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SHORT- AND LONG-RUN GROWTH EFFECTS OF AI ADOPTION ACROSS THE OECD

JOSHUA DUARTE
University of Coimbra
Coimbra, Portugal
joshua.duarte@fe.uc.pt

CARINA FREITAS
University of Coimbra
Coimbra, Portugal
uc2023188528@student.uc.pt

MARTA SIMÕES
University of Coimbra
Coimbra, Portugal
mcsimoes@fe.uc.pt

Abstract
Although technological progress is a key driver of modern economic growth and long-term improvements in living standards, its effects have often materialized with a delay. This lag is frequently due to adjustment costs, such as the need for complementary investments and workforce training, or the time it takes for induced sectoral shifts to fully take effect. This study explores these dynamics in the context of artificial intelligence (AI), whose rapid rise and increasing adoption have sparked high expectations about its potential to enhance macroeconomic performance and overall well-being. To investigate the short- and long-run effects of AI adoption on growth and standards of living we consider a sample of 35 OECD countries observed annually over the period 1995-2017 and estimate a panel ARDL model. Our findings confirm that AI adoption is already translating into faster growth in the short run, suggesting that firms and sectors are rapidly adjusting to this new technology with its broad applications. These findings are robust to the consideration of different proxies for AI adoption, estimation procedures, a higher number of lags and additional control variables, and survive a coefficient stability analysis. AI adoption also seems to lead to long run improvements in standards of living, though this result is not supported in all contexts. As AI adoption continues to accelerate, its impact remains uncertain, but our findings support optimistic views, with short-run growth effects already visbile.
Keywords: *artificial intelligence; technological progress; economic growth; OECD; panel ARDL.*
JEL Classification: C33; O33; O47

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).

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 *et al*. (2023), Bick *et al*. (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 and Seamans, 2019). Beyond its ability to significantly enhance total factor productivity by enabling more effective use of both human and capital inputs, AI also has 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.

However, there may 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 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 *et al.* (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.

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 *et al*. (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. To investigate the short- and long-run effects of AI adoption on economic growth and standards of living 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 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 *et al.* (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. 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 realized and the pace at which it will develop.

This study is organized in four sections. Section 1 contains the introduction including a literature overview of the relationship between AI and economic growth- Section 2 sets out the model and econometric methodology used. Section 3 contains the findings and discusses the short- and long-run effects of AI adoption. Finally, section 4 contains the main takeaways.

2. EMPIRICAL STRATEGY

2.1 Methodology

To estimate the short- and long-run effects of AI on economic growth and standards of living, we consider an expanded neoclassical growth model (see e.g. Gonzales (2023) and Kalai *et al.* (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. Writing the production function in intensive form, i.e. dividing both sides of 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):

$$logy_{i,t} = \alpha_{0,i} + \alpha_1 logk_{i,t} + \alpha_2 logh_{i,t} + \alpha_3 logai_{i,t} + \alpha_4 loginn_{i,t} + \varepsilon_{i,t} \qquad (1)$$

where $i = 1,2,\ldots,N$ denotes the country and $t = 1,2,\ldots,T$ 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 study using panel cointegration tests, we next define the panel Autoregressive Distributed Lag (ARDL) of our model given by equation (2):

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

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 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 *et al.* (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.

2.2 Data

Our panel dataset covers 35 OECD countries observed at a yearly frequency between 1995 to 2017. The countries included in the analysis are Australia, Austria, Belgium, Canada, Chile, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Slovenia, Spain, Sweden, Switzerland, Turkey, the United Kingdom and the United States. The choice of countries and time coverage was dictated by data availability for our explanatory variable of interest, AI adoption, and the intention to cover a wide number of countries.

