GOSPODARKA NARODOWA

3(323)2025, 31–46
DOI: 10.33119/GN/203715
gnpje.sgh.waw.pl
SGH

Special Issue

The Polish Journal of Economics
Istnieje od / Published since 1931

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# Generative AI and Income Growth: Early Evidence on Global Data

## Generatywna sztuczna inteligencja a wzrost dochodów – wstępne wnioski na podstawie danych globalnych

### Abstract

This paper investigates the relationship between artificial intelligence (AI) and global income growth, with a particular focus on the latest emerging category of digital technologies: generative AI (GenAI). GenAI introduces innovative methods for content creation and can assist with both manual and cognitive tasks, potentially transforming productivity, output, and employment dynamics. By analysing patent data from a global sample of countries, this study aims to assess whether GenAI, even in its early stages, exhibits a positive correlation with income growth. Our findings reveal a statistically significant, albeit quantitatively modest, association between GenAI and GDP per capita growth. Specifically, we estimate a growth premium of approximately 0.02 percentage points over a decade for countries adopting this emerging technology domain—reflecting the extensive margin of GenAI innovation. Additionally, when examining the scale of research efforts in this field (the intensive margin), we find that GenAI has contributed between 0.009 and 0.013 percentage points to GDP per capita growth since 2009.

**Keywords:**
generative artificial intelligence, income growth, world data

**JEL classification codes:**
O31, O33, O40

**Article history:**
submitted: November 29, 2024
revised: March 9, 2025
accepted: March 10, 2025

### Streszczenie

W artykule opisano badanie dotyczące związku między sztuczną inteligencją (AI) a globalnym wzrostem dochodów ze szczególnym uwzględnieniem jednej z nowo pojawiających się kategorii technologii cyfrowych – generatywnej AI (GenAI). GenAI wprowadza innowacyjne metody tworzenia treści i może stanowić wsparcie w zadaniach zarówno manualnych, jak i kognitywnych, potencjalnie zmieniając produktywność, wydajność i dynamikę zatrudnienia. W badaniu przeanalizowano dane patentowe z globalnej próby krajów w celu oceny tego, czy wykorzystywanie GenAI, nawet na jej wczesnych etapach rozwoju, wykazuje pozytywną korelację ze wzrostem dochodów. Stwierdzono statystycznie istotny, choć ilościowo umiarkowany związek między GenAI a wzrostem PKB per capita. Oszacowano premię za wzrost w wysokości około 0,02 p.p. w ciągu dekady dla krajów przyjmujących tę nową technologię, co odzwierciedla *extensive margin* dla innowacji GenAI. Ponadto, analizując skalę wysiłków badawczych w tej dziedzinie (*intensive margin*), stwierdzono, że od 2009 r. GenAI spowodowała wzrost PKB per capita od 0,009 do 0,013 p.p.

**Słowa kluczowe:**
generatywna sztuczna inteligencja, wzrost dochodów, dane światowe

**Kody klasyfikacji JEL:**
O31, O33, O40

**Historia artykułu:**
nadesłany: 29 listopada 2024 r.
poprawiony: 9 marca 2025 r.
zaakceptowany: 10 marca 2025 r.

## Introduction

Since OpenAI introduced ChatGPT in November 2022, the adoption of large language models (LLMs) and other generative AI (GenAI) tools, such as virtual assistants and chatbots, has grown significantly. In the United States, approximately 40% of individuals and 24% of workers use GenAI, with half of these workers using it regularly on a daily basis. The diffusion rate of GenAI seems significantly faster than that of computers and the internet in previous decades [**Bick et al., 2024**]. Around 5% of US companies use GenAI systems. Higher rates of adoption can be found in the finance and insurance industry, and in particular in the computing data, motion and recording sector, where adoption levels range from 25% to 35% [**Goldman Sachs, 2024**][1]. To date, the productivity impacts of generative AI (GenAI) have been studied on small-scale data and in specific fields. Experimental studies involving data scientists and information industry professionals indicate that GenAI enhances worker performance across various tasks. It enables users to solve business challenges more effectively, produce reports and written content more quickly, and generate targeted outputs. As a complementary technology, GenAI boosts productivity, making augmented (virtually assisted) workers more efficient than their non-augmented peers [**Wiles et al., 2024**]. **Noy and Zhang** [**2023**] investigate the impact of ChatGPT adoption on the productivity of mid-level professional (college-educated) writers. They report a 40% reduction in task completion time and an almost 20% improvement in output quality. In software programming and coding, the productivity gains from exposure to GenAI tools such as GitHub Copilot appear even more substantial, reaching approximately 55% [**Peng et al., 2023**][2]. **Brynjolfsson et al.** [**2023**] examine the productivity impact of GenAI-based virtual assistance on customer support agents. They find that worker productivity increased by 14% following the introduction of this technology, with the effect being more pronounced for low-skill workers compared to high-skill or experienced employees. This effect would reflect the dissemination of knowledge and best practices to less experienced workers. Based on this early evidence, the productivity boost from GenAI appears to be larger than the overall productivity gains attributed to AI as a whole [**Calvino, Fontanelli, 2023**; **Marioni et al., 2024**].

GenAI expands the scope of technological innovation and the development of novel ideas [**Korinek, 2023**]. The broad applicability of GenAI in innovation and research has accelerated technological advancements in various domains [**Wang et al., 2023**]. One particularly promising area is medicine, where GenAI plays a crucial role in drug discovery, treatment development, diagnosis, and personalised care recommendations [**Cesaro, de la Fuente-Nunez, 2023**; **Swanson et al., 2024**]. However, the diffusion of GenAI and its most advanced applications presents significant challenges. A central debate concerns the point at which AI might surpass human capabilities in generating original ideas. Legal frameworks, such as patent laws, currently impose constraints by not recognising AI as an inventor for patent purposes [**George, Walsh, 2022**]. This raises important questions about intellectual property rights and the evolving role of AI in innovation. Not less relevant are the social and economic threats brought about by AI, as it challenges job security and widens income inequality [**Filippucci et al., 2024**]. **Minniti et al.** [**2025**] document that AI, in general terms, has reduced the share of income accruing to workers, and this would exacerbate geographical disparities within Europe.

A key discussion point concerns the potential of GenAI to drive economic growth, which entails a complex interplay of factors beyond productivity, including employment dynamics and structural changes [**Trammell, Korinek, 2023**]. As with earlier digital technologies—such as computers, software, industrial robots, and traditional machine learning systems—the economic impact of GenAI is expected to unfold through

1 While traditional machine learning (ML) systems leverage data and algorithms to make predictions or decisions, GenAI extends this capability by employing supervised learning techniques to create new content. GenAI relies on "transformer" architectures—advanced deep neural networks that process data inputs in parallel. This new way of processing significantly enhances efficiency compared to earlier AI models, reducing both training and computing times. A key characteristic of GenAI is its interactive nature: users continuously collaborate with the machine, providing them feedback to refine outputs. GenAI systems can generate text, code, audio, and video in response to natural language inputs, assisting users across a wide range of tasks, both cognitive and complex manual activities.

