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Innovation, Digitalization, and AI-related Investment Activity: Cross-Country Evidence on Employment Across Agriculture, Industry, and Services

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Abstract

This study examines the statistical associations between innovation, digitalization, AI-related investment activity indicators, and the natural logarithm of employment shares across the agriculture, industry, and service sectors while controlling for key macroeconomic factors. Using a cross-country dataset from the World Bank covering 266 economy/country-territory observations, the analysis examines how innovation and digitalization are co-distributed with sectoral employment patterns. The results show that innovation and digitalization indicators are positively associated with employment shares in the service sector, exhibit a more nuanced and limited relationship with the industrial sector, and are negatively associated with agricultural employment shares. Among these indicators, internet usage is the most consistently correlated across sectors. To assess the pattern of AI-related investment activity, the analysis was conducted using OECD data covering 67 countries. The results support the main findings of the World Bank data, suggesting that higher levels of AI-related investment activity are associated with a higher service sector employment share and a lower agricultural employment share. These findings should be interpreted as statistical associations rather than causal effects because the analysis is based on cross-sectional regression models. These findings offer useful structural context for policymakers, researchers, managers, economists, and workforce agencies seeking to understand the labor market correlates of innovation and technological transformation.

Keywords: innovation, digitalization, artificial intelligence (AI), employment, labor markets, technological change, cross-country analysis, economic development

1. Introduction

The Fourth Industrial Revolution is transforming labor markets through advances in innovation, digitalization, and artificial intelligence. Although previous industrial revolutions have introduced machines capable of replacing manual labor, artificial intelligence has the potential to disrupt jobs previously thought impossible to be automated by robots—ones that utilize creativity and logic, characteristics that used to belong exclusively to human-made work (Bakhshi et al., 2015). As technological transformation continues to spread throughout the world, it is important for policymakers, researchers, and businesses to understand its potential implications. Regardless of how productivity gains from innovation and technological change play out, labor market adjustments are likely to occur. Therefore, it is crucial to understand which sectors are most affected and how these changes are taking place. How are labor markets associated with innovation, digitalization, and AI-related investment activity across different sectors? For which sectors is retraining most crucial? Understanding where and how these changes occur can provide policymakers with valuable insights regarding where to direct retraining programs and other necessary interventions.

Existing studies focusing on automation and labor market change have mainly focused on technological transformation within manual labor and industrialized settings (Carbonero et al., 2023). However, these analyses face several limitations. First, many studies treat technological transformation as a single phenomenon without differentiating the various channels through which innovation, digitalization, and AI activity relate to an economy (Georgieff and Hyee, 2022). For instance, R&D expenditure captures innovative capacity; high-technology exports reflect technological sophistication and competitiveness; internet usage measures digital adoption; and mobile subscriptions capture the diffusion of communication technologies. Second, many studies neglect developing countries where economic structures differ from those of developed economies (Carbonero et al., 2023). Third, cross-country studies rarely compare employment variations across agriculture, industry, and service sectors within a unified framework.

This study extends the existing literature by examining multiple innovation and digitalization indicators, including R&D expenditure, high-technology exports, internet usage, and mobile subscriptions. Together, these indicators capture different dimensions of technological transformation at the macroeconomic level. Furthermore, it compares employment patterns across the service, industry, and agricultural sectors, providing a broader perspective on how technological transformation is associated with sectoral employment. To further assess whether these relationships are consistent with measures of AI-related investment activity, this study incorporates AI-related investment activity indicators derived from OECD data on AI-related venture capital investments.

Economic and development studies commonly use macro-level indicators to capture countries' innovation capacity and level of digitalization. In this literature, national R&D intensity and the share of high-technology exports serve as indicators of technological capability and innovative capacity, while internet usage and mobile cellular subscriptions are used as measures of digital adoption and infrastructure. Both cross-country and single-country analyses include these indicators. Researchers typically use R&D expenditure (normalized by GDP) as a summary measure of a country's innovative effort (Martínez-Noya and García-Canal, 2021), with many empirical models including R&D/GDP as an explanatory variable for technology adoption, productivity, and economic development. Similarly, high-technology exports are commonly used as indicators of technological sophistication and competitiveness (Zapata et al., 2023). Internet penetration is frequently viewed as a measure of digitalization (Zghidi and Trabelsi, 2025), reflecting the extent to which individuals and businesses have access to digital technologies. Mobile subscriptions are likewise used as indicators of technology access and the

diffusion of modern communication technologies throughout society.

Thus, economists and researchers routinely use R&D/GDP, high-technology exports, internet usage, and mobile subscriptions as indicators of innovation and digitalization. Consistent with the existing literature, this study employs these variables as innovation and digitalization indicators to examine their association with sectoral employment patterns. In addition, this study incorporates AI-related investment activity indicators based on OECD data on AI-related venture capital investment to capture AI-related investment activity.

The purpose of this paper is to examine the statistical association between innovation, digitalization, and AI-related investment activity indicators and the natural logarithm of employment shares in the service, industrial, and agricultural sectors after controlling for key macroeconomic factors, using a comprehensive cross-country dataset covering 266 economies/country-territory observations. Because this study employs cross-sectional regression analysis, its objective is to identify systematic statistical associations between technological indicators and sectoral employment patterns rather than establish causal relationships.

The main findings indicate that innovation and digitalization indicators are positively associated with employment shares in the service sector and negatively associated with employment shares in the agricultural sector. The results for industrial employment are more mixed and depend on the specific technology indicator examined. In addition, the AI-related investment activity indicators provide broadly consistent results, suggesting that higher levels of AI-related investment activity are associated with larger service-sector employment shares and smaller agricultural employment shares. These associations are estimated from cross-sectional data and should not be interpreted as evidence that technology adoption caused workers to move between sectors.

This study makes several significant contributions to the existing body of literature. First, it differentiates employment across the three major economic sectors—service, industry, and agriculture—to better understand how innovation, digitalization, and AI-related investment activity are associated with different components of the labor market rather than treating employment as a single aggregate outcome. Second, rather than relying on one single measure of technological transformation, it employs four distinct innovation and digitalization indicators: R&D, high technology, internet usage, and mobile subscriptions. Collectively, these indicators capture different dimensions of innovation, technological capability, and digital adoption. In addition, this study incorporates AI-related investment activity indicators derived from OECD data on AI-related venture capital investments to assess whether the observed relationships are consistent with measures of AI-related investment activity. Third, this study is applied across an unusually broad sample of economies/country-territory observations (266), diverse by region and economic status, allowing for broader generalizability. Finally, the paper employs multiple regression analysis while controlling for macroeconomic factors such as the logarithmic transformation of GDP per capita level, population growth, urbanization, education and trade.

2. Literature Review

Various methodologies have been used to study the correlates of employment, including dynamic panel data (Masoud, 2025), ARDL (Kalai et al., 2024), panel data analysis (Gu et al., 2022; Shen & Zhang, 2024; Jung et al., 2020; Paul & Nayak, 2025), structural models (Yang et al., 2025), regression analysis (Shao et al., 2022; Zhang, 2023), GMM (X. Wang et al., 2024; Q. Wang et al., 2024), machine learning (Vuppalapati, 2021; Jha et al., 2019), quantile regression (Zhan & Yang, 2024), 2SLS

(Wang, 2021), probit models (Chen et al., 2025), and factor value-added methods (Chen et al., 2024). The diversity of these approaches reflects both the complexity of employment as an outcome and the lack of methodological consensus in the field, a point worth noting, as results across studies are difficult to compare directly when the underlying estimation strategies differ so substantially.

At the broadest level, the literature suggests that technological innovation, digitalization, and artificial intelligence (AI) activities tend to be associated with a structural restructuring rather than a uniform reduction in aggregate employment. Masoud (2025) finds that advanced digital technologies, machine learning, and data science are associated with lower unemployment in high-income countries, co-occurring with job creation and transformation, particularly under low-inflation conditions. Similarly, Shen & Zhang (2024) and Shen (2024) find that digital automation and AI activity in China are positively correlated with overall job creation, higher productivity, and human-machine collaboration, with positive associations observed across gender and industry, particularly in regions with stronger existing digital infrastructure. Q. Wang et al. (2024) extends this view further, finding that technological progress is broadly associated with sustainable development indicators, with R&D-driven innovation serving as a strong correlate depending on a country's level of urbanization.

However, these aggregate positive findings mask important distributional effects. X. Wang et al. (2024) find that while innovation and advanced technology adoption in China increased middle- and high-skilled employment, it simultaneously reduced the number of low-skilled jobs, with effects that spilled over across regions. Zhang (2023) similarly finds that digital economy growth polarizes low-skilled employment while increasing demand for high-skilled labor. Shao et al. (2022) corroborates this pattern in manufacturing specifically, finding that advanced technology adoption increases demand for high-skilled workers while displacing low-skilled roles, creating competitive pressure for firms to invest in R&D and smart production strategies. Kalai et al. (2024) add a macroeconomic caveat, finding that while technological innovation is associated with growth in Europe under normal conditions, its effects are asymmetric: economic downturns amplify negative output effects. Taken together, these findings suggest that the net employment effect of innovation and digital activity is positive in aggregate but regressive in distribution, disproportionately benefiting skilled workers and higher-income economies.

