Artificial Intelligence Innovation and Economic Performance

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Very Preliminary

Abstract

This study investigates the relationship between artificial intelligence (AI) innovation value and economic performances using a panel dataset of countries from 1985 to 2019. Utilizing AI patents as a measure of technological advancement, the research employs fixed effects and generalized method of moments (GMM) estimation. The empirical results demonstrate a positive and significant relationship between AI innovation and economic performance improvements. However, there might be some catch-up effect or diminishing marginal returns.

Keywords: Artificial Intelligence, Patents, Patent Value, Economic Performance

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I. Introduction

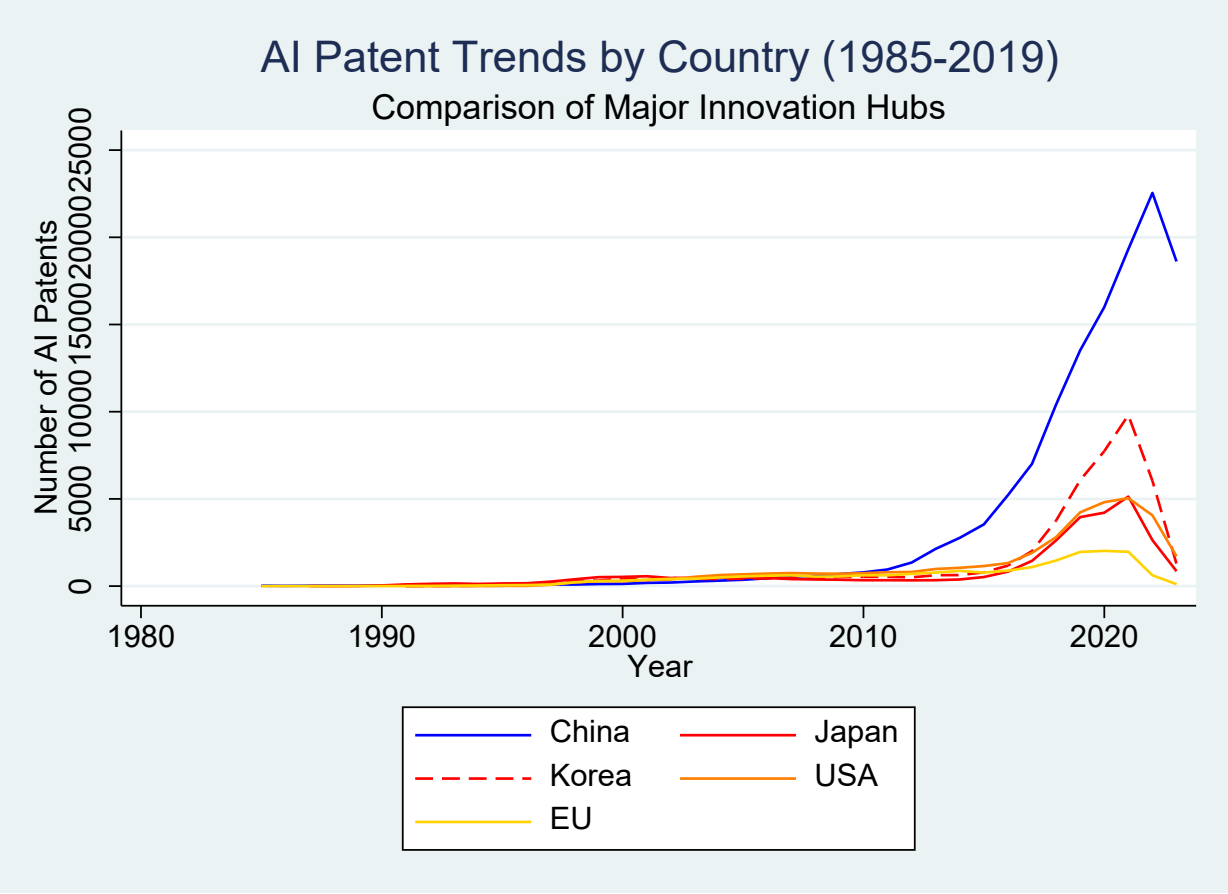
In the recent decade, artificial intelligence (AI) has become a central force in technological change and a potential driver of long-run economic growth. Broadly defined, AI refers to a set of machine-based systems and techniques, spanning machine learning, deep learning, natural language processing, and computer vision, that enable machines to perform tasks associated with human cognition such as learning, prediction, classification, and decision-making. The rapid progress of these methods, fueled by big data, declining computing costs, and algorithmic breakthroughs, has accelerated the usage of AI across a wide range of sectors including healthcare, finance, manufacturing, transportation, agriculture and etc. As a result, AI is increasingly viewed not as a narrowly specialized technology, but as a general-purpose technology (GPT) with broad applicability and the capacity to reshape production, innovation, market structure and thus, the future.

