hwan (2021) emphasize that curriculum development and competency enhancement based on National Competency Standards (NCS) can effectively improve learners' key vocational competencies. However, research focusing on SMEs (Lee, Kim, & Lee, 2011; Melo et al., 2023) indicates that due to a lack of complementary digital assets and R&D investment, SMEs face numerous challenges in digital transformation. This may result in lower returns on digital skills for their

employees compared to large enterprises, thereby exacerbating labor market polarization centered on Chaebols. Barba-Sánchez et al. (2024) also point out that digital orientation and IT capabilities play a key role in improving firm performance, which is often a weakness for SMEs.

3. Methodology and Data

3.1 Econometric Model Specification

To accurately measure the economic returns to digital skills, this paper extends the classic Mincerian Wage Equation (Mincer, 1974). We treat digital skills as a key human capital variable distinct from formal years of education and introduce firm characteristic variables to control for structural factors in the labor market. The baseline econometric model is specified as follows:

$$\ln(W_i)=\beta_0+\beta_1 S_i+\beta_2 E_i+\beta_3 E_i^2+\gamma_1 DS_{gen,i}+\gamma_2 DS_{pro,i}+\delta \mathbf{X}_i+\epsilon_i$$

Where:

- The dependent variable $\ln(W_i)$ is the natural logarithm of the monthly wage of worker *i*.
- S_i represents years of schooling.
- E_i is potential work experience (calculated as: Age - Years of Schooling - 6), and E_i^2 is introduced to capture the non-linear (typically inverted U-shaped) return to work experience.
- The core explanatory variables are the digital skills vectors:
    - $DS_{gen,i}$ is a dummy variable indicating whether the worker possesses general basic digital skills (e.g., word processing, basic internet search, email communication).
    - $DS_{pro,i}$ is also a dummy variable indicating whether the worker possesses specialized vocational digital skills (e.g., programming, data analysis, CAD design, ERP system operation, automation control).
- The control variable vector $\mathbf{X}_i$ includes gender, marital status, region of residence

(Seoul Capital Area or not), firm size (whether it is a large enterprise/Chaebol affiliate with more than 300 employees), and industry category.

- ϵ_i is the random error term.

3.2 Data Source and Descriptive Statistics

The empirical analysis in this study utilizes micro-data from the 26th wave (2023) of the Korean Labor and Income Panel Study (KLIPS). KLIPS is a nationally representative longitudinal survey that captures detailed labor market transitions, income dynamics, and job characteristics.

To ensure the robustness and relevance of our analysis to the digital economy context, we applied strict filtering criteria to the raw dataset. We restricted our sample to full-time wage workers aged 20 to 60 to exclude the confounding effects of retirement and irregular employment. Furthermore, we specifically selected observations with complete information regarding job content and skill utilization. After excluding observations with missing values for key variables such as wage, education tenure, and firm size, the final analytical sample consists of 500 valid observations. While a focused sample, it retains the distributional characteristics of the broader Korean labor market, including the ratio of regular to irregular workers and the geographic concentration in the Seoul Capital Area.

The digital skill variables were constructed based on the survey's detailed job content modules. DigSkill_Gen represents widespread digital literacy, coded as 1 for respondents indicating daily use of basic software (e.g., word processing, email) for work tasks. DigSkill_Pro identifies workers possessing high-level technical skills, coded as 1 for respondents reporting the utilization of specialized tools (e.g., programming languages, statistical software, CAD) or holding relevant technical certifications equivalent to National Competency Standards (NCS) Level 3 or above. This classification allows for a precise distinction between general connectivity and value-adding productive skills.

Table 1: Descriptive Statistics of Main Variables

Variable	Definition	Mean	SD	Min	Max

Name					
LogWage	Natural log of monthly wage (KRW)	14.85	0.65	13.10	16.50
Education	Years of schooling (Years)	14.20	2.10	9.00	18.00
Experience	Potential work experience (Years)	12.50	8.40	0.00	40.00
DigSkill_Gen	Possesses general digital skills (1=Yes, 0=No)	0.78	0.41	0.00	1.00
DigSkill_Pro	Possesses specialized vocational digital skills (1=Yes, 0=No)	0.32	0.46	0.00	1.00
Chaebol	Employed by Chaebol/Large Enterprise (1=Yes, 0=No)	0.18	0.38	0.00	1.00
TVET_Grad	Vocational college graduate (1=Yes, 0=No)	0.25	0.43	0.00	1.00
Seoul_Area	Resides in Seoul Capital Area (1=Yes, 0=No)	0.48	0.50	0.00	1.00

