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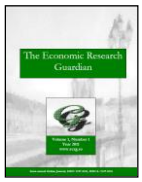

Artificial Intelligence and the Acceleration of Innovation: Evidence from Advanced and Emerging Economies

Nikola Marković
Faculty of Economics and Business Administration, West University of Timisoara, Timisoara, Romania
E-mail: nikola.markovic10@e-uvt.ro

Abstract

Artificial intelligence has emerged as a central driver of digital transformation, with the potential to reshape the process of innovation across economies. In this context, the paper analyses the impact of AI-driven digitalization on innovation outcomes, using patent applications as a proxy, for a panel of countries comprising the G7 and G20 over the period 2004–2024. The empirical approach relies on static panel data estimations, including pooled OLS, fixed-effects, and random-effects models, complemented by alternative specifications controlling for country-specific and time-specific heterogeneity. In addition, Method-of-Moments Quantile Regression (MMQR) models are employed as a robustness check to examine whether the AI-innovation relationship differs across the patent distribution. The main findings reveal that the relationship between AI and innovation is heterogeneous, non-linear, and sensitive to model specification. For advanced economies (G7), the results provide stronger evidence of an inverted U-shaped relationship, whereby AI initially stimulates innovation by enhancing knowledge recombination and research efficiency, but exhibits diminishing marginal returns at higher levels of intensity. In contrast, for the broader and more heterogeneous G20 sample, the mean-based results are weaker and less robust, while the MMQR results suggest that AI becomes relevant mainly among higher-patenting observations. These results suggest that AI does not operate as an autonomous driver of innovation, but rather as a technology whose impact depends critically on absorptive capacity, complementary assets, institutional quality, and the position of countries within the innovation distribution.

Keywords: Artificial intelligence, Innovation, Digitalization, Panel data, Economic growth

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1. Introduction

Over the past decades, advances in computing power, semiconductors, and digital technologies have fundamentally reshaped the global economic landscape, driving successive waves of technological progress and productivity growth. The rapid expansion of digitalization has accelerated the creation and diffusion of knowledge across economies, driven by declining data storage costs, increased connectivity, and the spread of algorithmic systems.

At the same time, recent stylized facts reveal a strong concentration of innovation activity within a limited subset of economies. As illustrated in Figure 1 (Appendix), patenting activity in the G20 is increasingly dominated by a few leading countries, most notably China, alongside established innovators such as the United States, Japan, Germany, and South Korea. While global innovation has expanded significantly in absolute terms, its distribution remains highly uneven, with a large share of countries exhibiting relatively modest and stable levels of patenting activity. This pattern reflects substantial cross-country differences in technological capabilities, digital infrastructure, and absorptive capacity, which condition how digital technologies translate into innovation outcomes. These differences motivate the distinction between advanced and emerging economies adopted later in this study.

In this context, artificial intelligence (AI) is redefining the boundaries of technological progress by not only automating production processes but also transforming the very process of knowledge creation and innovation. In an era where digital technologies increasingly shape economic structures, understanding how innovation is generated, diffused, and scaled has become central to explaining long-run growth and competitiveness. As AI begins to function as a "method of invention," its impact extends beyond efficiency gains, raising fundamental questions about the nature, speed, and distribution of innovation across economies.

Despite this growing importance, the empirical relationship between AI-driven digitalization and innovation remains unclear, particularly at the macroeconomic level. This lack of clarity is particularly important, as both policymakers and firms increasingly allocate resources toward digital transformation strategies without a clear understanding of whether and under what conditions AI effectively translates into innovation outcomes. As a result, identifying the mechanisms and limits through which digitalization shapes innovation has become a central economic and policy challenge.

The relationship between digitalization and innovation can be understood through several complementary theoretical channels. First, digital technologies, and particularly AI can act as a *general-purpose technology* (GPT), enhancing the productivity of research and innovation processes across sectors. In this sense, AI functions as an "invention of a method of invention," enabling faster hypothesis generation, experimentation, and knowledge recombination (Cockburn et al., 2018; Bresnahan & Trajtenberg, 1995). This mechanism suggests that digitalization can directly increase the rate of innovation by lowering the cost and time required to generate new ideas.

Second, digitalization facilitates the *diffusion and recombination of knowledge*, which are central drivers of innovation in endogenous growth theory. Increased connectivity, data availability, and digital platforms allow firms and researchers to access a broader set of ideas and technologies, thereby enhancing innovation through spillovers and learning effects (Romer, 1990; Aghion & Howitt, 1992). However, the effectiveness of this channel depends on absorptive capacity, including human capital and institutional quality, which determine a country's ability to transform digital inputs into innovative outputs.

Third, the impact of digitalization is mediated by the presence of *complementary assets*, such as organizational capital, skills, and data infrastructure. As emphasized in the literature on the productivity effects of digital technologies, the returns to AI and digitalization are not automatic but depend on the

alignment of these complementary factors (Brynjolfsson et al., 2017; Corrado et al., 2005). This implies that the relationship between digitalization and innovation may be non-linear, as insufficient complementary assets can limit or even reverse the benefits of technological adoption.

Building on these theoretical considerations, this study investigates the impact of digitalization, proxied by AI, on innovation outcomes at the macroeconomic level. The empirical analysis focuses on a panel of countries comprising the G20 economies, with a particular emphasis on the G7 as a sub-sample representing advanced, frontier economies. The objective of the paper is to assess whether and how AI-driven digitalization translates into measurable innovation output, while accounting for structural differences across countries.

To this end, the study employs a panel data approach over the period 2004–2024, allowing for the examination of both cross-country heterogeneity and time-specific dynamics. By comparing results across different model specifications, including pooled OLS, fixed-effects, random-effects, period-effects, and double fixed-effects estimations, the analysis assesses the sensitivity of the AI-innovation relationship to alternative assumptions regarding unobserved heterogeneity. In addition, Method-of-Moments Quantile Regression (MMQR) models are used as a robustness check to examine whether this relationship differs across lower-, median-, and higher-patenting observations.

The results reveal a differentiated and non-linear relationship across country groups. For the G7 economies, the findings provide stronger evidence of a concave, inverted U-shaped relationship, particularly in the preferred period-effects specification and in the lower-to-upper-middle quantiles of the patent distribution. This suggests that increases in AI activity may initially stimulate innovation, but that diminishing marginal effects emerge at higher levels of AI intensity. In contrast, for the broader G20 sample, the mean-based results are weaker and less stable, while the MMQR results indicate that AI becomes statistically meaningful mainly among higher-patenting observations. These findings highlight the importance of economic structure, absorptive capacity, and position within the innovation distribution in shaping the innovation effects of digitalization.

This study contributes to the literature in three ways. First, it provides a macroeconomic perspective on the relationship between AI and innovation, complementing existing research that predominantly focuses on firm-level evidence (e.g., Brynjolfsson et al., 2020; Calvino and Fontanelli, 2023), and highlighting the role of structural characteristics and global dynamics in shaping innovation outcomes. Second, it extends the empirical approach by employing a panel data framework that controls for cross-country heterogeneity and time-specific shocks through alternative fixed-effects and random-effects specifications. The study further complements these mean-based estimations with MMQR, allowing the analysis to examine whether the AI-innovation relationship differs across the patent distribution. Third, it introduces a novel proxy for AI activity based on Google Trends search intensity, offering a forward-looking measure of technological diffusion compared to traditional indicators such as R&D expenditure. It also uncovers heterogeneous AI-innovation patterns across G7 and G20 economies, showing that AI effects are stronger where innovation systems are already more developed and where countries are positioned closer to the technological frontier.

The paper is organized as follows. Section 2 reviews the literature, Section 3 presents the data and methodology, while Section 4 reports and discusses the empirical results, including the robustness

checks. Section 5 concludes with key findings, and Section 6 outlines the limitations and directions for future research.

2. Literature review

Early economic analyses of technological change focused on how new technologies emerge, diffuse, and gradually translate into productivity gains. Foundational contributions emphasized invention and innovation as cumulative and inherently uncertain processes, shaped by learning-by-doing, experimentation, and the slow adaptation of complementary inputs and organizational practices (Griliches, 1957; Arrow, 1962). This early work laid the empirical and conceptual groundwork for later formalization of innovation-driven growth.

The literature on the impact of AI on innovation, particularly within the context of digital transformation in business, can be organized into three strands. The first strand is related to economic growth through innovation dynamics. The second strand examines empirical evidence on AI adoption, productivity effects, diffusion gaps, and firm-level heterogeneity in innovation and performance outcomes, while the third strand addresses the mediating mechanisms that condition these effects, including labor reallocation, organizational restructuring, dynamic capabilities, and institutional frameworks.

(1) Building on these foundations, the first strand of the literature can be characterized as a macro-theoretical strand that seeks to explain long-run **economic growth through innovation dynamics**. Within this strand, three interrelated theoretical sub-directions can be distinguished.

The first sub-direction is *endogenous growth theory*, which formalized innovation as a purposeful economic activity driven by incentives, human capital, and the accumulation of knowledge (Romer, 1986, 1990; Lucas, 1988). Innovation is treated as an economic decision shaped by spillover and increasing returns to ideas. Aghion and Howitt (1992) further extended this framework by modelling growth as a process of creative destruction, in which successive innovations endogenously displace existing technologies. In this view, technological progress unfolds through competitive replacement, whereby new technologies systematically restructure industries and reallocate resources across firms.

The second sub-direction focuses on *general-purpose technologies (GPTs)*, which reshape economic systems through pervasiveness continuous improvement, and strong complementarities with downstream sectors (Bresnahan & Trajtenberg, 1995). Rather than providing comprehensive, definitive, solutions, GPTs function as enabling infrastructures that create new technological opportunities. Their economic impact depends critically on complementary investments, intangible capital accumulation, and organizational adaptation. This perspective highlights that productivity gains do not arise automatically from technological breakthroughs but require co-invention and systemic adjustment.

