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DOI: https://doi.org/10.14195/2183-203X_61_3

Economic Growth, AI Adoption and Human Capital Across the OECD: Evidence from a Panel ARDL Model

Crescimento Económico, Adoção de IA e Capital Humano nos Países da OCDE: Evidência a partir de um modelo ARDL de painel

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Received for publication: August 28, 2025
Revision accepted for publication: November 9, 2025

ABSTRACT
Technological progress is a key driver of long-term growth and increases in standards of living across generations, but its benefits often materialise with delay due to adjustment costs and the need for complementary investments. This study examines these dynamics for artificial intelligence (AI), whose rapid diffusion has raised expectations about its economic impact. As with previous waves of technological progress and innovation, there are also important concerns on how work will be shaped by the proliferation of AI as it may potentially benefit certain types of human capital. Using a panel ARDL model for 35 OECD countries from 1995 to 2017, we estimate the short- and long-run effects of AI adoption on growth and living standards. The ARDL framework captures the gradual adjustment process and allows us to incorporate human capital by interacting it with AI, assessing whether the benefits of AI differ across skill levels. Our preferred results, based on patents data and first differenced GMM, suggest that AI adoption already contributes to short-run growth and leads to long run improvements in standards of living, although these results are not supported in all contexts. Regarding the role of human capital, our aggregate data provides no evidence that AI benefits any particular group of workers, neither highly educated

nor less-educated ones. Our research is limited by the current state of AI technology, which is advancing rapidly, and proxies available; therefore, the validity of our present, optimistic findings must be continually re-evaluated.
Keywords: *Artificial Intelligence, Technological Progress, Human Capital, Economic Growth, OECD, Panel ARDL.*

JEL Classification: C33; O33; O47

RESUMO

O progresso tecnológico é um dos principais motores do crescimento de longo prazo e do aumento dos padrões de vida ao longo das gerações, mas os seus benefícios tendem a materializar-se com atraso devido a custos de ajustamento e à necessidade de investimentos complementares. Este estudo analisa estas dinâmicas no caso da inteligência artificial (IA), cuja rápida difusão elevou as expectativas quanto ao seu impacto económico. Tal como em vagas anteriores de progresso tecnológico e inovação, existem também importantes preocupações sobre a forma como o emprego será moldado pela proliferação da IA, uma vez que esta poderá potencialmente beneficiar certos tipos de capital humano. Utilizando um modelo ARDL em painel para 35 países da OCDE entre 1995 e 2017, estimamos os efeitos de curto e longo prazo da adoção de IA no crescimento e nos padrões de vida. O enquadramento ARDL capta o processo gradual de ajustamento e permite incorporar o capital humano mediante a sua interação com a IA, avaliando se os benefícios desta diferem consoante os níveis de qualificação. Os nossos resultados preferidos, baseados em dados de patentes e no método GMM em primeiras diferenças, sugerem que a adoção de IA já contribui para o crescimento de curto prazo e conduz a melhorias de longo prazo nos padrões de vida, embora estes resultados não se verifiquem em todos os contextos. Quanto ao papel do capital humano, os nossos dados agregados não fornecem evidência de que a IA beneficie qualquer grupo específico de trabalhadores, sejam eles mais ou menos qualificados. A nossa investigação é limitada pelo estado atual da tecnologia de IA, que evolui rapidamente, e pelas proxies disponíveis; por isso, a validade das nossas conclusões, atualmente otimistas, deve ser continuamente reavaliada.

Funding: This work has been funded by national funds through FCT – Fundaçãopara a Ciência e a Tecnologia, I.P., through project UIDB/05037/2025 with DOI 10.54499/UIDB/05037/2025.

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1. Introduction

Artificial intelligence (AI) stands out as a key driver of transformation, OECD (2019), Briggs and Kodnani (2023), Lagarde (2025). Economically, AI is reshaping how businesses operate, with the potential to boost productivity and efficiency, thereby fostering economic growth and enhancing the well-being of present and future generations. As AI continues to evolve, it becomes increasingly important to understand its impact on economic growth and standards of living, Trabelsi (2024). The implications of the widespread adoption of AI for business performance and economic growth are also tightly linked with human capital. While some workers may be negatively affected by AI technologies, others stand to benefit, largely depending on whether AI substitutes or complements their particular skill sets, see e.g. Autor (2015), Acemoglu & Restrepo (2019), Brynjolfsson, Li, & Raymond (2025), Bughin (2025).

Economic growth, i.e. the sustained increase in the capacity of production of goods and services by an economy is fundamental to ensuring the continuous improvement of living standards across generations. While growth can stem from greater availability of inputs such as physical and human capital, its most significant drivers are gains in efficiency and productivity in the use of these resources. Endogenous growth models identify technological progress and productivity improvements as the main source of growth, Romer (1986), Romer (1990), Jones (1995), but Solow (1956) already concluded that improvements in technology, considered exogenous, are a necessary condition for sustained growth. Indeed, since the pioneering contributions of Solow (1956) and Swan (1956), it has been widely accepted that technological progress is the primary engine of sustained output growth, enabling economies to overcome the limitations of diminishing marginal returns. In this context, AI, as a transformative technological innovation, holds the potential to become a key driver of sustained economic growth, Trammell and Korinek (2023).

Organizations such as the Organisation for Economic Cooperation and Development (OECD) and the European Commission (EC) project that AI could have a profound impact on the economy, potentially driving substantial gains in GDP (Filippucci et al. (2024); Righi et al. (2022)). For instance, Szczepański (2019) estimates that AI could contribute up to 13 trillion USD to the global economy by 2030, positioning it as a key engine of growth, particularly in OECD countries, where advanced technological and digital infrastructures are already in place. In these economies, AI is transforming sectors like marketing and sales, transportation, logistics, and manufacturing, fuelling a digital revolution that is significantly boosting productivity and supporting long-term, sustainable economic growth, OECD (2019). Briggs and Kodnani (2023) estimate that widespread AI adoption could eventually drive a 7% or almost seven trillion USD increase in annual global GDP over a 10-year period.

AI drives economic growth through multiple channels that enhance resource efficiency and stimulate innovation. One key mechanism is its ability to automate routine and time-consuming tasks. This automation frees up human capital for higher value-added activities, thereby improving efficiency and boosting productivity, Agrawal et al. (2019), Brynjolfsson, Li, & Raymond (2025), Bick, Blandin, and Deming (2025). Additionally, AI's powerful capacity to process and analyse vast amounts of data in real time fosters continuous innovation in production methods, leading to the creation of new products and services, Furman & Seamans (2019). Beyond its ability to significantly enhance total factor productivity by enabling more effective use of both human and capital inputs, AI has also the ability to enhance the competitiveness of firms. It empowers businesses to innovate continuously and respond to market shifts with greater agility and precision. Brynjolfsson and McAfee (2014) emphasize that AI encourages firms to embrace knowledge development and constant innovation, essential traits for staying adaptive in an increasingly competitive global market. Moreover, technological change driven by AI tends to be skill-biased; however, the extent to which different skills benefit from AI advancements depends on whether AI acts as a substitute or a complement. Empirical studies using microdata have yielded mixed and sometimes contradictory findings on this relationship. For instance, Bughin (2025) based on data from a global survey across 14 industries and 10 countries finds that while AI is skill-biased in favour of more advanced skills, the effect of AI on skill demand is usually positive for most skills. Brynjolfsson, Li, & Raymond (2025) study the effect of generative AI on productivity and worker experience in the customer-service sector and find that less-skilled workers benefit more.

There may also be different effects of AI on economic growth in the short and long run. In the short run, the impact of AI may be moderated by some transition factors, such as workforce adjustments and the initial costs of technological adoption. Expanding the use of AI requires large investments and at least some skilled labour, as well as a number of changes to production processes. Concerns about a potential surge in technological unemployment due to the unprecedented scale and impact of these innovations could also slow their adoption. These initial costs can cause economic growth to slow down, and thus it may take some time to realise that AI is having an impact on the economy.

Three recent studies examine the impact of AI on economic growth. While Gonzales (2023) and Kalai, Becha, and Helali (2024) do so directly, Parteka and Kordalska (2023) explore it through the lens of labour productivity. Our study builds on this prior research by examining the impact of AI on macroeconomic performance, with a particular focus on OECD countries and the distinction between short- and long-run effects. These three related studies reach different conclusion on the impact of AI on macroeconomic performance, the measure of which differs across studies, as well as the sample of countries analysed, time coverage and estimation procedures applied. Table 1 provides a summary and overview of the former studies.

Table 1. Summary and overview of prior background studies

Reference	Sample	Methods	Dependent variable	Explanatory variables	Main Results
Gonzales (2023)	165 countries 1970-2019 (data at 5-year intervals)	GMM	Growth of real GDP per capita	AI patents per million people. Gross capital formation per capita. Human capita index. Population growth. Government expenditure per capita. Trade openness. Inflation.	AI has a positive effect on growth , stronger in advanced economies. The effect is weaker or non-significant in developing countries.
Kalai, Becha, & Helali (2024)	30 European countries 2000-2021	PMG-ARDL PMG-NARDL	Growth of real GDP	Patents for technologies related to artificial intelligence. Labour force participation rate. Gross fixed capital formation (% of GDP). Foreign direct investment (% of GDP). R&D expenses (% of GDP). Inflation (% of consumer price index)..	AI has a positive long-run impact on output and growth. Evidence of asymmetric effects: negative shocks to AI have a stronger detrimental impact than the positive effect of AI increases.
Parteka & Kordalska (2023)	35 OECD plus 28 non-OECD countries 1985-2017 (5-period moving average)	OLS with fixed effects. IV estimation.	Labour productivity (output per hour worked/ per person employed) growth	AI patents identified by the applicant's country of residence per millions of persons employed. AI patents identified by the inventor's country of residence per millions of persons employed. Number of peer-reviewed AI scientific publications recorded in the Elsevier/Scopus database. General innovation. Human capital index. Trade openness. Regulatory quality index.	Limited evidence that AI patent stocks significantly drive productivity growth at aggregate level.

AI has been shown to positively influence economic growth by Gonzales (2023) that conducted a panel data study analysing the impact of AI on economic growth in both advanced and developing economies over the period from 1970 to 2019, with data taken at five-year intervals, covering a total of 165 countries. The study measured AI-driven technological adoption through the number of AI-related patents and included this proxy as the explanatory variable of interest in an ad hoc growth regression based on an aggregate Cobb-Douglas production function with physical and human capital. The level of technology is assumed to be endogenous, a la Romer (1990), and determined by AI related innovation. To address issues of endogeneity and reverse causality the growth regression was estimated using the Generalized Method of Moments (GMM). The findings indicate that AI has a positive effect on economic growth, measured as the growth rate of real GDP per capita, particularly in advanced economies that possess the capacity to implement and leverage these technologies effectively. In developing countries, the link between AI and economic growth tends to be weaker or non-existent. For a smaller and more homogenous group of countries composed of 30 European countries and distinguishing between medium- and long-term effects for a shorter overall period, 2000-2021, Kalai, Becha, and Helali (2024) also conclude, using symmetric (PMG-ARDL) and asymmetric (PMG-NARDL) models derived from an endogenous growth model as in Gonzales (2023), that there is positive impact of AI on growth to which accrues a positive long-run impact on the level of output, identifying also an asymmetric effect corresponding to a slightly more intense detrimental growth impact from a negative shock to AI. The dependent variable is the growth rate of total real GDP and the explanatory variable of interest the number of AI patents, considered alongside other determinants of growth identified by previous literature.

