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# Implications of AI innovation on economic growth: a panel data study

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## Abstract

The application of artificial intelligence (AI) across firms and industries warrants a line of research focused on determining its overall effect on economic variables. As a general-purpose technology (GPT), for example, AI helps in the production, marketing, and customer acquisition of firms, increasing their productivity and consumer reach. Aside from these, other effects of AI include enhanced quality of services, improved work accuracy and efficiency, and increased customer satisfaction. Hence, this study aims to gauge the impact of AI on the economy, specifically on long-run economic growth. This study conjectures a positive relationship between AI and economic growth. To test this hypothesis, this study makes use of a panel dataset of countries from 1970 to 2019, and the number of AI patents as a measure of AI. A text search query is performed to distinguish AI patents from other types of innovations in a public database. Employing fixed effects and generalized method of moments (GMM) estimation, this paper finds a positive relationship between AI and economic growth, which is higher than the effect of the total population of patents on growth. Furthermore, other results indicate that AI's influence on growth is more robust among advanced economies, and more evident towards the latter periods of the dataset.

**Keywords:** Artificial intelligence, Patents, Economic growth, GMM

## 1 Introduction

The developments in computer science and digital technology, including artificial intelligence (AI) and machine learning, naturally led to their application in key sectors such as healthcare, finance, manufacturing, and transport.[1] Their increasing use in industries has opened up questions as to whether these technologies may have an impact on economic variables. In neoclassical and endogenous economic growth models, for example, technical change brings about increases in productivity, leading to economic growth. Hence, breakthroughs in computing technology should also entail increases in growth rates.

In particular, the last 60 years have witnessed a shift in production from traditional inputs to more information and communications technology (ICT)-based,

[1] Yang et al. (2021), Mahalakshmi et al. (2022), Sood et al. (2022), etc.

capital-intensive tools. The introduction of modern computers and the Internet in the early 1990s, and more recently, AI, led to changes in the methods of production. In keeping with the rise of new technologies, Zeira (1998) proposed an economic growth model adopting technological innovations that reduce labor inputs but require more capital.[2] Furthermore, more recent empirical studies on the subject have found these technologies as potential sources of economies of scale (e.g., Nightingale 2000; Wang et al. 2011; Nchake and Shuaibu 2022). Thus, it is only expected that advancements in ICT may have a positive effect on overall productivity and economic growth.

This study continues this line of research by exploring the relationship between technical change, as manifested by modern developments in science and technology, and economic growth. Several economic papers have been published on the subject, of proxying technology with various forms of knowledge and ICT measures (e.g., patents and scientific journals, Internet penetration, computer ownership, etc.). This paper is similar to past academic papers, yet with a special focus on AI as a newer form of technology.

Estimation results reveal a positive and significant impact of AI on long-run economic growth in a cross-country panel dataset. The magnitude of AI's effect on growth is also higher than that of total patents. Furthermore, the contribution of AI to growth is more robust both for advanced economies and for the latter half of the period considered in the estimation.

## 2 Literature review

Endogenous growth models are central to much of the existing literature on technology and economic growth. Arrow (1962) associates technology as a "by-product of ordinary production" through knowledge accumulation, aptly termed "learning-by-doing." The process of learning through repetition and experience should manifest itself in increases in productivity, thus creating opportunities for economic growth.[3] Arrow (1962) assumes that technical change, born out of knowledge and experience, is embodied in new physical capital, which then enters the production process and improves "productive efficiency."[4]

The literature on technology and growth follows this line of thought, assuming that technological change increases capital productivity. In line with the Schumpeterian tradition, Zeira (1998) presents a theoretical framework involving intermediate goods in production. Technology adoption increases the intensity of capital and replaces labor in the production process. Technology is then adopted if it increases output; however, as technology requires more capital input, not all countries can keep up with the technological frontier.[5] The disparities in the levels of technology across countries then result in differences in overall output and productivity.

[2] Zeira (1998) notes that standard economic growth models that involve technology adoption encourage the accumulation of capital. However, this may not be necessary as "new technology increases output for any combination of inputs".

[3] Arrow (1962) assumes a competitive equilibrium. However, Dasgupta and Stiglitz (1988) reason that learning possibilities can only translate into growth if "learning spillovers are complete." In an oligopolistic market structure, for example, firms may not be able to learn "costlessly, completely, and instantaneously from the experience of others.".

[4] Arrow (1962) follows this idea from the standard neoclassical growth model. On the contrary, Bahk and Gort (1993) revealed that the effect of learning can also be disembodied from both capital and labor.

[5] Zeira (1998) ascribes this to the wage differential across countries. Countries with lower wages tend to have lower productivity; hence, they are unable to afford the high requirements of capital to adopt the latest technology.

Meanwhile, Acemoglu and Restrepo (2018) have constructed a "task-based" framework, treating automation and the creation of new tasks as types of technological innovation. Both types of technology are necessary to increase productivity. Initially, Acemoglu and Restrepo (2018) considered that all tasks could be done by labor, whereas "lower-indexed" tasks could and would be automated.[6] However, automation requires some capital investment, thus raising the share of capital and decreasing the share of labor in production. This is counterbalanced, though, by creating new and more sophisticated tasks, where labor has a "comparative advantage." In the long run, there is a "stable, balanced growth path" where the two types of innovations coexist and grow at the same rate.[7]

The aforementioned theoretical works help explain the relationship between modern science and ICT developments and economic growth. However, empirical evidence on more recent forms of technological innovation, such as AI and machine learning, is still limited. This can be attributed to an insufficient amount of data both at the firm and at macro levels, especially when dealing with long-run growth.[8] This study is an attempt to contribute to the body of literature on this subject despite limitations on data availability. In the following discussion in this section, this paper will revisit some recent publications regarding the relationship between technical change and economic growth, using common scientific knowledge and technology variables.

In empirical studies, the number of patents and scientific journals are common measures of technological innovation. In the Schumpeterian context, patents represent ownership of monopoly rents from the invention of new technology. Firms aim for exclusive rights over these monopoly rents; thus, new technologies that improve productivity are continuously invented, while dismantling obsolete ones in the process—the so-called "creative destruction." As better technologies are created, firms become more productive, possibly achieving increasing returns to scale status.[9] Hence, countries with higher concentrations of patents may signal higher productivity and levels of production, and of course, national growth.[10]

On the other hand, scientific journals index the level of research and development (R&D). Based on standard growth models, technical progress is a product of knowledge accumulation, which is made possible through continuous R&D efforts. According to Kim and Lee (2015), academic articles as a measure of scientific knowledge have been regarded as a contributor to economic growth, citing scientific journals published by institutions and universities as sources of "patents and industrial technology." Assuming

[6] Low-indexed tasks refer to tasks that require minimal skill. In general, low-indexed tasks are assigned to low-skilled labor.

[7] Acemoglu and Restrepo (2018) attribute the stability of the growth path to "self-correcting forces" of the factor prices. Furthermore, as both types of innovation advance at the same rate, the long-run growth rate path is characterized by a constant labor share.

[8] This study also suffers from this problem. For example, the chosen measure for AI may still not fully and accurately capture its effect on growth.

[9] See Aghion and Howitt (1990).

[10] Chu et al. (2016), however, claim that "patent breadth" only promotes growth in the short run by raising the "profit margin of monopolistic firms" and providing "more incentives for R&D." Accordingly, patents reduce growth in the long run but expand the total number of firms. Further, they state that an R&D subsidy is a more appropriate policy for "stimulating long-run economic growth.".

academic knowledge from journal articles can be transformed into concrete technological inputs for production, published research should then also contribute to overall productivity and growth.[11]

However, Kim and Lee (2015) conclude that it is patents and not scientific journals that contribute to economic growth. They considered academic articles to be sources of scientific knowledge, whereas patents are embodiments of technological knowledge. Technological knowledge, though, is more a product of the private R&D efforts of firms than of scientific research from academic institutions. Using panel data estimation and evidence from Latin American economies, Kim and Lee (2015) found an insignificant effect of scientific knowledge, while patents indicated significant and positive impacts on economic growth.

Studies about patents and growth are numerous, often arriving at similar results (e.g., Lach 1995; Sinha 2008; Kim et al. 2012). In an earlier work modeling innovation and entrepreneurship with economic growth, Wong et al. (2005) found a significant and positive effect of patent grants as an indicator of innovation on country growth rates. In contrast, recent studies such as those by Sweet and Eterovic (2019) and Blind et al. (2022) found no significant effect of patents on economic growth.

In another recent study, Nguyen and Doytch (2022) found a positive and significant effect of total patents on economic growth for advanced economies, but the magnitude of the effect of the technology variable weakens for emerging economies.[12] Moreover, ICT patents only contribute to economic growth among advanced economies. In addition, the authors found that total patents, regardless of domain, are not significant in the long run, but ICT patents remain positive and significant.

On the other hand, studies on the effect of scientific research, measured by the number of scientific journals, on cross-country growth tend to be mixed. As mentioned previously, Kim and Lee (2015) discovered no significant impact of scientific knowledge from academic articles on growth. Meanwhile, Ntuli et al. (2015) found differing results in determining causality between research output and growth among OECD countries. Research output exhibits "unidirectional causality" on growth in some countries such, as the United States, Finland, Hungary, and Mexico, but is negligible in other OECD members.

Existing literature suggests a weak or ambiguous relationship between academic research and national growth (e.g., Inglesi-Lotz et al. 2014; Hatemi-J et al. 2016).[13] In contrast, Solarin and Yen (2016) obtained a positive relationship between research publications and economic growth using a cross-country panel dataset. They found that the effect was significant "irrespective of whether the focus is on developed countries or developing nations." However, Solarin and Yen (2016) noted that the impact on growth is stronger in advanced economies.

[11] Kim and Lee (2015), however, recognize that this might only be plausible among advanced countries, where viable "national innovation systems" and infrastructures enable scientific research to be put into effective commercial use.

[12] This is similar to the finding of Kim et al. (2012), where they found no significant effect of patent intensity on growth among developing economies.

[13] In relation to this, Lee et al. (2011) highlight a "mutual causation" between research publications and GDP among Asian economies. This causation, however, is less clear in Western countries.

Interestingly, Mueller (2006) found that research output may be favorable to local economic performance. Mueller (2006) analyzed the impact of private industry and university R&D, along with measures of entrepreneurship and university-industry relations,[14] on regional aggregate output in West Germany. Regression results have established individual, positive effects of each variable on regional economic performance.

Further, at the firm level, "intangible assets" such as "R&D, goodwill, brand equity, patents, copyrights, software, licenses, image, and organization" are "enhancers" of total factor productivity (TFP) (Nakatani 2021). Comparing firms within the ICT sector across five countries, intangible assets revealed a significant impact, though differing in magnitude, on the productivity of ICT firms across countries.[15] This can be attributed to some countries already being at the forefront of the global technology frontier. Hence, the additional effect of intangible assets on firm productivity diminishes (Nakatani 2021).

This study, however, is more interested in a specific technological innovation different from ICT, namely AI, including machine learning. With AI swiftly becoming the new general-purpose technology (GPT) (Trajtenberg 2018), comparisons between AI and previous technologies, particularly ICT, have been raised (Lu and Zhou 2021). However, AI is considered to "impact a broader range of sectors," leading to "different implications at the aggregate level" and an "unpredictable future development." Furthermore, ICT is known to require high investments in capital over long periods, whereas AI can leverage data and cloud services that can help lower capital investments. These differences could potentially lead to a distinct "pathway" for AI adoption, different from that of previous technologies (Lu and Zhou 2021).

Because of the scarcity of data, there is a dearth of empirical evidence on the topic of AI as a driver of economic growth. Nonetheless, this article attempts to determine this relationship using an available measure that can indicate the level of AI per country.

### 2.1 What is AI?

AI encompasses a broad category of technology, and there is not a single, widely accepted definition. However, international organizations have similar definitions of AI. The European Parliamentary Research Service (EPRS), for example, refers to AI as machines that perform "human-like cognitive processes," namely, "learning, understanding, reasoning and interacting." As a general-purpose technology, AI can take many forms such as a "technical infrastructure (i.e., algorithms), a part of the (production) process, or an end-user product" (Szczepański 2019). Hence, in contrast with traditional technologies that automate routine processes, AI technologies even go further to mimic human activities that require cognition, and their application and use are not limited to the production process.

Meanwhile, the International Telecommunication Union (ITU) broadly defines AI as "self-learning, adaptive systems." Accordingly, there are several "approaches" in defining AI, namely: (1) in terms of "technologies, techniques and/or approaches" such as

[14] Mueller (2006) distinguishes the types of R&D (private and university) from each other and estimated the impact of each separately. Also, the university-industry relation was measured by industry grants per researcher.

[15] In the sample, Nakatani (2021) reveals an insignificant impact of intangible assets on TFP among South Korean firms, whereas a significant and positive contribution to TFP with the largest magnitude is found for ICT firms in the United Kingdom.

“a neural network approach to machine translation”; (2) in terms of “purpose,” which include facial and image recognition; (3) in terms of “functions,” such as the “ability to understand language, recognize pictures, solve problems, and learn”; and (4) in terms of “agents or machines or algorithms” such as robots and self-driving cars (International Telecommunication Union 2023).

