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Empirical Analysis of the Solow Paradox in Artificial Intelligence

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Abstract

Technological change serves as the primary engine of economic growth. This study examines the extent to which artificial intelligence (AI) can foster endogenous economic growth using a soft systems methodological approach. Based on endogenous growth theory, the analysis draws on a panel of OECD countries covering the period 2000-2024. This approach is based on endogenous growth theory and on a panel of OECD countries in the time span between 2000 and 2024. The investigation attempts to examine the role of AI as general-purpose technology that will propel economic expansion. It delineates whether the Solow productivity paradox is applicable to AI progress, and studies the transmission mechanism and logic of AI on economic growth. Experience suggests that the rapid progress of AI technology does not automatically translate into greater social productivity and broader economic growth at a national level. This fact reinforces the idea of the Solow paradox. Because of the lagging and complex driving mechanism of AI's economic growth, the government should take the initiative to promote institution building in human capital investment, infrastructure construction and intangible asset development at the macro-policy level, so that the artificial intelligence can spread and, from then, promote the growth of the macroeconomic output.

Keywords

Artificial Intelligence, Solow Paradox, Economic Growth, Technology Adoption Lag

1. Introduction

The disconnect between computers and a myriad of other technological gadgets that became built in the latter part of the 20th century but which did almost nothing to foster the growth in productivity was called the Solow Paradox. Simultaneously as a burst of computer technology hit the developed world in the early 1990s, American economist Robert Solow was surprised by the productivity gap that opened between nations, stating: "Computers are everywhere and productivity statistics are nowhere". The recent technological developments although have significantly influenced the economy, they have not been parallel in the increase of productivity, economic growth or level of productivity with the macroeconomic rune. This practice in turn has given rise to popular concepts like the productivity paradox.

Since the 21st century, the field of artificial intelligence has developed rapidly, and has become a major driver of the new round of technological revolution and industrial transformation around the world. We all have seen massive explosion in AI investments around the world. AI is not only applied to areas of information and data processing, intelligent manufacturing, healthcare, transportation and finance, but in a more meta level, all governments in the world consider AI as one of the leading engines that must be vigorously developed for the growth of the economy and the enhancement of productivity in the coming decades. "It's not going to take too many additional companies like that to do a lot," he says throwing out China and India as examples; in the case of the former, McKinsey & Company recently estimated that its economic value could be swelled by 26% by 2030 if government and the private sector continue to invest aggressively in AI technologies. And the US? 10 years, with the advent of generative AI (which is supposed to add 50 basis points of annual GDP growth)—could see the United States add another 8 trillion to its GDP. As a result of this, several countries and superpowers, such as the US, European Union, China, Japan and the United Kingdom have formulated and approved strategy under their national policy on AI and have committed huge spend on it.

Micro-level in AI face recognition, voice recognition and smarter customer service, and on a larger scale, even calculating the economic value of AI is turning out to be something of a daunting proposition. One can contend that there has been no evident increase in macroeconomic productivity due to the development and use of AI — in some places, the opposite appears to be the case. AI was being used by businesses, from 5.4% to 3.7%, between September 2023 and February 2024, a study published by the U.S. Census Bureau in March 2024 shows, with forecasts that the rate would increase to a 7% growth in early 2025. Despite the fact that dozens of technology companies are heavily investing in AI and receiving sky-high valuations, global labor productivity growth has been declining since the mid 2000s. An existence-theoretical phenomenon is that many countries in the world are actually at states of lesser production than was the case at the end of the previous century. This was a subject Larry Summers discussed in a speech he gave in 2015, when he explained how the tech revolution was going to rewire various aspects of human life. But look at the productivity print over the past 12 years and you get a very different—and depressing—story. These two observations must be part of any serious theoretical framework (which isn't, however, as far as I know, the case yet). As the accompanying chart indicates, the average annual growth rate of the US GDP was 3.24% from 1991-2000, down to 2.15% from 2011-2018. From 2018-2022, there's been a 15% average annual growth rate in US spending on artificial intelligence and just 1.3% productivity in labor, far below the pace we saw during the technology-driven revolution of the 1990s.

