

# BOK Issue Note

## AI Diffusion and Youth Employment

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- ① This paper analyzes the impact of AI diffusion on youth employment (ages 15 to 29) using subscriber records from the National Pension Service, a comprehensive administrative dataset. The major findings are as follows:
- ② First, **industries with high exposure to AI experienced significant declines in youth employment.** Over the past three years, youth jobs decreased by 211,000, of which 208,000 were in industries highly exposed to AI. In contrast, jobs held by those in their 50s increased by 209,000, of which 146,000 were in industries highly exposed to AI. In the early phase of AI diffusion, junior employment decreased while senior employment increased, exhibiting a pattern of ‘seniority-biased technological change’. ▷Refer to page 5.
- ③ Second, **in industries where AI is likely to augment human capabilities (characterized by high complementarity), youth employment decreased relatively less.** This indicates that even with high exposure to AI, jobs with high AI complementarity are less likely to be automated. ▷Refer to page 8.
- ④ Third, **the impact of AI diffusion on wages remains unclear, unlike its clearer effect on employment.** This suggests that due to wage stickiness—where wages are not easily adjusted in the short term—labor market adjustments first occur through changes in employment rather than wages. ▷Refer to Page 9.
- ⑤ **AI tends to easily replace codified, routine tasks typically performed by young entry-level workers.** Conversely, AI augments tasks requiring career-based tacit knowledge or social skills. These features of AI appear to be the fundamental drivers of seniority-biased technological change, where AI adoption impacts junior and senior roles differently within firms. ▷Refer to page 10.
- ⑥ However, **it is uncertain whether the contraction of youth employment observed in the early phase of AI diffusion will persist.** Businesses may choose to pursue sustainable talent management strategies over the long term rather than making simplistic workforce cuts, as a decline in youth employment could weaken the future talent pipeline. Given that AI dissemination is likely to have lasting effects on the career trajectories of young workers and income inequality, as well as on corporate talent cultivation methods, it is essential to continuously monitor these future trends. ▷Refer to page 11.

- Disclaimer: The views expressed herein are those of the authors, and do not necessarily reflect the official views of the Bank of Korea. When reporting or citing this paper, the authors’ names should be always explicitly stated.
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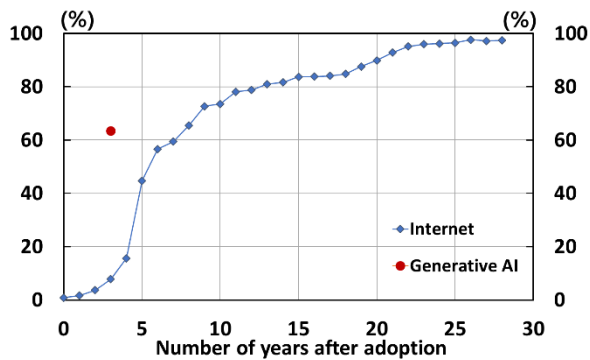
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## I. Introduction

Since the launch of ChatGPT in November 2022, numerous generative AI services have rapidly emerged in a highly competitive landscape, accelerating the pace of AI performance advancements. These improvements span a broad spectrum of applications, from back-office tasks like coding, document drafting, and data analysis to sophisticated functions involving high-level reasoning and multimodal task-handling. This simultaneous, cross-sector enhancement of AI capabilities is transforming workflows and productivity at an unprecedented rate.

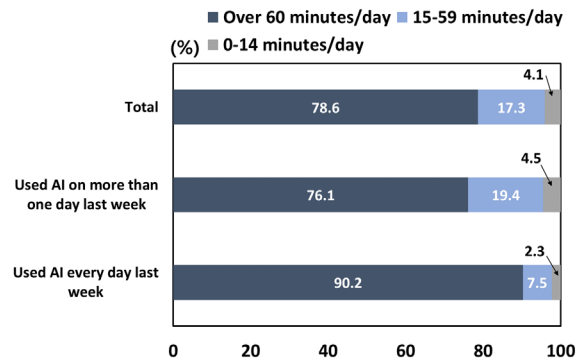
Moreover, AI technology is spreading at an unparalleled speed. According to Suh et al. (2025), as of May and June 2025, 63.5% of Korean workers reported using AI technologies, with 51.8% using AI specifically for business purposes.<sup>1</sup> Compared to the early phase of Internet adoption, AI is spreading at a rate eight times faster (Figure 1). Moreover, the share of heavy users—those engaging with AI for more than one hour per day—reached 78.6%, underscoring the intensity of AI utilization among users (Figure 2).

Figure 1. Comparison of AI<sup>1)</sup> vs. Internet<sup>2)</sup> adoption rates



Notes: 1) Generative AI adoption began from 2022, the year ChatGPT was launched.  
 2) Early Internet adoption started in 1995.  
 Source: cited again from Suh et al. (2025)

Figure 2. Intensity of AI use<sup>1)</sup>



Note: 1) Based on AI use specifically for business purposes.  
 Source: cited again from Suh et al. (2025)

With the fast pace of performance development and diffusion, the potential impact of AI on the labor market is diverse, ranging from optimism based on increased productivity to fear of massive job displacement and skepticism that actual effects will not be significant as expected. However, based on historical experience with technological change, it is reasonably certain that the impact of new technologies will vary significantly across tasks, occupations, and industries.

Recently, there has been growing concern that the rapid adoption of AI is disproportionately replacing jobs held by young workers, particularly those in entry-level positions. While earlier research relied mainly on anecdotal media reports, Brynjolfsson et al. (2025a) and Hosseini & Lichtinger (2025) provide rigorous empirical evidence from large administrative datasets and job posting data that confirm these trends have statistical significance in the U.S. labor market.<sup>2</sup>

This paper investigates whether AI adoption has a more pronounced negative impact on youth employment—in particular, whether there is evidence of seniority-biased technological change in the Korean labor market—using extensive administrative data from the National Pension Service. The analysis associates the number of National

<sup>1</sup> In the U.S., generative AI use for business purposes is estimated at approximately 26.5%, according to Bick et al. (2025), which is roughly half the reported rate for Korean workers. This disparity highlights the rapid adaptability and broader adoption of AI technologies among Korean workers compared to their U.S. counterparts.

<sup>2</sup> Brynjolfsson et al. (2025a) demonstrated through an analysis of ADP payroll data that occupations with higher exposure to AI experienced greater declines in entry-level employment beginning in the second half of 2022. Hosseini and Lichtinger (2025) identified a seniority-biased technological change associated with the spread of generative AI, characterized by a reduction in hiring for junior roles alongside an increase in employment for senior positions.