Historical experience suggests that GPTs generate economy-wide impacts through complementary investments and structural changes. In this perspective, AI may raise productivity and expand economic possibilities by improving automation and enhancing efficiency. At the same time, the aggregate effects of AI are unlikely to be uniform. They may depend on a country's industrial composition, human capital, institutional environment, and the extent to which complementary inputs (data infrastructure, computing, organizational capabilities) are developed. Additionally, the cultural and technological absorptive capacity of a country is likely to heavily influence whether or not AI outbreak will help or hurt economic growth. Importantly, recent work emphasizes that productivity effects may arrive with lags, and that AI can also introduce distributional and structural consequences, affecting labor markets and potentially reinforcing concentration through scale advantages.

In recent years, initiatives to achieve technological leadership in Artificial Intelligence

(AI) at the national level have intensified significantly and remain a primary objective for global innovation policy. Figure 1 illustrates these efforts over the past several decades. Throughout the 1980s and until the late 1990s, AI-related patent activity remained minimal, with fewer than 100 applications recorded across the five jurisdictions in the sample. However, starting in 2010, the volume of patent filings accelerated and persisted until the disruption caused by the COVID-19 pandemic. Although the pandemic resulted in a notable contraction in AI innovation output, a rapid recovery is anticipated, especially with the emergence and widespread adoption of Large Language Models (LLMs).

[Figure 1]



Building on the literature on how economic growth can be determined by artificial intelligence innovation, this study systematically assesses how AI influences national

economic growth. This study will contribute to clarifying the economic importance of AI by quantitatively analyzing how AI technologies affect national economic growth. The findings are expected to provide useful evidence for policymakers designing AI-related policies and for firms seeking to adopt AI effectively. Ultimately, this research aims to deepen our understanding of the channels through which AI can promote sustainable economic growth and to provide foundational empirical inputs for long-run growth strategies. We examine whether and to what extent the quantity and quality of AI patents influence the differences in economic growth across contributing countries, and what possible channels help explain the disparities.

The rest of this paper is as follows. Section II reviews literature on AI and economic growth. Section III describes the data and key variables. Section IV presents the results and Section V concludes.

II. Literature Review

Endogenous growth models serve as the central theoretical foundation for much of the existing literature regarding technology and economic growth. Arrow (1962) initially associated technology as a "by-product of ordinary production" through knowledge accumulation, a process aptly termed "learning-by-doing". Under this framework, technical change born out of knowledge and experience is embodied in new physical capital, which improves productive efficiency and creates opportunities for national growth. Following this line of thought, many scholars assume that technological change increases capital productivity. In keeping with the Schumpeterian tradition, Zeira (1998) proposed a model where technology adoption increases the intensity of capital and replaces labor. Because technology requires significant capital input, disparities in technology levels across countries result in differences in overall output, as lower-wage nations often cannot afford the high capital requirements to

adopt the latest innovations.

Meanwhile, Acemoglu and Restrepo (2018) constructed a "task-based" framework, treating automation and the creation of new tasks as distinct types of technological innovation. Initially, they considered that lower-indexed tasks would be automated, raising the share of capital in production. However, this is counterbalanced by the creation of new, more sophisticated tasks where labor has a "comparative advantage," eventually leading to a stable, balanced growth path where both types of innovations coexist. While these theoretical works explain the general relationship between science and growth, empirical evidence on AI and machine learning remains limited due to data scarcity at both firm and macro levels.

