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AI Adoption, Regional Productivity, and Inflation
Evidence from Korea and Implications for Monetary Policy

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ABSTRACT

This paper examines whether the early diffusion of artificial intelligence (AI) is visible in productivity and price outcomes relevant to monetary policy. We combine firm-level information on AI adoption from Korea's Survey of Business Activities with annual industry- and region-level data for 2017–2023. We construct value-added- and employment-weighted measures of AI intensity and use their 2019 values as predetermined measures of initial AI intensity. Both measures strongly predict the cross-sectional distribution of AI intensity in 2023. We then estimate reduced-form panel regressions that compare 2023 outcomes across industries and regions with different initial levels of AI intensity, controlling for unit and year fixed effects. We find no systematic evidence that more AI-intensive industries or regions experienced stronger output or labour-productivity growth in 2023. Industry-level price effects are also statistically insignificant and vary across price measures. At the regional level, however, employment-weighted AI intensity is positively associated with overall consumer price inflation, while restaurant price inflation is higher under both measures of AI intensity. These findings suggest that the supply-side benefits of AI had not yet become visible in aggregate productivity by 2023, whereas inflationary pressures may have emerged in some locally determined consumer services. This pattern is consistent with demand responding before productivity gains are fully realised, although our empirical design does not identify the underlying mechanism. The findings have important implications for monetary policy: during the early stages of AI diffusion, central banks should not assume that anticipated productivity gains will immediately expand effective supply or alleviate inflationary pressures. We discuss the implications of this transitional asymmetry for central banks in Asian economies, where rapid AI adoption may coincide with persistent supply constraints and sector-specific price pressures.

Keywords: Artificial Intelligence (AI), AI Adoption, Productivity Growth, Inflation, Monetary Policy and Central Banking

JEL Codes: E31, E52, O33, O47

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1. Motivation and Policy Relevance

AI is rapidly emerging as a general-purpose technology (Baily et al., 2025), with broad implications for productivity, labour markets, price dynamics, expectations, risk assessment, and financial conditions. These are precisely the variables that central banks seek to understand in the conduct of monetary policy and in the pursuit of macroeconomic and financial stability. Among them, four are especially central from a central bank perspective: employment, inflation, interest rate and financial stability.

Consider first the labour-market implications of AI. AI may excel at structured, repetitive, and data-intensive tasks, and may therefore reshape the workforce by augmenting or replacing these tasks. Recent empirical evidence shows limited or no significant economy-wide effects on unemployment, but entry-level roles in exposed sectors appear to be more affected (Hartley et al., 2026; Eloundou et al., 2024). Phillips-Robins (2026) find a 16% relative decline in employment among workers aged 22–25 in AI-exposed sectors following generative AI adoption in the US. Survey evidence from the Federal Reserve Bank of New York suggests that, while many firms have not yet engaged in large-scale layoffs, AI adoption may already be affecting hiring decisions, with some firms reporting plans to reduce new hiring rather than to cut existing jobs (Abel et al., 2025). Beyond its effect on aggregate employment, AI may also have important distributional consequences. It may widen inequality by separating workers and firms whose tasks are substituted by AI from those that can use AI as a productivity-enhancing tool. In particular, recent evidence suggests that AI may generate a form of seniority-biased technological change, operating less favourably for early-career workers than for more experienced workers. Hosseini et al. (2025) report that, in firms adopting AI, junior employment declines while senior employment remains largely unchanged. Brynjolfsson et al. (2025) provide related evidence, showing that employment declines in AI-exposed industries are concentrated among early-career workers. These findings suggest that AI may pose a dual labour-market challenge: it can weaken employment opportunities for some workers while also amplifying inequality across workers with different levels of experience and AI complementarity. Monetary policy cannot directly resolve these distributional consequences, but it must take them into account when assessing labour-market slack, wage pressures, and the broader employment side of the central bank mandate.

Second, AI may affect inflation dynamics through a combination of supply-side productivity gains and demand-side investment effects, but the path would be time-dependent and expectation-sensitive. If AI raises productivity or substitutes for tasks previously performed by workers, it may reduce unit labour costs and exert downward pressure on prices. However, such effects may not materialise immediately. Brynjolfsson et al. (2021) argue that the adoption of important new technologies often follows a J-curve pattern: measured productivity may respond only with a delay because realising the benefits of new technologies requires substantial complementary investments, especially in organisational redesign, workflow integration, and other intangible assets. Cook (2024) makes a similar point in the context of AI, emphasising that its productivity effects are likely to depend on the pace of firm-level experimentation, adaptation, and diffusion. If AI generates sufficiently large and persistent productivity gains, it could help contain inflationary pressure in the long- run. In that case, for a given increase in demand, the associated inflationary pressure would be lower, allowing central banks to achieve price stability with less monetary tightening than would otherwise be required. Hornstein (2024) also argues that AI may raise long-run productivity and potential output. At the same time, he notes that a sustained increase in trend productivity growth may raise the equilibrium real interest rate, r^*, thereby justifying a higher policy rate in the long-run.

The inflationary implications of AI are therefore complex. AI may exert a disinflationary force, especially when productivity gains are unexpected. Its net effect on inflation over the medium-term depends on expectation formation, speed and scale of AI-induced investments, and sectoral transmission and supply-demand linkages. Cipollone (2024) emphasises that despite AI's disinflationary effects through productivity gains and unit labour cost declines, AI can also generate upward price pressures. Rising demand for electricity, computing power, and data-centre capacity may increase input costs. AI may also facilitate real-time price discrimination, algorithmic pricing, and potentially algorithmic collusion, all of which could weaken competitive price adjustment. Moreover, AI may alter the transmission of monetary policy itself. If AI creates winners and losers in labour and capital markets, it may change the distribution of income and wealth, marginal propensities to consume, and access to credit, thereby affecting how aggregate demand responds to interest rate changes.

Third, AI-driven structural shifts may affect the long-term growth trend, the natural rate of interest, and the sensitivity of aggregate demand to interest rates around which monetary policy is calibrated (Simone Lenzu, 2026). The effect of AI on the natural rate of interest is ambiguous. Productivity gains and stronger investment demand may put upward pressure on r^*, whereas labour displacement and greater inequality may increase precautionary saving and place downward pressure on r^*. The uncertainty also arises from the varying effects of AI on different sectors and the potential for AI to create both demand and supply shocks. The upward pressure on the natural rate of interest can be also offset by the need for tighter monetary policy to manage inflationary pressures. Central banks must recalibrate their frameworks to account for these changes and navigate the challenges of AI's influence on the economy. If AI also contributes to the expansion of non-bank financial intermediation, it could further change the channels through which monetary policy is transmitted. AI impact on the financial system is already significant with implications for monetary policy transmission and financial stability. However, these issues are too broad and exceed the scope of this paper.

