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The Illusionary Model of Relative Economic Growth in the Era of Artificial Intelligence

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Abstract

Artificial Intelligence (AI) is increasingly viewed as a major driver of productivity growth and economic transformation. This paper challenges the assumption that AI-related technological expansion necessarily generates widespread macroeconomic productivity gains. Drawing on endogenous growth theory and the productivity paradox literature, it introduces the Relative Economic Growth Illusion (REGI) framework, which argues that contemporary AI-driven growth may operate through concentrated and intangible-intensive economic structures rather than through broad productivity diffusion across the economy. Using cross-country evidence from OECD Productivity, OECD STAN, OECD Patents, INTAN-Invest, and Functional Urban Areas (FUAs) databases, the study combines descriptive analysis with panel and robust regression techniques to examine the relationship between AI innovation, productivity, and intangible capital accumulation. The results show that AI patent intensity has weak and statistically insignificant associations with aggregate Total Factor Productivity (TFP), while intangible capital accumulation remains strongly linked to localized sectoral productivity gains. Evidence also reveals a marked geographical concentration of AI-related innovation within a limited number of technologically advanced economies. These findings suggest that AI-driven technological progress generates localized efficiency improvements while diffusing only weakly across the broader economy. As a result, observed economic expansion may increasingly reflect concentrated growth driven by intangible capital and technological concentration rather than broad-based productivity improvements.

JEL classification numbers: O33, O47, D43.
Keywords: Artificial Intelligence, Economic Growth, Productivity Paradox, Intangible Capital, Market Concentration, Technological Diffusion, Relative Growth.

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1. Introduction

Technological revolutions have historically been associated with expectations of accelerated productivity growth, structural transformation, and long-run economic prosperity. From industrial mechanization and electrification to the diffusion of digital computing, economic theory has traditionally considered technological innovation the principal driver of sustained economic expansion (Schumpeter, 1934; Solow, 1957; Romer, 1990). Within this historical framework, Artificial Intelligence (AI) is increasingly presented as the next major General Purpose Technology (GPT), capable of reshaping production systems, labor markets, and global competitiveness on an unprecedented scale (Brynjolfsson & McAfee, 2014; Cockburn et al., 2018). Over the last decade, the rapid diffusion of machine learning systems, predictive algorithms, and generative AI models has fueled growing optimism among policymakers, multinational corporations, and financial institutions regarding the future trajectory of economic growth. Recent estimates from international organizations and private financial institutions project that AI could contribute trillions of dollars to global GDP through automation, efficiency gains, and accelerated innovation (Goldman Sachs, 2023; International Monetary Fund [IMF], 2024). Under this dominant narrative, AI is expected to reverse the productivity slowdown that has characterized many advanced economies since the global financial crisis while simultaneously generating broad improvements in living standards and economic efficiency. However, despite extraordinary increases in AI-related investment and financial valuation, empirical evidence supporting a generalized macroeconomic productivity revolution remains limited. While AI-intensive firms have experienced substantial gains in market capitalization, operational efficiency, and revenue growth, aggregate productivity growth across advanced economies has remained comparatively weak (Gordon, 2016; Acemoglu, 2021). At the same time, labor income shares have declined, wage growth has stagnated across several middle-income occupations, and market concentration has intensified within highly digitized industries (Autor et al., 2020; De Loecker et al., 2020). This divergence between localized technological success and weak aggregate economic dynamism raises a central theoretical question: Does Artificial Intelligence generate broad productive expansion, or does it primarily redistribute economic gains toward techno-logically dominant firms and sectors?

This paper argues that the contemporary AI economy increasingly reflects what we define as a Relative Economic Growth Illusion (REGI). Under this framework, AI-driven growth is not necessarily associated with proportional increases in aggregate productive capacity across the wider economy. Instead, algorithmic technologies generate asymmetric gains concentrated among firms possessing superior computational infrastructures, proprietary datasets, network advantages, and access to intangible capital. Consequently, economic expansion appears substantial at the microeconomic and financial level while remaining structurally constrained at the macroeconomic level. Aggregate growth indicators may therefore partially reflect valuation effects, market concentration, and financialized expectations rather than broad improvements in real productive output and collective welfare (Haskel & Westlake, 2018; Stiglitz, 2019). The theoretical intuition behind this argument derives from the structural characteristics of AI-driven digital capitalism. Unlike previous industrial technologies, AI systems exhibit strong economies of scale, low marginal replication costs, and significant network externalities, dynamics that naturally favor winner-take-all market structures (Varian et al., 2004; Khan, 2017). Firms controlling cloud infrastructures, computational capacity, and large-scale datasets acquire cumulative competitive advantages that reinforce oligopolistic concentration and capital accumulation (Srnicek, 2017). Under these conditions, technological efficiency gains may remain localized within dominant firms while failing to diffuse throughout the broader productive system. Simultaneously, automation processes may compress labor demand in routine occupations and weaken aggregate demand dynamics, particularly when productivity gains are not redistributed across households and non-digital sectors (Acemoglu & Restrepo, 2019). This paper therefore introduces a distinction between absolute growth and relative growth. Absolute growth refers to broad-based expansion in productive capacity, rising real incomes, increasing aggregate demand, and widespread welfare improvements. Relative growth, by contrast, refers to redistributive gains generated through competitive displacement, efficiency asymmetries, and market concentration. Under AI-driven capitalism, technologically advanced firms may substantially outperform competitors without proportionally increasing total aggregate output. Growth consequently becomes concentrated within a limited number of technological hubs, while non-technology sectors experience stagnation, declining labor shares, and weak productivity diffusion. In this context, conventional macroeconomic indicators may systematically overestimate the transformative productive effects of Artificial Intelligence. The concerns surrounding automation and technological displacement are not entirely new. Keynes (1930) warned about the emergence of “technological unemployment” resulting from labor-saving innovations capable of outpacing the economy’s capacity to generate new forms of employment. More recently, Acemoglu and Restrepo (2019) demonstrate that automation technologies may reduce labor demand when technological progress substitutes rather than complements human labor. Similarly, Frey and Osborne (2017) estimate that a substantial proportion of existing occupations remain vulnerable to algorithmic substitution. These perspectives challenge the assumption that technological progress necessarily produces broad and evenly distributed macroeconomic prosperity. This study contributes to the literature in four principal ways. First, it introduces the concept of the Relative Economic Growth Illusion (REGI), providing a theoretical framework capable of distinguishing between localized technological gains and broad macroeconomic productivity expansion. Second, the paper extends a Romer-style endogenous growth model by incorporating AI-induced market concentration, asymmetric capital accumulation, and cross-sectoral productivity divergence. Third, it empirically evaluates the relationship between AI adoption, firm-level performance, market concentration, and aggregate productivity using cross-sectoral evidence from advanced economies. Finally, the paper develops counterfactual macroeconomic simulations demonstrating that, in the absence of redistributive and competitive policy interventions, AI-driven efficiencies may weaken long-run aggregate demand and intensify wealth polarization rather than sustain inclusive economic growth. The remainder of this paper is organized as follows. Section 2 reviews the literature on AI-driven productivity, technological stagnation, intangible capital accumulation, and market concentration dynamics. Section 3 presents the theoretical framework and empirical methodology underlying the Relative Economic Growth Illusion (REGI) model. Section 4 discusses the empirical results, including descriptive evidence, regression estimates, and concentration dynamics associated with AI-related innovation and intangible capital accumulation. Section 5 examines the broader economic and policy implications of the findings, with particular attention to competition policy, technological diffusion, and distributive governance in the AI era. Section 6 concludes.