Pension Service subscribers by age group and industry with AI exposure by industry, tracking these variables in a time series framework to detect shifts related to AI diffusion.

The key findings are as follows: First, youth employment declined significantly in industries highly exposed to AI. Over the past three years, 211,000 youth jobs (aged 15 to 29) disappeared, with 208,000 of these losses occurring in industries within the top 50% AI exposure quartile—accounting for 98.6% of the total decline in youth employment. Conversely, employment for workers in their 50s increased by 209,000 during the same period, with 146,000 of these gains being in highly AI-exposed industries, representing 69.9% of the total increase. This suggests that, akin to trends observed in the U.S. labor market, the domestic labor market is undergoing a seniority-biased technological change characterized by a decline in employment for junior workers alongside an increase in employment for senior workers during the early phase of generative AI adoption.

Second, in industries with high levels of AI augmentation, the decline in youth employment has been relatively modest. This suggests that even in industries with high AI exposure, the likelihood of automation replacing jobs is lower when AI functions primarily as an augmentation tool—enhancing rather than substituting human labor.

Third, unlike employment, the impact of AI diffusion on wages remains unclear. Wage stickiness, reflecting the difficulty of short-term wage adjustments, means that employment adjustments tend to occur first, with wage adjustments lagging.

Seniority-biased technological change suggests that AI technology more readily replaces tasks performed by junior workers that rely on codified, textbook knowledge, while it tends to augment tasks requiring career-based tacit knowledge and social or interpersonal skills, which are more common among senior workers.

However, it is uncertain whether the seniority-biased effect will persist. From an enterprise perspective, a reduction in youth hiring could undermine the future talent pipeline. Therefore, firms have an incentive to adopt sustainable talent cultivation strategies over simple short-term hiring cuts in order to support long-term workforce development. It is thus necessary to consider future trends in AI adoption because the spread of AI is poised to significantly influence key areas such as the career development trajectories of young workers, corporate talent cultivation strategies, and the broader issue of income inequality.

This study proceeds as follows: Chapter II explains the data used. Chapter III examines the impact of AI adoption on employment by age group and industry. Chapter IV describes key mechanisms, and Chapter V concludes with a final discussion.

## II. Data

### 1. Number of Employed Persons

To examine changes in employment, we use data on the number of subscribers of the National Pension Service by age group and industry (two-digit intermediate classification).<sup>3</sup> This dataset encompasses approximately 16 million workers, making it the nation's largest source of employment administrative statistics. Thus, even when segmented by industry and age group, it provides highly reliable and up-to-date employment trends. Meanwhile, to analyze the impact of AI adoption on wages, we utilize microdata from the regional employment survey, which includes detailed wage information.

### 2. AI Exposure

This study uses the AI Occupational Exposure (AIOE) index developed by Felten et al. (2021), a widely adopted measure in the literature. The AIOE captures occupation-specific exposure by quantifying associations between 10 AI application categories and 52 occupational abilities. To translate these occupation-level exposures into industry-level indicators, this study weights the AIOE scores by the occupational distribution within each industry.<sup>4</sup> Additionally, this study employs the AI usage rate by occupation from Suh et al. (2025) as a supplementary measure. While the AIOE index theoretically estimates the potential for AI to replace specific tasks, the AI usage rate provides empirical insight into the actual level of AI adoption and usage in workplace settings, based on survey data from workers.

### 3. AI Complementarity

To examine the impact of AI more comprehensively, both AI exposure and complementarity are considered. For AI complementarity, this study uses the potential complementarity measure developed by Pizzinelli et al. (2023), which evaluates the difficulty of substituting human labor with AI along social and physical dimensions. This measure is constructed from occupational environment and technology data sourced from the O\*NET database. Conceptually, AI exposure reflects the likelihood of task automation in an occupation, whereas AI complementarity indicates the likelihood that AI will augment rather than replace human labor.<sup>5</sup>

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<sup>3</sup> The statistics were obtained under a memorandum of understanding (MOU) between the Bank of Korea and the National Pension Service. The data span from July 2019 to July 2025 and have been seasonally adjusted. As of July 2025, there were 16.16 million registered members of the National Pension Service, comprising 71.8% of wage and salaried workers, and 96.7% of regular workers.

<sup>4</sup> AI exposure, AI usage rate, and AI complementarity are originally occupation-level indicators. To calculate industry-level measures, these indicators are averaged using weights based on the distribution of occupations within each industry (intermediate classification). The occupational distribution data are sourced from the regional employment survey (Ministry of Data and Statistics) for the first half of 2024. For AI exposure by each industry, refer to Box 1.

<sup>5</sup> For details on AI exposure and AI complementarity, refer to Pizzinelli et al. (2023) and Oh et al. (2025).