Table 1 contains a description of the variables used and respective sources. Our dependent variable is measured as the first difference of the log of real GDP per capita (y) from the PWT v.10.01 (Feenstra *et al.*, 2015), a widely recognized measure of intensive growth. The contribution of the immediate sources of growth corresponding to physical and human capital is measured using the capital stock at constant 2017 USD per capita and a human capital index that combines average years of education and returns to education, respectively, both from the PWT 10.01. We turn to Parteka and Kordalska (2023) for data on our variables concerning AI-related innovation and general innovation. Parteka and Kordalska (2023) compute three different proxies for AI adoption, one corresponding to the number of patents by applicants, identified in this study as *ai*, another to the number of patents by inventors (ai^{INV}), and the third one to the number of scientific publications (ai^{PUB}), all per million people employed. Since we want to highlight the impact of AI adoption on economic growth, we selected the metric most closely linked to the production process for use in the baseline model, specifically, patents by applicant. For robustness, we also present the results obtained using the other two proxies. The same rationale applies to the proxy for general innovation measured with the overall number of patents by applicants (*inn*) or by inventors (inn^{INV}) and with the overall number of publications (inn^{PUB}), all per million people employed.

Table 1. Variables and sources

Variable	Description	Source
y	Real GDP per capita (constant 2017 USD)	Penn World Table v.10.01
k	Capital stock per capita (constant 2017 USD)	Penn World Table v.10.01
h	Human capital index that combines average years of education and returns to education.	Penn World Table v.10.01
ai	Number of AI-related patents by applicants, per million people employed	Parteka and Kordalska (2023)
inn	Total number of patents by applicants, per million people employed	Parteka and Kordalska (2023)
ai^{INV}	Number of AI-related patents by inventors, per million people employed	Parteka and Kordalska (2023)
ai^{PUB}	Number of AI-related scientific publications, per million people employed	Parteka and Kordalska (2023)
inn^{INV}	Total number of patents by inventors, per million people employed	Parteka and Kordalska (2023)
inn^{PUB}	Total number of scientific publications, per million people employed	Parteka and Kordalska (2023)

Table 2 contains summary statistics for the variables included in our baseline model. Figure 1 plots the correlation matrix for these same variables. The correlation coefficients of the different variables with the log of output per capita are all positive as expected and higher for the overall innovation measure. This suggests that in modern knowledge-based economies – such as the OECD countries in our sample – technological progress is a primary driver of growth and rising living standards. AI adoption also shows a positive correlation with physical and human capital, considered essential for the successful integration of new technologies.

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	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	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

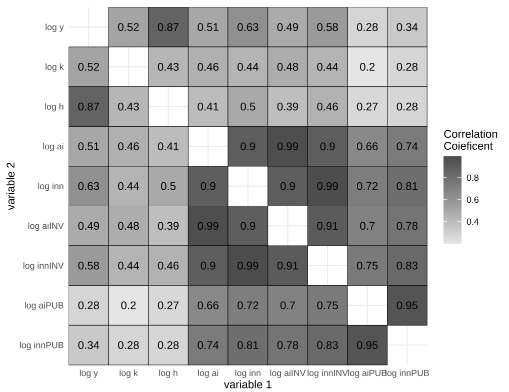

Figure 1. Correlation matrix

3. FINDINGS

We start by applying panel unit root rests to determine the order of integration of the series used, after which we proceed to testing for the existence of cointegration among the variables. We next carry out the estimation of the selected panel ARDL model.

3.1 Diagnostics and model selection

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 stationarity.

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	0.117	0.000	0.003	0.015	0.805	0.000	0.305	0.546
log h	1.000	0.969	0.983	0.956	1.000	1.000	1.000	1.000
log k	0.022	0.000	0.021	0.000	0.007	0.000	0.001	0.010
log ai	0.000	0.000	0.312	0.415	0.000	0.014	0.939	0.992
log inn	0.000	0.000	0.000	0.001	0.000	0.012	0.023	0.012
Δlog y	0.000	0.000	0.000	0.063	0.000	0.000	0.632	0.998
Δlog h	1.000	1.000	1.000	1.000	0.979	0.998	0.999	0.999
Δlog k	0.000	0.000	0.000	0.000	0.000	0.000	0.002	0.078
Δlog ai	0.000	0.000	0.000	0.279	0.000	0.000	0.006	0.985
Δlog inn	0.000	0.000	0.000	0.000	0.000	0.000	0.104	0.068

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.