2. Literature Review

2.1 Artificial Intelligence and Productivity Expectations

The economic literature on Artificial Intelligence has increasingly framed AI as a transformative technology with the potential to affect productivity, innovation, and firm organization. Early research on information technologies emphasized that digital systems can improve productivity when they are combined with organizational restructuring, complementary investment, and managerial adaptation (Brynjolfsson & Hitt, 2000; Jorgenson, 2001). More recent contributions extend this logic to AI, suggesting that machine learning and predictive systems may reduce the cost of prediction, improve decision-making, and reorganize production processes across firms and sectors (Agrawal et al., 2019; Goldfarb et al., 2022). However, this optimistic interpretation is not unconditional. Schumpeterian approaches stress that the growth effects of AI depend heavily on the institutional and competitive environment. Aghion et al. (2019) argue that AI may spur growth by substituting capital for labor in both production and idea generation, but they also emphasize that AI can inhibit growth when combined with inappropriate competition policy or excessive concentration. Thus, the literature does not imply that AI automatically generates broad macroeconomic prosperity; rather, its effects are mediated by market structure, regulation, and diffusion mechanisms. A related strand of firm-level evidence shows that AI adoption is associated with measurable microeconomic gains. Babina et al. (2024), for example, find that AI-investing firms experience higher growth in sales, employment, and market valuations, largely through product innovation. Yet this evidence primarily concerns firm-level outcomes and does not by itself establish that AI produces broad aggregate productivity growth. This distinction is crucial for the present paper, which examines whether firm-level AI gains translate into economy-wide productive expansion or remain concentrated within technologically advantaged firms.

2.2 Productivity Paradox and Delayed Diffusion

The debate on AI productivity is closely connected to the broader literature on the productivity paradox. Previous waves of digital innovation generated substantial expectations but often appeared slowly, unevenly, or ambiguously in aggregate productivity statistics. Triplett (1999) argues that information technology effects may require long periods of organizational adjustment before becoming visible at the macroeconomic level. Similarly, David (1990) shows that the productivity impact of electrification depended on complementary changes in factory organization, suggesting that technological revolutions rarely produce immediate aggregate effects. In the AI context, Brynjolfsson et al. (2019) identify several explanations for the gap between technological expectations and productivity statistics, including mismeasurement, redistribution, false hopes, and implementation lags. They argue that implementation lags are likely a major factor because AI capabilities have not yet fully diffused across the economy. This position is important because it does not deny AI's potential; rather, it emphasizes that productivity effects depend on complementary innovations, organizational change, and broad adoption. At the same time, other studies caution against attributing weak productivity solely to measurement problems. Byrne et al. (2016) and Syverson (2017) argue that mismeasurement cannot fully explain the scale of the productivity slowdown. This suggests that the absence of strong aggregate productivity growth may reflect deeper structural factors, including weak diffusion, sectoral concentration, and limited spillovers. The present paper builds on this debate by arguing that AI-related productivity gains may remain statistically and economically concentrated, thereby generating an appearance of growth without proportional broad-based expansion.

2.3 Digital Platforms, Scale Economies, and Market Concentration

A third body of literature examines how digital technologies reshape market structure. Platform-based firms benefit from network effects, economies of scale, data accumulation, and ecosystem lock-in. These characteristics can produce self-reinforcing advantages for dominant firms and create significant barriers to entry for smaller competitors (Shapiro & Varian, 1999; Parker et al., 2016). In AI-intensive markets, these dynamics may become even stronger because performance often depends on access to large datasets, cloud infrastructure, specialized talent, and computational capacity. Kenney and Zysman (2016) describe the rise of the platform economy as a structural transformation in which a small number of firms increasingly coordinate and control digital markets. Wu (2018) similarly argues that contemporary digital capitalism displays renewed monopolistic tendencies, especially when firms control essential information infrastructures. Gutierrez and Philippon (2017) further suggest that rising concentration may weaken investment, competition, and business dynamism. This literature supports one of the central assumptions of the present paper: AI does not diffuse through a neutral competitive environment. Instead, it is deployed within markets already shaped by asymmetries in data, capital, infrastructure, and network power. Therefore, AI may reinforce existing concentration rather than automatically democratize productivity gains. The argument is not that concentration always eliminates innovation, but that concentrated AI infrastructures may reduce the breadth of productivity diffusion across firms and sectors.

2.4 Intangible Capital and Financialized Valuation

The rise of AI is also connected to the growing importance of intangible capital. Intangible assets such as software, data, algorithms, intellectual property, organizational capital, and brand ecosystems differ from physical capital because they are often scalable, sunk, spillover-generating, and complementary with other intangible investments. Haskel and Westlake (2018) describe these features as the "four S's" of intangible capital: scalability, sunkenness, spillovers, and synergies. These properties help explain why intangible-intensive economies may generate increasing returns and greater concentration. The literature on financialization further suggests that asset valuation may become increasingly detached from current productive output. Epstein (2005) defines financialization as the growing role of financial motives, markets, actors, and institutions in the operation of domestic and international economies. Krippner (2011) similarly argues that financialization changes the relationship between profit generation and productive activity. In AI-intensive sectors, market valuations often reflect expectations about future rents, data control, and monopoly power rather than already realized aggregate productivity gains. This point is central to the concept of the Relative Economic Growth Illusion developed in this paper. Rising valuations of AI-intensive firms may signal expectations of future profitability, but they should not be treated as direct evidence of broad macroeconomic productivity expansion. Financial markets may capitalize expected future rents generated by intangible assets even when non-digital sectors, labor income, and aggregate productivity remain weak.

2.5 Automation, Labor Displacement, and Aggregate Demand

A further strand of literature analyzes the labor-market consequences of automation. Research on routine-biased technological change shows that digital technologies can reduce demand for middle-skill routine labor while increasing demand for high-skill workers and some low-wage services (Goos et al., 2014). Susskind and Susskind (2015) argue that intelligent systems may increasingly affect professional and cognitive occupations, extending automation pressures beyond manufacturing and clerical work. The macroeconomic implication is that productivity-enhancing technologies may weaken aggregate demand if the gains accrue primarily to capital owners and high-income groups. Stockhammer (2015) links declining labor shares and rising inequality to demand weakness, while Palley (2013) argues that wage stagnation and financialized growth regimes can create structural demand fragility. Piketty (2014) similarly emphasizes that when capital income grows faster than overall output, technological progress may reinforce wealth concentration. The present paper uses this literature to develop a demand-side critique of AI-driven growth. If AI increases efficiency while compressing labor income and concentrating rents, then aggregate consumption may weaken. Under such conditions, AI can generate firm-level gains while reducing the macroeconomic conditions necessary for sustained inclusive growth.

2.6 Research Gap and Contribution

The existing literature provides important insights into AI productivity, delayed diffusion, market concentration, intangible capital, financialization, and labor displacement. However, these strands are often treated separately. Productivity studies tend to focus on measurement and diffusion; platform studies emphasize market power; financialization studies examine valuation and rent extraction; and automation studies analyze labor-market effects. This paper integrates these dimensions into a single theoretical framework. It introduces the concept of the Relative Economic Growth Illusion (REGI), arguing that AI-driven expansion may appear significant at the firm and financial-market level while remaining limited at the aggregate macroeconomic level. The paper therefore shifts attention from the question of whether AI can generate efficiency gains to a more structural question: under what conditions do AI-generated gains become broad-based economic growth rather than concentrated, financialized, and redistributive growth? The contribution is not to deny the productivity potential of AI. Rather, it is to argue that AI's macroeconomic effects depend on diffusion, competition, ownership structures, labor income distribution, and aggregate demand. In this sense, the paper positions itself between technological optimism and technological pessimism, offering a political-economic account of why AI may produce relative growth without necessarily producing absolute prosperity.