Parteka and Kordalska (2023) explore the relationship between AI and aggregate labour productivity using data on AI-related patents and scientific publications across 35 OECD and 28 non-OECD countries from 1985 to 2017. Despite the evident increase in AI knowledge production, as reflected in the growth of patent and publication activity, the authors found limited evidence that accumulated AI patent stocks significantly contribute to productivity growth, both in OECD countries and in the broader sample. They suggest that other dynamics may be at play at the micro and sectoral levels, where the adoption of digital technologies could lead to productivity gains at the firm level, without necessarily translating into growth at the aggregate level. Furthermore, the study highlights that group preconditions, such as investment in human capital and supportive innovation policies, play a crucial role in shaping AI's economic impact.

In summary, the role of technological progress as a primary determinant of modern economic growth and long-term improvements in living standards is undeniable. However, its effects are frequently realized with a time lag. This delay can be attributed to adjustment costs, including the requirement for supporting investments and workforce reskilling, as well as the time needed for consequent sectoral transformations to fully manifest. This research examines these dynamics in relation to AI, a rapidly advancing technology whose increasing prevalence has fostered substantial expectations for its potential to enhance macroeconomic outcomes and societal well-being. We also examine whether the growth effects of AI vary across countries with different skill endowments, providing insight into whether AI complements or substitutes human capabilities at the aggregate level. To investigate the impact of AI adoption on economic growth and standards of living and the role of human capital we consider a sample of 35 OECD countries observed annually over the period 1995-2017 and estimate a panel autoregressive distributed lag (ARDL) model, assessing the existence of long-run relationships and identifying short-run impacts.

The contribution of this study is twofold. First, it adds to the discussion on the economic effects of AI adoption and what types of labour benefit more from AI advancements by taking stock of the evidence at the macroeconomic level. At the microeconomic level previous studies have identified productivity gains from AI adoption within firms, e.g. Damioli, Van Roy, and Vertesy (2021) using a worldwide sample of 5257 companies, and Zhai and Liu (2023) using a sample of Chinese-listed companies, but less is known about its effects for the aggregate economy. Micro-level evidence on the role of human capital remains mixed. Bughin (2025) finds that although AI is biased toward higher skills, it generally boosts demand across most skill levels. Brynjolfsson, Li, & Raymond (2025) show that generative AI can particularly benefit lower-skilled workers, enhancing their productivity. Second, we extend the limited set of papers examining the macroeconomic outcomes of AI adoption by disentangling the respective short and long-run effects. As Hornstein (2024) emphasizes, despite AI's considerable potential, there is still uncertainty regarding the extent to which it will be realised and the pace at which it will develop.

This study is organised in four sections. Section 1 contains the introduction including a literature overview of the relationship between AI and economic growth. Section 2 describes the main variables and defines the empirical model. Based on those foundations, Section 3 contains the findings and discusses the short- and long-run effects of AI adoption, as well as the possible role of human capital; while section 4 concludes.

2. Data and Methods

Our analysis draws on a panel dataset of annual observations from 1995 to 2017 covering 35 of the current 38 OECD member countries as this group of countries is better positioned to make AI a key engine of growth with advanced technological and digital infrastructures already in place. The OECD member countries not included are Colombia, Costa Rica and Lithuania. The selection of countries and time period was guided by the availability of data for AI adoption, as well as by the goal of including a broad range of countries.

2.1. Main variables

Economic growth is measured as the first difference of the log of real GDP per capita (y) from the PWT v.10.01, Feenstra, Inklaar, & Timmer (2015). Real GDP per capita is calculated as the ratio between GDP at constant 2017 USD and population, a standard measure of standards of living.

AI-related innovation and general innovation are measured at the country level using data from Parteka and Kordalska (2023) that compute three different proxies for AI adoption: (i) the number of patents by applicants, identified in this study as ai^{APP}; (ii) the number of patents by inventors (ai^{INV}), and (iii) the number of scientific publications (ai^{PUB}), all per million people employed. The same rationale applies to the proxy for general innovation measured by the overall number of patents by applicants (inn^{APP}) or by inventors (inn^{INV}) and by the overall number of publications (inn^{PUB}), all per million people employed.

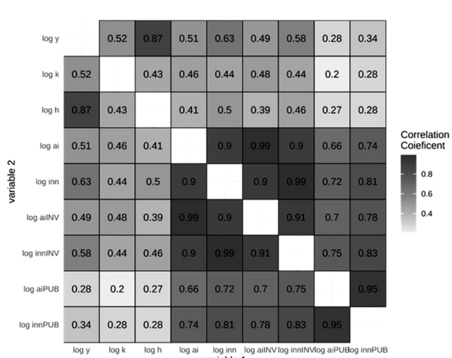
Besides innovation/productivity, the contribution of the remaining immediate sources of growth corresponding to physical and human capital is measured, respectively, using the capital stock at constant 2017 USD per capita (k) and a human capital index (h) that combines average years of education and returns to education, both from the PWT 10.01.

Table 2 contains summary statistics for the variables included in our baseline model, described in detail in the next section, and Figure 1 presents the correlation matrix. A positive simple correlation between AI and the log of real GDP per capita is found for our sample as reported in Figure 1. Notice also that the correlation is higher for the overall innovation measure confirming the idea that for the OECD countries in our sample, composed mostly of advanced knowledge-based economies, technological progress is a key driver of growth and rising living standards.

Table 2. Summary statistics

Variables	N	mean	st.dev.	min	max	median	skewness	kurtosis
log y	805	10.40	0.438	9.170	11.46	0.192	-0.480	3.030
log h	805	1.149	0.131	0.617	1.337	0.0172	-1.300	4.867
log k	805	11.80	0.551	10.05	12.88	0.303	0.303	-0.913
log ai^{APP}	805	1.805	1.862	0	7.225	3.467	0.941	3.120
log ai^{INV}	805	1.882	1.833	0	7.182	3.361	0.905	3.067
log ai^{PUB}	805	5.092	1.580	0	9.229	2.497	-0.546	3.603
log inn^{APP}	805	6.254	2.371	0.295	11.12	5.621	0.0226	2.260
log inn^{INV}	805	6.324	2.306	1.065	11.11	5.317	0.0577	2.236
log inn^{PUB}	805	9.749	1.556	4.796	13.46	2.420	-0.418	3.327

Figure 1. Correlation matrix



2.2. The baseline model

To estimate the effects of AI on economic growth and standards of living, we consider an expanded neoclassical growth model (see e.g. Gonzales (2023) and Kalai, Becha, and Helali (2024)) with a standard aggregate production function given by Y = AF(K,H,L), where Y is output, A is total factor productivity, K is the physical capital stock, H is the human capital stock and L is the labour force.[1] Writing the production function in intensive form, i.e. dividing both sides by L, log-linearising it, and considering that productivity depends on technology, namely AI, we start by assuming that there is a long-run relationship between per capita output and its determinants as expressed in equation (1):

$$\text{logy}_{i,t} = \alpha_{0,i} + \alpha_1 \text{logk}_{i,t} + \alpha_2 \text{logh}_{i,t} + \alpha_3 \text{logai}_{i,t} + \alpha_4 \text{loginn}_{i,t} + \varepsilon_{i,t} \tag{1}$$

where i = 1,2,…,N denotes the country and t = 1,2,…,T the years, y is output per capita, k is physical capital per capita, h is human capital per capita, AI adoption is denoted by ai, inn is a measure for general or overall innovation to control for the additional effort towards AI for a given technological level, $\alpha_{0,i}$ is a country-specific component and $\varepsilon_{i,t}$ stands for the error term.

Assuming the existence of a stable long-run relationship between the former variables, that we examine further along this section using panel cointegration tests, we next define a panel Autoregressive Distributed Lag (ARDL) model given by equation (2):

$$\begin{aligned} \Delta logy_{it} &= \mu_i + \beta_1 \Delta logk_{i,t} + \beta_2 \Delta logh_{i,t} + \beta_3 \Delta logai_{i,t} + \beta_4 \Delta loginn_{i,t} + \gamma logy_{i,t-1} + \alpha_1 logk_{i,t-1} \\ &+ \alpha_2 logh_{i,t-1} + \alpha_3 logai_{i,t-1} + \alpha_4 loginn_{i,t-1} + \epsilon_{it} \end{aligned} \tag{2}$$

where Δ is the first difference operator, μ_i denotes the country fixed effects, the β coefficients can be interpreted as short-run effects, the α coefficients as the long-run effects, and γ is the coefficient associated with the error correction term that measures the speed of adjustment to the long-run equilibrium given by equation (1). The error correction term in this context can also be interpreted as a test of the existence of convergence among the countries in the sample in which case we expect it to display a statistically significant negative coefficient.

An advantage of this specification is that the dependent variable is the rate of economic growth, which allows us to observe both the short-run effects of the former variables on economic growth but also how they impact the level of per capita income in the long-run. The adoption of AI is expected to positively impact economic growth in both the short- and long- term, resulting in positive coefficients for these effects. Similarly, the literature suggests

[1] As mentioned by an anonymous referee we treat AI adoption as an increase in the total factor productivity (TFP) index *A* and thus implicitly assume Hicks-neutral technological progress. In practice, however, AI does not enhance the productivity of capital and labour uniformly. As highlighted in modern task-based models, AI and automation technologies alter the allocation of tasks between capital and labour, simultaneously replacing workers with machines in certain functions while complementing human labour in others, see e.g. Acemoglu and Restrepo (2019), Autor (2015). These heterogeneous and factor-biased effects are effectively averaged out in our empirical specification, which is not problematic given that our objective is not to identify the direction or bias of technical change. We thank the anonymous referee for suggesting that we include this clarification.

that physical capital, human capital, and general innovation also contribute positively to economic growth. Therefore, we anticipate positive coefficients for these variables in both the short- and the long-run. In the presence of cointegration, this type of panel ARDL models have been introduced by Pesaran and Smith (1995) and Pesaran, Yongcheol, and and Smith (1999) to disentangle the short- from the long-run effects between the regressors and the dependent variable. As our panel model is dynamic in nature, we make use of the estimation techniques proposed in Arellano and Bond (1991), the difference-GMM (diff-GMM), and in Arellano and Bover (1995) and Blundell and Bond (1998), the system GMM (sys-GMM). These techniques allow us not only to deal with the dynamic panel specification but also with the endogeneity issues that may arise from the potential feedback effect between per capita income and innovation, both the overall level and the AI-directed one, as countries with higher income levels are likelier to allocate resources to innovation activities.

A pre-requisite for the estimation of a panel ARDL model is that the order of integration of the variables included are a mix of I(0) and I(1) or a combination of both, and none should be integrated of order 2, I(2). To ensure that this is the case we test for the presence of unit roots in our panel data series using the Pesaran (2007) cross-sectionally augmented IPS (CIPS) panel unit root test for which the null hypothesis is that of the existence of a unit root in the series. From the results presented in Table 3 we can see that, aside from the human capital variable, we have a combination of I(0) and I(1) variables in our model. As for human capital, we test its second difference for the existence of a unit root and obtain evidence that it is stationary.