Fourth, AI adoption may have important implications for financial stability. When adopted by banks and other financial institutions, AI can improve risk assessment, capital and liquidity planning, fraud detection, and compliance (ECB, 2024). At the same time, it may also create new vulnerabilities. Cipollone (2024) emphasises that widespread AI adoption in finance could increase operational risk, market concentration, supplier dependence, herd behaviour, market correlation, manipulation, deception, and conflicts of interest. Harker (2024) similarly argues that AI may enhance efficiency and fairness in financial services, but that biased data, common models, and shared algorithmic tools may also amplify consumer harm and systemic risk. Aldasoro et al. (2024b) develop this argument more systematically. They argue that AI can transform the financial system by expanding its information-processing capacity, but that the same forces may also increase model opacity, data dependence, algorithmic bias, market concentration, herding, cyber risk, and systemic fragility. These risks are likely to become more important as financial institutions rely increasingly on similar AI models, common data sources, and a concentrated set of third-party technology providers. The rise of AI therefore strengthens the case for central banks and financial authorities to incorporate new AI-related vulnerabilities into financial supervision, regulation, and macroprudential policy.

This paper is motivated by the first two policy concerns discussed above—labour-market adjustment and inflation—but its empirical analysis is deliberately narrower. We do not attempt to estimate the direct employment effects of AI, which have been examined more directly in recent studies using worker- and firm-level data. Instead, using Korean data, we examine whether AI intensity is associated with stronger productivity performance and how it is related to price dynamics. This focus allows us to study the productivity and inflation channels through which AI is most directly relevant for monetary policy. The third and fourth issues—AI-driven structural shift and financial stability—are also clearly important, but a full analysis of AI-related structural shift and financial stability risks lie beyond the scope of this paper. In this sense, our empirical exercise is modest in scope. It asks whether the early diffusion of AI is already visible in the real-activity and inflation outcomes that are most directly relevant for central-bank policy assessment.

Korea provides a useful setting for this question. First, Korea has a high level of digital readiness and a record of rapid adoption of new technologies. Second, detailed Korean industry and regional data make it possible to construct measures of AI intensity based on the distribution of AI-adopting firms across industries and regions. Third, recent studies by the Bank of Korea provide direct evidence on the rapid use of AI among Korean workers and on the heterogeneous employment effects of AI exposure across industries and age groups. Combining these sources with industry and regional data on output, productivity, and prices allows us to examine the early relationship between AI intensity, real activity, and inflation in a setting that is highly exposed to new digital technologies.

To examine these questions, we combine firm-level information on AI adoption from Korea's Survey of Business Activities with annual industry- and region-level data on output, labour productivity, and prices over 2017–2023. We construct value-added-weighted and employment-weighted measures of AI intensity for each industry and region and use their 2019 values as predetermined indicators of pre-existing AI intensity. We first confirm that the 2019 measures strongly predict the cross-sectional distribution of AI intensity in 2023. We then estimate reduced-form panel regressions that interact standardised 2019 AI intensity with an indicator for 2023, the first full post-diffusion year, while controlling for industry or region fixed effects and year fixed effects. This design does not identify the causal effect of AI adoption. Rather, it examines whether industries and regions with greater pre-existing AI intensity experienced systematically different real and price outcomes in 2023.

The results provide little evidence that industries or regions with greater pre-existing AI intensity experienced stronger output or labour-productivity growth in 2023. At the industry level, the estimated relationships with real GDP growth and labour-productivity growth are statistically insignificant. The price evidence is also mixed. GDP-deflator inflation is lower in more AI-intensive industries after the electricity and gas industry is excluded, whereas PPI inflation is higher, but neither relationship is statistically significant. At the regional level, AI intensity is likewise not systematically associated with stronger real activity. Some regional consumer-price estimates are positive, however. Total CPI inflation is significantly higher under the employment-weighted intensity measure, while restaurant-price inflation is positively associated with both intensity measures.

Taken together, these findings are broadly consistent with a temporal asymmetry between the demand- and supply-side effects of AI. The absence of visible productivity gains in 2023 is consistent with the productivity J-curve, under which the benefits of a general-purpose technology emerge only after firms undertake complementary investments in organisational capital, worker skills, and workflow redesign. Demand, however, may respond before these supply-side gains are realised. Aldasoro et al. (2024a) show in a multisector macroeconomic model that, when future AI-driven productivity gains are anticipated, consumption and inflation can increase before the associated expansion in productive capacity is fully realised. Expectations of higher future income stimulate current demand, thereby generating upward pressure on inflation during the transition. The combination of limited productivity gains and higher inflation in some regional consumer-price categories is consistent with this timing-based interpretation. Nevertheless, our empirical design does not directly identify the underlying mechanism. Moreover, because the analysis includes only one full post-diffusion year, the results cannot establish a productivity J-curve and should be interpreted as suggestive short-run associations rather than as causal effects of AI adoption.

The remainder of the paper is organised as follows. Section 2 describes the data, explains the construction of the AI-intensity measures, and presents descriptive evidence across industries and regions. Section 3 introduces empirical specification and reports the main industry- and regional-level results. Section 4 concludes by summarising the findings and discussing their implications for central-bank assessments of AI-related changes in productivity and inflation.

2. Data and Descriptive Evidence

The empirical analysis combines annual industry- and region-level outcome data for Korea over 2017–2023. Since the widespread diffusion of generative AI began only in late 2022, 2023 is the first full year in which its early economy-wide effects may be visible in the annual data. The sample therefore compares pre-diffusion outcomes with outcomes in 2023. Since the post-diffusion period contains only one year, the estimates should be interpreted as short-run differences associated with pre-existing AI intensity rather than as medium- or long-run effects of AI adoption.

The empirical analysis is conducted at both the industry and regional levels. Industries are defined using the broad one-digit divisions of the Korean Standard Industrial Classification. Regions correspond to Korea's 17 province-level administrative divisions, including special and metropolitan cities, Sejong Special Self-Governing City, and provinces. The regional analysis therefore treats Seoul and other major metropolitan cities as separate observational units alongside provinces such as Gyeonggi-do and Gyeongsangbuk-do.

Industries are classified according to the one-digit divisions of the 10th revision of the Korean Standard Industrial Classification (KSIC), published by Statistics Korea through the Korean Statistical Classification Portal. Industry-level output is obtained from KOSIS using the Bank of Korea's national-accounts table "GDP and GNI by Economic Activity," which reports annual nominal and real GDP by economic activity. We map the economic-activity categories in this table to the broad KSIC divisions used in the empirical analysis. Real industry GDP growth is measured as the annual log change in real GDP, while industry-level GDP-deflator inflation is calculated as the annual log change in the ratio of nominal to real GDP.

Because the measurement framework for employment changed in 2020, the survey-based series available before 2020 is not directly comparable with the register-based series used thereafter. To construct a consistent industry-level employment series for 2017–2024, we begin with employment counts reported for each region–industry cell under both frameworks in 2020, when survey-based and register-based data are simultaneously available. For each combination of Korea's 17 province-level administrative divisions and one-digit industries, we calculate the extent to which register-based employment exceeds or falls below the corresponding survey-based count. We then decompose this difference into common regional and industry components and use the estimated components to derive a conversion factor for each region–industry cell. For electricity, gas, steam and air-conditioning supply, whose 2020 differences are not well explained by the region-and-industry-effects model, we instead use the actual register-to-survey employment ratio observed for each region–industry cell. The resulting conversion factors are applied to the survey-based employment counts for 2017–2019 to express them on a register-based basis, while the original register-based observations are retained for 2020–2024. Finally, the harmonised region–industry employment counts are summed across the 17 regions to obtain a consistent national employment series for each one-digit industry. Labour productivity is defined as real industry GDP per employed worker. Industry-level price movements are also measured using producer price indexes from KOSIS, based on the annual series with 2020 as the reference year. These indexes are matched to the corresponding one-digit KSIC divisions where a consistent industry match is available.