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

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

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

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

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, considers 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
All Panels	0.0991	0.2050
Some Panels	0.1580	0.0025

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.

3.2 Estimation results for the baseline model

The estimation results of our preferred 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 *et al.,* 2020). To keep the number of moment conditions in the models tractable we use the Roodman (2009) collapse procedure. We also estimated equation (4) accounting only for omitted variable bias through the fixed effects estimator (results available from the authors). The short- and long-run estimated coefficients for all the AI measures are positive, but statistically significance varies with the proxy used. Only for AI-related scientific publications are the estimated coefficients not statistically significant in both the short and the long-run; on the other hand AI patents by applicants keeps significance in the short-run for both the Diff-GMM and the Sys-GMM estimations.

As can be seen from the inspection of the results presented in Tables 5 and 6, the findings for the models using as proxies for AI adoption ai, ai^{INV}, and ai^{PUB},are similar, but register some changes when using ai^{PUB}, which only displays an effect on the short-run, although the main results point in the same direction as those for the former two models. The effects of AI and general innovation on economic growth are positive in the diff-GMM estimations, indicating that an increase in overall innovation or in the effort put toward AI for any given level of innovation enhances growth in both the short- and the long-run. In the case of the sys-GMM estimations, the AI-related estimated coefficients are still mostly positive but only statistically significant in the short-run and only for the variable measuring AI adoption, loosing statistical significance in the case of overall innovation.

The estimated coefficients for physical and human capital when statistically significant in both the short- and the long-run display the expected signs, positive. 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. 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. As for model adequacy, the second order autocorrelation (AR2) tests do not detect problems as the null hypothesis is never rejected at the 10% significance level. The Hansen tests also never reject the null hypothesis that the instruments are valid at the 10% significance level. These diagnostic tests supporting instrument validity and model specification underscore the reliability of our results applying the GMM framework (Diff and Sys-GMM).

Table 5. Results for the baseline models

	Diff-GMM			**Sys-GMM**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Innovation/AI	***APP***	***INV***	***PUB***	***APP***	***INV***	***PUB***
$\Delta^2 logh_{i,t}$	-3.061	4.662	1.089	-3.468	-3.702	-0.0621
	(7.848)	(7.181)	(1.724)	(5.070)	(6.405)	(3.779)
$\Delta logk_{i,t}$	0.299**	0.287**	0.163**	0.260***	0.265***	0.194***
	(0.141)	(0.119)	(0.0694)	(0.0776)	(0.0742)	(0.0743)
$\Delta logai^{APP}_{i,t}$	0.0677***			0.0249**		
	(0.0224)			(0.0120)		
$\Delta loginn^{APP}_{i,t}$	0.0990***			0.0310		
	(0.0354)			(0.0294)		
$logy_{i,t-1}$	-0.626***	-0.575***	-0.107**	-0.111*	-0.137**	-0.0843**
	(0.108)	(0.128)	(0.0489)	(0.0583)	(0.0662)	(0.0421)
$\Delta logh_{i,t-1}$	-1.929	0.529	0.380	-1.784	-3.177	-2.314
	(7.366)	(7.541)	(2.189)	(3.266)	(3.928)	(2.738)
$logk_{i,t-1}$	0.168***	0.131***	-0.00895	0.0402	0.0584*	0.0447*
	(0.0422)	(0.0473)	(0.0379)	(0.0272)	(0.0310)	(0.0254)
$logai^{APP}_{i,t-1}$	0.0601***			0.00807		
	(0.0194)			(0.00904)		
$loginn^{APP}_{i,t-1}$	0.121***			0.00720		
	(0.0452)			(0.0124)		
$\Delta logai^{INV}_{i,t}$		0.0658***			0.0182	
		(0.0237)			(0.0120)	
$logai^{INV}_{i,t-1}$		0.0507**			0.00137	
		(0.0216)			(0.00836)	
$\Delta loginn^{INV}_{i,t}$		0.108**			0.0196	
		(0.0424)			(0.0229)	
$loginn^{INV}_{i,t-1}$		0.132***			0.0113	
		(0.0478)			(0.0112)	