Table 3. Results of the CIPS panel unit root tests

	No trend				**With Trend**			
Variables	**0 lags**	**1 lag**	**2 lags**	**3 lags**	**0 lags**	**1 lag**	**2 lags**	**3 lags**
$log\ y$	0.170	0.000	0.002	0.019	0.851	0.001	0.341	0.808
$log\ h$	1.000	0.989	0.990	0.965	1.000	1.000	1.000	1.000
$log\ k$	0.020	0.000	0.001	0.000	0.038	0.000	0.001	0.004
$log\ ai^{APP}$	0.000	0.000	0.102	0.161	0.000	0.001	0.796	0.957
$log\ inn^{APP}$	0.000	0.000	0.000	0.062	0.002	0.033	0.028	0.351
$log\ ai^{INV}$	0.000	0.000	0.147	0.383	0.000	0.000	0.844	0.877
$log\ inn^{INV}$	0.000	0.000	0.000	0.041	0.000	0.002	0.001	0.187
$log\ ai^{PUB}$	0.000	0.008	0.000	0.000	0.000	0.130	0.000	0.026
$log\ inn^{PUB}$	0.000	0.000	0.000	0.286	0.000	0.487	0.000	0.139
$\Delta log\ y$	0.000	0.000	0.000	0.129	0.000	0.000	0.582	0.999
$\Delta log\ h$	1.000	1.000	1.000	1.000	0.984	0.998	0.999	0.995
$\Delta log\ k$	0.000	0.000	0.000	0.000	0.000	0.000	0.003	0.080
$\Delta log\ ai^{APP}$	0.000	0.000	0.213	0.498	0.000	0.020	0.973	0.999
$\Delta log\ inn^{APP}$	0.000	0.000	0.038	0.013	0.002	0.003	0.091	0.023

$\Delta log\ ai^{INV}$	0.000	0.000	0.032	0.330	0.000	0.000	0.411	0.992
$\Delta log\ inn^{INV}$	0.000	0.000	0.000	0.000	0.001	0.198	0.429	0.198
$\Delta log\ ai^{PUB}$	0.000	0.176	0.100	0.517	0.000	0.473	0.000	0.018
$\Delta log\ inn^{PUB}$	0.142	0.836	0.025	0.579	0.235	0.965	0.001	0.971

Notes: The table contains the p-values for the CIPS panel unit root test (Pesaran, 2007). The null of the test is the existence of a unit root in the series.

Based on the above described results, we modify our long-run model, which now considers Δh instead of h, given by equation (3):

$$logy_{it} = \alpha_{0,i} + \alpha_1 logk_{i,t} + \alpha_2 \Delta logh_{i,t} + \alpha_3 logai_{i,t} + \alpha_4 loginn_{i,t} + \varepsilon_{it} \quad (3)$$

and the corresponding panel ARDL model is given by equation (4):

$$\Delta logy_{it} = \mu_i + \beta_1 \Delta logk_{i,t} + \beta_2 \Delta^2 logh_{i,t} + \beta_3 \Delta logai_{i,t} + \beta_4 \Delta loginn_{i,t} + \gamma logy_{i,t-1} + \alpha_1 logk_{i,t-1} + \alpha_2 \Delta logh_{i,t-1} + \alpha_3 logai_{i,t-1} + \alpha_4 loginn_{i,t-1} + \epsilon_{it} \quad (4)$$

To further validate the models given by equations (3) and (4) we perform panel cointegration tests (see Table 4) using the procedure proposed by Westerlund (2005). The null hypothesis of this test is the absence of cointegration, and we consider two versions of the test. The first, defines as the alternative hypothesis that only some of the cross-sectional units display cointegration while the second version takes as the alternative hypothesis the possibility that all the panel units display cointegration. In both cases, we perform the test with and without a trend in the model. The results provide evidence in favour of the existence of cointegration among the variables we consider in the long-run regression given by equation (3).

Table 4. Results of the Westerlund (2005) panel cointegration tests

		No Trend	**With Trend**
APP	All Panels	0.0773	0.3935
	Some Panels	0.0453	0.0379
INV	All Panels	0.1157	0.1644
	Some Panels	0.0686	0.0060
PUB	All Panels	0.1631	0.0306
	Some Panels	0.1326	0.0008

Notes: the table contains the p-values for the Westerlund panel cointegration test Westerlund (2005). The null of the test is the absence of cointegration among the series.

3. Findings

We start by presenting the results of the estimation of the baseline panel ARDL model. We next present the outcomes of several robustness checks. Finally, we analyse nonlinear growth effects of AI through human capital.

3.1. Baseline results

The estimation results of our baseline model with diff-GMM and sys-GMM are reported in Table 5. Besides addressing omitted variable bias due to unmeasured differences between countries, these methodologies account for the possibility of endogeneity resulting from the consideration of the lagged dependent variable in dynamic panel models by using GMM-style internal instruments. In addition to this, where we treat $logy_{i,t-1}$ as predetermined, we also consider the variables related to AI and innovation to be endogenous – and similarly to lagged income we also use GMM-style internal instruments – as it is likely to exist a feedback effect between these and economic growth which can generate a simultaneity issue in the model. More advanced economies will have an incentive to adopt AI faster since they already possess related know-how, e.g. because automation is already well-established, and the necessary infrastructure is already in place, or because they have higher wages as total factor productivity is higher and higher wages induce firms in advanced economies to use labour-replacing AI more intensively, Alonso, Kothari, & Rehman (2020). To keep the number of moment conditions in the models tractable we use the Roodman (2009) collapse procedure and selected the number of instruments (lagged values) immediately below the number of countries or cross-section units as recommended in the literature. We also estimated equation (4) accounting only for omitted variable bias through the fixed effects estimator (results available from the authors).

The results using the first differenced GMM estimator (Diff-GMM) presented in Table 5 point to positive and statistically significant short- and long-run estimated coefficients for the AI measures using data on patents, both patents by applicants and patents by inventors. For AI measures based on scientific publications, however, none of the estimated coefficients are statistically significant. The latter also applies to the results for all AI measures using the Sys-GMM estimator. However, while model adequacy tests regarding instrument validity and model specification present no problems for Diff-GMM, the same does not apply when using Sys-GMM. Indeed, the second order autocorrelation (AR2) tests do not detect problems for Diff-GMM as the null hypothesis is never rejected at conventional significance levels, but with Sys-GMM AR2 still applies. The Hansen tests also never reject the null hypothesis that the instruments are valid with Diff-GMM, but with Sys-GMM the null is either rejected or the p-value is borderline (very close to 10%). These diagnostic tests for Sys-GMM advise caution regarding the reliability our results applying the Sys-GMM methodology. This is reinforced by the fact that lagged income presents a negative and statistically significant coefficient, which is in line with the results from the cointegration tests, indicating that a lower starting point for per capita income is associated with higher economic growth rates, but the estimated coefficient is only statistically significant when using Diff-GMM and patents-based AI data. Given the specification we adopted for our model, the negative sign for the estimated coefficient of lagged income can also be interpreted as an error correction term for disequilibria relative to the long-run relationship. The estimated coefficients for physical and human capital, when statistically significant, in both the short- and the long-run display the expected signs, positive.

Table 5. Results for the baseline model

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation/AI	*APP*	*INV*	*PUB*	*APP*	*INV*	*PUB*
$\Delta^2 logh_{i,t}$	2.357	2.890*	0.371	0.259	0.168	0.158
	(1.998)	(1.511)	(1.941)	(1.057)	(1.307)	(1.172)
$\Delta logk_{i,t}$	0.173**	0.151*	0.0621	0.123	0.132	0.124*
	(0.0776)	(0.0775)	(0.0668)	(0.0782)	(0.0925)	(0.0659)
$\Delta logai^{APP}_{i,t}$	0.0639***			-0.00692		
	(0.0231)			(0.0103)		
$\Delta loginn^{APP}_{i,t}$	0.132			0.00885		
	(0.0937)			(0.0307)		
$logy_{i,t-1}$	-0.663***	-0.592***	0.0908	-0.0360	-0.0721	-0.0208
	(0.203)	(0.202)	(0.0726)	(0.0489)	(0.0490)	(0.0415)
$\Delta logh_{i,t-1}$	2.425	0.814	-0.180	0.0225	-0.0672	-0.642
	(2.248)	(1.765)	(1.556)	(0.871)	(0.857)	(1.092)
$logk_{i,t-1}$	0.127*	0.111*	-0.104**	0.00518	0.0314	0.00158
	(0.0710)	(0.0637)	(0.0525)	(0.0266)	(0.0284)	(0.0244)
$logai^{APP}_{i,t-1}$	0.0724***			-0.00504		
	(0.0196)			(0.00896)		
$loginn^{APP}_{i,t-1}$	0.141***			0.00722		
	(0.0542)			(0.00838)		
$\Delta logai^{INV}_{i,t}$		0.0547**			0.00363	
		(0.0259)			(0.0157)	
$logai^{INV}_{i,t-1}$		0.0584***			-0.00164	
		(0.0193)			(0.0110)	
$\Delta loginn^{INV}_{i,t}$		0.109			-0.0130	
		(0.0718)			(0.0328)	
$loginn^{INV}_{i,t-1}$		0.117*			0.00385	
		(0.0693)			(0.00730)	
$\Delta logai^{PUB}_{i,t}$			0.0188			0.0215
			(0.0275)			(0.0136)
$logai^{PUB}_{i,t-1}$			-0.00887			0.00886
			(0.0214)			(0.0118)
$\Delta loginn^{PUB}_{i,t}$			0.00295			-0.0120
			(0.0426)			(0.0219)
$loginn^{PUB}_{i,t-1}$			0.0208			-0.0108
			(0.0311)			(0.0151)

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Observations	680	680	680	714	714	714
No. of Countries	34	34	34	34	34	34
No. of instruments	24	24	24	30	30	30
AR1 (p-value)	0.151	0.0730	0.000712	0.000349	0.000620	0.000439
AR2 (p-value)	0.153	0.238	0.216	0.0909	0.0726	0.161
Hansen-J	17.67	19.28	20.27	27.92	30.19	26.98
Hansen-J (p-value)	0.280	0.201	0.162	0.111	0.0668	0.136

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

3.2. Robustness analysis

In this subsection section we present the outcomes of several robustness checks: (i) the consideration of different lag orders in the ARDL model; (ii) including other growth determinants in the set of control variables; (iii) measuring AI adoption as a stock variable; and (iv) testing for the stability of the estimated coefficients. We conducted this analysis using models that included each of the three proxies for AI and overall innovation variables, as in the previous section.

3.2.1. *Different lag orders*

As the results may be sensitive to the number of lags included in the short-run dynamics of the ARDL model, our first robustness check re-estimates each of the three model specifications using alternative lag lengths for the short-run terms. Due to data restrictions and given that we are using annual data we only experiment with up to two lags. Across the various alternative specifications we test, see Tables 6-8, the core results remain largely consistent although introducing additional lags leads to a loss of statistical significance also for Diff-GMM results. However, the BIC criterion favours models without additional lags in the short-run terms, corresponding to the baseline models from the previous section and replicated in columns (1) and (4) of Tables 6 to 8.

