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On the Impact of Artificial Intelligence on Employment: Empirical Evidence from Selected Countries

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Abstract: This study investigates the impact of artificial intelligence (AI) on employment in a panel of selected countries. Using a dynamic framework, we employ the two-step System Generalized Method of Moments (System-GMM) estimator with Windmeijer correction to address endogeneity and account for the persistence of labor market dynamics. High-quality AI publications are used as a proxy to measure AI development. Employment is disaggregated by gender, skill level, and age groups to capture heterogeneous effects across the labor force. The empirical results indicate that AI adoption exerts differentiated effects on employment, with younger and low-skilled workers being more exposed to displacement risks, while high-skilled groups show signs of complementarity. These findings suggest that the labor market implications of AI are uneven and depend on demographic and skill characteristics. Policy implications emphasize the importance of targeted education, skill upgrading, and adaptive labor market policies to mitigate risks and harness the potential benefits of AI-driven technological change.

Keywords: Artificial Intelligence, employment, system GMM

Introduction

Although discussions on the effects of technological change on the labor market are considered new, the debate has a long history. Say (1803), a prominent figure in classical economics, argued that process innovation would not only displace workers employed in industries using newly invented machines but could also positively affect the workforce by creating new lines of work in the industries that produced them. Schumpeter (1912) also endorsed Say's perspective, arguing that technological advances supported employment growth by leading not only to process innovation but also to product innovation, which, by their nature, required the creation of new jobs. However, some perspectives suggest that the benefits of process innovation may not entirely offset the initial job losses (Feldmann, 2013). For instance, Ricardo (1821) stated that the laboring class's view that using machinery in production is detrimental to their interests aligns more with fundamental economic principles than mere prejudice. According to Marx (1992), technological innovations in the capitalist system will cause an increase in capital accumulation, and as a result of this increase, the current workforce will be forced to work at a lower wage level by choosing a production technique that saves labor in the economy. In the labor market, at this new wage level below the minimum subsistence wage level, some workers will choose not to work instead of working and will become unemployed. As long as the increase in capital accumulation continues, this process will continue and ultimately lead to the emergence of the “industrial reserve army” in Marxist doctrine. Keynes (1930) also stated, in line with Marx, that rapidly developing technologies will replace labor and create a new problem in the economy called “technological unemployment”. Another prominent economist, Wassily Leontief, echoed a pessimistic perspective on this issue, stating in an interview that labor would become increasingly less significant as machines replace more and more workers (Brynjolfsson & McAfee, 2014).

The topic remains highly relevant today. Some research suggests that automation will not only enhance production efficiency but also expand production scale and market demand, thereby increasing the need for labor (Aghion et al., 2020; Autor, 2015; Zeira, 1998). Conversely, other studies highlight that digital transformation and automation could pose significant risks for workers who struggle to adapt, potentially having adverse effects on the labor market overall (Acemoglu & Restrepo, 2020; Aghion et al., 2019; Bertani et al., 2020; Ni & Obashi, 2021). Also, Nguyen and Vo (2022) identify a non-linear relationship between AI and employment.

A growing body of research on the labor market implications of technological change and AI suggests that the heterogeneity of findings in the literature is largely due to differential exposure of occupations and tasks to technological advancements. This discrepancy in exposure is primarily attributed to the varying skill requirements associated with different types of jobs. Two complementary hypotheses have emerged from this perspective: Skill-Biased Technological Change (SBTC) and Routine-Biased Technological Change (RBTC). According to the SBTC hypothesis, technological progress complements the skills of highly skilled workers rather than displacing them, thereby boosting their productivity and increasing the demand for skilled jobs relative to unskilled ones in the labor market (Acemoglu, 2002; Acemoglu & Autor, 2011; Katz & Autor, 1999). This shift has also led to a rise in wage inequality (Goldin & Katz, 2007). Although the SBTC hypothesis effectively accounts for skill-based income disparities driven by technological change at the macro level, supported by decades of empirical evidence, it falls short in explaining the wage and job polarization that became pronounced in the early 1990s, particularly with the displacement of many medium-skilled workers in routine-intensive jobs (Albanesi et al., 2025).