As for last sub-direction, the recent advances in *artificial intelligence (AI)* occupy a central position within this macro-theoretical strand. By increasingly functioning not only as an output of innovation but also as an input into the production of new ideas, AI challenges the traditional assumption that inventive activity is predominantly labor-intensive. The time to invention, and consequently innovation, appears

to be accelerating, making it essential to distinguish clearly between invention and innovation. Invention refers to the creation or discovery of a novel idea, product, process, or method that did not previously exist. Innovation, by contrast, encompasses the practical implementation and commercialization of inventions, as well as the introduction of significant improvements to existing products, processes, or services to enhance value and market impact. This distinction is particularly relevant in the context of AI, where the mere development of advanced algorithms does not automatically translate into widespread productivity gains without substantial complementary investments and organizational restructuring (Calvino & Fontanelli, 2023).

While endogenous growth models and GPT theory have been highly successful in explaining long-run technological progress, they share an implicit assumption that the production of new ideas remains predominantly human-driven, relying on cognition, experimentation, and accumulated experience (Romer, 1990; Aghion & Howitt, 1992). Recent theoretical work has begun to relax this assumption by incorporating AI into growth models (Aghion et al., 2017). However, these contributions typically treat AI as an efficiency-enhancing input into research rather than as a technology that partially automates idea generation itself. By increasingly functioning as a "method of invention" (Cockburn et al., 2018), AI raises questions that are not fully addressed within existing growth and innovation frameworks (Bresnahan & Trajtenberg, 1995; Agrawal et al., 2018b). As a result, the macro-theoretical strand lacks a systematic framework for analyzing how innovation-driven growth unfolds when the invention process itself becomes technologically augmented.

Taken together, this first strand establishes the macro-theoretical foundations of innovation-driven growth and positions AI within the tradition of general-purpose technologies. However, it remains limited in explaining how AI-related digitalization translates into measurable innovation outcomes across countries, particularly when economies differ in absorptive capacity, institutional quality, and proximity to the technological frontier. This leaves open an important macro-empirical question: whether AI is associated with stronger patenting activity uniformly across countries, or whether its effects depend on the position of economies within the global innovation distribution.

(2) Addressing these limitations, the second strand of the literature turns from theoretical modelling toward empirical investigations of **AI adoption, productivity dynamics, and heterogeneity in technological outcomes across firms, sectors, and economies**.

Despite rapid advances in AI and widespread expectations of substantial efficiency gains, aggregate productivity growth in advanced economies has remained modest over the past decades. This apparent contradiction is often referred to as the *modern productivity paradox*. In the context of AI, this paradox has re-emerged with renewed intensity, as technological optimism contrasts sharply with persistent productivity slowdowns (Brynjolfsson et al., 2017). The literature offers several explanations for this disconnect between technological progress and measured productivity outcomes. First, early expectations regarding the economic impact of AI may be overstated, particularly when technological feasibility is conflated with effective economic deployment. Second, productivity gains associated with AI may be systematically mismeasured, especially when improvements manifest through quality enhancements, new varieties, or intangible outputs that are imperfectly captured by conventional national accounts (Corrado et al., 2005). Third, AI adoption may primarily redistribute rents rather than generate net efficiency gains, particularly in markets characterized by increasing returns, data

advantages, and concentration. Finally, and most prominently, implementation lags may delay observable productivity effects, as firms require time to reorganize production processes, accumulate complementary assets, and develop the capabilities necessary to exploit AI effectively (Brynjolfsson et al., 2017). Taken together, these explanations suggest that the productivity paradox should not be interpreted as evidence of AI's limited potential. Rather, it reflects the complex and time-consuming process through which GPTs diffuse and reshape economic activity. This perspective shifts attention away from the question of whether AI enhances productivity toward the conditions under which such enhancements become visible and sustainable.

Building on this insight, recent research conceptualizes productivity dynamics following the adoption of GPTs as following a J-shaped curve. According to the productivity J-curve hypothesis, initial phases of technological adoption are characterized by declining or stagnant productivity as firms incur adjustment costs associated with learning, experimentation, and organizational change. Productivity gains materialize only later, once complementary investments have been made and new production routines have stabilized (Brynjolfsson et al., 2020). Central to this argument is the role of intangible and digital capital. Unlike traditional physical capital, intangible assets (i.e. software, data, organizational know-how, and firm-specific human capital) are difficult to measure, slow to accumulate, and often expensed rather than capitalized in official statistics (Corrado et al., 2009). AI technologies, in particular, exhibit strong complementarities with such intangibles, as their effective use depends on high-quality data, redesigned workflows, and skilled personnel capable of interpreting and acting upon algorithmic outputs (Tambe & Hitt, 2011).

At the macroeconomic level, empirical research has primarily examined whether advances in digital technologies and AI translate into higher aggregate productivity and economic growth. These studies emphasize mismeasurement of intangible outputs, implementation lags, and the slow accumulation of complementary assets as key factors obscuring the short-run effects of AI and related digital technologies (Corrado et al., 2005, 2009; Tambe & Hitt, 2011; Brynjolfsson et al., 2017, 2020). Other macro-empirical research highlights the importance of diffusion speed and heterogeneity in innovation dynamics. Comin and Mestieri (2018), using cross-country panel data and technology diffusion curves, show that the growth impact of new technologies depends critically on the rate at which they are adopted and integrated across sectors. Complementary evidence from OECD-based analyses demonstrates that aggregate productivity trends increasingly reflect widening gaps between frontier and non-frontier firms, driven by uneven diffusion of new technologies rather than a slowdown in frontier innovation itself (Andrews et al., 2016). While this macro-level evidence is informative about long-run productivity and diffusion dynamics, it remains limited in explaining whether AI-related digitalization translates into measurable innovation outcomes across countries. As a result, macro-empirical studies motivate, but do not fully resolve, questions concerning the relationship between AI activity, national innovation capacity, and the uneven distribution of patenting outcomes.

In contrast to macro-level analyses, a growing micro-empirical literature examines how AI and digital technologies affect firm behavior, innovation activity, and business performance. Firm-level panel studies consistently document substantial heterogeneity in outcomes, with productivity and performance gains concentrated among firms that combine digital technology adoption with complementary investments in human capital, data infrastructure, and organizational change (Tambe & Hitt, 2011; Tambe et al., 2020). These findings suggest that AI does not operate as a uniform

productivity shock but rather amplifies existing differences in firms' innovative and organizational capabilities. A subset of this literature explicitly focuses on innovation processes. Cockburn et al. (2018), using firm and patent data, show that AI functions as a "method of invention," increasing the efficiency of search and recombination in research and development activities. Related evidence by Bloom, Schankerman, and Van Reenen (2013), based on dynamic firm-level innovation regressions, emphasizes that innovation outcomes unfold over time and are shaped by knowledge accumulation and spillovers. While these studies provide important insights into how AI and related technologies affect inventive activity, they are largely abstract from downstream business performance and the timing with which innovation translates into economic value.

Empirical work linking innovation more directly to firm performance further underscores this gap. Kogan et al. (2017), using an event-study approach based on stock-market reactions to patent grants, demonstrate that innovation events generate economically meaningful and highly heterogeneous firm-level value effects. Calvino and Fontanelli (2023), exploiting firm-level data for French firms and an instrumental-variable strategy to address endogeneity in AI adoption, find that productivity gains from AI materialize only when firms possess sufficient complementary assets. Despite these advances, existing micro-empirical studies typically examine either innovation outcomes or performance outcomes in isolation and rely predominantly on static or average effects. Consequently, there remains limited macro-level evidence on whether AI-related digitalization translates into measurable innovation outcomes across countries, and whether this relationship differs between advanced and more heterogeneous economies. This empirical gap motivates the present country-level panel analysis.

The accumulation of digital capital further explains why productivity and innovation outcomes differ across firms and economies. Frontier actors are more likely to benefit from AI because they possess scalable digital assets, stronger data infrastructures, and accumulated organizational capabilities, while laggards may struggle to convert adoption into measurable gains (Tambe et al., 2020). This reinforces the view that AI should be analysed as part of a broader process of digital capital formation rather than as an isolated technological shock.

Although this strand provides extensive empirical evidence on productivity effects and complementary assets, it typically analyses innovation outputs and performance outcomes separately and often relies on static average effects.

(3) To explain the heterogeneity and fragmented findings identified in the second strand, the third strand of the literature shifts attention to the mediating mechanisms that shape how AI-driven innovation affects **labor markets, organizational structures, and institutional dynamics**.

Productivity growth can be attributed to innovation, where the output per worker increases as the technological factor gets more advanced. On the other hand, a rise in productivity can also arise from other sources, including capital restructuring and optimizing the production process without necessarily having any innovative precursor.

Although productivity growth is generally desirable, it may also arise through mechanisms that create labor-market adjustment costs. Acemoğlu and Restrepo (2018) describe this as the displacement effect, whereby technological progress substitutes for certain tasks rather than simply augmenting workers.

As machines and algorithms realize a growing share of tasks within the production process, firms are able to increase output without a substantial expansion in employment. Consequently, productivity growth may become decoupled from labor demand, leading to stagnant wages and a declining labor share of income even as aggregate output rises. From a social perspective, these displacement effects are not fully internalized by firms when adopting new technologies, placing labor displacement as a negative externality associated with productivity-enhancing innovation in the short run.

Technological revolutions have been accompanied by the emergence of new tasks and occupations that partially offset displacement, a process referred to as *task reinstatement* (Acemoğlu & Restrepo, 2018). However, this rebalancing mechanism is neither automatic nor immediate. While task displacement can occur rapidly as technologies diffuse, the creation of new tasks depends on demand expansion, skill adaptability, and the capacity of the economy to reallocate labor toward newly productive activities. As a result, periods of rapid productivity growth may coincide with transitional unemployment, job polarization, or wage stagnation, even in economies experiencing sustained technological progress (Aghion & Howitt, 1992).

The diffusion of AI has the potential to intensify these dynamics. Unlike earlier waves of mechanization that primarily automated routine or manual tasks, AI increasingly substitutes for cognitive and decision-oriented activities, including prediction, classification, and information processing (Brynjolfsson & McAfee, 2014; Agrawal et al., 2018a). By expanding the range of tasks susceptible to automation, AI may amplify displacement effects relative to task creation, particularly if complementary investments and institutional mechanisms fail to facilitate the redeployment of labor toward emerging activities. In this sense, AI-driven productivity growth raises fundamental questions not only about efficiency gains, but also about the distribution and adjustment costs associated with technological change.