2 **Hoffmann et al.** [**2024**] document that access to Copilot enables software developers—particularly those with lower skill levels—to focus more on core coding tasks, work more independently, and engage in greater exploration.

multiple channels. First, replacement effects arise from the reduction of manual and cognitive jobs currently performed by humans. Second, reallocation effects occur as resources shift between different sectors of the economy. Third, productivity-enhancing effects emerge from the creation of new tasks and jobs, enabled by advanced content generation capabilities. The net impact of these mechanisms will likely depend on the proportion of productive tasks that are exposed to AI integration. **Acemoglu** [**2024**] estimates that AI, in aggregate, will contribute to a cumulative increase of 0.7% in the rate of total factor productivity (TFP) growth over the next decade. The cumulative impact on gross domestic product (GDP) growth is projected to be slightly larger, ranging from 0.9% to 1.1%. Less conservative estimates suggest that GenAI alone could speed up the rate of GDP growth by between 0.5 and 1 percentage points annually in the medium run [**Goldman Sachs, 2024**; **Ernst & Young, 2024**].

Quantifying the growth impact of generative AI (GenAI) is inherently challenging due to its rapid evolution and the difficulty of accurately measuring emerging technologies at an early stage. However, advancing economic research in this area requires anchoring analyses in reliable data and applying rigorous quantitative methods. This paper addresses this gap in the literature by leveraging patent data from a global sample of countries to examine the statistical relationship between GenAI innovation and per capita income growth. Our analysis provides two key findings. First, we show that countries engaged in GenAI innovation have experienced faster GDP per capita growth compared to those not yet active in this technological domain. Although modest, this growth premium—representing the extensive margin of GenAI innovation—amounts to approximately 0.02 percentage points over a decade, reflecting the benefits of entering the emerging digital technology category. Second, we explore the intensive margin by assessing the relationship between the cumulative value of GenAI-related patents (a proxy for innovation effort) and income growth. We find a positive and statistically significant association, with GenAI contributing between 0.009 and 0.013 percentage points to GDP per capita growth since 2009. While these estimates are conservative compared to some optimistic projections in the literature, they provide valuable evidence and underscore the importance of further economic analysis in this rapidly evolving field.

The structure of the paper is the following. Section 2 illustrates the design of the empirical analysis. Section 3 illustrate the data. Section 4 presents estimation results. Section 5 concludes.

## Empirical strategy

Our primary objective is to investigate whether countries specialising in the development of new digital technologies have a differential income growth performance compared to countries not involved in AI innovation in the broad sense. AI innovation has the potential to significantly impact a country's income levels through various mechanisms. These technologies can enhance productivity levels by increasing efficiency, improving technological capabilities, and facilitating knowledge spillovers. However, they may also affect job opportunities and wage conditions for workers. Our focus is on examining the correlation between AI and income growth to determine the overall impact of these forces.

In order to identify the linkage between AI innovation and economic growth (measured by GDP per capita growth), we conduct a growth regression analysis using various indicators of AI innovation capacity, based on a static model of conditional income convergence. We run our regression model using two different types of GenAI variables, each providing complementary insights into the income growth performance of countries engaged in innovation in this new digital field. In our first regression model, we seek to determine whether countries that prioritise AI innovation experience greater income growth compared to countries without AI innovation. To investigate this, we incorporate into our growth equation a variable that identifies countries with AI patents developed over the sample period interacted with a time trend. Our baseline specification is therefore shaped as:

$$\Delta \ln Y_{it} = \alpha_i + \beta \ln Y_{it-1} + \gamma AI_i \times t + \rho \ln X_{it-1} + \alpha_t + \epsilon_{it}. \tag{1}$$

where $i$ denotes countries and $t$ denotes year. This specification includes country fixed effects, $\alpha_i$, to neutralise the effect of unobserved heterogeneity, such as the differences in technological capabilities, patent propensity, institutional setting, rule of law, etc., that differ across countries but do not change over time. Time fixed effects $\alpha t$ are used to collect the impact of common shocks, such as technological change, globalisation waves, producing similar effects among countries in income dynamics or AI innovation processes. $\epsilon_{it}$ is the disturbance term[3]. The dependent variable is defined as the annual rate of change (log-change) in GDP per capita. $AI_i$ is a dummy variable indicating whether country $i$ has innovated (patented) in AI in the sample period. The interaction term, $AI_i \times t$, therefore captures whether the per capita income of AI-innovating countries has grown over time—specifically, year by year—at a faster rate compared to non-AI-innovating countries[4].

To account for the income convergence of laggard countries toward the richest economies during transitional dynamics, we include GDP per capita (in logarithmic form) at time $t - 1$ as a regressor. We also consider additional factors, $X$, that could impact the dynamics of GDP per capita, specifically the overall innovation capabilities of the country, as well as capabilities developed in technology domains close to AI, such as information and communication technology ICT [**Igna, Venturini, 2023**; **Minniti et al., 2025**]. Further controls will be introduced in the following sections.

In the second specification, we use a continuous variable reflecting the extent of innovation capabilities developed by each country in AI fields. In Eq. (2), $AI_{it}$ is a time-varying regressor, defined as the per capita stock of AI-related patents, built as detailed below:

$$\Delta \ln Y_{it} = \alpha_i + \beta \ln Y_{it-1} + \gamma \ln AI_i - 1 + \rho \ln X_{it-1} + \alpha_t + \epsilon_{it}. \tag{2}$$

In the light of the different nature of the explanatory variables, $\gamma$ in Eq. (2) quantifies the unit impact associated with being a country engaged in AI innovation. It therefore identifies the extensive margin of AI, namely the income growth premium associated with the status of AI innovator. In Eq. (1), $\gamma$ is a semi-elasticity capturing the intensive margin of AI, namely the income growth premium associated with an increase in AI-related knowledge stock.

We use these equations to assess the impact of AI in a broad sense, focusing on the income growth effects of the innovation category of generative AI (GenAI). This constitutes the novel contribution of this paper to the literature.

## Data and descriptive evidence

### Sources and methods

Innovation in artificial intelligence is quantified by analysing data filed with the United States Patent and Trademark Office[5]. This source provides valuable insights into the key trends shaping the global technology market. Patent data does not capture all AI-related innovations, as some developments may not meet patent eligibility criteria, while others may be intentionally withheld. Companies might choose not to disclose their algorithms as prior art or may only patent certain aspects of their innovations, sometimes those of lower commercial value. Nonetheless, patents remain one of the most valuable sources of information on innovation, offering highly standardised and detailed data that can be compared over time and across regions. The USPTO provides detailed information on patents that are ultimately granted, which we classify based on application data. We classify patents based on the country of residence of the applicant and distinguishing them by the filing year. AI patents are identified using the Cooperation Patent Classification developed together by the

3 All estimates use heteroskedasticity and autocorrelation robust (HAC) standard errors.
4 The main impact associated with the status of being an AI innovating country is accounted for by fixed effects.
5 https:/patentsview.org/download/detail_desc_text (accessed on: 24.11.2024).

United States Patent and Trademark Office and the European Patent Office. There are two main categories of AI innovations that we consider. We first identify the full set of AI patents as of the WIPO categorisation [WIPO, 2019]. Generative AI patents represent a subset of this larger group, specifically those falling under the G06N3/045 class of CPC ("auto-encoder networks; encoder-decoder networks"; [WIPO, 2024]). GenAI corresponds to the application of specific software methods to large datasets involving the generation of digital entities, such as images, text or data through the use of specific machine learning algorithms. While the employed category of patents primarily encompasses innovations characteristic of generative AI, it may also include similar innovations, such as technical methods utilised in processes leading to the creation of new products such as 3D printers or cameras. In this respect, our statistics on GenAI may be seen as upper bound values[6]. It is important to note that while many of these innovations have been introduced in recent years, we consider a relatively long time interval of data, specifically from 2010 onwards. For example, the first application of large language models dates back to 2017. However, as demonstrated below, earlier innovations related to the broad domain of GenAI can be traced back to the 1990 s according to our classification procedure. In computational terms, the amount of GenAI applications is then subtracted from the bulk of AI patents, and the resulting sub-aggregate is treated as our proxy for general (or non-generative) AI patents, referred to as AI hereinafter.