Notably, researchers have heavily concentrated the literature on the aggregate relationships between digital innovation and employment in China and high-income countries. This geographic skew is a significant gap: the dynamics of digitalization and technology adoption in lower-income or heavily agrarian economies, where labor market structures, institutional capacity, and digital infrastructure differ substantially, remain underexplored.

The aggregate picture obscures important sectoral differences, and several studies point to divergent effects across services, industry, and agriculture. In the service sector, Gu et al. (2022) found that digital development in China's service industry boosted employment and wages while also driving labor reallocation away from manufacturing, though these gains were unevenly distributed across regions. Yang et al. (2025) add discussion at the firm level, finding that employee interaction fluency with digital tools improves service performance through perceived empathy and competence, suggesting that complementarity between human workers and technology is a meaningful driver of service sector outcomes. Conversely, Chen et al. (2024) find that advanced technology adoption in China's service sector reduced labor's income share by displacing low-educated and frontline workers while increasing capital returns, a finding that complicates the broadly positive narrative from Gu et al. (2022) and highlights that employment gains in services may not translate to

wage or income gains for all workers.

In the industrial sector, evidence is similarly mixed. Shao et al. (2022) find that technological innovation in manufacturing increases demand for high-skilled labor while shrinking low-skilled roles. However, the literature on industrial employment effects beyond manufacturing is sparse, and few studies examine how innovation and digital activity affect industrial employment at the cross-country level where sectoral composition varies widely.

In agriculture, the existing literature focuses primarily on productivity rather than employment. Vuppalapati (2021) finds that smart technologies and connected sensors boosted agricultural productivity in India and Brazil, addressing workforce challenges without directly examining displacement. Jha et al. (2019) similarly focus on how advanced computing and deep learning can optimize crop selection, reduce manual labor requirements, and support food security through real-time monitoring, framing labor reduction as a benefit rather than a cost.

A separate but related strand of the literature focuses on internet access and mobile connectivity as primary pillars of digitalization and catalysts for broader technology adoption. Zhan & Yang (2024) find that internet use improves employment quality for rural and female workers both directly and through expanded access to social capital, suggesting that digital connectivity has distributional benefits beyond aggregate employment levels. Wang (2021) finds that rising mobile broadband access in the United States reduced income inequality and unemployment by boosting mid-level earnings and enabling gig work, particularly for lower-income workers. These findings are relevant to the present study because internet usage and mobile subscriptions serve as direct proxies for digitalization and readiness for advanced technology activity. The evidence that digital connectivity independently shapes employment outcomes supports their use as meaningful indicators of a nation's digital landscape.

Not all findings in this strand are positive, however. Kemeny & Osman (2018) find that high-tech employment growth raises real wages in non-tradable sectors by only 0.1-0.7% for every 10% increase in tech jobs, directly challenging the assumption that technology-driven growth broadly lifts local labor markets. This tempering result is important context for interpreting positive aggregate findings elsewhere.

Several patterns emerge from this review that motivate the present paper. First, most existing studies treat technological advancement as a single, undifferentiated phenomenon, often over-specifying it as narrow AI. This paper uses four distinct proxies—R&D expenditure, high-technology exports, internet usage, and mobile subscriptions—to comprehensively capture technology across its core dimensions of innovation, production, and digital diffusion. Second, the literature concentrates geographically on China and high-income economies, which leaves cross-country comparative evidence limited. This paper draws on data from 266 economy/country-territory observations, including a large number of developing and agrarian economies where the employment stakes of technological transitions are particularly high. Third, sectoral comparisons in existing cross-country studies rarely extend beyond manufacturing. By examining agriculture, industry, and services simultaneously within a consistent econometric framework, this paper enables direct comparison of the sectoral effects of innovation and digitalization in a way that existing single-country or single-sector studies cannot.

An extensive review of literature on the drivers of employment is presented in Appendix 1, in the appendix below.

3. Empirical Evidence

3.1. Data

This study uses cross-sectional data obtained from two major international databases: the World Bank World Development Indicators, which covers 266 economy/country-territory observations, and the OECD AI Policy Observatory, which covers 67 countries. While the initial dataset comprised 266 economies and territories, the analytical sample used in each specification varies because observations are restricted by the availability of the outcome, technology indicators, and control variables. Consequently, the actual regression sample sizes differ across models. These datasets provide information on different types of employment, innovation, digitalization, AI-related activities, and macroeconomic indicators. Employment is broken down into employment in agriculture as a percentage of total employment (empa), employment in services as a percentage of total employment (emps), and employment in industry as a percentage of total employment (empi).

Innovation and digitalization are captured via research and development expenditure as a percentage of GDP (R&D), high-technology exports as a percentage of manufactured exports (High_Tech), individuals using the internet as a percentage of the population (Internet_Usage), mobile cellular subscriptions per 100 people (Mobile_Sub), and AI-related venture capital investment (AI_Venture_Capital).

To control for broader economic conditions, the analysis incorporates a logarithmic transformation of GDP per capita level (Log GDP_per_capita level), trade openness as a percentage of GDP (Trade), annual population growth (Pop_Growth), urban population share (Urban_Pop), and educational attainment (Education), along with geographic regional dummies. Appendix 1 provides detailed variable definitions and sources. Future research may incorporate additional structural controls such as institutional governance indicators or policy framework indices.

The Research and Development (R&D) variable is based on data from 2020, while all other variables are based on data from 2023. These years were selected because they provide the most comprehensive data coverage available for the variables included in our analysis.

Due to varying data availability across the primary technological indicators and macro-demographic proxies, the final regression models utilize unbalanced sample sizes. Baseline observation counts vary across specifications depending on data missingness within specific country-year reporting windows, particularly regarding localized research and development (R&D) expenditures and specialized institutional data compiled by the OECD AI Policy Observatory. To minimize sample selection bias while preserving maximum statistical power, models are estimated using all available country observations matching the complete criteria for each respective indicator's framework, as delineated in the primary regression tables.

Overall, the combination of World Bank and OECD datasets enables an extensive cross-country examination of how innovation, digitalization, and AI-related activities are associated with employment patterns across the agricultural, industrial, and service sectors.

Because different variables contain different numbers of missing observations, the regression sample varies across

specifications. Each model is estimated using all available observations after listwise deletion of missing values.

3.2. Model

$$ln\,(Y_i) = \beta_0 + \beta_1 X_{1i} + \beta_2 ln(GDPpc_i) X_{2i} + \beta_3 Pop_Growth_i X_{3i} + \beta_4 TradeX_{4i} + \beta_5 EducationX_{5i}$$

$$+ \beta_6 Urban_PopX_{6i} + \sum_{r=1}^{R-1} \gamma_r Region_{ri} + \epsilon_i$$

Where $ln\,(Y_i)$ is the dependent variable for observation i, which refers to logarithmic emps, empi, and empa, respectively. β_0 is the constant term representing the expected value of the dependent variable when both the independent and control variables are zero. β_1 is the coefficient for the independent variables. β_2 to β_6 are the control variables such as logarithmic transformation of GDP per Capita Level, Pop_Growth, Urban_Pop, Trade, Education, and regional dummies. $Region_{ri}$ represents a set of regional dummy variables with Europe serving as a reference category. Regional dummy variables were included to control for unobserved regional differences in economic structure, institutional characteristics, and development patterns. Countries were classified into four regions: Europe, Africa, Asia, and America. One regional dummy (Europe) was omitted as the reference category. ε_i is the error term, which represents the difference between the actual value and the predicted value from the model. By using this general equation, we estimated different models to explain different characteristics of employment across the service, industry, and agriculture sectors, using different proxies for innovation and digitalization listed below. The dependent variable was transformed into a natural logarithm to reduce skewness, stabilize variance, mitigate the influence of outliers, and allow the coefficient to be interpreted in percentage terms rather than absolute change. We use four different innovation and digitalization indicators in the model: R&D, High_Tech, Internet_Usage, and Mobile Subscriptions. We use an additional AI proxy from the OECD database, which is the total global venture capital investments and AI-related ones in USD millions.

One important caveat applies to the interpretation of all models. Because we measure employment in agriculture, industry, and services as a share of total employment, the three dependent variables sum to 100 across sectors. This compositional constraint means that an estimated positive association with one sector's employment share necessarily implies a relative decline in at least one other sector. Readers should therefore interpret all results as reflecting shifts in the sectoral composition of employment rather than absolute changes in the number of jobs within any given sector. A decline in a sector's employment share is therefore consistent with either a fall in absolute employment in that sector or continued growth in that sector at a slower rate than employment elsewhere in the economy; the two cannot be distinguished with these data. To address the compositional nature of sectoral employment shares, we additionally estimate log-ratio models in which service and industrial employment shares are expressed relative to agricultural employment.