In empirical studies, the number of patents and scientific journals are the most common measures of technological innovation. In a Schumpeterian context, patents represent ownership of monopoly rents from the invention of new technology, driving firms to continuously invent and dismantle obsolete methods through "creative destruction" (Aghion and Howitt, 1990). Kim and Lee (2015) concluded that it is patents, rather than scientific journals, that contribute to economic growth, as patents serve as embodiments of technological knowledge more closely linked to private R&D efforts. While early studies by Wong et al. (2005) found a positive effect of patent grants on country growth rates, more recent findings by Sweet and Eterovic (2019) have found no significant effect, suggesting the relationship may be weakening or domain-specific.

Comparing AI to previous technologies, Lu and Zhou (2021) raised comparisons between AI and Information and Communications Technology (ICT). He (2019) uses an AI measure as the ratio of fixed asserts investment in IT industry to GDP and find positive association with economic growth. AI is considered to impact a broader range of sectors, leading to different implications at the aggregate level and a more unpredictable future

development path. Furthermore, while ICT requires high capital investments over long periods, AI can leverage data and cloud services to help lower capital requirements, potentially leading to a distinct pathway for AI adoption. Lu (2021) further traces the impact of AI on endogenous growth by enhancing human capital, noting that AI is a "nonrival input" that can learn and accumulate knowledge by itself. This suggests that AI is disembodied from physical capital and should be considered a separate input in modern production functions.

Despite the growing use of AI, general sentiment suggests its effect on growth is complex and difficult to measure. Intuitively, this is because of its multifaceted role as an input to production, acting as a "technical infrastructure, a part of the production process, or an end-user product".

Finally, the relationship between AI and economic performance is often viewed through the lens of supply and demand gains. On the supply side, AI drives business productivity through process automation and improvements in the labor force. On the demand side, AI generates increases in consumer demand by making personalized and higher-quality products available. Recent evaluations of firm-level productivity in Taiwan by Yang (2022) revealed that AI patents contribute significantly to total factor productivity (TFP), supporting the framework that AI technology has a greater effect on capital productivity than on labor productivity alone.

At the micro level, emerging evidence suggests that AI investments are strongly associated with firm growth, but the key channel may be product innovation rather than pure process efficiency. Using a new firm-level measure of AI investment based on AI-skilled human capital, recent research finds that AI-investing firms experience faster growth in sales, employment, and market valuation, driven primarily by increased product innovation (e.g., more product patents, trademarks, and product portfolio expansion). Moreover, this AI-

powered growth tends to concentrate among larger firms and is associated with rising industry concentration, consistent with the view that data and complementary intangible assets create scale advantages in AI adoption (Furman and Seamans, 2019).

Despite this progress, macro-level evidence on the relationship between AI and long-run economic growth remains comparatively limited. A core challenge is measurement: AI is multifaceted, definitions vary, and consistent cross-country time-series indicators of AI adoption and capability are scarce. Against this background, an increasingly common approach is to proxy AI-related technological progress using AI patents, which are observable, comparable across countries, and available over long horizons. Recent cross-country panel evidence employing AI patent counts as a measure of AI innovation reports a positive association between AI and long-run growth Gonzales (2023). The effects appear more pronounced among advanced economies and in later periods.

III. Data and Methodology

This study utilizes a dataset that combines macroeconomic indicators from international sources such as the World Bank and the Penn World Table. Patent data is from WIPSON, a comprehensive system for searching global patent registrations and applications. WIPSON provides data on AI-related patent filings by country and includes citation counts, allowing for an assessment of patent value. Although relying solely on citations to determine value has limitations, this study adopts citation rates following the methodology of Hall, Jaffe, and Trajtenberg (2005). While Kogan et al. (2017) measure patent value through stock market reactions, that approach was deemed inappropriate for this research, which focuses on national-level aggregates. At the national level, AI patent counts and each patent's citations are used to construct the primary explanatory variable, patent efficiency. Patent efficiency is the number

of citations per AI patent indicating how much value was generated from the patents. Although this measure may not be the perfect measure of AI innovation, we argue that this better represents the channel than the simple count. As Hall, Jaffe, and Trajtenberg (2005) mentioned, a patent has a significant value and impact, enough to have effect at the national level, only if the knowledge is shared and expanded through other patent citations.