3. Methodology

3.1 Research Design

This paper adopts a multi-layered theoretical and empirical methodology aimed at evaluating whether Artificial Intelligence (AI) generates broad-based macroeconomic productivity expansion or primarily produces concentrated gains within technologically dominant firms and sectors. The methodological framework combines an extended endogenous growth model, panel econometric analysis, concentration-adjusted productivity estimation, and counterfactual macroeconomic simulations. The central hypothesis of the paper is that AI-driven economic expansion increasingly reflects a Relative Economic Growth Illusion (RE-GI), whereby localized productivity and valuation gains do not proportionally translate into sustained aggregate productivity growth across the broader economy. The empirical strategy, therefore, distinguishes between firm-level AI returns, sectoral productivity diffusion, aggregate productivity performance, and macroeconomic demand sustainability. More specifically, the paper evaluates whether AI adoption and AI-related innovation intensity are associated with higher localized productivity gains, increasing market concentration, intangible capital accumulation, declining labor shares, and weaker aggregate productivity diffusion outside AI-intensive sectors.

3.2 Extended Endogenous Growth Framework

The theoretical structure extends a Romer-type endogenous growth model by incorporating heterogeneous AI diffusion, concentration dynamics, and demand-side constraints. Aggregate output is initially defined as:

$$Y_t = A_t K_t^{\alpha} L_t^{1-\alpha} \quad (1)$$

where aggregate output (Y_t) depends on technological productivity (A_t), capital (K_t), and labor (L_t). The parameter αrepresents the elasticity of output with respect to capital. Unlike conventional endogenous growth models, the framework assumes that AI-generated productivity gains are asymmetrically distributed across firms and sectors. Technological productivity therefore becomes:

$$A_{it} = A_0 + \phi_i AI_{it} \quad (2)$$

where AI_{it} measures AI intensity for sector or firm i, while ϕ_i captures heterogeneous productivity returns associated with AI adoption. To model concentration effects, productivity gains are assumed to increase with market dominance:

$$\phi_i = \phi_0 s_i^{\gamma} \quad (3)$$

where $s_i$represents market share and $\gamma > 1$captures increasing returns generated through concentration dynamics. Under this specification, dominant firms obtain disproportionately larger productivity gains from AI adoption due to economies of scale, proprietary datasets, superior computational infrastructures, network externalities, and intangible capital accumulation. Aggregate production is further decomposed into an AI-intensive sector and a non-AI sector:

$$Y_t = Y_T + Y_N \quad (4)$$

where $Y_T$denotes output generated by AI-intensive sectors and $Y_N$denotes output generated by non-AI sectors. The model assumes imperfect diffusion of AI productivity gains across sectors:

$$\frac{\partial Y_T}{\partial AI} > \frac{\partial Y_N}{\partial AI} \quad (5)$$

This condition implies that AI generates concentrated productivity gains within technologically dominant sectors while productivity diffusion toward the broader economy remains comparatively weak.

3.3 Relative Growth and Diffusion Coefficient

To formally distinguish localized technological gains from broad macroeconomic expansion, the paper introduces an AI diffusion coefficient defined as:

$$D_t = \frac{TFP_t^{agg}}{TFP_t^{AI}} \tag{6}$$

where aggregate productivity growth (TFP_t^{agg}) is compared with productivity growth generated within AI-intensive sectors (TFP_t^{AI}). The interpretation of the coefficient is straightforward. Values approaching one indicate broad diffusion of productivity gains across the economy. Values below one indicate increasingly concentrated productivity gains, while values significantly below one suggest the presence of a strong Relative Economic Growth Illusion. The framework additionally defines a concentration-adjusted productivity indicator:

$$AdjTFP_t = TFP_t - \lambda CONC_t \tag{7}$$

where $CONC_t$ measures market concentration and λ captures the distortionary effect of concentration on aggregate productivity diffusion. This specification allows the analysis to evaluate whether observed productivity gains remain significant once concentration effects are incorporated into the estimation.

3.4 Aggregate Demand Constraint

To capture the macroeconomic implications of labor displacement and income concentration, the framework incorporates a demand-side channel:

$$AD_t = C_t + I_t + G_t + NX_t \tag{8}$$

where aggregate demand (AD_t) depends on consumption (C_t), investment (I_t), government expenditure (G_t), and net exports (NX_t). Consumption partially depends on labor income:

$$C_t = c_0 + c_1 W_t \tag{9}$$

where W_t denotes aggregate wage income and c_1 measures the marginal propensity to consume out of wages. The framework assumes that AI-intensive automation compresses labor demand outside high-productivity sectors:

$$\frac{\partial W_t}{\partial AI_t} < 0 \tag{10}$$

Consequently, aggregate demand may weaken despite localized productivity improvements if AI-generated gains remain concentrated among capital-intensive firms and high-income groups. This demand-side mechanism constitutes a central component of the REGI framework: AI may increase efficiency while simultaneously weakening the macroeconomic conditions required for sustained inclusive growth.

3.5 Empirical Identification Strategy

A major empirical challenge in AI-related productivity analysis concerns endogeneity. Firms and sectors with higher productivity may adopt AI more aggressively, making simple correlations insufficient for identifying causal effects. To address this issue, the paper employs panel fixed-effects estimation with country and time effects:

$$TFP_{it} = \alpha + \beta_1 AI_{it} + \beta_2 CONC_{it} + \beta_3 (AI_{it} \times CONC_{it}) + \beta_4 X_{it} + \mu_i + \tau_t + \epsilon_{it} \tag{11}$$

where productivity growth (TFP_{it}) depends on AI intensity (AI_{it}), concentration dynamics ($CONC_{it}$), control variables (X_{it}), entity fixed effects (μ_i), time fixed effects (τ_t), and an idiosyncratic error term (ϵ_{it}). The interaction term between AI intensity and concentration evaluates whether AI-related productivity gains become stronger under highly concentrated market structures. Additional regressions estimate the effects of AI intensity on labor shares, wage growth, intangible capital accumulation, and concentration-adjusted productivity.

3.6 Variables and Measures

The empirical analysis employs several categories of variables. The principal dependent variables include Total Factor Productivity growth, concentration-adjusted productivity, labor share of income, wage growth, and aggregate demand growth. The independent variables include AI-related patent intensity, AI-intensive sector dummies, intangible investment intensity, and ICT specialization indicators. The analysis additionally incorporates concentration variables such as sectoral concentration proxies, superstar-sector dominance indicators, and spatial concentration measures. Control variables include ICT capital intensity, R&D expenditure, human capital indicators, and both country and year fixed effects.