3.3. Descriptive Statistics

Table 1: *Descriptive Statistics*

Variable	Obs	Mean	Std. Dev.	Min	Max
emps	232	56.884	17.23	11.88	92.859
empi	232	19.961	7.095	3.066	40.157
empa	232	23.156	20.058	.091	85.054
Internet_Usage	186	71.961	24.395	11.1	100
Mobile_Sub	189	116.962	35.533	34.059	319.494
R&D	114	1.302	1.124	.0405	5.796
High_Tech	189	12.058	12.637	0	72.315
Log GDP_per_capita level	203	11.557	2.405	5.616	20.573
Trade	212	88.511	54.434	2.474	404.458
Pop_Growth	265	1.124	1.523	-8.423	6.527
Education	164	3.747	0.7406	1.596	5.106
Urban_Pop	263	61.262	22.454	13.723	100
Log AI_Venture_Capital	68	1.774	0.969	0.301	3.628

Table 1 provides descriptive statistics for different types of employment and various economic indicators. Agricultural employment (empa) has 232 observations with a mean of 23.156 and a standard deviation of 20.058, ranging from a minimum of 0.091 to a maximum of 85.054. This suggests a large cross-country variation in agricultural dependence, meaning the data includes countries on both extremes—highly industrialized economies as well as agrarian ones with high agricultural employment shares. Service employment (emps) has 232 observations with a mean of 56.884 and a standard deviation of 17.23, ranging from a minimum of 11.88 to a maximum of 92.859, indicating that while most countries are structurally developed beyond primary industries, there is still considerable heterogeneity present in the data. Industry employment (empi) has 232 observations with a mean of 19.961 and a standard deviation of 7.095, ranging from a minimum of 3.066 to a maximum of 40.157, showing a more stable distribution between nations.

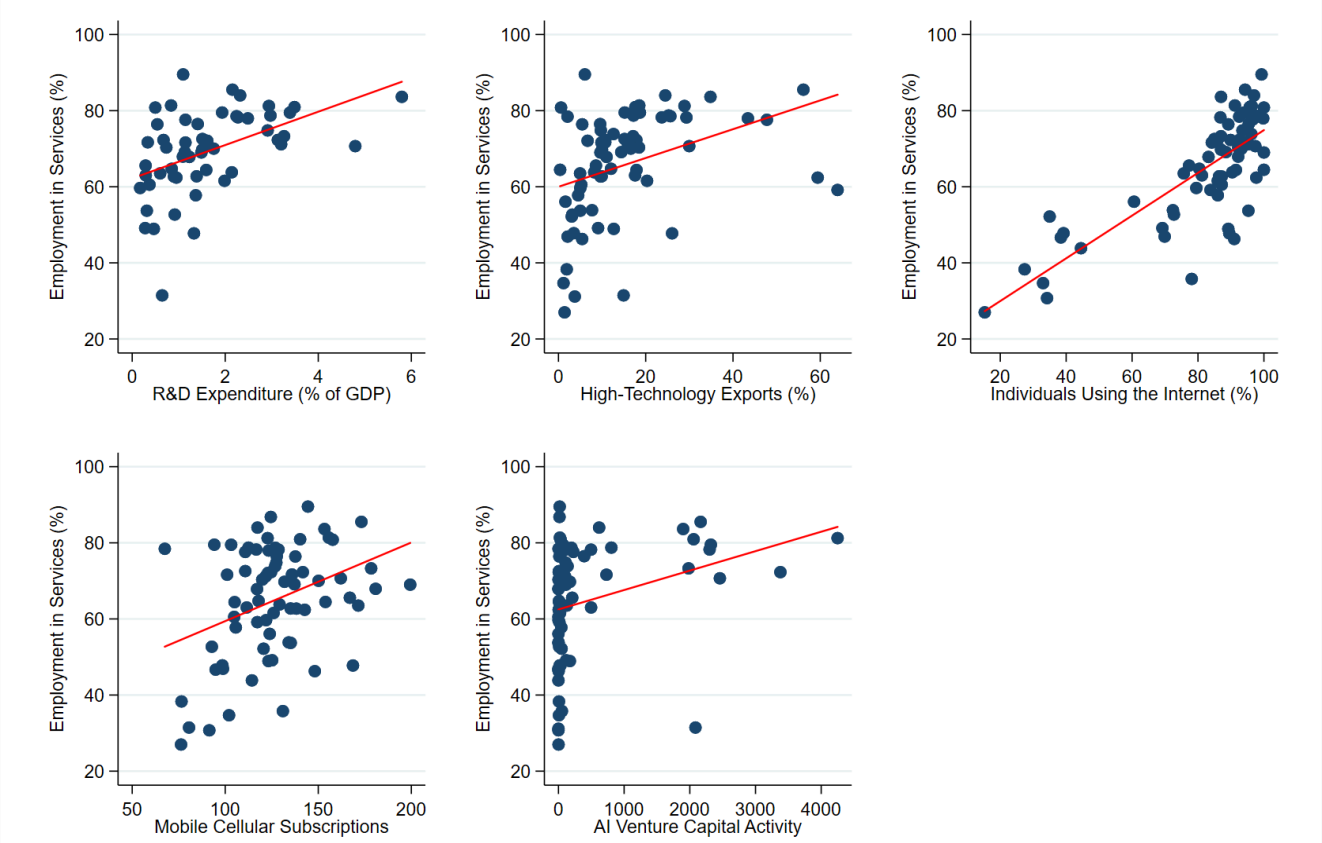

Figure 1: *Scatterplot graphics for Employment in Services and technology indicators.*

Among the primary independent variables, Internet_Usage (mean = 71.961, SD = 24.395) and Mobile_Sub (mean = 116.962, SD = 35.533) display a wide range, showing that digital reliance and penetration vary considerably across countries. R&D (mean = 1.302, SD = 1.124) and High_Tech exports (mean = 12.058, SD = 12.637) further indicate that technological investment capability is unevenly distributed globally, which may be associated with differences in broader economic outcomes. Log AI_Venture_Capital (mean = 1.774, SD = 0.969) has 68 observations and the relatively small sample size reflects the concentration of AI investment activity across a specific subset of countries.

Regarding the baseline control variables, Log GDP_per_capita level (mean = 11.557, SD = 2.405) varies substantially, and Trade (mean = 88.511, SD = 54.434) confirms structural openness disparities across countries. The differing spread of Pop_Growth (mean = 1.124, SD = 1.523) and Urban_Pop (mean = 61.262, SD = 22.454) similarly maps onto distinct demographic and developmental characteristics.

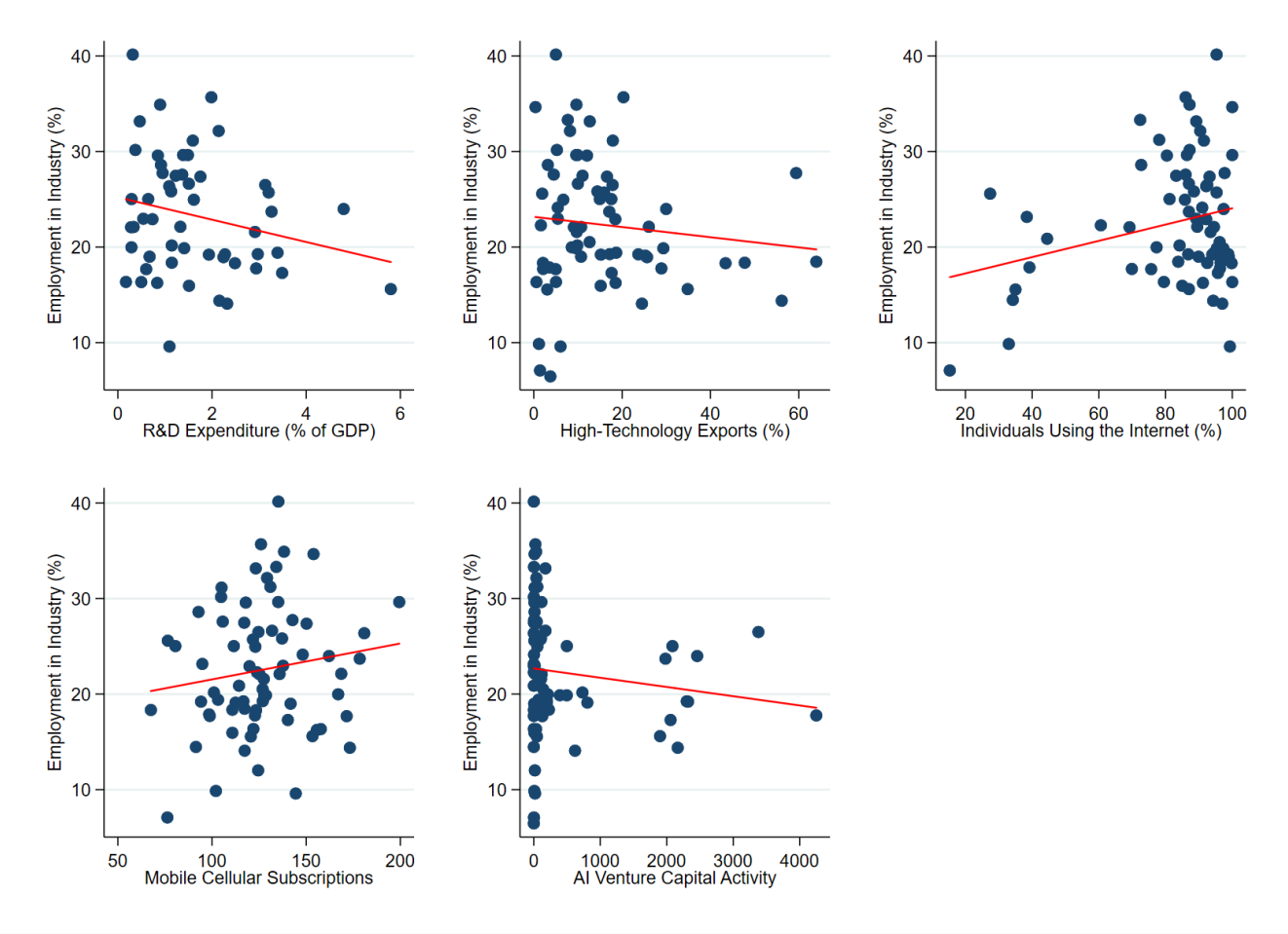

Figure 2: *Scatterplot graphics for Employment in Industry and technology indicators.*