Table 6. Results using different lag orders – ai^{APP}

	Diff-GMM			Sys-GMM		
	No lags	1 lag	2 lags	No lags	1 lag	2 lags
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta^2 logh_{i,t}$	2.357	1.928	2.285	0.259	-2.849	11.24
	(1.998)	(1.742)	(2.792)	(1.057)	(4.423)	(8.528)
$\Delta logk_{i,t}$	0.173**	0.0999	0.0671	0.123	0.171**	0.0348
	(0.0776)	(0.138)	(0.306)	(0.0782)	(0.0829)	(0.127)
$\Delta logai^{APP}_{i,t}$	0.0639***	0.0443	0.0286	-0.00692	0.0239	0.0519
	(0.0231)	(0.0460)	(0.0690)	(0.0103)	(0.0257)	(0.0404)
$\Delta loginn^{APP}_{i,t}$	0.132	0.0753	0.0534	0.00885	0.161**	-0.201*
	(0.0937)	(0.0467)	(0.590)	(0.0307)	(0.0751)	(0.120)
$logy_{i,t-1}$	-0.663***	-0.973*	-0.830	-0.0360	-0.0719	-0.116
	(0.203)	(0.558)	(1.154)	(0.0489)	(0.0773)	(0.104)
$\Delta logh_{i,t-1}$	2.425	-37.98*	-66.62	0.0225	2.618	-2.440
	(2.248)	(22.86)	(62.81)	(0.871)	(3.207)	(8.394)
$\Delta^2 logh_{i,t-1}$		40.60*	70.38		-14.66	39.74
		(21.90)	(61.81)		(16.89)	(37.85)
$\Delta^2 logh_{i,t-2}$			3.988			-43.28*
			(64.36)			(22.91)
$logk_{i,t-1}$	0.127*	0.165	0.0331	0.00518	0.0313	0.0454
	(0.0710)	(0.173)	(0.241)	(0.0266)	(0.0478)	(0.0565)
$\Delta logk_{i,t-1}$		-0.0870	-0.0429		0.368	-0.152
		(0.117)	(0.351)		(0.262)	(0.294)
$\Delta logk_{i,t-2}$			0.450			0.1000
			(0.656)			(0.389)
$logai^{APP}_{i,t-1}$	0.0724***	0.0994*	0.0872	-0.00504	0.0109	-0.00178
	(0.0196)	(0.0583)	(0.0997)	(0.00896)	(0.0113)	(0.0120)
$\Delta logai^{APP}_{i,t-1}$		-0.0195	-0.00991		0.00400	0.0374
		(0.0120)	(0.0469)		(0.00922)	(0.0240)
$\Delta logai^{APP}_{i,t-2}$			0.00658			0.0251
			(0.0352)			(0.0221)
$loginn^{APP}_{i,t-1}$	0.141***	0.172*	0.169	0.00722	0.00734	-0.00129
	(0.0542)	(0.104)	(0.256)	(0.00838)	(0.0111)	(0.0167)
$\Delta loginn^{APP}_{i,t-1}$		0.000233	0.0452		0.0525**	0.0265
		(0.0296)	(0.135)		(0.0213)	(0.0433)
$\Delta loginn^{APP}_{i,t-2}$			0.0218			-0.0481
			(0.0995)			(0.0351)
Observations	680	646	612	714	680	646
No. of Countries	34	34	34	34	34	34
No. of instruments	24	22	20	30	28	26
AR1 (p-value)	0.151	0.841	0.993	0.000	0.006	0.034
AR2 (p-value)	0.153	0.639	0.717	0.091	0.252	0.843
Hansen-J	17.671	5.544	1.438	27.923	20.102	8.940
Hansen-J (p-value)	0.280	0.785	0.697	0.111	0.127	0.347
BIC	2039.347	2574.424	2485.685	-4373.548	-3624.726	-2760.609

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Table 7. Results using different lag orders – ai^{INV}

	Diff-GMM			Sys-GMM		
	No lags	1 lag	2 lags	No lags	1 lag	2 lags
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta^2 logh_{i,t}$	2.890*	2.741	2.206	0.168	6.176	13.86*
	(1.511)	(2.046)	(3.290)	(1.307)	(5.552)	(7.710)
$\Delta logk_{i,t}$	0.151*	0.101	0.0143	0.132	0.0755	0.0480
	(0.0775)	(0.159)	(0.644)	(0.0925)	(0.116)	(0.172)
$\Delta logai^{INV}_{i,t}$	0.0547**	0.0369	-0.0204	0.00363	-0.00963	-0.00363
	(0.0259)	(0.0333)	(0.129)	(0.0157)	(0.0343)	(0.108)
$\Delta loginn^{INV}_{i,t}$	0.109	0.160	0.293	-0.0130	0.0834	-0.0337
	(0.0718)	(0.127)	(0.217)	(0.0328)	(0.0615)	(0.135)
$logy_{i,t\text{-}1}$	-0.592***	-0.564	-0.546	-0.0721	-0.0375	-0.00960
	(0.202)	(0.495)	(1.098)	(0.0490)	(0.0708)	(0.163)
$\Delta logh_{i,t\text{-}1}$	0.814	-32.51	-68.62	-0.0672	-6.033	-14.70*
	(1.765)	(32.60)	(55.04)	(0.857)	(7.484)	(8.817)
$\Delta^2 logh_{i,t\text{-}1}$		33.68	69.22		24.74	64.94*
		(33.02)	(54.13)		(30.12)	(34.44)
$\Delta^2 logh_{i,t\text{-}2}$			13.16			-15.19
			(124.8)			(35.40)
$logk_{i,t\text{-}1}$	0.111*	0.0824	0.0154	0.0314	0.0134	-0.0159
	(0.0637)	(0.0830)	(0.208)	(0.0284)	(0.0355)	(0.0772)
$\Delta logk_{i,t\text{-}1}$		-0.00680	-0.0445		0.0762	-0.141
		(0.136)	(0.319)		(0.286)	(0.927)
$\Delta logk_{i,t\text{-}2}$			0.289			0.0392
			(0.545)			(0.339)
$logai^{INV}_{i,t\text{-}1}$	0.0584***	0.0528	0.0137	-0.00164	-0.00845	-0.0192
	(0.0193)	(0.0388)	(0.126)	(0.0110)	(0.0165)	(0.0385)
$\Delta logai^{INV}_{i,t\text{-}1}$		-0.000696	0.00301		0.00940	0.0304
		(0.0120)	(0.0557)		(0.00859)	(0.0314)
$\Delta logai^{INV}_{i,t\text{-}2}$			-0.00544			0.0116
			(0.0632)			(0.0293)
$loginn^{INV}_{i,t\text{-}1}$	0.117*	0.0928	0.158	0.00385	0.00306	0.00322
	(0.0693)	(0.127)	(0.259)	(0.00730)	(0.00982)	(0.0202)
$\Delta loginn^{INV}_{i,t\text{-}1}$		0.0286	0.0892		0.0553	0.0577
		(0.0486)	(0.230)		(0.0375)	(0.0628)
$\Delta loginn^{INV}_{i,t\text{-}2}$			0.0454			0.00635
			(0.0488)			(0.0597)
Observations	680	646	612	714	680	646
No. of Countries	34	34	34	34	34	34
No. of instruments	24	22	20	30	28	26
AR1 (p-value)	0.073	0.517	0.991	0.001	0.035	0.285
AR2 (p-value)	0.238	0.517	0.891	0.073	0.272	0.334
Hansen-J	19.279	12.808	1.786	30.189	21.918	11.236
Hansen-J (p-value)	0.201	0.171	0.618	0.067	0.080	0.189
BIC	1919.975	1951.134	1968.215	-4332.376	-3710.615	-2639.977

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Table 8. Results using different lag orders – ai^{PUB}

	Diff-GMM			Sys-GMM		
	No lags	1 lag	2 lags	No lags	1 lag	2 lags
	(1)	(2)	(3)	(4)	(5)	(6)
$\Delta^2 logh_{i,t}$	0.371	3.337**	2.649	0.158	1.827	-1.519
	(1.941)	(1.441)	(2.481)	(1.172)	(1.395)	(3.459)
$\Delta logk_{i,t}$	0.0621	0.0169	0.247	0.124*	0.0967*	0.167
	(0.0668)	(0.0954)	(0.187)	(0.0659)	(0.0496)	(0.164)
$\Delta logai^{PUB}{}_{i,t}$	0.0188	-0.113	0.0542	0.0215	0.00194	0.0420
	(0.0275)	(0.0730)	(0.162)	(0.0136)	(0.0252)	(0.123)
$\Delta loginn^{PUB}{}_{i,t}$	0.00295	0.152	0.326	-0.0120	0.0380	0.212
	(0.0426)	(0.226)	(0.472)	(0.0219)	(0.0449)	(0.377)
$logy_{i,t\text{-}1}$	0.0908	0.348	-0.111	-0.0208	0.0655	-0.146
	(0.0726)	(0.613)	(0.820)	(0.0415)	(0.0613)	(0.306)
$\Delta logh_{i,t\text{-}1}$	-0.180	-18.69	45.90	-0.642	0.999	-5.519
	(1.556)	(28.95)	(39.44)	(1.092)	(1.705)	(12.70)
$\Delta^2 logh_{i,t\text{-}1}$		20.65	-44.14		0.625	1.558
		(28.83)	(39.44)		(4.925)	(18.37)
$\Delta^2 logh_{i,t\text{-}2}$			8.490			26.98
			(44.82)			(54.56)
$logk_{i,t\text{-}1}$	-0.104**	-0.130	0.213	0.00158	-0.0553	0.0743
	(0.0525)	(0.0994)	(0.271)	(0.0244)	(0.0425)	(0.195)
$\Delta logk_{i,t\text{-}1}$		-0.213	-0.564		-0.274**	-0.325
		(0.345)	(0.395)		(0.118)	(0.571)
$\Delta logk_{i,t\text{-}2}$			0.769*			0.514
			(0.462)			(0.320)
$logai^{PUB}{}_{i,t\text{-}1}$	-0.00887	-0.114	0.120	0.00886	0.0235**	0.0135
	(0.0214)	(0.107)	(0.200)	(0.0118)	(0.0111)	(0.0376)
$\Delta logai^{PUB}{}_{i,t\text{-}1}$		-0.00724	-0.0283		-0.00776	-0.00143
		(0.0123)	(0.0443)		(0.00927)	(0.0373)
$\Delta logai^{PUB}{}_{i,t\text{-}2}$			-0.0304*			-0.0141
			(0.0167)			(0.0155)
$loginn^{PUB}{}_{i,t\text{-}1}$	0.0208	0.116	-0.205	-0.0108	-0.0226*	-0.0184
	(0.0311)	(0.153)	(0.268)	(0.0151)	(0.0135)	(0.0337)
$\Delta loginn^{PUB}{}_{i,t\text{-}1}$		0.0188	0.0571		0.0167	0.0130
		(0.0238)	(0.0449)		(0.0148)	(0.0409)
$\Delta loginn^{PUB}{}_{i,t\text{-}2}$			0.0422*			0.0171
			(0.0225)			(0.0167)
Observations	680	646	612	714	680	646
No. of Countries	34	34	34	34	34	34
No. of instruments	24	22	20	30	28	26
AR1 (p-value)	0.001	0.043	0.504	0.000	0.003	0.387
AR2 (p-value)	0.216	0.462	0.704	0.161	0.308	0.536
Hansen-J	20.269	5.776	1.498	26.978	16.760	14.951
Hansen-J (p-value)	0.162	0.762	0.683	0.136	0.269	0.060
BIC	-2519.428	1224.373	-1215.983	-4378.942	-3993.296	-3247.209

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010

3.2.2. *Additional controls*

Since we use a standard growth regression framework, we introduce additional control variables to both allow for potential model extensions given the 'open-endedness' of growth theory and to mitigate the risk of omitted variable bias, see e.g. Brock and Durlauf (2001), D'Andrea (2022), Chen and Yu (2024). As a robustness check, we add these extra controls, all previously suggested in the literature, one at a time, to evaluate the extent to which they affect the results for our baseline model. The additional control variables are *trade*, the degree of openness of an economy measured as the ratio between the sum of export and imports and GDP, *rqe*, a measure of regulatory quality retrieved from Parteka and Kordalska (2023), *inds*, the value added by the manufacturing sector as a percentage of GDP, *g*, public consumption as a percentage of GDP, *inf*, the inflation rate measured as the growth rate of the consumer price index, *fdi*, net inflows of foreign direct investment as a percentage of GDP, and *urban*, the urban population as a percentage of total population. Data for these control variables were retrieved from the World Bank online Databank, except for *rqe*. The inclusion of these additional variables does not significantly alter our findings regarding the relationship between AI, overall innovation, and economic growth across any of the previously estimated model variants, see Tables 9-14. As for the control variables, the most consistent result across the estimated specifications is the negative and statistically significant coefficient for public consumption as a percentage of GDP.