To address this gap, Autor et al. (2003) proposed the RBTC framework, arguing that computerization displaces workers in routine cognitive and manual tasks while complementing workers performing non-routine, problem-solving, and complex communication tasks. Accordingly, technological advances have increased labor demand in non-routine cognitive fields such as software development, research, management, and finance, which are typically high wage and education intensive, as well as in non-routine manual occupations such as cleaning, childcare, and construction, which are generally lower in both educational requirements and wage (Goos & Manning, 2007). The decline in demand for routine tasks, which medium-skilled workers predominantly carry out, has contributed to a U-shaped employment structure characterized by growth in both high- and low-skilled jobs but a contraction in middle-skill employment leading to what is commonly referred to as job polarization (Autor & Dorn, 2013; Goos et al., 2014).

The remainder of this paper is structured as follows. The next section offers a comprehensive review of the literature. Section III describes the data and presents the empirical findings. The final section concludes with policy recommendations.

Literature Review

The literature on the net impact of AI and robotics on total employment highlights two opposing perspectives: the displacement effect and the reinstatement effect. The displacement effect suggests that AI and robotics reduce employment and wages by replacing workers in tasks they previously performed. However, technologies that introduce new tasks where labor maintains a comparative advantage can mitigate the adverse effects of automation. These new tasks not only boost productivity but also trigger the reinstatement effect, re-integrating labor into a broader range of activities and shifting the task composition of production in favor of labor. In contrast to the displacement effect, the reinstatement effect positively influences labor demand and wages (Acemoglu & Restrepo, 2019b; Fossen & Sorgner, 2022).

Crucially, the existence of the displacement effect does not necessarily imply that automation will lead to a persistent decline in employment. Several countervailing forces can mitigate its negative impact, indicating that automation, AI, and robotics may stimulate labor demand. The first is the productivity effect, which arises when inexpensive machines replace human labor (Autor, 2015). This effect reduces the production costs of automated tasks, drives economic growth, and increases labor demand in non-automated sectors (Acemoglu & Restrepo, 2020). The second is capital accumulation, whereby the increase in capital accumulation spurred by automation also boosts labor demand. The third is the deepening of automation: as technology advances, machines become more efficient in already automated tasks, generating additional productivity gains without causing further displacement, thus further supporting labor demand (Acemoglu & Restrepo, 2019a).

In their seminal paper, Acemoglu and Restrepo (2018) explored concerns that automation, driven by new technological advancements, might render labor redundant in tasks that previously held a comparative advantage. Within their growth model with fixed capital and exogenous technology, they propose that automation reduces employment, the labor share, and wages, while introducing new tasks offsets these impacts. Additionally, in their growth model, where both technology and capital accumulation are endogenous, they argue that if the long-run rental rate of capital relative to wages is sufficiently low, full automation of jobs will occur in the long-run equilibrium. Conversely, if this rate is higher, automation lowers production costs by employing labor, thereby limiting further automation and fostering the creation of new jobs.

In another study, Acemoglu and Restrepo (2020) examined the effects of industrial robots on the United States (US) labor market, demonstrating theoretically and empirically that increased reliance on robots in production negatively impacts wages and employment. Similarly, Frey and Osborne (2017) analyzed the susceptibility of 702 occupations in the US labor market to computerization and reported that approximately 47% of US jobs fall into the high-risk category, likely to be automated in the near future. They also provided evidence of a strong negative relationship between wages, educational attainment, and the likelihood of computerization.

Dengler and Matthes (2018) investigated the automation potential of tasks rather than entire occupations, arguing that studies focusing solely on the automation of occupations tend to overestimate the results. Analyzing approximately 8,000 tasks using a German occupational database, they concluded that if all occupations were assumed to be replaceable, 47% of jobs could be automated, consistent with other studies. However, when considering only certain tasks as replaceable, they found that only 15% of German employees are at risk. Bertani et al. (Bertani et al., 2020), in their empirical study using data from 15 developed countries between 1995 and 2016, concluded that intangible digital investments, such as software, AI, various web services, and digital platforms, are likely to result in technological unemployment in the long run.

Ni and Obashi (2021), based on their analysis of firms in the Japanese manufacturing industry between 1995 and 2017, concluded that robot adoption at the industry level positively influenced both the job creation rate and the job destruction rate at the firm level. However, since the effect on job destruction was greater, robot adoption generally had a negative impact on firms' net employment growth. Additionally, their study indicates that the displacement effect due to robotic technology and the creation of new jobs driven by technological change can coexist at the firm level.