Furthermore, Montagnier and Ek (2021) cite several definitions of AI by individual countries and organizations such as the European Commission and the OECD. For instance, the OECD defines AI as a “machine-based system” that can “make predictions, recommendations, or decisions” and “operate with varying levels of autonomy” (Yeung 2020). Additionally, the European commission (2021) provides some examples of AI, which include “chatbots” and “virtual assistants,” “face recognition systems,” “machine translation software,” “data analysis based on machine learning,” “autonomous robots,” and “autonomous drones.” On the other hand, national statistics institutions such as the French Institut national de la statistique et des études économiques (INSEE) (2019) describe AI as “technologies” that can perform “cognitive tasks traditionally performed by humans,” whereas Statistics Sweden (2020) notes that physically, AI may be “purely software based or embedded in hardware.”

Because of its broad definition and the lack of a single, universally accepted descriptor of AI, classifying existing AI technologies is also a difficult task. In spite of this, Sarker (2022) categorized AI into five types, which include analytical, functional, interactive, textual, and visual.[16] However, the most commonly heard terms in AI are the “techniques” used in developing intelligent and smart systems in various real-world application areas.” Sarker (2022) identified at least ten “potential categories,” namely:

- Machine learning,
- Neural network and deep learning (including generative AI),
- Data mining, knowledge discovery, and advanced analytics,
- Rule-based modeling and decision-making,
- Fuzzy logic-based approach,
- Knowledge representation, uncertainty reasoning, and expert system modeling,
- Case-based reasoning,
- Text mining and natural language processing,
- Visual analytics, computer vision, and pattern recognition,
- Hybrid approach, searching, and optimization.

While each AI technique has its scope and specific applications, it is often that existing technologies are combinations and applications of various categories. Thus, grouping AI systems according to specific types or techniques is not always feasible. Moreover, AI development is a wide and ongoing practice, and more and newer forms of AI technologies are continuously produced over time. For example, ChatGPT, a form of generative

[16] Analytical AI refers to technologies that help in the identification of “new insights, patterns, and relationships or dependencies” in data for decision-making. Functional AI executes or implements actions, instead of generating recommendations. Interactive AI enables “interactive communication” between the user and a smart system to provide user assistance (e.g., chatbots and smart personal assistants). Textual AI typically covers textual analytics and natural language processing. Finally, visual AI can be considered a “branch of computer science” that “trains” machines to learn images and visual data (Sarker 2022).

AI technology that employs deep learning, was released to the public in 2022, and quickly became a groundbreaking AI technology due to its ability to interact with individuals and provide "comprehensive and practical responses" (Marr 2023).[17] ChatGPT is built upon "foundational large language models" (LLMs), which go beyond conventional natural language algorithms.

In addition, AI development may be unique to its industry due to the nature of AI itself. Coiera (2019) identifies three main stages of AI development, termed "miles." The "first mile" consists of data acquisition, pre-processing, or "cleaning." The "middle mile" includes "developing and testing the technical performance of different algorithms" that are built using the data acquired in the first stage. After all tests and tuning are completed, an AI system enters the last mile, where it is "embedded in real-world processes and tested for impact on real-world outcomes."

However, each stage of AI development has its challenges. The first mile entails "foundational challenges," such as "gathering and curating" huge amounts of high-quality data. Acquiring large amounts of data presents a potential "bottleneck," and "translates into a roadblock to technology application." Meanwhile, the middle mile involves the difficulties of "data-driven algorithm development," such as "biases, replicability, causal inference, avoiding overfitting on training data, and enhancing the generalizability of any models and algorithms" (Coiera 2019).[18]

Finally, and likely the hardest task, occurs in the third mile. As it turns out, "AI does not do anything on its own"; therefore, AI systems must somehow "connect" to the real world. Simply, the impact of an AI system must be "consequential" and "meaningful." For example, the current setting does not necessitate better diagnoses of cancer but "more nuanced" and "less aggressive" approaches to detection and management. Hence, the last mile refers to the implementation of AI itself in real-world processes. AI implementation faces a plethora of challenges, which can be classified under "measurement," "generalization and calibration," and "local context" (Coiera 2019).[19]

### 2.2 AI and economic growth

AI drives economic growth by stimulating gains both from the supply side and the demand side. AI can drive business productivity through (1) automation of processes with the use of robots and "autonomous vehicles," and (2) improvements in the existing labor force by equipping them with AI technologies. On the other hand, AI can generate an increase in consumer demand with the availability of "personalised and/or higher-quality" products and services. Accordingly, it is expected that AI could contribute up to USD 15.7 trillion to the global economy in 2030 (Rao and Verweij 2017).

Furthermore, the contributions of AI may be specific to the sectors where it is applied, such as manufacturing, health, finance, energy, and transport. For example, AI supports

[17] The period considered in the analysis may not cover recent generative AI such as ChatGPT, unless these inventions have been patented years before their release.

[18] Aside from these challenges, training AI models is typically associated with enormous costs, both in time and resources.

[19] Challenges in measurement gauge how well an AI performs its assigned tasks. On the other hand, generalization and calibration refer to the performance and replicability of an AI system to different populations or datasets. Local context encompasses the "act of fitting" new technology and its "goodness of fit" into a pre-existing organizational network (Coiera 2019).

healthcare services through early detection and diagnosis of illnesses, identification of "potential pandemics and tracking incidence," and "imaging diagnostics" in radiology and pathology. Meanwhile, AI contributions to the financial sector include applications for fraud detection and anti-money laundering. Also, AI developments such as "robo-advice" make "customized investment solutions" possible in managing financial goals and optimizing clients' funds. In addition, AI enables "autonomous trucking and delivery," traffic control systems, and improved security in the transport sector (Rao and Verweij 2017).

Recently, Lu (2021) built a theoretical framework that traces the impact of AI on endogenous growth. Lu (2021) likens AI to human capital accumulation, "as it can learn and accumulate knowledge by itself." Secondly, AI is a "nonrival input," which can be used in production without having it "detract from its ability to accumulate AI." This implies that AI is disembodied from physical capital, and should be considered a separate input.[20] Moreover, Lu (2021) unveils a balanced growth path in the three-sector endogenous growth model, where production and factors including AI grow at the same rate.[21]

Using provincial data from China, He (2019) estimated the effect of AI on regional economic growth. Unlike most innovation studies on ICT and growth, He (2019) makes use of fixed assets investment in ICT to GDP as a measure of AI,[22] rather than AI-specific patents or published articles. Similarly, Fan and Liu (2021) tested AI as a tool for the sustainable economic development of Chinese provinces.[23] The results in both studies are consistent with theories on the growth-enhancing capability of AI.

Furthermore, Yang (2022) evaluated the effect of both AI and non-AI patents on firm-level productivity and employment in Taiwan. Both types of patents were found to improve productivity and employment among Taiwanese electronic firms. Estimation results revealed that both AI and non-AI patents contribute to TFP, and the difference in elasticities between the two patent types is insignificant. Moreover, when TFP is replaced by labor productivity, the estimated coefficient for AI patents is lower than in the model with TFP as a dependent variable. Yang (2022) suggested that this can be attributed to AI technology having a "greater effect on capital productivity," which is consistent with the frameworks of Arrow (1962) and Zeira (1998).

At present, there are limited empirical works regarding AI as an engine of economic growth, primarily because of the unavailability of data.[24] Though extant literature on the topic finds a positive relationship between AI technology and economic growth, general sentiment suggests the effect of AI on growth is complex (He 2019) and difficult to

[20] This is similar to the Bahk and Gort (1993) model. Lu (2021) further adds that AI may replace human labor in the future, which subsequently has welfare implications.

[21] The balanced growth path by Lu (2021) shows output, human capital, physical capital, AI, and consumption grow at the same rate.

[22] Specifically, He (2019) measures AI as "the ratio of fixed assets investment in information transmission computer services and software industry to GDP.".

[23] Fan and Liu (2021) have developed an index to measure AI level based on three aspects, namely "infrastructure development, technology application, and market benefits.".

[24] On the other hand, Oxford Insights (2022) has developed an AI readiness index per country, available in the annual reports published since 2017. However, the current dataset lacks enough observation in terms of the time dimension. Thus, using the index was ruled out in favor of long-run analysis. Nonetheless, this study recommends using the index and/or other related AI measures for future research once more data are available.

measure. Intuitively, this can be because of its multifaceted role as an input to production. Still, with the increasing use of AI across countries and industries, this article seeks to measure the impact of AI on national growth rates amidst empirical constraints.

## 3 Theoretical framework

This study follows an endogenous growth framework. An endogenous model of economic growth often starts with the basic Cobb–Douglas function. However, this study also takes into account human capital as an input to production:

$$Y = AK^{\alpha}L^{\beta}H^{\gamma}, \tag{1}$$

where $Y$ is the total output, $K$ stands for capital, $L$ for labor, and $H$ is human capital. The elasticities of output to capital, labor, and human capital are denoted by $\alpha$, $\beta$, and $\gamma$, respectively. Meanwhile, $A$ is the level of knowledge, or as proposed by Jones and Williams (1998), the stock of ideas, available in an economy.

To obtain the output per unit of labor, Eq. (1) is divided on both sides by $L$. Multiplying the right-hand side with $\frac{L^{\alpha+\gamma}}{L^{\alpha+\gamma}} = \frac{L^{\alpha}}{L^{\alpha}} \cdot \frac{L^{\gamma}}{L^{\gamma}} = 1$ and assuming constant returns to scale, $\alpha + \beta + \gamma = 1$, results in Eq. (2):

$$\frac{Y}{L} = A\left(\frac{K^{\alpha}}{L^{\alpha}}\right)\left(\frac{H^{\gamma}}{L^{\gamma}}\right) = A\left(\frac{K}{L}\right)^{\alpha}\left(\frac{H}{L}\right)^{\gamma}. \tag{2}$$

For simplicity, the per unit of labor variables are replaced by small letters, as with Eq. (3):

$$y = Ak^{\alpha}h^{\gamma}. \tag{3}$$

The technology factor $A$ is seen as the available knowledge stock at time $t$. Romer (1990) proposed that since knowledge is a nonrival input, all researchers can utilize existing knowledge stock at the same time. Summing across all individual efforts in research yields Eq. (4):

$$\dot{A} = \delta R^{\theta} A, \tag{4}$$

where $R$ is the research effort or resources devoted to research. The function is assumed to be increasing in $R$, as more research leads to more ideas. Jones and Williams (1998), though, noted that Eq. (4) may be increasing or decreasing in $A$, depending on how previous ideas affect current research.

A basic (and crucial) assumption is that the parameter $\theta$ is assumed to be 1, to show that the increase in $R$ results in an increase in new ideas.[25] Meanwhile, the coefficient $\delta$ depicts the productivity of research, as proposed by Romer (1990) and Jones and Williams (1998).

To estimate Eq. (3), the equation is transformed into its natural log form. Further, the differenced natural logged form of Eq. (3) is obtained to calculate the growth rate:

[25] Jones and Williams (1998) explored the idea of a non-constant return to $R$ and $A$. They introduce additional parameters that represent "congestion externality," "knowledge spillovers," and "fishing out effects" in research, allowing the parameter $\theta$ to fall between 0 and 1 and assume non-linearity in $A$.

$$\Delta \ln y = \Delta \ln A + \alpha \Delta \ln k + \gamma \Delta \ln h. \tag{5}$$

The growth rate of $y$ is defined as $g_y = \frac{\dot{y}}{y}$, where $\dot{y} = \frac{dy}{dt}$. The term $\dot{y}$ represents the difference, or change, in output per worker between two time periods (the change in $t$). Mathematically, the growth rate can be further expressed as $g_y = \frac{dy/dt}{y} = \frac{d\ln y}{dt} = \frac{\ln y_t - \ln y_{t-s}}{s}$. Therefore, dividing Eq. (5) by the change in $t$ yields the growth rate equation:[26]

$$\frac{\dot{y}}{y} = \frac{\dot{A}}{A} + \alpha \frac{\dot{k}}{k} + \gamma \frac{\dot{h}}{h}. \tag{6}$$

Substituting Eq. (4) for the value of $\dot{A}$ in Eq. (6) and simplifying the resulting equation yields:

$$\frac{\dot{y}}{y} = \frac{\delta R^{\theta} A}{A} + \alpha \frac{\dot{k}}{k} + \gamma \frac{\dot{h}}{h}. \tag{7}$$

Finally, the growth rate of $y$ can be written as:

$$g_y = \delta R + \alpha g_k + \gamma g_h. \tag{8}$$

This study focuses on determining the relationship between AI innovation and economic growth. Thus, the variable $R$ is proxied by the level of AI innovation in the economy, given by the amount of AI patents published within a certain period. Notably, this is slightly different from the theoretical specification, which indicates $R$ as inputs or resources devoted to research (e.g., R&D expenditure, share of labor assigned to R&D, etc.). In general, patents are precisely the output of these R&D efforts. The choice of R&D input, such as the number of researchers, or output, such as the number of patents, in economic analysis, has been discussed by Griliches (1998). Ultimately, this decision depends on the size of the error terms in the relationships among patents, research, and knowledge stock.[27] Moreover, Griliches (1998) conjectures that if the "stochastic component" of knowledge stock is captured to some extent by patenting, using patents may have some "value added" over the use of common research inputs as an indicator of knowledge.