Table 9. Results with Diff-GMM and additional control variables – ai^{APP}

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	2.357	1.481	2.545	2.188	1.421	4.015*	1.581	2.304
	(1.998)	(2.571)	(2.443)	(1.709)	(1.346)	(2.314)	(2.323)	(1.947)
$\Delta logk_{i,t}$	0.173**	0.181*	0.168**	0.259**	0.158*	0.213**	0.168*	0.168**
	(0.0776)	(0.104)	(0.0760)	(0.102)	(0.0930)	(0.0896)	(0.0897)	(0.0727)
$\Delta logai^{APP}_{i,t}$	0.0639***	0.0491	0.0757**	0.0592*	0.0449*	0.0609**	0.0681***	0.0623***
	(0.0231)	(0.0344)	(0.0336)	(0.0323)	(0.0250)	(0.0259)	(0.0204)	(0.0229)
$\Delta loginn^{APP}_{i,t}$	0.132	0.0997	0.149*	0.150**	0.138**	0.176**	0.145*	0.129
	(0.0937)	(0.0703)	(0.0842)	(0.0683)	(0.0564)	(0.0686)	(0.0792)	(0.0909)
$logy_{i,t-1}$	-0.663***	-0.493**	-0.637***	-0.646***	-0.523***	-0.709***	-0.698***	-0.636***
	(0.203)	(0.203)	(0.194)	(0.208)	(0.197)	(0.200)	(0.171)	(0.219)
$\Delta logh_{i,t-1}$	2.425	1.423	1.471	1.670	0.355	1.598	3.326	2.360
	(2.248)	(2.323)	(2.230)	(1.972)	(1.603)	(2.182)	(2.304)	(2.340)
$logk_{i,t-1}$	0.127*	0.0954	0.130*	0.158*	0.0962	0.156**	0.159**	0.119
	(0.0710)	(0.0721)	(0.0722)	(0.0828)	(0.0745)	(0.0714)	(0.0665)	(0.0762)
$logai^{APP}_{i,t-1}$	0.0724***	0.0476	0.0799***	0.0546**	0.0467**	0.0615***	0.0739***	0.0712***
	(0.0196)	(0.0292)	(0.0275)	(0.0243)	(0.0214)	(0.0220)	(0.0171)	(0.0203)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$loginn^{APP}_{i,t\text{-}1}$	0.141***	0.107**	0.137***	0.137***	0.124***	0.138***	0.151***	0.137**
	(0.0542)	(0.0496)	(0.0485)	(0.0490)	(0.0416)	(0.0463)	(0.0516)	(0.0548)
$\Delta trade_{i,t}$		0.00200						
		(0.00142)						
$\Delta rqe_{i,t}$			-0.0637					
			(0.0553)					
$\Delta inds_{i,t}$				0.0237*				
				(0.0126)				
$\Delta g_{i,t}$					-0.031***			
					(0.0106)			
$\Delta inf_{i,t}$						0.00628*		
						(0.00376)		
$\Delta fdi_{i,t}$							0.00190	
							(0.00165)	
$\Delta urban_{i,t}$								-0.0275
								(0.147)
Observations	680	680	680	680	680	680	680	680
No. of Countries	34	34	34	34	34	34	34	34
No. of instruments	24	24	24	24	24	24	24	24
AR1 (p-value)	0.151	0.066	0.070	0.067	0.027	0.066	0.137	0.137
AR2 (p-value)	0.153	0.617	0.372	0.431	0.685	0.807	0.862	0.145
Hansen-J	17.671	20.846	13.562	16.001	15.553	15.328	14.657	17.501
Hansen-J (p-value)	0.280	0.106	0.483	0.313	0.341	0.356	0.402	0.230
BIC	2039.347	1636.655	1952.223	1885.498	1718.234	2096.858	2018.807	1993.661

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Table 10. Results with Sys-GMM and additional control variables – ai^{APP}

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	0.259	1.180	0.185	0.297	0.112	1.490	0.0193	0.927
	(1.057)	(0.906)	(0.904)	(0.874)	(1.344)	(1.139)	(1.314)	(1.197)
$\Delta logk_{i,t}$	0.123	0.140*	0.139*	0.165**	0.160	0.174**	0.118	0.136**
	(0.0782)	(0.0766)	(0.0811)	(0.0654)	(0.0999)	(0.0771)	(0.0807)	(0.0677)
$\Delta logai^{APP}_{i,t}$	-0.00692	-0.00105	-0.00763	-0.00270	-0.00644	0.00259	-0.00516	-0.00696
	(0.0103)	(0.0121)	(0.0107)	(0.0100)	(0.0119)	(0.0113)	(0.0102)	(0.00614)
$\Delta loginn^{APP}_{i,t}$	0.00885	0.0122	0.00967	0.0141	0.0130	0.0294	0.00202	0.0129
	(0.0307)	(0.0238)	(0.0347)	(0.0267)	(0.0401)	(0.0291)	(0.0353)	(0.0297)
$logy_{i,t-1}$	-0.0360	-0.0141	-0.0507	-0.0513	0.0122	-0.0756	-0.0385	-0.0340
	(0.0489)	(0.0535)	(0.0541)	(0.0540)	(0.0967)	(0.0658)	(0.0456)	(0.0417)
$\Delta logh_{i,t-1}$	0.0225	0.327	-0.385	-0.212	0.00715	-0.00515	-0.187	1.328
	(0.871)	(0.932)	(0.890)	(0.721)	(0.826)	(0.952)	(0.817)	(1.406)
$logk_{i,t-1}$	0.00518	-0.0117	0.0112	0.0134	-0.0212	0.0227	0.00614	0.00736
	(0.0266)	(0.0364)	(0.0311)	(0.0319)	(0.0549)	(0.0331)	(0.0224)	(0.0234)
$logai^{APP}_{i,t-1}$	-0.00504	-0.00453	-0.00526	-0.00440	-0.00966	-0.00329	-0.00428	-0.00563
	(0.00896)	(0.00946)	(0.00799)	(0.00995)	(0.0115)	(0.00829)	(0.00876)	(0.00619)
$loginn^{APP}_{i,t-1}$	0.00722	0.00889	0.00882	0.00708	0.00774	0.00885	0.00604	0.00956
	(0.00838)	(0.00769)	(0.00717)	(0.00753)	(0.00671)	(0.00851)	(0.00843)	(0.00790)
$\Delta trade_{i,t}$		0.00272***						
		(0.000593)						
$\Delta rqe_{i,t}$			-0.00835					
			(0.0273)					
$\Delta inds_{i,t}$				0.0112				
				(0.0151)				
$\Delta g_{i,t}$					-0.0282			
					(0.0198)			
$\Delta inf_{i,t}$						0.00431		
						(0.00338)		
$\Delta fdi_{i,t}$							-0.000075	
							(0.000676)	
$\Delta urban_{i,t}$								-0.0739
								(0.0634)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	714	714	714	714	714	714	714	714
No. of Countries	34	34	34	34	34	34	34	34
No. of instruments	30	30	30	30	30	30	30	30
AR1 (p-value)	0.000	0.001	0.000	0.001	0.002	0.001	0.000	0.000
AR2 (p-value)	0.091	0.723	0.085	0.167	0.602	0.405	0.151	0.092
Hansen-J	27.923	20.607	25.083	25.729	28.137	28.987	25.374	23.904
Hansen-J (p-value)	0.111	0.359	0.158	0.138	0.081	0.066	0.149	0.200
BIC	-4373.548	-4438.911	-4343.215	-4408.075	-4586.347	-4358.672	-4366.859	-4275.090

Notes: robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.010$.

Table 11. Results with Diff-GMM and additional control variables – ai^{INV}

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	2.890*	1.712	2.671*	1.527	-0.0423	3.016*	3.767**	2.941*
	(1.511)	(1.734)	(1.553)	(1.575)	(1.340)	(1.786)	(1.520)	(1.582)
$\Delta logk_{i,t}$	0.151*	0.117*	0.141*	0.176***	0.0896	0.135	0.172**	0.146***
	(0.0775)	(0.0708)	(0.0748)	(0.0661)	(0.0720)	(0.0850)	(0.0726)	(0.0545)
$\Delta logai^{INV}_{i,t}$	0.0547**	0.0416*	0.0491**	0.0352*	0.0228	0.0452*	0.0632**	0.0536***
	(0.0259)	(0.0214)	(0.0247)	(0.0213)	(0.0180)	(0.0263)	(0.0292)	(0.0173)
$\Delta loginn^{INV}_{i,t}$	0.109	0.0627	0.117*	0.106*	0.0968**	0.105	0.108	0.142*
	(0.0718)	(0.0603)	(0.0690)	(0.0556)	(0.0459)	(0.0659)	(0.0821)	(0.0776)
$logy_{i,t-1}$	-0.592***	-0.541**	-0.585***	-0.541***	-0.347**	-0.576***	-0.607***	-0.678***
	(0.202)	(0.211)	(0.213)	(0.191)	(0.161)	(0.168)	(0.216)	(0.257)
$\Delta logh_{i,t-1}$	0.814	0.236	0.858	0.340	-1.606	0.682	0.443	0.785
	(1.765)	(1.514)	(1.902)	(1.912)	(1.500)	(1.747)	(1.666)	(2.171)
$logk_{i,t-1}$	0.111*	0.0919	0.109*	0.0972	0.0416	0.115**	0.103	0.140*
	(0.0637)	(0.0571)	(0.0639)	(0.0648)	(0.0563)	(0.0569)	(0.0691)	(0.0850)
$logai^{INV}_{i,t-1}$	0.0584***	0.0443**	0.0537***	0.0420*	0.0252	0.0488**	0.0643***	0.0578***
	(0.0193)	(0.0183)	(0.0200)	(0.0222)	(0.0166)	(0.0217)	(0.0212)	(0.0183)
$loginn^{INV}_{i,t-1}$	0.117*	0.116	0.117*	0.124**	0.0974**	0.109*	0.117	0.140*
	(0.0693)	(0.0777)	(0.0689)	(0.0573)	(0.0385)	(0.0602)	(0.0715)	(0.0788)
$\Delta trade_{i,t}$		0.00199**						
		(0.000872)						