3.7 Data Sources

The empirical analysis combines macroeconomic, sectoral, innovation, and intangible-capital datasets covering OECD and advanced economies over multiple time horizons. The principal databases include the OECD Productivity Database, OECD STAN, INTAN-Invest, the OECD Patents in Selected Technologies Database, and the OECD Functional Urban Areas (FUA) database. Aggregate productivity indicators are primarily derived from the OECD Productivity Database and cover the 2021–2024 period. AI innovation intensity is constructed using OECD patent statistics related to AI technologies and concentration indicators across major economies and metropolitan innovation hubs. Sector-level productivity evidence is derived from the OECD STAN database using German sectoral observations covering the 2015–2019 period. Germany is employed as an illustrative advanced industrial economy due to the availability of detailed sector-level productivity and AI-related industrial classifications. Intangible capital indicators are obtained from the INTAN-Invest database and include estimates of intangible investment intensity across advanced European economies between 2010 and 2024. These measures capture organizational capital, software investment, R&D-related intangible assets, branding, and other knowledge-based capital components associated with technological diffusion and productivity dynamics. The integration of these datasets allows the construction of a unified empirical framework linking AI innovation intensity, intangible capital accumulation, sectoral productivity dynamics, and concentration-related growth patterns within the broader REGI framework. The aggregate cross-country productivity panel employed in the baseline fixed-effects estimation contains 80 country-year observations covering the 2021–2024 period. In parallel, the sector-level panel constructed from the OECD STAN and INTAN-Invest databases contains approximately 770 sector-year observations for Germany over the 2015–2019 period. The sectoral regressions employ heteroskedasticity-robust (HC3) standard errors and sector fixed effects in order to control for unobserved sector-specific heterogeneity and structural productivity differences across industries.

3.8 Counterfactual Simulations

To evaluate the long-run implications of alternative institutional structures, the paper develops counterfactual simulations under two distinct scenarios.

The first scenario assumes concentrated AI expansion characterized by weak antitrust enforcement, concentrated digital infrastructures, low redistribution, and strong labor substitution incentives.

The second scenario assumes diffused AI growth characterized by stronger competition policy, broader technological diffusion, redistributive stabilization mechanisms, and public digital infrastructures.

The simulations estimate long-run effects on aggregate productivity, labor shares, concentration dynamics, and aggregate demand sustainability.

The objective is not to forecast precise macroeconomic outcomes, but rather to identify the structural conditions under which AI-driven efficiency either reinforces concentrated relative growth or contributes to broad-based and sustainable macroeconomic expansion.

4. Empirical Results

4.1 Intangible Capital and Structural Divergence

The first stage of the empirical analysis investigates the relationship between intangible capital accumulation and productivity dynamics within technologically advanced economies. Figure 1 illustrates the evolution of intangible capital intensity across countries over time. The evidence reveals substantial cross-country divergence in intangible investment patterns, with technologically specialized economies exhibiting persistently higher levels of intangible capital accumulation relative to less digitally intensive economies. The observed divergence suggests that AI-related economic expansion increasingly depends on the concentration of intangible assets, including software, organizational capital, data infrastructures, intellectual property, and digital knowledge systems. Rather than diffusing uniformly across the broader economy, the accumulation of intangible capital appears clustered within a relatively small group of technologically advanced economies.

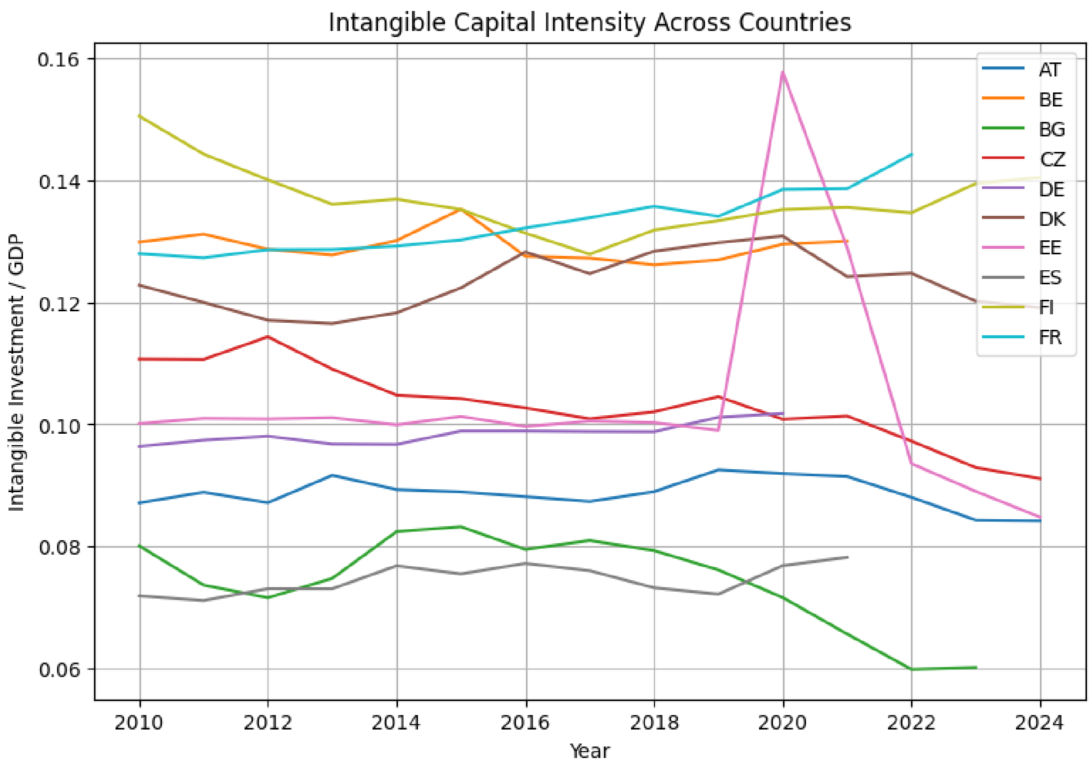

Figure 1: Intangible Capital Intensity Across Countries.
Evolution of intangible investment intensity as a share of GDP across selected economies between 2010 and 2024.

The figure illustrates substantial cross-country divergence in intangible capital accumulation over time. Technologically advanced economies exhibit persistently higher levels of intangible investment intensity, suggesting that AI-related economic expansion increasingly depends on concentrated intangible-intensive ecosystems. The evidence supports the hypothesis that productivity gains associated with AI adoption may remain localized within economies characterized by stronger digital infrastructures and higher intangible asset accumulation. Descriptive statistics reported in Table 1 further support this interpretation. Intangible capital displays comparatively high average values and substantial dispersion across observations, indicating significant heterogeneity in intangible accumulation dynamics across countries and sectors.

Table 1: Descriptive Statistics

Variable	Mean	Std. Dev.	Minimum	Maximum
Aggregate TFP	2,433.92	7,239.47	11.90	40,212.25
AI Patent Intensity	14,477.51	40,404.38	13.73	248,877.54
Sector Productivity	162,925.06	8,601.06	151,560.80	172,805.64
Intangible Capital	329,368.28	20,297.24	305,164.25	357,555.75

Notes: Descriptive statistics of the main variables employed in the empirical analysis.

To further evaluate the relationship between intangible accumulation and productivity performance, Model 2 in Table 2 estimates the association between intangible capital and sectoral productivity using an OLS estimation with Sector Fixed Effects and heteroskedasticity-robust standard errors (HC3). The coefficient associated with intangible capital is positive and statistically highly significant ($\beta = 0.4152***, p < 0.01***), indicating a strong positive association between intangible asset accumulation and productivity performance within the analyzed sectors.