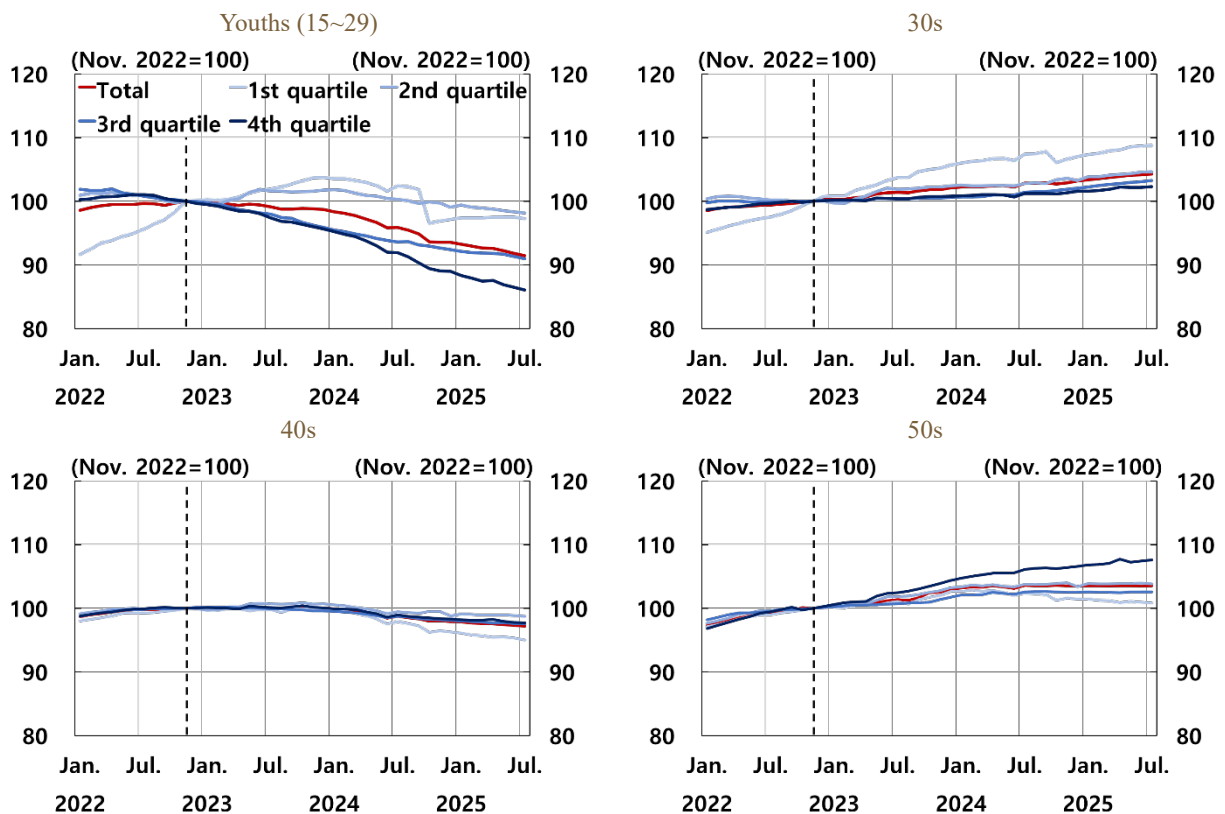
### III. The Impact of AI Diffusion

#### 1. The Decrease in Youth Employment Is Concentrated in Industries Highly Exposed to AI.

Youth employment fell more in highly AI-exposed industries. Classifying the number of employed persons by age group into AI exposure quartiles (from 1st to 4th quartile), the decline in youth employment since the second half of 2022<sup>6</sup> is found primarily in industries with high AI exposure (3rd and 4th quartiles). Notably, the decrease is most pronounced in industries within the highest AI exposure quartile (4th quartile). Conversely, industries in the lower exposure quartiles (1st and 2nd quartiles) did not see significant changes in youth employment during this period.

While those in their 30s and 40s showed no consistent employment patterns with respect to AI exposure, individuals in their 50s experienced employment growth primarily in industries with high AI exposure. Employment among individuals in their 50s has been gradually increasing since the second half of 2022, with particularly steep growth observed in industries with the highest AI exposure (4th quartile). This suggests that the Korean labor market is exhibiting seniority-biased characteristics, where youth employment is declining in industries with significant AI exposure, while employment among individuals in their 50s is increasing in those same industries. These results are consistent when using the supplementary indicator (AI usage rate-based exposure).<sup>7</sup>

Figure 3. Number of employed persons by AI exposure level<sup>1)</sup>



Note: 1) November 2022 corresponds to the launch of ChatGPT.

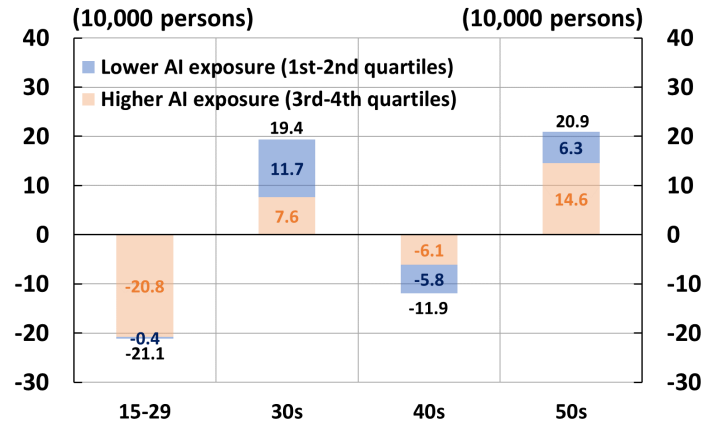
Sources: National Pension Service, Regional Employment Survey, Felten et al. (2021), authors' estimation

<sup>6</sup> In November 2022, generative AI began to spread among the public with the launch of ChatGPT.

<sup>7</sup> For results of industries classified based on AI usage rate, rather than AI exposure, refer to Box 2. For regression analysis results controlling for industries and time fixed effects, refer to Box 3.

Based on an examination of employment changes by age group over the past three years (July 2022 to July 2025), youth employment declined by 211,000, with 208,000 of these losses occurring in industries with high AI exposure (3rd and 4th quartiles), accounting for 98.6% of the total decline. In contrast, employment among individuals in their 50s increased by 209,000, of which 146,000 were in industries with high AI exposure, representing 69.9% of the increase.

Figure 4. Variation in employment by AI exposure level<sup>1)</sup> and age group<sup>2)</sup>



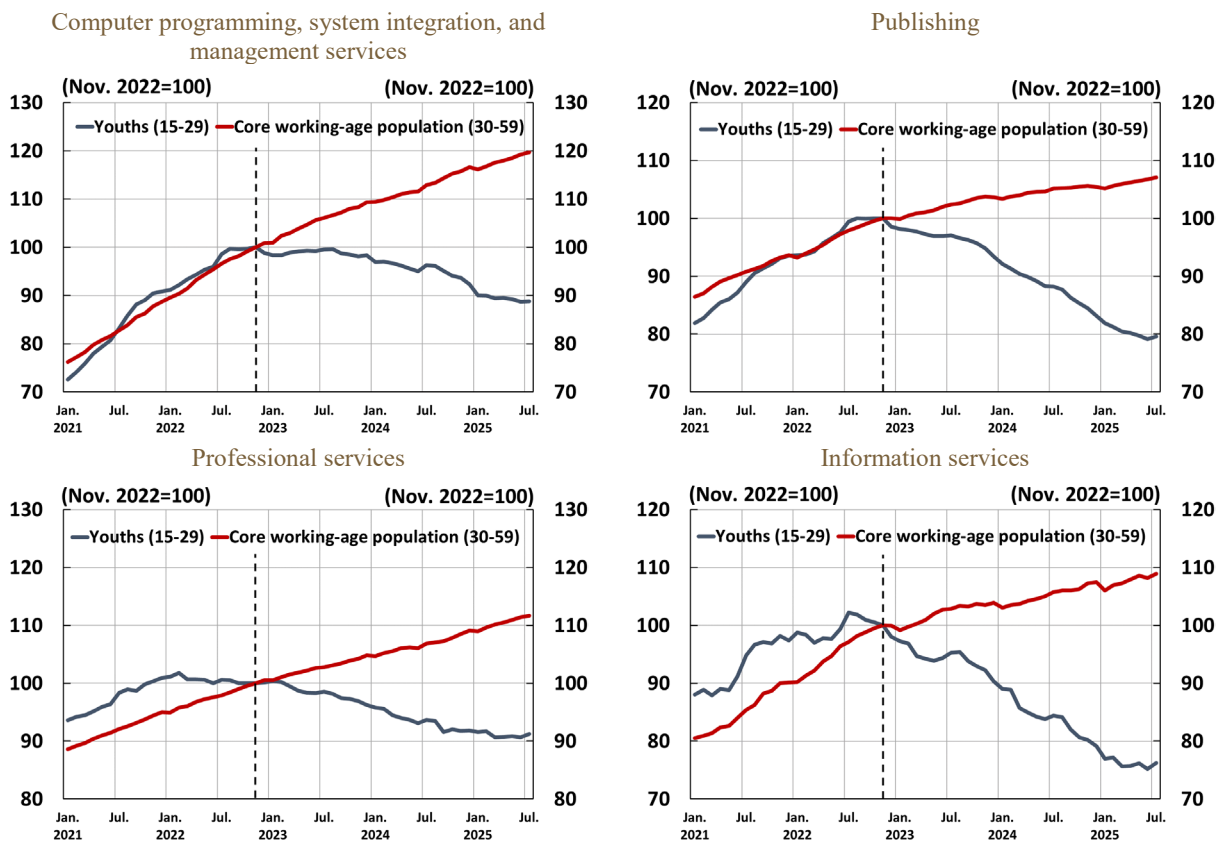
Notes: 1) Industries are divided into four quartiles based on AI exposure levels.