Regions are defined as Korea's 17 province-level administrative divisions, including Seoul and the other metropolitan cities, Sejong Special Self-Governing City, and the provinces. Regional output data are drawn from the regional income accounts disseminated through KOSIS. These accounts report annual nominal and real Gross Regional Domestic Product (GRDP) for each region and are compiled in accordance with the System of National Accounts. Because the regional accounts use source data and estimation procedures that differ from those underlying the national accounts, the sum of GRDP does not necessarily coincide with national GDP. We use nominal and real GRDP to construct real GRDP growth and implicit GRDP-deflator inflation. Regional employment data, also obtained from KOSIS, are used to calculate labour productivity as real GRDP per employed worker. In addition to total CPI inflation, we construct annual inflation rates for services, personal services, and restaurant prices from the corresponding regional indexes. These disaggregated measures allow us to compare broad consumer-price movements with price pressures in service categories that are more closely linked to local demand and labour-market conditions.

AI intensity is constructed from the Survey of Business Activities, an annual firm-level survey conducted by Statistics Korea. A firm is classified as an AI adopter if it reports using AI-related technologies. For each industry-year and region-year, we aggregate these firm-level adoption indicators using two alternative weighting schemes. The value-added-weighted measure is the share of total value added accounted for by AI-adopting firms, while the employment-weighted measure is the share of total employment accounted for by those firms. These measures capture the economic importance of AI-adopting firms within each industry or region rather than the simple frequency of firms reporting AI adoption.

The analysis therefore uses two complementary dimensions of cross-sectional variation. The industry panel examines whether industries with greater pre-existing AI intensity experienced different changes in output, productivity, and prices in 2023. The regional panel examines whether regions in which AI-adopting firms accounted for larger shares of value added or employment experienced different changes in output, productivity, and inflation. In both panels, the main intensity measures are based on AI adoption observed before 2023 and are therefore predetermined relative to the 2023 outcomes. The firm-level survey data needed to construct these measures are available only through 2023, which limits the analysis to the first post-diffusion year.

Tables 1 and 2 report descriptive statistics for industry and regional panels. Several patterns are worth noting. First, AI intensity is unevenly distributed across both industries and regions. In the industry panel, value-added-weighted AI intensity in 2019 has a mean of 0.157, a median of 0.078, and a maximum of 0.655. The regional measure is similarly concentrated, with a mean of 0.111, a median of 0.042, and a maximum of 0.516. The large differences between the means, medians, and maximum values indicate that AI-adopting firms are concentrated in a relatively small number of industries and regions rather than being evenly distributed across the economy.

Second, value-added-weighted AI intensity is generally higher and more dispersed than employment-weighted AI intensity. In the industry panel, the mean value-added-weighted intensity in 2019 is 0.157, compared with 0.125 for the employment-weighted measure. In the regional panel, the corresponding means are 0.111 and 0.075. This pattern indicates that AI-adopting firms tend to account for a larger share of value added than of employment. The value-added-weighted measure captures the share of production accounted for by AI-adopting firms, whereas the employment-weighted measure captures the share of workers employed by those firms. The baseline analysis uses value-added-weighted AI intensity, with employment-weighted intensity reported as an alternative intensity measure.

Third, the industry outcomes display substantial variation across industries and years. Average real industry GDP growth is 2.1%, while average labour-productivity growth is 1.1%. GDP-deflator inflation is particularly volatile: although its mean is 1.9%, it ranges from −258.6% to 269.4%. Both extreme observations occur in the electricity and gas sector, whose GDP deflator exhibits unusually large movements during the sample period. Producer-price inflation is considerably less volatile and therefore provides a complementary measure of industry-level price changes. However, there is no robust relationship between inflation outcomes and industry-level AI adoption.

Fourth, regional outcomes are generally less volatile than their industry-level counterparts. Average real GRDP growth is 1.9%, and average labour-productivity growth is 0.7%. Implicit GRDP-deflator inflation averages 1.7%, while total CPI inflation averages 2.2%. Service CPI inflation averages 1.9%, whereas personal-service and restaurant-price inflation are higher, averaging 2.9% and 3.6%, respectively. Overall, Tables 1 and 2 show substantial cross-sectional variation in AI intensity and considerable heterogeneity in real activity, productivity, and price outcomes.

Figures 1–4 provide descriptive evidence on the distribution of AI intensity and the annual outcome patterns of industries and regions with higher and lower AI intensity. The figures report raw data and group averages rather than regression estimates. They are intended to summarise the variation in AI intensity and the corresponding outcome patterns over the sample period. Figure 1 shows that AI intensity is concentrated in a relatively small number of industries and regions. Panel A reports value-added-weighted AI intensity by industry in 2019 and 2023. In 2019, AI intensity is highest in information and communication, finance and insurance, electricity and gas, and manufacturing, while many other industries record relatively low levels. Panel B shows a similarly uneven distribution across regions. Gyeonggi-do has the highest value-added-weighted AI intensity in 2019, followed by Gyeongbuk and Seoul, while measured AI intensity is considerably lower in many other regions.

Figure 2 compares the value-added-weighted and employment-weighted measures of AI intensity. Panel A shows a positive relationship between the two measures across industries in both 2019 and 2023. Industries in which AI-adopting firms account for a larger share of industry value added also tend to be industries in which these firms account for a larger share of industry employment. Panel B shows a corresponding positive relationship across regions, although the association is less tight than at the industry level. The two measures therefore capture related but distinct dimensions of the economic importance of AI-adopting firms. The empirical analysis uses value-added-weighted AI intensity as the baseline intensity measure and employment-weighted intensity as an alternative.

Figure 3 presents annual industry outcomes for high- and low-AI-intensity industries. Industries are classified according to whether their value-added-weighted AI intensity in 2019 is above or below the sample median. Panel A shows that the high-intensity group records somewhat higher real industry GDP growth than the low-intensity group in 2023. Panel B also shows differences in labour-productivity growth between the two groups, although the relative pattern is less clear and varies across years. However, the gaps between the two groups vary considerably across earlier years. Panel C shows that GDP-deflator inflation declines in the high-intensity group relative to the low-intensity group in 2023. The electricity and gas sector is excluded from this panel because of its extreme GDP-deflator movements. Panel D does not show a comparable decline in PPI inflation. The industry-level price pattern therefore differs depending on the price measure used.

Figure 4 presents the corresponding regional comparisons. Regions are classified according to whether their value-added-weighted AI intensity in 2019 is above or below the regional median, and the national aggregate is excluded. Panels A and B show that high-intensity regions record somewhat stronger real GRDP and labour-productivity growth in 2023. Panels C–F show no broad-based decline in regional inflation. In 2023, implicit GRDP-deflator inflation is lower in the high-intensity group, while personal-service inflation is somewhat higher. Total and service CPI inflation are relatively similar across the two groups.

Overall, Figures 1–4 show that AI intensity is unevenly distributed across industries and regions and that the 2023 outcome patterns differ across measures. The descriptive evidence suggests some differences in real outcomes between high- and low-intensity groups in 2023, but the patterns are not uniform across output and labour productivity. Industry GDP-deflator inflation and the regional implicit GRDP deflator are lower in the high-intensity groups, but comparable declines are not observed in PPI inflation or consistently across the regional CPI measures.