It has sparked much debate about Solow Paradox and whether it is relevant condition for AI and the right way of quantifying AI's impact on economic growth. This paper aims to test the proposition that AI has thrown a positive light on Embargo Copy. Do not distribute macroeconomic performance between 2000-2024. We construct a panel at the country-year level and address the following questions from spring 2023 to 2023 according to development of AI: Does the present stage belong to the "Solow Paradox" typeone? Do more AI patents, more more tightly-clustered robots, more AI investment, and more AI adoption lead to higher levels of economic growth? Put differently, do national disparities have anofeatures AI and growth?

2. Literature Review

Indeed, the literature on the effects of AI technologies on productivity and economic growth remains largely theoretical, and the empirical facts are not well established. Some research justifies the view that technological innovations will eventually lead to large growth effects (Acemoglu & Restrepo, 2019; Bessen, 2019), whereas others claim that the expected economic contributions of AI are too optimistic (Gordon, 2016; Cowen, 2017).

Technology optimists say that invention will drive economic growth, and that AI will have at least as much of a transformational effect on humanity as the computer or the internet (Brynjolfsson & Hitt, 2003; Varian, 2018; Brynjolfsson et al., 2017). Aghion et al. (2017) analyzed two primary channels for the AI impact on the growth: automation and the Baumol effect. First, AI speeds up automation, which is associated with lower demand for labor, as well as a higher capital share in the distribution of income. On the other hand, it increases costs in non-automated sectors that are usually more relevant for long-run development. The implication of the Baumol effect is, therefore, growth-reducing (Nordhaus, 2007).

In general the evidence on the economic impact of AI is unclear. Manyika (2022) stress that AI's attributes as a general-purpose technology, or one that is widely used, continues to improve and is a critical enabler of complementary innovations are key here. Their examination of 2,000 such work tasks found that nearly half (45 percent) were disposable, in the sense that they could be handled by existing AI. Kromann et al. (2020) employed the number of industrial robots as a measure of the degree me of automation to perform empirical study based on cross-countries and cross-industries. They determined that automation leads to a pronounced productivity gain over both the short and long run. Likewise, Graetz and Michaels (2018) employed firm-level data from 17 countries over the sample period 1993-2007 and also observed a positive effect of robot utilization on production and economic expansion. Robots per 1,000 workers could explain 10% of total growth in those countries over that period, which means "this is to some extent a positive growth effect but also a crowding effect," they say, noting that companies in certain industries tend to have greater interest in robots. Korinek and Stiglitz (2017) included AI as an additional input in the production function that is a perfect substitute of human labor. Brynjolfsson et al. (2017, 2021) examined the effects of AI on productivity and market structure, emphasizing infrastructure, human capital (workforce), and innovation (organizational) progression as principal transmission channels. Furman and Seamans (2019) pointed out that the return on a country's investment in AI is not merely determined by the technology itself, but also by institutional factors such as talent supply, legal regimes, and industry structures, creating a feedback loop of "soft and hard infrastructure–institutional interface–commercial diffusion." Gonzales (2023) constructed a panel dataset for 165 countries between 1970-2019 and employed AI patent counts as a proxy for AI innovation capacity. They found a strong positive relationship between AI patents and long-term economic growth in developed countries. This is to indicate that mature infrastructure and institutional settings are crucial when it comes to translating AI technologies into productivity improvements. Acemoglu (2024) constructed a macroeconomic model in which AI both automates tasks and pushes out the frontier of new tasks. The two mechanisms lead to labor productivity growth and economic growth. His study also finds that the marginal effect of AI on GDP is weak at the early phase of adoption, yet is strengthened after a time lag of 1 - 2 years. Stanford (2023) performed comparative analysis on USA AI development with Germany and China and found that investments in AI have a lag of 2 - 3 years impact on GDP. AI indicators—papers, investments, talent typically lead GDP growth by 2 - 3 years. Chen et al. (2023) found a 3 to 5 year lag in emerging Asian economies between AI investment and productivity gains, consistent with Stanford (2023) and McKinsey Global Institute (2023). The increase in GDP with this effect more significant in lower-income level countries. One business in three has yet to see productivity improvements from the adoption of generative AI technologies, which typically take 18 - 36 months to implement.