2) Employment figures show changes from July 2022 to July 2025.

Sources: National Pension Service, Regional Employment Survey, Felten et al. (2021), authors' estimation

By detailed industry, the contraction in youth employment is even more pronounced. Figure 5 illustrates employment trends by age group across the four industries with the highest AI exposure. In all of these industries, youth employment growth shifted to a decline beginning in the second half of 2022. Specifically, since the launch of ChatGPT, youth employment has declined by 11.2% in computer programming and system integration and management, 20.4% in publishing, 8.8% in professional services, and 23.8% in information services. In contrast, the core working-age population, including those in their 50s, maintained their positive employment growth trends without significant changes. This pattern is also evident in other highly AI-exposed occupations, such as those in the financial industry.

Figure 5. Number of employed persons by age group<sup>1)</sup>

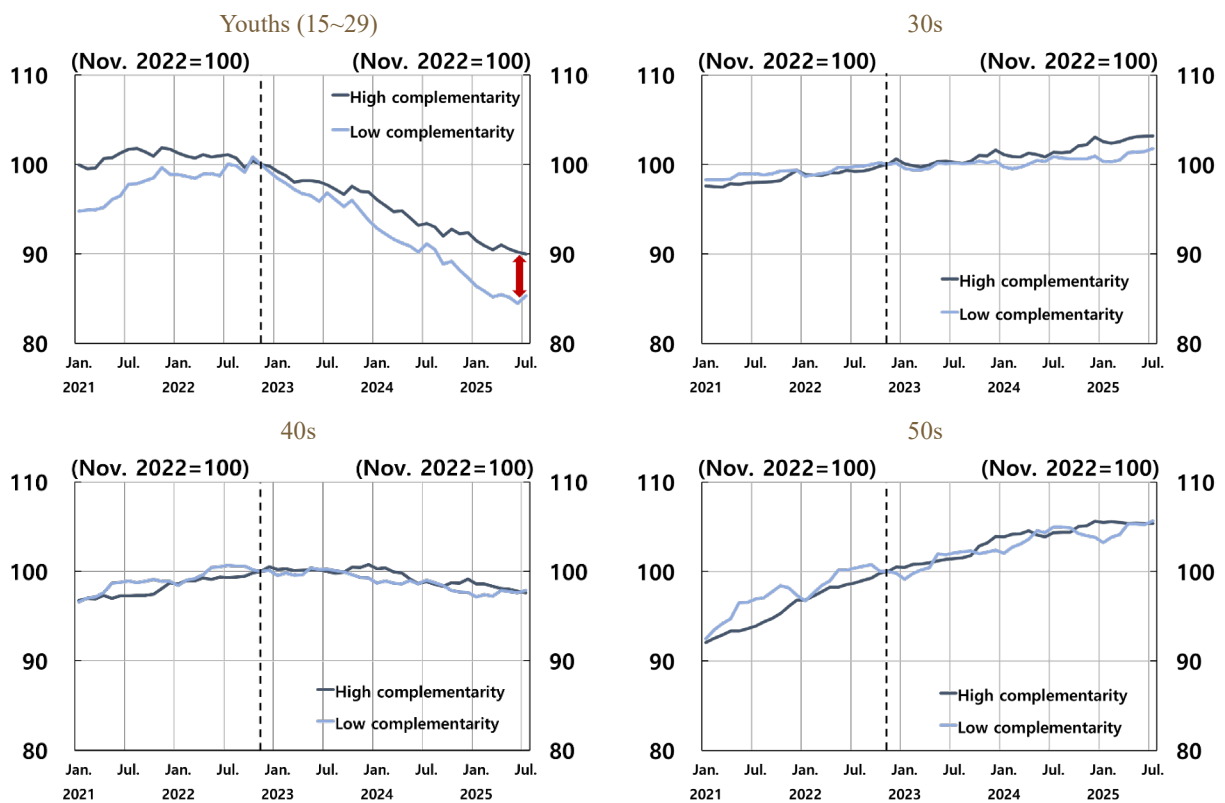


Note: 1) November 2022 corresponds to the launch of ChatGPT.  
Source: National Pension Service

## 2. In Industries with High AI Complementarity, the Decrease in Youth Employment Was Relatively Weak.

Figure 6 compares employment trends by age group for industries with high AI exposure, further divided into those with high AI complementarity and low AI complementarity.<sup>8</sup> As discussed in the previous chapter, youth employment declined overall in industries with high AI exposure; however, the magnitude of the decline was relatively smaller in jobs characterized by high AI complementarity. For instance, the decline in youth employment was significant in industries with high AI exposure but low complementarity, such as computer programming, system integration and management services, publishing, professional services, and information services. However, in industries with high AI exposure and high complementarity, such as health services, educational services, and air transportation services, youth employment did not decline. This indicates that occupations with high AI exposure but high complementarity are less likely to be replaced or automated. On the other hand, in other age groups where overall employment did not decline, employment trends showed little variation with respect to AI complementarity.