3. Empirical Specifications

Before estimating the main outcome regressions, we first examine whether pre-existing AI intensity in 2019 predicts AI intensity in 2023. This exercise is not intended to identify a causal relationship. Rather, it assesses whether the predetermined 2019 measure contains information about the subsequent cross-sectional distribution of AI intensity. If 2019 AI intensity, $Z^m_{j,2019}$, were unrelated to the corresponding measure in 2023, $AI^m_{j,2023}$, the use of the 2019 measure as a predetermined indicator of later AI intensity would be difficult to justify.

Specifically, we estimate the following cross-sectional regression:

$$AI^m_{j,2023} = a + \pi Z^m_{j,2019} + u_j, \qquad (1)$$

where j denotes an industry or region and m denotes the weighting scheme. The variable $Z^m_{j,2019}$ is the standardised 2019 AI-intensity measure, while $AI^m_{j,2023}$ is the corresponding unstandardised measure in 2023. We estimate the regression separately using value-added-weighted and employment-weighted AI intensity. The value-added-weighted measure is the share of total value added accounted for by AI-adopting firms, while the employment-weighted measure is the share of total employment accounted for by those firms. The national aggregate is excluded from the regional regressions. The coefficient π measures the difference in 2023 AI intensity associated with a one-standard-deviation higher level of the corresponding AI-intensity measure in 2019.

Table 3 reports the estimates of π. AI intensity in 2019 is positively and statistically significantly associated with AI intensity in 2023 in both the industry and regional panels. A one-standard-deviation increase in value-added-weighted AI intensity in 2019 is associated with an increase of 0.205 in the corresponding 2023 industry-level measure and 0.112 in the regional measure. The employment-weighted estimates are also positive and statistically significant, at 0.197 for industries and 0.077 for regions. The 2019 measures explain a particularly large share of the cross-sectional variation in 2023 AI intensity across industries, while their explanatory power is somewhat lower but still substantial across regions. These results support the use of 2019 AI intensity as a predetermined intensity measure and indicate that the cross-sectional distribution of AI intensity is persistent over time. This exercise documents persistence and predictive content rather than the causal effect of AI adoption.

We estimate a set of reduced-form intensity regressions to examine whether industries or regions with greater pre-existing AI intensity experienced different output, productivity, and price outcomes in 2023, the first full post-diffusion year in the baseline analysis. The empirical analysis uses annual industry- and region-level panels for Korea over 2017–2023. The main specification relates differences in 2023 outcomes to predetermined AI intensity measured in 2019, before the broad diffusion of generative AI. The design does not identify the causal effect of AI adoption. Rather, it examines whether units with a more AI-intensive economic structure before the broad diffusion of generative AI experienced systematically different outcomes in 2023.

The baseline specification is

$$y_{j,t} = \alpha_j + \lambda_t + \beta\left(Z_{j,2019}^{VA} \times Post2023_t\right) + \varepsilon_{j,t} \quad (2)$$

Here, $y_{j,t}$ denotes an outcome for industry or region j in year t. The outcomes include real industry GDP growth, real GRDP growth, labour-productivity growth, industry GDP-deflator inflation, producer-price inflation, and regional consumer-price inflation measures. The terms α_j and λ_t denote unit fixed effects and year fixed effects, respectively. Unit fixed effects absorb time-invariant differences across industries or regions, while year fixed effects absorb common aggregate shocks in each year. The variable $Z_{j,2019}^{VA}$ is the standardised value-added-weighted AI intensity of industry or region j in 2019. The indicator $Post2023_t$ equals one in 2023 and zero otherwise. The coefficient of interest is β. It measures whether industries or regions with higher value-added-weighted AI intensity in 2019 experienced different outcomes in 2023 relative to less AI-intensive units, after controlling for unit fixed effects and common year effects. Because $Z_{j,2019}^{VA}$ is standardised, β can be interpreted as the differential 2023 outcome associated with a one-standard-deviation higher pre-existing AI intensity. When the outcome is output or labour productivity growth, a positive coefficient would indicate stronger real activity in more AI-intensive units. When the outcome is inflation, a negative coefficient would be consistent with a disinflationary supply-side interpretation, whereas a positive coefficient would indicate stronger sectoral or local price pressures.

Table 4 reports the baseline industry-level intensity regressions. For each outcome, the table presents estimates based on value-added-weighted and employment-weighted AI intensity. The results provide little evidence that industries with greater pre-existing AI intensity experienced stronger real GDP or labour-productivity growth in 2023. The coefficient for real industry GDP growth is negative under both intensity measures, at −0.53 for the value-added-weighted measure and −0.95 for the employment-weighted measure, but neither estimate is statistically significant. For labour-productivity growth, the corresponding coefficients are also negative, at −0.28 and −0.93, and are statistically insignificant. The baseline industry results therefore show no systematic relationship between pre-existing AI intensity and real activity or productivity growth in 2023.

The industry-level price estimates do not provide statistically robust evidence of a disinflationary effect of AI intensity in 2023. Because the electricity and gas sector exhibits extreme GDP-deflator movements, it is excluded from the GDP-deflator regressions. In this restricted sample, the coefficients for GDP-deflator inflation are negative under both intensity measures, at −2.25 for the value-added-weighted measure and −2.05 for the employment-weighted measure, but neither estimate is statistically significant. By contrast, the PPI coefficients are positive, at 0.77 and 1.57, and are also statistically insignificant. The two price measures therefore point in different directions, with neither showing a statistically significant relationship between pre-existing AI intensity and industry-level inflation in 2023. Taken together with the real-activity results, the baseline industry regressions provide no systematic evidence that industries with greater pre-existing AI intensity experienced either stronger productivity growth or lower inflation in 2023.

Table 5 reports the corresponding regional intensity regressions. As in the industry analysis, the table presents results based on value-added-weighted and employment-weighted AI intensity. The national aggregate is excluded, so the estimates use variation across Korea's 17 province-level administrative divisions. The real-activity results provide little evidence that regions with greater pre-existing AI intensity experienced stronger output or productivity growth in 2023. For real GRDP growth, the coefficient is −0.196 under the value-added-weighted measure and 0.588 under the employment-weighted measure. For labour-productivity growth, the corresponding estimates are −0.054 and 0.500. None of these coefficients is statistically significant. The regional data therefore show no systematic relationship between pre-existing AI intensity and real GRDP or labour-productivity growth in 2023.

The regional price estimates are more suggestive. For total CPI inflation, the value-added-weighted coefficient is positive but statistically insignificant at 0.116, while the employment-weighted coefficient is 0.195 and statistically significant at the 5 percent level. Restaurant-price inflation is positively associated with both intensity measures: the value-added-weighted coefficient is 0.159 and the employment-weighted coefficient is 0.202, with both estimates statistically significant at the 5% level. These results do not support a disinflationary relationship between AI intensity and regional consumer prices in 2023. Instead, they indicate that regions with higher pre-existing AI intensity experienced higher inflation in some consumer-price categories, particularly when intensity is measured by the employment share of AI-adopting firms.