While macroeconomic and technological factors shape the potential impact of AI, a growing body of literature emphasizes that *organizational transformation* constitutes the primary bottleneck in realizing productivity gains. The adoption of AI does not automatically translate into improved performance; rather, it requires fundamental changes in organizational structures, decision-making processes, and coordination mechanisms. As such, organizations act as the critical mediating layer between technological possibility and economic outcome. Research on digital transformation highlights that digital technologies reconfigure firms through modular, layered architectures that separate data, analytics, and application layers, enabling rapid recombination but also increasing organizational complexity (Yoo et al., 2010; Vial, 2019). In this context, innovation becomes increasingly distributed across internal units and external ecosystems, challenging traditional hierarchical forms of coordination and control (Nambisan et al., 2017). Firms that fail to adapt their organizational logic may experience limited or even negative productivity effects despite substantial investments in AI.

From a strategic management perspective, the concept of dynamic capabilities provides a useful framework for understanding these differences. Dynamic capabilities, defined as the firm's ability to sense opportunities, seize them, and reconfigure assets accordingly, determine whether digital technologies are effectively integrated into productive activities (Teece et al., 1997; Teece, 2007). AI intensifies the importance of such capabilities by accelerating feedback loops, shortening innovation cycles, and increasing the premium on organizational agility. This literature suggests that the constraints

on AI-driven productivity growth are less technological than organizational. Firms may possess access to similar technologies yet exhibit widely divergent outcomes depending on their capacity to redesign processes, invest in skills, and align incentives. As a result, understanding AI's economic impact requires moving beyond adoption metrics toward a deeper analysis of organizational change and capability development.

Whether the economic effects of AI-driven innovation ultimately materialize through task creation or displacement is not technologically predetermined. Rather, the extent to which AI translates into sustained productivity growth and broad-based economic gains depends critically on *the institutional environment within which technological change* unfolds. While GPTs expand the set of feasible production and innovation possibilities, institutions shape the incentives governing adoption, diffusion, and labor reallocation.

From a Schumpeterian perspective, creative destruction is not an automatic outcome of technological progress but a selective process dependent on competition, market entry, and the ability of new firms and technologies to displace incumbents. Acemoğlu and Robinson (2012) further emphasize that inclusive economic institutions facilitate this process by encouraging experimentation, investment, and labor mobility, whereas extractive or rigid institutional frameworks may suppress innovation or concentrate its benefits among a narrow set of actors for power preservation. In the context of AI, institutional arrangements governing competition policy, data access, labor-market flexibility, and skill formation play a central role in determining whether productivity gains are diffused or remain localized, and whether displaced labor is redeployed into newly created activities or excluded from the growth process.

This strand emphasizes that the economic consequences of AI are not technologically predetermined but depend on organizational capabilities and institutional environments that condition diffusion, labor reallocation, and competitive restructuring.

Across these three strands, the literature provides important but incomplete insights into the economic implications of AI. The macro-theoretical strand conceptualizes innovation-driven growth and situates AI within the tradition of general-purpose technologies, but it remains limited in explaining how AI-related digitalization translates into measurable innovation outcomes across countries. The empirical strand documents productivity effects, diffusion gaps, and heterogeneous technology adoption, yet it often focuses on productivity rather than innovation output. The mediation strand highlights labor-market, organizational, and institutional mechanisms, but these mechanisms are rarely connected to cross-country differences in patenting activity. As a result, the literature leaves open whether AI is associated with stronger innovation uniformly across economies, or whether its effects depend on structural conditions and the position of countries within the innovation distribution.

What remains insufficiently explored is how AI-related digitalization affects innovation outcomes at the macroeconomic level, and whether this relationship differs across countries with different levels of technological development, institutional quality, and absorptive capacity. In particular, the literature lacks sufficient cross-country evidence on whether AI is associated with stronger patenting activity across the full innovation distribution, rather than only at the conditional mean. Addressing this gap

requires a macro-level panel analysis that accounts for country heterogeneity, time-specific shocks, and distributional differences in innovation outcomes.

3. Data and methodology

3.1. Data

The relationship between AI activity and innovation performance is examined using a panel-data approach for two distinct country samples. The first sample consists of the G7 countries, while the second sample includes the broader G20 group, which encompasses both advanced and emerging economies. The dataset covers the period 2004–2024, with annual observations determined by data availability. This sample separation enables a comparative assessment of heterogeneity in the AI-innovation relationship across different levels of economic development, in line with the literature highlighting systematic differences in technological adoption and innovation dynamics between advanced and emerging economies. The initial country coverage follows the G20 framework; however, the European Union is excluded from the sample, as its inclusion would overlap with several of its member states already present in the dataset (e.g., Germany, France, and Italy), potentially introducing redundancy and bias due to overlapping economic structures and double representation within the sample. The final panel composition depends on the availability of data across all selected variables. Consequently, the dataset is unbalanced, as observations are missing for certain country-year combinations; however, all available data are retained to avoid unnecessary data loss, in line with standard panel-data practices.

The dependent variable is patent applications by residents, used as a proxy for innovation output. Patent-based measures are widely employed in the innovation literature because they reflect codified inventive activity and provide a comparable cross-country indicator of technological output. Patents capture the outcome of inventive processes by formalizing new knowledge into legally protected innovations, thereby serving as a measurable output of research and development activity (Griliches, 1990). The use of patent data as an innovation proxy is well established in empirical research, particularly in cross-country and panel studies, due to its availability, comparability, and direct link to technological change (Acs et al., 2002; Furman et al., 2002). While patent-based indicators do not capture all forms of innovation (particularly non-patented or incremental innovations) they remain one of the most widely accepted proxies for technological output in macro-level empirical analyses.

The main explanatory variable of interest is AI, proxied by Google Trends search intensity for AI-related terms. This choice follows the growing literature on internet-based indicators, which utilizes online search behaviour as a real-time measure of economic and social activity. In particular, the work of Askitas and Zimmermann (2015) highlights that internet search data can capture otherwise unobservable processes by reflecting the demand for information, thereby serving as a proxy for underlying behaviour, expectations, and attention dynamics. More broadly, studies such as Choi and Varian (2012) demonstrate that Google search query data improve short-term predictions of economic activity, supporting the interpretation of search intensity as an indicator of economic relevance and public attention. Google Trends provides a normalized index ranging from 0 (the lowest) to 100 (the

highest), where each observation reflects the relative search interest for a given term across time and geography. This feature makes the indicator particularly suitable for capturing the salience and diffusion of AI-related topics, especially in a context where technological adoption is closely linked to awareness, expectations, and information demand. Prior research has shown that such measures can effectively proxy latent economic processes, including consumption behaviour, business cycles, and innovation-related dynamics (Vosen & Schmidt, 2011; Saiz & Simonsohn, 2013).

A set of control variables is introduced in order to isolate the effect of AI interest on innovation output. The first is GDP per capita (constant 2015 US$), which captures the level of economic development and resource availability in each country. Higher levels of income are associated with more advanced infrastructure, stronger innovation systems, and greater absorptive capacity, all of which facilitate knowledge creation and technological progress. The inclusion of GDP per capita as a control variable is well established in the innovation literature, where it is commonly used to account for cross-country differences in development and innovative capacity (Furman et al., 2002).

The second control variable is total population, which captures country size. Population size affects the scale of economic activity and the potential pool of inventors, researchers, and consumers, thereby influencing innovation outcomes. Larger economies may benefit from scale effects and a broader knowledge base, consistent with endogenous growth theory, which links population size to the generation of ideas and technological progress (Romer, 1990; Jones, 1999). However, the expected effect is not strictly unidirectional, as population alone does not guarantee higher innovation without complementary institutional and human capital factors.

The third control variable is researchers in R&D, which measures the stock of human capital directly involved in knowledge creation. This variable represents a key input into the innovation process, as researchers contribute to basic research, applied research, and experimental development. The inclusion of R&D personnel is strongly supported by the literature on innovation and endogenous growth, where human capital is a central driver of technological progress (Romer, 1990; Aghion & Howitt, 1992). Empirical studies also highlight the importance of research capacity in determining national innovative performance (Furman et al., 2002). A positive relationship with patent output is therefore expected.

The fourth control variable is rule of law, used as a proxy for institutional quality. Strong legal institutions, effective contract enforcement, and secure property rights are essential for fostering innovation, as they reduce uncertainty and ensure that innovators can appropriate the returns from their investments. The role of institutions in shaping economic performance and innovation has been widely emphasized in the literature, particularly in the context of cross-country differences in development (Acemoğlu et al., 2005). By improving incentives for investment and reducing transaction costs, stronger institutions are expected to positively influence innovation outcomes. The Worldwide Governance Indicators define rule of law as perceptions of the extent to which agents have confidence in and abide by the rules of society, with values typically ranging from –2.5 (the lowest) to 2.5 (the highest) (WB, 2026).

Detailed information on the variables is presented in Table 1 (Appendix), which includes the variable name, description, unit of measure, data source, and expected sign. Since the variables are measured

in different units and may exhibit substantial skewness, the empirical analysis uses logarithmic transformations for variables such as patent, AI, GDPc, pop, and res. Such transformations help reduce heteroskedasticity, improve comparability across countries, and allow coefficients to be interpreted in elasticity terms. Variables already expressed as standardized indices, such as rule, are kept in level form.

3.2. Methodology

The impact of AI on innovation is analysed using a panel data approach across countries included in the G7 and G20 groups, respectively. These two groups are expected to exhibit different elasticity responses of innovation outcomes with respect to AI adoption. In this context, G7 countries are likely to be more sensitive to AI-related shocks, given their higher level of technological advancement, stronger digital infrastructure, and greater accumulation of complementary assets. By contrast, a certain rigidity may be present within the broader G20 group, where heterogeneity in development levels may slow down the transmission of AI effects. Not least, this sample split allows for controlling structural differences between highly developed economies and more heterogeneous country groups, while also accounting for cross-country disparities in innovation capacity.