	Diff-GMM			Sys-GMM		
	(1)	(2)	(3)	(4)	(5)	(6)
Innovation/AI	***APP***	***INV***	***PUB***	***APP***	***INV***	***PUB***
$\Delta logai^{PUB}_{i,t}$			0.0426**			0.0147
			(0.0178)			(0.00993)
$logai^{PUB}_{i,t-1}$			0.0316**			0.00625
			(0.0135)			(0.0139)
$\Delta loginn^{PUB}_{i,t}$			-0.0315			-0.0123
			(0.0310)			(0.0158)
$loginn^{PUB}_{i,t-1}$			-0.0145			-0.0120
			(0.0253)			(0.0186)
Observations	700	700	700	735	735	735
No. of Countries	35	35	35	35	35	35
No. of instruments	49	49	49	55	55	55
AR1 (p-value)	0.0779	0.0158	0.000651	0.00133	0.00167	0.000627
AR2 (p-value)	0.149	0.258	0.167	0.163	0.141	0.109
Hansen-J	24.36	32.38	31.43	30.47	30.46	32.88
Hansen-J (p-value)	0.976	0.799	0.832	0.952	0.952	0.910

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

3.3 Robustness checks

To validate our findings for the baseline model, we conducted a robustness analysis to the consideration of different lag orders in the ARDL model, including other growth determinants in the set of control variables and test for the stability of the coefficients. We performed these analyses using the models with each of the three proxies for AI and overall innovation variables as before. For economy of space reasons, we only report in this section the results for the models using patents by the applicant. The remaining results are available from the authors.

As the results may may depend on the number of lags for the short-run terms of the ARDL model included, as our first robustness check we estimate each of the three versions of the previous models for different numbers of lags in the short-run. Due to data restrictions and given that we are using annual data we only experiment with up to three lags. Across the various alternative specifications we test, see Tables 6-7, the core results remain largely consistent. The BIC criterion generally favours models without additional lags in the short-run terms, corresponding to the baseline models from the previous section replicated in column (1) of both Tables 6 and 7. In instances i.e. when models with additional lags are preferred, they tend to exhibit other problems, such as a coefficient for lagged income which is not statistically significant, which contradicts our initial assumption of a stable long-run relationship between the variables.