To address the constraint that many countries have very limited AI patenting activity, we focus on major AI-patenting jurisdictions—Korea, the United States, Japan, China, and the European Union. The five samples together account for a substantial share of global AI inventive activity and provide a meaningful comparison set for evaluating cross-country heterogeneity in AI-driven growth. Key control variables are from World Bank's World Development Indicator database. The control variables used for the analysis are GDP in dollars, Inflation rate, Foreign Direct Investment, Trade Amount, CO2 Emission, Research and Development, and Gross Capital Formation. Total Factor Productivity is from Penn World Table.

In constructing the AI patent measure, patents are identified using AI-related keywords and classification logic designed to capture AI-relevant inventions while minimizing noise. A practical limitation is that patent publication is subject to administrative lags (often on the order of 18 months), implying that some applications filed in the most recent years may not yet be publicly available and thus may be missing from the dataset. This timing issue explains why patent data from the latest periods are missing. The data on AI patents ranges from 1985 to 2019 but the range varies by countries. We utilize the full sample for the multinational analysis.

We use fixed-effect panel regression to evaluate the relationship between AI patent efficiency and economic performance. GDP growth rates and per capita GDP growth rate are provided for all samples by World Development Indicators. However, Total Factor Productivity

of each country is provided by Penn World Table but not for the European Union. Thus, the analysis using TFP excludes Europe. All control variables are lagged a year to avoid the issue of reverse causality. In addition, to address the possible endogeneity issues, we conduct Generalized Method of Moment (GMM) panel regression and find consistent results.

$$Economic\ Performance_{i,t} = \alpha + \beta_1 PatentEfficiency_{i,t} + \beta_2 Controls + \gamma_i + \delta_t + \varepsilon_{i,t}$$

IV. Result

Table 1 shows the summary statistics for the primary variables used in this study. Economic growth is characterized by an average %GDPChange of 3.95% and a %GDP per capita Change of 3.42%, though both exhibit significant volatility with standard deviations of approximately 3.90 and 3.67, respectively. This is possibly due to China and Korea experiencing high growth rates while others remain relatively stable as shown in Figure 2. Innovation activity, a central component of the dataset, seems to be a highly skewed. PatentCount has a mean of 1,499.57 but reaches a maximum of 22,546, while R&D expenditures average 2.51. Trade openness, shown by Trade % of GDP averaging 46.50%, ranges from 15.72% to 103.7%. Other macroeconomic factors show moderate stability on average, including an inflation rate of 2.72% and Foreign Direct Investment (FDI) at 1.80%. Financial openness, represented by Domestic Credit, shows a mean of 136.73. Lastly, patent efficiency is measured by how many AI patents are cited on average. The average times an AI patent gets cited is 5.23.

[Table 1] Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
%GDPChange	176	3.947	3.901	-5.693	14.3

%GDP per capita Change	176	3.417	3.673	-5.681	13.555
%TFPChange	126	.677	.218	.336	1
PatentCount	176	1499.574	3339.483	1	22546
PatentEfficiency	176	5.232	7.658	0	58.487
Foreign Direct Investment	176	1.803	1.816	-1.369	10.004
Gross Capital	165	3.842	7.029	-26.592	25.991
Inflation rate	176	2.723	3.2	-1.881	20.641
Trade % of GDP	176	46.496	23.865	15.723	103.706
CO2	176	.598	.535	.161	2.643
Domestic Credit	165	136.73	45.177	46.973	223.775
R&D	130	2.512	.847	.563	4.93

Patent efficiency is computed in this study as the average citation frequency of AI-related filings, serving as a critical proxy for the qualitative and importance of innovation. While simple patent counts reflect the scale of R&D investment, the frequency of forward citations provides a more value signal of a patent's technological relevance and its role as a building block for subsequent inventions. Furthermore, the high variance surrounding this mean (Std. Dev: 7.66) highlights the presence of valuable patents but also negligible patents as well. This may be a factor in inducing a disproportionate influence on the trajectory of global AI development.

