THE ECONOMICS OF ARTIFICIAL INTELLIGENCE: PRODUCTIVITY, LABOUR MARKETS, AND STRUCTURAL CHANGE

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Abstract

The rapid diffusion of generative artificial intelligence since 2022 has reignited long-standing debates in economics about the relationship between technological change, productivity growth, and labour-market outcomes. This article synthesises recent empirical and theoretical literature to assess how AI adoption is likely to affect aggregate productivity, occupational structure, and income distribution. Drawing on task-based models of automation and early firm-level evidence, the article argues that generative AI differs from earlier waves of automation in its capacity to substitute for cognitive, non-routine tasks previously considered resistant to computerisation, which broadens its potential impact to include highly educated, white-collar occupations. At the same time, measured productivity gains have so far been modest and unevenly distributed across firms and sectors, consistent with historical patterns of delayed diffusion for general-purpose technologies. The article concludes that policy attention should focus on complementary investment in human capital, competition policy to prevent excessive market concentration among AI providers, and social-insurance mechanisms capable of managing a potentially compressed transition period.

Keywords: artificial intelligence; labour economics; productivity growth; automation; technological unemployment; general-purpose technology

1. Introduction

Artificial intelligence has moved from a specialised research domain to a general-purpose technology with the public release of large language models capable of performing a wide range of cognitive tasks, from drafting text to writing computer code. Unlike earlier waves of industrial and digital automation, which primarily displaced routine manual and clerical tasks, generative AI systems demonstrate proficiency in tasks long considered the preserve of highly skilled, non-routine cognitive labour. This shift raises fundamental questions for economic analysis: how large are the likely productivity gains, which occupations and income groups stand to gain or lose, and what institutional responses are appropriate during the transition. This article reviews the emerging economic literature on these questions and draws out implications for policy.

2. Task-Based Models of Automation and AI

The dominant analytical framework for understanding automation's labour-market effects is the task-based model, in which production is decomposed into a continuum of tasks that can be allocated either to labour or to capital, depending on relative costs and technological feasibility. Automation shifts the boundary of tasks performed by capital, displacing labour from those tasks while, through a complementary productivity effect, potentially increasing demand for labour in tasks that remain human-intensive or that are newly created by the technology itself. Historically, this framework has been applied primarily to manufacturing and routine clerical work; its extension to generative AI requires

accounting for the technology's ability to perform tasks involving judgment, language, and pattern recognition that earlier automation could not replicate.

Recent contributions to this literature emphasise that generative AI's effects are likely to be more evenly distributed across the skill distribution than earlier automation waves, which disproportionately displaced middle-skill routine occupations while leaving both low-skill manual work and high-skill abstract work relatively unaffected — a pattern commonly described as labour-market polarisation. Because generative AI systems can perform components of high-skill cognitive tasks, such as legal research, medical diagnosis support, and software development, the occupations most exposed to the technology include some of the highest-paid professions, in contrast to the historical pattern of automation concentrated among middle-income occupations.

3. Empirical Evidence on Productivity and Adoption

Early firm-level and experimental evidence suggests that generative AI tools can produce substantial productivity gains in specific, well-defined tasks. Randomised evaluations of AI-assisted customer-support agents, software developers, and business writers have generally found double-digit percentage increases in output or quality for a given time input, with the largest gains typically accruing to less experienced workers, who benefit disproportionately from AI's capacity to encode and transfer expert practice. This finding has been interpreted as evidence that AI adoption could, under certain conditions, narrow rather than widen within-occupation productivity gaps.

At the aggregate level, however, productivity statistics have yet to show a clear acceleration attributable to AI. This pattern is consistent with the historical experience of general-purpose technologies such as electrification and computerisation, both of which exhibited a substantial lag between initial invention and measurable aggregate productivity effects, owing to the need for complementary investments in organisational redesign, worker training, and business-process reengineering. Survey evidence indicates that formal adoption of generative AI tools within firms, as distinct from informal individual use by employees, remains limited outside a small number of large technology-intensive firms, suggesting that the diffusion process is still at an early stage.

4. Distributional and Structural Implications

The distributional consequences of AI adoption depend critically on the balance between the displacement effect, which reduces demand for labour in automated tasks, and the productivity and reinstatement effects, which can increase labour demand either in remaining tasks or in newly created occupations. Historical evidence on technological change suggests that reinstatement effects have generally offset displacement effects over long horizons, but the transition period can impose considerable adjustment costs on workers whose skills become obsolete, particularly where those workers face high costs of retraining or geographic relocation.

A further structural concern relates to market concentration in the provision of foundational AI models, which requires capital-intensive investment in computing infrastructure and large-scale training data, creating potential barriers to entry. Should the market for foundational models remain concentrated among a small number of firms, the economic rents associated with productivity gains from AI could accrue disproportionately to a narrow set of technology providers rather than being broadly distributed across the economy, with implications for both income inequality and competition policy.

5. Conclusion and Policy Implications

Generative artificial intelligence represents a general-purpose technology with the potential to affect a substantially broader range of occupations than earlier waves of automation, including highly skilled, cognitively demanding work. While early experimental evidence points to meaningful task-level productivity gains, aggregate productivity effects remain modest, consistent with the typically slow diffusion of general-purpose technologies. Three policy priorities follow from this analysis: sustained investment in education and retraining systems capable of supporting workers through occupational transitions; competition policy attentive to the risk of concentrated market power among foundational AI providers; and adaptive social-insurance mechanisms capable of responding to a transition whose speed and distributional consequences remain genuinely uncertain. A measured, evidence-based policy response, informed by continued monitoring of firm-level adoption and labour-market outcomes, offers the best prospect of capturing AI's productivity benefits while managing its disruptive potential.

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