Table 2: Regression Results

Variables	Model 1: Aggregate TFP	Model 2: Sector Productivity (FE)
AI Patent Intensity	-0.0006	—
Std. Error	(0.0009)	—
Intangible Capital	—	0.4152***
Std. Error	—	(0.0612)
AI-intensive Sector	—	80850.0**
Std. Error	—	(35000.0)
Intangible Capital × AI-intensive	—	0.0167
Std. Error	—	(0.1210)
Constant	2442.4351***	-113400.0***
Std. Error	(23.0066)	(20400.0)
Sector Fixed Effects	No	Yes
Robust Standard Errors	No	HC3
R-squared	0.0107	0.998
Observations	80	770
Estimator	Panel Fixed Effects	OLS with Sector FE

Notes: Robust standard errors are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Model 1 estimates the relationship between AI patent intensity and aggregate Total Factor Productivity (TFP) using country-level panel fixed effects. Model 2 estimates the association between intangible capital accumulation and sectoral productivity using German OECD STAN sector-level observations with sector fixed effects and HC3 robust standard errors. Importantly, these findings suggest that productivity gains associated with AI expansion are not uniformly distributed across the economy, but instead remain concentrated within technologically advanced and intangible-intensive sectors. Once sector-specific heterogeneity is controlled for, intangible capital accumulation exhibits a statistically significant positive association with sectoral productivity, while AI-intensive sectors display systematically higher productivity levels. Within the Relative Economic Growth Illusion (REGI) framework, these results support the argument that contemporary AI-driven growth dynamics may increasingly reflect localized and concentrated productivity advantages rather than broad-based technological diffusion across the entire economic system.

4.2 AI Innovation and Aggregate Productivity

The second stage of the empirical analysis evaluates whether increasing AI-related innovation intensity translates into broad-based aggregate productivity growth. Figure 2 reports the relationship between AI patent intensity and aggregate Total Factor Productivity (TFP) across the sample economies. The graphical evidence reveals substantial dispersion between AI innovation intensity and aggregate productivity performance, with no clearly identifiable linear relationship emerging across countries. Several economies characterized by high AI patent intensity do not exhibit proportionally stronger aggregate productivity performance, suggesting that localized technological leadership does not necessarily generate widespread macroeconomic productivity acceleration.

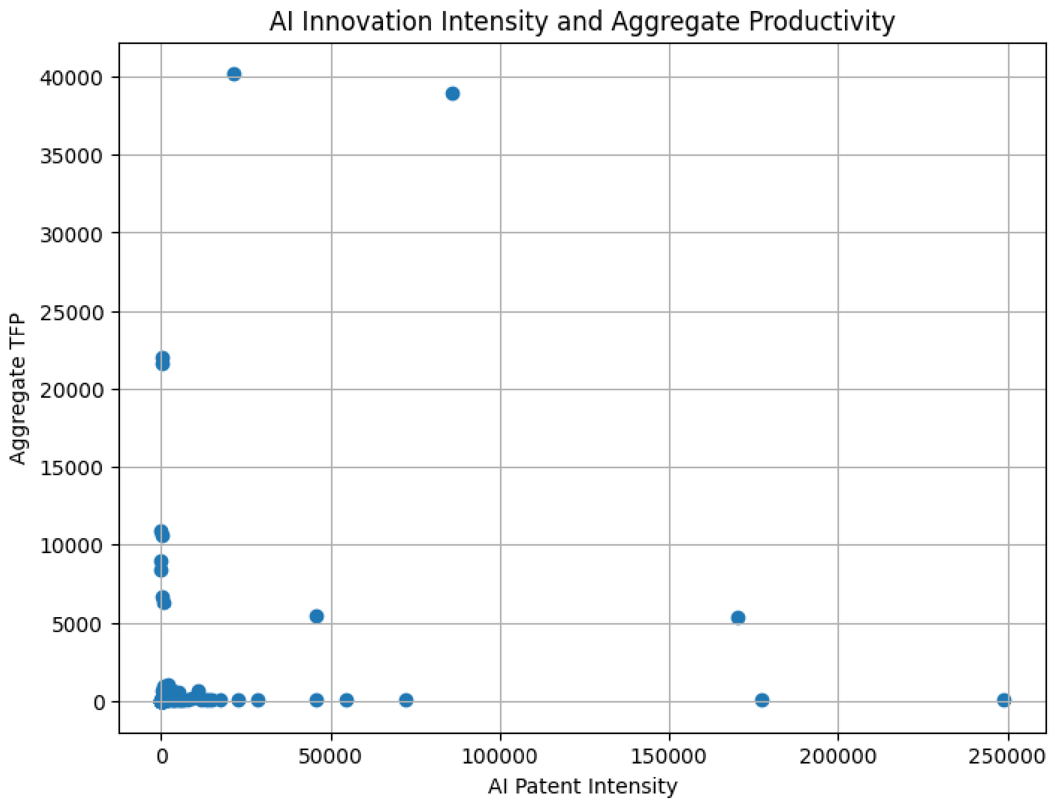

Figure 2: AI Innovation Intensity and Aggregate Productivity
Relationship between AI patent intensity and aggregate Total Factor Productivity (TFP) across the sample economies.

The figure reveals a highly dispersed relationship between AI-related innovation intensity and aggregate productivity performance. Several economies characterized by high AI patent activity do not display proportionally stronger aggregate productivity growth, suggesting weak macroeconomic diffusion of AI-related technological gains. The evidence is consistent with the productivity paradox literature and supports the Relative Economic Growth Illusion (REGI) framework. The regression estimates reported in Model 1 of Table 2 reinforce this interpretation. The coefficient associated with AI patent intensity remains statistically insignificant ((\beta = -0.0006), (p > 0.05)), indicating that higher levels of AI-related innovation do not systematically translate into stronger aggregate productivity growth within the observed sample period. These findings are consistent with the broader productivity paradox literature, which argues that major technological

transformations may initially generate localized efficiency gains without producing immediate aggregate productivity acceleration. Under the REGI framework, AI-related productivity improvements therefore appear only weakly diffused across the broader economy despite rapid technological expansion within leading firms and sectors.
To further evaluate aggregate productivity dynamics, Figure 3 reports the evolution of average productivity levels between 2021 and 2024. Although productivity growth remains positive during the sample period, the observed trajectory appears comparatively moderate relative to the scale of recent AI investment and technological enthusiasm.