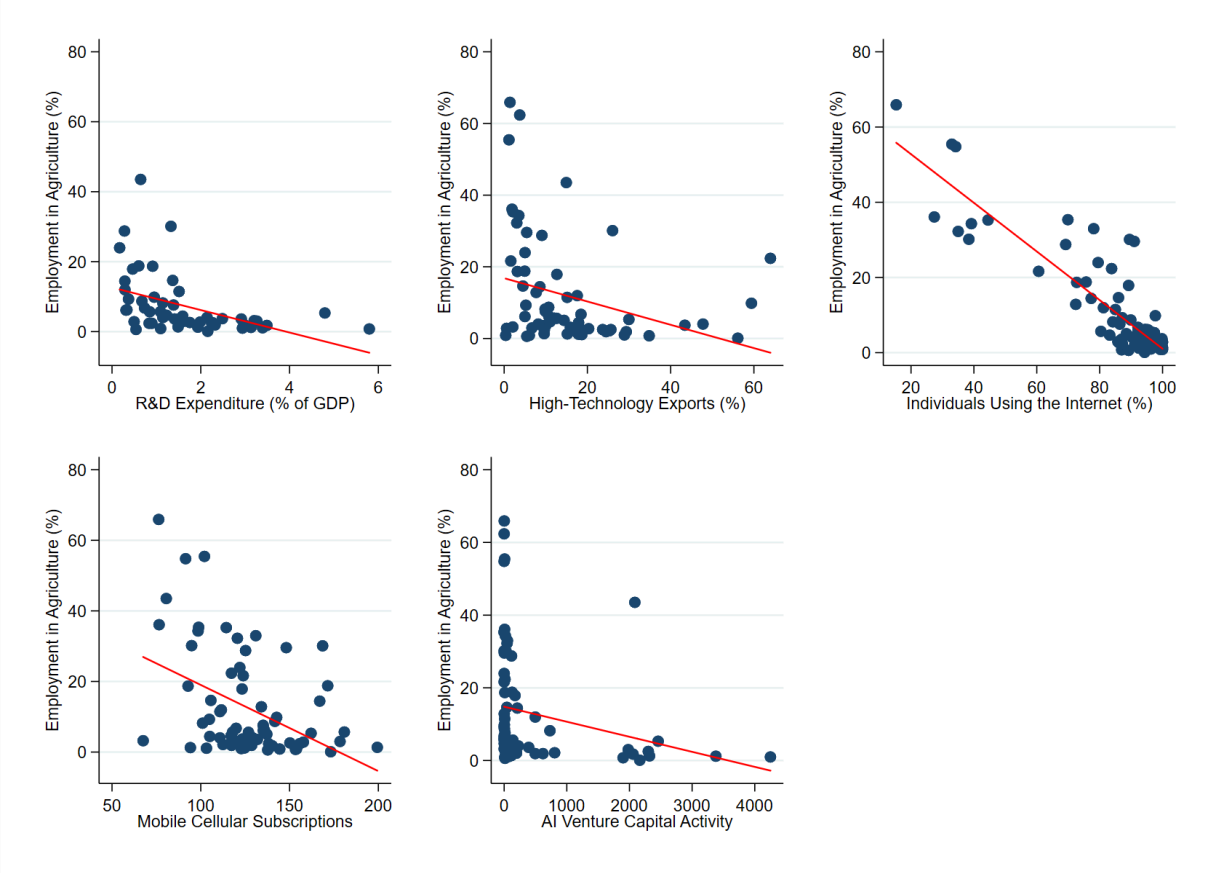

Figure 3: *Scatterplot graphics for Employment in Agriculture and technology indicators.*

Figures 1-3 show patterns between employment shares and proxy variables for innovation, digitalization, and AI-related investment activity. Service employment (emps) rises with all proxy variables, including R&D, high technology, internet usage, mobile cellular subscriptions, and AI venture capital activity, reflecting a consistent positive association between innovation, digitalization, and AI-related investment activity with the demand for service sector jobs.

Industrial employment (empi) moves in the negative direction in association with R&D expenditure as a proxy for innovation, high-technology exports, and AI venture capital activity but moves in the positive direction in association with individuals using the internet and mobile cellular subscriptions.

Agricultural employment (empa) follows the opposite of the service sector employment pattern—R&D, high technology, internet usage, mobile cellular subscriptions, and AI venture capital activity all associate negatively with agricultural employment.

Table 2 presents regression results for each employment share (agricultural employment, industrial employment, and service employment) as the dependent variable, with high technology, GDP per growth, population growth, GDP growth, and trade as controls held constant across models. Statistical significance is denoted at the 1% (***), 5% (**) and 10% (*) levels, with coefficient signs indicating the direction of the association.

Table 2: *Regression analysis for research and development*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
R&D	0.099***	0.085***	0.066***	0.046***
	(0.017)	(0.020)	(0.017)	(0.016)
Pop_Growth			0.070***	0.025
			(0.017)	(0.017)
Urban_Pop				0.006***
				(0.001)
Trade				0.001**
				(0.000)
Log GDP per capita level		-0.001	0.003	-0.003
		(0.011)	(0.011)	(0.009)
Education		0.190**	0.207***	0.097**
		(0.083)	(0.076)	(0.043)

Asia	-0.091	-0.060	-0.126*	-0.071
	(0.062)	(0.078)	(0.074)	(0.048)
Africa	-0.043	0.154	0.095	0.188*
	(0.097)	(0.133)	(0.143)	(0.106)
Americas	0.107**	0.150***	0.112**	0.074*
	(0.045)	(0.049)	(0.051)	(0.044)
Constant	4.043***	3.258***	3.134***	3.219***
	(0.048)	(0.342)	(0.313)	(0.172)
Observations	84	71	71	71
R-squared	0.310	0.447	0.563	0.712

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2 shows that R&D expenditure is positively and significantly associated with service sector employment across all model specifications. The estimated coefficient remains statistically significant after controlling for GDP per capita level, education, regional differences, population growth, urbanization, and trade, although its magnitude gradually declines as additional controls are introduced. This pattern suggests that the positive association between R&D expenditure and service sector employment is robust across alternative model specifications. However, the gradual decline in magnitude suggests that a portion of the R&D coefficient's initial magnitude is attenuated by broader structural and economic indicators.

Table 3: *Regression analysis for High_Tech*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
High_Tech	0.005***	0.003**	0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Pop_Growth			0.062***	0.027
			(0.021)	(0.020)
Urban_Pop				0.006***
				(0.001)
Trade				0.000
				(0.000)
Log GDP per capita level		-0.014	-0.011	-0.012
		(0.010)	(0.010)	(0.009)
Education		0.196***	0.215***	0.144**
		(0.055)	(0.056)	(0.058)
Asia	-0.094	-0.004	-0.042	-0.000
	(0.057)	(0.064)	(0.062)	(0.051)

Africa	-0.359***	-0.024	-0.104	-0.029
	(0.075)	(0.105)	(0.109)	(0.102)
Americas	0.033	0.123*	0.090	0.024
	(0.045)	(0.062)	(0.061)	(0.050)
Constant	4.129***	3.468***	3.345***	3.215***
	(0.045)	(0.256)	(0.261)	(0.238)
Observations	136	96	96	92
R-squared	0.316	0.413	0.465	0.612

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 3 shows that high-technology exports (High_Tech) are positively associated with service-sector employment in the baseline models. However, the association becomes statistically insignificant after introducing the full set of control variables. The loss of statistical significance after introducing additional controls suggests that the observed association is sensitive to model specification.

Table 4: *Regression analysis for Individuals using the internet*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
Internet_Usage	0.011***	0.010***	0.010***	0.006**
	(0.001)	(0.002)	(0.002)	(0.002)
Pop_Growth			0.051***	0.021

			(0.019)	(0.019)
Urban_Pop				0.006***
				(0.001)
Trade				0.000
				(0.000)
Log GDP per capita level		-0.017*	-0.016*	-0.015**
		(0.009)	(0.009)	(0.008)
Education		0.098**	0.112**	0.079
		(0.049)	(0.048)	(0.050)
Asia	-0.031	0.004	-0.034	0.006
	(0.047)	(0.051)	(0.052)	(0.048)
Africa	0.058	0.126	0.049	0.017
	(0.071)	(0.093)	(0.091)	(0.096)
Americas	0.139***	0.193***	0.175***	0.070
	(0.037)	(0.051)	(0.051)	(0.050)
Constant	3.176***	3.023***	2.983***	3.076***

	(0.125)	(0.228)	(0.231)	(0.227)
Observations	167	114	114	108
R-squared	0.591	0.602	0.628	0.689

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

This regression shows that internet usage is positively and significantly associated with service sector employment across all four model specifications. In the initial baseline model, the estimated coefficient is 0.011, and this association remains virtually unchanged at 0.010 in Models 2 and 3 as regional, income, and demographic controls are introduced. However, the estimated coefficient decreases in the fully specified model but still remains statistically significant at the 5% level. This suggests that digital adoption and connectivity have a robust and consistent positive association with a larger service-sector employment share, even after controlling for broader developmental and structural factors. This finding is consistent with the view that internet diffusion may be associated with facilitating business modernization.