Figure 6. Number of employed persons by level of AI complementarity<sup>1)2)</sup>



Notes: 1) Industries in the upper 50% of AI exposure are further divided into those with high complementarity (upper 50%) and those with low complementarity (lower 50%).

2) November 2022 corresponds to the launch of ChatGPT.

Sources: National Pension Service, Felten et al. (2021), Pizzinelli et al. (2023), authors' estimation

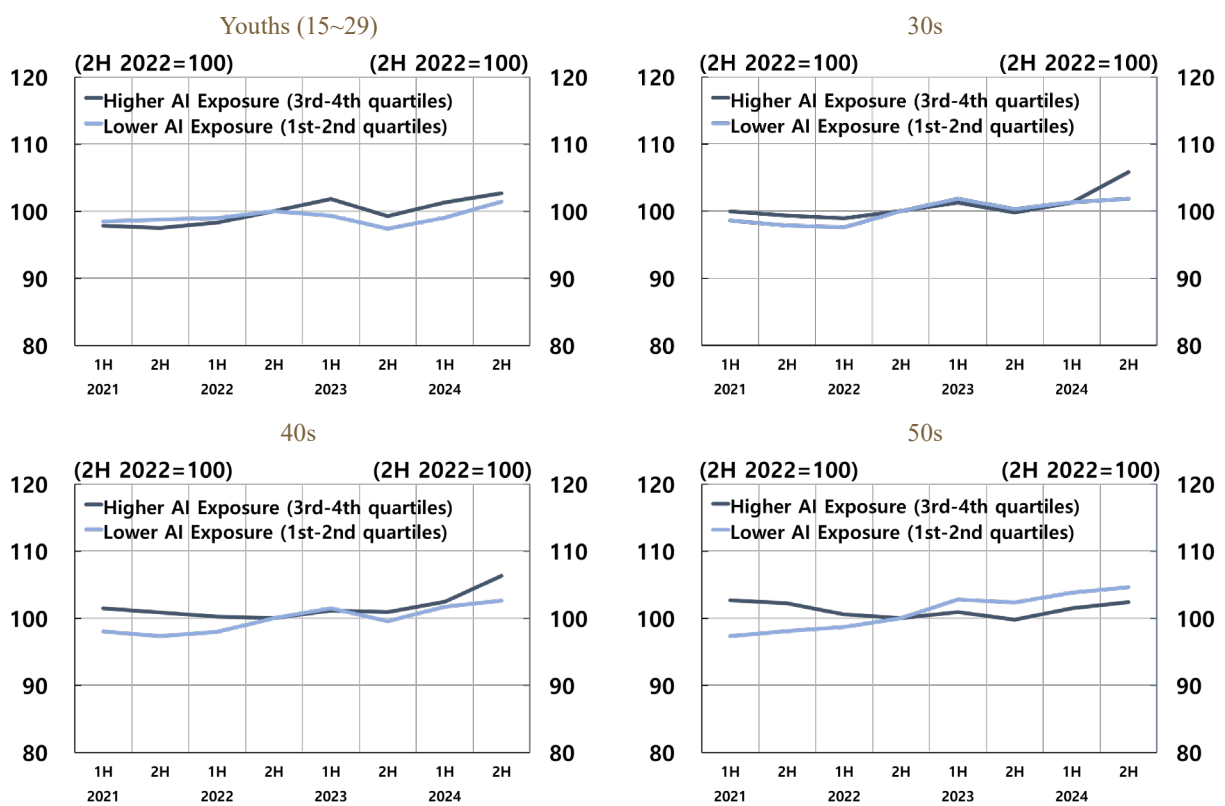
<sup>8</sup> For industries with low AI exposure, considering further AI complementarity has limited significance. For details on the categorization of upper and lower AI exposure and complementarity by industry, refer to Box 4.

### 3. The Impact of AI Tech Diffusion on Wages Remains Unclear, Unlike Its More Apparent Effects on Employment.

If AI adoption reduces labor demand, it could exert downward pressure on wages. However, a comparison of real wage trends across AI exposure quartiles (1st to 4th) shows no statistically significant differences (Figure 7).<sup>9</sup> In other words, recent labor market adjustments have primarily occurred through changes in employment rather than wages.<sup>10</sup>

This can be primarily explained by wage stickiness, which refers to the tendency of wages to not adjust easily or quickly in the short term. At the same time, alternative explanations are possible. For example, even though hiring decreased, wages for existing employees may have risen or remained stable due to productivity gains from AI adoption, offsetting any downward pressure on average wages (composition effect). Still, due to data limitations, it is difficult to definitively determine the short-term impact of AI adoption on wages.

Figure 7. Wages by AI exposure level<sup>1)</sup>



Note: 1) AI exposure groups are based on occupational sub-groups.  
Sources: Regional Employment Survey, Felten et al. (2021), authors' estimation

<sup>9</sup> A similar phenomenon has been observed in the U.S. labor market. Brynjolfsson et al. (2025a) showed, using U.S. data, that AI adoption has not had a significant impact on wages.

<sup>10</sup> Hosseini and Lichtinger (2025) found that the decline in junior employment in the United States is primarily driven by a reduction in inflows (new hires) rather than by increased outflows (separations due to job changes or retirements). In the context of Korea, where employment protection regulations are more stringent, the impact of reduced hiring on junior employment is expected to be even more pronounced.

## IV. Why Is Youth Employment Declining with AI Diffusion?

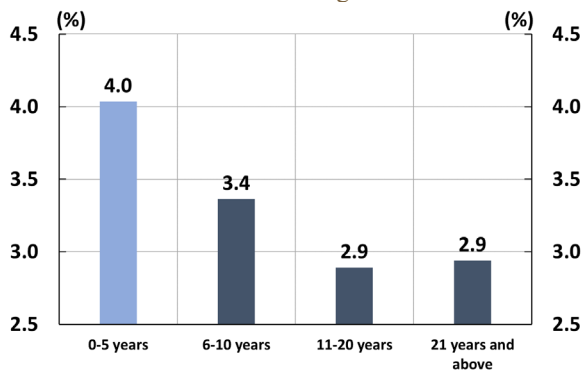
Youth employment is most severely affected in the early stages of generative AI diffusion because young workers predominantly perform codified, routine, and textbook knowledge tasks—such as coding and data processing—which are more easily automated by AI systems.