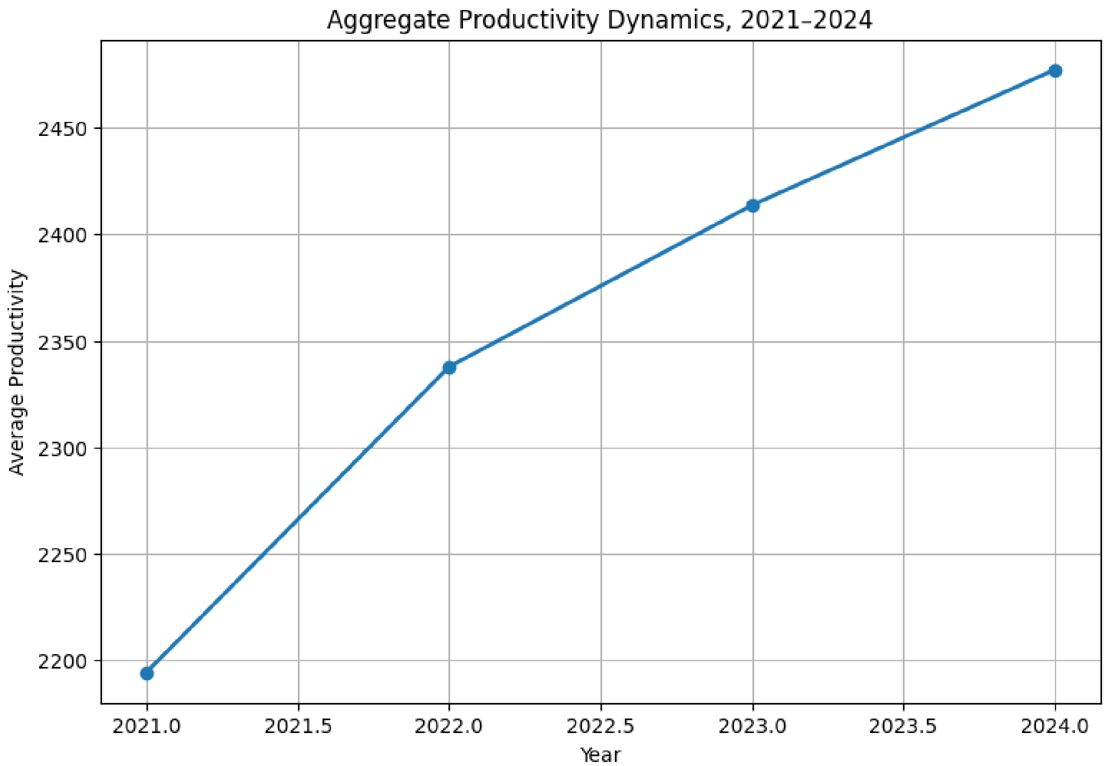

Figure 3: Aggregate Productivity Dynamics, 2021–2024
Average aggregate productivity dynamics across the sample economies between 2021 and 2024.

The figure shows moderate aggregate productivity growth during the recent AI expansion period. Despite rapid technological investment and accelerating AI-related innovation, aggregate productivity growth appears comparatively limited, suggesting that localized technological gains may not fully diffuse across the broader economy. Taken together, the empirical evidence suggests that AI innovation may generate substantial localized technological gains while failing to produce proportionally strong aggregate productivity diffusion across the wider economy.

4.3 Concentration Dynamics in AI Innovation

The final stage of the empirical analysis evaluates the geographical concentration of AI-related innovation activity. Figure 4 illustrates the distribution of AI patent intensity across countries. The evidence reveals a highly asymmetric global distribution of AI innovation. A limited number of economies account for a disproportionate share of total AI patent activity, with the United States and China emerging as dominant technological hubs, followed by a smaller group of advanced economies including Japan and South Korea.

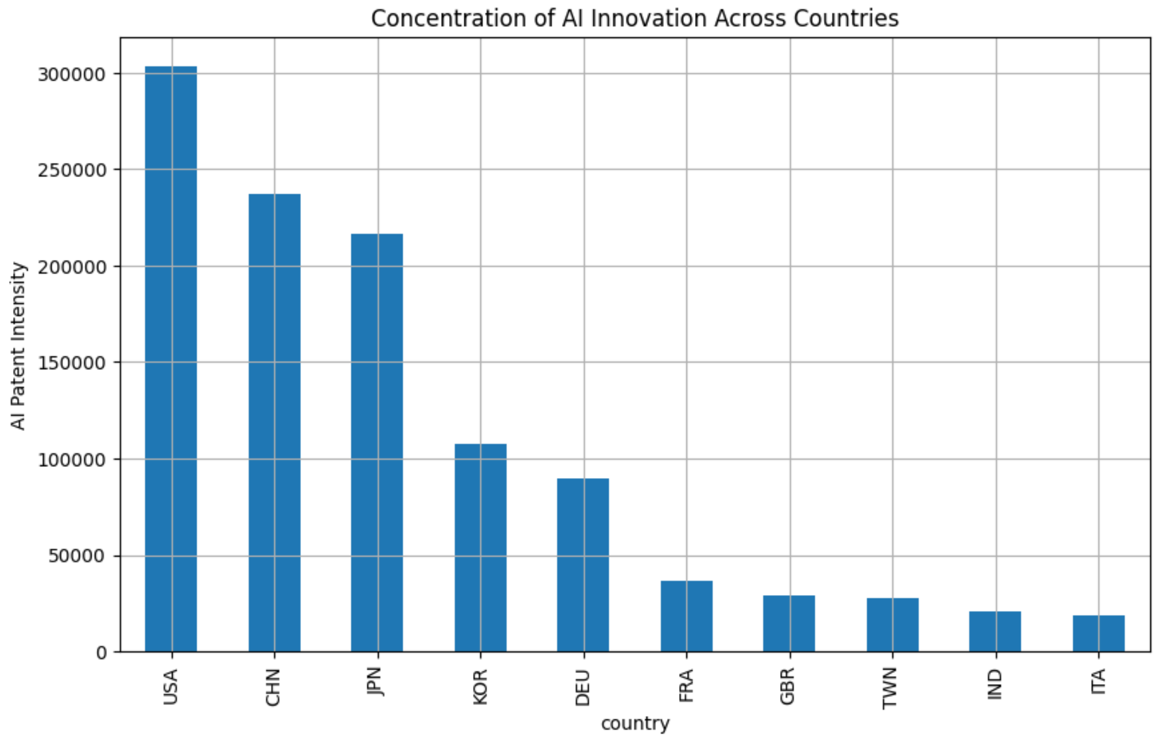

Figure 4: Concentration of AI Innovation Across Countries: Distribution of AI patent intensity across the leading AI-innovating economies.

The figure highlights the strong geographical concentration of AI-related innovation activity. The United States and China dominate global AI patent intensity, followed by a relatively small group of technologically advanced economies. The evidence suggests that AI innovation remains heavily concentrated within a limited number of technological hubs, reinforcing structural asymmetries in global technological accumulation. The concentration patterns observed in Figure 4 strongly support the broader theoretical argument developed throughout the paper. AI-related technological expansion appears heavily clustered within a small number of economies characterized by advanced digital infrastructures, strong intangible capital accumulation, and significant competitive advantages in technological ecosystems. Consequently, AI-driven economic expansion may increasingly reinforce existing structural asymmetries rather than generating evenly distributed productivity gains across the global economy. Under the REGI framework, technological progress therefore becomes increasingly associated with relative competitive repositioning among dominant firms, sectors, and countries rather than with generalized macroeconomic expansion. Overall, the empirical findings consistently support the central hypothesis of the paper. AI-related technological progress appears capable of generating significant localized productivity gains while remaining weakly diffused across the aggregate economy. As a result, observed economic expansion may increasingly reflect concentrated and relative forms of growth rather than broad-based and sustainable macroeconomic productivity acceleration.