The empirical strategy comprises static panel estimations, applied separately for the G7 and G20 samples, in order to ensure robustness of the results across different country groupings.

(i) The static approach includes classical OLS models, fixed-effects and random-effects models. A preamble with naïve OLS models including polynomial transformations of the AI variable is employed in order to check for any non-linearity between AI and innovation outcomes.

The extended classical OLS panel model is as follows:

$$Y_{it} = \alpha + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \sum_{k=1}^{n} \beta_k X'_{k,it} + \varepsilon_{it} \quad (1)$$

where Y represents the dependent variable (patent), α is the intercept, β are the coefficients of the explanatory variables, AI reflects the main variable of interest, and AI^2 captures potential non-linear effects. $X'$is the control variable k by n type (including GDPc, pop, res, and rule), i denotes the country, t is the time period, and ε_{it} is the error term, varying across both countries and time.

The panel may suffer from homogeneity issues. Often, such estimators are affected by unobservable factors that are correlated with the explanatory variables. In this context, the fixed-effects panel model is a suitable solution to eliminate omitted variable bias. Hence, the estimator captures the disparities between cross-sections and controls for unobservable heterogeneity. It is defined as follows:

$$Y_{it} = \alpha_i + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \sum_{k=1}^{n} \beta_k X'_{k,it} + \varepsilon_{it} \quad (2)$$

On the other hand, the fixed-effects model does not control for all stable covariates and may reduce efficiency when the variation within entities is limited. In this context, the random-effects model may provide more efficient estimations, under the assumption that the unobservable individual effects are

not correlated with the explanatory variables. The random-effects panel model treats the intercept as a random variable and has the following form:

$$Y_{it} = \alpha + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \sum_{k=1}^{n} \beta_k X'_{k,it} + (\nu_i + \varepsilon_{it}) \quad (3)$$

where ν_i denotes the country-specific random effect with zero mean.

The selection between pooled OLS and fixed-effects models, as well as between fixed-effects and random-effects models, is based on the results of F-tests and Hausman tests, respectively.

Furthermore, the inclusion of the squared AI term allows us to test for potential non-linear relationships between AI and innovation. This is motivated by the assumption that the effects of AI may not be linear but instead may follow a pattern characterized by initial adjustment costs followed by stronger positive effects as adoption intensifies (Brynjolfsson et al., 2017, 2020).

In addition, different specifications of time effects are considered in order to control for global shocks and common technological trends affecting all countries simultaneously (Comin & Mestieri, 2018). More precisely, models including fixed period effects, random period effects, and double fixed effects (both country and time fixed effects) are estimated. The fixed period effects model extends the specification by incorporating time-specific intercepts, capturing common shocks that affect all countries in a given period. It is as follows:

$$Y_{it} = \alpha + \gamma_t + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \sum_{k=1}^{n} \beta_k X'_{k,it} + \varepsilon_{it} \quad (4)$$

where γ_t denotes the fixed time effects.

On the other hand, the random period effects model treats time-specific effects as random components of the error term, assuming that they are not correlated with the explanatory variables. It is defined as follows:

$$Y_{it} = \alpha + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \sum_{k=1}^{n} \beta_k X'_{k,it} + (\lambda_t + \varepsilon_{it}) \quad (5)$$

where λ_t denotes the random time effects.

Furthermore, the double fixed effects model accounts for both country-specific and time-specific unobservable heterogeneity, by including both individual and period fixed effects. It is as follows:

$$Y_{it} = \alpha_i + \gamma_t + \beta_1 AI_{it} + \beta_2 AI_{it}^2 + \sum_{k=1}^{n} \beta_k X'_{k,it} + \varepsilon_{it} \quad (6)$$

These specifications allow for capturing unobservable time-specific factors, such as global technological waves or economic shocks, which may influence innovation outcomes across all countries. However, given that AI adoption follows a strong global trend, the inclusion of period effects may absorb a significant part of its variation, potentially reducing its statistical significance.

As an additional robustness check, the study employs MMQR models. This approach follows Machado and Silva (2019), who develop a method-of-moments framework for estimating quantile regressions in the presence of individual effects. While the baseline panel estimations examine the conditional mean of innovation outcomes, MMQR allows the relationship between AI and patenting activity to vary across different points of the conditional distribution. This is particularly relevant because innovation output is unevenly distributed across countries, meaning that the effect of AI may differ between lower-, median-, and higher-innovation observations.

The MMQR model is specified as follows:

$$Y_{it} = \alpha_i + W'_{it}\beta + (\delta_i + W'_{it}\gamma)\varepsilon_{it} \tag{7}$$

where Y_{it} denotes patenting activity, α_i represents country-specific location effects, W_{it} is the vector of explanatory variables. The parameter β refers to the location coefficient, δ_i accounts for country-specific scale effects and γ denotes the scale coefficient. Finally, ε_{it} is the error term. In this study, W_{it} includes AI_{it}, AI_{it}^2, and the control variables $X'_{k,it}$.

The corresponding conditional quantile function is:

$$Q_\tau(Y_{it}|W_{it}) = \alpha_i(\tau) + \beta_{1\tau}AI_{it} + \beta_{2\tau}AI_{it}^2 + \sum_{k=1}^{n}\beta_{k\tau}X'_{k,it} \tag{8}$$

where $Q_\tau(Y_{it}|W_{it})$ denotes the conditional quantile of patenting activity at quantile τ, with $\tau = 0.25, 0.50, 0.75, 0.95$. The term $\alpha_i(\tau)$ represents country-specific heterogeneity at each quantile. The coefficient $\beta_{1\tau}$ measures the effect of *AI* at each quantile, while $\beta_{2\tau}$ reflects the non-linear component of the relationship. In this framework, the quantile-specific country effect is given by $\alpha_i(\tau) = \alpha_i + \delta_i q_\tau$, while the quantile-specific slope coefficients are obtained as $\beta_\tau = \beta + \gamma q_\tau$, where q_τ denotes the $\tau - \text{th}$ quantile of the error term.

A second MMQR specification includes shock dummy variables to account for the global financial crisis and the COVID-19 pandemic period. Since the MMQR specification does not include full period fixed effects, these dummies are introduced explicitly to control for major time-specific shocks that may affect patenting activity across countries:

$$Q_\tau(Y_{it}|W_{it}, D_t) = \alpha_i(\tau) + \beta_{1\tau}AI_{it} + \beta_{2\tau}AI_{it}^2 + \sum_{k=1}^{n}\beta_{k\tau}X'_{k,it} + \sum_{j=1}^{2}\lambda_{j\tau}D_{j,t} \tag{9}$$

where $D_{j,t}$ represents the vector of shock dummy variables, with $j = 1,2$. More specifically, $D_{1,t}$ denotes the global financial crisis dummy, while $D_{2,t}$ denotes the COVID-19 pandemic dummy. The coefficients $\lambda_{j\tau}$ capture the effect of each shock at quantile τ.

The following section presents the empirical results. It begins with naïve specifications aimed at testing potential non-linear relationships between AI and innovation, followed by baseline panel models, including pooled OLS, fixed-effects, and random-effects estimations. In addition, alternative specifications incorporating cross-sectional effects, period effects, and double fixed effects are

reported. Finally, MMQR models are used as an additional robustness check to assess whether the estimated AI-innovation relationship differs across different parts of the patent distribution.

4. Results and discussion

The descriptive statistics analysis is presented in Tables 2 and 3 (Appendix), which provide an overview of the main characteristics of the variables for the G7 and G20 samples. In the case of the G7 countries, the average number of *patent* is substantially higher compared to the G20 sample, reflecting a more advanced innovation capacity. At the same time, *GDPc* and *rule* exhibit higher mean values in the G7 group, confirming the higher level of economic development and institutional quality.

In contrast, the G20 sample displays significantly higher variability across all variables, particularly in terms of *pop*, *patent*, and *res*. This suggests a greater degree of heterogeneity within the G20 group, which may affect the transmission of *AI* effects on innovative outcomes. Additionally, the skewness and kurtosis statistics indicate deviations from normality for several variables in both samples, supporting the use of logarithmic transformations in the empirical analysis.

The correlation matrices reported in Tables 4 and 5 (Appendix) further highlight the relationships between the variables. In both samples, the dependent variable, *patent*, is positively correlated with *GDPc*, *pop*, *res*, and *rule*, confirming the expected theoretical relationships. However, the correlation between *AI* and *patent* is relatively weak, particularly in the G7 sample, suggesting that *AI-innovation* link may not be straightforward.

Moreover, a high correlation between *AI* and its squared term is observed, which is expected due to their functional relationship, but does not necessarily indicate problematic multicollinearity. Overall, the correlation analysis provides preliminary evidence that traditional determinants of innovation may play a stronger role than *AI* proxies in explaining *patent* activity.

The first outputs in Tables 6 and 7 (Appendix) reveal the results of the naïve OLS specifications testing for non-linear relationships between *AI* and innovation outcomes. In the case of the G7 sample, the coefficients of the main variable, *AI*, are generally insignificant in the simplest specification, while the squared term appears significant in Model 2, suggesting a potential non-linear relationship in which increases in *AI* may initially affect innovation positively, followed by diminishing effects at higher levels. However, this result is not robust, as the inclusion of higher-order terms (Model 3) leads to the loss of statistical significance of both linear and non-linear components.

A similar pattern is observed in the G20 sample. While the linear and squared terms of *AI* are significant in the initial specifications (Model 5), their significance disappears once higher-order polynomial terms are introduced in Model 6. This instability across specifications suggests that the evidence for a strong non-linear (exponential) relationship is weak. Consequently, the remainder of the analysis does not impose a strict higher-order non-linear functional form, while preserving flexibility through the inclusion of a quadratic specification for *AI*. Given the lack of robustness across specifications, the naïve OLS models are not suitable for drawing reliable conclusions regarding the

relationship between *AI* and innovation, and are used primarily as an initial diagnostic for functional form.