The analysis of household survey data by Suh et al. (2025) reveals that workers with five years or less of career experience who use generative AI see a 4% decline in the time spent completing tasks, the largest reduction among all experience groups. As workers’ career length increases, the productivity gains and corresponding decline in task hours decrease (Figure 8).<sup>11</sup> Brynjolfsson et al. (2025b) find that among early-career, lower-skilled workers, generative AI leads to larger reductions in task hours. Similarly, Dillon et al. (2025) report that these task hour reductions are especially pronounced for codified, individual tasks such as email management and document writing. This means that codified, textbook-like knowledge tasks—primarily performed by junior or early-career workers—can now be completed with less human labor.

In contrast, experienced senior workers possess tacit knowledge—such as deep understanding of business contexts, interpersonal skills, and organizational management—that AI cannot replicate. Thus, AI tools serve a complementary role for these workers rather than replacing them.

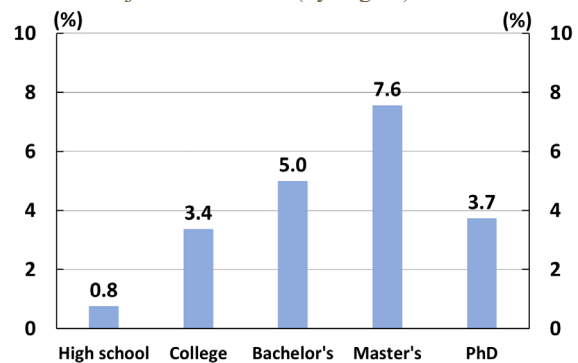
The observed U-shaped pattern in junior workers’ task hours reduction rates by degree reflects how young workers with middle and high levels of education are more susceptible to AI automation. As shown in Figure 9, master’s degree holders experience the highest reduction rate at 7.6%, followed by bachelor’s degree holders at 5.0%, PhD holders at 3.7%, college graduates at 3.4%, and high school graduates at 0.8%.<sup>12</sup>

Figure 8. Rate of reduction in task hours due to AI by career length



Source: household survey data from Suh et al. (2025)

Figure 9. Rate of reduction in task hours due to AI for junior workers<sup>1)</sup> (by degree)



Note: 1) Workers with a career length of five years or less.  
Source: household survey data from Suh et al. (2025)

<sup>11</sup> The reduction rate of 4% is calculated by summing the reported hours saved per week across all tasks due to generative AI use, and then dividing this total by the actual weekly work hours. Therefore, a 4% reduction corresponds to a time savings of 1.6 hours in a standard 40-hour workweek.

<sup>12</sup> Hosseini and Lichtinger (2025) analyzed U.S. labor market data and found clear evidence of a U-shaped pattern in AI’s impact on employment by education level. Specifically, junior workers who graduated from mid-high tier educational institutions experienced the sharpest declines in employment following AI adoption.

## V. Conclusion

Using large-scale administrative data from the National Pension Service, we examine labor market changes over the past three years following the diffusion of AI. Our key finding is that AI adoption has decreased junior employment while increasing senior employment, indicating a seniority-biased technological change in the labor market. Since the second half of 2022, most of the decline in youth employment occurred in industries with high AI exposure, while employment among workers in their 50s increased mainly in these same highly AI-exposed industries. This can be explained by the fact that AI relatively easily replaces codified tasks, which are mostly performed by younger, less-experienced workers, while it complements tasks requiring social skills and tacit knowledge that are developed with career experience.

However, the findings of this paper should be interpreted with caution. First, they do not establish definitive causality. AI adoption by enterprises is not arbitrary but influenced by the unique characteristics of each occupation. Therefore, understanding AI's impact on youth employment requires causality testing over a longer-term horizon, considering occupational differences. Nevertheless, this study shows that there is a strong short-term correlation between AI diffusion and the contraction of youth employment.

Second, these trends may not persist. In the short term, uncertainty around technological change and the drive for cost savings may reduce new hiring. However, cutting entry-level positions could harm a company's long-term talent pipeline. Consequently, enterprises are likely to pursue sustainable strategies such as cultivating talent capable of collaborating with AI, establishing AI collaboration systems, and redesigning tasks, rather than opting for workforce reductions. In addition, increased productivity driven by AI could boost labor demand in the long term, benefiting youths.

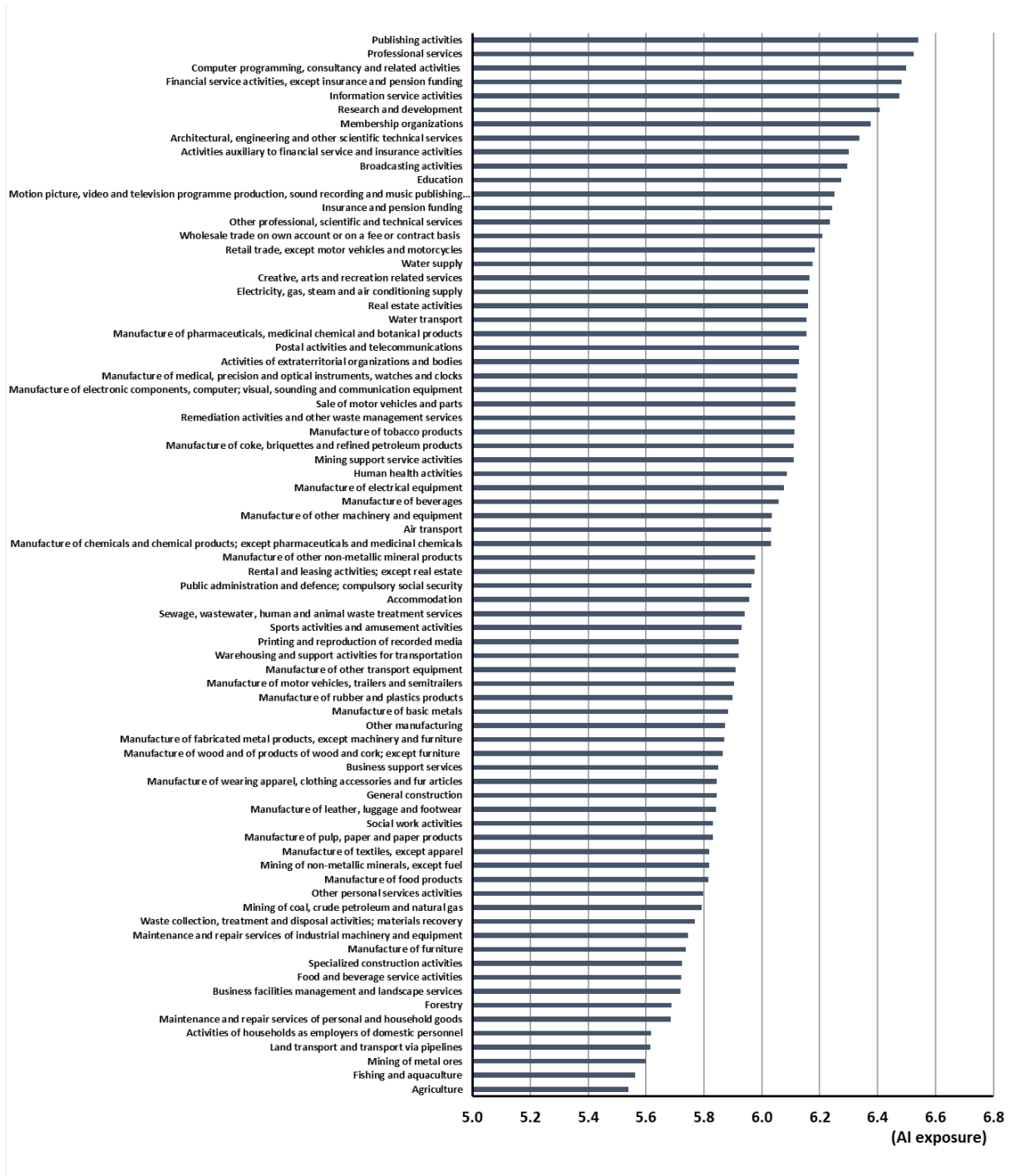
In summary, the contraction of youth employment observed in the early phases of AI diffusion is likely to have lasting effects on how enterprises cultivate talent, the career development trajectories of young workers, and overall income inequality. Therefore, it is crucial to continuously monitor these trends and conduct rigorous analyses focused on establishing causality to inform effective policy and corporate responses.