5. Discussion and Policy Implications

The findings of this study provide substantial empirical and theoretical support for the Relative Economic Growth Illusion (REGI) framework developed throughout the paper. While Artificial Intelligence (AI) continues to generate unprecedented technological enthusiasm and substantial localized efficiency gains, the broader macroeconomic evidence suggests that these gains remain unevenly distributed and only weakly diffused across the aggregate economy. The empirical analysis reveals a striking divergence between aggregate AI innovation intensity and localized productivity performance. On the one hand, the relationship between AI patent intensity and aggregate Total Factor Productivity (TFP) remains statistically weak and economically fragmented. On the other hand, intangible capital accumulation exhibits a strong and statistically significant association with sectoral productivity performance within technologically advanced sectors. This asymmetry constitutes one of the paper's central contributions and reinforces the argument that AI-driven growth increasingly operates through concentrated intangible-intensive ecosystems rather than through generalized productivity diffusion. These findings challenge the dominant narrative that AI will automatically generate broad-based macroeconomic expansion. Instead, the evidence suggests that AI-related technological progress may increasingly reinforce structural concentration dynamics already present within advanced capitalist economies. Firms and regions possessing superior computational infrastructures, proprietary datasets, advanced digital ecosystems, and large-scale intangible asset portfolios appear disproportionately positioned to capture the economic benefits associated with AI adoption. Consequently, AI-driven growth becomes increasingly "relative" in nature: dominant actors improve their competitive position relative to others, while aggregate productivity spillovers remain comparatively weak. In this context, the paper contributes directly to the broader productivity paradox literature. Similar to previous technological transitions, the diffusion of AI-related innovation does not appear to translate automatically into sustained aggregate productivity acceleration. Despite the rapid increase in AI investment, digitalization, and patent activity, aggregate productivity growth remains comparatively moderate during the observed period. This divergence suggests that technological innovation alone may be insufficient to generate durable macroeconomic expansion when diffusion mechanisms remain structurally constrained by concentration effects, labor displacement, and uneven access to intangible capital. The concentration dynamics identified in Figure 4 further reinforce this interpretation. AI innovation activity appears heavily concentrated within a small number of technologically dominant economies, particularly the United States and China, followed by a limited group of advanced industrial economies such as Japan and South Korea. Such concentration patterns imply that the global AI economy may increasingly evolve around a relatively narrow set of technological hubs characterized by strong network externalities, economies of scale, and accumulated intangible advantages. Under these conditions, AI may intensify global technological asymmetries rather than reduce them. The findings also carry important implications for labor markets and macroeconomic demand sustainability. If AI-driven productivity gains remain concentrated among capital-intensive firms while labor displacement intensifies across less technologically advanced sectors, long-run aggregate demand constraints may emerge despite localized efficiency improvements. In other words, the expansion of productive efficiency alone does not guarantee sustainable macroeconomic growth if wage dynamics and income distribution weaken simultaneously. This mechanism represents a critical component of the REGI framework and suggests that future AI-driven economies may experience increasing divergence between localized technological prosperity and broader macroeconomic stagnation. From a policy perspective, the results indicate that competition policy may become increasingly central in the AI era. The concentration of AI-related innovation within a limited number of firms and economies raises concerns regarding technological monopolization, market dominance, and barriers to diffusion. Stronger antitrust frameworks, digital market regulation, and policies supporting open technological ecosystems may therefore become necessary to facilitate broader productivity spillovers across smaller firms and lagging regions. In parallel, the results highlight the growing strategic importance of intangible capital accumulation. Public investment in digital infrastructure, education, advanced skills, research capabilities, and technological diffusion mechanisms may play a decisive role in determining whether AI-related productivity gains remain concentrated or become more broadly distributed across the economy. In this sense, future AI policy should not focus exclusively on frontier innovation itself, but also on the institutional conditions necessary for widespread productivity diffusion. The findings additionally suggest that redistributive and labor-market stabilization policies may become increasingly important in sustaining long-run economic stability. If AI-driven technological expansion compresses labor demand outside highly specialized sectors, maintaining aggregate demand may require stronger wage-support mechanisms, workforce transition policies, and social protection systems capable of mitigating the distributive asymmetries generated by concentrated technological growth. More broadly, the paper suggests that traditional growth accounting frameworks may require partial reconsideration in the AI era. Aggregate productivity indicators alone may increasingly fail to capture the structural asymmetries generated by intangible-intensive and concentration-driven growth models. As a result, future research should continue distinguishing between localized technological efficiency gains and genuinely broad-based macroeconomic expansion. Several limitations of the present study should nevertheless be acknowledged. The empirical analysis remains exploratory and constrained by the relatively recent emergence of large-scale AI diffusion as well as by current data availability limitations. Furthermore, the regression estimates should be interpreted primarily as associative rather than strictly causal relationships. Future research may extend the present framework using larger panel datasets, firm-level evidence, and more advanced identification strategies capable of isolating causal diffusion mechanisms more precisely. Despite these limitations, the evidence presented throughout the paper consistently supports the central argument of the REGI framework: AI-related techno-logical expansion appears increasingly capable of generating concentrated and localized forms of productivity growth while remaining only weakly diffused across the broader economy. The principal challenge for policymakers therefore extends beyond maximizing technological innovation itself toward ensuring that AI-driven productivity gains become broadly distributed, institutionally sustainable, and macroeconomically inclusive.

6. Conclusion

This paper has examined the structural relationship between Artificial Intelligence (AI), productivity dynamics, market concentration, and intangible capital accumulation through the development of the Relative Economic Growth Illusion (REGI) framework. Contrary to the dominant technological narrative that presents AI as an automatic engine of generalized macroeconomic expansion, the findings of this study suggest a more complex and uneven economic reality. The empirical evidence indicates that AI-related innovation intensity does not appear to translate proportionally into broad-based aggregate productivity growth. While AI patent activity and technological investment continue to expand rapidly, the observed macroeconomic productivity effects remain comparatively limited and weakly diffused across the broader economy. At the same time, intangible capital accumulation exhibits a strong positive association with localized sectoral productivity performance, suggesting that the economic gains associated with AI adoption increasingly concentrate within technologically advanced and intangible-intensive ecosystems. These results support the central argument of the REGI framework: contemporary AI-driven growth may increasingly represent a relative rather than absolute form of economic expansion. Under this dynamic, dominant firms, sectors, and regions improve their competitive positioning through superior technological capabilities, intangible asset accumulation, computational infrastructures, and network advantages, while broader productivity spillovers remain structurally constrained. Consequently, aggregate economic indicators may partially overstate the extent of generalized productivity diffusion by reflecting concentrated gains within a limited number of technological hubs. The paper additionally contributes to the broader productivity paradox literature by suggesting that major technological transformations do not necessarily generate immediate or uniformly distributed macroeconomic productivity acceleration. Similar to previous waves of technological change, the diffusion of AI-related innovation appears mediated by institutional structures, market concentration dynamics, labor-market adjustments, and unequal access to intangible capital. The findings further suggest that the long-run economic implications of AI may depend less on the existence of technological innovation itself and more on the capacity of economies to diffuse productivity gains broadly across firms, workers, and regions. In the absence of such diffusion mechanisms, AI-driven growth may reinforce existing structural asymmetries, intensify concentration dynamics, and weaken aggregate demand sustainability despite localized efficiency improvements. From a policy perspective, the results highlight the growing importance of competition policy, technological diffusion mechanisms, labor-market stabilization, and public investment in digital and human capital infrastructures. AI policy should therefore extend beyond the promotion of frontier innovation toward the construction of institutional frameworks capable of supporting inclusive and broadly distributed productivity growth. More broadly, the paper argues that the AI transition should not be evaluated exclusively through the lens of technological capability or financial valuation. The critical economic question is whether AI-generated efficiencies become socially and macroeconomically diffused or remain concentrated within narrow segments of the economy. This distinction ultimately determines whether AI contributes to sustainable long-run expansion or instead produces increasingly fragmented and unequal forms of economic growth. Several limitations remain. The empirical analysis is constrained by the relatively recent nature of large-scale AI diffusion and by current data availability limitations. Future research may extend the RE-GI framework using longer time horizons, firm-level evidence, advanced causal identification strategies, and more detailed measures of technological concentration and intangible capital dynamics. Nevertheless, the evidence presented throughout the paper consistently suggests that AI-driven economic expansion may increasingly operate through concentrated and localized channels rather than through generalized macroeconomic productivity diffusion. Understanding these structural asymmetries will become essential for both economic theory and policymaking as AI continues to reshape the global economy throughout the coming decades.