Patents embody the quantity, type, inventiveness, and complexity of innovation created in a given time (Griliches 1998). Although not without disadvantages, patents can serve as a good indicator of technical knowledge. More importantly, patent data are more readily available for analysis than research input measures, especially for AI. Hence, this study makes use of the number of AI and total patents as a proxy for R&D.

Furthermore, while the model discussed in this section explains how traditional research translates to economic growth, the current model might not fully encapsulate

[26] Equation (6) is the (short-run) growth equation when $dt = 1$. For long-run growth rates, the change in $t$ is greater than 1 ($dt > 1$) to indicate longer periods.

[27] Griliches (1998), however, acknowledges the difficulty of measuring these relationships, as knowledge stock is unobservable.

the effect of AI.[28] As stated previously, the employed model assumes constant returns to research (and by extension, AI). However, because of the nonrivalry of data and the possibility of AI "outpacing" human intelligence, continuous AI invention may exhibit increasing returns, further leading to a "technological singularity," or explosion of growth rates (Aghion et al. 2018). Exploring empirical evidence of such a mechanism is beyond the scope of this study; however, it is a highly recommended topic for future research.[29]

## 4 Data and methodology

For this study, the primary challenge to perform econometric analysis is obtaining data that can measure the level of AI in a cross-country, panel dataset format. As discussed in the previous sections, the most common indicator of technological innovation is patent publications. Therefore, this study uses AI patents as a measure of AI.

Data for AI patents are available from the Google Patents Public Data, provided by the Information for Industry, Inc. (IFI) CLAIMS Patent Services. To identify AI patents, a text search query was performed in the patents database. The text search includes common words or phrases related to AI, such as "artificial intelligence," "face recognition," "virtual assistant," "machine learning," etc.[30] Meanwhile, data for the dependent and control variables are sourced from the United Nations (UN) Department of Economic and Social Affairs Statistics Division and the World Bank.

This study echoes the econometric models of Wong et al. (2005), Kim and Lee (2015), and He (2019) among others. Estimating Eq. (8) from the previous section, the econometric model follows the equation:

$$\mathrm{Growth}_{it} = \varphi_0 + \varphi_1 \mathrm{Growth}_{i,t-1} + \varphi_2 GDPpc_{i,t-1} + \varphi_3 \mathrm{Patents}_{it} + \varphi X_{it} + \varepsilon_{it}, \quad (9)$$

where $\mathrm{Growth}_{it}$ is the annual average real GDP per capita growth rate of country $i$ over a certain period $t$, i.e., five years, calculated by dividing the difference between the natural log value of end-of-period real GDP per capita (in USD and constant 2015 prices) and the natural log value of initial real GDP, by the number of years in period $t$. Hence, $\mathrm{Growth}_{it}$ is the instantaneous growth rate of the real GDP of country $i$ in period $t$.

The lagged variable of growth rate is added to control for any potential endogeneity brought by the omitted variable, in the case when a large influence on current growth by its lagged value is present. Likewise, the lagged value of real GDP per capita is included to test for the convergence effect between high-income and low-income countries. The

[28] Lu and Zhou (2021) note that the definition of AI in theoretical models can be "very broad," whereas empirical data tend to have "narrow" definitions, resulting in a gap between the two. Theoretical models typically depict AI as a type of automation, but continuous AI development may be capable of replacing even high-skilled labor. In addition, AI raises the question of what a "human being" is in economics, where the human being is often "narrowed down" to "labor" and an "optimization agent." Aside from the current lack of clarity of whether AI is a "new production technology" or simply a new input of production, the question of which input (e.g., labor, human capital, or an "independent decision-making agent") is AI used as a substitute for also persists.

[29] In addition, Brynjolfsson et al. (2018) highlighted the "modern productivity paradox" in the age of AI. AI is indeed capable of many promising feats; however, productivity growth remained stagnant over the past decade. They attributed this inconsistency to several reasons, such as the difficulty of measuring AI capital because of its mostly intangible outputs, and the amount of time and resources required for the impact of technology to be fully reflected in productivity.

[30] Because of the mode of data extraction, the AI patent variable may be prone to accuracy and measurement error. As much as possible, the list of common AI terms used in the text search has been exhaustive. Furthermore, some technical jargon may be shared among multiple branches of knowledge that include AI. Hence, the word list has been limited to the most common and specific AI terms. An exact search of the identified terms and/or phrases was then performed.

lagged real GDP per capita refers to the 5-year average of real GDP per capita in the period $t-1$.

The variable Patents$_{it}$ stands for the level of AI innovation per country, measured by the total number of AI-related patents per million people in a 5-year average population within period $t$. This measure is the same intensity index used by Kim and Lee (2015) and was also converted into natural logarithms.[31] AI patents are then replaced by the total number of patents to determine the relationship between total technological innovation and economic growth (see Table 3). The expected sign of both patent variables is positive.

$X_{it}$ represents a set of control variables that include population growth, real gross capital formation growth rate per capita, real government expenditure growth rate per capita, trade openness, and inflation.[32] All control variables are 5-year average growth rates except for trade openness, which is the 5-year average ratio of trade volume (exports plus imports) to GDP.[33] The control variables appear in similar literature, such as in the seminal works of Grier and Tullock (1989) and Barro (1997), and in the more recent studies of Bassanini et al. (2001), Ulku (2004), Kim et al. (2012), and Fan and Liu (2021).

In addition to the control variables, an index using data for years of schooling and returns to education, obtained from the Penn World Table (PWT) by Feenstra et al. (2015), is taken as a proxy for human capital.[34] The index makes use of average years of schooling, while also considering decreasing returns to education. Despite this, the index, like other usual human capital measures, ignores cognitive skills, which may be more important in capturing the real effect of human capital (Feenstra et al. 2013). This measure also enters the model as a 5-year average growth rate.

Specific time period effects and advanced economic status are indicated using dummy variables. There are ten $t$ periods in total consisting of five years each, spanning from 1970 to 2019. Advanced economies are countries with more than USD 10,000 of the 5-year average real GDP per capita. Finally, to control for any interaction effect between the level of economic development and patent creation, an interaction term between advanced economic status and patent variables was introduced. The expected sign of the interaction term is negative, implying a lower impact of patent creation on long-run growth among advanced economies.

Statistical treatment was initially done using ordinary least squares (OLS) and fixed effects in panel data. However, because of the inclusion of the lagged growth rate, the model is prone to the Nickell bias, which is unaccounted for in the fixed effects estimation of dynamic panels (Nickell 1981; Roodman 2009). In addition, bias due to reverse causality between growth rate and patents might be present in the model. Hence, the

[31] Several studies make use of R&D "intensity" as a measure of innovation (e.g. Jones and Williams 1998; Blind et al. 2006; Yanhui et al. 2015). Other examples of R&D intensity measures include patent applications per R&D expenditure, R&D over sales for firm-level data, number of researchers per million people, etc.

[32] Because of data availability, this study makes use of the implicit price deflator (rather than the consumer price index) to calculate inflation.

[33] Except for trade, all variables in $X_{it}$ are also expressed as instantaneous growth rates.

[34] This comes from Wößmann (2003), who argues that common proxies for human capital such as school enrollment rates and average years of schooling either insufficiently or incorrectly model the "development effect" of human capital. Specifically, Wößmann (2003) explains that enrollment ratios are flow variables, and enrolled students are not yet part of the labor force, and thus are excluded from economic production. On the other hand, average years of schooling "misspecifies" human capital by placing the "same weight on any year of schooling" of a person, and does not input the "quality of education system.".

Anderson-Hsiao (AH) and generalized method of moments (GMM) estimation techniques are employed to minimize endogeneity issues (Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998).[35]

The next section presents the results of the panel data regressions.

## 5 Results and discussion

Table 1 presents the descriptive statistics of the panel data, consisting of ten periods with 5-year intervals between 1970 and 2019. Because of data availability issues, the dataset used is an unbalanced panel data, as indicated by the unequal number of observations ($N$) and number of groups ($n$) across variables.

Five-year growth rates averaged around 1.30%, with a standard deviation of 3.55 across countries in the dataset.[36] Intuitively, high-income countries will typically have lower growth rates because of the convergence effect. To control for this effect, the estimations presented later include the 5-year average real GDP per capita variable from the previous period. The mean 5-year real GDP per capita is USD 11,990.25.

Table 2 summarizes the economic performance measures such as real GDP per capita and real GDP per capita growth rates, and technological progress in terms of AI and total patents per level of economic development. This follows the classification of Kim and Lee (2015), where countries with real GDP per capita above USD 10,000 are considered to be in an advanced development stage. Countries with real GDP per capita below the threshold are classified as less developed.

As expected, high-income countries post higher technology output, in terms of patents per million people, between the two income groups. With 165 countries in the dataset, less developed economies are the larger group of the two, and with slightly higher average real GDP per capita growth (1.39%). Illustratively, patent output and income per capita across countries are displayed in Fig. 1.

Figure 1 depicts the patent publications and level of income per capita. In terms of patents, advanced economies such as Japan, the United States, Germany, South Korea, France, and China have had the highest output between 1970 and 2019. Overall, China has had the highest cumulative AI and total patents within the period, with 849,752 AI and 32,317,932 total patents. This is followed by Japan (365,409 AI and 18,965,778 total patents), and the United States (259,844 AI and 12,883,662 total patents), respectively.

Regardless, all countries started with low levels of AI and total patents in the early 1970s, as illustrated in Fig. 2. While global AI and total patent counts have steadily increased since the 1970s, China has had a dramatic increase in the number of patents from 2000 onwards. This dwarfs the patent output of other advanced economies (see top panel of Fig. 2). The explosion of Chinese patents can be attributed to the growth of R&D expenditure, FDI, and patent subsidies in the country (Chen and Zhang, 2019).[37]

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[35] The full list of variables is available in Table 12 in the appendix. Additional variables are considered (e.g., Internet users, non-patent literature) as part of the robustness checks. See Sect. 5.1 under Sect. 5.

[36] The presence of positive and negative outliers contributed to a relatively high standard deviation. Calculated five-year real GDP per capita growth rates range between − 24.52% and 23.59% in the dataset, across countries and periods.

[37] The driving forces, however, have had specific and varying effects per type of patent filing. Chen and Zhang (2019) note that R&D spending generally boosts Chinese patent creation, while FDI is only robust for utility and design patents. Patent subsidies, on the other hand, have a positive effect on design patents.

**Table 1** Summary statistics

| Variable | (1) *N* | (2) *n* | (3) Mean | (4) Std. Dev |
|---|---|---|---|---|
| Real GDP per capita (USD) | 2080 | 208 | 11,990.25 | 20,181.72 |
| Real GDP per capita growth rate (%) | 1936 | 208 | 1.30 | 3.55 |
| AI patents per million people | 2165 | 217 | 98.14 | 475.69 |
| Total patents per million people | 2165 | 217 | 9532.16 | 31,989.98 |
| Population | 2170 | 217 | 25,300,000 | 105,000,000 |
| Population growth rate (%) | 2163 | 217 | 1.35 | 1.32 |
| Gross capital formation per capita | 1927 | 207 | 2809.10 | 4658.01 |
| Gross capital formation per capita growth rate (%) | 1924 | 207 | 1.41 | 8.10 |
| Government expenditure per capita | 1925 | 207 | 2308.52 | 3692.08 |
| Government expenditure per capita growth rate (%) | 1923 | 207 | 1.45 | 5.07 |
| Human capital index | 1387 | 145 | 2.19 | 0.73 |
| Human capital index growth rate (%) | 1386 | 145 | 0.77 | 0.58 |
| Trade ratio to GDP (%) | 1839 | 196 | 76.45 | 58.56 |
| Inflation (%) | 1928 | 207 | 2.86 | 5.34 |

All variables are 5-year averages except for patent variables, which are the total number of patents over the 5-year period divided by the 5-year average of population, and then multiplied by 1 million. Values appearing in the table are based on the author's calculation using the datasets available from the Google Patents Public Data, the Penn World Table, the World Bank Development Indicators, and the United Nations National Accounts—Analysis of Main Aggregates

**Table 2** Average economic and technology output across income classification

| Variable | (1) Advanced economies | (2) Less advanced economies |
|---|---|---|
| Real GDP per capita (USD), 5-year average | 34,371.61 | 2637.98 |
| Real GDP per capita growth rate (%), 5-year average | 1.10 | 1.39 |
| AI patents per million people | 290.95 | 6.21 |
| Total patents per million people | 27,876.77 | 785.32 |
| *N* | 703 | 1467 |
| *n* | 91 | 165 |

Values appearing in the table are based on the author's calculation using the datasets available from the Google Patents Public Data, the Penn World Table, the World Bank Development Indicators, and the United Nations National Accounts—Analysis of Main Aggregates

Meanwhile, the East Asian economies of Japan and South Korea, have led in terms of patent "intensity," defined as the number of patents per million people (see bottom panel of Fig. 2). Japanese AI and total patents per million people have demonstrated sharp increases since the 1970s but generally declined by the mid-2000s.[38] On the other hand, South Korea has also witnessed substantial growth in both AI and total patents per million people since the early 1990s. This trend has continued in the subsequent periods, with South Korea eventually overtaking Japan by the early 2010s.

The main estimation results are presented in Table 3. The estimation techniques used are panel OLS, fixed effects, AH, and GMM. Both models with AI patents and

[38] The gradual decrease in domestic patenting was due to Japanese firms being selective in their patent registrations, focusing more on the quality than the number of filings (Japan Patent Office 2015).