Entering the control variables, the baseline panel OLS models reported in Tables 8 and 9 (Appendix) provide more stable insights. In the case of the G7 countries, the coefficients of *AI* remain positive and statistically significant in several specifications, while the squared term is often negative and, in some cases, significant, suggesting, particularly in Models 7 and 10, the presence of a concave (inverted U-shaped) relationship, whereby increases in *AI* are associated with higher levels of innovation up to a certain point, after which the marginal effect diminishes. However, this pattern is not consistent across all models, indicating that the evidence for a systematic non-linear effect remains limited. Therefore, the inclusion of the quadratic term should be interpreted as allowing for possible curvature rather than confirming a strong non-linear functional form. Among the control variables, *GDPc*, *pop*, and *res* are consistently significant and positively correlated with *patent*, reflecting the importance of economic development, market size, and human capital in driving innovation. *Rule* also exhibits a positive and significant effect in most specifications, highlighting the role of institutional quality. These results suggest that baseline panel OLS models provide a more reliable framework than naïve specifications, although they do not fully account for unobserved heterogeneity across countries and over time.

In contrast, the G20 results display a more heterogeneous pattern. Although the coefficient of *AI* is initially positive and significant in the simpler models, it becomes insignificant or even negative once additional controls and alternative specifications are included. The squared term does not exhibit a stable or consistent pattern either, further suggesting that any non-linear relationship is weak and sensitive to model specification. This indicates that the effect of *AI* on innovation is less robust across the broader and more diverse group of countries. The control variables, however, remain strongly significant, with *GDPc*, *res*, and *pop* consistently exerting positive effects on *patent*. *Rule* also shows a generally positive contribution, although its significance varies across models. Therefore, while baseline OLS models improve upon naïve specifications, the instability of the *AI* coefficient indicates the need for panel estimators that explicitly control for unobserved heterogeneity. Overall, for the G20 sample, no consistent U-shaped or inverted U-shaped relationship can be identified, as the sign and significance of both the linear and quadratic terms vary substantially across Models 16-19 in Table 9.

Further, the comparison between pooled OLS and panel estimators highlights the presence of unobserved heterogeneity. In the G7 sample, the F-test strongly rejects the pooled OLS specification in favor of fixed-effects models, while the Hausman test indicates that fixed-effects are preferred over random-effects, suggesting that country-specific effects are correlated with the regressors. The inclusion of cross-sectional fixed effects substantially alters the estimated relationship between *AI* and *patent*: the linear term becomes negative and highly significant, while the squared term turns positive and significant in Model 11 in Table 8. This reversal in signs implies a convex (U-shaped) relationship, where at lower levels of *AI*, increases are associated with lower innovation, while beyond a certain threshold, further increases in *AI* are associated with higher innovation. Given the results of the Hausman test and the robustness of Model 11, the cross-sectional fixed-effects specification provides an improvement over pooled OLS and random-effects models by controlling for country-specific heterogeneity, although it does not account for time-specific shocks.

A different pattern emerges in the G20 sample. While the Hausman test results are less conclusive for some specifications, they still point toward the relevance of fixed-effects models in capturing unobserved heterogeneity. The inclusion of cross-sectional fixed effects reduces the significance of *AI* in Model 20 in Table 9, with the linear term becoming weakly negative and only marginally significant, while the squared term loses significance. This indicates that, in the more heterogeneous G20 group, cross-country structural differences play a dominant role, and the direct effect of *AI* on innovation becomes less robust once these differences are accounted for. Therefore, in the G20 sample, fixed-effects models (particularly Model 20) suggest that the relationship between *AI* and innovation is weak and does not exhibit a stable non-linear pattern once country-specific heterogeneity is accounted for.

The introduction of period effects (Models 13-14 in Table 8 and 22-23 in Table 9) allows for testing whether the relationship between *AI* and *patent* is driven by common time-specific shocks, such as global technological waves, macroeconomic cycles, and structural changes affecting all countries simultaneously. In the G7 sample, the F-test for period fixed effects (Model 13) does not provide strong statistical support for their inclusion, indicating that time effects may be redundant from a purely statistical perspective. However, the Hausman test rejects the random-effects specification (Model 14), suggesting that time-specific effects are correlated with the regressors. Consequently, despite the weak F-test evidence, period fixed effects are preferred for interpretation, as they allow for controlling unobserved global shocks that are plausibly linked to the evolution of *AI*. Under this specification, both the linear and squared *AI* terms remain statistically significant, indicating an inverted U-shaped relationship between *AI* and *patent*, whereby increases in *AI* initially foster innovation, but beyond a certain threshold the marginal effect diminishes, reflecting within-country dynamics rather than purely global trends.

In contrast, the G20 results point to a different structure. The F-test for period fixed effects (Model 22) fails to reject the null hypothesis, indicating that fixed time effects are redundant. Furthermore, the Hausman test does not reject the random-effects specification (Model 23), suggesting that time-specific effects are not systematically correlated with the regressors. As a result, period random effects provide a more appropriate specification for the G20 sample. Under this framework, the inclusion of time effects substantially weakens the *AI* coefficients, rendering them statistically insignificant.

This divergence highlights a key structural difference between the two groups: while global technological dynamics appear to play a meaningful and correlated role in shaping innovation outcomes in G7 economies, they are less systematically transmitted across the more heterogeneous G20 countries. Consequently, Model 13 is preferred for interpreting the G7 results, whereas Model 23 is preferred for the G20 sample.

The double fixed effects specification (Model 15 in Table 8 and Model 24 in Table 9), which simultaneously controls for both country-specific and time-specific heterogeneity, provides the most stringent test of the relationship. In both G7 and G20 samples, this specification renders the coefficients of both the linear and quadratic *AI* terms statistically insignificant. However, this result should be interpreted with caution. Given the strong global trend in *AI*, the inclusion of both country and time fixed effects absorb a substantial portion of its variation, potentially limiting the ability to identify its independent effect. As such, the loss of significance likely reflects over-controlling rather than the absence of an economic relationship. Consequently, while the double fixed effects model

serves as a robustness check, period fixed and random effects models provide a more informative framework for economic interpretation, as they balance the need to control for global shocks while preserving sufficient variation to identify the relationship between *AI* and innovation.

4.1. Robustness check

The robustness check based on MMQR models is reported in Tables 10-13 (Appendix). This additional analysis examines whether the relationship between AI and innovation differs across the conditional distribution of patenting activity, rather than only at the conditional mean. This is particularly relevant given the unequal distribution of patent applications across countries, where some economies are located at the upper end of the innovation distribution, while others display significantly lower patenting intensity.

In the G7 sample, the MMQR results without shock controls, reported in Table 10, provide further evidence of a positive AI-innovation relationship across most of the patent distribution. The *AI* coefficient is positive and significant at the 25th, 50th, and 75th quantiles. The squared term is negative throughout the distribution, although only the median estimate reaches statistical significance. At the 95th quantile, both the linear and squared *AI* terms become statistically insignificant, suggesting that the AI-innovation relationship is weaker among the highest-patenting observations. This may indicate that countries already operating at very high levels of innovation experience weaker additional gains from AI-related activity, consistent with the presence of diminishing marginal effects.

The inclusion of shock dummy variables strengthens the evidence for a concave relationship in the G7 sample. As shown in Table 12, *AI* remains positive and statistically significant at the 25th, 50th, and 75th quantiles, while the squared *AI* term is negative and statistically significant at the 50th and 75th quantiles. This indicates that, after accounting for major shocks, the inverted U-shaped pattern becomes clearer around the median and upper-middle parts of the patent distribution. The crisis dummy remains statistically insignificant across all quantiles, while the pandemic dummy is negative and significant at the 25th, 50th, and 75th quantiles. This suggests that the pandemic period had a stronger adverse effect on lower-, median-, and upper-middle innovation observations within the G7 sample, while its effect becomes insignificant at the 95th quantile.

For the G20 sample, the MMQR results reveal a more heterogeneous pattern. In Table 11, *AI* is statistically insignificant at the 25th and 50th quantiles, becomes weakly significant at the 75th quantile, and is positive and statistically significant at the 95th quantile. This indicates that AI-related activity is more clearly associated with patenting activity among higher-innovation observations. At the same time, the squared *AI* term is positive and significant at the 25th quantile, but negative and significant only at the 95th quantile. Therefore, the evidence for diminishing marginal effects in the G20 sample is concentrated mainly at the upper tail of the patent distribution.

The inclusion of shock dummies leaves this pattern largely unchanged. As reported in Table 13, *AI* remains insignificant at the 25th and 50th quantiles, but becomes positive and significant at the 75th and 95th quantiles. The squared *AI* term is positive and significant at the 25th quantile, but negative and significant at the 95th quantile. The crisis and pandemic dummies are statistically insignificant across all quantiles, indicating that these shocks do not materially alter the estimated distributional

pattern for the G20 sample. Overall, the MMQR results suggest that AI effects in the G20 are concentrated mainly among higher-patenting observations, with the clearest evidence of concavity appearing at the upper tail of the distribution.

Taken together, the MMQR results confirm that the AI-innovation relationship is distributionally heterogeneous. In the G7 sample, *AI* is positively associated with innovation mainly between the 25th and 75th quantiles, while the evidence of diminishing marginal effects becomes clearer once shock controls are included. In the G20 sample, the effect of *AI* is concentrated mainly in the upper quantiles, particularly at the 95th quantile, suggesting that AI translates more clearly into patenting activity among higher-innovation observations. These results should be interpreted alongside the fixed-effects and random-effects specifications rather than as a replacement for them. While the main panel models assess the sensitivity of the relationship to unobserved heterogeneity and time effects, the MMQR models show whether the estimated AI-innovation relationship differs across low-, median-, and high-patenting observations.