Our first proxy for AI innovation (both generative and non-generative) is defined in binary terms, namely with a dummy indicating whether a country has patent applications in this domain in the analysed time interval. Our second proxy is defined as the cumulative value of patent counts, constructed with the perpetual inventory method, using a depreciation rate of 15% and the Hall-Mairesse formula to compute the initial patent stock [see Bontadini et al., 2023].

Our main outcome variable is the annual log-change in GDP (expenditure definition) per capita, expressed in PPP at constant price 2017. This data is derived from World Bank and spans from 1990 to 2022[7]. As an alternative, we rely upon the Penn World Table (Release 10.01)[8]. The latter source covers a shorter time interval (until 2019) but offers information on some more countries and makes available data on possible confounding factors.

To mitigate omitted variable bias, we use two groups of control variables. The first set captures the technological capabilities of the countries, including the number of patents developed in the information and communication technology (ICT) sector, which is recognised as the technological precursor to AI [see Inaba, Squicciarini, 2017; Igna, Venturini, 2023]. This group of controls also includes a proxy for general innovation, which encompasses all patent applications not related to the digital technologies considered in our research (specifically GenAI, AI, and ICT). These variables, similar to our primary regressors, are defined as the stock of patents per capita and are derived from data in the USPTO patent database. The second group of controls consists of proxies for structural characteristics of the economy identified in the literature as influencing economic growth. These include the capital intensity of production, the level of skills and technological competencies unrelated to patenting. These factors are approximated by the investment share of GDP, human capital as proxied by average years of education, and the productivity gap relative to the United States. Data for these variables are sourced from the PWT database. Finally, we account for differences in sectoral structure, including the manufacturing share of GDP, using World Development Indicators. We incorporate this variable in all regressions based on World Bank data and include it in robustness checks using Penn World Table data.

6 WIPO [2024, p. 71] identifies GenAI innovations by conducting a semantic search on the content (document) of patents within the G06N3/045 class. In this study, we treat the entire corpus of patent applications within this class as GenAI technologies.

7 Source: https://ourworldindata.org/ (accessed on: 24.11.2024).

8 Source: https://www.rug.nl/ggdc/productivity/pwt/?lang=en (accessed on: 24.11.2024).

## Summary statistics

Our data sources allow us to analyse the period from 1991 to 2022, which serves as our baseline. However, we primarily focus on the years from 2010 onward to capture the period immediately before and after the introduction of GenAI innovations. Our full sample includes 181 countries, of which 55 have developed AI innovations, and 33 have developed GenAI innovations.

Table 1 presents the summary statistics, including the mean and standard deviation, for the key variables used in the regression analysis. These variables consist of the annual rate of change in GDP per capita and its levels (not in logarithmic form), the stock of patent applications in various digital sectors such as ICT, AI, and Generative AI, as well as the number of patent applications in other technology domains.

**Table 1. Summary statistics**

| | 1991–2022 | | 2010–2022 | |
|---|---|---|---|---|
| | Mean | Standard Deviation | Mean | Standard Deviation |
| Income pc growth (%) | 1.8 | 6.0 | 1.6 | 5.3 |
| Income pc (USD) | 19 102 | 20 948 | 22 057 | 22 547 |
| AI patent stock | 2.1 | 14.6 | 2.9 | 22.2 |
| GenAI patent stock | 1.2 | 3.6 | 1.3 | 4.2 |
| ICT patent stock | 193 | 2 007 | 291 | 2 703 |
| Other patent stock | 534 | 2 694 | 548 | 3 552 |

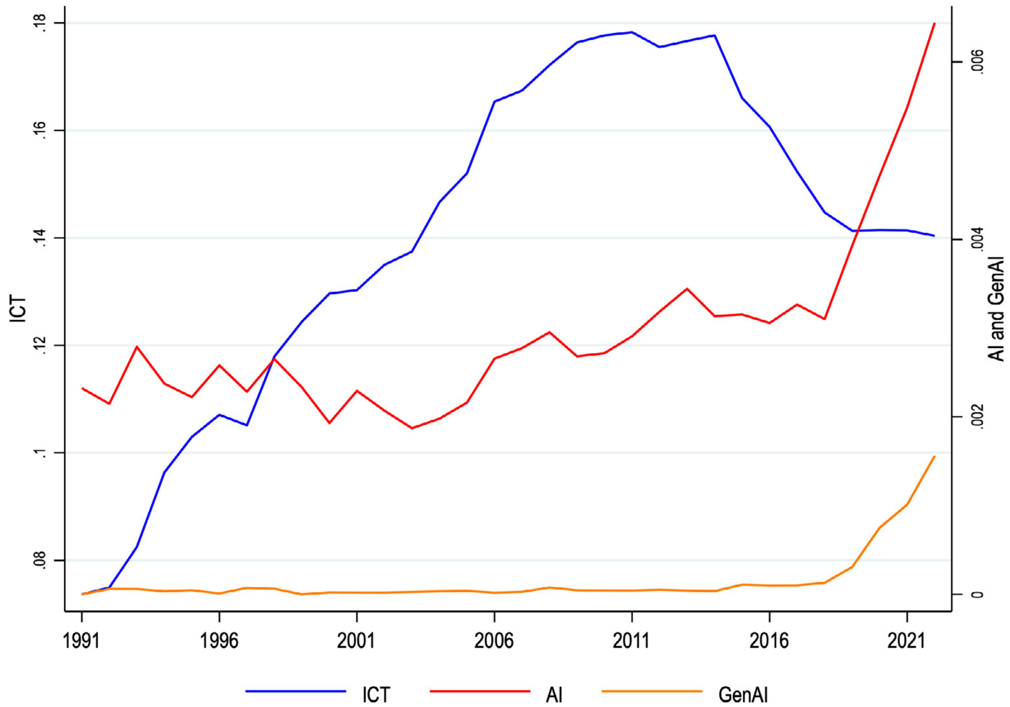
Notes: Unweighted data. Income pc is GDP per capita (pc). Patent statistics are expressed in per million inhabitants.
Source: Author's own elaboration based on World Development Indicators (World Bank) and USPTO patent database.

The unweighted annual rate of change in GDP per capita has been 1.8% over the entire time period, slowing slightly after 2009. Despite the recent global economic slowdown, there has been an increase in income levels, with GDP per capita averaging around USD 22,000 in the most recent period. When focusing on data since 2010, it is observed that the cumulative value of AI patents is nearly 3 per million inhabitants, while generative AI patents are around 1.3. These figures are significantly lower than the number of patent applications in ICT and other fields, which stand at 291 and 548 cumulative patents per million inhabitants respectively. It is important to note that, relatively to the mean, the standard deviation of GenAI is much narrower compared to all other patent categories, indicating that GenAI is primarily developed by a select few countries.