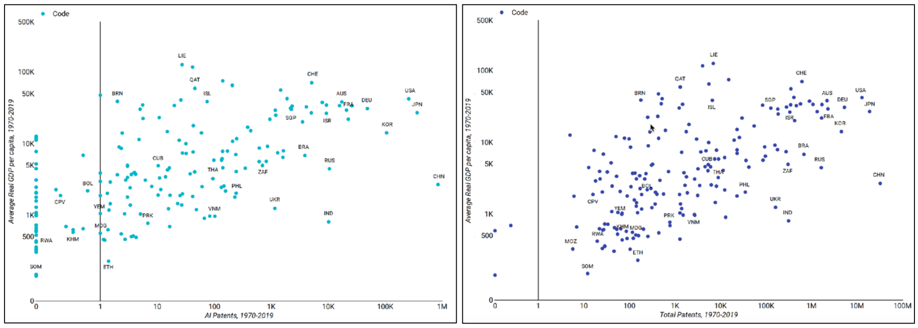


**Fig. 1** AI patents (left), total patents (right), and average real GDP per capita, 1970–2019

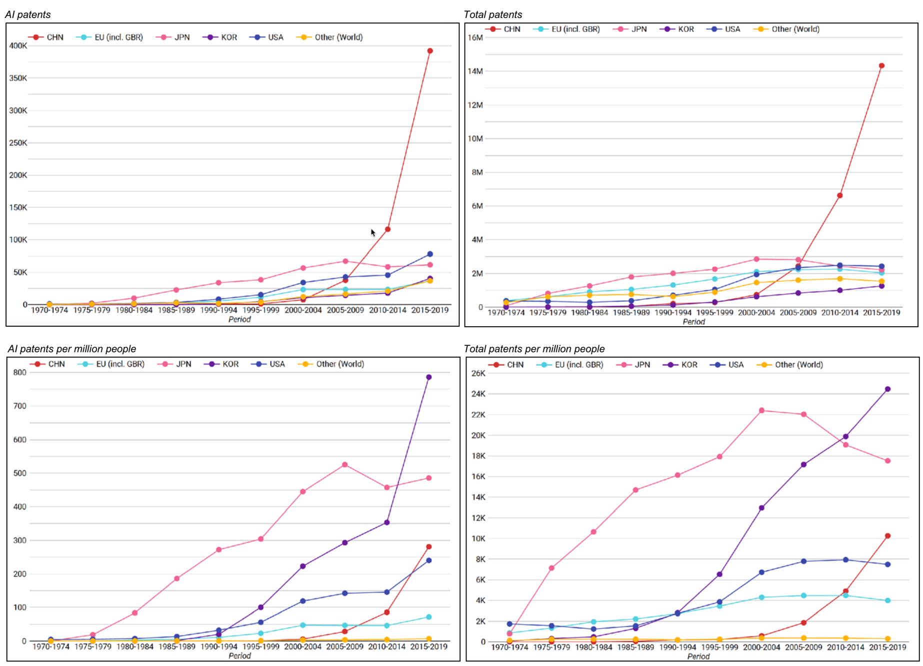


**Fig. 2** AI patents (left) and total patents (right) of selected countries by period, 1970–2019

total patents were estimated; columns 1–4 estimate models with the log of AI patents per million people, while columns 5–8 test for the effect of the log of total patents per million people on the dependent variable, denoted by the 5-year average real GDP growth rate. Separate interaction terms between advanced economic status and the patent variables are also included.

As mentioned earlier, the lagged dependent variable in a dynamic panel regression is susceptible to the Nickell bias. Hence, both the AH and GMM estimations are employed to minimize this issue. While the lagged growth rate is positive in all models, it is only statistically significant in the AH estimation among the AI patents models (columns 1–4) and insignificant among the total patents models (columns 5–8). The lack of significance and small magnitude of the coefficients indicate the minimal impact of the first-order lagged growth rate on the contemporaneous growth rate.

Lagged real GDP per capita is statistically significant and negative in all models except in column 8, where it is negative but not significant. The results suggest a strong convergence effect as observed in extant literature. Similarly, population growth has a negative and significant effect on per capita growth in columns 1, 2, 3, and 5, but is insignificant in other estimations. The negative sign of population growth in some estimates is in line with growth theories, but the actual overall effect of population growth across countries is unclear. Kelley and Schmidt (1995) attribute this mixed result between population growth and economic growth in the long run to the "offsetting" mechanism of "intertemporal demographic effects." Accordingly, population growth rates are characterized by strong autocorrelation; thus, cross-sectional evidence that uses contemporaneous indicators of population inevitably captures "both the negative impacts of current births and positive impacts of past births."[39]

Meanwhile, both gross capital formation and government expenditure growth rates manifest significantly positive effects in all models, implying that investments in physical capital and public infrastructure positively contribute to economic growth. Likewise, trade openness is statistically significant and positive in most equations, which is consistent with the existing growth literature. Inflation and human capital, however, are not significant in all models. The lack of significance of human capital can be attributed to (1) the limitations of the measure, and (2) the substitution of labor and/or human capital with AI as an input to production, as raised by Zeira (1998) and Lu (2021) among others.

The variables of interest, the extent of AI and total innovation, are taken as the log number of AI patents per million people. As depicted in Table 3, AI patents have a significant and positive impact on economic growth in all models. This is consistent with the findings of other studies by Lu (2021) and Yang (2022). On the other hand, total patents also significantly and positively affect economic growth; however, the magnitude of the effect is lower than AI patents. This is somewhat consistent with the findings of Nguyen and Doytch (2022), wherein total patents do not display a significant impact on the long-run growth rate. In addition, Nguyen and Doytch (2022) conclude that ICT patents have a more significant impact on economic growth than other kinds of patents.[40]

To address potential endogeneity either by omitted variables or reverse causality, the patent variables are instrumented in GMM estimations (columns 4 and 8).[41] Estimated coefficients of AI innovation seem to be consistent and significant at least at the 10% level. On the other hand, total innovation is significant at least at the 10% level in OLS, fixed effects, and AH, but insignificant in GMM.

Moreover, the level of economic development (advanced economy) variable is insignificant in all estimated models except in column 6. Meanwhile, the interaction term

[39] Kelley and Schmidt (1995), however, note that this does not imply that demographic effects on per capita growth are unimportant. Empirical results only highlight the need to study the long-run dynamics between population growth and output growth more carefully.

[40] Aside from the technology "intensity index" given by the log number of patents per million people, the log number of patents was also used directly in the estimations. Results of these estimations reveal similar results (positive and significant coefficient for AI patents, and weak significance for total patents).

[41] The period (1970–2019) considered for estimation covers several socio-economic, political, and technological events (e.g., military conflicts, oil shocks, financial crises, Internet diffusion, etc.) that may have affected inter-country growth rates. All estimated models include time dummies; however, they may not fully capture the influence of external events on long-run growth rates. As part of the robustness checks, the average five-year growth rate of Internet users per country, for example, was included as a control variable. Results are available in Table 10 in the appendix.

**Table 3** Main estimation results

| **Dependent variable: real GDP growth rate per capita (5-year average)** | **(1) OLS** | **(2) FE** | **(3) AH** | **(4) GMM** | **(5) OLS** | **(6) FE** | **(7) AH** | **(8) GMM** |
|---|---|---|---|---|---|---|---|---|
| Real GDP growth rate per capita ($t-1$) | 0.037 (0.037) | 0.024 (0.028) | 0.063** (0.028) | 0.034 (0.057) | 0.025 (0.047) | − 0.069 (0.048) | − 0.025 (0.027) | − 0.054 (0.061) |
| Log of real GDP per capita ( $t-1$) | − 0.437** (0.202) | − 1.865*** (0.455) | − 1.672*** (0.450) | − 1.593*** (0.570) | − 0.414*** (0.103) | − 2.284*** (0.422) | − 2.042*** (0.391) | − 0.602 (0.904) |
| Log of AI patents per million people | 0.178*** (0.067) | 0.264*** (0.078) | 0.246*** (0.089) | 0.275* (0.152) | – | – | – | – |
| Log of total patents per million people | – | – | – | – | 0.172*** (0.048) | 0.131* (0.071) | 0.124* (0.069) | 0.197 (0.177) |
| Population growth rate | − 0.462*** (0.154) | − 0.371* (0.210) | − 0.391*** (0.107) | 0.085 (0.361) | − 0.206* (0.120) | 0.043 (0.232) | 0.034 (0.115) | − 0.724 (0.532) |
| Gross capital formation growth rate (per capita) | 0.164*** (0.043) | 0.162*** (0.045) | 0.166*** (0.011) | 0.149*** (0.047) | 0.173*** (0.023) | 0.145*** (0.022) | 0.148*** (0.012) | 0.224*** (0.062) |
| Government expenditure growth rate (per capita) | 0.268*** (0.048) | 0.262*** (0.049) | 0.259*** (0.026) | 0.335** (0.169) | 0.244*** (0.041) | 0.210*** (0.043) | 0.209*** (0.021) | 0.538*** (0.165) |
| Trade openness (5-year average) | 0.004** (0.002) | 0.004** (0.002) | 0.004* (0.002) | 0.009*** (0.003) | 0.004*** (0.001) | 0.006** (0.003) | 0.005* (0.003) | 0.006 (0.009) |
| Human capital index growth rate | − 0.045 (0.150) | 0.005 (0.146) | 0.008 (0.162) | − 0.028 (0.269) | 0.028 (0.138) | 0.004 (0.138) | 0.000 (0.223) | 0.992 (0.674) |
| Inflation (5-year average) | − 0.001 (0.023) | − 0.007 (0.023) | − 0.013 (0.019) | − 0.039 (0.031) | 0.010 (0.019) | 0.012 (0.018) | 0.007 (0.020) | 0.038 (0.138) |
| Advanced economy (dummy) | − 0.196 (0.334) | 0.223 (0.326) | 0.125 (0.461) | 0.505 (0.519) | − 0.457 (0.619) | 1.421* (0.771) | 1.177 (1.120) | − 0.146 (3.005) |
| Advanced x Log of AI patents per million people | − 0.032 (0.061) | − 0.096 (0.081) | − 0.082 (0.094) | − 0.227* (0.129) | – | – | – | – |
| Advanced x Log of total patents per million people | – | – | – | – | 0.026 (0.069) | − 0.196** (0.098) | − 0.170 (0.129) | 0.020 (0.358) |
| Constant | 4.224*** (1.636) | 17.210*** (4.324) | – | 14.172** (5.487) | 3.238*** (0.820) | 19.710*** (3.786) | – | 4.106 (8.366) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of instruments | – | – | – | 65 | – | – | – | 32 |

**Table 3** (continued)

| Dependent variable: real GDP growth rate per capita (5-year average) | (1) OLS | (2) FE | (3) AH | (4) GMM | (5) OLS | (6) FE | (7) AH | (8) GMM |
|---|---|---|---|---|---|---|---|---|
| Sargan-Hansen test (p-value) | – | – | – | 0.426 | – | – | – | 0.581 |
| AR(1) (p-value) | – | – | – | 0.001 | – | – | – | 0.000 |
| AR(2) (p-value) | – | – | – | 0.661 | – | – | – | 0.257 |
| *N* | 616 | 616 | 616 | 616 | 1140 | 1140 | 1140 | 1140 |
| *n* | 122 | 122 | 122 | 122 | 144 | 144 | 144 | 144 |

Robust (OLS, FE, GMM) and bootstrapped (AH) standard errors are enclosed in parentheses. AH estimation does not report a constant term. Values appearing in the table are based on the author's calculation using the datasets available from the Google Patents Public Data, the Penn World Table, the World Bank Development Indicators, and the United Nations National Accounts—Analysis of Main Aggregates

*** Significant at 1% level

**Significant at 5% level

*Significant at 10% level

between the level of economic status and patent creation is negative and significant in columns 4 and 6. The negative sign implies that AI and overall innovation exhibit less impact on economic growth among advanced economies, which is similar to the convergence effect stated previously.

Furthermore, the Sargan-Hansen test provides the test for overidentifying restrictions for the GMM model. The p-values of the Sargan-Hansen statistic of the GMM models for AI and total patents are 0.426 and 0.581, respectively. Thus, the null hypothesis that the instruments are valid is not rejected.[42] Also, the Arellano-Bond AR(1) and AR(2) tests for GMM are presented for reference. The p-values of the AR tests indicate the presence of serial correlation only at the first differences.[43]

Results indicate that AI-related innovation drives long-run economic growth. The wide applicability of AI across industries can be one reason for its positive contribution. AI systems can be implemented in manufacturing, ICT, transportation, finance, and medical services among other industries (Mou 2019). Self-learning and monitoring benefit the manufacturing sector by increasing precision and efficient utilization of physical capital, reducing defects and delays (Rao and Verweij 2017). More recent and practical forms of AI such as voice-to-text applications and speech recognition allow businesses

[42] The reliability of the Sargan-Hansen statistic, however, weakens as the number of instruments increases. Thus, the number of instruments was reduced to avoid this issue as much as possible. Roodman (2009) recommends that the total number of instruments should be less than the total number of individual units in a panel dataset. To reduce the number of instruments, the optimal number of lags is chosen per GMM estimation. A maximum of five lags is used, but the model should simultaneously satisfy the Sargan-Hansen and AR(2) tests, while also considering the explanatory power of the variable(s) of interest and control variables. Following these specifications, the AI patents model passes the Sargan-Hansen and AR(2) tests until the fifth-order lagged instruments, while the total patents model only passes both tests at the second lag; hence, the difference in the number of instruments (column 4 with 65 and column 8 with 32).