[Figure 2]

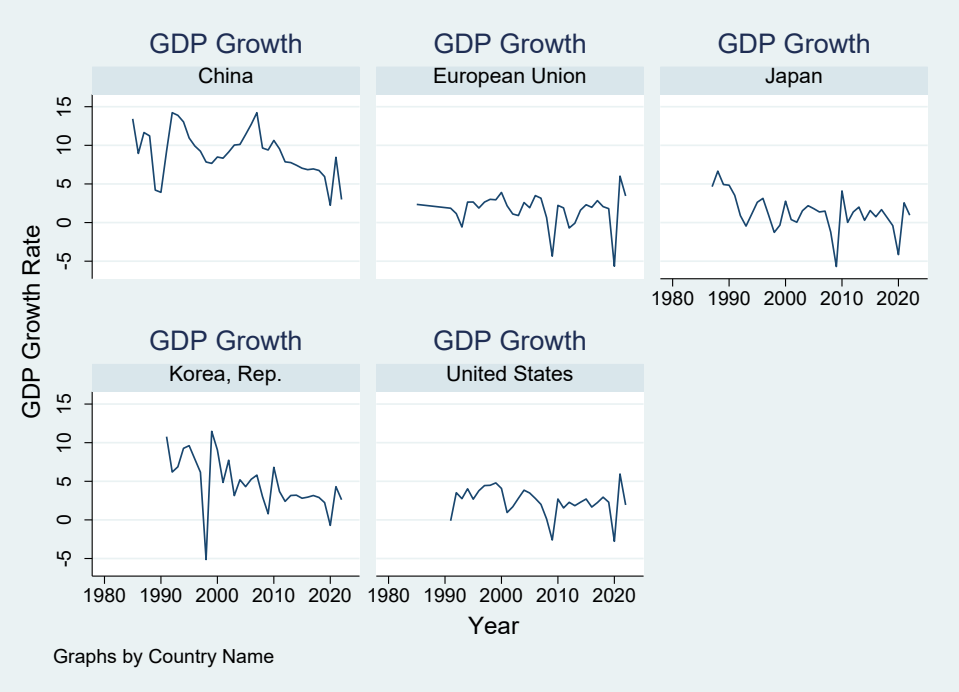


Figure 2 illustrates the trends in economic growth rates across the analyzed countries. China has exhibited high growth rates over the past 30 years, although it has recently shown a slowdown. Europe and Japan generally maintain positive growth rates, despite at lower levels. However, they occasionally record negative growth during abnormal shocks such as the Global Financial Crisis and COVID-19 Pandemic. The United States has demonstrated consistent growth, maintaining rates between 0% and 5%, with the exception of the global crises as other countries.

Since 1990, the starting point of the available data, South Korea has achieved high growth. It recorded high growth rates in the late 1990s and early 2000s except for the period of the Asian Financial crisis, but has recently seen lower rates. Notably, among the countries in the dataset, South Korea is the only nation that did not experience a recession during the Global Financial Crisis.

Table 3 presents the empirical findings of the fixed-effect panel regression analysis, which accounts for both country-specific and time-variant unobserved heterogeneity. The dependent variables vary across the specifications: Column (1) utilizes the growth rate of GDP (%GDPChange), Column (2) focuses on the growth rate of GDP per capita, and Column (3) examines Total Factor Productivity (%TFPChange).

The regression results demonstrate a robust and statistically significant positive relationship between Patent Efficiency, our qualitative proxy for innovation impact, and all three measures of economic performance. Specifically, a unit increase in patent efficiency is associated with a 1.200 percentage point increase in GDP growth and a 1.244 percentage point increase in GDP per capita growth, both significant at the 1% level.

