Unveiling the impact of artificial intelligence on economic growth: An inter-regional evidence from macroeconomic panel data

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Artificial Intelligence, Economic Growth, East Asia, Eastern Europe, Latin America and the Caribbean, Western Europe

Abstract

Purpose of the research: *Artificial Intelligence (AI) is a major technological upheaval of Industry 4.0 with far reaching macro-economic implications across the globe. This study investigate the impact of AI on economic growth using macro dataset of 45 global economies during 2010-2023. The economies are grouped into four regions including Latin America and the Caribbean, Western Europe, Eastern Europe and East Asia.*

Methodology: *The economic growth is modelled as a function of AI innovations, production inputs including physical capital and human capital, control regressor including institutional quality and inflation. The study employs PMG-ARDL (Panel Pooled Mean Grouped-Autoregressive Distributed Lag) method.*

Findings: *The significant positive impact of AI innovations on productivity led growth is only found in the sample of Western Europe. The short run and long run results empirically confirm regional heterogeneity in the AI-economic growth relationship.*

Practical implications and Conclusions: *The regional heterogeneity reflect differences in economic characteristics, degree of AI adoption, quality of institutions and human skills across regions. Therefore, provision of more stable AI landscape and striking a balance between automating human tasks and augmenting human skills with AI is needed.*

Introduction

In neoclassical and endogenous economic growth models, technical change brings about significant increases in productivity, resulting in economic growth. To align with this, breakthroughs in computing technology i.e. Artificial Intelligence (AI) should also necessitate increase in economic growth. Furman and Seamans (2019) describe AI as a range of advanced technologies including machine learning, autonomous robotics, language processing, and computer vision, virtual agents that exhibit human-like intelligence. Both optimistic and pessimistic views related to AI induced economic growth are reported in literature. In context to optimistic views, the IMF simulations performed by Cerutti et al. (2025) claimed that, global total factor productivity grows by 2.4% in 10 years (in the first scenario of rapid adoption and diffusion of AI) leading to a 4% increase in global GDP compared with the trajectory without AI. In the second scenario of slower adoption and diffusion of AI, total factor productivity grows by only 1.8% with limited GDP growth to 1.3% in 10 years. Misch et al. (2025) projected persistent gaps even within Europe. They estimated an average productivity gain of 0.8 percent but with significant disparities i.e. up to 1 percent in Luxembourg but barely 0.5 percent in Romania. These geographical differences are due to various institutional and structural factors for each country. The integration of AI in developed EU regions is supported by skilled workforce and necessary infrastructure, whereas, the integration of AI in less developed EU regions is constrained by skill shortages. In context to pessimistic views pertaining to AI-growth nexus, the acceleration of AI development and its diffusion has not been significantly associated with higher productivity augmented growth so far. The delayed productivity augmented growth responses are common to General Purpose Technologies as supported by Brynjolfsson et al. (2021). They argued that new technologies initially require substantial investment in complementary inputs (intangible investment) before they can bring productivity augmented gains. This leads to a J-shaped productivity curve. Another plausible cause of delayed effects of AI on economic growth provided by Bughin et al. (2018) is S-curve pattern of AI adoption. This is due to the slow adoption by many countries at the beginning, high costs, and the necessary investments of adapting the technology to ensure the full adoption of these technologies.

In the light of the previous discussion, this research aims to contribute in literature to bridge the gap between theoretical findings and contradictory empirics regarding AI-growth nexus. The study's originality lies in its geographical focus and methodological considerations. The study augment traditional Cobb Douglas production function by explicitly taking AI as a technology factor alongside conventional production inputs. Unlike conventional aggregated cross country studies, this study offers region specific insights on the subject matter.

Literature review

Several economic papers including Lach (1995) and Kim et al. (2012) have been published on subject matter approximating technology with divergent measures including patents, scientific journals, internet penetration, robot density, AI readiness index, computer ownership, generative AI adoption, AI software expenditure and AI publications. The Schoenherr et al. (2020) showed that AI has a positive impact on GDP. They found that a 10 percent increase in AI intensity (approximated by the number of AI patents per capita) is associated with a 0.3 percent increase in GDP. They also found that the impact of AI on GDP is stronger in high-income countries and particularly in the services sector compared to other sectors. In contrast to this, Blind et al. (2022) found no significant impact of patents on economic growth. Gonzales (2023) concluded robust positive long-run relationship between economic growth and AI during 1970-2019 in case of advanced economies. He utilized number of patents as a measure of AI and claimed that positive impact of AI was more evident towards latter periods of the data. A recent study by Kalai et al. (2024) investigated symmetric and non-symmetric effects of AI on economic growth for 30 European countries during 2000-2021. They concluded that 1 percent positive shock in AI increases economic growth by 0.217 percent, whereas, 1 percent negative shock in AI leads to decline in economic growth by 0.0029 percent.