Taken together, the regional regressions provide no systematic evidence that regions with greater pre-existing AI intensity experienced stronger real activity in 2023. The price estimates are more positive, particularly for employment-weighted AI intensity and restaurant-price inflation, but the pattern is not uniform across intensity measures or price categories. These results should therefore be interpreted as suggestive short-run associations rather than as evidence of a general relationship between AI intensity and regional inflation.

4. Conclusion

This paper provides early evidence on whether the initial diffusion of AI is visible in productivity and price outcomes relevant to monetary policy. Using the firm-level AI adoption data, we constructed the measures of value-added-weighted and employment-weighted AI intensity. Then, using annual industry- and region-level panels for Korea over 2017–2023, we find little evidence that areas with greater AI intensity experienced stronger output growth or labour-productivity gains by 2023. We also find no robust evidence that AI intensity reduced producer or consumer prices at the industry level. These results suggest that, at least during the early stages of deployment, the productivity-enhancing effects of AI had not yet become sufficiently widespread or large enough to be manifested in industry- and region-level outcomes.

In contrast, our regional analysis points to emerging inflationary pressures in certain consumer price categories. Regions with higher employment-weighted AI intensity experienced higher overall consumer price inflation, while restaurant price inflation was positively associated with both measures of AI intensity. Although our empirical framework does not identify the underlying transmission mechanisms, they are consistent with the possibility that demand-side effects may precede measurable productivity gains during the initial phase of AI diffusion. Firms investing in AI may increase expenditures on digital infrastructure, computing power, electricity and energy, and employees before efficiency gains are fully realised. AI diffusion can initially act as a demand shock to the region. That is, demand-side effects associated with AI adoption can raise local income and spending, putting upward pressure on consumer prices.

Taken together, the results point to a possible timing asymmetry in the early economic effects of AI diffusion. During the initial phase of adoption, AI-related investment, hiring, and workforce upskilling can stimulate demand and place upward pressure on prices, even when measurable productivity gains remain limited. The supply-side benefits of AI, by contrast, may require time for organisational learning, technology integration, and complementary investments to take effect. As a result, inflationary pressures may appear before productivity-driven disinflation becomes visible in aggregate statistics.

These findings are particularly relevant for Asian economies, where AI adoption is proceeding rapidly alongside demographic shifts, labour market tightness, and structural bottlenecks. Central banks should therefore remain cautious when incorporating assumptions about AI-driven productivity growth into inflation and output forecasts. Future research using longer time horizons and richer micro-level data will be essential for determining whether the inflationary effects observed during the transition phase eventually give way to the productivity gains and disinflationary forces.

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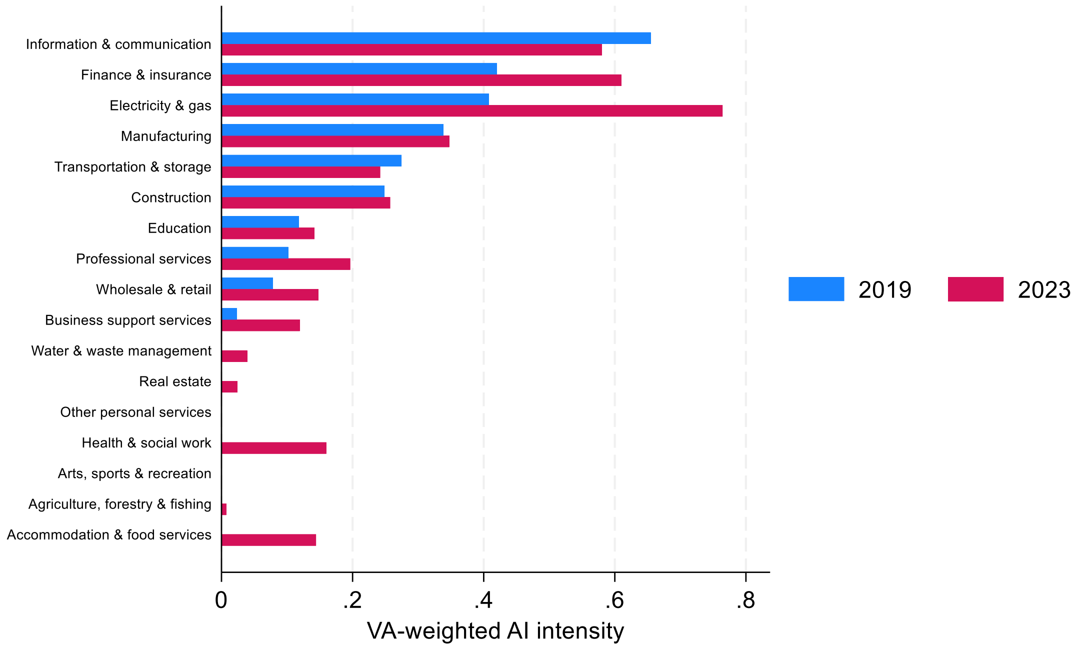
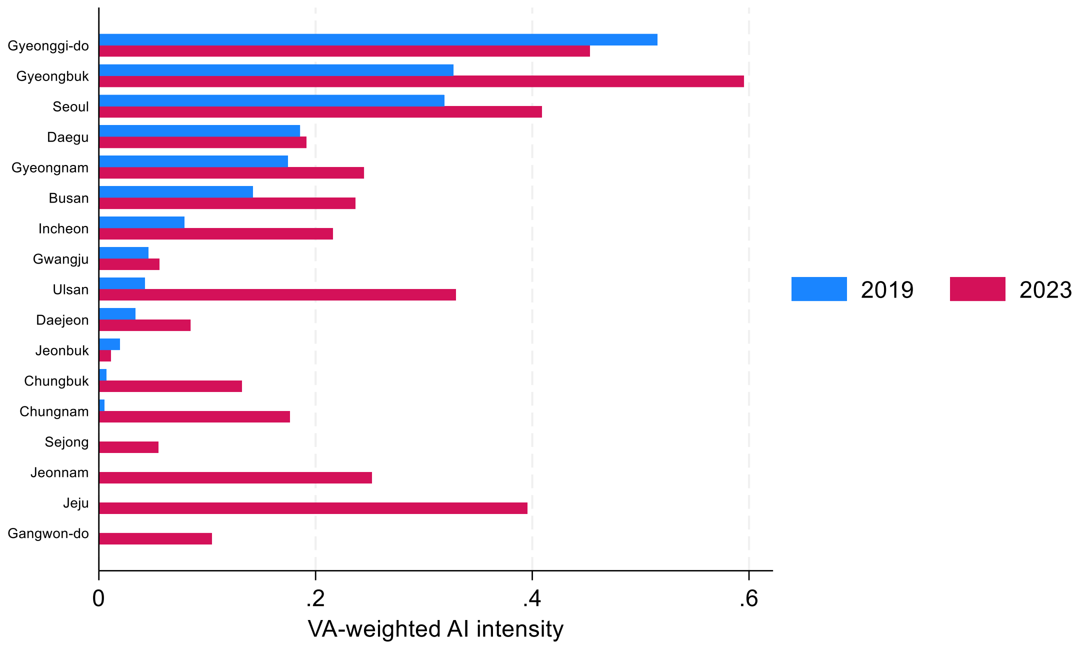
Figure 1. AI Intensity Measures by Industry and Region