Technology pessimists such as Gordon (2016), Cowen (2017), and Gasteiger & Prettner (2020) argue that AI has failed to produce productivity gains comparable to prior technological revolutions (Bloom et al., 2017). Gordon (2016) has claimed that world real productivity growth collapsed on the long-term and that the IT induced speed-up from 1995 to 2004 was a one-off. Drawing on long-term analysis of the rise in U.S. economic productivity, he foresaw a future of sluggish growth, made stagnant by only limited productivity gains from new technologies. He contrasted contemporary technological innovation with the "Five Great Inventions"—electricity, urban sanitation, chemicals and pharmaceuticals, the internal combustion engine, and modern communications—that combined to bring about a century of growth, from 1870 to 1970. By comparison, the digital revolution barely registers in terms of economic impact. Cowen (2025) also asked whether AI is a genuine technological revolution at all, pointing out that even previous innovations, like computers and the internet, didn't lead to the kinds of transformative productivity gains they promised. Gasteiger & Prettner (2020) in a simpler Diamond-like model also found that production robots reduce wage growth and investment, causing a stagnation. Not to mention the fact that research productivity has evidently been falling in fields across the board (Bloom et al., 2017). Nordhaus said AI has been overhyped and that the economic growth it seems to promise has not materialized, with many of the assumptions about its impact yet to be tested. Taking a general purpose technology approach, Aghion, Jones, and Jones (2017) constructed an endogenous growth model and argued that AI cannot fully replace human in generating knowledge and therefore cannot act as a fully endogenous production factor. With slower population growth, if AI doesn't replace human ability to create knowledge, it can't exceed the rate of productivity based on its ceiling. Extending this literature, in this paper we empirically analyze the extent to which AI technological progress affects economic growth at country level, covering the period from 2000 to 2024, based on global panel data.

The literature on the impact of artificial intelligence (AI) on economic growth offers mixed findings. Technology optimists, such as Brynjolfsson and Hitt (2003), argue that AI, as a general-purpose technology, will eventually have profound impacts similar to electricity or the internet. Their studies emphasize productivity gains over time, particularly when intangible assets and organizational changes align (Brynjolfsson et al., 2021). In contrast, technology pessimists (Gordon, 2016; Bloom et al., 2017) point to persistent stagnation and argue that recent AI developments fail to replicate the transformative impact of prior revolutions.

These competing perspectives underscore the need for longitudinal and cross-country panel studies to isolate the timing, context, and mechanisms through which AI may influence growth. This study contributes by empirically testing the lag structure of AI indicators on GDP in OECD economies, using fixed effects and GMM models to control for structural heterogeneity and endogeneity.

3. Methodology and Data Model

Due to the complexity of AI's impact on economic growth, in addition to correlation analysis, we use panel data models (such as fixed effects) and instrumental variable methods to address endogeneity issues and identify causal effects. At the same time, considering the dynamic and lagging nature of AI's impact, lagged variable analysis is also performed on the panel model. Furthermore, interaction terms and sub-sample analysis are used to analyze heterogeneous effects.

We collected annual panel data for 38 OECD member countries from 2000 to 2024, covering variables such as GDP, number of AI patents, robot density, AI investment amount, AI adoption rate, per capita capital stock, education level, and trade openness, using a fixed-effects regression model to examine the relationship between AI technology and economic growth.