Table 6. Results using Diff-GMM and different lag orders

Variables	No lags	1 lag	2 lags	3 lags
	(1)	(2)	(3)	(4)
$\Delta^2 logh_{i,t}$	-3.061	3.456	5.223	-17.80
	(7.848)	(6.457)	(9.135)	(10.98)
$\Delta logk_{i,t}$	0.299**	0.237	0.387**	0.472
	(0.141)	(0.159)	(0.187)	(0.329)
$\Delta logai^{APP}_{i,t}$	0.0677***	0.0684***	0.0879**	0.0941***
	(0.0224)	(0.0205)	(0.0442)	(0.0340)
$\Delta loginn^{APP}_{i,t}$	0.0990***	0.126***	0.132**	0.274*
	(0.0354)	(0.0475)	(0.0553)	(0.140)
$logy_{i,t-1}$	-0.626***	-0.642***	-0.543**	-0.376
	(0.108)	(0.247)	(0.244)	(0.251)
$\Delta logh_{i,t-1}$	-1.929	2.686	1.551	-7.410
	(7.366)	(10.34)	(13.05)	(20.91)
$logk_{i,t-1}$	0.168***	0.161***	0.146*	0.157
	(0.0422)	(0.0578)	(0.0760)	(0.109)
$logai^{APP}_{i,t-1}$	0.0601***	0.0637**	0.0587	0.0512
	(0.0194)	(0.0278)	(0.0385)	(0.0345)
$loginn^{APP}_{i,t-1}$	0.121***	0.143**	0.113*	0.102
	(0.0452)	(0.0656)	(0.0676)	(0.0896)
$\Delta^2 logh_{i,t-1}$		-0.512	-3.416	-0.136
		(6.186)	(10.04)	(9.976)
$\Delta^2 logh_{i,t-2}$			-0.0431	3.416
			(8.538)	(15.02)
$\Delta^2 logh_{i,t-3}$				16.54
				(15.07)
$\Delta logk_{i,t-1}$		-0.0423	-0.0680	-0.0256
		(0.154)	(0.189)	(0.240)
$\Delta logk_{i,t-2}$			0.0792	-0.0506
			(0.0912)	(0.251)
$\Delta logk_{i,t-3}$				-0.185*
				(0.101)
$\Delta logai^{APP}_{i,t-1}$		-0.00360	0.00577	-0.00111
		(0.0112)	(0.0150)	(0.0140)
$\Delta logai^{APP}_{i,t-2}$			0.0139	0.00600
			(0.0121)	(0.0127)
$\Delta logai^{APP}_{i,t-3}$				-0.00217
				(0.00873)
$\Delta loginn^{APP}_{i,t-1}$		0.0117	0.0132	0.0756
		(0.0315)	(0.0492)	(0.0787)
$\Delta loginn^{APP}_{i,t-2}$			-0.00559	0.0439
			(0.0224)	(0.0642)
$\Delta loginn^{APP}_{i,t-3}$				0.0380
				(0.0273)
Observations	700	665	630	595
No. of Countries	35	35	35	35
No. of instruments	49	49	49	49
AR1 (p-value)	0.078	0.176	0.096	0.029
AR2 (p-value)	0.149	0.370	0.877	0.979
Hansen-J	24.361	20.134	20.975	8.045
Hansen-J (p-value)	0.976	0.985	0.932	1.000
BIC	1863.909	1801.414	1467.645	419.641

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

Table 7. Results using Sys -GMM and different lag orders

Variables	No lags	1 lag	2 lags	3 lags
	(1)	(2)	(3)	(4)
$\Delta^2 logh_{i,t}$	-3.468	0.254	3.683	0.805
	(5.070)	(4.710)	(4.022)	(9.190)
$\Delta logk_{i,t}$	0.260***	0.311***	0.330***	0.389***
	(0.0776)	(0.0725)	(0.0635)	(0.133)
$\Delta logai^{APP}_{i,t}$	0.0249**	0.0425***	0.0526**	0.0576
	(0.0120)	(0.0125)	(0.0235)	(0.0436)
$\Delta loginn^{APP}_{i,t}$	0.0310	0.124***	0.0709	0.0892
	(0.0294)	(0.0459)	(0.0722)	(0.167)
$logy_{i,t-1}$	-0.111*	-0.167	-0.311	-0.359
	(0.0583)	(0.135)	(0.204)	(0.448)
$\Delta logh_{i,t-1}$	-1.784	-0.805	-1.776	-15.26
	(3.266)	(3.774)	(8.773)	(14.49)
$logk_{i,t-1}$	0.0402	0.0611	0.100	0.147
	(0.0272)	(0.0432)	(0.0623)	(0.125)
$logai^{APP}_{i,t-1}$	0.00807	0.0217*	0.0265	0.0184
	(0.00904)	(0.0113)	(0.0232)	(0.0170)
$loginn^{APP}_{i,t-1}$	0.00720	0.0210	0.0378	0.0117
	(0.0124)	(0.0271)	(0.0364)	(0.0439)
$\Delta^2 logh_{i,t-1}$		-0.950	0.489	7.769
		(4.306)	(7.604)	(11.83)
$\Delta^2 logh_{i,t-2}$			4.764	14.94*
			(6.652)	(8.205)
$\Delta^2 logh_{i,t-3}$				12.37
				(12.57)
$\Delta logk_{i,t-1}$		0.0310	0.0558	0.0545
		(0.0728)	(0.0916)	(0.130)
$\Delta logk_{i,t-2}$			0.0691	0.0461
			(0.0607)	(0.0858)
$\Delta logk_{i,t-3}$				-0.113
				(0.296)
$\Delta logai^{APP}_{i,t-1}$		0.00378	0.0121	0.0125
		(0.00648)	(0.0116)	(0.0149)
$\Delta logai^{APP}_{i,t-2}$			0.0173*	0.0206
			(0.00994)	(0.0142)
$\Delta logai^{APP}_{i,t-3}$				-0.000814
				(0.00665)
$\Delta loginn^{APP}_{i,t-1}$		0.0387	0.00972	0.000830
		(0.0422)	(0.0499)	(0.104)
$\Delta loginn^{APP}_{i,t-2}$			0.00311	-0.00858
			(0.0164)	(0.0569)
$\Delta loginn^{APP}_{i,t-3}$				0.00917
				(0.0195)
Observations	735	700	665	630
No. of Countries	35	35	35	35
No. of instruments	55	55	55	55
AR1 (p-value)	0.001	0.015	0.022	0.221
AR2 (p-value)	0.163	0.407	0.910	0.644
Hansen-J	30.473	20.456	19.277	15.440
Hansen-J (p-value)	0.952	0.997	0.993	0.996
BIC	-4247.427	-3322.029	-2691.902	-2777.735