Figure 1 depicts the evolution of the share of digital patent categories relative to total patent applications over time. This analysis is conducted at the individual country level and then aggregated for the entire sample using weights that correspond to the total patent counts of each economy. The vertical axis on the left-hand side represents the share of ICT patents, while the shares of AI and GenAI are displayed on the right-hand side. The graph clearly illustrates a significant increase in the share of ICT patents up until the early 2010 s, with this proportion rising from 8% to 18% of total patents during that period. However, there has been a noticeable decline since the mid-2010 s, and currently, the share of ICT patents has stabilised at around 14%. Concurrently, there has been a substantial increase in the share of patents in emerging digital fields, with general AI accounting for 0.7% of total applications and GenAI representing 0.2%. When considering both AI categories together, they now make up 1% of total applications at the USPTO and approximately 7% of patents in digital fields (ICT, AI, and GenAI combined).

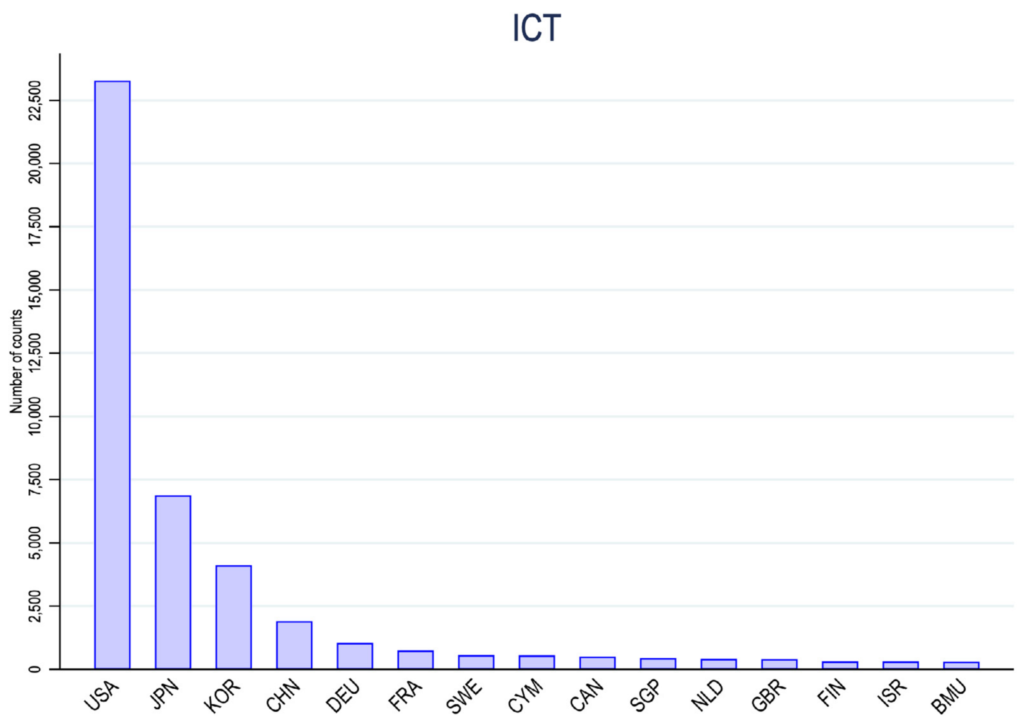
Figure 2 illustrates the distribution of patent applications in digital fields by country, showing the average number of applications since 2010 for the top-performing economies. The United States, followed by Japan, China, and South Korea, stand out as the most active innovators in these sectors. The United States leads the pack, with over 22,000 ICT-related applications per year. This advantage can in part be attributed to the preference for filing patents at the USPTO (the so-called home bias). A similar gap is evident in AI, where the United States files about 650 patents annually, compared to roughly 125 in Japan. In the case of GenAI, however, US dominance is less pronounced: while the United States still leads with around 60 patents per year, China emerges as a strong challenger, whereas Japan appears to lag behind.

**Figure 1. Share of digital patents, 1991–2022**

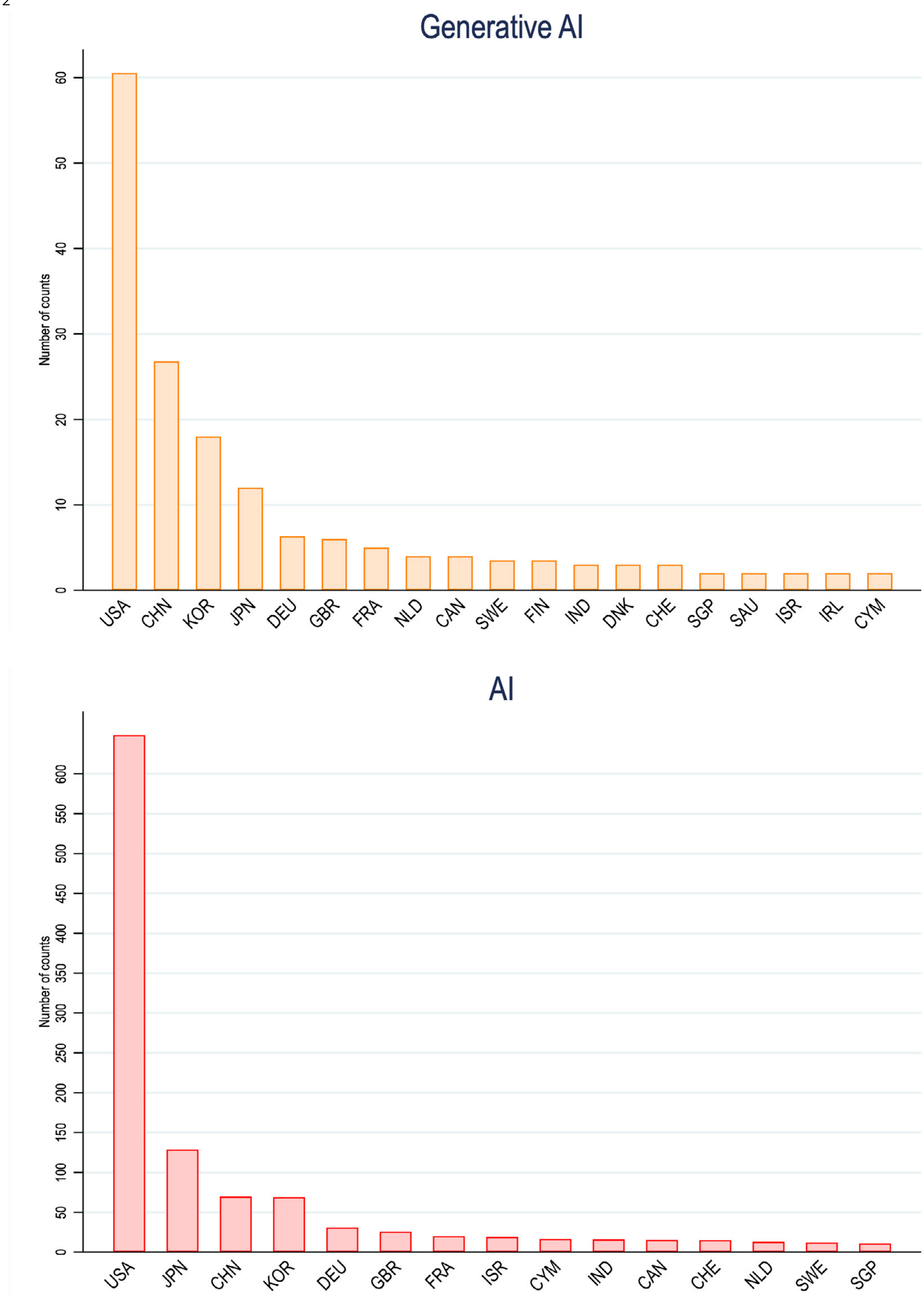



Notes: Statistics are weighted by patent counts.
Source: Author's own elaboration based on USPTO patent database.