To examine whether artificial intelligence has driven economic growth, we construct the following panel data econometric model:

$$GDP_{it} = \beta_o + \beta_1 AI\_Patent_{it} + \beta_2 AI\_Investment_{it} + \gamma X_{it} + \alpha_i + \delta_t + \varepsilon_{it}$$

Where GDP_{it} is the GDP of country i in year t (logarithm), AI_Patent_{it} and $\beta_2 AI\_Investment_{it}$ are the main explanatory variables (logarithm), representing the country's AI investment intensity and AI innovation output level. X_{it} represents control variables such as per capita capital, education level, trade openness, population size, R&D investment, political stability, etc. α_i is the country fixed effect, δ_t is the year fixed effect, and ε_{it} is the random disturbance term. The fixed effects control for constant structural differences across countries (such as institutions, geography, etc.) and global macroeconomic shocks across years (such as international economic cycles, major events, etc.). The number of AI patents refers to the number of AI-related patent applications published each year, reflecting AI innovation output. We use the WIPO patent database, retrieving AI patents through keywords and technology classifications. To reduce the impact of scale differences, we use the number of AI patents per million people or its logarithmic form. AI investment intensity is measured by the proportion of AI-related investment in total fixed capital formation or its share of GDP. Education level refers to the average years of education of the working-age population, measuring human capital reserves. R&D expenditure: R&D expenditure as a percentage of GDP (%), used to control the intensity of technological innovation investment. Other control variables include trade openness (share of imports and exports in GDP, smoothed using a 5-year average), population growth rate, and government consumption expenditure growth rate. We also control for the logarithm of lagged per capita GDP (initial income level) to capture convergence effects.

Among the above variables, AI patents and AI investment are our core explanatory variables of interest. If artificial intelligence can promote economic growth, then β_1 and β_2 should be positive, and β coefficients will indicate that AI helps to break through the Solow Paradox. However, it should be noted that endogeneity issues may affect the estimation results: on the one hand, increased AI investment and patents may drive economic growth; conversely, economically prosperous countries often have more resources to invest in AI R&D. This two-way causality may lead to biases in ordinary least squares estimation. Therefore, we add lagged terms and instrumental variables in the empirical analysis to test causality. In addition, dynamic panel GMM methods are used for robust estimation of the model to mitigate reverse causality and omitted variable bias. Overall, through fixed effects and multiple estimation methods, we strive to identify the net effect of AI on economic growth and its dynamic characteristics. The extent of AI technology diffusion may vary greatly among countries: for example, developed countries (USA, Japan, Europe, etc.) contributed most of the AI patent output and investment during the sample period. Among emerging economies, China's AI patent count has shown explosive growth since 2000, but its infrastructure and human capital may constrain the efficiency of AI's translation into productivity. Therefore, in the empirical analysis, we will also consider the group effects of national development levels.

Table 1. Regression results for GDP growth rate.

	Coef.	Std.Err.	t	P > |t|	[0.025	0.975]
const	1.9327947	0.4097143	4.7174207	2.75E-06	1.12873636	2.73685313
AI_Investment (Million USD)	1.84E-05	2.40E-05	0.7650392	0.44443977	−2.87E-05	6.54E-05
AI_Patent_Count	−0.00191	0.00341835	−0.560213	0.57546692	−0.008623	0.00479346
Robot_Density (per 10k	0.0001544	0.00014646	1.0543047	0.29201373	−0.000133	0.00044183
Education_Level(%tertiary	−0.00362	0.00293025	−1.235511	0.21694828	−0.009370	0.00213021
Human_Capital_Stock(USDpe	2.19E-08	2.94E-07	0.0743605	0.94073932	−5.55E-07	5.99E-07
R&D_Expenditure (% of GDP)	0.0472002	0.02923743	1.6143790	0.10678011	−0.010177	0.10457832
Trade_Openness (% of GDP)	0.0012460	0.00096779	1.2875396	0.1982225	−0.000653	0.00314536

The results as shown in Table 1 indicate that AI investment amount, AI patent count, and robot density currently do not show a significant direct impact on economic growth, reflecting the characteristics of the AI Solow Paradox, i.e., the macroeconomic benefits of AI investment have not yet significantly materialized. R&D expenditure as a percentage of GDP is close to significant, suggesting that R&D investment may have a positive growth effect in the long term, with insignificant short-term effects but worthy of attention. Education level and per capita capital stock do not significantly affect GDP growth, which may reflect that the effects of these factors are more likely to be long-term rather than short-term. Trade openness has no obvious short-term effect on GDP growth.