Consistent with Acemoglu and Restrepo (2018), Fossen and Sorgner (2022) found in their study on the US that labor-displacing digital technologies increase the risk of unemployment for individuals and suppress wage growth. In contrast, labor-reinstituting digital technologies have a positive impact on the workforce. In contrast to these studies, some research suggests that AI will increase labor demand and wages through productivity, capital accumulation, deepening automation, and reinstatement effects, which were discussed earlier.

Van Reenen (1997) conducted an empirical investigation employing fixed effects and GMM estimation techniques on a panel dataset comprising 598 firms in the British manufacturing sector over the period 1976–1982. The findings indicate that innovation exerted a positive and statistically significant impact on employment, whereas industry-level wages and union power were found to have no significant effect.

Van Roy et al. (2018) employed the system-GMM method to analyze micro-level data on European firms from 2003 to 2012. Their findings indicate that innovation, measured by citation-weighted patents, had a positive and labor-friendly effect on employment, but only within high-technology manufacturing sectors. No statistically significant relationship was observed for low-technology manufacturing and service sector firms.

Focacci (2021) provided evidence that robots do not always lead to technological unemployment in China and South Korea during the period 2008–2018. Similarly, Mutascu (2021), through an econometric analysis of 23 advanced OECD and non-OECD countries with high technology, found a non-linear relationship between the use of artificial intelligence and unemployment. He concluded that accelerating AI, particularly in low-inflation environments, can help reduce unemployment. Aligning with these findings, Dağlı (2021), using the meta-analysis method to investigate whether robots cause unemployment, concluded that using robots in production increases employment. Yang (2022) examined the impact of AI technology on firms' productivity and employee profiles in Taiwan and found that AI is positively associated with both productivity and employment. He further noted that AI has significantly altered the labor composition of firms, particularly by reducing the proportion of employees with college-level or lower educational qualifications.

Data and findings

To examine the impact of AI on employment, we estimate the following model:

$$\ln(EMP_{it}) = \alpha_i + \tau_t + \rho \ln\left(EMP_{i,t-1}\right) + \beta_1 \ln\left(AI_{pub_{i,t-1}}\right) + \beta_2 \ln(Patent_{t-1}) + \gamma_1 \ln(Prod_{it}) + \gamma_2 \ln(Wage_{it}) + \gamma_3 GDP_{growth_{it}} + \gamma_4 Openness_{it} + \gamma_5 Pop_{it} + \epsilon_{it} \quad (1)$$

where *ln* denotes the natural logarithm, α_i represents country fixed effects, τ_t denotes time fixed effects. In Eq. (1), employment (*EMP*) is the dependent variable, disaggregated by gender (male and female); age group (15–24, 25–54, 55–64), and job skill level (low-, medium-, and high-skill jobs). EMP_{t-1} captures the dynamic persistence of employment, reflecting the extent to which current employment depends on its past level due to labor market frictions and gradual adjustment processes. AI_{pub} represents AI intensity, –the key independent variable– proxied by high-quality AI publications, while *Patent* measures total patent applications and serves as an indicator of the broader technological environment. *Prod* (Productivity), *Wage* (minimum wage), GDP_{growth} (GDP per capita growth rate), *Openness* (trade openness), *Pop* (working-age population) are the control variables. The index $i = 1,2 \ldots 78$ denotes countries in the sample, $t = 2000 \ldots 2023$ indicates years, and ϵ_{it} is the idiosyncratic error term. The description of the variables along with the sources are given in Table 1.

Table 1. Description and source of the variables

Variable	Description	Source
EMP	Employment by sex, age and, occupation (thousands)	International Labour Organization (ILO, 2025)
AI_{pub}	Number of high-impact AI publications	Organization for Economic Co-operation and Development (OECD.AI, 2025)
AI_{pat}	Patent publications for AI-related technologies	World Intellectual Property Organization (WIPO, 2025)
$Prod$	Output per worker (GDP constant 2021 international $ at PPP)	International Labor Organization (ILO, 2025)
$Wage$	Minimum wage, private sector (US$)	International Labor Organization (ILO, 2025)
GDP_{growth}	GDP per capita growth (annual %)	World Development Indicators (World Bank, 2025)
$Openness$	The ratio of the sum of exports and imports to GDP	World Development Indicators (World Bank, 2025)
Pop	Population ages 15-64 (% of total population)	World Development Indicators (World Bank, 2025)

Due to the short time dimension, possible endogeneity, dynamic structure (lagged dependent variable) and heteroskedasticity/autocorrelation within units we applied two-step system GMM approach. The estimated effects of high-impact total AI scientific publications on employment, controlling for worker characteristics such as gender, skill level, and age, are reported in Tables 2–4.