**Figure 2. Number of digital patent applications by country, absolute values 2010–2022**



cont. Figure 2



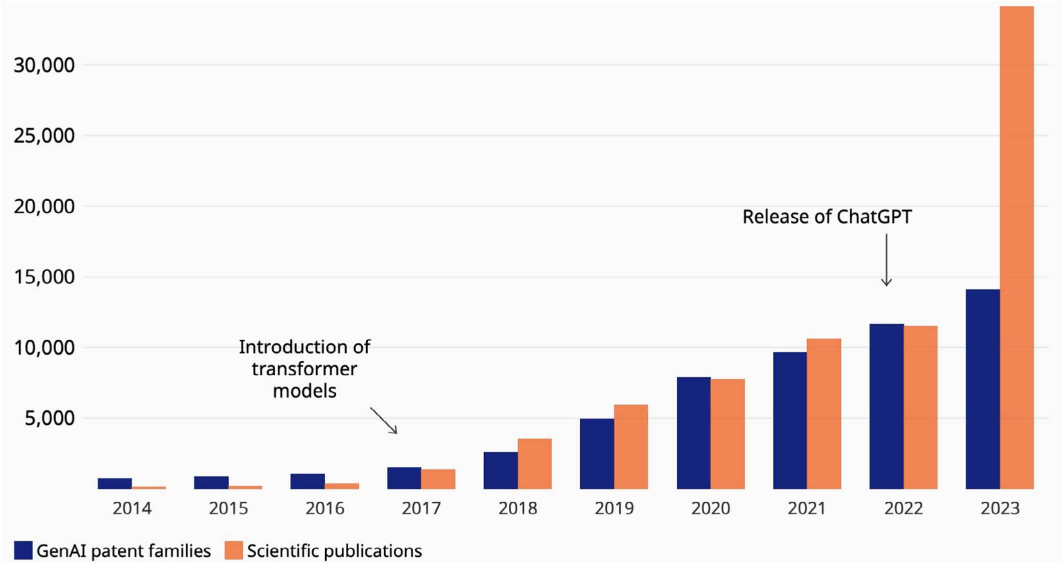

Source: Author's own elaboration based on USPTO.

One clear limitation of this analysis is its focus on generative AI innovation, which significantly narrows the range of potential effects this emerging digital technology may generate. To fully capture GenAI's broad economic impact across sectors, one would need to consider adoption, usage, and investment rates. Key sources of information in this regard include AI VC investments and trade data. When assessing innovation performance, scientific publications in the field serve as a valuable alternative to patent statistics. However, consistent global data on GenAI-specific publications remain unavailable[9]. To provide a broader perspective on

[9] The OECD AI Observatory provides publication data by year and country for total AI publications, derived from OpenAlex. However, country-level statistics on GenAI publications are not available as of this manuscript revision.

the evolution of technological knowledge in GenAI, we report statistics from WIPO [2024]. Figure 3 shows that, at the global level, GenAI publications have grown at a faster rate than GenAI patent families since the introduction of LLMs in 2017. This suggests that our patent-based measure of a country's innovation capacity in GenAI may underestimate the true extent of innovation, making our estimates potentially conservative.

**Figure 3. Global patent families, by publication year, and scholarly publications in GenAI, 2014–2023**




Source: WIPO [2024], Figure 10.

## Econometric evidence

### World Bank Data

Table 2 presents our first set of results, based on World Bank data, for the regression utilising a binary indicator to represent the status of AI patenting countries. Our analysis reveals a compelling pattern of income convergence among countries in our global sample, with a convergence parameter of –0.060 in the data since 1991-column (1). Interestingly, our baseline regression does not show any statistically significant effects from either general innovation or ICT innovation. However, upon narrowing our focus to the period following the Great Recession, we observe a positive relationship between ICT innovation and the rate of income per capita—column (2). Quantitatively, any additional patent in this field is associated with a 0.004 percentage-point increase in the rate of income growth (1/193× 0.007× 100 = 0.004% where 193 is the mean ICT patent stock per capita in the sample). Proportionally, by increasing (decreasing) the stock of ICT patents by 50% and 100% would deliver an acceleration (deceleration) in the rate of GDP per capita by 0.4% and 0.7%, over (below) an average rate of 1.6% since 2010 (see Table 1).

The positive income growth effect associated with ICT-related knowledge is a common trend among countries actively engaged in the field of AI, taken as a whole. Indeed, in column (3), we run the previous regression incorporating the term capturing the income growth differential for economies active in general AI innovation. This variable has a positive and statistically significant coefficient, while that of the ICT patent stock per capita loses significance, suggesting that there is a wide overlap in the effects of the two regressors. This finding confirms the results of the earlier microeconomic literature, highlighting a shift of the most productive innovators from traditional ICT fields to the emerging AI sector [see WIPO, 2019]. According to the estimates in column (3), an AI-innovating country is projected to experience GDP per capita growth at an annual rate 0.002 percentage points higher than the control group. Over the full duration of the regression analysis (approximately one decade), this effect would cumulatively amount to an impact of 0.020. This value is smaller, yet of a similar scale, to the estimates provided by Acemoglu [2024] for the United States. This cumulative impact will then be compared with the semi-elasticity associated with the continuous variable that captures the intensive margin of AI innovation—specifically the log-value of AI patent stock per capita, estimated in the following analysis.

**Table 2. AI innovation and income growth: AI and GenAI countries (World Bank sample)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Lagged income pc | −0.062***<br>(0.009) | −0.083***<br>(0.025) | −0.086***<br>(0.025) | −0.084***<br>(0.025) | −0.087***<br>(0.025) | −0.085***<br>(0.025) |
| General patent stock pc | 0.000<br>(0.002) | 0.004<br>(0.003) | 0.004<br>(0.003) | 0.004<br>(0.003) | 0.004<br>(0.003) | 0.004<br>(0.003) |
| ICT patent stock pc | 0.001<br>(0.001) | 0.006*<br>(0.003) | 0.001<br>(0.004) | 0.004<br>(0.003) | 0.001<br>(0.004) | 0.005<br>(0.003) |
| AI country × trend | | | 0.002***<br>(0.001) | | 0.002***<br>(0.001) | |
| GenAI country × trend | | | | 0.001**<br>(0.001) | −0.000<br>(0.001) | |
| AI country (restricted) × trend | | | | | | 0.002**<br>(0.001) |
| GenAI country (restricted) × trend | | | | | | −0.001<br>(0.002) |
| Manufacturing share of GDP | −0.070*<br>(0.040) | −0.069<br>(0.099) | −0.059<br>(0.099) | −0.074<br>(0.098) | −0.056<br>(0.099) | −0.057<br>(0.101) |
| Time period | 1991–2022 | 2010–2022 | 2010–2022 | 2010–2022 | 2010–2022 | 2010–2022 |
| Observations | 4,838 | 2,148 | 2,148 | 2,148 | 2,148 | 2,148 |
| R-squared | 0.041 | 0.034 | 0.040 | 0.035 | 0.040 | 0.036 |

Notes: The dependent variable is the log-change in GDP per capita (pc). All continuous explanatory variables are expressed in logs and taken with one-year lag with respect to the dependent variable. All regressions include country- and year-fixed effects. Heteroskedasticity and autocorrelation robust (HAC) standard errors in parentheses. ***, **, * significant at 1%, 5%, 10% respectively.