[43] Unit root tests (Fisher-type based on augmented Dickey-Fuller) for unbalanced panel data were also performed to check for random walk. The tests revealed that the variables contain at least one stationary panel (the null hypothesis that all *n* panels contain unit roots is rejected). However, the test could not be performed for the log of AI patents per million people due to missing observations.

to reach and respond to customers in real time (Mou 2019), inducing an increase in the volume of consumer transactions. AI technologies can be implemented in financial systems to detect fraudulent activities, preventing theft and loss (Bose 2006; Akhilomen 2013). Furthermore, predictive modeling with AI can analyze and manage traffic flow (Mou 2019; Yigitcanlar et al. 2020), which is notoriously known to cause negative externalities, more effectively.

### 5.1 Robustness checks

For additional robustness checks, periodic estimations in the dataset are also performed. The dataset is divided into two periods, 1970–1994 and 1995–2019, consisting of 25 years each. Due to limited AI and non-AI patent data, the 1970–1994 period has fewer observations. Additionally, most countries that published and applied for AI-related patents within this period are advanced economies, as shown in the number of groups (*n*) and the lack of an estimated coefficient for the "advanced" dummy in columns 2 and 3 in Table 4.[44] Therefore, a comparison of impacts on long-run growth brought by technological innovation, specifically those on AI, between advanced and less advanced economies might not be intuitively useful for observations within this time frame.

Table 4 displays the estimation results of the models for both AI and total patents for the 1970–1994 period, whereas Table 5 provides the results of estimations for the period 1995–2019. As indicated in Table 4, the effect of AI on growth is not statistically significant for the period 1970–1994, which can be due to (1) the limited number of observations, (2) the lesser number of AI patents, and (3) the relatively less technically advanced nature of AI innovation during this period. Interestingly, the effect of total patents is significant and positive during the same period, as shown in columns 5–8. Hence, the results suggest that other types of patents compared to early AI technologies might have had a more substantial effect on growth rates before 1995.

On the other hand, the estimated fixed effects, AH, and GMM coefficients are significant for AI patents in the 1995–2019 period in columns 2–4 in Table 5. The significance of the estimates provides evidence of AI being a driver of long-run economic growth for the latter half of the time frame in the dataset. More surprisingly, the value of the coefficient of AI patents in the GMM model is relatively large compared to estimated parameters in other models. Meanwhile, the total patents variable is insignificant for long-run growth rate in all models, except in OLS in column 5. In addition, the interaction terms between patent creation and economic status are mostly insignificant in both periods. Hence, there is no clear distinction on the effect of patent creation between developed and less developed economies on long-run growth in both periods.[45]

An obvious implication of the above results is that the effect of AI has become increasingly evident toward the latter years of the dataset, while innovations from other disciplines have extended relatively less impact on growth.[46] Notably, AI patent registration

[44] The "advanced" dummy variable was dropped due to collinearity.

[45] A short-run analysis was also conducted to check for the short-run impacts of technical innovation on economic growth. Instead of a five-year average growth rate, the yearly real GDP growth rate per capita growth rate was used as the dependent variable. Likewise, annual levels and growth rates of the patent and control variables were used in the regressions. The results are available in Table 9 in the appendix.

[46] Distinguishing the effect of AI from non-AI patents on growth might be a challenging task when using patents as an indicator of technological innovation. As AI becomes increasingly and deeply embedded in production tools and pro-

had started picking up by the mid-1990s, especially among advanced economies (see Fig. 2), which naturally contributed to a heightened impact of AI in the second half of the entire period. Arguably, the quality of AI technologies within this period has also improved compared to earlier forms of AI prior to the last two to three decades.

Furthermore, separate estimations between advanced and less advanced economies were also done, both for AI and total patents. As defined in the previous section, advanced countries are those with more than USD 10,000 of the 5-year average real GDP per capita. The results can be found in both Tables 6 and 7.

The effect of AI is strongly and positively significant among advanced economies in columns 1–4 in Table 6, but does not entail any implication on long-run growth among less advanced or emerging economies in Table 7.[47] This suggests that viable infrastructures and institutions, which may only be available in developed countries, are necessary to leverage AI in the economy. This, in turn, translates into positive contributions to economic growth. More importantly, this finding resembles the theory proposed by Zeira (1998), which explains the differences in the type and level of technologies available across countries.

Meanwhile, total patents engender a quite similar effect on growth between advanced and less advanced economies. Coefficients of the patent variable are positive and significant in OLS, but negligible in fixed effects, AH, and GMM, which is true for both groups of countries. This indicates that total patents do not contribute to long-run economic growth regardless of a country's level of development. Thus, more specific, technical, and practical innovations, such as those of AI or ICT in nature, are more important than other types of innovations in terms of their effect on economic growth.

Finally, the possibility of an external instrument is not precluded and has been explored to further address endogeneity. As mentioned earlier, the estimated model is susceptible to bias, either due to omitted variables or bi-directional causality between patent creation and economic growth. Hence, aside from fixed effects and GMM, fixed effects estimation with instrumental variable (FE-IV) is also considered as a means of obtaining unbiased estimates.

The number of non-patent literature (NPL) cited by the patents is used as an instrument for both AI and total patents. NPL refers to the cited articles of a patent document that are not patents themselves (e.g., scientific publications, books, online sources, conference proceedings, etc.) to "justify" an invention's "novelty." Furthermore, NPL citations help gauge "the impact of scientific production cited in patents," or conversely, "the technological impact of scientific publications" (Velayos-Ortega and Lopez-Carreño 2021).

Non-patent references contribute to patent creation by providing justification and a scientific foundation for the technology being patented. Hence, a rich amount of non-patent knowledge should positively contribute to patent creation. Scientific knowledge

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Footnote 46 (continued)

cesses, any new invention might have some AI component in it. Hence, disembodying AI from the "non-AI" component of an invention, for example, to estimate AI's true effect on growth might present a challenge for future research.

[47] Because of the limited number of countries, the number of instruments (42) used in the GMM estimation among advanced economies for AI patents is relatively close to the number of individual panels $n$ (53). While the number of instruments is still lower than the number of individual groups, it is more desirable to have the number of instruments as few as possible.

**Table 4** Period estimations results, 1970–1994

| Dependent Variable: real GDP growth rate per capita (5-year average) | (1) OLS | (2) FE | (3) AH | (4) GMM | (5) OLS | (6) FE | (7) AH | (8) GMM |
|---|---|---|---|---|---|---|---|---|
| Real GDP growth rate per capita ($t-1$) | 0.159** (0.066) | 0.122 (0.077) | 0.223** (0.089) | − 0.156 (0.174) | 0.055 (0.061) | − 0.189*** (0.067) | − 0.074* (0.042) | − 0.125 (0.118) |
| Log of real GDP per capita ($t-1$) | − 0.291 (0.206) | − 0.535 (0.855) | − 0.377 (1.145) | − 1.333 (1.240) | − 0.352** (0.162) | − 4.796*** (1.096) | − 4.608*** (0.935) | − 4.141** (1.850) |
| Log of AI patents per million people | 0.113 (0.118) | 0.151 (0.130) | 0.142 (0.156) | − 0.186 (0.252) | – | – | – | – |
| Log of total patents per million people | – | – | – | – | 0.140** (0.066) | 0.274* (0.155) | 0.254** (0.129) | 0.741*** (0.269) |
| Population growth rate | 0.036 (0.190) | 0.135 (0.310) | 0.084 (0.283) | 0.230 (0.991) | − 0.194 (0.266) | 0.565 (0.504) | 0.494 (0.337) | 0.713 (0.762) |
| Gross capital formation growth rate (per capita) | 0.228*** (0.023) | 0.223*** (0.025) | 0.237*** (0.019) | 0.155*** (0.042) | 0.185*** (0.029) | 0.113*** (0.028) | 0.120*** (0.018) | 0.074 (0.104) |
| Government expenditure growth rate (per capita) | 0.172*** (0.054) | 0.146** (0.061) | 0.156*** (0.055) | 0.123 (0.150) | 0.239*** (0.060) | 0.189*** (0.067) | 0.189*** (0.031) | 0.069 (0.085) |
| Trade openness (5-year average) | 0.004 (0.004) | − 0.002 (0.002) | − 0.002 (0.004) | 0.002 (0.007) | 0.005** (0.002) | 0.005 (0.007) | 0.005 (0.007) | − 0.007 (0.011) |
| Human capital index growth rate | 0.301 (0.240) | − 0.142 (0.222) | − 0.162 (0.371) | 0.325 (0.770) | 0.238 (0.216) | − 0.152 (0.303) | − 0.199 (0.293) | − 0.049 (0.679) |
| Inflation (5-year average) | − 0.065*** (0.017) | − 0.057*** (0.019) | − 0.069*** (0.020) | − 0.036 (0.038) | − 0.005 (0.026) | 0.023 (0.029) | 0.017 (0.026) | 0.075 (0.084) |
| Advanced economy (dummy) | 0.318 (0.530) | – | – | 7.091** (2.849) | − 1.14 (0.786) | − 1.157 (1.086) | − 1.667 (1.594) | − 3.105 (3.211) |
| Advanced x Log of AI patents per million people | − 0.007 (0.122) | 0.059 (0.122) | 0.037 (0.146) | 0.392 (0.286) | – | – | – | – |
| Advanced x Log of total patents per million people | – | – | – | – | 0.151* (0.091) | 0.223 (0.187) | 0.278 (0.254) | 0.353 (0.466) |
| Constant | 2.353 (1.666) | 5.018 (8.030) | – | 7.991 (10.972) | 1.900 (1.428) | 37.680*** (9.198) | – | 30.000* (15.420) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of instruments | – | – | – | 31 | – | – | – | 33 |

**Table 4** (continued)

| Dependent Variable: real GDP growth rate per capita (5-year average) | (1) OLS | (2) FE | (3) AH | (4) GMM | (5) OLS | (6) FE | (7) AH | (8) GMM |
|---|---|---|---|---|---|---|---|---|
| Sargan-Hansen overidentification test (*p*-value) | – | – | – | 0.542 | – | – | – | 0.155 |
| AR(1) (*p*-value) | – | – | – | 0.999 | – | – | – | 0.003 |
| AR(2) (*p*-value) | – | – | – | 0.178 | – | – | – | 0.326 |
| *N* | 158 | 158 | 158 | 158 | 428 | 428 | 428 | 428 |
| *n* | 61 | 61 | 61 | 61 | 123 | 123 | 123 | 123 |

*** Significant at 1% level; ** significant at 5% level; *significant at 10% level. Robust (OLS, FE, GMM) and bootstrapped (AH) standard errors are enclosed in parentheses. AH estimation does not report a constant term. Values appearing in the table are based on the author's calculation using the datasets available from the Google Patents Public Data, the Penn World Table, the World Bank Development Indicators, and the United Nations National Accounts—Analysis of Main Aggregates

itself is vast and varied; however, only the cited literature in the patents themselves is specific and relevant to the inventions.

As expected, the direct effect of scientific publications, as a measure of scientific knowledge, on economic growth has been well-studied in the literature (e.g., Kim and Lee 2015; Solarin and Yen 2016; Maradana et al. 2017; Pinto and Teixeira 2020). While the non-significance of academic research on economic growth has been found in some studies, general sentiment and results still regard academic publications as a direct and positive contributor to growth. This notion casts some doubt on whether scientific literature can serve as a valid instrument for patent creation.

This study, however, suggests that for research output to be translated into an object of economic value, it has to be transformed first into an input (or intermediate good), to be used later in the production of other goods.[48] The knowledge contained in relevant and cited NPL, for example, is used by patent creators, or inventors, to create new products, services, modes of production, processes, frameworks, and/or other kinds of inventions used for enterprise building. Thus, the transformation of scientific knowledge into intermediate, technology-based capital goods is embodied in the patents themselves. Finally, the high patent output indicates the availability of technology that helps in the production of final goods, which then ultimately leads to economic growth.[49]

The results of the FE-IV regression are shown in Table 8, alongside the OLS, fixed effects, and GMM estimations. Due to the limited data on the instruments, the number of observations and groups in Table 8 is lower compared to the number of observations

[48] Although Pinto and Teixeira (2020) use research output instead of patents as a measure of knowledge as a good, the authors illustrate how research ultimately contributes to economic growth (see Fig. 1 of Pinto and Teixeira 2020).

[49] Moreover, to strengthen the exogeneity assumption, only the NPL cited in the patents themselves is used as an instrument, rather than the entire population of scientific and academic publications. Hence, the instrument used has a direct causal link to patent creation and is more likely to manifest an effect on growth only through the patents.