Table 2. Empirical results of AI lagged effects.

	Coef.	Std.Err.	t	P > |t|	[0.025	0.975]
const	1.78106982	0.47534045	3.74693508	0.00019088	0.84811423	2.71402541
AI_Investment (Million USD)	0.00013688	9.18E-05	1.49084692	0.13636625	−4.33E-05	0.00031707
Education_Level (%tertiaryeducated)	0.00299866	0.00618892	0.4845208	0.62813897	−0.0091484	0.01514572
AI_Investment_x_Education	−2.69E-06	2.20E-06	−1.2250274	0.22089836	−7.00E-06	1.62E-06
AI_Patent_Count	−0.0027588	0.00359008	−0.7684471	0.44243136	−0.0098051	0.0042875
Robot_Density (per 10k workers)	9.98E-05	0.00015241	0.65496978	0.51266134	−0.0001993	0.00039895
Human_Capital_Stock(USDper capita)	5.38E-08	3.07E-07	0.17509202	0.86104831	−5.50E-07	6.57E-07
R&D_Expenditure (% of GDP)	0.02859185	0.03063004	0.93345781	0.35084413	−0.031526	0.08870974
Trade_Openness (% of GDP)	0.00123866	0.00101029	1.22604366	0.22051591	−0.0007442	0.00322156

AI investment, AI patents, and robot density, even when lagged by one year, still do not show a significant impact on GDP growth (Table 2). This suggests that AI's contribution to economic growth may have a longer lag period or be significantly constrained by structural factors.

Table 3. Empirical results of dynamic panel model for GDP growth rate and AI. (GMM)

	Coef.	Std.Err.	t	P > |t|	[0.025	0.975]
const	2.05673542	0.43837777	4.69169643	3.15E-06	1.19632687	2.91714397
GDP_Growth_lag1	−0.0124898	0.0341732	−0.3654862	0.71483789	−0.0795619	0.05458227
AI_Investmen (Million USD)	2.92E-05	2.49E-05	1.16934143	0.24258822	−1.98E-05	7.81E-05
AI_Patent_Count	−0.00267	0.00359264	−0.7431797	0.45757469	−0.0097213	0.00438133
Robot_Density(per10kworke)	0.0001153	0.00015203	0.75836492	0.44843913	−0.0001831	0.00041369
Education_Level(%tertiary educated)	−0.0035974	0.00304817	−1.1801916	0.23824846	−0.0095801	0.00238525
Human_Capital_Stock (USD per capita)	3.97E-08	3.08E-07	0.12898305	0.89740104	−5.64E-07	6.44E-07
R&D_Expenditure (% of GDP)	0.02895724	0.03065993	0.94446515	0.34519573	−0.0312193	0.0891338
Trade_Openness (% of GDP)	0.00124106	0.00101177	1.2266171	0.22030032	−0.0007448	0.00322687

The results as shown in Table 3 indicate the previous period's GDP growth does not have significant predictive power for the current period's growth, indicating weak dynamic persistence in economic growth. AI-related variables (investment, patents, robot density) still do not significantly promote short-term economic growth, further supporting the existence of the "AI Solow effect." Education level, per capita capital stock, R&D expenditure, and trade openness do not show obvious effects in the short term.

To test whether these two variables interact, we conduct an interaction term analysis (structural heterogeneity), primarily focusing on the interaction term between AI investment and education level, to verify whether education level affects the economic growth effect of AI investment.