Panel A: VA-weighted AI Intensity by Industry, 2019 and 2023



Panel B: VA-weighted AI Intensity by Region, 2019 and 2023

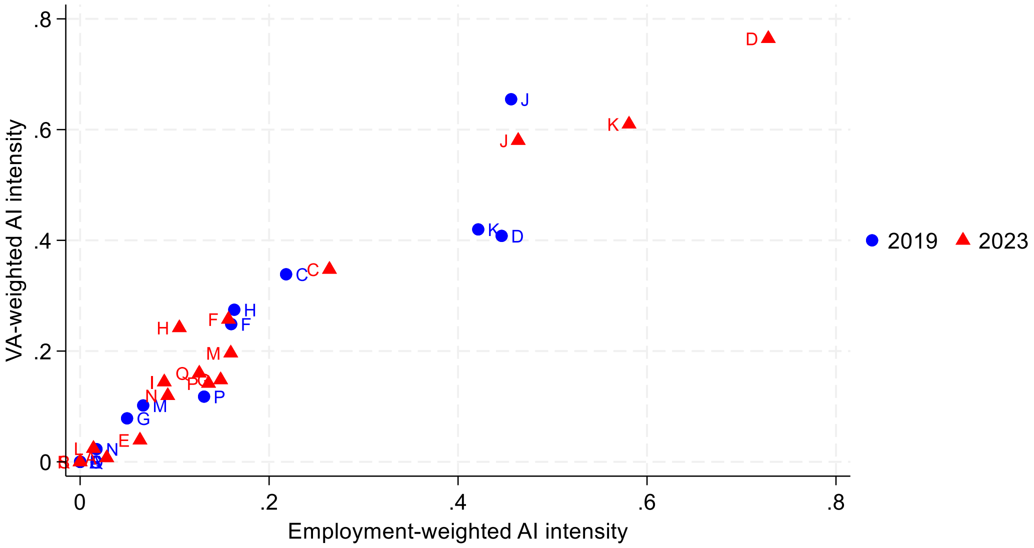


Note: Panel A reports VA-weighted AI intensity by industry in 2019 and 2023. Panel B reports VA-weighted AI intensity by region in 2019 and 2023. Industries and regions are ranked by their 2019 values.

Source: Authors' calculations.

Figure 2. AI Intensity Comparison, 2019 and 2023

Panel A: Industry Level, 2019 and 2023



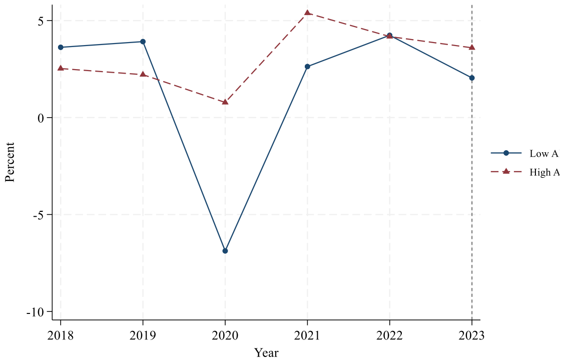
A Agriculture, forestry & fishing; B Mining; C Manufacturing; D Electricity & gas; E Water & waste management
F Construction; G Wholesale & retail; H Transportation & storage; I Accommodation & food services; J Information & communication
K Finance & insurance; L Real estate; M Professional services; N Business support services; O Public administration
P Education; Q Health & social work; R Arts, sports & recreation; S Other personal services; T Household services; U International organizations

Panel B: Region Level, 2019 and 2023

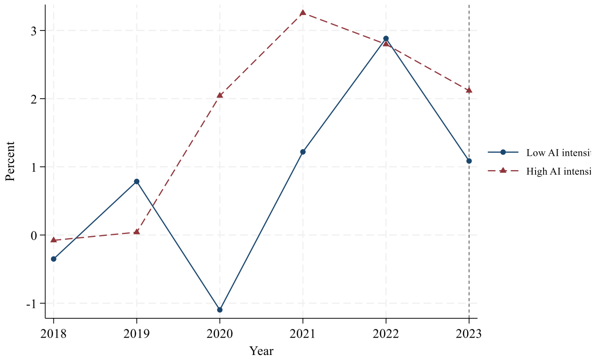
Note: Panel A compares employment-weighted and value-added-weighted AI intensity by industry in 2019 and 2023. Panel B compares employment-weighted and value-added-weighted AI intensity by region in 2019 and 2023. Blue circles denote 2019 observations, and red triangles denote 2023 observations. Industry codes in Panel A correspond to the one-digit KSIC industry divisions. Marker labels in Panel B identify regions.

Source: Authors' calculations.

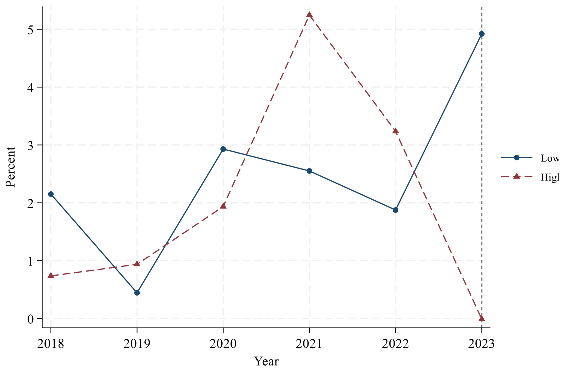
Figure 3. Industry Outcome Trends by AI Intensity