Table 5: *Regression analysis for Mobile cellular subscriptions*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
Mobile_Sub	0.003***	0.003***	0.003***	0.001**
	(0.001)	(0.001)	(0.001)	(0.001)
Pop_Growth			0.060***	0.016
			(0.020)	(0.021)
Urban_Pop				0.008***
				(0.002)
Trade				0.000

				(0.000)
Log GDP per capita level		-0.024**	-0.023**	-0.018**
		(0.010)	(0.010)	(0.007)
Education		0.236***	0.246***	0.143***
		(0.054)	(0.054)	(0.051)
Asia	-0.161***	-0.024	-0.074	-0.016
	(0.054)	(0.067)	(0.063)	(0.051)
Africa	-0.333***	-0.024	-0.100	-0.054
	(0.065)	(0.096)	(0.097)	(0.094)
Americas	0.057	0.123**	0.107*	0.009
	(0.048)	(0.061)	(0.059)	(0.043)
Constant	3.781***	3.092***	3.018***	3.036***
	(0.095)	(0.270)	(0.274)	(0.226)
Observations	151	104	104	101
R-squared	0.367	0.570	0.607	0.704

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5 shows mobile sector subscriptions are positively and significantly associated with service sector employment across all model specifications. In Models 1, 2, and 3, the estimated coefficient for mobile subscriptions remains highly stable at 0.003 and is statistically significant at the 1% level. In the fully specified Model 4 with the complete set of socioeconomic controls, the coefficient drops slightly to 0.001 but still is statistically significant at the 5% level. This suggests a positive association between mobile connectivity and service-sector employment share across the model specifications. However, given the presence of relatively high observations in the mobile-subscription data, the estimated relationship should be interpreted cautiously.

Table 6: *Regression analysis of empi for research and development*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
R&D	-0.024	-0.015	-0.003	0.010
	(0.025)	(0.033)	(0.030)	(0.034)
Pop_Growth			-0.047	0.010
			(0.035)	(0.036)
Urban_Pop				-0.006**
				(0.003)
Trade				-0.001*
				(0.001)
Log GDP per capita level		0.002	-0.000	0.005
		(0.015)	(0.015)	(0.016)
Education		-0.067	-0.078	0.035

		(0.134)	(0.125)	(0.099)
Asia	0.038	0.006	0.049	-0.022
	(0.079)	(0.110)	(0.109)	(0.082)
Africa	0.006	-0.064	-0.025	-0.151
	(0.111)	(0.201)	(0.203)	(0.119)
Americas	-0.101	-0.101	-0.076	-0.081
	(0.072)	(0.091)	(0.094)	(0.101)
Constant	3.128***	3.381***	3.463***	3.415***
	(0.074)	(0.550)	(0.515)	(0.366)
Observations	84	71	71	71
R-squared	0.036	0.029	0.066	0.221

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 6 shows that R&D expenditure is not significantly associated with industrial employment across any of the model specifications. The estimated coefficient remains statistically insignificant after inclusion of additional control variables suggesting no robust association between R&D and industrial employment. In contrast to the service sector, where research and development expenditure is positively correlated with employment, Table 6 shows that there is a neutral and statistically insignificant relationship between R&D expenditure and industrial employment across all four model specifications. One possible interpretation is that R&D intensity is uncorrelated with two offsetting compositional patterns---a shift toward higher-skilled industrial roles and a shift away from lower-skilled ones---that leave the aggregate industrial employment share unchanged in the cross-country data. This interpretation is speculative, however, since the cross-sectional design cannot separate compositional change within industry from a genuinely null association.

Table 7: *Regression analysis of empi for High_Tech*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
High_Tech	-0.004*	-0.006**	-0.004	-0.004
	(0.002)	(0.003)	(0.003)	(0.003)
Pop_Growth			-0.046	0.009
			(0.036)	(0.040)
Urban_Pop				-0.007***
				(0.002)
Trade				-0.000
				(0.001)
Log GDP per capita level		-0.002	-0.005	-0.003
		(0.015)	(0.015)	(0.016)
Education		0.107	0.093	0.294***
		(0.077)	(0.074)	(0.091)
Asia	0.049	0.096	0.124	0.095
	(0.069)	(0.091)	(0.094)	(0.090)

Africa	-0.469***	-0.170	-0.111	-0.043
	(0.109)	(0.163)	(0.163)	(0.146)
Americas	-0.099	-0.022	0.002	-0.006
	(0.066)	(0.084)	(0.085)	(0.083)
Constant	3.118***	2.712***	2.803***	2.420***
	(0.068)	(0.355)	(0.351)	(0.374)
Observations	136	96	96	92
R-squared	0.239	0.154	0.174	0.271

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The regression shows that high-technology exports have a weak and ultimately non-robust relationship with industrial employment across the model specifications. In the baseline model, high-technology exports show a small negative association which becomes slightly stronger in the second model when income and education is controlled for. However, once population growth, urbanization, and trade is accounted for in Models 3 and 4, as well as the full suite of macroeconomic controls, the variable loses all statistical significance. This lack of significance in the final fully specified models indicates that high-tech exports do not independently associate with industrial employment shares.

Table 8: *Regression analysis of empi for individuals using the internet*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
Internet_Usage	0.009***	0.009***	0.007*	0.008**
	(0.002)	(0.002)	(0.004)	(0.004)

Pop_Growth			-0.082**	-0.031
			(0.032)	(0.036)
Urban_Pop				-0.006**
				(0.002)
Trade				-0.001
				(0.001)
Log GDP per capita level		-0.002	-0.003	0.008
		(0.011)	(0.013)	(0.012)
Education			0.055	0.168*
			(0.086)	(0.094)
Asia	0.072	0.073	0.121	0.081
	(0.073)	(0.074)	(0.086)	(0.083)
Africa	-0.031	-0.029	0.123	0.110
	(0.106)	(0.108)	(0.144)	(0.148)
Americas	0.003	0.003	0.061	0.068
	(0.067)	(0.068)	(0.086)	(0.089)

Constant	2.240***	2.272***	2.320***	2.041***
	(0.168)	(0.197)	(0.332)	(0.365)
Observations	167	166	114	108
R-squared	0.342	0.332	0.247	0.299

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8's results demonstrate that internet usage has a consistently positive and statistically significant relationship with industrial employment shares across all four model specifications. In the baseline specifications (Models 1 and 2), the estimated coefficient is 0.009 and is highly significant at the 1% level. While adding in additional demographic controls attenuates the significance and coefficient to 0.007, the fully specified model 4 rebounds to significance at the 5% level and a coefficient of 0.008. This suggests that digital connectivity is positively associated with industrial employment. Economically, this may indicate that internet access enhances supply chain coordination and expands the reach for e-commerce markets for manufactured goods, or else complements technical manufacturing roles, preventing the labor displacement that is usually seen with other technologies.

Table 9: *Regression analysis of empi for mobile cellular subscriptions*

Variable	**(Model 1)**	**(Model 2)**	**(Model 3)**	**(Model 4)**
Mobile_Sub	0.003**	0.003*	0.000	-0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Pop_Growth			-0.075**	-0.035
			(0.036)	(0.042)
Urban_Pop				-0.004

				(0.003)
Trade				-0.000
				(0.001)
Log GDP per capita level		-0.008	-0.006	0.005
		(0.014)	(0.017)	(0.016)
Education			0.158*	0.300***
			(0.087)	(0.083)
Asia	-0.037	-0.019	0.128	0.119
	(0.077)	(0.082)	(0.094)	(0.093)
Africa	-0.342***	-0.344***	-0.002	0.030
	(0.095)	(0.100)	(0.165)	(0.161)
Americas	-0.099	-0.097	-0.018	-0.037
	(0.064)	(0.065)	(0.097)	(0.090)
Constant	2.752***	2.832***	2.448***	2.129***
	(0.171)	(0.216)	(0.432)	(0.412)
Observations	151	147	104	101

R-squared	0.210	0.212	0.217	0.268

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 9 wraps up industrial sector employment analysis by evaluating the association of mobile cellular subscriptions. Ultimately, the relationship between mobile subscriptions and industrial employment is weak and lacks long-term statistical significance. In the baseline model (Model 1), mobile subscriptions show a small and positive association with industrial employment. Yet, the significance drops and the coefficient shrinks to zero once the full suite of controls is added. This indicates that the initial positive association attenuates substantially once demographic and structural controls are included. The pattern is consistent with the possibility that the baseline association reflects other country-level characteristics captured by the additional controls rather than an independent relationship. Given the presence of unusually high mobile-subscription observations in some countries, this relationship should also be interpreted cautiously.