[Table 3] Fixed-Effect Panel Regression

VARIABLES	(1) %GDPChange	(2) %GDP per capita Change	(3) %TFPChange
Patent Efficiency	1.200***	1.244***	0.018***
	(2.71)	(2.82)	(3.08)
Patent*GDP	-0.000***	-0.000***	-0.000***
	(-2.69)	(-2.73)	(-6.03)
Patent*Capital	0.002	0.002	-0.000
	(0.51)	(0.52)	(-0.49)
Patent*Trade	-0.001	-0.001	-0.000**
	(-0.15)	(-0.25)	(-2.12)
Patent*R&D	-0.315*	-0.328*	-0.001
	(-1.79)	(-1.87)	(-0.27)
GDP	0.000	0.000	0.000***
	(0.70)	(0.62)	(7.32)
FDI	0.036	0.041	0.009**
	(0.19)	(0.22)	(2.15)
Capital	-0.037	-0.039	0.000
	(-1.02)	(-1.09)	(1.12)
Inflation	0.073	0.076	0.002*
	(0.64)	(0.66)	(1.81)
Trade	0.062*	0.062*	0.001
	(1.80)	(1.79)	(1.32)
Credit	-0.017	-0.016	0.001***
	(-1.42)	(-1.35)	(4.20)
CO2	4.695	4.380	0.047
	(1.00)	(0.94)	(0.93)
R&D	-0.065	-0.046	-0.015
	(-0.08)	(-0.05)	(-0.96)
Constant	-1.417	-2.070	0.467***
	(-0.26)	(-0.38)	(7.73)
Observations	125	125	92
R-squared	0.7406	0.7339	0.8528
Number of id	5	5	4
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Furthermore, we explore the conditional effects of innovation through various interaction terms. Notably, the interaction between Patent and GDP is consistently negative and statistically significant across all columns (-0.000*), potentially indicating a "catch-up" effect or diminishing returns to patent efficiency in larger, more mature economies. Similarly, the interaction between Patent and R&D yields negative and significant coefficients in the growth models (-0.315* in Column 1 and -0.328* in Column 2), suggesting that the economic returns

to patent quality may decrease at extremely high levels of R&D expenditure, perhaps due to inefficiencies in knowledge diffusion or innovations from other technological advances excluding AI make the impact smaller. These results underscore the complexity of the innovation-growth nexus, highlighting that the economic impact of AI patents is modulated by a nation's existing economic scale and its research and development intensity.

Table 4 presents the results of the Arellano-Bond GMM Dynamic Panel Regression, a methodology employed to address potential endogeneity and capture the persistent nature of economic growth over time. Consistent with the earlier fixed-effect models, Patent Efficiency continues to exert a positive and statistically significant influence on both GDP growth (0.841*) and GDP per capita growth (0.978*), with both coefficients significant at the 1% level. Interestingly, while the impact on growth remains robust, the main effect of patent efficiency on Total Factor Productivity (%TFPChange) is not statistically significant in this dynamic specification (0.003), suggesting that the immediate growth effects might be driven by factors beyond immediate productivity shifts when accounting for lagged dependent variables. It is shown that the as in Table 3, GDP and R&D are the only variables that have interacting effects.

[Table 4] Arellano-Bond GMM Dynamic Panel Regression

	(1)	(2)	(3)
VARIABLES	%GDPChange	%GDP per capita Change	%TFPChange
Patent Efficiency	0.841***	0.978***	0.003
	(2.75)	(3.25)	(0.92)
Patent*GDP	-0.000*	-0.000*	-0.000**
	(-1.90)	(-1.96)	(-2.19)
Patent*Capital	-0.008***	-0.009***	-0.000***
	(-2.68)	(-2.89)	(-3.25)
Patent*Trade	0.001	0.001	-0.000
	(0.26)	(0.33)	(-0.89)
Patent*R&D	-0.226*	-0.285**	0.001
	(-1.83)	(-2.35)	(0.44)
GDP	0.000***	0.000***	0.000**