**Table 5** Period estimations results, 1995–2019

| Dependent Variable: Real GDP growth rate per capita (5-year average) | (1) OLS | (2) FE | (3) AH | (4) GMM | (5) OLS | (6) FE | (7) AH | (8) GMM |
|---|---|---|---|---|---|---|---|---|
| Real GDP growth rate per capita (*t*-1) | − 0.015 (0.070) | − 0.004 (0.040) | 0.062 (0.039) | 0.002 (0.109) | 0.029 (0.088) | − 0.187** (0.074) | − 0.106*** (0.036) | − 0.182** (0.092) |
| Log of real GDP per capita (*t*-1) | − 0.377 (0.264) | − 1.790*** (0.660) | − 2.004*** (0.545) | − 3.048** (1.512) | − 0.491*** (0.173) | − 3.412*** (0.934) | − 3.230*** (0.615) | − 1.489 (1.794) |
| Log of AI patents per million people | 0.124 (0.085) | 0.207** (0.098) | 0.256** (0.104) | 0.741** (0.371) | – | – | – | – |
| Log of total patents per million people | – | – | – | – | 0.219*** (0.077) | − 0.102 (0.157) | − 0.109 (0.150) | − 0.352 (0.496) |
| Population growth rate | − 0.512*** (0.157) | − 0.436** (0.197) | − 0.451*** (0.112) | − 0.450 (0.298) | − 0.239 (0.151) | 0.055 (0.296) | 0.071 (0.133) | − 0.613 (0.519) |
| Gross capital formation growth rate (per capita) | 0.201*** (0.029) | 0.206*** (0.028) | 0.215*** (0.014) | 0.232*** (0.067) | 0.165*** (0.033) | 0.114*** (0.035) | 0.118*** (0.013) | 0.154 (0.101) |
| Government expenditure growth rate (per capita) | 0.245*** (0.046) | 0.227*** (0.046) | 0.223*** (0.043) | 0.291 (0.192) | 0.224*** (0.045) | 0.177*** (0.049) | 0.176*** (0.021) | 0.180* (0.108) |
| Trade openness (5-year average) | 0.004* (0.002) | 0.004 (0.005) | 0.004 (0.005) | 0.018* (0.010) | 0.004*** (0.001) | 0.017* (0.009) | 0.015*** (0.005) | 0.001 (0.017) |
| Human capital index growth rate | − 0.193 (0.179) | − 0.076 (0.144) | − 0.064 (0.150) | 0.375 (0.718) | − 0.106 (0.217) | − 0.028 (0.264) | − 0.027 (0.244) | 0.115 (0.810) |
| Inflation (5-year average) | 0.009 (0.024) | 0.005 (0.027) | − 0.001 (0.022) | − 0.103* (0.057) | 0.027 (0.025) | 0.046* (0.027) | 0.038 (0.026) | 0.140 (0.120) |
| Advanced economy (dummy) | − 1.147** (0.556) | − 1.226 (0.889) | – | 2.417 (1.745) | − 0.041 (0.970) | 1.463 (2.570) | 1.196 (2.465) | 12.930 (10.580) |
| Advanced x Log of AI patents per million people | 0.183 (0.120) | 0.305 (0.218) | 0.082 (0.087) | − 0.749 (0.494) | – | – | – | – |
| Advanced x Log of total patents per million people | – | – | – | – | − 0.057 (0.099) | − 0.187 (0.310) | − 0.152 (0.284) | − 1.504 (1.254) |
| Constant | 3.919* (2.003) | 16.246*** (5.887) | – | 25.426** (12.761) | 3.940*** (1.198) | 29.990*** (8.082) | – | 17.880 (15.970) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of instruments | – | – | – | 33 | – | – | – | 33 |

**Table 5** (continued)

| Dependent Variable: Real GDP growth rate per capita (5-year average) | (1) OLS | (2) FE | (3) AH | (4) GMM | (5) OLS | (6) FE | (7) AH | (8) GMM |
|---|---|---|---|---|---|---|---|---|
| Sargan-Hansen overidentification test (*p*-value) | – | – | – | 0.407 | – | – | – | 0.110 |
| AR(1) (*p*-value) | – | – | – | 0.005 | – | – | – | 0.004 |
| AR(2) (*p*-value) | – | – | – | 0.210 | – | – | – | 0.415 |
| *N* | 388 | 388 | 388 | 388 | 570 | 570 | 570 | 570 |
| *n* | 120 | 120 | 120 | 120 | 144 | 144 | 144 | 144 |

*** Significant at 1% level; ** significant at 5% level; *significant at 10% level. Robust (OLS, FE, GMM) and bootstrapped (AH) standard errors are enclosed in parentheses. AH estimation does not report a constant term. Values appearing in the table are based on the author's calculation using the datasets available from the Google Patents Public Data, the Penn World Table, the World Bank Development Indicators, and the United Nations National Accounts—Analysis of Main Aggregates

and groups in the main results (see Table 3).[50] For convenience, the same panel groups used in the FE-IV regression are used in the OLS, fixed effects, and GMM estimations as well to allow comparison of the estimates.

The log number of AI patents per million people is significantly positive in all models (at the 10% level in GMM and FE-IV), and the magnitudes of the AI coefficients are relatively consistent among the fixed effects, GMM, and FE-IV estimations in columns 2, 3, and 4 in Table 8, respectively. Notably, the magnitudes of the coefficients are larger than the estimates in the main results in Table 3. On the other hand, total patents are only significant and positive in OLS and fixed effects in columns 5 and 6. In addition, the magnitude of the coefficient of total patents in the FE-IV regression (column 8) is inconsistent with the other estimations.

Several tests were performed to check for the validity of the instruments in both the GMM and FE-IV models. The null hypothesis is not rejected for the Sargan-Hansen test for overidentifying restrictions in both the GMM and FE-IV estimations, suggesting no overidentification in the first-stage regressions. This is true for both the AI and total patents models (columns 3, 4, 7, and 8 in Table 8). Meanwhile, the null hypothesis of the Kleibergen-Paap test for weak instruments is rejected for the FE-IV estimates of both the AI and total patents models, implying the first stage FE-IV regressions are not underidentified. Hence, both tests seem to confirm the validity of the instruments used, especially for the FE-IV estimations.

The p-values of the endogeneity test, however, differ between the AI patents and total patents models in FE-IV (columns 4 and 8). Under the null hypothesis, the regressors, or the instruments, can be treated as exogenous. Rejection of the null hypothesis means the

[50] Both the current and lagged values of the (natural log) number of non-patent literature are used as instruments to ensure the validity and precision of the FE-IV estimates. Also, the interaction term between advanced economic status and patent variable is instrumented. The first stage results are available in Table 11 in the appendix.

**Table 6** Effect of patents on economic growth, advanced economies

| **Dependent Variable: Real GDP growth rate per capita (5-year average)** | **(1) OLS** | **(2) FE** | **(3) AH** | **(4) GMM** | **(5) OLS** | **(6) FE** | **(7) AH** | **(8) GMM** |
|---|---|---|---|---|---|---|---|---|
| Real GDP growth rate per capita ($t-1$) | 0.034 (0.054) | − 0.065 (0.054) | − 0.023 (0.045) | − 0.040 (0.056) | 0.064 (0.065) | − 0.059 (0.042) | − 0.007 (0.059) | − 0.070 (0.110) |
| Log of real GDP per capita ($t-1$) | − 0.618** (0.298) | − 2.159** (0.880) | − 1.999*** (0.587) | − 2.855* (1.611) | − 0.857** (0.360) | − 3.376*** (0.996) | − 3.121*** (0.609) | − 4.001 (3.422) |
| Log of AI patents per million people | 0.223*** (0.086) | 0.367*** (0.116) | 0.354*** (0.096) | 0.299** (0.121) | – | – | – | – |
| Log of total patents per million people | – | – | – | – | 0.250** (0.105) | 0.151 (0.146) | 0.143 (0.149) | 0.010 (0.432) |
| Population growth rate | − 0.295** (0.151) | − 0.317 (0.234) | − 0.319*** (0.107) | − 0.025 (0.249) | − 0.212 (0.148) | − 0.347** (0.165) | − 0.358** (0.174) | 0.19 (0.790) |
| Gross capital formation growth rate (per capita) | 0.218*** (0.031) | 0.205*** (0.032) | 0.211*** (0.017) | 0.248*** (0.040) | 0.226*** (0.036) | 0.205*** (0.040) | 0.209*** (0.019) | 0.167** (0.079) |
| Government expenditure growth rate (per capita) | 0.359*** (0.062) | 0.343*** (0.059) | 0.337*** (0.039) | 0.265** (0.120) | 0.203*** (0.074) | 0.206*** (0.068) | 0.200*** (0.055) | − 0.0391 (0.189) |
| Trade openness (5-year average) | 0.004** (0.001) | − 0.002 (0.004) | − 0.002 (0.004) | 0.002 (0.006) | 0.004*** (0.002) | 0.005 (0.005) | 0.005 (0.004) | 0.001 (0.012) |
| Human capital index growth rate | 0.091 (0.260) | − 0.073 (0.219) | − 0.071 (0.209) | − 0.547 (0.477) | − 0.002 (0.188) | − 0.029 (0.276) | − 0.039 (0.289) | 1.026 (1.840) |
| Inflation (5-year average) | − 0.066*** (0.024) | − 0.063*** (0.023) | − 0.070*** (0.020) | − 0.099 (0.063) | − 0.086** (0.044) | − 0.078* (0.044) | − 0.087*** (0.031) | − 0.009 (0.207) |
| Constant | 5.423** | 21.465** | – | 28.858* | 6.829** | 34.180*** | – | 42.350 |
| | (2.706) | (9.233) | – | (16.954) | (2.799) | (11.080) | – | (34.470) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of instruments | – | – | – | 42 | – | – | – | 28 |
| Sargan-Hansen overidentification test ($p$-value) | – | – | – | 0.750 | – | – | – | 0.683 |
| AR(1) ($p$-value) | – | – | – | 0.005 | – | – | – | 0.077 |
| AR(2) ($p$-value) | – | – | – | 0.766 | – | – | – | 0.967 |
| $N$ | 299 | 299 | 299 | 299 | 352 | 352 | 352 | 352 |
| $n$ | 53 | 53 | 53 | 53 | 53 | 53 | 53 | 53 |

*** Significant at 1% level; **significant at 5% level; *significant at 10% level. Robust (OLS, FE, GMM) and bootstrapped (AH) standard errors are enclosed in parentheses. Anderson-Hsiao estimation does not report constant term. Values appearing in the table are based on the author's calculation using the datasets available from the Google Patents Public Data, the Penn World Table, the World Bank Development Indicators, and the United Nations National Accounts—Analysis of Main Aggregates

**Table 7** Effect of patents on economic growth, less advanced economies

| Dependent Variable: Real GDP growth rate per capita (5-year average) | (1) OLS | (2) FE | (3) AH | (4) GMM | (5) OLS | (6) FE | (7) AH | (8) GMM |
|---|---|---|---|---|---|---|---|---|
| Real GDP growth rate per capita ($t-1$) | 0.043 (0.048) | 0.030 (0.030) | 0.078* (0.045) | 0.015 (0.051) | 0.006 (0.057) | − 0.100* (0.053) | − 0.054 (0.037) | − 0.024 (0.100 |
| Log of real GDP per capita ($t-1$) | − 0.256 (0.328) | − 1.606*** (0.480) | − 1.351* (0.718) | − 1.237 (0.745) | − 0.282** (0.132) | − 1.659*** (0.475) | − 1.408*** (0.454) | − 0.113 (0.934) |
| Log of AI patents per million people | 0.031 (0.073) | 0.087 (0.080) | 0.076 (0.122) | 0.265 (0.208) | – | – | – | – |
| Log of total patents per million people | – | – | – | – | 0.159*** (0.056) | 0.030 (0.081) | 0.027 (0.118) | 0.062 (0.204) |
| Population growth rate | − 0.741*** (0.172) | − 0.559** (0.241) | − 0.680* (0.354) | − 0.228 (0.456) | − 0.073 (0.191) | 0.857*** (0.271) | 0.833*** (0.217) | 0.271 (0.816) |
| Gross capital formation growth rate (per capita) | 0.113** (0.051) | 0.111** (0.054) | 0.114*** (0.016) | 0.086 (0.068) | 0.164*** (0.025) | 0.125*** (0.023) | 0.129*** (0.012) | 0.153 (0.097) |
| Government expenditure growth rate (per capita) | 0.198*** (0.037) | 0.177*** (0.033) | 0.176*** (0.045) | 0.255* (0.135) | 0.246*** (0.043) | 0.194*** (0.040) | 0.194*** (0.021) | 0.454** (0.186) |
| Trade openness (5-year average) | 0.007*** (0.002) | 0.009*** (0.003) | 0.009*** (0.003) | 0.004 (0.004) | 0.004** (0.002) | 0.0110*** (0.004) | 0.011** (0.004) | 0.001 (0.009) |
| Human capital index growth rate | − 0.066 (0.183) | − 0.004 (0.142) | − 0.017 (0.262) | 0.227 (0.466) | 0.029 (0.176) | 0.052 (0.159) | 0.057 (0.217) | 0.767 (0.673) |
| Inflation (5-year average) | 0.032 (0.029) | 0.031 (0.029) | 0.026 (0.029) | − 0.006 (0.058) | 0.018 (0.022) | 0.019 (0.021) | 0.014 (0.023) | − 0.022 (0.206) |
| Constant | 3.220 (2.727) | 14.108*** (4.136) | – | 10.358* (6.138) | 2.139* (1.131) | 12.400*** (3.848) | – | − 0.236 (7.238) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of instruments | – | – | – | 55 | – | – | – | 28 |
| Sargan-Hansen overidentifcation test ($p$-value) | – | – | – | 0.342 | – | – | – | 0.571 |
| AR(1) ($p$-value) | – | – | – | 0.005 | – | – | – | 0.000 |
| AR(2) ($p$-value) | – | – | – | 0.281 | – | – | – | 0.131 |
| $N$ | 301 | 301 | 301 | 301 | 763 | 763 | 763 | 763 |
| $n$ | 83 | 83 | 83 | 83 | 110 | 110 | 110 | 110 |