4.2. Discussion

Overall, the mean-based and MMQR results suggest that the estimated association between AI and patenting activity is sensitive both to model specification and to the position of countries within the patent distribution. While positive and sometimes non-linear effects are observed in simpler specifications, these effects weaken or disappear when more comprehensive controls for unobserved heterogeneity are introduced. At the same time, the MMQR results show that the AI-innovation relationship is not evenly distributed across countries: in the G7 sample, the effect is more visible across the lower, median, and upper-middle quantiles, while in the G20 sample it becomes statistically meaningful mainly at the upper end of the patent distribution. In contrast, traditional determinants of innovation, such as economic development, human capital, and population size, remain more robust and consistently significant across specifications.

From an economic perspective, these findings suggest that AI-driven digitalization does not operate as a uniform innovation shock. Rather, its effect appears to depend on diffusion dynamics, absorptive capacity, and the accumulation of complementary assets. In early stages, increases in AI activity may enhance innovation by improving knowledge recombination, reducing search costs, and accelerating research processes. However, as adoption expands, the marginal contribution of AI may decline due to saturation effects, coordination frictions, and the need for complementary investments in skills, organizational capital, data infrastructure, and research capabilities. This interpretation is consistent with the productivity J-curve argument, according to which the gains from GPTs become visible only after complementary intangible investments have been accumulated (Brynjolfsson et al., 2017, 2020).

The distributional evidence from the MMQR results further reinforce this interpretation. The stronger AI effects at higher quantiles, particularly in the G20 sample, suggest that countries with stronger innovation systems are better able to transform AI-related activity into patenting outcomes. This is in line with the literature on technology diffusion and frontier heterogeneity, which argues that the economic impact of new technologies depends not only on their availability, but also on the capacity of countries and firms to absorb, adapt, and integrate them into productive activities (Comin &

Mestieri, 2018; Andrews et al., 2016). Therefore, the weak average effect observed in some panel specifications may conceal stronger effects among countries already positioned closer to the technological frontier.

These findings are also consistent with the broader literature on technological change and innovation. In line with Schumpeterian growth theory, innovation is shaped by structural and institutional factors that determine the capacity of economies to generate, absorb, and commercialize new technologies (Aghion et al., 2013). Similarly, the results support the GPT perspective, according to which the benefits of major technological paradigms depend on complementary innovation, organizational adaptation, and institutional readiness (Bresnahan & Trajtenberg, 1995). In this sense, AI should not be interpreted as an autonomous driver of patenting activity, but rather as an enabling technology whose impact depends on the broader innovation ecosystem in which it is embedded.

Moreover, the weaker and less robust average effects for the AI variable align with the notion of the modern productivity paradox. According to this view, the benefits of new digital technologies may take time to materialize and may not be immediately reflected in observed productivity or innovation indicators (Brynjolfsson et al., 2017). This interpretation is further supported by the framework of Acemoğlu and Restrepo (2018, 2020), who emphasize that the economic impact of automation depends on the balance between displacement effects, productivity effects, and the creation of new tasks. Although the present study focuses on patents rather than labor-market outcomes, the same logic applies: technological adoption alone is insufficient unless it is accompanied by complementary adjustment mechanisms.

At the same time, the results differ from several micro-level studies that identify stronger positive effects of AI on productivity and innovation. For example, Brynjolfsson et al. (2025) report substantial productivity gains from generative AI at the worker level, while Calvino and Fontanelli (2023) find positive productivity effects for AI developers at the firm level. Likewise, Cockburn et al. (2018) argue that AI can operate as a "method of invention." By contrast, the present results suggest that, at the cross-country level, the AI-innovation relationship is more conditional and becomes weaker once country-specific and time-specific heterogeneity are controlled for. This divergence may reflect differences in level of analysis, measurement, and the fact that country-level patent outcomes depend on broader institutional and structural conditions that are not fully visible in firm-level studies.

Finally, the stronger and more consistent effects observed in the G7 sample, together with the upper-quantile effects observed in the G20 sample, especially at the 95th quantile, support the view that AI is more effective where innovation systems are already relatively developed. Advanced economies are better positioned to exploit new technological paradigms because they possess stronger human capital, institutional quality, digital infrastructure, and research capacity. In contrast, the heterogeneity observed in the G20 sample reinforces the importance of development gaps and structural constraints in shaping the economic impact and diffusion of AI. Therefore, the main conclusion emerging from both the mean-based and MMQR models is that AI contributes to innovation only under specific structural conditions, rather than producing uniform effects across all countries.

5. Conclusions

This study shows that the relationship between AI and innovation is neither linear nor universal, but instead shaped by the structural characteristics of economies and their position relative to the technological frontier. When focusing on the preferred specifications, a clear distinction emerges between advanced and more heterogeneous economies, revealing different mechanisms through which AI interacts with the innovation process. The MMQR robustness check further reinforces this interpretation by showing that the AI–innovation relationship is not only sensitive to model specification, but also to the position of countries within the patent distribution.

For the G7 countries, the results provide stronger evidence of a concave, inverted U-shaped relationship between AI and innovation, particularly in the preferred period-effects specification and around the median and upper-middle quantiles of the patent distribution once shock controls are included. At lower levels of AI intensity, increases in digitalization appear to act as enablers of innovation by improving knowledge recombination, reducing search costs, accelerating data processing, and facilitating research activity. In this phase, AI operates as a complement to human capital and existing research infrastructure, thereby amplifying the productivity of innovative activities.

However, as AI becomes more prevalent, its marginal contribution appears to decline. This does not imply that AI loses relevance, but rather that its effectiveness becomes increasingly conditional on deeper structural adjustments. At higher levels of adoption, economies may face coordination frictions, organizational rigidities, and increasing complexity in integrating advanced technologies into innovation systems. Moreover, the benefits of AI may become concentrated in specific sectors or firms, leading to diminishing aggregate returns. In this stage, further gains require substantial complementary investments in skills, data infrastructure, institutional quality, and research capabilities.

In contrast, the evidence for the G20 economies remains weaker in the mean-based specifications, but the MMQR results indicate that AI becomes relevant mainly among countries or observations located at the upper end of the patent distribution. This suggests that AI-related activity translates more clearly into innovation where innovation systems are already relatively developed. Many G20 economies operate below the technological frontier, where innovation is driven less by frontier creation and more by diffusion, imitation, and structural transformation. In this context, AI adoption does not automatically generate higher patenting activity, as the capacity to absorb and utilize new technologies varies substantially across countries.

Taken together, these findings suggest that AI should not be viewed as an autonomous driver of innovation, but rather as a technology that amplifies existing economic structures. Its impact depends critically on complementary assets, including skilled labor, research capabilities, institutional quality, digital infrastructure, and organizational flexibility. In economies where these conditions are well developed, AI can support innovation, although diminishing marginal effects may emerge at higher levels of intensity. In economies where these foundations are weaker, AI alone is insufficient to generate sustained innovation gains.

From a policy perspective, these results imply that innovation strategies should move beyond a narrow focus on AI adoption and instead emphasize the development of supporting assets. For advanced

economies, this means investing in advanced education, research ecosystems, data infrastructure, and organizational capabilities that allow AI to be integrated into innovation processes. For emerging and less developed economies, the priority lies in strengthening absorptive capacity through education, institutional quality, digital infrastructure, and mechanisms that facilitate technology diffusion. For firms and public institutions alike, AI adoption should therefore be accompanied by workforce development, organizational change, and data-management capabilities.

In sum, the economic impact of AI on innovation is best understood not as a simple cause-and-effect relationship, but as part of a broader process in which technology interacts with structural conditions, institutional frameworks, and stages of development. The observed differences between the G7 and G20 economies, together with the MMQR results, underscore that the returns to AI are inherently conditional. Technological progress is therefore not only about the presence of AI itself, but also about the economic and institutional environment in which it is embedded.

6. Limitations and future research directions

Despite providing relevant insights into the relationship between AI and innovation, this study is subject to several limitations that should be acknowledged. First, the measurement of AI activity relies on Google Trends search intensity, which captures attention and interest rather than actual adoption or deployment of AI technologies. While this proxy is useful for capturing diffusion dynamics and expectations, it may not fully reflect the intensity or quality of AI implementation across countries. As a result, measurement error may attenuate the estimated relationship between AI and innovation and contribute to instability across model specifications.

Second, the analysis is conducted at an aggregate, country level, which limits the ability to capture firm-level heterogeneity and sector-specific dynamics. As emphasized in the literature, the effects of AI are highly uneven across firms and industries, depending on complementary assets, organizational capabilities, and data availability. Aggregation may therefore mask important micro-level mechanisms through which AI influences innovative outcomes, particularly in economies with uneven technological diffusion.

Third, an important limitation relates to the overlap and heterogeneity between the G7 and G20 samples. While the analysis distinguishes between advanced and more heterogeneous economies by estimating separate models, the G7 countries are a subset of the G20, implying that the two samples are not fully independent. As a result, the G20 estimates partly embed the dynamics of advanced economies, while also incorporating substantial cross-country heterogeneity from emerging economies. This compositional structure may attenuate the estimated relationships and contribute to the weaker and less stable results observed for the G20 sample.

Fourth, the empirical approach relies on static panel models, which do not fully account for dynamic adjustment processes, diffusion lags, and potential endogeneity between AI activity and innovation. Although the MMQR robustness checks provide additional evidence on distributional heterogeneity and account for country-specific effects, they should not be interpreted as causal specifications. In particular, the MMQR models do not include full period fixed effects and therefore do not absorb common time shocks in the same way as the period-effects and double fixed-effects specifications.

Given that technological adoption and innovation often unfold over time, the absence of a dynamic framework may limit the ability to capture delayed, cumulative, or feedback effects between variables.

These limitations suggest several directions for future research. First, the use of more direct measures of AI adoption, such as firm-level data on AI investments or usage, could improve the identification of its economic effects. Second, integrating micro-level and macro-level data would allow for a more comprehensive understanding of how AI-driven innovation translates into aggregate outcomes. Third, future studies could employ dynamic panel methods, causal identification strategies, or panel quantile models with richer time effects to better capture the temporal dimension, address endogeneity concerns, and examine whether distributional heterogeneity persists after controlling more rigorously for unobserved heterogeneity. Finally, further research could explore sectoral heterogeneity and the role of complementary assets in shaping the effectiveness of AI, particularly in the context of technological convergence and divergence across countries.