Source: Author's own elaboration.

Similar findings emerge for the group of countries which innovate in the field of GenAI—column (4). However, when we analyse both groups of AI innovating countries together, only the coefficient associated with the broader category of AI remains significant—column (5). A key concern in the latter estimates is that the outcomes may be influenced by a subset of countries that are highly active in both streams of AI innovations (general and generative AI). To address this, we replicate the previous two regressions by focusing on countries that have innovations only in the field of AI or in the field of GenAI—column (6). These results remain consistent with those of the previous regression.

Table 3 illustrates the results obtained using the stock of AI patents per capita as regressors. The coefficients of these variables reflect the intensive margin related to involvement in the emerging digital fields. Columns (1)–(4) encompass all countries within the sample, while the subsequent two columns focus on those having only AI and GenAI patents respectively. The outcomes of this second group of regressions are wholly consistent with those previously displayed. Notably, the results indicate a positive impact on income growth for GenAI, in particular when excluding countries engaged in both categories of AI innovation. The association between GenAI and the annual rate of GDP per capita appears to be larger than for non-generative AI. Our findings indicate that doubling GenAI is associated with an increase of 0.07% in the rate of GDP per capita growth (above the mean of 1.6% annually). The per capita stock of GenAI has increased by 13% since 2010 onwards, and 18% from 2017, implying a contribution to the acceleration of income between 0.009% and 0.013% according to our estimates. Again, these figures are at a lower bound but not far from the forecasts presented in earlier academic works and business reports (see Section 1). There are several factors that may explain the differences in quantification between, for instance, Acemoglu [2024] and our work. First, Acemoglu [2024] relies on more recent data, capturing a period when the impact of generative AI is more pronounced, whereas our study spans a broader time frame. Second, while Acemoglu [2024] focuses on the United States–-one of the leading AI innovators—our sample includes multiple countries with lower levels of AI adoption. Finally, his work examines AI exposure and usage, which is widespread across sectors and influences the entire economy, whereas we focus on AI innovation, a more specialised and concentrated process within a narrower segment of the economy[10]. AI, like any disruptive technology, takes time to generate significant aggregate effects. At the microeconomic level, its impact on the performance of adopters and developers can materialise relatively quickly [Marioni et al., 2024]. However, at the macroeconomic level, these effects are partially offset by disparities between firms that adopt AI and those that do not, as well as between first movers and late adopters [Venturini, 2022]. Additionally, the integration of data and intelligent technologies may initially reduce efficiency or necessitate substantial yet hard-to-measure complementary intangible investments, potentially causing productivity to decline—either in real terms or as an artifact of measurement challenges [Farboodi et al., 2019, Brynjolfsson et al., 2021].

**Table 3. AI innovation and income growth: AI and GenAI patent stock (World Bank sample, 2010–2022)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Lagged income pc | −0.062*** (0.009) | −0.083*** (0.025) | −0.087*** (0.025) | −0.085*** (0.025) | −0.084*** (0.028) | −0.087*** (0.032) |
| General patent stock pc | 0.000 (0.002) | 0.004 (0.003) | 0.004 (0.003) | 0.004 (0.003) | 0.005 (0.003) | 0.004 (0.004) |
| ICT patent stock pc | 0.001 (0.001) | 0.006* (0.003) | 0.003 (0.004) | 0.005 (0.003) | 0.003 (0.005) | −0.003 (0.007) |
| AI patent stock p.c. GenAI patent stock pc | | | 0.009** (0.004) | 0.006 (0.004) | 0.012* (0.006) | 0.059** (0.028) |
| Manufacturing share of GDP | −0.070* (0.040) | −0.069 (0.099) | −0.076 (0.097) | −0.063 (0.100) | −0.147 (0.110) | −0.172 (0.121) |
| Observations | 4,838 | 2,148 | 2,148 | 2,148 | 1,694 | 1,447 |
| R-squared | 0.041 | 0.034 | 0.036 | 0.034 | 0.033 | 0.031 |

Notes: The dependent variable is the log-change in GDP per capita (pc). All continuous explanatory variables are expressed in logs and taken with one-year lag with respect to the dependent variable. All regressions include country- and year-fixed effects. Heteroskedasticity and autocorrelation robust (HAC) standard errors in parentheses. ***, **, * significant at 1%, 5%, 10% respectively.

Source: Author's own elaboration.

We conduct a series of robustness checks on our previous results, presented in Table 4. The first two columns report the main findings from the previous set of estimates. Columns (3) and (4) employ a measure of fractional patent counts, where each patent is proportionally assigned to a country in inverse relation to the number of applicants based in different countries. Columns (4) and (5) use the full count of patents but incorporate triadic patent families—sourced from the OECD—as an alternative patent variable. Triadic patent families, as defined by the OECD, consist of patent applications filed in the three major global technology markets: the European Patent Office (EPO), the United States Patent and Trademark Office (USPTO), and the Japan Patent Office (JPO). The OECD consolidates patents related to the original priority application into a single record to form a unique patent family. This first set of robustness regressions yields results that are largely consistent with those in Table 3.

Another key consideration is whether the impact of AI varies with the level of economic development, measured as the mean GDP per capita over the study period. To examine this, we replicate the benchmark estimation from columns (1) and (2), distinguishing between countries above and below the sample median income. These estimates indicate that only countries in the lower half of the income distribution fully capitalise on the growth potential of new digital technologies. This finding suggests that these economies, having greater room for development, may experience a magnified growth effect from AI development.

10 This dataset is constructed by integrating a dictionary of tasks that can be performed by AI systems with employment data from 2020 and 2021.

**Table 4. AI innovation and income growth: robustness checks (World Bank sample, 2010–2022)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Lagged income pc | −0.084*** (0.028) | −0.087*** (0.032) | −0.084*** (0.028) | −0.087*** (0.032) | −0.082*** (0.026) | −0.090*** (0.030) | −0.112*** (0.027) | −0.115*** (0.028) | −0.044 (0.050) | −0.032 (0.079) |
| General patent stock pc | 0.005 (0.003) | 0.004 (0.004) | 0.005 (0.003) | 0.005 (0.004) | −0.004 (0.006) | −0.004 (0.007) | 0.007* (0.004) | 0.002 (0.005) | 0.002 (0.006) | 0.006 (0.010) |
| ICT patent stock pc | 0.003 (0.005) | −0.003 (0.007) | 0.004 (0.005) | −0.002 (0.007) | −0.003 (0.003) | −0.002 (0.003) | −0.003 (0.008) | −0.009 (0.009) | 0.005 (0.006) | −0.001 (0.009) |
| AI patent stock pc | 0.012* (0.006) | | 0.011* (0.007) | | 0.006 (0.005) | | 0.033** (0.015) | | 0.004 (0.009) | |
| GenAI patent stock pc | | 0.059** (0.028) | | 0.059** (0.028) | | 0.074*** (0.027) | | 0.058* (0.030) | | 0.027 (0.084) |
| Manufacturing share of GDP | −0.147 | −0.172 | −0.143 | −0.171 | −0.119 | −0.148 | −0.285** | −0.335** | 0.099 | 0.105 |
| | (0.110) | (0.121) | (0.111) | (0.121) | (0.105) | (0.114) | (0.136) | (0.145) | (0.174) | (0.203) |
| Patent counts | Full | Full | Fractional | Fractional | Full | Full | Full | Full | Full | Full |
| Patent source | USPTO | USPTO | USPTO | USPTO | Triadic | Triadic | USPTO | USPTO | USPTO | USPTO |
| Income pc | Full | Full | Full | Full | Full | Full | Lower than 50% | Lower than 50% | Higher than 50% | Higher than 50% |
| Observations | 1,694 | 1,447 | 1,694 | 1,447 | 1,863 | 1,616 | 1,044 | 992 | 650 | 468 |
| R-squared | 0.033 | 0.031 | 0.034 | 0.031 | 0.030 | 0.034 | 0.078 | 0.081 | 0.010 | 0.004 |

Notes: The dependent variable is the log-change in GDP per capita (pc). All continuous explanatory variables are expressed in logs and taken with one-year lag with respect to the dependent variable. All regressions include country- and year-fixed effects. Heteroskedasticity and autocorrelation robust (HAC) standard errors in parentheses. ***, **, * significant at 1%, 5%, 10% respectively.