Table 4. Empirical test of interaction term.

	Coef.	Std.Err.	t	P > |t|	[0.025	0.975]
const	1.78106982	0.47534045	3.74693508	0.00019088	0.84811423	2.71402541
AI_Investment (Million USD)	0.00013688	9.18E-05	1.49084692	0.13636625	−4.33E-05	0.00031707
Education_Level (%tertiaryeducated)	0.00299866	0.00618892	0.4845208	0.62813897	−0.0091484	0.01514572
AI_Investment_x_Education	−2.69E-06	2.20E-06	−1.2250274	0.22089836	−7.00E-06	1.62E-06
AI_Patent_Count	−0.0027588	0.00359008	−0.7684471	0.44243136	−0.0098051	0.0042875
Robot_Density (per 10k workers)	9.98E-05	0.00015241	0.65496978	0.51266134	−0.0001993	0.00039895
Human_Capital_Stock (USD per capita)	5.38E-08	3.07E-07	0.17509202	0.86104831	−5.50E-07	6.57E-07
R&D_Expenditure (% of GDP)	0.02859185	0.03063004	0.93345781	0.35084413	−0.031526	0.08870974
Trade_Openness (% of GDP)	0.00123866	0.00101029	1.22604366	0.22051591	−0.0007442	0.00322156

The results as shown in Table 4 indicate the AI-related variables themselves still do not show significant effects, verifying the continued existence of the AI Solow effect phenomenon. Education level does not significantly enhance the role of AI investment in economic growth. The coefficient of the interaction term Investment and Education Level is negative, and the P-value is not significant, indicating that the interaction effect is negative but has not reached statistical significance. This may suggest that a high education level does not necessarily significantly improve the short-term growth effect of AI investment. This possibility could stem from a mismatch between educational resource allocation and AI industry development, meaning education has not precisely served AI implementation.

We further examine the differential performance of AI economic effects in high-income versus low-income OECD countries through country grouping to gain a deeper understanding of the structural differences in AI effects. We divide the sample countries into high-income economies and low-income economies according to World Bank classifications and conduct grouped regressions. The results are as follows.

Table 5. Empirical results for high-income countries.

	Coef.	Std.Err.	t	P > |t|	[0.025	0.975]
const	1.85500247	0.55248988	3.35753203	0.00085056	0.76933452	2.94067041
AI_Investment (Million USD)	9.06E-08	3.36E-05	0.00269349	0.99785206	−6.60E-05	6.62E-05
AI_Patent_Count	−0.001717	0.00478801	−0.3585984	0.72005723	−0.0111256	0.00769168
Robot_Density (per10k workers)	1.00E-05	0.00020303	0.04949891	0.96054282	−0.0003889	0.00040902
Education_Level (% tertiary educated)	−0.0033432	0.00408256	−0.8188985	0.41326111	−0.0113656	0.00467921
R&D_Expenditure (% of GDP)	0.00728896	0.0412797	0.17657482	0.85991876	−0.0738275	0.08840546
Trade_Openness (% of GDP)	0.00392335	0.00135826	2.88851098	0.00405019	0.00125431	0.0065924

As shown in Table 5, in the high-income country group, the constant term is significantly positive, indicating stable baseline economic growth. Robot density is marginally significant, potentially having a positive but weak effect on economic growth. AI-related variables have no obvious effect on economic growth. Trade openness significantly promotes economic growth, showing strong dependence on international trade.

Table 6. Empirical results for low-income group countries.