Table 10: *Regression analysis of empa for research and development*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
R&D	-0.586***	-0.507***	-0.370***	-0.340***
	(0.108)	(0.122)	(0.107)	(0.112)
Pop_Growth			-0.521***	-0.233***
			(0.108)	(0.083)
Urban_Pop				-0.023**
				(0.009)
Trade				-0.007***
				(0.002)

Log GDP per capita level		0.050	0.021	0.044
		(0.057)	(0.055)	(0.045)
Education		-0.982*	-1.110**	-0.608**
		(0.558)	(0.486)	(0.256)
Asia	0.122	-0.088	0.399	0.037
	(0.367)	(0.518)	(0.423)	(0.293)
Africa	0.614	-0.421	0.016	-0.641
	(0.396)	(0.724)	(0.764)	(0.563)
Americas	-0.031	-0.323	-0.046	-0.205
	(0.292)	(0.366)	(0.350)	(0.364)
Constant	2.449***	6.002***	6.924***	6.834***
	(0.240)	(2.187)	(1.934)	(1.152)
Observations	84	71	71	71
R-squared	0.298	0.392	0.584	0.748

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 10 examines the association of R&D expenditure on agricultural employment. Unlike non-agricultural sectors, R&D intensity displays a consistently negative and statistically significant relationship with employment across all four models. In

the baseline model (Model 1), the coefficient for R&D is -0.586. Even when controlling for comprehensive macroeconomic and demographic controls in the fully specified Model 4, which dramatically improves the model's explanatory power to an R-squared of 0.748, the coefficient remains heavily negative and significant at the 1% level. This shows that higher levels of R&D expenditure are associated with lower agricultural employment shares. These findings are consistent with previous studies reporting lower agricultural employment shares in countries with higher levels of innovation. Instead of complementing the human workforce, the findings are consistent with the possibility that technological innovation may correlate with a reduction in labor intensity in agriculture.

Table 11: *Regression analysis of empa for high technology*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
High_Tech	-0.026**	-0.023*	-0.005	0.004
	(0.012)	(0.014)	(0.011)	(0.006)
Pop_Growth			-0.505***	-0.286***
			(0.098)	(0.081)
Urban_Pop				-0.031***
				(0.006)
Trade				-0.006***
				(0.002)
Log GDP per capita level		0.045	0.015	0.009
		(0.052)	(0.048)	(0.037)
Education		-0.799***	-0.954***	-0.555**

		(0.259)	(0.259)	(0.224)
Asia	0.257	-0.049	0.256	0.030
	(0.315)	(0.374)	(0.330)	(0.244)
Africa	1.521***	0.320	0.970*	0.414
	(0.273)	(0.481)	(0.504)	(0.445)
Americas	0.446	-0.010	0.256	0.414
	(0.274)	(0.361)	(0.357)	(0.312)
Constant	1.957***	4.808***	5.806***	6.845***
	(0.270)	(1.263)	(1.267)	(0.917)
Observations	136	96	96	92
R-squared	0.337	0.366	0.500	0.725

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In Table 11, high-technology exports are negatively and statistically significantly associated with agricultural employment in Models 1 and 2. After the inclusion of population growth in Model 3, however, the coefficient becomes statistically insignificant, and it remains insignificant in the fully specified Model 4, where the coefficient changes sign. At the same time, the model's explanatory power increases substantially. This pattern suggests that the initial negative association is sensitive to the inclusion of broader demographic and structural controls. The attenuation of the High_Tech coefficient after the inclusion of urbanization and trade is consistent with the possibility that high-technology exports capture variation associated with broader patterns of economic development rather than an independent relationship with agricultural employment.

Table 12: *Regression analysis of empa for individuals using the internet*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
Internet_Usage	-0.041***	-0.039***	-0.034***	-0.004
	(0.004)	(0.008)	(0.008)	(0.007)
Pop_Growth			-0.479***	-0.295***
			(0.093)	(0.080)
Urban_Pop				-0.028***
				(0.006)
Trade				-0.005***
				(0.001)
Log GDP per capita level		0.029	0.022	0.026
		(0.037)	(0.036)	(0.031)
Education		-0.322	-0.458*	-0.483**
		(0.262)	(0.248)	(0.217)

Asia	0.124	-0.044	0.316	0.113
	(0.255)	(0.323)	(0.264)	(0.222)
Africa	0.011	-0.223	0.504	0.422
	(0.284)	(0.419)	(0.386)	(0.411)
Americas	0.158	-0.093	0.079	0.422
	(0.214)	(0.291)	(0.280)	(0.293)
Constant	5.251***	6.182***	6.566***	6.492***
	(0.398)	(0.908)	(0.867)	(0.794)
Observations	167	114	114	108
R-squared	0.541	0.474	0.607	0.734

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In Table 12, internet usage remains negatively and statistically significantly associated with agricultural employment until the fully specified model, where it loses all statistical significance. Upon introducing the full suite of macroeconomic and demographic explanatory controls in Model 4, the model's explanatory power jumps up to 0.734. The attenuation and eventual loss of statistical significance of the Internet_Usage coefficient suggests that the initial relationship may partly reflect variation captured by other country-level characteristics included in the fuller specifications.

Table 13: *Regression analysis of empa for mobile cellular subscriptions*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
Mobile_Sub	-0.014***	-0.013***	-0.012***	-0.005**

	(0.003)	(0.003)	(0.003)	(0.002)
Pop_Growth			-0.514***	-0.289***
			(0.087)	(0.086)
Urban_Pop				-0.031***
				(0.006)
Trade				-0.004**
				(0.002)
Log GDP per capita level		0.070	0.059	0.042
		(0.049)	(0.042)	(0.033)
Education		-0.767***	-0.858***	-0.498**
		(0.214)	(0.195)	(0.200)
Asia	0.574**	0.034	0.461	0.159
	(0.259)	(0.351)	(0.292)	(0.233)
Africa	1.361***	0.386	1.042***	0.496
	(0.225)	(0.410)	(0.393)	(0.420)
Americas	0.368	0.056	0.196	0.365

	(0.284)	(0.371)	(0.360)	(0.315)
Constant	3.434***	5.805***	6.441***	6.692***
	(0.386)	(1.027)	(0.969)	(0.809)
Observations	151	104	104	101
R-squared	0.370	0.455	0.606	0.737

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 13 concludes the exploration of the primary sector by analyzing mobile cellular subscriptions with employment in agriculture. Across the baseline models (1-3), the mobile penetration displays a significant and negative association with employment in agriculture. In the fully specified Model 4, the coefficient is substantially attenuated, declining from -0.012 to -0.005, although it remains statistically significant at the 5% level. The smaller magnitude of the coefficient suggests that part of the baseline association is accounted for by the additional demographic and structural controls. Given the presence of relatively high observations in the mobile-subscription data, the remaining association should be interpreted cautiously and should not be taken as evidence of a specific causal mechanism.

Table 14: *Regression analysis of emps for AI-related activity*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
Log AI_Venture_Capital	0.028*	0.033**	0.000	0.003
	(0.014)	(0.015)	(0.015)	(0.011)
Pop_Growth			0.056***	0.004
			(0.020)	(0.016)
Urban_Pop				0.009***

				(0.001)
Trade				0.000
				(0.000)
Log GDP per capita level		-0.029*	-0.014	-0.015**
		(0.016)	(0.012)	(0.007)
Education			0.243***	0.069
			(0.061)	(0.047)
Constant	4.053***	4.370***	3.295***	3.380***
	(0.072)	(0.163)	(0.287)	(0.235)
Observations	67	67	58	58
R-squared	0.072	0.135	0.396	0.692

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 15: *Regression analysis of empi for AI-related activity*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
Log AI_Venture_Capital	0.000	0.002	-0.017	-0.020
	(0.017)	(0.018)	(0.016)	(0.015)

Pop_Growth			-0.049	0.006
			(0.040)	(0.042)
Urban_Pop				-0.009***
				(0.003)
Trade				-0.000
				(0.001)
Log GDP per capita level		-0.008	0.001	0.002
		(0.020)	(0.014)	(0.013)
Education			-0.001	0.182*
			(0.085)	(0.102)
Constant	3.061***	3.149***	3.229***	3.142***
	(0.097)	(0.217)	(0.400)	(0.381)
Observations	67	67	58	58
R-squared	0.000	0.003	0.068	0.276

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 16: *Regression analysis of empa for AI-related activity*

Variable	(Model 1)	(Model 2)	(Model 3)	(Model 4)
Log AI_Venture_Capital	-0.186***	-0.215***	-0.072	-0.110**
	(0.066)	(0.068)	(0.065)	(0.051)
Pop_Growth			-0.507***	-0.213**
			(0.121)	(0.082)
Urban_Pop				-0.034***
				(0.006)
Trade				-0.006***
				(0.001)
Log GDP per capita level		0.170***	0.109**	0.108***
		(0.053)	(0.046)	(0.030)
Education			-1.178***	-0.429**
			(0.248)	(0.208)
Constant	2.444***	0.591	5.944***	5.883***
	(0.307)	(0.637)	(1.148)	(0.825)

Observations	67	67	58	58
R-squared	0.125	0.206	0.493	0.742

Note. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

The analysis is extended using data from the OECD AI Policy Observatory. The AI_Venture_Capital variable is entered in logarithmic form in all empirical specifications. This section estimates the same baseline model using an alternative explanatory variable as AI-related venture capital investment, which is a more direct measurement of AI-related activity. This variable named AI_Venture_Capital uses worldwide venture capital (VC) tracking from Preqin to isolate private institutional investments flowing directly into artificial intelligence and data start-ups. All models include the same control variables: the logarithmic transformation of GDP per capita level, population growth, urbanization, trade, and education as a share of GDP.