Source: Author's own elaboration.

## Penn World Tables Data

In the following regressions, we provide confirmation of the previous results using data from the PWT. Estimates based on the binary indicator for countries with innovation in AI fields closely align with the earlier findings, both in terms of significance and effect size (see Table 6). This holds whether we consider countries active in both domains of AI (generative and non-generative) or separately those active in only one of the two areas—see columns (5) and (6) respectively. Compared to the WDI dataset, the PWT data encompasses a larger set of countries and extends further back in time, predating the COVID-19 pandemic. On the one hand, this has the advantage of avoiding the potential bias stemming from the economic downturn caused by lockdowns and production disruptions during the pandemic. On the other hand, the main drawback of using PWT data is its lack of coverage for the most recent period of rapid GenAI development. When using PWT data, it is also noteworthy that the income convergence parameter (i.e., the lagged log of income per capita) is estimated with low precision and does not fall within significance thresholds. Nonetheless, its magnitude remains consistent with the values obtained from regressions using World Bank data.

**Table 5. AI innovation and income growth: AI and GenAI countries (PWT sample, 2010–2019)**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Lagged income pc | −0.066*** (0.014) | −0.057 (0.049) | −0.058 (0.049) | −0.057 (0.049) | −0.058 (0.049) | −0.058 (0.049) |
| General patent stock pc | −0.002 (0.002) | 0.001 (0.007) | 0.000 (0.007) | 0.001 (0.007) | −0.000 (0.007) | 0.000 (0.007) |
| ICT patent stock pc | 0.001 (0.002) | 0.015** (0.006) | 0.009 (0.006) | 0.014** (0.006) | 0.008 (0.006) | 0.012** (0.006) |
| AI country × trend | | | 0.003*** (0.001) | | 0.004*** (0.001) | |
| GenAI country × trend | | | | 0.002 (0.001) | −0.001 (0.001) | |

cont. Table 5

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| AI country (restricted) × trend | | | | | | 0.002** (0.001) |
| GenAI country (restricted) × trend | | | | | | −0.008 (0.006) |
| Time period | 1991–2022 | 2010–2022 | 2010–2022 | 2010–2022 | 2010–2022 | 2010–2022 |
| Observations | 7,448 | 1,810 | 1,810 | 1,810 | 1,810 | 1,810 |
| R-squared | 0.034 | 0.016 | 0.018 | 0.016 | 0.018 | 0.017 |

Notes: The dependent variable is the log-change in GDP per capita (pc). All continuous explanatory variables are expressed in logs and taken with one-year lag with respect to the dependent variable. All regressions include country- and year-fixed effects. Heteroskedasticity and autocorrelation robust (HAC) standard errors in parentheses. ***, **, * significant at 1%, 5%, 10% respectively.

Source: Author's own elaboration.

Table 6 presents the results based on PWT data, using the cumulative value of patents as a proxy for AI innovation. In this case, the impact of generative AI is larger than the effects reported earlier in Table 3, columns (1)–(4). This difference becomes even more pronounced when the regression is restricted to countries specialising in only one of the two categories of emerging digital patents—see columns (5) and (6) of Table 6. Next, we examine how the log-transformation of our explanatory variable influences the results. Since several countries in our sample lack AI patents, we applied a log-transformation to the corresponding stock using the formula ln (1 + stock), a common approach in the literature, to maintain a sufficient number of observations in the regression. To test the robustness of this assumption, we replicated the regressions in columns (5) and (6) using the inverse hyperbolic sine transformation [Bellemare, Wichman, 2020], which allows the explanatory variables to enter the regression without being logged. The results of this sensitivity analysis, shown in columns (7) and (8), indicate that the parameter estimates are more conservative than those obtained using the log transformation—columns (4) and (5). Nevertheless, the findings remain broadly consistent with the pattern observed in the World Bank data regressions—see columns (5) and (6) of Table 3.

**Table 6. AI innovation and income growth: AI and GenAI patent stock (PWT sample, 2010–2019)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| Lagged income pc | −0.057 (0.049) | −0.058 (0.049) | −0.058 (0.049) | −0.058 (0.049) | −0.054 (0.049) | −0.047 (0.052) | −0.065 (0.054) | −0.057 (0.056) |
| General patent stock pc | 0.001 (0.007) | 0.000 (0.007) | 0.001 (0.007) | 0.000 (0.007) | 0.002 (0.007) | 0.003 (0.009) | 0.001 (0.008) | 0.001 (0.011) |
| ICT patent stock pc | 0.015** (0.006) | 0.009 (0.006) | 0.012** (0.006) | 0.009 (0.006) | 0.011* (0.006) | 0.005 (0.009) | 0.017*** (0.006) | 0.008 (0.008) |
| AI patent stock pc | | 0.014* (0.007) | | 0.010 (0.007) | 0.019** (0.009) | | 0.012 (0.009) | |
| GenAI patent stock pc | | | 0.034** (0.016) | 0.027* (0.016) | | 0.177*** (0.068) | | 0.108* (0.060) |
| Patent variable | 1+stock | 1+stock | 1+stock | 1+stock | 1+stock | 1+stock | Arcsinh | Arcsinh |
| Sample | All | All | All | All | All | All | non-GenAI | GenAI |
| Observations | 1,810 | 1,810 | 1,810 | 1,810 | 1,620 | 1,300 | 1,458 | 1,170 |
| Groups | 181 | 181 | 181 | 181 | 145 | 124 | 131 | 112 |
| R-squared | 0.016 | 0.017 | 0.017 | 0.018 | 0.016 | 0.015 | 0.022 | 0.017 |

Notes: The dependent variable is the log-change in GDP per capita (pc). All continuous explanatory variables are expressed in logs and taken with one-year lag with respect to the dependent variable. All regressions include country- and year-fixed effects. Heteroskedasticity and autocorrelation robust (HAC) standard errors in parentheses. ***, **, * significant at 1%, 5%, 10% respectively.

Source: Author's own elaboration.

As a final step in the analysis, we assess the robustness of the benchmark estimates from columns (5) and (6) of Table 6 by incorporating additional control variables into the specification (see Table 7). The first half of the regression table includes non-GenAI as the explanatory variable, while the second half incorporates

GenAI. In both cases, the sample is limited to countries that are not active in the other category of AI innovations. In these regressions, the GDP share of capital investment is included to isolate the primary driver of industrialisation for most countries globally. The estimates indicate that a one-percentage-point increase in the investment share corresponds to approximately a one-tenth-percentage-point increase in the rate of GDP per capita growth. This result is highly stable across regressions. We then include a measure of human capital based on the average number of years of education. This variable is positively correlated with income growth in the specification using GenAI as the explanatory variable, but not in the specification using general AI. This suggests that human capital is more strongly linked to innovation capabilities in digital fields for countries specialised in other areas of AI rather than in GenAI. The productivity gap relative to the United States is used as a proxy for technology transfers from the global frontier. While this variable has a positive coefficient, it is statistically significant only at the 10% level in column (8). Most importantly, the inclusion of these covariates does not materially alter the estimated impact of the main regressors, which remain largely consistent with previous findings.