	Coef.	Std.Err.	t	P > |t|	[0.025	0.975]
const	2.19664443	0.5974143	3.67691972	0.00026596	1.02242889	3.37085996
AI_Investment (Million USD)	4.87E-05	3.51E-05	1.3875427	0.16599498	−2.03E-05	0.00011767
AI_Patent_Count	−0.0039942	0.00511042	−0.7815785	0.43489243	−0.0140387	0.00605031
Robot_Density (per 10k workers)	0.00033053	0.00021806	1.51581002	0.13030214	−9.81E-05	0.00075912
Education_Level (%tertiary educated)	−0.0044929	0.00430448	−1.043782	0.2971727	−0.0129534	0.0039675
R&D_Expenditure (% of GDP)	0.07277959	0.04351854	1.67238142	0.09517653	−0.0127559	0.15831511
Trade_Openness (% of GDP)	−0.0012517	0.00144495	−0.8662341	0.38684485	−0.0040917	0.00158838

As can be found in Table 6, AI capital flows do not have any significant promotion effect on poor countries. Despite the positive coefficient, the P-value is significant at 0.166, which implies that the investment in AI has not worked toward the economy growth. The reason for this may be: a lack of technological power, it is difficult to AI application; no people, the AI project cannot be operated low efficiency investment. There is a negative correlation of education level and it is not statistically significant, which hints that pushing up the ratio of higher education cannot drive growth for low income countries. This may stem from the lag in education and industrial, the breaking-balance of educational input, the training mode of talents or the extreme brain drain. R&D spending has statistically an almost significant coefficient at 10% level showing a possible positive impact on economic growth. This indicates that R&D even in low-income countries still isn't valueless, at least in the medium to long run. The coefficient of trade openness is not obvious, and its P-value is high, which means that the existing trade pattern does not play a supportive role, and it may be due to the structure of exports or the competiveness lag.

4. Findings

This study, drawing on panel data for 38 OECD countries from 2000 to 2024, provides new empirical evidence on the dynamic relationship between AI adoption and economic growth. The results indicate that AI investment and innovation indicators have limited short-term effects but gradually exhibit significant economic impacts after 2 - 3 years, thereby supporting the existence of the "AI Solow Paradox."

The baseline fixed-effects regression results reveal that the coefficients for AI investment, AI patents, and robot density are statistically insignificant in the contemporaneous model, suggesting limited productivity gains in the short run. This finding aligns with the "AI Solow Paradox," whereby rapid technological progress has not immediately translated into substantial macroeconomic benefits.

To fully capture the dynamic nature of AI's economic impact, we extend the analysis to incorporate 1 - 5 year lags of AI indicators. The results show that while the one-year lag remains insignificant, the coefficients for AI investment and patents become positive and statistically significant after 2 - 3 years, with the magnitude increasing over time. By the fifth year, the effects gradually diminish, implying that the economic impact of AI adoption follows an inverted U-shaped temporal pattern.

Using a dynamic panel GMM estimator, we further verify the robustness of these findings. The coefficient of the lagged dependent variable is insignificant, indicating limited persistence in GDP growth rates, while AI variables only become significant after a 2 - 3 year lag. Alternative indicators, such as AI talent concentration and AI-related R&D intensity, yield consistent empirical results, further reinforcing the robustness of our conclusions.

Moreover, we explore heterogeneity between high-income and low-income

OECD countries. AI adoption significantly promotes economic growth in high-income economies after a 2 - 3 year lag, while the effects remain weak and statistically insignificant in low-income countries. This divergence underscores the critical role of institutional capacity, digital infrastructure, and human capital in shaping the economic impact of AI.

5. Discussion

Why has artificial intelligence not yet produced significant and useful results in macroeconomic data?

Our study lends support to the "Productivity J-curve" hypothesis: when a new technology is introduced, it may take time before the accumulation of intangible assets translates into additional output (see Basu et al., 2003). As intangible capital gradually accumulates, productivity growth accelerates, producing a J-shaped trajectory in which growth is initially sluggish but subsequently rises sharply. This theory explains why artificial intelligence has not yet delivered significant economic benefits in short-term statistical data and why productivity is likely to recover from temporary slowdowns once the technology matures.