The results are broadly consistent with the main findings. For service employment, AI venture capital shows a positive and statistically significant association at the 10% level in Model 1, strengthening to the 5% level once log GDP per capita level and population growth are introduced as controls (Model 2). The coefficient becomes insignificant in the highly-specified Models 3 and 4.

For industrial employment, AI venture capital shows no statistically significant association across any of the four models, consistent with the weak and inconsistent results found for R&D and high-technology exports in the main analysis.

For agricultural employment, AI venture capital is negatively and highly statistically significantly associated with agricultural employment at the 1% level in Model 1. However, this relationship loses significance in Model 3, but returns to significance at the 5% level in the fully specified Model 4.

All together, the models show that AI-related investment activity is associated with a compositional shift away from agricultural employment and toward service sector employment, with a limited and inconsistent association with industrial employment.

4. Discussion

The results of this regression show that innovation, digitalization, and AI-related investment activity indicators are associated with a shift in employment away from the agricultural sector toward the service sector, with a limited association for the industrial sector. This pattern is consistent across multiple proxies and is corroborated by the OECD venture capital data and log-ratio transformation model. Thus, the direction of this association should hold, even if the individual coefficients vary across models.

4.1. Service Sector

The service sector sees a strong positive association with digitalization and AI-related investment activity indicators.

Indeed, internet usage is robustly and positively associated with employment in the service sector at the 1% significance level across the first three specifications, remaining significant at the 5% level in the final specification. While high-technology exports display strong positive significance in baseline frameworks and are fully mediated when urbanization and trade are introduced, mobile cellular subscriptions remain statistically significant at the 5% level in the final specification. Notably, internet usage produces the highest baseline explanatory power among the standalone technological proxies. This suggests that the measure of how widely digital tools and connectivity have penetrated a society is a more resilient early indicator of service sector growth than upstream innovation metrics like R&D intensity or targeted venture capital. One interpretation of this result is that service sector employment expands not necessarily because companies are innovating more advanced technologies locally, but because widespread digital access is associated with increased market demand for secondary digital services—such as digital finance, logistics platforms, and telecommunications—that utilize human labor to deliver. This is broadly consistent with Gu et al. (2022) and Shen & Zhang (2024), who found that digital development and AI activity in China's service sector correlated with employment expansion rather than labor reduction, and with Wang (2021), who found that digital connectivity is positively associated with broader employment expansion.

4.2. Industrial Sector

The findings in the industrial sector demonstrate mixed results that diverge significantly depending on the specific innovation indicator examined. While infrastructure-level digital adoption is positively and significantly associated with industrial employment across all specifications, upstream innovation and specialized AI indicators show no such robust relationship. Specifically, in Table 8, internet usage maintains a consistently positive association across all four specifications, remaining significant at the 5% level in the fully controlled framework. In contrast, high-technology exports (Table 7) display a weak negative association in baseline models before collapsing to complete statistical insignificance in Models 3 and 4. Furthermore, mobile cellular subscriptions (Table 9) lose all statistical significance after baseline controls are introduced, and upstream metrics such as R&D intensity (Table 6) and specialized AI venture capital flows (Table 15) demonstrate a completely null and statistically insignificant relationship with industrial employment shares across all specifications.

This mixed pattern indicates that downstream digital connectivity metrics are more consistent macro-correlated indicators of aggregate industrial employment shares than pure innovation or targeted financing proxies. Increased digital penetration is likely associated with expanded labor utilization via optimized supply chain logistics and broader access to international B2B marketplaces. Conversely, the null association for R&D and venture capital intensity is consistent with several possible explanations, including a structural pattern in which capital-intensive industrial technology is associated with both fewer frontline manual roles and more technical roles. This interpretation is consistent with Shao et al. (2022), who observed that technology adoption in manufacturing is associated with a compositional shift toward high-skilled technicians alongside a reduction in manual roles. One possible explanation, consistent with but not confirmed by this analysis, is that opposing compositional dynamics within industrial employment offset one another in the aggregate cross-country coefficient. Future research splitting the sample by income levels might reveal that R&D and AI-related investment activity have a positive relationship with employment in high-income economies while exhibiting a negative association in lower-income groups.

4.3. Agricultural Sector

The agricultural models yield some of the most robust insights of this study. Internet usage shows a strong, independent

negative relationship with agricultural employment shares at the 1% significance level across the first three specifications, before losing significance in the fully controlled model, which displays remarkable explanatory power (0.734 for R^2 in the fully controlled model). Crucially, and contrary to patterns observed in other sectors, research and development expenditure and AI-related venture capital activity remain negatively associated with agricultural employment shares after the inclusion of control variables, with R&D highly significant at the 1% level and AI venture capital significant at the 5% level in the final models. This pattern is consistent with, though not direct evidence for, the possibility that R&D-intensive economies invest disproportionately in labor-saving agricultural mechanization; the cross-sectional design cannot confirm this mechanism. In contrast, the associations of high-technology exports undergo full attenuation, while mobile subscriptions undergo partial attenuation but maintain significance at the 5% level in the final specifications, indicating that their relationship with a shrinking agrarian workforce is heavily diminished or operated through general urbanization and trade. These findings are directly corroborated by the explicit OECD AI venture capital robustness check. The agricultural findings may be informative for policymakers considering how digital infrastructure investment interacts with agricultural employment composition.

4.4. Cross-Sectoral Pattern

With all three sectors, however, there is a clear pattern that emerges. Countries with a higher prevalence of innovation, digitalization, and AI-related investment activity have smaller agricultural employment and larger service employment, with industrial employment positively correlated with digital connectivity but not to innovation-based proxies like R&D or specialized venture capital. However, because the three employment shares sum to 100, these results reflect the compositional reallocation rather than any net job creation or destruction.

4.5. Limitations

This study has several limitations that you should consider when examining the results.

First, the dependent variables of agricultural employment, industrial employment, and service employment sum up to 100, meaning that a positive coefficient in one must lead to a negative coefficient in another. Thus, a positive coefficient does not mean an increase in jobs but rather a shift towards that sector.

Although we have incorporated a robust suite of macroeconomic and demographic controls, there is still potential for omitted variable bias that is an inherent limitation of cross-country observational data. In macro-level regressions, it is impossible to fully capture every determinant of labor market composition. Consequently, if unobserved factors are simultaneously correlated with a nation's digital infrastructure adoption and sectoral employment, the baseline coefficients may absorb this variance, leading to endogeneity. Future iterations of this research could mitigate OVB by employing a fixed-effects panel data approach to control for time-invariant, country-specific unobservables, or by identifying a suitable instrumental variable to isolate the exogenous variation.

Secondly, the proxies used for innovation, digitalization, and AI-related investment activity prevalence, such as R&D expenditure, high-tech exports, internet usage, mobile subscriptions, and targeted venture capital flows, are broad and aggregate indicators. Thus, while they can capture the general technological intensity and financing, they cannot distinguish between which sectors within a country are adopting these technologies at higher rates, nor how adoption varies geographically within developing or developed countries. A country with a higher concentration of internet penetration or

VC funding near urban cities may have the same proxy value as one with evenly distributed rural digital access, although both circumstances lead to very different implications for the labor market.

Third, this study relies on cross-sectional data, which limits the causal inference. The results cannot necessarily establish the direction of causality because it is possible, for instance, that countries with larger service sectors invest more in digital infrastructure or attract more AI venture capital rather than digital infrastructure leading to larger service sectors. Future research may consider using panel data analysis that incorporates both time-series and cross-sectional variation to allow for a stronger causal claim. Future studies may also consider applying the Granger causality test to better determine the direction of the relationship.

Finally, because employment shares are compositional by nature, we also estimated logarithmic transformations of the dependent variables, expressing service and industrial employment as log ratios relative to agricultural employment as the baseline sector and rerunning OLS regressions using the same innovation, digitalization, and AI-related investment activity proxies and control variables.

The OECD AI Venture Capital indicator measures AI-related investments in start-ups and enterprises, not AI adoption, implementation, or application. This metric should be used as a proxy for AI-related investment activity and investor interest in AI, not AI dissemination. Countries with more AI venture capital may not have more AI adoption in enterprises, industries, or labor markets. Future studies may employ more direct measures of AI adoption, such as firm-level AI usage, AI patent activity, AI-related employment exposure indices, or sector-specific AI implementation indicators.

Because our study relies on cross-sectional regression analysis, the findings should be interpreted as statistical associations rather than causal effects.

5. Conclusion

As the Fourth Industrial Revolution reshapes labor markets worldwide, it is important to understand the implications of the diffusion of innovation, digitalization, and AI-related investment activity through different employment sectors for policymakers, businesses, and researchers attempting to anticipate the movements of the labor market. This study examines the relationship between innovation, digitalization, AI-related activity, and sectoral employment patterns using cross-country data covering up to 266 economies/country-territory observations. Using a comprehensive dataset of countries and multiple regression models, these findings show the distinct sectoral associations of innovation, digitalization, and AI-related investment activity indicators such as R&D, High_Tech, Internet_Usage, Mobile_Sub, and targeted venture capital investments.