	(4.32)	(4.40)	(2.18)
FDI	0.274**	0.277**	0.003
	(2.10)	(2.16)	(1.20)
Capital	0.307***	0.309***	0.001***
	(12.66)	(12.98)	(6.69)
Inflation	0.060	0.077	0.001
	(0.71)	(0.92)	(1.41)
Trade	0.010	0.014	0.000
	(0.44)	(0.64)	(0.51)
Credit	-0.009	-0.009	0.000
	(-0.95)	(-0.98)	(1.16)
CO2	11.852***	11.152***	-0.011
	(3.49)	(3.34)	(-0.36)
R&D	0.235	0.502	-0.012*
	(0.40)	(0.87)	(-1.75)
L. %GDPChange	-0.128**		
	(-2.21)		
L. %GDP per capita Change		-0.147**	
		(-2.55)	
L.TFP			0.768***
			(11.43)
Constant	-9.686**	-10.639***	0.136***
	(-2.56)	(-2.85)	(3.21)
Observations	120	120	92
Number of id	5	5	4
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

Table 5 presents the results of the Dynamic System GMM Panel Regression, which further confirms the robust and positive impact of Patent Efficiency on all three measures of economic performance: GDP growth (0.728*), GDP per capita growth (0.897), and Total Factor Productivity (0.012). The results are consistent with what was shown in Table 3 and 4.

[Table 5] Dynamic System GMM Panel Regression

	(1)	(2)	(3)
VARIABLES	%GDPChange	%GDP per capita Change	%TFPChange
Patent Efficiency	0.728***	0.897***	0.012***
	(2.73)	(2.82)	(3.54)
Patent*GDP	-0.000***	-0.000	-0.000***
	(-3.07)	(-1.61)	(-8.34)
Patent*Capital	-0.010***	-0.009***	-0.000***
	(-3.48)	(-2.72)	(-4.89)

Patent*Trade	0.003	-0.001	0.000*
	(1.16)	(-0.16)	(1.87)
Patent*R&D	-0.189*	-0.247*	-0.001
	(-1.78)	(-1.93)	(-0.84)
GDP	0.000***	0.000***	0.000***
	(3.96)	(3.89)	(10.25)
FDI	0.124	0.251*	0.004
	(1.10)	(1.84)	(1.38)
Capital	0.332***	0.317***	0.001***
	(14.69)	(12.66)	(5.34)
Inflation	0.194**	0.033	0.002**
	(2.47)	(0.38)	(2.11)
Trade	-0.017	0.020	-0.000
	(-1.01)	(0.84)	(-1.03)
Credit	-0.021***	-0.004	0.000***
	(-2.73)	(-0.48)	(5.97)
CO2	0.305	0.355	-0.010
	(0.65)	(0.58)	(-1.27)
R&D	4.140***	9.933***	0.126***
	(4.20)	(2.83)	(3.98)
Constant	0.649	-10.337***	0.441***
	(0.42)	(-2.61)	(11.78)
Observations	125	125	96
Number of id	5	5	4
Firm FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes

V. Conclusion

This study provides empirical analysis that confirms that this qualitative innovation capacity, measured as Patent Efficiency, is a robust driver of national economic performance. Across multiple econometric specifications—including fixed-effect, Arellano-Bond GMM, and System GMM models—patent efficiency exerts a statistically significant positive effect on GDP growth, GDP per capita, and Total Factor Productivity (TFP). These findings underscore that the economic value of AI innovation is derived not from the sheer quantity of filings, but from the quality and subsequent "reference importance" of those patents within the global knowledge network. However, the research also identifies diminishing marginal

returns to innovation quality in economies with high capital accumulation and extreme R&D intensity, suggesting that structural maturity can modulate the impact of technological progress.

The future of Korea's competitiveness in the AI era depends on transitioning from a high-concentration, large-firm-led model toward a more diverse and inclusive innovation ecosystem that creates more values than volumes. Strategic policy interventions should focus on maintaining Korea's status as a global technology source while actively promoting the diffusion of knowledge from leading conglomerates to SMEs and academic institutions. By leveraging its high qualitative standing and addressing the structural constraints of its innovation architecture, Korea can ensure that its technological advancements translate into sustainable and broad-based economic growth.

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