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta rqe_{i,t}$			0.00507					
			(0.0207)					
$\Delta inds_{i,t}$				0.0182*				
				(0.0108)				
$\Delta g_{i,t}$					-0.038***			
					(0.0104)			
$\Delta inf_{i,t}$						0.00413		
						(0.00573)		
$\Delta fdi_{i,t}$							-0.00107	
							(0.00108)	
$\Delta urban_{i,t}$								0.0228
								(0.212)
Observations	680	680	680	680	680	680	680	680
No. of Countries	34	34	34	34	34	34	34	34
No. of instruments	24	24	24	24	24	24	24	24
AR1 (p-value)	0.073	0.088	0.054	0.044	0.008	0.062	0.072	0.105
AR2 (p-value)	0.238	0.516	0.295	0.298	0.555	0.626	0.337	0.345
Hansen-J	19.279	18.419	18.468	19.632	13.883	17.463	18.350	15.452
Hansen-J (p-value)	0.201	0.188	0.186	0.142	0.458	0.232	0.191	0.348
BIC	1919.975	1826.340	1904.225	1789.356	1270.474	1871.554	1997.590	2052.225

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Table 12. Results with Sys-GMM and additional control variables – ai^{INV}

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	0.168	-0.721	0.130	0.0908	-0.232	1.660	1.223	0.404
	(1.307)	(1.331)	(1.377)	(1.337)	(1.594)	(1.339)	(1.227)	(1.087)
$\Delta logk_{i,t}$	0.132	0.122	0.143	0.158**	0.121	0.159**	0.166*	0.156**
	(0.0925)	(0.0954)	(0.0966)	(0.0752)	(0.0833)	(0.0808)	(0.0862)	(0.0783)
$\Delta logai^{INV}_{i,t}$	0.00363	0.00259	0.00242	0.00340	-0.00185	0.0122	0.0181	-0.00502
	(0.0157)	(0.0131)	(0.0138)	(0.0106)	(0.0164)	(0.0153)	(0.0238)	(0.0172)
$\Delta loginn^{INV}_{i,t}$	-0.0130	-0.0612*	-0.0128	-0.00318	-0.00618	-0.0129	-0.000280	-0.0197
	(0.0328)	(0.0321)	(0.0334)	(0.0420)	(0.0345)	(0.0263)	(0.0369)	(0.0250)
$logy_{i,t\text{-}1}$	-0.0721	-0.0152	-0.0755	-0.0430	0.0148	-0.0928	-0.0952*	-0.0547
	(0.0490)	(0.0546)	(0.0537)	(0.0628)	(0.0661)	(0.0590)	(0.0544)	(0.0539)
$\Delta logh_{i,t\text{-}1}$	-0.0672	-0.0954	-0.174	-0.305	-0.585	-0.109	-0.192	0.679
	(0.857)	(0.823)	(0.935)	(0.842)	(0.756)	(1.080)	(0.923)	(1.679)
$logk_{i,t\text{-}1}$	0.0314	-0.00867	0.0322	0.0106	-0.0194	0.0301	0.0393	0.0143
	(0.0284)	(0.0351)	(0.0320)	(0.0399)	(0.0355)	(0.0330)	(0.0295)	(0.0260)
$logai^{INV}_{i,t\text{-}1}$	-0.00164	-0.00195	-0.00203	-0.000962	-0.00633	0.000973	0.00484	-0.00466
	(0.0110)	(0.00948)	(0.0102)	(0.00920)	(0.0117)	(0.0108)	(0.0142)	(0.0128)
$loginn^{INV}_{i,t\text{-}1}$	0.00385	0.00202	0.00484	0.00296	0.00150	0.00427	0.00229	0.00915
	(0.00730)	(0.00664)	(0.00707)	(0.00772)	(0.00764)	(0.00843)	(0.00875)	(0.00804)
$\Delta trade_{i,t}$		0.00306**						
		(0.00129)						
$\Delta rqe_{i,t}$			0.00477					
			(0.0171)					
$\Delta inds_{i,t}$				0.0192				
				(0.0163)				
$\Delta g_{i,t}$					-0.0340**			
					(0.0140)			
$\Delta inf_{i,t}$						0.00718***		
						(0.00228)		
$\Delta fdi_{i,t}$							-0.00113	
							(0.000943)	
$\Delta urban_{i,t}$								-0.0542
								(0.125)
Observations	714	714	714	714	714	714	714	714

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
No. of Countries	34	34	34	34	34	34	34	34
No. of instruments	30	30	30	30	30	30	30	30
AR1 (p-value)	0.001	0.001	0.001	0.001	0.002	0.001	0.001	0.001
AR2 (p-value)	0.073	0.392	0.082	0.200	0.516	0.278	0.100	0.072
Hansen-J	30.189	26.306	29.319	27.696	29.366	29.503	28.094	27.966
Hansen-J (p-value)	0.067	0.122	0.061	0.089	0.060	0.058	0.082	0.084
BIC	-4332.376	-4412.179	-4320.102	-4398.874	-4576.881	-4310.827	-4215.965	-4285.112

Notes: robust standard errors in parentheses. * $p<0.10$, ** $p<0.05$, *** $p<0.010$.

Table 13. Results with Diff-GMM and additional control variables – ai^{PUB}

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	0.371	1.139	0.0379	-0.671	0.382	2.051	0.186	0.442
	(1.941)	(1.639)	(2.155)	(1.663)	(1.795)	(2.324)	(1.875)	(1.462)
$\Delta logk_{i,t}$	0.0621	0.0816	0.0791	0.0954**	0.0904	0.00798	0.0567	0.0709
	(0.0668)	(0.0535)	(0.0798)	(0.0417)	(0.0617)	(0.0668)	(0.0668)	(0.0671)
$\Delta logai^{PUB}_{i,t}$	0.0188	0.000496	0.0195	0.0370*	0.0222	0.0128	0.0203	0.00836
	(0.0275)	(0.0257)	(0.0306)	(0.0195)	(0.0161)	(0.0248)	(0.0268)	(0.0505)
$\Delta loginn^{PUB}_{i,t}$	0.00295	0.0228	-0.00165	-0.0340	-0.0138	0.0214	0.00776	0.0190
	(0.0426)	(0.0348)	(0.0447)	(0.0334)	(0.0256)	(0.0398)	(0.0423)	(0.0799)
$logy_{i,t-1}$	0.0908	0.0410	0.0946	0.0894	0.107*	0.0437	0.0740	0.0390
	(0.0726)	(0.0613)	(0.0926)	(0.0553)	(0.0618)	(0.0952)	(0.0732)	(0.0791)
$\Delta logh_{i,t-1}$	-0.180	0.287	-0.270	-0.681	0.357	0.591	0.283	0.387
	(1.556)	(1.402)	(1.703)	(1.673)	(1.321)	(1.804)	(1.539)	(1.664)
$logk_{i,t-1}$	-0.104**	-0.0559	-0.103**	-0.0953**	-0.099***	-0.118*	-0.096**	-0.0689
	(0.0525)	(0.0409)	(0.0502)	(0.0373)	(0.0368)	(0.0622)	(0.0488)	(0.0525)
$logai^{PUB}_{i,t-1}$	-0.00887	-0.00680	-0.00848	0.00767	-0.000282	-0.00566	-0.00944	-0.00427
	(0.0214)	(0.0175)	(0.0227)	(0.0161)	(0.0142)	(0.0198)	(0.0225)	(0.0355)
$loginn^{PUB}_{i,t-1}$	0.0208	0.0139	0.0192	-0.00628	0.000839	0.0353	0.0288	0.0123
	(0.0311)	(0.0227)	(0.0300)	(0.0214)	(0.0209)	(0.0280)	(0.0380)	(0.0532)
$\Delta trade_{i,t}$		0.00257***						
		(0.000815)						

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta rqe_{i,t}$			0.0153					
			(0.0399)					
$\Delta inds_{i,t}$				0.0291***				
				(0.00732)				
$\Delta g_{i,t}$					-0.034***			
					(0.0105)			
$\Delta inf_{i,t}$						0.00815***		
						(0.00291)		
$\Delta fdi_{i,t}$							0.000850	
							(0.00129)	
$\Delta urban_{i,t}$								0.241
								(0.251)
Observations	680	680	680	680	680	680	680	680
No. of Countries	34	34	34	34	34	34	34	34
No. of instruments	24	24	24	24	24	24	24	24
AR1 (p-value)	0.001	0.001	0.002	0.001	0.002	0.001	0.008	0.002
AR2 (p-value)	0.216	0.650	0.270	0.276	0.614	0.359	0.627	0.184
Hansen-J	20.269	11.562	18.709	12.072	12.824	14.569	19.455	23.626
Hansen-J (p-value)	0.162	0.641	0.176	0.601	0.540	0.408	0.148	0.051
BIC	-2519.428	-2528.241	-2835.680	-1869.963	-3433.720	-575.648	-2476.49	-1646.936

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

Table 14. Results with Sys-GMM and additional control variables – ai^{PUB}

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	0.158	0.495	-0.255	0.0159	0.256	1.276	0.114	-0.746
	(1.172)	(1.230)	(1.700)	(1.210)	(1.285)	(1.066)	(1.357)	(1.318)
$\Delta logk_{i,t}$	0.124*	0.138**	0.121*	0.121**	0.112	0.0889*	0.125	0.128**
	(0.0659)	(0.0694)	(0.0668)	(0.0604)	(0.0853)	(0.0518)	(0.0792)	(0.0587)
$\Delta logai^{PUB}{}_{i,t}$	0.0215	0.0218	0.0235	0.0280*	0.0187*	0.00786	0.0258	0.0135
	(0.0136)	(0.0133)	(0.0163)	(0.0151)	(0.0112)	(0.0138)	(0.0198)	(0.0158)
$\Delta loginn^{PUB}{}_{i,t}$	-0.0120	-0.0206	-0.0135	-0.0218	-0.0145	0.00471	-0.0160	-0.00118
	(0.0219)	(0.0206)	(0.0280)	(0.0261)	(0.0174)	(0.0202)	(0.0269)	(0.0248)
$logy_{i,t-1}$	-0.0208	0.0112	-0.0125	0.0111	0.0644	-0.0208	-0.0146	-0.0278
	(0.0415)	(0.0351)	(0.0363)	(0.0560)	(0.0789)	(0.0310)	(0.0449)	(0.0408)
$\Delta logh_{i,t-1}$	-0.642	-0.814	-0.744	-0.429	0.0713	0.356	-0.490	-1.920
	(1.092)	(1.000)	(1.361)	(0.896)	(1.439)	(1.059)	(1.196)	(1.502)
$logk_{i,t-1}$	0.00158	-0.0148	-0.00377	-0.0198	-0.0502	-0.00614	-0.00209	-0.00200
	(0.0244)	(0.0236)	(0.0225)	(0.0353)	(0.0526)	(0.0206)	(0.0255)	(0.0251)
$logai^{PUB}{}_{i,t-1}$	0.00886	0.00931	0.0127	0.0122	0.00804	0.00104	0.0109	-0.00136
	(0.0118)	(0.0100)	(0.0155)	(0.0142)	(0.00970)	(0.0141)	(0.0119)	(0.0140)
$loginn^{PUB}{}_{i,t-1}$	-0.0108	-0.0161	-0.0151	-0.0153	-0.0143	0.00104	-0.0124	0.00389
	(0.0151)	(0.0127)	(0.0198)	(0.0177)	(0.0117)	(0.0177)	(0.0155)	(0.0174)
$\Delta trade_{i,t}$		0.00256***						
		(0.000583)						
$\Delta rqe_{i,t}$			0.0336					
			(0.0425)					
$\Delta inds_{i,t}$				0.0122				
				(0.0150)				
$\Delta g_{i,t}$					-0.0347**			
					(0.0165)			
$\Delta inf_{i,t}$						0.00642**		
						(0.00257)		
$\Delta fdi_{i,t}$							0.000494	
							(0.00102)	
$\Delta urban_{i,t}$								0.111**
								(0.0554)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	714	714	714	714	714	714	714	714
No. of Countries	34	34	34	34	34	34	34	34
No. of instruments	30	30	30	30	30	30	30	30
AR1 (p-value)	0.000	0.001	0.001	0.001	0.002	0.000	0.003	0.001
AR2 (p-value)	0.161	0.667	0.279	0.223	0.593	0.270	0.414	0.159
Hansen-J	26.978	20.411	27.971	25.292	23.300	23.576	26.511	22.628
Hansen-J (p-value)	0.136	0.370	0.084	0.151	0.224	0.213	0.117	0.254
BIC	-4378.942	-4432.491	-4362.254	-4431.002	-4533.846	-4411.335	-4361.146	-4087.719