Conflict of interest

The author declares that he does not have any conflict of interest.

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Appendix

Figure 1. Patent Applications in the G20

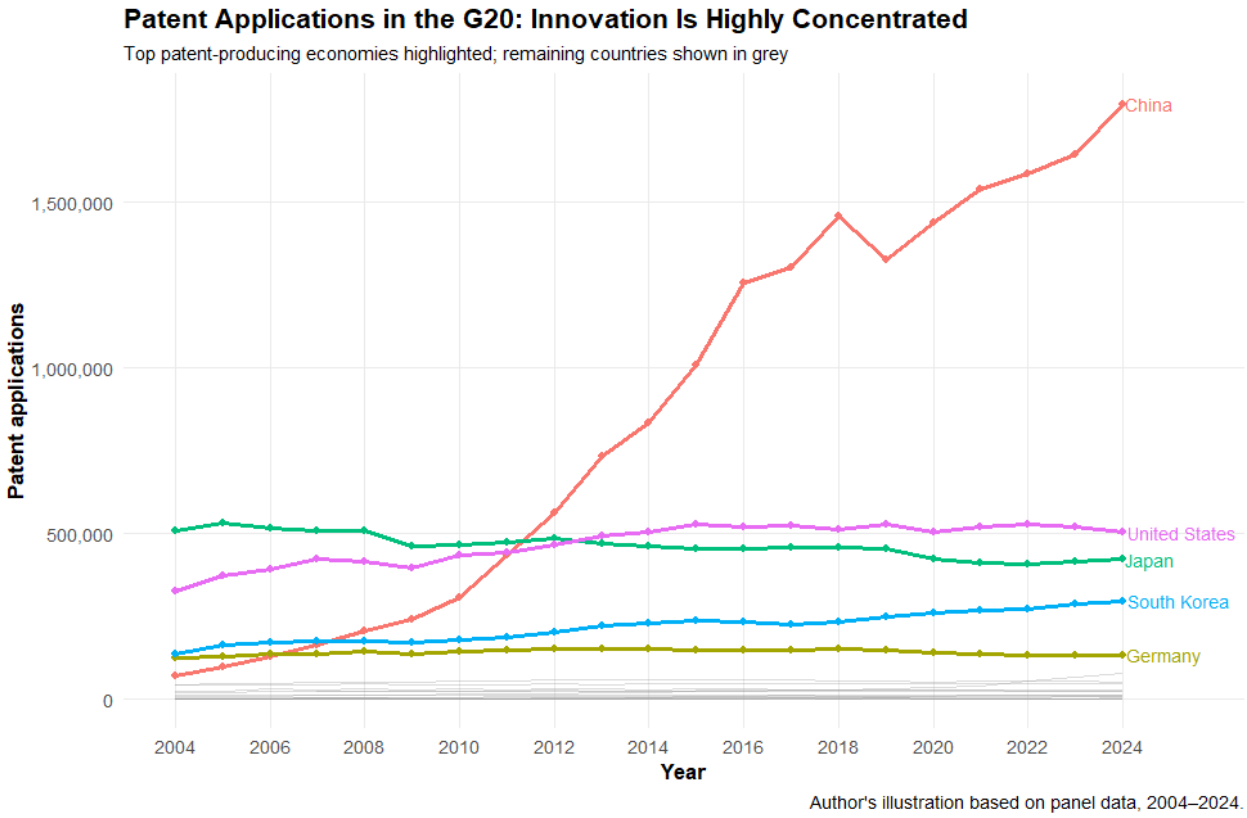

Table 1. Description of variables

Variable	Description	Unit	Source	Expected sign
Patent application by residents (patent)	Measure of innovation output, capturing the number of patent applications filed by residents. It reflects a country's technological progress and inventive activity.	Number	WIPO (2026)	
Artificial Intelligence (AI)	Proxy for artificial intelligence activity, measured using Google Trends search intensity for AI-related terms. It captures public and economic interest in AI technologies, with a scale between 0 and 100 (0 the lowest, 100 the highest).	Index points	Google Inc. (2026)	+/-
Gross Domestic Product per capita (GDPc)	Gross Domestic Product per capita, representing the level of economic development and income per individual.	USD (constant prices, 2015)	WB (2026)	+
Researchers in R&D (res)	Number of researchers engaged in R&D activities reflecting human capital dedicated to innovation, expressed as the number of researchers per million inhabitants.	Number of researchers	WB (2026)	+
Total Population (pop)	Total population measures the number of people residing within a country, capturing its demographic size.	Number of persons	WB (2026)	+/-
Rule of Law (rule)	Institutional quality indicator measuring the extent to which agents have confidence in and abide by societal rules (property rights, contract enforcement), with a scale between -2.5 and 2.5 (-2.5 the lowest, 2.5 the highest).	Index points	WB (2026)	+

Table 2. Descriptive statistics – G7

	patent	AI	GDPc	res	pop	rule
Mean	178621.00	8.19	41364.17	4071.16	107532349.27	1.39
Median	54731.00	3.00	40834.51	4218.41	66984000.00	1.53
Maximum	529424.00	46.00	66356.17	5787.44	340110988.00	1.89
Minimum	19027.00	1.00	29469.80	1242.49	31938807.00	0.21
Std. Dev.	191977.9	11.06	8039.41	1075.36	90188639.00	0.44
Skewness	0.86	1.96	0.99	-0.87	1.73	-1.59
Kurtosis	1.94	5.78	3.64	3.18	4.49	4.31
Jarque-Bera	141.34***	141.34***	7.90***	15.91***	86.87***	69.07***
Observations	143	147	147	126	147	140

Note: (1) ***,**, and * show significance at 1, 5 and 10% level of significance, respectively.

Table 3. Descriptive statistics – G20

	patent	AI	GDPc	res	pop	rule
Mean	127939.43	6.68	24534.57	2769.32	232656434.23	0.49
Median	23746.00	3.00	22827.67	2784.09	77181884.00	0.15
Maximum	1796738.00	53.00	66356.17	9434.76	1450935791.00	1.92
Minimum	179.00	0.00	892.60	88.33	19669480.00	-1.20
Std. Dev.	265654.00	9.93	18031.52	2033.39	387457791.74	0.93
Skewness	3.58	2.58	0.38	0.48	2.41	0.10
Kurtosis	18.00	9.00	1.84	2.56	7.18	1.45
Jarque-Bera	4500.79***	1042.85***	32.06***	13.42***	678.05***	38.83***
Observations	391	399	399	290	399	380

Note: (1) ***,**, and * show significance at 1, 5 and 10% level of significance, respectively.

Table 4. Matrix of Correlation – G7

Variable	log(patent)	log(AI)	$\log(AI)^2$	log(GDPc)	log(res)	log(pop)	rule
log(patent)	1						
log(AI)	0.007	1					
$\log(AI)^2$	-0.056	0.984	1				
log(GDPc)	0.305	-0.521	-0.506	1			
log(res)	0.412	-0.345	-0.460	0.291	1		
log(pop)	0.887	-0.042	-0.052	0.481	0.095	1	
rule	0.236	-0.564	-0.606	0.571	0.726	0.052	1

Table 5. Matrix of Correlation – G20

Variable	log(patent)	log(AI)	$\log(AI)^2$	log(GDPc)	log(res)	log(pop)	rule
log(patent)	1						
log(AI)	0.085	1					
$\log(AI)^2$	0.096	0.970	1				
log(GDPc)	0.523	0.111	0.092	1			
log(res)	0.707	0.072	0.114	0.834	1		
log(pop)	0.412	-0.040	-0.071	-0.421	-0.258	1	
rule	0.558	-0.060	-0.070	0.836	0.715	-0.291	1

Table 6. Empirical results for nonlinear assumptions – G7

Dependent variable: log(patent)			
Independent variables	Model		
	(1)	(2)	(3)
log(AI)	0.000	1.538**	0.966
	(0.116)	(0.692)	(2.629)
$\log(AI)^2$		-0.346**	-0.056
		(0.154)	(1.295)
$\log(AI)^3$			-0.044
			(0.194)
Intercept	11.42	10.06***	10.40***
	(0.222)	(0.643)	(1.614)
Type of estimation	Naïve-OLS	Naïve-OLS	Naïve-OLS
Adj. R-squared	-0.007	0.021	0.015
Observations	143	143	143

Note: (1) (…) denotes the standard errors; (2) ***,**, and * show significance at 1, 5 and 10% level of significance, respectively.

Table 7. Empirical results for nonlinear assumptions – G20

Dependent variable: log(patent)			
Independent variables	Model		
	(4)	(5)	(6)
log(AI)	0.436***	1.983***	1.119
	(0.132)	(0.577)	(1.472)
$\log(AI)^2$		-0.368***	0.146
		(0.134)	(0.817)
$\log(AI)^3$			-0.086
			(0.134)
Intercept	9.223***	7.941***	8.347***
	(0.236)	(0.521)	(0.824)
Type of estimation	Naïve-OLS	Naïve-OLS	Naïve-OLS
Adj. R-squared	0.025	0.041	0.039
Observations	391	391	391

Note: (1) (…) denotes the standard errors; (2) ***,**, and * show significance at 1, 5 and 10% level of significance, respectively.