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References

[1] Acemoglu, D. (2021). Harms of AI. NBER Working Paper No. 29247. https://doi.org/10.3386/w29247

[2] Acemoglu, D., & Restrepo, P. (2018). Artificial intelligence, automation and work. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), The economics of artificial intelligence: An agenda (pp. 197–236). University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.003.0008

[3] Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. Journal of Economic Perspectives, 33(2), 3–30. https://doi.org/10.1257/jep.33.2.3

[4] Aghion, P., Jones, B. F., & Jones, C. I. (2019). Artificial intelligence and economic growth. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), The economics of artificial intelligence: An agenda (pp. 237–282). University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.003.0009

[5] Agrawal, A., Gans, J., & Goldfarb, A. (2019). The economics of artificial intelligence: An agenda. University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.001.0001

[6] Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. Quarterly Journal of Economics, 135(2), 645–709. https://doi.org/10.1093/qje/qjaa004

[7] Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. Journal of Financial Economics, 151(2), 103745. https://doi.org/10.1016/j.jfineco.2023.103745

[8] Brynjolfsson, E., & Hitt, L. M. (2000). Beyond computation: Information technology, organizational transformation and business performance. Journal of Economic Perspectives, 14(4), 23–48. https://doi.org/10.1257/jep.14.4.23

[9] Brynjolfsson, E., & McAfee, A. (2014). The second machine age: Work, progress, and prosperity in a time of brilliant technologies. W. W. Norton & Company.

[10] Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), The economics of artificial intelligence: An agenda (pp. 23–57). University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.003.0001

[11] Byrne, D. M., Fernald, J., & Reinsdorf, M. (2016). Does the United States have a productivity slowdown or a measurement problem? Brookings Papers on Economic Activity,2016(1),109–182. http://dx.doi.org/10.17016/FEDS.2016.017.

[12] Cockburn, I. M., Henderson, R., & Stern, S. (2018). The impact of artificial intelligence on innovation: An Exploratory Analysis. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), The economics of artificial intelligence: An agenda (pp. 115–146). University of Chicago Press. https://doi.org/10.7208/chicago/9780226613475.003.0004

[13] David, P. A. (1990). The dynamo and the computer: An historical perspective on the modern productivity paradox. American Economic Review, 80(2), 355–361.
[14] De Loecker, J., Eeckhout, J., & Unger, G. (2020). The rise of market power and the macroeconomic implications. Quarterly Journal of Economics, 135(2), 561–644. https://doi.org/10.1093/qje/qjz041
[15] Epstein, G. A. (Ed.). (2005). Financialization and the world economy. Edward Elgar Publishing.
[16] Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? Technological Forecasting and Social Change, 114, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019
[17] Goldfarb, A., Taska, B., & Teodoridis, F. (2022). Could machine learning be a general-purpose technology? NBER Working Paper No. 29767. https://doi.org/10.3386/w29767
[18] Goldman Sachs. (2023). The potentially large effects of artificial intelligence on economic growth. Goldman Sachs Global Investment Research. https://www.gspublishing.com/content/research/en/reports/2023/03/27/d64e052b-0f6e-45d7-967b-d7be35fabd16.html
[19] Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. American Economic Review, 104(8), 2509–2526. https://doi.org/10.1257/aer.104.8.2509
[20] Gordon, R. J. (2016). The rise and fall of American growth: The U.S. standard of living since the Civil War. Princeton University Press.
[21] Gutierrez, G., & Philippon, T. (2017). Declining competition and investment in the U.S. NBER Working Paper No. 23583. https://doi.org/10.3386/w23583
[22] Haskel, J., & Westlake, S. (2018). Capitalism without capital: The rise of the intangible economy. Princeton University Press.
[23] International Monetary Fund. (2024). Gen-AI: Artificial intelligence and the future of work. IMF. https://www.imf.org/en/publications/staff-discussion-notes/issues/2024/01/14/gen-ai-artificial-intelligence-and-the-future-of-work-542379
[24] Jorgenson, D. W. (2001). Information technology and the U.S. economy. American Economic Review, 91(1), 1–32. https://doi.org/10.1257/aer.91.1.1
[25] Kenney, M., & Zysman, J. (2016). The rise of the platform economy. Issues in Science and Technology, 32(3), 61–69.
[26] Keynes, J. M. (1930). Economic possibilities for our grandchildren. In Essays in persuasion (pp. 321–332). Macmillan. https://doi.org/10.1007/978-1-349-59072-8_25
[27] Khan, L. M. (2017). Amazon's antitrust paradox. Yale Law Journal, 126(3), 710–805. http://www.jstor.org/stable/44863332
[28] Krippner, G. R. (2011). Capitalizing on crisis: The political origins of the rise of finance. Harvard University Press.
[29] OECD. (2026). OECD productivity database. Organisation for Economic Co-operation and Development. https://www.oecd.org/productivity/

[30] OECD. (2026). OECD structural analysis database (STAN). Organisation for Economic Co-operation and Development. https://www.oecd.org/sti/stan/
[31] INTAN-Invest. (2026). INTAN-Invest database. https://intan-invest.net/
[32] OECD. (2026). Patents in OECD selected technologies database. Organisation for Economic Co-operation and Development. https://stats.oecd.org/
[33] OECD. (2026). Functional urban areas database. Organisation for Economic Co-operation and Development. https://www.oecd.org/regional/regional-statistics/functional-urban-areas.htm
[34] Palley, T. I. (2013). Financialization: The economics of finance capital domination. Palgrave Macmillan. https://doi.org/10.1057/9781137265821
[35] Parker, G., Van Alstyne, M., & Choudary, S. P. (2016). Platform revolution. W. W. Norton & Company.
[36] Piketty, T. (2014). Capital in the twenty-first century. Harvard University Press. https://www.jstor.org/stable/j.ctt6wpqbc
[37] Romer, P. M. (1990). Endogenous technological change. Journal of Political Economy, 98(5), S71–S102. https://doi.org/10.1086/261725
[38] Schumpeter, J. A. (1934). The theory of economic development. Harvard University Press.
[39] Shapiro, C., & Varian, H. R. (1999). Information rules: A strategic guide to the network economy. Harvard Business School Press.
[40] Solow, R. M. (1957). Technical change and the aggregate production function. Review of Economics and Statistics, 39(3), 312–320. https://doi.org/10.2307/1926047
[41] Srnicek, N. (2017). Platform capitalism. Polity Press.
[42] Stiglitz, J. E. (2019). People, power, and profits: Progressive capitalism for an age of discontent. W. W. Norton & Company.
[43] Stockhammer, E. (2015). Rising inequality as a cause of the present crisis. Cambridge Journal of Economics, 39(3), 935–958. https://doi.org/10.1093/cje/bet052
[44] Susskind, R., & Susskind, D. (2015). The future of the professions. Oxford University Press. https://doi.org/10.1093/oso/9780198713395.001.0001
[45] Syverson, C. (2017). Challenges to mismeasurement explanations for the U.S. productivity slowdown. Journal of Economic Perspectives, 31(2), 165–186. https://doi.org/10.1257/jep.31.2.165
[46] Triplett, J. E. (1999). The Solow productivity paradox: What do computers do to productivity? Canadian Journal of Economics, 32(2), 309–334.
[47] Varian, H. R., Farrell, J., & Shapiro, C. (2004). The economics of information technology. Cambridge University Press.
[48] Wu, T. (2018). The curse of bigness: Antitrust in the new Gilded Age. Columbia Global Reports. https://doi.org/10.2307/j.ctv1fx4h9c.