Notes: robust standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

3.2.3. *Alternative AI adoption measures: stocks*

Given the cumulative nature of knowledge and technology, a case can be made for considering our patent and publication variables in terms of stocks instead of a yearly flow. We thus estimated our baseline model using the stocks of the three AI proxies, also retrieved from Parteka & Kordalska (2023), which the authors compute using the flows and applying the perpetual inventory method. Using the stocks of the AI variables we had to remove Latvia from our sample for which no data is available. As can be seen from the inspection of Table 15, there are some interesting differences in the results, despite the overall effect of AI metrics on growth remaining positive in most cases. The results using the stocks of AI patents lead to a loss of statistical significance of the short-run effects while the long-run effect remains unchanged, positive and statistically significant (with Diff-GMM). On the other hand, AI related publications now display positive and statistically significant estimated coefficients in the short and long-run (with Diff-GMM).

Table 15. Results using AI stock variables

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation/AI	*APP*	*INV*	*PUB*	*APP*	*INV*	*PUB*
$\Delta^2 logh_{i,t}$	1.942	1.026	0.890	0.899	1.355	0.0551
	(1.633)	(0.917)	(1.280)	(1.433)	(1.337)	(2.522)
$\Delta logk_{i,t}$	0.173***	0.152**	0.111	0.189***	0.196***	0.154**
	(0.0584)	(0.0680)	(0.0786)	(0.0705)	(0.0619)	(0.0638)
$\Delta logai^{APP}_{i,t}$	0.104			0.0243		
	(0.112)			(0.0282)		
$\Delta loginn^{APP}_{i,t}$	0.791***			0.112		
	(0.234)			(0.120)		
$logy_{i,t-1}$	-0.727***	-0.575***	-0.422***	-0.113**	-0.122**	-0.0419
	(0.135)	(0.103)	(0.0805)	(0.0503)	(0.0519)	(0.0344)
$\Delta logh_{i,t-1}$	0.176	-1.303	1.627	-0.342	0.761	-0.168
	(1.382)	(1.323)	(1.897)	(1.180)	(1.840)	(1.735)
$logk_{i,t-1}$	0.135***	0.119***	0.0597	0.0560*	0.0594**	0.0196
	(0.0403)	(0.0287)	(0.0366)	(0.0294)	(0.0277)	(0.0218)
$logai^{APP}_{i,t-1}$	0.0691**			-0.00409		
	(0.0279)			(0.00604)		
$loginn^{APP}_{i,t-1}$	0.153***			0.00872		
	(0.0335)			(0.00545)		
$\Delta logai^{INV}_{i,t}$		0.0696			0.0757	
		(0.0642)			(0.0643)	
$logai^{INV}_{i,t-1}$		0.0364*			0.00339	
		(0.0187)			(0.00728)	
$\Delta loginn^{INV}_{i,t}$		0.635***			0.132	
		(0.211)			(0.119)	
$loginn^{INV}_{i,t-1}$		0.117***			0.00784	
		(0.0324)			(0.00716)	
$\Delta logai^{PUB}_{i,t}$			0.228***			0.195***
			(0.0733)			(0.0503)

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation/AI	*APP*	*INV*	*PUB*	*APP*	*INV*	*PUB*
$logai^{PUB}_{i,t-1}$			0.128***			0.00647
			(0.0401)			(0.0180)
$\Delta loginn^{PUB}_{i,t}$			-0.201			-0.313*
			(0.219)			(0.168)
$loginn^{PUB}_{i,t-1}$			-0.0960*			-0.00730
			(0.0528)			(0.0211)
Observations	680	680	680	714	714	714
No. of Countries	34	34	34	34	34	34
No. of instruments	34	34	34	40	40	40
AR1 (p-value)	0.0447	0.0128	0.0028	0.0010	0.0021	0.0007
AR2 (p-value)	0.253	0.283	0.167	0.121	0.166	0.0800
Hansen-J	30.74	32.08	33.18	29.40	30.92	32.90
Hansen-J (p-value)	0.198	0.156	0.127	0.497	0.419	0.327

Notes: obust Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010

3.2.4. *Coefficient stability*

The stability over time of the estimated coefficients is a key concern when working with panel data. In our study, the importance of this issue is heightened by the evolving discourse surrounding AI in recent years. Although automation, robotisation, and AI have been long-standing topics of interest, the significant breakthroughs observed in recent years are likely to cause notable shifts in economic behaviour. To assess the robustness of our results, we re-estimate the model over successive time windows – starting with the period 1995-2005 and incrementally adding one year at a time. Figures 2-3 illustrate how the estimated coefficients of interest – those related to AI, general innovation, and the model's error correction term – evolve in this recursive estimation process. To conserve space, we present here only the results from the models using patents by applicant. The remaining results are available upon request. Our findings indicate that the coefficients remain largely stable as the time window expands when using the patents measures; however, some variability is observed when using the scientific publications measure (these results are available from the authors).

Figure 2. Diff-GMM estimated coefficients over expanding windows (ai^{APP}; inn^{APP})

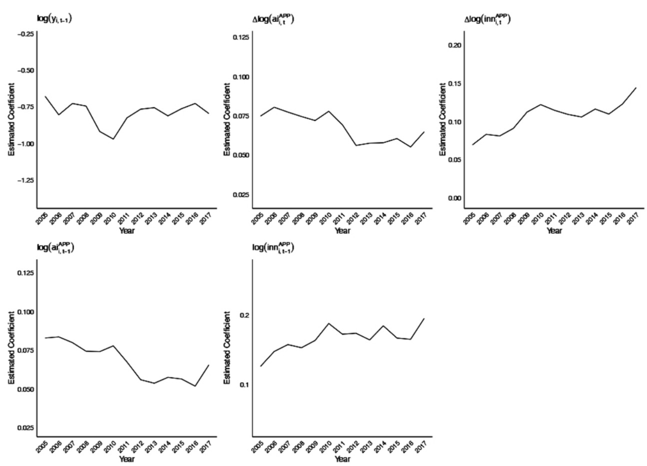
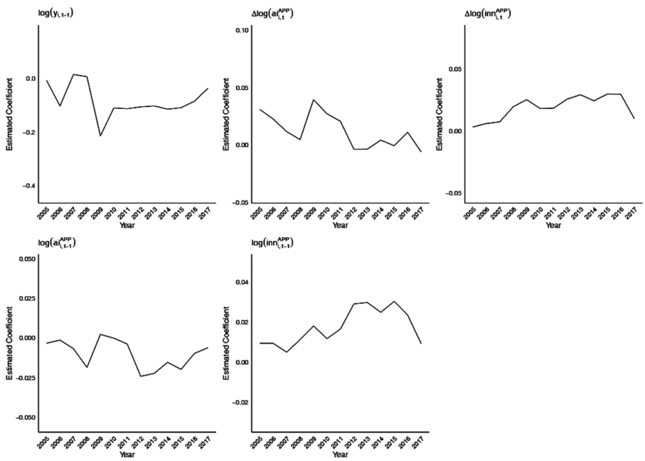


Figure 3. Sys-GMM estimated coefficients over expanding windows (ai^{APP}; inn^{APP})



Despite the overall stability suggested by the results in Figures 2 and 3, a slight downward trend can be observed in the estimated coefficients of AI, particularly in the Diff-GMM results shown in Figure 2. Since these estimates are based on flow measures of AI, one possible explanation is that, as the stock of AI accumulates over time, the marginal impact of new patents and scientific publications decreases, reflecting potential diminishing returns. To examine this possibility, we replicated the coefficient stability analysis using stock-based AI variables (see Figures 4 and 5). The results confirm that the previously observed downward trend in the estimated AI coefficients is much less pronounced.

Figure 4. Diff-GMM estimated coefficients over expanding windows (ai^{APP}; inn^{APP}) – stock variables

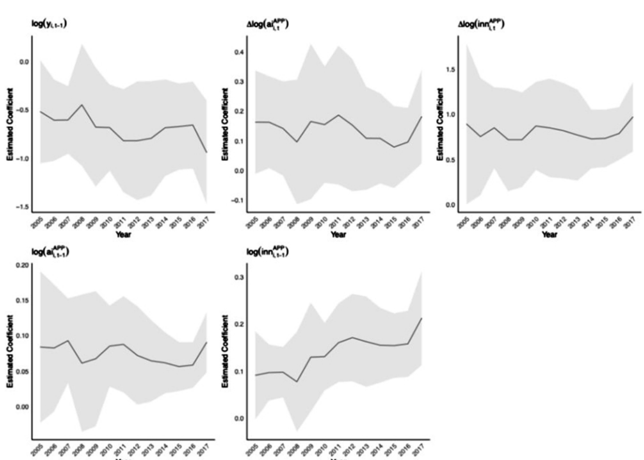
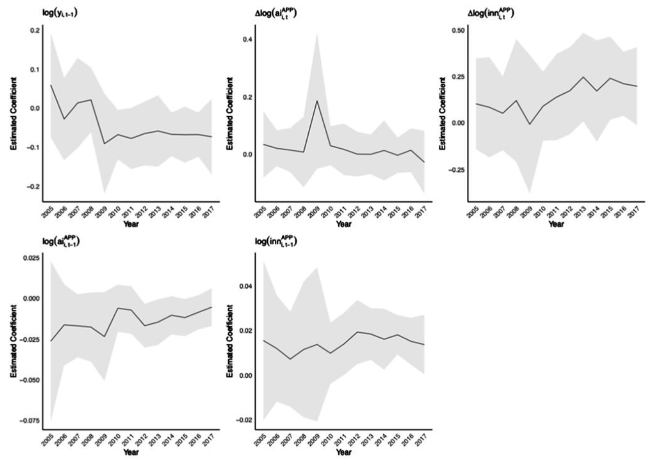