*** Significant at 1% level; ** significant at 5% level; *significant at 10% level. Robust (OLS, FE, GMM) and bootstrapped (AH) standard errors are enclosed in parentheses. AH estimation does not report a constant term. Values appearing in the table are based on the author's calculation using the datasets available from the Google Patents Public Data, the Penn World Table, the World Bank Development Indicators, and the United Nations National Accounts—Analysis of Main Aggregates

**Table 8** Estimation results with fixed effects-IV regression

| **Dependent Variable: Real GDP growth rate per capita (5-year average)** | **(1) OLS** | **(2) FE** | **(3) GMM** | **(4) FE-IV** | **(5) OLS** | **(6) FE** | **(7) GMM** | **(8) FE-IV** |
|---|---|---|---|---|---|---|---|---|
| Real GDP growth rate per capita ($t-1$) | 0.087* | − 0.081* | − 0.029 | − 0.018 | 0.003 | − 0.135* | − 0.160 | − 0.100** |
| | (0.045) | (0.044) | (0.052) | (0.038) | (0.078) | (0.069) | (0.107) | (0.046) |
| Log of real GDP per capita ($t-1$) | − 0.586*** | − 4.223*** | − 2.721*** | − 2.964*** | − 0.692*** | − 2.703*** | − 1.474 | − 3.505*** |
| | (0.116) | (0.665) | (0.848) | (0.795) | (0.160) | (0.661) | (1.232) | (0.863) |
| Log of AI patents per million people | 0.222*** | 0.668*** | 0.535* | 0.499* | – | – | – | – |
| | (0.077) | (0.172) | (0.269) | (0.256) | – | – | – | – |
| Log of total patents per million people | – | – | – | – | 0.217*** | 0.207** | 0.177 | 0.536 |
| | – | – | – | – | (0.080) | (0.101) | (0.221) | (0.329) |
| Population growth rate | − 0.516*** | − 0.614*** | − 0.819*** | − 0.563*** | − 0.180 | 0.045 | − 0.388 | 0.065 |
| | (0.131) | (0.076) | (0.218) | (0.194) | (0.162) | (0.305) | (0.350) | (0.269) |
| Gross capital formation growth rate (per capita) | 0.220*** | 0.173*** | 0.196*** | 0.188*** | 0.155*** | 0.142*** | 0.132** | 0.141*** |
| | (0.023) | (0.025) | (0.032) | (0.018) | (0.040) | (0.042) | (0.063) | (0.027) |
| Government expenditure growth rate (per capita) | 0.291*** | 0.258*** | 0.309*** | 0.211*** | 0.262*** | 0.233*** | 0.347** | 0.216*** |
| | (0.052) | (0.043) | (0.058) | (0.037) | (0.048) | (0.052) | (0.145) | (0.040) |
| Trade openness (5-year average) | 0.003*** | 0.003 | − 0.001 | 0.001 | 0.003** | 0.004 | − 0.002 | 0.011*** |
| | (0.001) | (0.003) | (0.008) | (0.003) | (0.001) | (0.003) | (0.011) | (0.004) |
| Human capital index growth rate | − 0.197 | − 0.035 | − 0.606 | 0.047 | − 0.198 | − 0.152 | 0.353 | − 0.187 |
| | (0.121) | (0.129) | (0.428) | (0.180) | (0.215) | (0.236) | (0.743) | (0.193) |
| Inflation (5-year average) | − 0.038* | − 0.001 | − 0.012 | − 0.025 | 0.042 | 0.047 | 0.073 | 0.019 |
| | (0.020) | (0.021) | (0.051) | (0.020) | (0.031) | (0.031) | (0.080) | (0.025) |
| Advanced economy (dummy) | 0.521 | 3.797*** | 2.134 | 1.945*** | 0.106 | 1.801 | 6.973 | 7.114*** |
| | (0.412) | (0.808) | (1.815) | (0.663) | (0.733) | (1.404) | (4.611) | (2.036) |
| Advanced x Log of AI patents per million people | − 0.120 | − 0.743*** | − 0.398 | − 0.375*** | – | – | – | – |

**Table 8** (continued)

| **Dependent Variable: Real GDP growth rate per capita (5-year average)** | **(1) OLS** | **(2) FE** | **(3) GMM** | **(4) FE-IV** | **(5) OLS** | **(6) FE** | **(7) GMM** | **(8) FE-IV** |
|---|---|---|---|---|---|---|---|---|
| | (0.083) | (0.189) | (0.395) | (0.136) | – | – | – | – |
| Advanced x Log of total patents per million people | – | – | – | – | − 0.005 | − 0.217 | − 0.867 | − 0.857*** |
| | – | – | – | – | (0.082) | (0.166) | (0.573) | (0.252) |
| Constant | 5.592*** | 39.950*** | 26.250*** | – | 5.465*** | 24.110*** | 14.180 | – |
| | (0.892) | (6.257) | (7.434) | – | (1.106) | (6.117) | (10.780) | – |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of instruments | – | – | 46 | 21 | – | – | 46 | 21 |
| Sargan-Hansen overidentification test (*p*-value) | – | – | 0.983 | 0.138 | – | – | 0.149 | 0.414 |
| Kleibergen-Paap underidentification test (*p*-value) | – | – | – | 0.000 | – | – | – | 0.000 |
| Endogeneity test (for IV estimation, *p*-value) | – | – | – | 0.605 | – | – | – | 0.000 |
| *N* | 258 | 258 | 258 | 326 | 692 | 692 | 692 | 836 |
| *n* | 65 | 65 | 65 | 65 | 135 | 135 | 135 | 135 |

*** Significant at 1% level; ** significant at 5% level; *significant at 10% level. Robust standard errors are enclosed in parentheses. FE-IV estimation does not report a constant term. Values appearing in the table are based on the author's calculation using the datasets available from the Google Patents Public Data, the Penn World Table, the World Bank Development Indicators, and the United Nations National Accounts—Analysis of Main Aggregates

regressors are not exogenous and thus may not be considered acceptable instruments. According to the test, the null hypothesis is not rejected for AI patents but is rejected for the total patents model at standard significance levels. The result indicates that the validity of instruments and parameter estimates is only applicable to the former, whereas estimates for the latter model are likely inconsistent and biased.

Overall, the results of the main estimations and robustness checks reveal a strong positive relationship between AI innovation and long-run economic growth. This is consistent with the endogenous growth theories and with the findings of existing literature such as Kim and Lee (2015), He (2019), and Nguyen and Doytch (2022). On the other hand, total patents still contribute to long-run economic growth, albeit to a lesser extent compared to more technical innovations such as those developed in ICT. This is particularly true to more recent observations in the dataset. Moreover, AI has had a more robust and significant effect on the long-run growth among advanced economies, while total innovation exhibits almost no impact on growth for both advanced and emerging countries.

In addition, an IV estimation with fixed effects using cited NPL has been employed to further minimize the endogeneity issue. The FE-IV estimates are valid for the AI patents model, but not for the total patents model. The FE-IV estimates are also comparable with the results of other estimation techniques such as fixed effects and GMM, suggesting that cited non-patent references may serve as an instrument for specific types of patents such as those related to AI.

## 6 Conclusion

Innovations in AI have been around as early as the 1970s, but their application and impact have only been more apparent and pervasive in the last ten to twenty years. The huge surge in AI and total patent registrations by the turn of the century, alongside the obvious physical and non-physical embodiments of innovative technologies consumed daily, is evidence of how AI and related technologies have changed the economic landscape. Several companies, especially those in e-commerce, have been leveraging natural language processing to predict customer behavior to increase sales. Meanwhile, multinational companies rely on AI and machine learning to optimize their supply chains through predictive scheduling, demand forecasting, inventory and risk management, and predictive maintenance among many other purposes (Rao and Verweij 2017; Ashcroft 2023). In general, advancements in AI and related ICT technologies have ultimately helped in modernizing production processes, minimizing manual inefficiency, and enhancing overall customer experience across firms and industries.

This study sets out to determine the relationship between the level of AI innovation and long-run economic growth, using a panel dataset across countries between 1970 and 2019. The main finding demonstrates that there exists a positive and significant impact of AI patenting on average long-run economic growth. Additionally, the effect of AI is more apparent in the latter period, because of the increasing quantity and quality of AI innovation generated over time. Overall, the positive impact of AI found in this study is consistent with the results of other studies focusing on AI and growth such as those by He (2019), Fan and Liu (2021), and Yang (2022).

Meanwhile, there is also some evidence of the positive contribution of total patent creation on economic growth. This positive effect of patenting is consistent with the findings of Wong et al. (2005), Kim and Lee (2015), and Nguyen and Doytch (2022). The effect, however, is notably smaller and weaker compared to the effect of AI patents on growth. Total patents, however, have exhibited significantly positive effects in the earlier periods of the dataset. The muted effect of patent publication on long-run economic growth is similar to the results found by Chu et al. (2016), Blind et al. (2022), and Nguyen and Doytch (2022) in their studies.

Furthermore, the effect of AI on growth is more robust among advanced economies, which is in line with the theory of machine automation proposed by Zeira (1998). Because of differences in capital endowments, not all countries can keep up with the pace of a constantly shifting technological frontier. As AI requires physical, and oftentimes ICT-related capital and technical know–how, not all countries can implement and use AI technologies effectively. In the meantime, more developed economies can leverage AI in production and business operations because of the availability of knowledge and infrastructure that complement AI, which engenders a strong positive contribution of AI to economic growth.

Finally, cited non-patent references in AI patents may serve as a valid instrument for AI patent creation. The estimates obtained from the FE-IV regression are consistent with the fixed effects estimation and GMM, and are also supported by various tests on instrument validity. Further work on this topic is recommended to future researchers, either by discovering other possible instruments or expanding the use of the instrument to other types of patents and/or measures of innovation.

## Appendix

See Tables 9, 10, 11, 12.

**Table 9** Estimation results between patents and short-run economic growth

| Dependent variable: real GDP growth rate per capita (annual) | (1) OLS | (2) FE | (3) AH | (4) GMM | (5) OLS | (6) FE | (7) AH | (8) GMM |
|---|---|---|---|---|---|---|---|---|
| Real GDP growth rate per capita ($t-1$) | 0.307*** (0.035) | 0.288*** (0.034) | 0.312*** (0.032) | 0.260*** (0.047) | 0.259*** (0.061) | 0.207*** (0.057) | 0.228*** (0.017) | 0.232*** (0.055) |
| Log of real GDP per capita ($t-1$) | − 0.830*** (0.185) | − 3.442*** (0.842) | − 2.909 (2.022) | − 3.954*** (1.235) | − 0.498*** (0.125) | − 3.762*** (0.794) | − 2.991** (1.376) | 0.460 (0.805) |
| Log of AI patents per million people | 0.181*** (0.069) | 0.360*** (0.113) | 0.359 (0.490) | 0.426* (0.253) | – | – | – | – |
| Log of total patents per million people | – | – | – | – | 0.076 (0.057) | 0.195* (0.106) | 0.194 (0.267) | 0.123 (0.132) |
| Population growth rate | − 0.440*** (0.078) | − 0.386*** (0.114) | − 0.384* (0.227) | − 0.338 (0.216) | − 0.310*** (0.084) | 0.000 (0.166) | − 0.003 (0.403) | − 0.27 (0.293) |
| Gross capital formation growth rate (per capita) | 0.117*** (0.030) | 0.107*** (0.033) | 0.106*** (0.024) | 0.061 (0.062) | 0.095*** (0.009) | 0.090*** (0.009) | 0.089*** (0.014) | 0.082*** (0.027) |
| Government expenditure growth rate (per capita) | 0.081*** (0.030) | 0.083** (0.032) | 0.082 (0.053) | 0.125* (0.071) | 0.097*** (0.024) | 0.091*** (0.023) | 0.090*** (0.034) | 0.094 (0.057) |
| Trade openness | 0.007*** (0.002) | 0.010** (0.004) | 0.010 (0.019) | 0.020 (0.015) | 0.006*** (0.001) | 0.009** (0.004) | 0.009 (0.012) | − 0.014 (0.009) |