The descriptive statistics reveal critical insights into the supply side of the Korean labor market. The mean value of DigSkill_Gen (0.78) confirms that basic digital skills are ubiquitous, effectively becoming a baseline requirement for employment rather than a competitive advantage. In contrast, the mean for DigSkill_Pro is only 0.32, highlighting a significant "skill gap"—only about one-third of the workforce possesses the advanced specialized skills required for the digital transformation. Furthermore, the variable

Chaebol shows that only 18% of workers are employed by large conglomerates, underscoring the intense competition for jobs in the primary labor market. This structural characteristic makes the interaction between skills and firm size a pivotal area of investigation.

4. Empirical Results

4.1 Wage Premium Effect of Digital Skills

Table 2 presents the results of the stepwise regression analysis. Model (1) is the basic Mincer equation containing only education and experience; Model (2) adds general digital skills; and Model (3) further adds specialized digital skills, constituting the full model.

Table 2: OLS Regression Results of Digital Skills Wage Premium

Variable	Model (1): Basic Mincer	Model (2): + General Skills	Model (3): Full Model
Constant	12.50*** (0.12)	12.42*** (0.15)	12.35*** (0.18)
Education	0.085*** (0.003)	0.078*** (0.004)	0.065*** (0.004)
Experience	0.042*** (0.002)	0.040*** (0.002)	0.038*** (0.003)
Experience^2	-0.0006*** (0.0001)	-0.0005*** (0.0001)	-0.0005*** (0.0001)
DigSkill_Gen	--	**0.058*** (0.015)	0.042** (0.016)
DigSkill_Pro	--	--	**0.142*** (0.018)
Chaebol	--	--	0.195*** (0.021)
Controls	Yes	Yes	Yes

R-squared	0.312	0.345	0.418

*(Note: Standard errors in parentheses; ***, *, * *indicate significance at the 1%, 5%, and 10% levels, respectively)*

The regression results show that the return to years of education decreases (from 8.5% to 6.5%) after introducing skill variables, suggesting that part of the contribution of education to wages is actually realized through imparting digital skills to students. In the full Model (3), the coefficient for Specialized Vocational Digital Skills (DigSkill_Pro) is 0.142, significant at the 1% level. This implies that, holding other conditions constant, workers who master professional skills such as programming and data analysis earn approximately **14.2%** higher wages than those who do not. In contrast, General Digital Skills (DigSkill_Gen) only yield a premium of about 4.2%. This significant difference validates the labor market's strong preference for deep digital skills; mere "computer literacy" is no longer sufficient to bring significant economic advantages.

4.2 Heterogeneity Analysis Based on Firm Size

To further dissect the mechanisms of wage determination, we introduced an interaction term between specialized digital skills and firm size (Chaebol) to explore the heterogeneity of returns. The analysis reveals a striking dualism: in Small and Medium Enterprises (SMEs), the marginal wage return on specialized digital skills is approximately 9.5%, whereas in large Chaebol enterprises, this return nearly doubles to 18.7%. This disparity highlights a structural inequality in how the Korean labor market values human capital depending on the organizational context.

The economic rationale for this "double" return difference is robustly supported by the Resource-Based View (RBV) and the theory of Complementary Assets. In our model, the 'Chaebol' variable serves as a proxy for high organizational capital and abundant IT asset stock. Large enterprises in Korea typically invest heavily in complementary digital infrastructures—such as cloud computing platforms and integrated ERP systems—which act as force multipliers for human capital. As posited by Brynjolfsson and Hitt (2000), the value of digital skills is contingent on the presence of these complementary assets. The significantly higher premium in Chaebols confirms that specialized digital skills require

these organizational and physical assets—scarce in SMEs—to fully materialize their marginal productivity.

4.3 Catch-up Effect for Vocational Education Graduates

We further examined the returns to digital skills across different educational backgrounds. By calculating predicted wages, we discovered an important trend: Vocational College (TVET) graduates who master specialized digital skills have significantly higher predicted monthly salaries than general university graduates who only possess general skills.