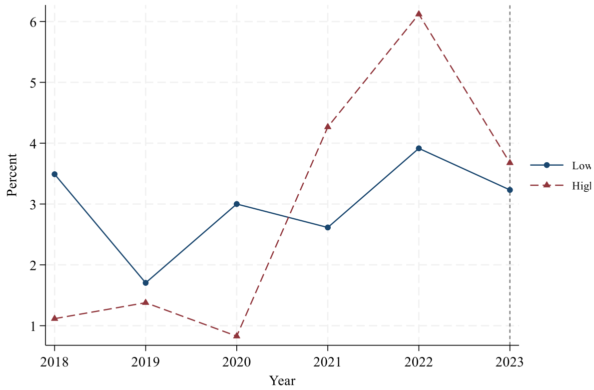
Panel A. Real industry GDP growth



Panel B. Labour-productivity growth



Panel C. Implicit GDP deflator inflation

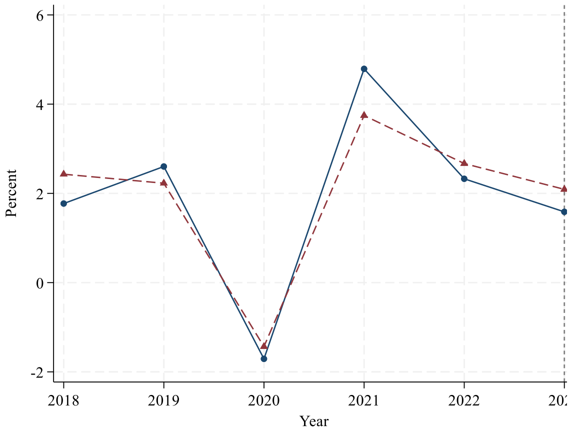


Panel D. PPI inflation

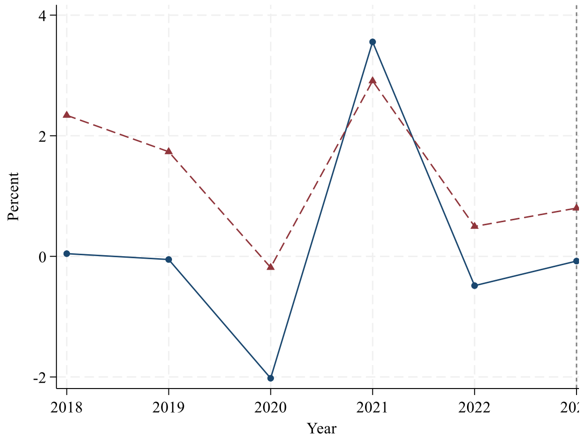
Note: Industries are classified as having high or low AI intensity according to whether their value-added-weighted AI intensity in 2019 is above or below the sample median. Each line reports the annual average outcome for the corresponding group. Panel A reports real industry GDP growth, Panel B labour-productivity growth, Panel C GDP-deflator inflation, and Panel D producer-price inflation. The vertical dashed line marks 2023, the first full post-diffusion year in the baseline analysis. The electricity and gas sector is excluded only from Panel C because of its extreme GDP-deflator movements during the sample period.

Source: Authors' calculations.

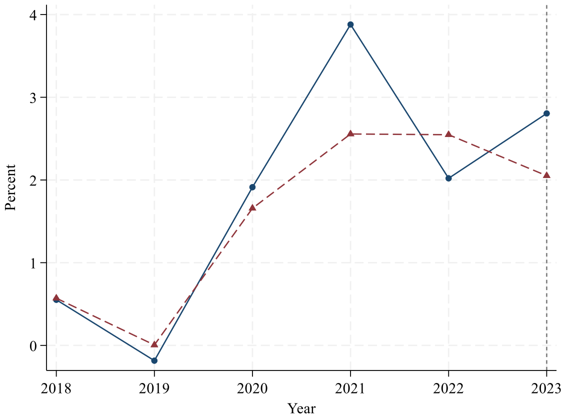
Figure 4. Regional Outcome Trends by AI Intensity



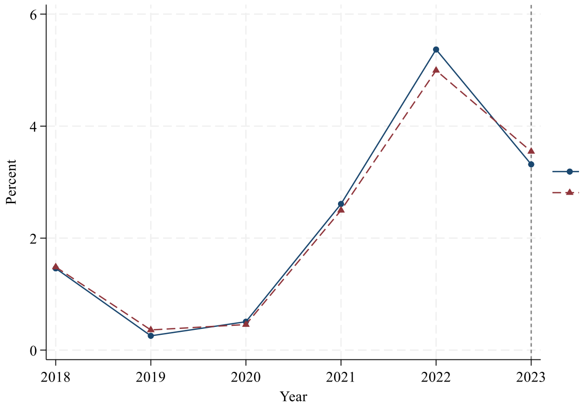
Panel A. Real GRDP growth



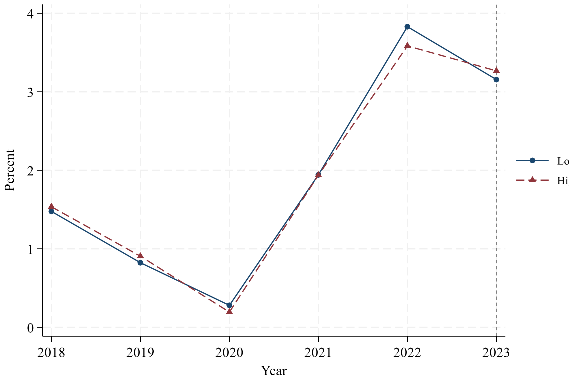
Panel B. Labour-productivity growth



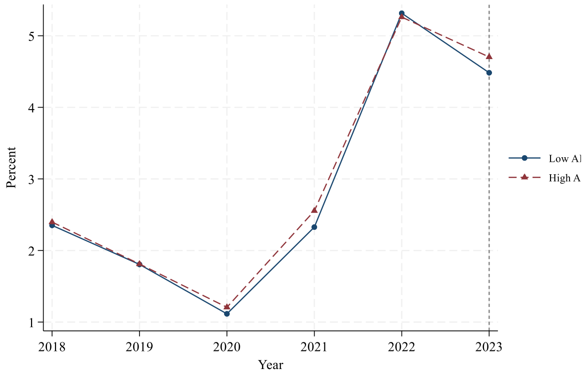
Panel C. Implicit GDP deflator inflation



Panel D. Total CPI inflation



Panel E. Service CPI inflation



Panel F. Personal-service CPI inflation

Note: Regions are classified as high or low AI intensity according to whether their value-added-weighted AI intensity in 2019 is above or below the sample median. Each line reports the annual average outcome within the corresponding group. Panel A reports real GRDP growth, Panel B labour-productivity growth, Panel C implicit GDP deflator inflation, Panel D total CPI inflation, Panel E service CPI inflation, and Panel F personal-service CPI inflation. The vertical dashed line marks 2023, the first post-diffusion year in the baseline analysis. The national aggregate is excluded.

Source: Authors' calculations.

Table 1. Descriptive Statistics: Industry Panel

Variable	N	Mean	Std. dev.	Min	Median	Max
AI intensity, VA-weighted, 2019	17	0.157	0.199	0.000	0.078	0.655
AI intensity, employment-weighted, 2019	17	0.125	0.166	0.000	0.050	0.456
AI intensity, VA-weighted, 2017-2019 avg.	18	0.111	0.155	0.000	0.043	0.476
AI intensity, employment-weighted, 2017-2019 avg.	18	0.093	0.133	0.000	0.045	0.416
Real industry GDP growth	114	2.082	5.966	-30.155	2.844	15.536
Labour productivity growth	114	1.118	4.652	-15.069	1.142	13.343
GDP deflator inflation	114	1.947	35.618	-258.591	2.148	269.421
PPI inflation	96	3.073	4.094	-6.268	2.327	22.670

Note: AI intensity variables are measured at the industry level. The 2019 measures refer to predetermined industry AI intensity measured in 2019, while the 2017–2019 measures are averages over the pre-period. Growth and inflation variables are annual log changes multiplied by 100. The GDP deflator is constructed as the ratio of nominal to real industry GDP. The electricity and gas sector is included in the descriptive statistics and accounts for both the minimum and maximum observations of GDP-deflator inflation.

Source: Authors' calculations.

Table 2. Descriptive Statistics: Regional Panel

Variable	N	Mean	Std. dev.	Min	Median	Max
AI intensity, VA-weighted, 2019	17	0.111	0.150	0.000	0.042	0.516
AI intensity, employment-weighted, 2019	17	0.075	0.086	0.000	0.056	0.266
AI intensity, VA-weighted, 2017-2019 avg.	17	0.096	0.117	0.000	0.058	0.440
AI intensity, employment-weighted, 2017-2019 avg.	17	0.061	0.060	0.000	0.046	0.182
Real GRDP growth	102	1.924	2.714	-10.109	2.264	7.129
Labou r productivity growth	102	0.720	2.873	-10.843	1.266	7.464
Implicit GDP deflator inflation	102	1.706	2.022	-2.752	1.323	9.857
Total CPI inflation	102	2.239	1.742	-0.321	1.904	5.838
Service CPI inflation	102	1.911	1.269	-0.322	1.788	4.345
Personal-service CPI inflation	102	2.942	1.535	0.630	2.508	6.383
Restaurant CPI inflation	99	3.562	2.326	0.313	2.907	7.864

Note: AI intensity variables are measured at the regional level after excluding the national aggregate. Growth and inflation variables are annual log changes multiplied by 100.