Table 2 presents results for different skill–age groups without gender differentiation. According to these estimates, the focal variable of the analysis, $lnAI_{t-1}$, is positive and statistically significant for all subgroups except medium-skilled workers (across all age categories) and low-skilled prime-age workers (aged 25–54), implying that countries with higher levels of AI research tend to experience stronger job creation or retention. The strongest positive effects are observed for high-skilled workers aged 25–54 and 55–64, with coefficients of 0.196 and 0.231, respectively.

Table 2. Employment-TOTAL: AI Publications

Variables	**Low-skilled**			**Medium-skilled**			**High-skilled**		
	15-24	25-54	55-64	15-24	25-54	55-64	15-24	25-54	55-64
$lnemp_{t-1}$	0.627***	0.821***	0.558***	0.920***	0.865***	0.897***	0.491***	0.443*	0.375*
	(0.199)	(0.109)	(0.184)	(0.136)	(0.287)	(0.293)	(0.176)	(0.248)	(0.224)
$lnAI_{t-1}$	0.162*	0.069	0.130*	0.027	0.044	0.026	0.132*	0.196**	0.231**
	(0.096)	(0.044)	(0.071)	(0.048)	(0.116)	(0.106)	(0.078)	(0.097)	(0.095)
$lnpatent_{t-1}$	0.082	0.045*	0.150***	0.024	0.038	0.039	0.179***	0.173*	0.173**
	(0.077)	(0.027)	(0.054)	(0.044)	(0.077)	(0.093)	(0.049)	(0.099)	(0.068)
$lnprod_t$	-1.033*	-0.387*	-0.739**	-0.172	-0.233	-0.178	-0.683**	-0.608*	-0.485**
	(0.620)	(0.231)	(0.321)	(0.265)	(0.487)	(0.469)	(0.285)	(0.343)	(0.201)
$lnwage_t$	0.138*	0.022	0.028	0.013	-0.003	-0.003	0.047	0.009	-0.011
	(0.085)	(0.018)	(0.049)	(0.021)	(0.034)	(0.038)	(0.049)	(0.058)	(0.044)
$GDPgrowth_t$	0.011***	0.003**	0.007**	0.007***	0.002	0.003	0.009**	0.005	0.005*
	(0.003)	(0.001)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
$openness_t$	-0.001	-0.0007	-0.001	-0.0004	-0.0009	-0.0001	-0.002	-0.001	-0.002*
	(0.001)	(0.0005)	(0.001)	(0.0009)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
pop_t	-0.049*	-0.006*	-0.018	-0.010	-0.008	-0.007	-0.042**	-0.015	-0.036*
	(0.029)	(0.004)	(0.014)	(0.013)	(0.015)	(0.019)	(0.021)	(0.022)	(0.020)
$constant$	15.467*	5.675*	10.779***	2.927	4.137	2.963	11.604***	11.147**	10.836**
	(8.770)	(3.275)	(4.119)	(4.379)	(8.294)	(7.866)	(4.360)	(5.284)	(4.245)
$year\_dummy$	Included	Included	Included	Included	Included	Included	Included	Included	Included
Wald test p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
AR(1) p-value	0.004***	0.071*	0.014**	0.065*	0.179	0.088*	0.025**	0.049**	0.009***
AR(2) p-value	0.534	0.729	0.642	0.164	0.212	0.166	0.131	0.126	0.390
Hansen test p-value	0.331	0.168	0.809	0.116	0.193	0.602	0.245	0.142	0.421
Number of obs	1086	1086	1086	1086	1086	1086	1086	1086	1086
No. of instruments	34	34	52	34	34	36	53	53	33

Notes: Robust standard errors in parentheses. The instrumental variables consist of one- and two-year lags.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Turning to the results for female workers in Table 3, lagged AI publications positively and significantly affect all categories except for low- and medium-skilled prime-age women (aged 25–54). Notably, for high-skilled women aged 25–54 and 55–64, the coefficients on $lnAI_{t-1}$ are 0.386 and 0.303, respectively, the largest values across all female subgroups. These evidences suggest that AI technologies are especially compatible with the occupational structure of high-skilled, prime-age female workers, such as those in healthcare, education, and administrative services. AI tends to play a strongly complementary rather than a displacing role in this labor force segment.