**Table 9** (continued)

| Dependent variable: real GDP growth rate per capita (annual) | (1) OLS | (2) FE | (3) AH | (4) GMM | (5) OLS | (6) FE | (7) AH | (8) GMM |
|---|---|---|---|---|---|---|---|---|
| Human capital index growth rate | − 0.143 (0.107) | − 0.196 (0.136) | − 0.198 (0.555) | − 0.416 (0.371) | 0.128 (0.127) | − 0.004 (0.135) | − 0.014 (0.580) | 0.215 (0.268) |
| Inflation | 0.002 (0.010) | 0.013 (0.010) | 0.013 (0.023) | 0.092 (0.070) | − 0.001 (0.012) | 0.004 (0.011) | 0.004 (0.024) | 0.043 (0.047) |
| Advanced economy (dummy) | 0.931** (0.374) | 1.596*** (0.477) | 1.537 (2.178) | 2.197*** (0.762) | 0.107 (0.543) | 2.486** (0.963) | 2.375 (2.499) | 0.615 (0.997) |
| Advanced x Log of AI patents per million people | − 0.165* (0.091) | − 0.370** (0.149) | − 0.368 (0.558) | − 0.681** (0.275) | – | – | – | – |
| Advanced × Log of total patents per million people | – | – | – | – | 0.029 (0.078) | − 0.227 (0.151) | − 0.212 (0.390) | − 0.114 (0.162) |
| Constant | 7.706*** (1.560) | 32.653*** (7.960) | – | 37.607*** (11.363) | 4.314*** (0.956) | 32.655*** (7.035) | – | − 2.888 (6.704) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of instruments | – | – | – | 121 | – | – | – | 110 |
| Sargan-Hansen test (*p*-value) | – | – | – | 0.143 | – | – | – | 0.375 |
| AR(1) (*p*-value) | – | – | – | 0.001 | – | – | – | 0.000 |
| AR(2) (*p*-value) | – | – | – | 0.236 | – | – | – | 0.727 |
| *N* | 2261 | 2261 | 2261 | 2261 | 4905 | 4905 | 4905 | 4905 |
| *n* | 120 | 120 | 120 | 120 | 141 | 141 | 141 | 141 |

*** Significant at 1% level; ** significant at 5% level; *significant at 10% level. Robust (OLS, FE, GMM) and bootstrapped (AH) standard errors are enclosed in parentheses. AH estimation does not report a constant term. Values appearing in the table are based on the author's calculation using the datasets available from the Google Patents Public Data, the Penn World Table, the World Bank Development Indicators, and the United Nations National Accounts—Analysis of Main Aggregates

**Table 10** Estimation results with the growth of Internet users

| Dependent Variable: Real GDP growth rate per capita (5-year average) | (1) OLS | (2) FE | (3) AH | (4) GMM | (5) OLS | (6) FE | (7) AH | (8) GMM |
|---|---|---|---|---|---|---|---|---|
| Real GDP growth rate per capita ($t-1$) | − 0.003 (0.052) | − 0.002 (0.030) | 0.048* (0.029) | − 0.104 (0.084) | 0.030 (0.051) | − 0.072 (0.045) | − 0.011 (0.029) | 0.089 (0.060) |
| Log of real GDP per capita ($t-1$) | − 0.227 (0.233) | − 2.208*** (0.660) | − 2.002*** (0.574) | − 2.395** (1.068) | 0.173** (0.070) | 0.182 (0.114) | 0.172 (0.120) | 0.168 (0.573) |
| Log of AI patents per million people | 0.102 (0.065) | 0.277*** (0.083) | 0.252** (0.104) | 0.769** (0.346) | – | – | – | – |
| Log of total patents per million people | – | – | – | – | − 0.408** (0.163) | − 3.309*** (0.747) | − 2.996*** (0.536) | − 1.395 (1.669) |
| Population growth rate | − 0.589*** (0.104) | − 0.599*** (0.126) | − 0.619*** (0.104) | − 0.468 (0.355) | − 0.303** (0.142) | − 0.241 (0.225) | − 0.256** (0.116) | − 0.233 (0.945) |
| Gross capital formation growth rate (per capita) | 0.134*** (0.046) | 0.124** (0.048) | 0.128*** (0.013) | 0.056 (0.059) | 0.121*** (0.032) | 0.096*** (0.031) | 0.099*** (0.013) | 0.237** (0.114) |
| Government expenditure growth rate (per capita) | 0.250*** (0.050) | 0.229*** (0.047) | 0.224*** (0.031) | 0.455** (0.203) | 0.190*** (0.035) | 0.138*** (0.034) | 0.138*** (0.022) | 0.062 (0.158) |
| Trade openness (5-year average) | 0.003** (0.002) | 0.009* (0.005) | 0.009* (0.005) | 0.022** (0.009) | 0.003*** (0.001) | 0.012** (0.006) | 0.012*** (0.004) | 0.017 (0.012) |
| Human capital index growth rate | − 0.040 (0.122) | − 0.073 (0.152) | − 0.061 (0.147) | − 0.173 (0.707) | 0.055 (0.139) | − 0.059 (0.210) | − 0.043 (0.194) | 0.208 (0.624) |
| Inflation (5-year average) | 0.055 (0.035) | 0.048 (0.034) | 0.042* (0.022) | 0.025 (0.054) | 0.061** (0.027) | 0.066** (0.028) | 0.059** (0.024) | − 0.062 (0.195) |
| Internet users growth rate (5-year average) | 0.006 (0.006) | 0.001 (0.005) | 0.000 (0.007) | 0.016 (0.027) | 0.008 (0.006) | 0.008 (0.006) | 0.007 (0.005) | − 0.014 (0.035) |
| Advanced economy (dummy) | − 0.287 (0.327) | 0.690 (0.570) | 0.541 (0.646) | 2.825** (1.113) | 0.379 (0.713) | 3.995 (2.517) | 3.555* (2.054) | 4.247 (7.260) |
| Advanced × Log of AI patents per million people | − 0.054 (0.073) | − 0.270* (0.156) | − 0.233* (0.127) | − 1.043*** (0.345) | – | – | – | – |
| Advanced × Log of total patents per million people | – | – | – | – | − 0.084 (0.079) | − 0.516* (0.294) | − 0.468** (0.238) | − 0.566 (0.908) |
| Constant | 3.095* (1.806) | 20.597*** (5.951) | – | 20.330** (9.692) | 3.570*** (1.136) | 28.720*** (6.496) | – | 11.410 (14.600) |
| Time dummies | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Number of instruments | – | – | – | 55 | – | – | – | 27 |
| Sargan-Hansen test (p-value) | – | – | – | 0.405 | – | – | – | 0.149 |
| AR(1) (p-value) | – | – | – | 0.003 | – | – | – | 0.002 |

**Table 10** (continued)

| Dependent Variable: Real GDP growth rate per capita (5-year average) | (1) OLS | (2) FE | (3) AH | (4) GMM | (5) OLS | (6) FE | (7) AH | (8) GMM |
|---|---|---|---|---|---|---|---|---|
| AR(2) (p-value) | – | – | – | 0.741 | – | – | – | 0.659 |
| *N* | 463 | 463 | 463 | 463 | 676 | 676 | 676 | 676 |
| *n* | 119 | 119 | 119 | 119 | 143 | 143 | 143 | 143 |

*** Significant at 1% level; ** significant at 5% level; *significant at 10% level. Robust (OLS, FE, GMM) and bootstrapped (AH) standard errors are enclosed in parentheses. AH estimation does not report a constant term. Values appearing in the table are based on the author's calculation using the datasets available from the Google Patents Public Data, the Penn World Table, the World Bank Development Indicators, and the United Nations National Accounts—Analysis of Main Aggregates

**Table 11** First-stage FE-IV regression results

| Instruments | Instrumented Variables | | | |
|---|---|---|---|---|
| | (1) Log of AI patents per million people | (2) Advanced × Log of AI patents per million people | (3) Log of total patents per million people | (4) Advanced × Log of total patents per million people |
| Log of cited non-patent literature | 0.182*** (0.038) | − 0.060*** (0.020) | 0.172*** (0.033) | 0.001 (0.011) |
| Log of cited non-patent literature ($t-1$) | 0.058* (0.032) | 0.010 (0.021) | 0.088*** (0.027) | 0.011 (0.011) |
| Advanced × Log of cited non-patent literature | − 0.048 (0.049) | 0.240*** (0.040) | 0.009 (0.040) | 0.253*** (0.024) |
| Advanced × Log of cited non-patent literature ($t-1$) | 0.007 (0.034) | 0.101*** 0.031) | − 0.022 (0.020) | 0.012 (0.014) |
| Real GDP growth rate per capita ($t-1$) | 0.064*** (0.021) | 0.020 (0.015) | 0.016 (0.013) | 0.006 (0.005) |
| Log of real GDP per capita ($t-1$) | 1.484*** (0.365) | 0.332 (0.303) | 1.090*** (0.306) | 0.116 (0.109) |
| Population growth rate | − 0.111** (0.048) | − 0.049 (0.044) | − 0.132*** (0.037) | − 0.101*** (0.022) |
| Gross capital formation growth rate (per capita) | − 0.003 (0.012) | − 0.00567 (0.009) | 0.007 (0.005) | 0.003 (0.002) |
| Government expenditure growth rate (per capita) | 0.075*** (0.023) | 0.026 (0.022) | 0.016 (0.010) | 0.006 (0.004) |
| Trade openness (5-year average) | − 0.001 (0.002) | 0.001 (0.002) | − 0.000 (0.001) | 0.001 (0.001) |
| Human capital index growth rate | − 0.223** (0.112) | − 0.090 (0.077) | − 0.098 (0.068) | − 0.030 (0.035) |
| Inflation (5-year average) | − 0.007 (0.014) | − 0.002 (0.011) | 0.005 (0.008) | − 0.004 (0.004) |
| Advanced economy (dummy) | 0.290 (0.411) | 2.201*** (0.437) | 0.102 (0.411) | 5.511*** (0.283) |
| Time dummies | Yes | Yes | Yes | Yes |
| *N* | 326 | 326 | 836 | 836 |
| *n* | 65 | 65 | 135 | 135 |

*** Significant at 1% level; **significant at 5% level; *significant at 10% level. Robust standard errors are enclosed in parentheses. FE-IV estimation does not report a constant term. Values appearing in the table are based on the author's calculation using the datasets available from the Google Patents Public Data, the Penn World Table, the World Bank Development Indicators, and the United Nations National Accounts—Analysis of Main Aggregates

**Table 12** List of variables

| Variable | Description | Source |
|---|---|---|
| Real GDP growth rate per capita | Five-year average of real GDP per capita growth rate (dependent variable) | UN National Accounts |
| Real GDP growth rate per capita ($t-1$)[a] | Lagged 5-year average of real GDP per capita growth rate | UN National Accounts |
| Log of real GDP per capita ($t-1$)[a] | Lagged log of the 5-year average of real GDP per capita (USD) | UN National Accounts |
| Log of AI patents per million people[a] | Log ratio of the 5-year total number of AI patents per one million people in a 5-year average population | Google Patents |
| Log of total patents per million people[a] | Log ratio of the 5-year total number of patents per one million people in a 5-year average population | Google Patents |
| Population growth rate[a] | Five-year average of population growth rate | World Bank |
| Gross capital formation growth rate (per capita)[a] | Five-year average of gross capital formation growth rate | UN National Accounts |
| Government expenditure growth rate (per capita)[a] | Five-year average of government expenditure growth rate | UN National Accounts |
| Trade openness (5-year average)[a] | Five-year average of trade volume (exports plus imports) ratio to GDP | World Bank |
| Human capital index growth rate[a] | Five-year average of human capital index growth rate | Penn World Table |
| Inflation (5-year average)[a] | Five-year average of inflation (using GDP deflator) | UN National Accounts |
| Internet users growth rate (5-year average)[b] | Five-year average of Internet users growth rate | World Bank |
| Advanced economy (dummy)[a] | 1 for observations with 5-year average real GDP per capita exceeding USD 10,000; 0 otherwise | – |
| Advanced × Log of AI patents per million people[a] | Interaction term between the advanced economy (dummy) and the log of AI patents per million people | – |
| Advanced × Log of total patents per million people[a] | Interaction term between the advanced economy (dummy) and the log of total patents per million people | – |
| Log of cited non-patent literature[c] | Log of the 5-year total number of cited non-patent literature | Google Patents |
| Advanced × Log of cited non-patent literature[c] | Interaction term between the advanced economy (dummy) and the log of cited non-patent literature | – |

[a] The lags of the listed variables are used in the GMM estimation. The number of lags may vary for each GMM estimation (a maximum of five lags is considered). All estimations use 5-year totals/averages of the variables except in the short-run analysis (see Table 9)

[b] Additional variable for robustness check (see Table 10)

[c] First-stage instruments for the AI patents, total patents, and interaction terms in the FE-IV estimation (see Table 11, Table 12)

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**Declarations**
The author confirms to have read, understood, and agreed to the submission guidelines, policies, and submission declaration of the journal. The author confirms that the manuscript is the author's original work and that the manuscript has not received prior publication and is not under consideration for publication elsewhere. The author confirms that the paper now submitted is not copied or plagiarized version of some other published work.

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**Availability of data and materials**
The datasets used and/or analyzed during the current study are available from the corresponding author upon reasonable request. However, the datasets supporting the conclusions of this article are also available in the following repositories: Google Patents Data: https://console.cloud.google.com/bigquery?ws=!1m4!1m3!3m2!1spatents-public-data!2sgoogle_patents_research. Penn World Table: https://www.rug.nl/ggdc/productivity/pwt/?lang=en. United Nations Statistics: https://unstats.un.org/unsd/snaama/Downloads. World Bank Development Indicators: https://databank.worldbank.org/source/world-development-indicators.

## Declarations

**Competing interests**
The author confirms that the manuscript has no competing interest to declare. The author declares that there are no competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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