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

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 models. 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 alter our findings regarding the relationship between AI, overall innovation, and economic growth across any of the previously estimated model variants, see Tables 8-9. In the model with patents by aplicants the controls that show statistically significant coefficients are openness, public expenditures, and inflation. In the other model versions, these variables continue to exhibit significant effects, with industrialization also emerging as a statistically significant factor.

Table 8. Results with Diff-GMM and additional control variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	-3.061	-3.262	2.814	-4.874	-1.419	6.544	-3.826	0.519
	(7.848)	(6.520)	(4.719)	(5.760)	(5.992)	(5.734)	(9.413)	(6.832)
$\Delta logk_{i,t}$	0.299**	0.333***	0.177	0.251**	0.253***	0.290***	0.321**	0.359**
	(0.141)	(0.0884)	(0.128)	(0.128)	(0.0589)	(0.0958)	(0.154)	(0.140)
$\Delta logai^{APP}_{i,t}$	0.0677***	0.0644***	0.0593***	0.0688***	0.0516***	0.0539***	0.0678***	0.0564***
	(0.0224)	(0.0172)	(0.0208)	(0.0209)	(0.0163)	(0.0175)	(0.0194)	(0.0162)
$\Delta loginn^{APP}_{i,t}$	0.0990***	0.0919**	0.103***	0.0999***	0.0777**	0.0734*	0.106**	0.0850**
	(0.0354)	(0.0465)	(0.0284)	(0.0302)	(0.0309)	(0.0376)	(0.0425)	(0.0382)
$logy_{i,t-1}$	-0.626***	-0.562***	-0.692***	-0.639***	-0.422**	-0.502***	-0.555***	-0.570***
	(0.108)	(0.118)	(0.123)	(0.0735)	(0.171)	(0.117)	(0.149)	(0.145)
$\Delta logh_{i,t-1}$	-1.929	-0.840	5.693	0.853	-1.211	4.519	-0.578	2.977
	(7.366)	(5.730)	(3.546)	(7.215)	(5.437)	(5.856)	(7.576)	(6.665)
$logk_{i,t-1}$	0.168***	0.158***	0.160***	0.165***	0.0980**	0.122***	0.163***	0.147***
	(0.0422)	(0.0391)	(0.0392)	(0.0353)	(0.0489)	(0.0428)	(0.0464)	(0.0536)
$logai^{APP}_{i,t-1}$	0.0601***	0.0552***	0.0501***	0.0582***	0.0402**	0.0398**	0.0545***	0.0466***
	(0.0194)	(0.0153)	(0.0188)	(0.0184)	(0.0174)	(0.0172)	(0.0187)	(0.0156)
$loginn^{APP}_{i,t-1}$	0.121***	0.103**	0.165***	0.123***	0.0834*	0.0908***	0.103*	0.116***
	(0.0452)	(0.0418)	(0.0431)	(0.0222)	(0.0440)	(0.0285)	(0.0535)	(0.0413)
$\Delta trade_{i,t}$		0.00135						
		(0.000835)						
$\Delta rqe_{i,t}$			-0.0119					
			(0.0353)					
$\Delta inds_{i,t}$				-0.00112				
				(0.00647)				
$\Delta g_{i,t}$					-0.0206**			
					(0.0102)			
$\Delta inf_{i,t}$						0.0068***		
						(0.00202)		
$\Delta fdi_{i,t}$							0.00134	
							(0.00108)	
$\Delta urban_{i,t}$								-0.0377
								(0.0533)