Table 3. Employment-FEMALE: AI Publications

Variables	Low-skilled			Medium-skilled			High-skilled		
	15-24	25-54	55-64	15-24	25-54	55-64	15-24	25-54	55-64
$lnemp_{t-1}$	0.594***	1.132***	0.478***	0.896***	0.763***	0.817***	0.409**	-0.102	-0.592
	(0.139)	(0.192)	(0.170)	(0.062)	(0.207)	(0.081)	(0.166)	(0.485)	(0.325)
$lnAI_{t-1}$	0.208**	-0.053	0.142**	0.062**	0.093	0.060*	0.120*	0.386*	0.303**
	(0.094)	(0.078)	(0.069)	(0.031)	(0.076)	(0.031)	(0.070)	(0.208)	(0.135)
$lnpatent_{t-1}$	0.070	-0.027	0.156***	0.023	0.059	0.061**	0.250***	0.317**	0.286**
	(0.067)	(0.042)	(0.056)	(0.025)	(0.059)	(0.027)	(0.074)	(0.155)	(0.116)
$lnprod_t$	-1.063**	0.253	-0.706**	-0.265*	-0.389	-0.287**	-0.797***	-1.214**	-0.171
	(0.487)	(0.403)	(0.279)	(0.138)	(0.316)	(0.119)	(0.295)	(0.592)	(0.287)
$lnwage_t$	0.147*	-0.017	0.045	0.015	-0.008	-0.004	0.056	0.084	-0.157
	(0.083)	(0.039)	(0.049)	(0.016)	(0.025)	(0.016)	(0.054)	(0.090)	(0.141)
$GDPgrowth_t$	0.008	0.005**	0.007	0.010***	0.003	0.004**	0.007*	0.010*	0.004
	(0.005)	(0.002)	(0.005)	(0.002)	(0.002)	(0.001)	(0.004)	(0.006)	(0.007)
$openness_t$	-0.001	0.0004	-0.002	0.0004	-0.001	-0.0008	-0.002	-0.003	-0.005**
	(0.001)	(0.0007)	(0.002)	(0.0004)	(0.001)	(0.0006)	(0.001)	(0.002)	(0.002)
pop_t	-0.044**	0.0003	-0.005	-0.009	-0.009	-0.007	-0.046*	-0.033	-0.033
	(0.022)	(0.004)	(0.020)	(0.007)	(0.009)	(0.005)	(0.023)	(0.039)	(0.038)
$constant$	16.403***	-3.386	9.647***	3.913*	6.592	4.486**	12.587***	26.448**	9.287*
	(6.256)	(5.256)	(3.550)	(2.021)	(5.338)	(1.873)	(3.921)	(10.195)	(4.919)
$year\_dummy$	Included	Included	Included	Included	Included	Included	Included	Included	Included
Wald test p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
AR(1) p-value	0.000***	0.043**	0.007***	0.028**	0.086*	0.053*	0.007***	0.003***	0.055*
AR(2) p-value	0.430	0.730	0.597	0.143	0.147	0.236	0.106	0.147	0.562
Hansen test p-value	0.472	0.216	0.571	0.864	0.141	0.268	0.130	0.570	0.689
Number of obs	1079	1086	1085	1086	1086	1086	1086	1086	1086
No. of instruments	35	33	52	36	32	52	53	37	53

Notes: Robust standard errors in parentheses. The instrumental variables consist of one- and two-year lags.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Similar patterns emerge in Table 4, which reports results for male workers disaggregated by age and skill. Specifically, lagged high-impact AI publications have no significant effect on medium-skilled male workers across all age groups, potentially reflecting that automation risks and skill polarization are more concentrated in middle-skill routine occupations. On the other hand, they positively and significantly affect low-skilled male workers, except those aged 25–54. Moreover, for high-skilled male workers across all age categories, lagged AI activity significantly increases employment, with the largest effects again observed for the 25–54 and 55–64 age groups (0.215 and 0.224, respectively), echoing Blanas et al. (2019) on high-skilled older men. These groups may benefit from AI-related productivity enhancements in manufacturing, engineering, and technical services. These findings are broadly consistent with the RBTC hypothesis, whereby technology disproportionately complements high-skilled and non-routine work and creates complementary opportunities for some low-skilled groups, especially at early career stages.