Ongoing social discussions on policy directions are also essential. For instance, strengthening support for startups could enable young people to use AI as a complementary tool to innovate, explore new markets, and develop new business models. While startups require creativity in defining problems, implementing ideas through experimentation, and exploring markets—tasks that are not easily automated by AI—they can still enhance the efficiency of codified tasks by leveraging AI technologies. Therefore, it is important to help young people adapt proactively to AI by expanding educational programs that improve AI utilization skills, increasing access to public data, and fostering an inclusive startup ecosystem that supports the exploration of new industry opportunities in the AI era.

Box 1.

AI Exposure by Industry

Figure 10. AI exposure by industry<sup>1)2)</sup>



Notes: 1) AI exposure by industry is calculated by weighting each occupation’s exposure score by its employment share within the industry (intermediate industry classification) and then taking the weighted average to derive the industry’s overall AI exposure.

2) Official industry names are used in this figure; minor adjustments have been made in the main text (and Box 4) for clarity.

Sources: Felten et al. (2021), Regional Employment Survey (2H, 2024), authors’ estimation

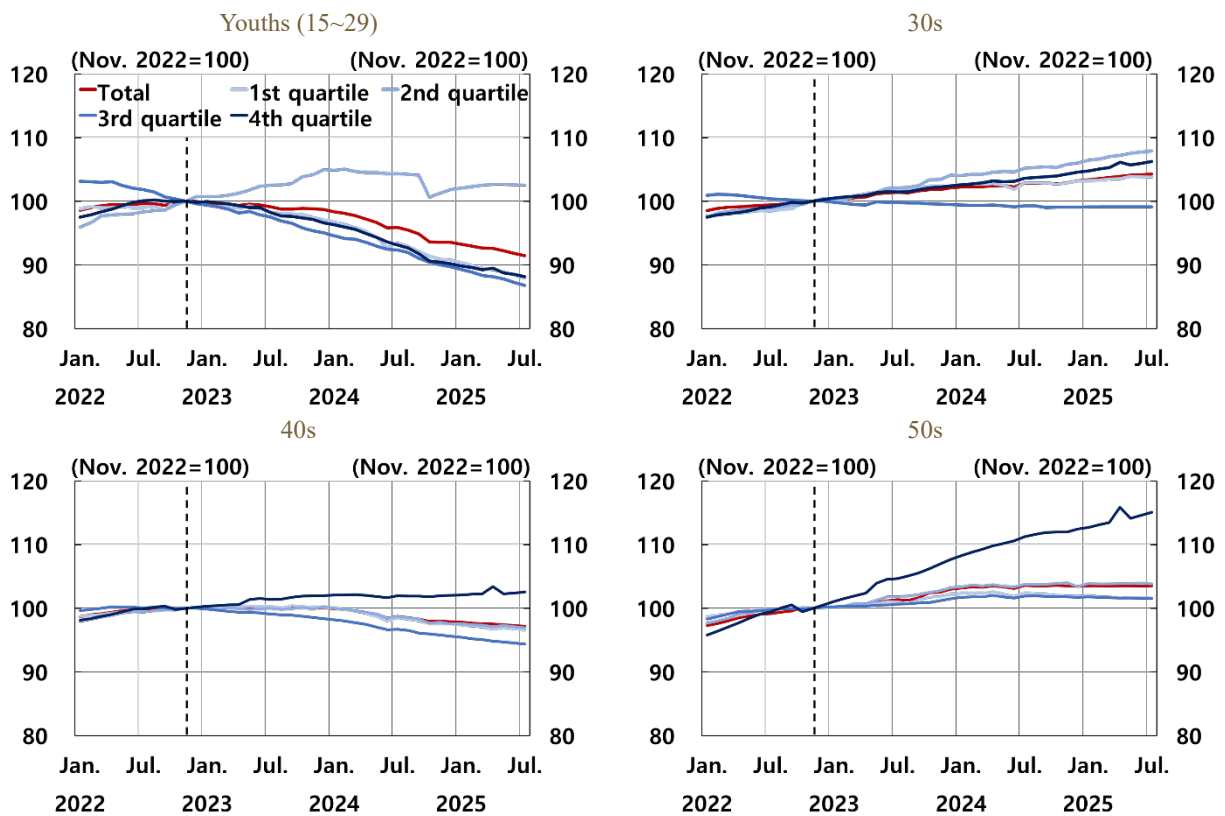
**Box 2.**

**Trends of Employment by Age Group Using Supplementary Index of AI Usage Rate**

The main analysis employs the AI exposure index (AIOE) developed by Felten et al. (2021). In contrast, Box 2 utilizes an AI usage rate index derived from the household survey data of Suh et al. (2025), serving as an alternative proxy for AI exposure. While the AIOE index theoretically estimates the potential for AI to replace specific tasks, the AI usage rate offers empirical insight into the actual adoption and utilization level of AI in workplace settings, based on survey data collected from workers.