In Table 8, we conduct a series of robustness checks on PWT data, following the same approach as in Table 4. We replicate our benchmark regression using fractional patent counts and triadic patent families, and we examine the relationship across country groups based on their level of development. The results are largely consistent with the robustness checks presented in Table 4, with one notable exception: in this case, wealthier countries appear to benefit more from AI-driven income growth. This finding contrasts with the results obtained using World Bank data, suggesting that the relationship between AI adoption and economic growth may be sensitive to data sources and measurement approaches. Further investigation is needed to understand this discrepancy, which will be the focus of future research.

**Table 7. AI innovation and income growth: control variables (PWT sample, 2010–2019)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Lagged income pc | −0.054<br>(0.049) | −0.066<br>(0.045) | −0.012<br>(0.043) | −0.079<br>(0.054) | −0.111**<br>(0.053) | −0.047<br>(0.052) | −0.058<br>(0.049) | 0.001<br>(0.045) | −0.091*<br>(0.054) | −0.149**<br>(0.069) |
| General patent stock pc | 0.002<br>(0.007) | 0.000<br>(0.007) | 0.005<br>(0.007) | 0.009<br>(0.009) | −0.003<br>(0.009) | 0.003<br>(0.009) | −0.000<br>(0.009) | 0.008<br>(0.010) | 0.022*<br>(0.012) | 0.000<br>(0.010) |
| ICT patent stock pc | 0.011*<br>(0.006) | 0.008<br>(0.006) | 0.016**<br>(0.007) | 0.018**<br>(0.007) | 0.017**<br>(0.007) | 0.005<br>(0.009) | 0.001<br>(0.009) | 0.017*<br>(0.009) | 0.024**<br>(0.010) | 0.017**<br>(0.009) |
| AI patent stock pc | 0.019**<br>(0.009) | 0.017*<br>(0.009) | 0.012<br>(0.009) | 0.014<br>(0.009) | 0.018*<br>(0.010) | | | | | |
| GenAI patent stock pc | | | | | | 0.177***<br>(0.068) | 0.179***<br>(0.068) | 0.179**<br>(0.079) | 0.227***<br>(0.087) | 0.292***<br>(0.081) |
| Investment share | | 0.104***<br>(0.039) | 0.107**<br>(0.043) | 0.140***<br>(0.047) | 0.020<br>(0.015) | | 0.105***<br>(0.040) | 0.109**<br>(0.044) | 0.150***<br>(0.043) | 0.028*<br>(0.016) |
| Human capital | | | 0.027<br>(0.054) | 0.010<br>(0.063) | −0.052<br>(0.058) | | | 0.132**<br>(0.065) | 0.151**<br>(0.074) | 0.098<br>(0.069) |
| Productivity gap to the US | | | | 0.131<br>(0.102) | −0.096**<br>(0.042) | | | | 0.177*<br>(0.100) | −0.059<br>(0.043) |
| Manufacturing share of GDP | | | | | −0.283<br>(0.216) | | | | | −0.263<br>(0.310) |
| Observations | 1,620 | 1,619 | 1,269 | 1,009 | 978 | 1,300 | 1,299 | 979 | 719 | 698 |
| R-squared | 0.016 | 0.093 | 0.113 | 0.174 | 0.109 | 0.015 | 0.096 | 0.124 | 0.210 | 0.116 |

Notes: The dependent variable is the log-change in GDP per capita (pc). All continuous explanatory variables are expressed in logs and taken with one-year lag with respect to the dependent variable. All regressions include country- and year-fixed effects. Heteroskedasticity and autocorrelation robust (HAC) standard errors in parentheses. ***, **, * significant at 1%, 5%, 10% respectively.

Source: Author's own elaboration.

**Table 8. AI innovation and income growth: robustness checks (PWT sample, 2010–2022)**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| Lagged income pc | −0.054 (0.049) | −0.047 (0.052) | −0.050 (0.051) | −0.045 (0.052) | −0.053 (0.049) | −0.049 (0.051) | 0.001 (0.057) | 0.001 (0.057) | −0.243*** (0.049) | −0.299*** (0.067) |
| General patent stock pc | 0.002 (0.007) | 0.003 (0.009) | 0.001 (0.008) | 0.007 (0.010) | 0.006 (0.011) | 0.004 (0.011) | 0.010 (0.010) | 0.014 (0.013) | −0.010 (0.010) | −0.008 (0.011) |
| ICT patent stock pc | 0.011* (0.006) | 0.005 (0.009) | 0.015** (0.006) | 0.004 (0.009) | 0.010 (0.009) | 0.011 (0.010) | −0.003 (0.012) | 0.001 (0.014) | 0.025*** (0.009) | 0.008 (0.012) |
| AI patent stock pc | 0.019** (0.009) | | 0.020 (0.013) | | 0.033*** (0.011) | | 0.041 (0.030) | | 0.023** (0.011) | |
| GenAI patent stock pc | | 0.177*** (0.068) | | 0.179*** (0.069) | | 0.195*** (0.062) | | 0.032 (0.094) | | 0.462*** (0.098) |
| Patent counts | Full | Full | Fractional | Fractional | Full | Full | Full | Full | Full | Full |
| Patent source | USPTO | USPTO | USPTO | USPTO | Triadic | Triadic | USPTO | USPTO | USPTO | USPTO |
| Income pc | Full | Full | Full | Full | Full | Full | Lower than 50% | Lower than 50% | Higher than 50% | Higher than 50% |
| Observations | 1,620 | 1,300 | 1,450 | 1,240 | 1,580 | 1,380 | 890 | 860 | 740 | 450 |
| R-squared | 0.016 | 0.015 | 0.014 | 0.014 | 0.016 | 0.019 | 0.002 | 0.002 | 0.149 | 0.210 |

Notes: The dependent variable is the log-change in GDP per capita (pc). All continuous explanatory variables are expressed in logs and taken with one-year lag with respect to the dependent variable. All regressions include country- and year-fixed effects. Heteroskedasticity and autocorrelation robust (HAC) standard errors in parentheses. ***, **, * significant at 1%, 5%, 10% respectively.

Source: Author's own elaboration.

## Concluding remarks

This study has explored the global dissemination of GenAI innovation using count data on patent applications filed at the USPTO. As of 2022, thirty-three countries were active in this new technology domain—out of 55 involved in AI innovation overall—reflecting rapid worldwide diffusion. Our regression analysis shows that these countries experienced a faster rate of income growth, which we estimate as a cumulative increase of 0.02 percentage points over a decade. This represents the extensive margin of GenAI innovation, or the growth premium for a country from embracing the emerging category of new digital technologies. We also assessed the intensive margin by examining the relationship between the per capita stock of AI patents and GDP per capita growth. We find that GenAI has contributed between 0.009 and 0.013 percentage points to GDP growth since 2009. While these magnitudes are modest compared to the more optimistic projections in the literature, they nevertheless provide valuable empirical evidence and highlight the importance of further economic analysis in this area.

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