Table 4. Employment-MALE: AI Publications

Variables	Low-skilled			Medium-skilled			High-skilled		
	15-24	25-54	55-64	15-24	25-54	55-64	15-24	25-54	55-64
$lnemp_{t-1}$	0.527***	0.678***	0.690***	0.875***	0.769***	0.685***	0.747***	0.483**	0.453**
	(0.189)	(0.238)	(0.125)	(0.107)	(0.297)	(0.178)	(0.125)	(0.191)	(0.184)
$lnAI_{t-1}$	0.184**	0.106	0.092*	0.039	0.067	0.105	0.090*	0.215**	0.224***
	(0.084)	(0.081)	(0.050)	(0.036)	(0.112)	(0.069)	(0.052)	(0.085)	(0.082)
$lnpatent_{t-1}$	0.122	0.098	0.117**	0.040	0.072	0.096*	0.076**	0.125**	0.145***
	(0.085)	(0.089)	(0.052)	(0.042)	(0.083)	(0.057)	(0.036)	(0.062)	(0.055)
$lnprod_t$	-1.239**	-0.698	-0.614**	-0.251	-0.397	-0.444	-0.394**	-0.556*	-0.495***
	(0.564)	(0.548)	(0.258)	(0.214)	(0.528)	(0.308)	(0.183)	(0.291)	(0.193)
$lnwage_t$	0.127*	0.035	0.026	0.010	-0.004	-0.017	0.026	0.025	0.010
	(0.075)	(0.045)	(0.031)	(0.021)	(0.037)	(0.044)	(0.021)	(0.048)	(0.028)
$GDPgrowth_t$	0.011***	0.005*	0.009***	0.008***	0.003	0.007**	0.012***	0.005	0.004*
	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.003)	(0.001)	(0.004)	(0.002)
$openness_t$	-0.002*	-0.001	-0.001	-0.0008	-0.001	-0.001	-0.0008	-0.001	-0.002*
	(0.001)	(0.001)	(0.001)	(0.0009)	(0.001)	(0.001)	(0.0007)	(0.001)	(0.001)
pop_t	-0.057**	-0.017	-0.008	-0.010	-0.009	-0.011	-0.023**	-0.016	-0.026*
	(0.026)	(0.015)	(0.012)	(0.010)	(0.016)	(0.015)	(0.010)	(0.015)	(0.015)
$constant$	18.549**	10.196	8.015**	3.868	6.518	7.340	6.424**	10.263**	9.645***
	(7.809)	(7.500)	(3.150)	(3.161)	(8.526)	(4.493)	(2.886)	(4.096)	(3.501)
$year\_dummy$	Included	Included	Included	Included	Included	Included	Included	Included	Included

Wald test p-value	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
AR(1) p-value	0.004***	0.023**	0.007***	0.059*	0.182	0.098*	0.004***	0.033**	0.006***
AR(2) p-value	0.420	0.944	0.870	0.189	0.226	0.150	0.109	0.106	0.263
Hansen test p-value	0.326	0.402	0.813	0.474	0.177	0.682	0.407	0.249	0.300
Number of obs	1086	1086	1086	1086	1086	1086	1086	1086	1086
No. of instruments	33	33	52	53	35	53	23	53	33

Notes: Robust standard errors in parentheses. The instrumental variables consist of one- and two-year lags.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Conclusion

The results from our model highlight that artificial intelligence, measured by high-quality AI publications, has a significant and heterogeneous impact on employment. While AI adoption poses displacement risks for younger and low-skilled workers, it appears to complement high-skilled employment, supporting the notion that technological progress generates uneven labor market outcomes. These findings underscore the need for policies that promote skill upgrading and adaptability to ensure that the benefits of AI are broadly shared across the workforce.

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