Although the AI usage rate is a supplementary indicator, a similar seniority-biased technological change is still observed. Employment declines were concentrated among youths in industries within the 3rd and 4th quartiles, which have high AI usage rates. In contrast, for individuals in their 50s, employment increased sharply, mostly in 4th quartile industries with the highest exposure to AI (see Figure 11).

Figure 11. Number of employed persons by AI usage rate level<sup>1)2)</sup>



Notes: 1) Index data from July 2019 to July 2025 are seasonally adjusted.

2) November 2022 corresponds to the launch of ChatGPT.

Sources: National Pension Service, Regional Employment Survey, Suh et al. (2025), authors' estimation

### Box 3.

#### Identification of Seniority-Biased Employment Effect of AI Diffusion

To demonstrate that the seniority-biased effect of AI adoption is not merely coincidental or driven by unique business characteristics of individual industries, we estimated a Difference-in-Difference-in-Difference (DDD) regression model. This model controls for industry fixed effects and monthly time fixed effects, isolating the effect more robustly.  $y$  represents the number of National Pension Service subscribers and is used as an employment indicator.  $young_\alpha$  is a dummy variable that takes the value of 1 for youths aged 15 to 29 and 0 for individuals in their 50s, classified by age group ( $\alpha$ ).<sup>13</sup>  $post_t$  is a dummy variable that equals 1 for time periods ( $t$ ) after November 2022 and 0 for time periods before then.  $AIOEpct_i$  denotes the percentile rank of AI exposure by sector ( $i$ ).<sup>14</sup> The fixed effects,  $\alpha_i$ , represent industry fixed effects (75 intermediate-level industries), and  $\delta_t$  represents monthly time fixed effects (from July 2019 to July 2025).

$$\ln(y)_{iat} = \beta_0 + \beta_1 young_\alpha AIOEpct_i + \beta_2 young_\alpha + \beta_3 post_t young_\alpha + \beta_4 post_t AIOEpct_i + \beta_5 post_t young_\alpha AIOEpct_i + \alpha_i + \delta_t + \varepsilon_{iat}$$

Table 1. Regression coefficient estimation results<sup>1)2)</sup>

<i>young<sub>α</sub>AIOEpct<sub>i</sub></i>	0.0151068*** (0.0003645)
<i>young<sub>α</sub></i>	-1.445769*** (0.0178256)
<i>post<sub>t</sub>young<sub>α</sub></i>	-0.0173127 (0.026603)
<i>post<sub>t</sub>AIOEpct<sub>i</sub></i>	0.0024888*** (0.0003474)
<i>post<sub>t</sub>young<sub>α</sub>AIOEpct<sub>i</sub></i>	<b>-0.0021727***</b> <b>(0.0005187)</b>
Observations	10,844
Adjusted R-squared	0.9707
Within R-squared	0.5385

Notes: 1) Robust standard errors are shown in parentheses.

2)\* p-value<0.1, \*\* p-value<0.05, \*\*\* p-value<0.01

According to the estimation results, for individuals in their 50s, a 25-percentile increase in AI industrial exposure (equivalent to moving up one quartile) corresponds to a 6.2% ( $\widehat{\beta}_4 \times 100 \times 25$ ) increase in employment after November 2022 on average. However, the employment increase for youths was 5.4 percentage points ( $\widehat{\beta}_5 \times 100 \times 25$ ) lower than that for individuals in their 50s under the same conditions. This suggests that, even after controlling for individual industry effects, youth employment remains relatively weak in occupations with high AI exposure, indicating a seniority-biased employment effect.

<sup>13</sup> A comparison is made between youths and individuals in their 50s, who have shown clear changes in employment since AI adoption.

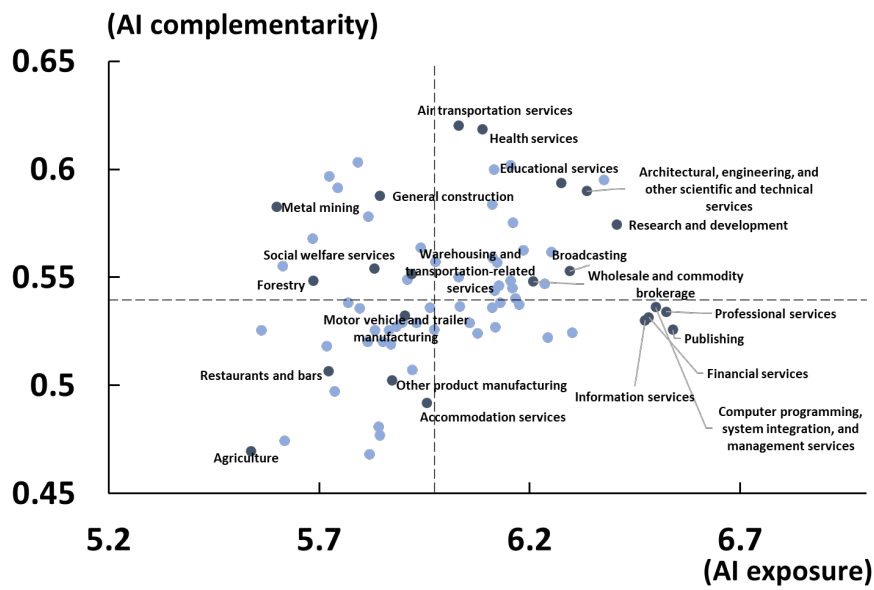
<sup>14</sup> Industries with a higher percentile closer to 100 indicate greater AI exposure. The AI exposure level used (in Box 1) serves as the variable for identifying heterogeneous employment effects by age group according to their AI exposure.

**Box 4.**

**AI Exposure and Complementarity by Industry**

Figure 12 illustrates two key industry characteristics related to AI. Higher values on the X-axis correspond to industries with greater AI exposure, while higher values on the Y-axis indicate sectors that utilize AI more effectively in a complementary role.<sup>15</sup>

Figure 12. AI exposure and complementarity by industry<sup>1)</sup>



Note: 1) Dotted lines indicate the upper and lower 50%.

Sources: Felten et al. (2021), Pizzinelli et al. (2023), Regional Employment Survey (2H, 2024), authors' estimation

<sup>15</sup> Figures on occupation-level AI exposure and complementarity based on the original data can be found in Oh et al. (2025).

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