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Observations	700	700	700	700	700	700	700	700
No. of Countries	35	35	35	35	35	35	35	35
No. of instruments	49	49	49	49	49	49	49	49
AR1 (p-value)	0.078	0.010	0.097	0.004	0.023	0.018	0.093	0.054
AR2 (p-value)	0.149	0.244	0.041	0.060	0.381	0.767	0.744	0.125
Hansen-J	24.361	21.326	21.686	20.760	22.306	25.072	26.875	25.245
Hansen-J (p-value)	0.976	0.990	0.989	0.993	0.985	0.959	0.929	0.957
BIC	1863.909	1686.197	2037.761	1919.196	1408.072	1632.461	1627.160	1746.691

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

Table 9. Results with Sys-GMM and additional control variables

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\Delta^2 logh_{i,t}$	-3.468	-1.777	-1.811	-0.856	-2.551	-4.098	-3.594	-2.645
	(5.070)	(3.686)	(3.103)	(3.448)	(3.689)	(3.353)	(3.641)	(1.708)
$\Delta logk_{i,t}$	0.260***	0.322***	0.321***	0.333***	0.223***	0.252***	0.301***	0.285***
	(0.0776)	(0.0802)	(0.0941)	(0.0949)	(0.0762)	(0.0495)	(0.0909)	(0.0872)
$\Delta logai^{APP}_{i,t}$	0.0249**	0.0546***	0.0295**	0.0287**	0.0145*	0.0532***	0.0249**	0.0243**
	(0.0120)	(0.0142)	(0.0134)	(0.0131)	(0.00857)	(0.0187)	(0.0123)	(0.0121)
$\Delta loginn^{APP}_{i,t}$	0.0310	0.0637**	0.0189	0.0162	0.0238	0.114**	0.0288	0.0287
	(0.0294)	(0.0284)	(0.0150)	(0.0150)	(0.0176)	(0.0455)	(0.0191)	(0.0275)
$logy_{i,t-1}$	-0.111*	-0.401***	-0.156**	-0.153*	-0.0328	-0.366***	-0.130*	-0.0868
	(0.0583)	(0.143)	(0.0735)	(0.0805)	(0.0529)	(0.104)	(0.0690)	(0.0635)
$\Delta logh_{i,t-1}$	-1.784	1.243	-2.669	-2.655	-0.602	0.420	-1.008	-0.328
	(3.266)	(3.034)	(2.070)	(2.592)	(2.697)	(2.076)	(2.963)	(1.722)
$logk_{i,t-1}$	0.0402	0.108**	0.0587*	0.0570	0.0000388	0.0993***	0.0507*	0.0317
	(0.0272)	(0.0476)	(0.0352)	(0.0383)	(0.0266)	(0.0230)	(0.0303)	(0.0291)
$logai^{APP}_{i,t-1}$	0.00807	0.0394***	0.0128	0.0123	0.00272	0.0348**	0.0107	0.00666
	(0.00904)	(0.0122)	(0.00916)	(0.0105)	(0.00626)	(0.0153)	(0.0101)	(0.00850)
$loginn^{APP}_{i,t-1}$	0.00720	0.0757**	0.00979	0.00993	0.00382	0.0786**	0.00868	0.00784
	(0.0124)	(0.0323)	(0.0107)	(0.0112)	(0.00816)	(0.0330)	(0.0122)	(0.0109)
$\Delta trade_{i,t}$		0.00186**						
		(0.000935)						
$\Delta rqe_{i,t}$			-0.00982					
			(0.0216)					
$\Delta inds_{i,t}$				0.00458				
				(0.00641)				
$\Delta g_{i,t}$					-0.0327***			
					(0.00788)			
$\Delta inf_{i,t}$						0.00251		
						(0.00305)		
$\Delta fdi_{i,t}$							0.000831	
							(0.000604)	
$\Delta urban_{i,t}$								-0.0363
								(0.0312)
Observations	735.000	735.000	735.000	735.000	735.000	735.000	735.000	735.000
No. of Countries	35.000	35.000	35.000	35.000	35.000	35.000	35.000	35.000
No. of instruments	55.000	55.000	55.000	55.000	55.000	55.000	55.000	55.000
AR1 (p-value)	0.001	0.002	0.002	0.004	0.003	0.001	0.007	0.002
AR2 (p-value)	0.163	0.384	0.145	0.168	0.491	0.663	0.505	0.177
Hansen-J	30.473	20.381	27.852	28.782	26.992	18.421	29.206	27.969
Hansen-J (p-value)	0.952	0.999	0.973	0.963	0.980	1.000	0.958	0.971
BIC	-4247.427	-2285.135	-4030.863	-4056.765	-4626.364	-2267.373	-4116.390	-4291.678