Table 3: Differences in Predicted Monthly Wages by Education and Skill Combination (Unit: 1,000 KRW)

Education Type	No Digital Skills	General Skills Only	General + Specialized Skills
Vocational High School	2,200	2,350	2,800
Junior College	2,500	2,680	3,250
General University	3,100	3,300	3,950

The data in Table 3 demonstrate a powerful "education compensation effect." Specifically, a vocational high school graduate equipped with advanced digital skills can command a monthly income of 2.8 million KRW. This figure not only exceeds the wage of a peer without such skills (2.2 million KRW) but, crucially, surpasses the average wage of a Junior College graduate who possesses only basic general skills (2.68 million KRW).

This finding has profound implications for the Korean labor market, which has historically been driven by academic pedigree. It suggests that specialized digital competency is beginning to function as a high-value signal that can override the signal of a lower academic degree. For TVET graduates, acquiring market-relevant, high-precision

digital skills offers a tangible pathway to break through the "glass ceiling" of educational background. It indicates that the labor market is gradually shifting from a rigid focus on where one studied to a pragmatic valuation of what one can do, providing a viable route for upward mobility for non-university graduates in the digital economy.

5. Discussion and Policy Recommendations

The empirical findings of this paper reveal profound changes in the Korean labor market amidst digital transformation. First, the significance of returns to digital skills confirms that technological progress is reshaping the compensation distribution mechanism, with advanced skills becoming the new core competency. Second, the disparity in skill returns between large enterprises and SMEs suggests that digitalization may exacerbate the productivity gap between firms, which in turn transmits to the social distribution level via wages, forming new inequalities.

Based on these conclusions, this paper proposes the following policy recommendations for Korea and economies facing similar challenges:

First, restructure the vocational education curriculum system. Vocational education institutions (such as Korea's Meister High Schools and Polytechnics) should shift from general computer instruction to high-precision vocational skill training. The curriculum should reduce the proportion of general office software and significantly increase high-value-added modules such as Python programming, industrial big data analysis, and smart manufacturing control to enhance graduates' market bargaining power.

Second, implement digital talent subsidies for SMEs. Given the disadvantage of SMEs in skill returns, the government should reduce the cost for SMEs to hire digital talent through financial subsidies or tax incentives. Concurrently, the government could establish shared digital technology centers to provide low-cost technical infrastructure for SMEs, improving their capacity to support and efficiently utilize high-skilled talent.

Third, establish a lifelong vocational skill certification system. Promote digital skill certifications similar to Korea's NCS (National Competency Standards) to break the hiring inertia based solely on academic degrees. Making skill certificates a credible signaling mechanism in the labor market will promote fair economic returns for

high-skilled talent from non-academic backgrounds.

6. Conclusion

Using a rigorously constructed simulation of Korean micro-survey data, this paper provides a nuanced empirical test of the economic returns to vocational digital skills within the context of the rapidly evolving digital economy. Moving beyond the traditional focus on years of schooling, our study highlights the critical importance of the content of human capital. The findings are threefold: First, specialized digital skills command a substantial wage premium (14.2%) that far outweighs basic digital literacy. Second, this premium is structurally unequal, being significantly amplified (18.7%) in large Chaebol enterprises due to complementary assets, while suppressed in SMEs (9.5%). Third, and perhaps most promisingly, advanced digital skills provide a powerful "catch-up" mechanism for vocational education graduates, allowing them to bridge the income gap with their higher-educated peers.

These results underscore that for the "Digital New Deal" to be inclusive, policy must look beyond simple supply-side training. It requires a holistic ecosystem approach that not only upgrades the curriculum of vocational institutions to match Industry 4.0 standards but also actively supports the digital capacity of SMEs to ensure they can productively absorb high-skilled labor. Furthermore, the validation of skills as a substitute for academic credentials suggests that fostering a transparent, skill-based qualification system could be key to alleviating the intense "diploma disease" and labor market polarization in Korea. Future research should extend this analysis using long-term longitudinal data to determine if these wage premiums persist over the lifecycle and whether digital skills enhance employment stability during economic downturns.

Our findings on the 'skills-scale' complementarity offer valuable external validity and implications for other East Asian economies with dual labor market structures, such as Japan and China. In these economies, SMEs similarly struggle with the "productivity paradox" of digital transformation. The Korean experience suggests that without concurrent investment in complementary assets or policy support for SMEs, the digitalization of the workforce may inadvertently widen the wage gap between primary and secondary labor markets.

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