With this review of literature, it can be safely concluded that association between economic growth and AI is a complex and evolving area of research. Furthermore, AI led long-run productivity gains and growth potentials are likely to be uncertain and greatly depends on various conditions thus leads to productivity paradox. This in turn calls for more research on the subject matter.

Research methodology

Data

Our sample of 45 global economies are grouped as (i) Latin America and Caribbean (LA&C), (ii) Western Europe (WE), (iii) Eastern Europe (EE) (iv) East Asia (EA). The regional grouping is adapted from Oxford Insights (2023) Government AI readiness index. Few regions are excluded owing to missing observations (e.g. Africa) and inadequate number of cross sectional units in a panel to satisfy empirical methodological requirements (e.g. North America). The data has been sourced from Penn World Table, World Intellectual Property Organization, World Governance Indicators and World Development Indicators. Table 1 reports study variables in detail.

Variables	Symbols	Proxies
Economic Growth	$\mathbf{y}_{it}$	Growth rate of real output per employed person (%)
Artificial Intelligence	$\mathbf{AI}_{it}$	Patent publications for AI-related technology by origin (Numbers)
Capital	$\boldsymbol{K}_{it}$	Growth rate of real capital stock per employed person (%)
Human Capital	$\mathbf{hc}_{it}$	Growth rate of human capital index (%)
Institutional Quality	$\mathbf{IQ}_{it}$	Rule of law index (0-100)
Inflation	$\mathbf{Inf}_{it}$	Consumer Price index based inflation rate (%)

Table 1: Delineate of the Indicators

Model Specification

To unveil the impact of AI on economic growth, augmented Cobb-Douglas production function is utilized for 45 economies during 2010-2023. The following econometric specification is used in this study.

$$y_{it} = \psi_0 + \psi_1 \ln AI_{it} + \psi_2 k_{it} + \psi_3 hc_{it} + \psi_4 \ln IQ_{it} + \psi_5 Inf_{it} + \varepsilon_{it}$$

The symbols of variables are discussed in table 1. The psi naught $\psi_0 \ldots\ \psi_5$ are regression coefficients, "ln" denotes log and ε_{it} is the residual term.

Econometric Methodology

After examining cross sectional dependence and panel unit root properties of the data, we use Pooled Mean Group–Autoregressive Distributed Lag (PMG-ARDL) method proposed by Pesaran et al. (1999). The PMG-ARDL method is strongly recommended dynamic panel estimation strategy as (i) it allows variables to be of mixed order integration i.e. I(0) and I(1) (ii) it reduces dynamic specification bias by explicitly modelling lag structures (iii) it allows heterogeneity in short run coefficients while maintain homogeneity in long run coefficients. After estimating PMG-ARDL model, this study employs Pesaran CD (Cross sectional Dependence) test to check whether residuals are cross-sectionally dependent or independent? The PMG-ARDL results are deemed reliable if there is no cross sectional dependence. If there is cross sectional dependence then the literature recommends to use Common Correlated Effects (CCE) augmented PMG-ARDL estimator.

Findings

The results of pre-estimation tests i.e. summary statistics, correlation test, CD test, panel unit root test, Pedroni Co-integration test and Hausman test are not reported here to conserve the space. However, the detailed results can be obtained from the author upon reasonable request. In table 2, probability values are reported in parenthesis below the estimated regression coefficients. The PMG-ARDL model assumes homogeneity in the long run results.