These findings indicate that innovation, digitalization, and AI-related investment activity indicators are positively associated with service sector employment, consistent with a pattern in which the service sector's employment share grows alongside technological and digital indicators, though the mechanism cannot be established from cross-country association data.

In the industrial sector, High_Tech shows a net-neutral association under full controls, while Internet_Usage and Mobile_Sub show stronger positive relationships. Therefore, although to a lesser extent than the service sector, digital connectivity and technological production are associated with higher industrial employment shares. Conversely, in the agricultural sector, High_Tech loses significance under full controls, while R&D and Internet_Usage demonstrate a notable

negative relationship, and Mobile_Sub shows a weaker negative relationship. The results are consistent with the possibility that agricultural employment shares decline as technology adoption and digital diffusion increase, highlighting the uneven association of innovation and digital development across labor sectors.

To strengthen the validity of the findings, the analysis was extended using an OECD data set on AI-related venture capital investment. The results support the main conclusion. Countries with higher levels of AI-related investment activity are associated with lower agricultural employment and higher service sector employment.

From a policy perspective, these findings underscore the importance of targeted sector-specific policies. These patterns may offer useful background for policymakers weighing retraining or digital-infrastructure investments. Strategic investment in education will be critical to prepare the upcoming workforce for an increasingly technologically integrated employment landscape.

Future studies can extend on this paper by taking into account the developing countries by dividing samples based on developing status, as well as using the Granger causality test to understand the causality direction between employment and innovation, digitalization, and AI-related investment activity indicators. Furthermore, other studies can control microeconomic indicators as well, as this study solely focused on controlling macroeconomic indicators. Future studies can apply panel data analysis by taking into account both time and cross-sectional data—as well as expanding data coverage for direct AI tracking metrics like targeted venture capital flows—to get more robust evidence. Additionally, future research can further examine the robustness of these relationships using alternative samples and panel-data approaches. By better understanding how innovation, digitalization, and AI-related investment activity are associated with employment composition across sectors and regions, researchers, policymakers, businesses, and governments can better anticipate where structural change is concentrated and design policy responses accordingly.

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Code & Data Availability Statement

All data and Stata analysis scripts (.do files) used in this study are publicly available on GitHub at https://github.com/clairey551/innovation_digitalization

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AI Tools and Use Statement

No AI tools or large language models were used in the generation, writing, or research for this manuscript.

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Mentor Contribution Statement

Professor Abdullah Yalaman served as the primary mentor for this project, guiding both the brainstorming and writing stages. In the initial stages of research, he guided the development of the research question, ensuring the topic was one with limited attention and overlooked novelty. As the author reviewed the literature, Professor Yalaman taught the author effective ways to summarize academic papers and synthesize key findings into a cohesive argument. Throughout the

writing process, he consistently challenged the author's argument to produce a stronger paper that is precise and well supported by the literature. After the first draft was completed, he provided additional feedback and contextual insight that strengthened the paper's relevance.

Appendix

Appendix 1: *Data Definition Table*

Symbol	Variable	Definition	Category	Source	Year	Transformation	Final Sample Size
empa	Employment in agriculture (% of total employment) (modeled ILO estimate)	The agriculture sector consists of activities in agriculture, hunting, forestry, and fishing.	Employment	WDI World Bank	2023	Logarithmic transformation	232
emps	Employment in services (% of total employment) (modeled ILO estimate)	The services sector consists of wholesale and retail trade and restaurants and hotels; transport, storage, and communications; financing, insurance, real estate, and business services; and community, social, and personal services.	Employment	WDI World Bank	2023	Logarithmic transformation	232
empi	Employment in industry (% of total	The industry sector consists of mining and quarrying, manufacturing, construction, and public	Employment	WDI World Bank	2023	Logarithmic transformation	232

	employment) (modeled ILO estimate)	utilities (electricity, gas, and water).					
Internet_Usage	Individuals using the Internet (% of population)	Internet users are individuals who have used the Internet (from any location) in the last 3 months.	Digitalization	WDI World Bank	2023	Level	186
Mobile_Sub	Mobile cellular subscriptions (per 100 people)	Mobile cellular telephone subscriptions are subscriptions to a public mobile telephone service	Digitalization	WDI World Bank	2023	Level	189
R&D	Research and development expenditure (% of GDP)	Gross domestic expenditures on research and development (R&D), expressed as a percent of GDP.	Innovation	WDI World Bank	2020	Level	114
High_Tech	High-technology exports (% of manufactured	High-technology exports are products with high R&D intensity.	Innovation	WDI World Bank	2023	Level	189

	exports)						
GDP_per_capita level	GDP per capita (constant LCU)	Gross domestic product is the total income earned through the production of goods and services in an economic territory during an accounting period. It can be measured in three different ways: using either the expenditure approach, the income approach, or the production approach. The core indicator has been divided by the general population to achieve a per capita estimate.This indicator is expressed in constant prices, meaning the series has been adjusted to account for price changes over time. The reference year for this adjustment varies by country. This series is expressed in local currency units.	Control Variable	WDI World Bank	2023	Logarithmic transformation	203
Trade	Trade (% of GDP)	Trade is the sum of exports and imports of goods and services.	Control Variable	WDI World Bank	2023	Level	212

Pop_Growth	Population Growth	Annual population growth rate for year t is the exponential rate of growth of midyear population from year t-1 to t, expressed as a percentage.	Control Variable	WDI World Bank	2023	Level	265
Urban_Pop	Urban Population	Urban population refers to people living in urban areas as defined by national statistical offices.	Control Variable	WDI World Bank	2023	Level	263
Education	School enrollment, tertiary (% gross)	Gross enrollment ratio is the ratio of total enrollment, regardless of age, to the population of the age group that officially corresponds to the level of education shown. Tertiary education, whether or not to an advanced research qualification, normally requires, as a minimum condition of admission, the successful completion of education at the secondary level.			2023	Level	164
Log AI_Venture	Venture	Measures worldwide venture capital (VC) tracking from Preqin to	Artificial Intelligenc	OECD	2023	Logarithmic transformation	68

_Capital		isolate private institutional investments flowing directly into artificial intelligence and data start-ups.	e				

Appendix 2: *An extensive summary of existing literature on the determinant factors of employment*

Author	Year	Key Variables	Key Methodology	Country / Region	Key Findings	Time Period
Masoud	2025	Unemployment, AI engagement	GMM	High-income	AI reduces unemployment in high-income economies.	2015-2023
Kalai et al.	2024	GDP Growth, R&D	PMG-ARDL, NARDL	EU	AI is associated with economic growth in Europe.	2000-2021
Gu et al.	2022	Wage, size, AI, inflation, internet penetration	Panel data	China	AI development in the service industry is associated with employment and wages.	2007-2020
Yang et al.	2025	Gender, age, education, in-vehicle AI services	Structural Model	China	Employee-AI interaction fluency improves service performance directly and indirectly.	2022

Shao et al.	2022	AI Enterprise Scope	Regression	China	AI adoption in manufacturing is associated with demand for high-skilled labor and cuts low-skilled roles.	2012-2019
Zhang	2023	Low and high skill share, Trade	Benchmark Regression	China	AI in China shows that digital economy growth is associated with demand for high-skilled labor while polarizing low-skilled jobs.	2006-2020
Shen & Zhang	2024	Labour productivity	Panel data, TSLS	China	AI and automation positively impact China's labor market.	2006-2020
X. Wang et al.	2024	ISA, ISR	GMM	China	AI in China reduced low-skilled jobs while increasing middle- and high-skilled employment.	2010-2019
Vuppalapati	2021	Rural population, life expectancy	ML	Brazil, India	AI and IoT-enabled sensors can boost agricultural productivity.	1990-2009
Jha et al.	2019	Tea, rice, general crops, wheat	AI-based models	Global	AI, deep learning, and IoT can modernize agriculture.	1980-2018
Kemeny & Osman	2018	Wage, High-technology tradable	BLS	US	Growth in local high-tech employment only modestly raises real wages for workers	2001-2015

		employment			in nontradable sectors.	
Zhan & Yang	2024	Internet use, social capital	Quantile Regression	China	Internet use improves workers' employment.	2018-2020
Wang	2021	Mobile BB Subscription, Home Internet Access, Earnings Gini	2SLS	US	Rising mobile broadband use reduces income inequality and unemployment.	2016-2018
Jung et al.	2020	Sales amount, Capital stock, ICT investment	Panel OLS	Korea	ICT investment affects employment differently by type.	2009-2013
Paul & Nayak	2025	Trade Orientation, Difference in Per Capita Income	Static Panel Data	Asia	GDP and trade openness promote IIT, while income disparities and TRIMs hinder it.	1990-2019
Chen et al.	2025	Village official status, educational attainment	Probit	China	Internet use significantly increases rural laborers' likelihood of entering non-agricultural employment.	2020-2022
Chen et al.	2024	AI Technology, Wage-productivity effect	Benchmark Regression	China	AI adoption in China's service industry reduces labor's	2008-2022

					income share.	
Shen	2024	Road accessibility, industrial structure	GMM	China	AI and automation in China overall promote job creation rather than replacement.	2006-2022
Q. Wang et al.	2024	Sustainable development, AI Index, FDI	GMM	Global	AI generally promotes sustainable development with AI R&D.	2020-2024