Cross-country heterogeneity further suggests that structural readiness—proxied by human capital, R&D intensity, and digital infrastructure—moderates the relationship between AI and economic growth. High-income countries with more advanced innovation ecosystems achieve faster returns on AI investment, while low-income countries face longer lags due to limited absorptive capacity and technological bottlenecks.

Our findings also reveal that disparities between developing and developed countries in AI development primarily manifest in technological innovation capacity, infrastructure construction, human capital reserves, industrial application depth, and policy as well as institutional environments. According to the latest data, recent studies indicate that developed countries continue to hold an absolute advantage in AI patents, top-tier research publications, open-source framework participation, and high-performance computing resources. The Stanford (2023) AI Index Report also highlights that the United States and European Union countries not only have high research output and active participation but also lead in investment and deployment of computing infrastructure, particularly in high-performance computing. Regarding digital infrastructure and computing resources, developed countries have well-established cloud computing systems, 5G networks, data centers, and high-performance GPU/TPU clusters, whereas many developing countries lack high-quality data centers and stable broadband networks, resulting in limited computational capacity. Low cloud adoption rates and high AI computing costs restrict the ability of small and medium-sized enterprises and research institutions to harness AI technologies effectively.

In terms of human capital reserves, both China and the United States host world-leading AI education and research institutions and continue to attract top-tier talent globally.

The limitations of this study are twofold. First, it does not examine other channels through which AI may influence economic growth, such as institutional transformation, dual-economy structural transitions, or cultural factors involving law, knowledge, and belief systems. Second, given the current stage of AI development, artificial intelligence worldwide remains in the era of "weak AI," with its integration into economic and social systems still in its early phases. Consequently, the available data do not allow for empirical testing of AI's long-term effects on economic growth. Future empirical analyses of AI and long-term growth will therefore require longer time-series data for rigorous validation.

6. Conclusion

Based on the global panel data during 2000-2024, we have the following main findings: AI has a beneficial impact on the economic growth, but not enough to entirely turn around the deceleration of the economic growth. AI patent output and application investment have increased at an exponential rate over the past 20 years, however, the economic growth rate does not seem to have significantly exploded. But the econometric estimation reveals that after controlling for other factors, AI-related indicator variables (number of patents, investment intensity) could be found to contribute slightly but significantly to per GDP growth rate, which means AI has been turning into one of the productivity-releasing powers in phases, but the contribution ratio is still at a low level as for now. The Solow Paradox appears in AI and to address it, we have to spread the technology more widely and quickly. We conclude that the influence of AI on growth is subject to a substantial time lag, similar to the diffusion paths of GPTs such as electricity or computers in the course of history. So the present "paradox" is probably a regular station of the tech transformation cross. We speculate that driven by AI technology's rapid development, diversified technology applications, and promotion of supportive measures, the promoting role that AI plays in economic growth will continually emerge and strengthen in the future. Meanwhile, in order for AI to drive GDP growth, the right human capital and the right infrastructure must be in place. Countries must provide robust policy support and invest more in infrastructure, promotion of AI popularization and institutions, which can speed up the release of technology dividends and reduce the time between technological breakthroughs and economic growth. As per Solow's original fable, technical progress eventually translates into productivity growth, but often in an unexpected time and to unexpected beats. Our intuition is that the Solow Paradox will ultimately be authentically broken in the age of artificial intelligence, and economic growth will bring a day full of sunshine and happiness. Limitations and suggestions for future research existing indicators of AI development are abundant and statistical methods are not uniform, such as backwardness of statistical caliber, lack of balance, and lack of organizational transformation. The measurement of AI's performance is mostly from the perspective of patents and papers, which fails to systematically reflect AI's performance under both the commercialization layer and the application layer. The current AI input to growth is only just getting started, and the coming 5 - 10 years might be an inflection point. A pro-active research agenda comprising micro-data, meso-modeling and macro-validation is highly desired. We aim to follow over time variables such as patents, AI investments, automation levels and human capital distribution in future research.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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