PMG-ARDL Homogenous Long Run Results

Region	LA&C	WE	EE	EA
AI_{it}	-0.002 (0.790)	0.016* (0.005)	0.002 (0.558)	0.001 (0.627)
k_{it}	-0.049 (0.547)	0.213* (0.000)	-0.125* (0.005)	-0.032* (0.003)
hc_{it}	-0.888 (0.806)	0.642 (0.550)	-0.685 (0.285)	0.995* (0.004)
IQ_{it}	0.295* (0.000)	0.128* (0.028)	0.069 (0.229)	0.070* (0.002)
Inf_{it}	-0.002 (0.246)	-0.001 (0.181)	-0.001 (0.190)	0.004* (0.000)
ECT_{t-1}	-0.59* (0.00)	-0.86* (0.00)	-0.88* (0.00)	-0.99* (0.00)
ΔAI_{it}	0.011 (0.364)	-0.007 (0.478)	0.005 (0.437)	-0.014 (0.416)
Δk_{it}	0.365* (0.030)	0.217 (0.375)	1.069* (0.001)	0.256 (0.501)
Δhc_{it}	-1.606 (0.297)	1.842 (0.071)	0.452 (0.832)	0.0516 (0.914)
ΔIQ_{it}	.1869* (0.009)	0.438 (0.254)	-0.021 (0.882)	-0.268 (0.610)
ΔInf_{it}	0.003 (0.143)	0.006* (0.000)	0.009* (0.000)	-0.001 (0.280)
Constant	1.063* (0.000)	-2.003* (0.000)	1.186* (0.000)	0.110* (0.000)

Table 2: PMG-ARDL Results

The statistical significance and negative sign of lagged error correction term (ECT_{t-1}) in all four panels confirm presence of long run relationship among the variables. The lowest speed of adjustment towards long run equilibrium is reported in case of Latin America and the Caribbean i.e. 59% per annum. The positive impact of AI on productivity augmented growth is observed in the sample of Western Europe, Eastern Europe and East Asia. However, it is statistically significant only in Western Europe. The coefficient of AI in Western Europe can be interpreted as one percent increase in AI innovations (approximated by AI patents), on average, has increased economic growth (approximated by growth rate of output per worker) by 0.016 percent in the long run. This finding is consistent with the empirical work of Gonzales (2023). In the sample of Latin America and Caribbean, the impact of AI on economic growth is negative and insignificant. This in turn confirms the hypothesis that impact of AI on economic growth is not uniform across all regions around the globe during our sample period. This finding is empirically consistent with Blind et al. (2022). In Western Europe sample, all three variables i.e. physical capital, human capital and institutional quality have positively contributed in economic growth, whereas, inflation appeared to be statistically insignificant. In Latin America and the Caribbean sample, out of five variables, only institutional quality appeared to be statistically significant. In case of Eastern Europe, physical capital is statistically significant determinant of economic growth but its relationship is theoretically unexpected. This can be explained as many Eastern European economies have witnessed structural transformation during 1990s and 2000s. They have witnessed capital deepening but lesser efforts were made to focus on technological advancements and human capital advancements. Moreover, these economies have also experienced population ageing and emigration of skilled workers which can be attributed to negative impact of capital per worker on output per worker during reference period. In case of East Asia, out of five variables, four variables are statistically significant long run determinants of economic growth. The institutional quality, human capital and inflation all three variables have appeared to be growth inducing during reference period. Whereas, on average, capital per worker growth has a negative statistical significant impact on output per worker growth. The negative impact of capital per worker on output per worker can be justified as our sample of East Asia includes economies like South Korea, China, Japan and Singapore. All these economies have successfully climbed advanced stages of development where capital accumulation may not be regarded as primary driver of productivity led growth. The post estimation diagnostic check of PMG-ARDL long run results is done with Pesaran CD residual test, and all results are found to be reliable.

PMG-ARDL Country Specific Short Run Results

The PMG-ARDL technique allows to calculate country specific heterogeneous short run results. In our sample, the Latin America & Caribbean panel includes Argentina, Barbados, Brazil, Chile, Colombia and Mexico. The Western Europe panel includes Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Iceland, Ireland, Italy, Luxembourg, Malta, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland and United Kingdom. The Eastern Europe panel includes Bulgaria, Croatia, Czech Republic, Estonia, Hungary, Poland, Romania, Russian Federation, Serbia, Slovakia, Slovenia, and Ukraine. The East Asia panel includes China, Japan, Malaysia, Philippines, Republic of Korea, Singapore and Thailand. The detailed short run results of PMG-ARDL model pertaining to 45 cross sectional units are not reported to conserve the space.