Source: Authors' calculations.

Table 3. Predictive Content of 2019 AI Intensity for 2023 AI Intensity

	(1) Industry VA	(2) Industry emp.	(3) Region VA	(4) Region emp.
AI intensity, VA-weighted, 2019	0.205***		0.112***	
	(0.038)		(0.030)	
AI intensity, employment-weighted, 2019		0.197***		0.077***
		(0.027)		(0.011)
Unit	Industry	Industry	Region	Region
Intensity measure	VA 2019	Employment 2019	VA 2019	Employment 2019
Dependent variable	VA AI intensity, 2023	Employment AI intensity, 2023	VA AI intensity, 2023	Employment AI intensity, 2023
Observations	17	17	17	17
R-squared	0.800	0.877	0.489	0.625

Note: The dependent variable is the corresponding AI intensity measure in 2023. The explanatory variable is the standardised 2019 AI intensity measure shown in each row. Columns (1) and (2) use industry-level observations, and columns (3) and (4) use regional observations excluding the national aggregate. Robust standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Source: Authors’ calculations.

Table 4. Industry Regressions: AI Intensity and Output and Price Outcomes in 2023

	(1) Real GDP	(2) Real GDP	(3) Labour prod.	(4) Labour prod.	(5) GDP deflator	(6) GDP deflator	(7) PPI	(8) PPI
AI intensity x Post2023	-0.53		-0.28		-2.25		0.77	
	(0.96)		(1.14)		(1.41)		(1.22)	
AI intensity x Post2023		-0.95		-0.93		-2.05		1.57
		(0.83)		(1.11)		(1.17)		(1.54)
Intensity measure	VA 2019	Employment 2019	VA 2019	Employment 2019	VA 2019	Employment 2019	VA 2019	Employment 2019
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	17	17	17	17	16	16	15	15
Obs.	102	102	102	102	96	96	90	90
Adjusted R-squared	0.112	0.115	0.094	0.100	0.037	0.021	0.134	0.155

Note: The dependent variables are annual log changes multiplied by 100. The baseline intensity measure is value-added-weighted AI intensity in 2019; employment-weighted AI intensity is reported as an alternative measure. All intensity measures are standardised at the industry level before estimation. All specifications include industry and year fixed effects. The electricity and gas industry is excluded only from the GDP-deflator regressions because of the extreme movements in its GDP deflator during the sample period. Standard errors clustered at the industry level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Authors' calculations.

Table 5. Regional Regressions: AI Intensity and Output and Price Outcomes in 2023

	(1) Real GRDP	(2) Real GRDP	(3) Labour prod.	(4) Labour prod.	(5) Total CPI	(6) Total CPI	(7) Restaurant CPI	(8) Restaurant CPI
AI intensity x Post2023	-0.196		-0.054		0.116		0.159**	
	(0.625)		(0.543)		(0.077)		(0.075)	
AI intensity x Post2023		0.588		0.500		0.195**		0.202**
		(0.930)		(0.723)		(0.073)		(0.080)
Intensity measure	VA 2019	Employment 2019	VA 2019	Employment 2019	VA 2019	Employment 2019	VA 2019	Employment 2019
Region fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clusters	17	17	17	17	17	17	17	17
Obs.	102	102	102	102	102	102	99	99
Adjusted R-squared	0.423	0.430	0.312	0.317	0.980	0.981	0.958	0.958

Note: The dependent variables are annual log changes multiplied by 100. The national aggregate is excluded from all regional regressions. The baseline intensity measure is value-added-weighted AI intensity in 2019; employment-weighted AI intensity is reported as an alternative measure. All intensity measures are standardised at the regional level before estimation. All specifications include region and year fixed effects. Standard errors clustered at the regional level are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Source: Authors' calculations.

Appendix Table A1. Definitions of Variables and Data Sources

Variables	Description and Construction	Frequency	Data Source
AI intensity, employment-weighted, 2017–2023	Share of total employment accounted for by AI-adopting firms within each industry or region	year	Survey of Business Activities, Statistics Korea, via MDIS
AI intensity, value-added-weighted, 2017–2023	Share of total value added accounted for by AI-adopting firms within each industry or region	year	Survey of Business Activities, Statistics Korea, via MDIS
Industry GDP, 2017–2023	Nominal and real GDP by economic activity, mapped to broad industry divisions used in the empirical analysis	year	Bank of Korea national accounts, "GDP and GNI by Economic Activity," via KOSIS
Industry real GDP growth, 2017–2023	Annual log change in real industry GDP by broad industry, multiplied by 100	year	Authors' calculations using Bank of Korea industry GDP via KOSIS
Industry employment, 2017-2023	Number of employed workers by broad industry division; used to construct industry labour productivity	year	Statistics Korea, Census on Establishments, survey-based and register-based series, via KOSIS; authors' calculations
Industry labour productivity growth, 2017–2023	Annual log change in real industry GDP per employed worker by broad industry, multiplied by 100	year	Authors' calculations using Bank of Korea industry GDP and Statistics Korea's Census on Establishments, via KOSIS
Industry producer-price inflation, 2017–2023	Annual log change in producer price indexes matched to corresponding one-digit KSIC industry divisions, multiplied by 100	year	KOSIS producer price index, 1989–2024, 2020 = 100
Regional GRDP, 2017–2023	Nominal and real gross regional domestic product by region	year	KOSIS regional accounts, Statistics Korea
Real GRDP growth, 2017–2023	Annual log change in real GRDP by region, multiplied by 100	year	Authors' calculations using KOSIS
Regional labour productivity growth, 2017–2023	Annual log change in real GRDP per employed worker by region, multiplied by 100	year	Authors' calculations using KOSIS
Regional employment, 2017–2023	Number of employed workers by region; used to construct regional labour productivity	year	KOSIS, Statistics Korea
Regional CPI inflation, 2017–2023	Annual log change in total consumer price index by region, multiplied by 100	year	KOSIS consumer price index, Statistics Korea
Regional service CPI inflation, 2017–2023	Annual log change in the regional service CPI index, multiplied by 100	year	KOSIS province-level consumer price index, Statistics Korea
Regional personal-service CPI inflation, 2017–2023	Annual log change in the regional personal-service CPI index, multiplied by 100	year	KOSIS province-level consumer price index, Statistics Korea
Regional restaurant-price inflation, 2017–2023	Annual log change in the regional restaurant-price CPI index, multiplied by 100	year	KOSIS province-level consumer price index, Statistics Korea

Notes: AI = artificial intelligence, CPI = consumer price index, ECOS = Economic Statistics System, GDP = gross domestic product, GRDP = gross regional domestic product, KSIC = Korean Standard Industrial Classification, KOSIS = Korean Statistical Information Service, MDIS = MicroData Integrated Service.

Source: Authors' compilation.