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

The stability of estimated coefficients over time 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. 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).

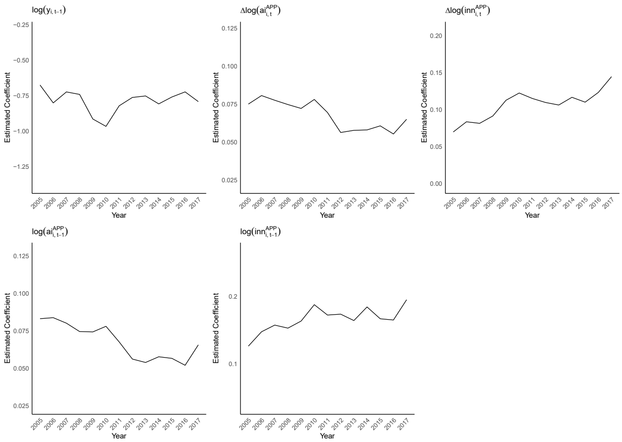

Figure 2. Diff-GMM estimated coefficients over expanding windows *(ai^{APP}; inn^{APP})*

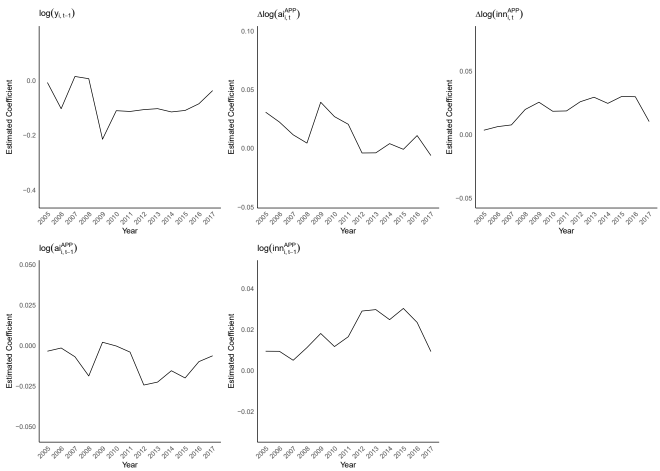

Figure 3. Sys-GMM estimated coefficients over expanding windows *(ai^{APP}; inn^{APP})*

4. CONCLUSION

This paper delved into the effects of AI adoption 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.

Our findings indicate that AI adoption positively affects economic growth. This conclusion holds true across measures of AI adoption, estimation procedures, different model specifications and considering additional short-run lags. We also found that AI adoption has a long-run positive impact on real GDP per capita, especially when AI patents by applicants are considered. Capitalising on this 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.

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