The country specific lagged error correction terms are negatively signed and statistically significant (except for few countries) thus confirming convergence to long run equilibrium with varying degrees of adjustment. In LA&C panel, no variable is appeared to be statistically significant determinant of economic growth in Argentina. In Barbados, only AI innovations with reported coefficient 0.069 have contributed positively towards productivity augmented growth. In Brazil, capital per worker growth with coefficient 0.62, institutional quality with coefficient 0.22 and inflation with coefficient 0.002 are statistical significant determinants of output per worker growth. In case of Chile, two variables i.e. physical capital with coefficient 0.52 and institutional quality with coefficient 0.39 have positively contributed short run productivity augmented growth. In Colombia, human capital with coefficient 0.89 and institutional quality with coefficient 0.31 are statistically significant and have exerted positive impact on our outcome variable. In Mexico, all variables are statistically significant determinants of economic growth.

In Western Europe panel, the impact of AI innovations on economic growth is statistically significant only in Denmark, France, Malta and UK with reported coefficients 0.031, 0.08, -0.07 and -0.09 respectively. The variable physical capital appeared to be statistically significant in Austria, Ireland, Italy, Netherlands and Switzerland with mixed impacts. In addition, positive and significant impact of human capital on economic growth is found in Austria, Finland, Germany, Greece, Iceland, Italy, Spain, Switzerland and United Kingdom. The highest magnitude of human capital is reported in case of United Kingdom i.e. 9.131 units. The other two explanatory variables i.e. institutional quality and inflation are appeared to be statistically significant. The institutional quality variable is significant in Belgium, France, Iceland, Ireland, Netherlands, Norway, Sweden and Switzerland. The variable inflation is significant in France, Greece, Iceland, Ireland, Netherlands, Norway, Portugal, Spain and Switzerland during sample period. In Eastern Europe panel, mixed impact of AI innovations on economic growth is found in Bulgaria, Czech Republic, Hungary, Romania, Slovakia and Ukraine with reported coefficients i.e. -0.04, 0.04, 0.02, 0.02, 0.03 and -0.03 respectively. The other significant short run determinants of economic growth are divergent across twelve economies of Eastern Europe. In Eastern Asia panel, AI innovations and institutional quality are appeared to be significantly impacting productivity led growth in China. In Japan and Republic of Korea, none of the variable is appeared to be statistically significant during reference period. In Malaysia, only inflation has appeared significantly associated with economic growth. In Philippines, all variables are significantly impacting growth except institutional quality. In Singapore, all variables are impacting economic growth except inflation. In Thailand, all variables are significantly impacting economic growth except human capital and inflation.

Discussions and conclusion

This study empirically investigate the impact of AI on economic growth using PMG-ARDL method across 45 economies during 2010-2023. The long run empirical results shows positive impact of AI on economic growth (productivity led growth) in three regions except Latin America and Caribbean. However, it is statistically significant only in Western Europe. The insignificance of AI innovations for long run economic growth in our three regions can be explained as these regions are highly diversified in terms of AI patents, AI readiness, human capital development and technology diffusion. For instance, in case of Eastern Europe panel, we have economies like Estonia, Czech Republic (best performers in terms of AI innovation, adoption and diffusion) and Bosnia and Herzegovina (lagging in terms of AI innovation, adoption and diffusion).This in turn can lead to dismal picture (on average) regarding impact of AI on economic growth. Same phenomenon is observed in case of Latin America and the Caribbean panel as it is comprising of Brazil (leading economy in terms of AI innovation, adoption and diffusion) and Haiti (lagging economy in terms of AI innovation, adoption and diffusion) as compared to other economies in the respective region. The region of East Asia also show similar trends as it includes South Korea, China, Singapore (leading economies) and Myanmar (lagging economy) as compared to other economies in the region. Based on these findings, it is strongly recommended that inter-regional and intra-regional differences in degree of AI adoption in case of Latin America and Caribbean, Eastern Europe and East Asia needs to be reduced. This can only be achieved by providing more stable AI landscape and striking a balance between automating human tasks (substitution) and augmenting human skills (complementing) with AI. Whereas, developed economies (Western Europe) are encouraged to further strengthen AI-innovations ecosystem to reap growth inducing benefits.

Limitations and direction for future research

Several paths for future research can be pursued. Prominent are calculations of asymmetric impacts of AI on economic growth and utilization of Panel Smooth Transition Regression (PSTR) model to calculate threshold levels of AI adoption.

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