Table 8. Empirical results – G7

Dependent variable: log(patent)									
Independent variables	Model								
	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
log(AI)	2.448***	2.379**	0.171	0.612**	-0.255***	0.612***	1.093***	0.612**	-0.084
	(0.671)	(1.175)	(0.304)	(0.254)	(0.080)	(0.070)	(0.299)	(0.252)	(0.086)
$\log(AI)^2$	-0.526***	-0.458	-0.016	-0.113*	0.046**	-0.113***	-0.230***	-0.113*	0.008
	(0.148)	(0.307)	(0.079)	(0.065)	(0.020)	(0.018)	(0.077)	(0.065)	(0.021)
log(GDPc)	2.543***	2.645***	-1.704***	-2.357***	0.437**	-2.357***	-2.142***	-2.357***	0.657***
	(0.530)	(0.637)	(0.194)	(0.179)	(0.175)	(0.049)	(0.233)	(0.177)	(0.204)
log(res)		1.193**	1.687***	0.992***	0.068	0.992***	1.031***	0.992***	0.424***
		(0.510)	(0.131)	(0.139)	(0.072)	(0.038)	(0.186)	(0.138)	(0.108)
log(pop)			1.766***	1.855***	1.522***	1.855***	1.828***	1.855***	1.868***
			(0.043)	(0.037)	(0.206)	(0.010)	(0.041)	(0.037)	(0.279)
rule				0.691***	-0.083	0.691***	0.573***	0.691***	-0.040
				(0.089)	(0.083)	(0.025)	(0.134)	(0.088)	(0.109)
Intercept	-17.84***	-28.82***	-16.94***	-7.255***	-21.15***	-7.255***	-9.604***	-7.225***	-32.99***
	(5.844)	(6.991)	(1.805)	(1.928)	(3.514)	(0.533)	(2.825)	(1.913)	(6.398)
Type of estimation	Panel OLS	Panel OLS	Panel OLS	Panel OLS	Panel FE:CS	Panel RE:CS	Panel FE:PR	Panel RE:PR	Panel Double FE
Adj. R-squared	0.154	0.276	0.953	0.969	0.998	0.969	0.969	0.969	0.998
F-test					232.19		1.10		91.03
[p-value]					[0.000]		[0.365]		[0.000]
Hausman test						1393.18		18.15	
[p-value]						[0.000]		[0.006]	
Observations	143	122	122	122	122	122	122	122	122

Note: (1) (…) denotes the standard errors; (2) ***,**, and * show significance at 1, 5 and 10% level of significance, respectively; (3) [] stands for p-value.

Table 9. Empirical results – G20

Dependent variable: log(patent)									
Independent variables	Model								
	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
log(AI)	1.286**	-1.386**	0.051	0.218	-0.218*	-0.077	0.451	0.218	-0.022
	(0.527)	(0.660)	(0.313)	(0.283)	(0.125)	(0.121)	(0.324)	(0.291)	(0.146)
$\log(AI)^2$	0.252**	0.408**	0.029	0.026	0.043	0.006	-0.028	0.026	-0.010
	(0.121)	(0.179)	(0.085)	(0.077)	(0.034)	(0.033)	(0.088)	(0.079)	(0.039)
log(GDPc)	0.900***	-0.593***	0.598***	0.049	2.392***	2.020***	0.036	0.049	2.602***
	(0.096)	(0.184)	(0.094)	(0.109)	(0.137)	(0.120)	(0.115)	(0.112)	(0.140)
log(res)		1.878***	1.382***	1.354***	-0.038	0.024	1.346***	1.354***	0.046
		(0.155)	(0.074)	(0.067)	(0.087)	(0.079)	(0.070)	(0.069)	(0.083)
log(pop)			1.502***	1.464***	0.104	1.501***	1.466***	1.465***	1.846***
			(0.048)	(0.043)	(0.372)	(0.123)	(0.045)	(0.044)	(0.486)
rule				0.601***	-0.288***	-0.060	0.613***	0.601***	-0.285***
				(0.075)	(0.108)	(0.093)	(0.080)	(0.077)	(0.106)
Intercept	-0.062	2.901**	-33.91***	-28.18***	-14.50**	-37.42***	-28.23***	-28.18***	-49.50***
	(0.972)	(1.171)	(1.288)	(1.366)	(6.356)	(2.492)	(1.431)	(1.404)	(8.962)
Type of estimation	Panel OLS	Panel OLS	Panel OLS	Panel OLS	Panel FE:CS	Panel RE:CS	Panel FE:PR	Panel RE:PR	Panel Double FE
Adj. R-squared	0.217	0.517	0.894	0.913	0.991	0.702	0.908	0.913	0.992
F-test					128.94		0.21		73.00
[p-value]					[0.000]		[1.000]		[0.000]
Hausman test						52.41		3.369	
[p-value]						[0.000]		[0.761]	
Observations	391	286	286	286	286	286	286	286	286

Note: (1) (…) denotes the standard errors; (2) ***,**, and * show significance at 1, 5 and 10% level of significance, respectively; (3) [] stands for p-value.

Table 10. Robustness check without shocks – G7

Dependent variable: log(patent)				
Independent variables	Model			
	(25)	(26)	(27)	(28)
	Q0.25	Q0.50	Q0.75	Q0.95
log(AI)	0.708**	0.598**	0.533**	0.390
	(0.311)	(0.253)	(0.263)	(0.387)
$\log(AI)^2$	-0.119	-0.112*	-0.107	-0.098
	(0.079)	(0.064)	(0.066)	(0.097)
log(GDPc)	-2.063***	-2.399***	-2.597***	-3.037***
	(0.206)	(0.172)	(0.172)	(0.293)
log(res)	1.038***	0.985***	0.954***	0.885***
	(0.179)	(0.145)	(0.151)	(0.222)
log(pop)	1.839***	1.857***	1.868***	1.892***
	(0.043)	(0.035)	(0.036)	(0.053)
rule	0.637***	0.699***	0.735***	0.816***
	(0.125)	(0.102)	(0.106)	(0.157)
Intercept	-10.66***	-6.762***	-4.460**	0.642
	(2.361)	(1.973)	(1.964)	(3.368)
Type of estimation	Panel MMQR	Panel MMQR	Panel MMQR	Panel MMQR
Observations	122	122	122	122

Note: (1) (…) denotes the standard errors; (2) ***,**, and * show significance at 1, 5 and 10% level of significance, respectively.

Table 11. Robustness check without shocks – G20

Dependent variable: log(patent)				
Independent variables	Model			
	(29)	(30)	(31)	(32)
	Q0.25	Q0.50	Q0.75	Q0.95
log(AI)	-0.103	0.126	0.539*	1.020**
	(0.197)	(0.217)	(0.316)	(0.486)
$\log(AI)^2$	0.129***	0.056	-0.076	-0.231*
	(0.049)	(0.054)	(0.078)	(0.121)
log(GDPc)	0.118	0.069	-0.021	-0.124
	(0.094)	(0.102)	(0.150)	(0.230)
log(res)	1.344***	1.351***	1.364***	1.379***
	(0.059)	(0.063)	(0.094)	(0.143)
log(pop)	1.502***	1.475***	1.427***	1.371***
	(0.034)	(0.037)	(0.055)	(0.084)
rule	0.600***	0.600***	0.601***	0.602***
	(0.068)	(0.074)	(0.110)	(0.167)
Intercept	-29.72***	-28.62***	-26.64***	-24.33***
	(1.120)	(1.227)	(1.797)	(2.758)
Type of estimation	Panel MMQR	Panel MMQR	Panel MMQR	Panel MMQR
Observations	286	286	286	286

Note: (1) (…) denotes the standard errors; (2) ***,**, and * show significance at 1, 5 and 10% level of significance, respectively.

Table 12. Robustness check with shocks – G7

Dependent variable: log(patent)				
Independent variables	Model			
	(33)	(34)	(35)	(36)
	Q0.25	Q0.50	Q0.75	Q0.95
log(AI)	0.791**	0.725***	0.681***	0.596
	(0.333)	(0.260)	(0.262)	(0.372)
$\log(AI)^2$	-0.132	-0.140**	-0.145**	-0.155
	(0.085)	(0.066)	(0.066)	(0.094)
log(GDPc)	-1.857***	-2.175***	-2.390***	-2.799***
	(0.253)	(0.203)	(0.204)	(0.295)
log(res)	1.334***	1.131***	0.994***	0.734***
	(0.230)	(0.182)	(0.184)	(0.263)
log(pop)	1.810***	1.829***	1.843***	1.868***
	(0.048)	(0.037)	(0.038)	(0.054)
rule	0.432**	0.553***	0.635***	0.791***
	(0.167)	(0.131)	(0.132)	(0.189)
dummy_pandemic	-0.255***	-0.185***	-0.138**	-0.048
	(0.085)	(0.067)	(0.067)	(0.096)
dummy_crisis	0.034	0.017	0.006	-0.016
	(0.071)	(0.056)	(0.056)	(0.080)
Intercept	-14.54***	-9.740***	-6.502**	-0.338
	(3.283)	(2.660)	(2.678)	(3.887)
Type of estimation	Panel MMQR	Panel MMQR	Panel MMQR	Panel MMQR
Observations	122	122	122	122

Note: (1) (…) denotes the standard errors; (2) ***,**, and * show significance at 1, 5 and 10% level of significance, respectively.

Table 13. Robustness check with shocks – G20

Dependent variable: log(patent)				
Independent variables	Model			
	(37)	(38)	(39)	(40)
	Q0.25	Q0.50	Q0.75	Q0.95
log(AI)	-0.078	0.167	0.607*	1.092**
	(0.206)	(0.226)	(0.331)	(0.502)
$\log(AI)^2$	0.123**	0.046	-0.094	-0.247**
	(0.051)	(0.056)	(0.082)	(0.125)
log(GDPc)	0.117	0.073	-0.007	-0.095
	(0.095)	(0.103)	(0.152)	(0.228)
log(res)	1.349***	1.352***	1.358***	1.365***
	(0.059)	(0.064)	(0.095)	(0.142)
log(pop)	1.505***	1.477***	1.427***	1.373***
	(0.034)	(0.037)	(0.055)	(0.083)
rule	0.598***	0.596***	0.591***	0.585***
	(0.069)	(0.075)	(0.111)	(0.166)
dummy_pandemic	-0.075	-0.078	-0.083	-0.089
	(0.097)	(0.105)	(0.156)	(0.234)
dummy_crisis	0.055	0.013	-0.063	-0.147
	(0.080)	(0.087)	(0.129)	(0.194)
Intercept	-29.83***	-28.73***	-26.75***	-24.57***
	(1.135)	(1.239)	(1.824)	(2.756)
Type of estimation	Panel MMQR	Panel MMQR	Panel MMQR	Panel MMQR
Observations	286	286	286	286

Note: (1) (…) denotes the standard errors; (2) ***,**, and * show significance at 1, 5 and 10% level of significance, respectively.