Figure 5. Sys-GMM estimated coefficients over expanding windows (ai^{APP}; inn^{APP}) – stock variables



3.3. The role of human capital

In this section we extend the analysis to account for the role of human capital by including an interaction term between AI and human capital. This enables us to assess whether the growth effects of AI differ across countries with varying skill endowments, shedding light on whether AI acts as a complement or substitute to human capabilities in the aggregate in line with the approaches developed by, among others, Autor (2015) and Acemoglu & Restrepo (2019), and recently tested using microdata by Bughin (2025) and Brynjolfsson, Li, & Raymond (2025). The long-run relationship is now given by equation (5):

$$logy_{i,t} = \alpha_{0,i} + \alpha_1 logki,t + \alpha_2 \Delta logh_{i,t} + \alpha_3 logai_{i,t} + \alpha_4 loginn_{i,t} + \alpha_5 logh_{i,t} \text{ x } logai_{i,t} + \quad + \varepsilon_{i,t} \tag{5}$$

where we augment equation (3) to include $logh_{i,t}$ x $logai_{i,t}$, the interaction term between AI and human capital, with the sign of the respective estimated coefficient indicating whether human capital amplifies or dampens the AI effect. A positive estimated coefficient for AI combined with an also positive estimated coefficient for the interaction term suggests complementarity, i.e. AI raises productivity and thus growth more where human capital is higher, in line with the literature that poses that AI is skill-biased in favour of more advanced skills, see e.g. Acemoglu & Restrepo (2019), with the scope of human-machine collaboration with AI greater for high-skilled workers. Thus, technology complementarity favours highly skilled workers at the expense of lower-skilled workers that perform less cognitive and more repetitive tasks. On the contrary, a positive estimated coefficient for AI combined with a negative estimated coefficient for the interaction term indicates that AI increases productivity and output overall but less so where human capital is higher, in other words producing relatively larger marginal gains at lower human-capital levels. The latter is consistent with the customer service firm microdata results obtained by Brynjolfsson, Li, & Raymond (2025) according to which the workers that benefit most from AI shocks associated with the introduction and spread of the more recent large language models (LLMs) proxied by generative AI–based conversational assistants are the lower-skilled workers for whom AI assistance disproportionately facilitates learning.

We first performed panel cointegration tests for the long-run relationship described by equation (5) using the procedure proposed by Westerlund (2005), see Table 16, considering the two versions of the test. The first, with the alternative hypothesis that only some of the cross-sectional units display cointegration and the second version considering as the alternative hypothesis the possibility that all the panel units display cointegration. In both cases, we perform the test with and without a trend in the model. The results provide evidence in favour of the existence of cointegration among the variables included in the long-run regression given by equation (5) when we consider a trend in the model.

Table 16. Results of the Westerlund (2005) panel cointegration tests

		No Trend	**With Trend**
APP	All Panels	0.1949	0.0339
	Some Panels	0.3109	0.0000
INV	All Panels	0.3367	0.0028
	Some Panels	0.4851	0.0000
PUB	All Panels	0.4763	0.0000
	Some Panels	0.3301	0.0000

Notes: the table contains the p-values for the Westerlund panel cointegration test Westerlund (2005). The null of the test is the absence of cointegration among the series.

Table 17 reports the findings of estimating the ARDL with the introduction in the long-run relationship of the interaction term between AI and human capital considering our three proxies of AI adoption and both Diff-GMM and Sys-GMM estimators. Taken together, the results do not seem to endorse a relevant role for human capital in the aggregate and for the period considered as most of the estimated coefficients for the interaction terms are not statistically significant (nine out of twelve). Additionally, the statistically significant results lead to quite different interpretations concerning the role of human capital depending on the AI proxy used. With AI patents data (columns (4) and (5)), the results support that in the short-run AI leads to larger marginal gains at lower human-capital levels. On the contrary, using AI scientific publications points to AI being skill-biased in the long-run (column (3)). Based on these results with aggregate data, it is does not seem possible to have a clear picture about of what type of labour is benefitting more from AI advancements. In any case, at the more disaggregate industry or firm-level studies point to disproportionate gains to either high or low-skilled workers depending on the specific sectors/firms under analysis and these opposite sign effects can cancel out when using aggregate data.

Table 17. Results including an interaction term between AI and human capital

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation/AI	*APP*	*INV*	*PUB*	*APP*	*INV*	*PUB*
$\Delta^2 logh_{i,t}$	3.054	0.822	0.917	-1.163	-0.396	-1.200
	(1.946)	(1.534)	(1.198)	(2.150)	(1.506)	(2.196)
$\Delta logk_{i,t}$	0.185***	0.113	0.0282	0.139*	0.115	0.150***
	(0.0545)	(0.0726)	(0.0398)	(0.0759)	(0.0866)	(0.0497)
$\Delta logai^{APP}_{i,t}$	-0.122			0.452*		
	(0.179)			(0.265)		
$\Delta loginn^{APP}_{i,t}$	0.152***			0.00574		
	(0.0343)			(0.0270)		
$logy_{i,t-1}$	-0.765***	-0.569***	0.0879	-0.118	-0.119**	-0.0623
	(0.198)	(0.135)	(0.0683)	(0.0726)	(0.0557)	(0.0450)
$\Delta logh_{i,t-1}$	1.958	-0.920	0.223	-0.423	-1.144	-3.500
	(1.619)	(1.770)	(0.834)	(1.904)	(1.200)	(2.910)
$logk_{i,t-1}$	0.145**	0.0880*	-0.209***	0.0470	0.0598	0.0358
	(0.0734)	(0.0465)	(0.0547)	(0.0465)	(0.0369)	(0.0290)
$logai^{APP}_{i,t-1}$	-0.113			0.00846		
	(0.125)			(0.106)		
$loginn^{APP}_{i,t-1}$	0.202***			0.0164		
	(0.0407)			(0.0106)		
$logh_{i,t}$ x $\Delta logai^{APP}_{i,t}$	0.140			-0.393*		
	(0.152)			(0.221)		
$logh_{i,t}$ x $logai^{APP}_{i,t-1}$	0.137			-0.0125		
	(0.0939)			(0.0770)		
$\Delta logai^{INV}_{i,t}$		0.259			0.499*	
		(0.286)			(0.259)	
$logai^{INV}_{i,t-1}$		-0.0772			0.0358	
		(0.140)			(0.0856)	
$\Delta loginn^{INV}_{i,t}$		0.125**			0.00401	
		(0.0488)			(0.0351)	

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation/AI	*APP*	*INV*	*PUB*	*APP*	*INV*	*PUB*
$loginn^{INV}_{i,t\text{-}1}$		0.149***			0.00637	
		(0.0499)			(0.0113)	
$logh_{i,t}$ x $\Delta logai^{INV}_{i,t}$		-0.201			-0.425**	
		(0.236)			(0.212)	
$logh_{i,t}$ x $logai^{INV}_{i,t\text{-}1}$		0.0999			-0.0267	
		(0.109)			(0.0600)	
$\Delta logai^{PUB}_{i,t}$			-0.0697			0.0647
			(0.142)			(0.0781)
$logai^{PUB}_{i,t\text{-}1}$			-0.173***			0.0357
			(0.0461)			(0.0395)
$\Delta loginn^{PUB}_{i,t}$			0.0841***			-0.0196
			(0.0263)			(0.0207)
$loginn^{PUB}_{i,t\text{-}1}$			0.112***			-0.0124
			(0.0383)			(0.0137)
$logh_{i,t}$ x $logai^{PUB}_{i,t}$			0.0384			-0.0359
			(0.121)			(0.0622)
$logh_{i,t}$ x $ogai^{PUB}_{i,t\text{-}1}$			0.108***			-0.0219
			(0.0341)			(0.0264)
Observations	700	700	700	735	735	735
No. of Countries	35	35	35	35	35	35
No. of instruments	24	24	24	30	30	30
AR1 (p-value)	0.458	0.0146	0.0011	0.0035	0.0007	0.0004
AR2 (p-value)	0.293	0.113	0.142	0.831	0.557	0.111
Hansen-J	7.360	14.13	8.594	21.46	19.45	23.54
Hansen-J (p-value)	0.833	0.365	0.803	0.206	0.303	0.171

Notes: the results presented in columns (1), (4) and (5) include the first lag of the dependent variable to deal with the rejection of the AR2 test. Robust Standard errors in parentheses. * p<0.10, ** p<0.05, *** p<0.010.

4. Conclusion

It is widely accepted that technological progress underpins economic growth. This paper delved into the effects of AI adoption, a recent and promising form of technological progress, on economic growth and standards of living across a sample of 35 OECD countries over a little more than two decades, from 1995 to 2017. Panel autoregressive distributed lag (ARDL) models were employed to evaluate the long-run relationship and short-run impacts of AI adoption proxied by AI patents by applicants or inventors and AI-related scientific publications. While AI adoption may fluctuate in the short run, it could tend to correlate more consistently with real GDP per capita over the long run. It is therefore important to assess whether there is an enduring connection between these variables, distinguishing it from the short-run fluctuations. The prospect of skill-biased technological change in the context of AI, which may favour highly skilled workers while displacing those performing routine manual tasks, raises concerns about wage and employment polarisation. However, recent developments in generative AI suggest potential benefits for lower-skilled workers. Examining the nonlinear interaction between AI and human capital can help shed some light on these effects from a broader macroeconomic perspective.

Using patent data and a first-differenced GMM approach, our preferred results indicate that AI adoption is already fostering short-term economic growth and, over time, contributing to higher living standards. However, these effects are not uniform across all settings. When examining human capital, these aggregate results reveal no clear advantage for any particular group of workers. Capitalising on the AI potential advises putting in place policies that tackle obstacles and challenges such as providing the necessary infrastructure, addressing skills shortages or prioritising governance, transparency and AI ethics. As Autor (2022), p. 26 writes '(…) absent complementary institutional investments, technological innovation alone will not generate broadly shared gains.' He also explains where he thinks these institutional investments should concentrate: education and training, labor market institutions, and innovation policy.

As each new wave of AI is anticipated to have a growing impact on the economy, our estimates should be considered a lower bound that advises continuing monitoring of the effects of AI on economic growth and standards of living, bearing in mind that the associated increases in real GDP per capita do not necessarily imply shared prosperity. If and when artificial general intelligence (AGI) becomes a reality, i.e. artificial intelligence that 'possesses the ability to understand, learn, and perform any intellectual task a human being can perform' Korinek (2023), p. 31, even though the benefits in terms of growth and standards of living may accelerate, real GDP per capita is just an average, not accounting for income distribution. It is thus possible to envisage a scenario where AGI leads to massive job losses and unemployment, instead of primarily complementing human work, and widening income inequality will follow threatening future wellbeing, Autor (2022). To address this question, future research could tackle both effects simultaneously by e.g. estimating adequate models to account for the interactions and feedback effects between AI adoption, economic growth and inequality. Another important consideration is that, at the micro and sectoral levels, AI can enhance productivity by substituting for certain skill sets while complementing others. However, these heterogeneous effects may be obscured in aggregate analyses, underscoring the need for more disaggregated studies.

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