The Economic Implications of AI-Driven Automation: A Dynamic General Equilibrium Analysis

HARIT, ADITYA

1 October 2024

The Economic Implications of AI-Driven Automation: A Dynamic General Equilibrium Analysis

Aditya Harit

Abstract

This paper develops a dynamic general equilibrium (DGE) model to assess the impact of AI-driven automation on labor and capital allocation in an economy. The model considers the endogenous response of firms to task automation and labor substitution, showing how the increasing use of AI affects total output (GDP), wages, and capital returns. By introducing task complementarity and dynamic capital accumulation, the paper explores how automation impacts labor dynamics and capital accumulation. Key results show that while AI enhances productivity and GDP, it can also reduce wages and increase income inequality, with long-run effects that depend on the elasticity of substitution between labor and capital.

Keywords: AI-driven Automation, Dynamic General Equilibrium, Labor Markets, Capital Accumulation, Income Distribution, Technological Change, Task Automation, Economic Inequality, Labor Demand, Capital Returns, Economic Policy, Neoclassical Growth Theory, Labor-Capital Dynamics.

1 Introduction

The rapid advancement of artificial intelligence (AI) in recent years has introduced transformative shifts in how economic systems function, particularly within labor markets. The capabilities of AI, from performing routine tasks to managing complex data-driven processes, are enabling firms to reconfigure their production strategies. As a result, AI-driven automation is progressively replacing human labor in various industries, which raises crucial questions about its broader economic implications. This transformation is part of a broader technological evolution that has seen machines and algorithms taking over an increasing number of human-performed tasks. Although AI has undeniably enhanced productivity and efficiency, its impact on wages, employment, and income distribution remains a topic of intense debate. This paper seeks to analyze the macroeconomic consequences of AI-driven automation by building a dynamic general equilibrium model that captures the interplay between labor, capital, and automation.

The industrial revolution and later waves of technological advancement, such as robotics and information technology, have historically reshaped labor markets. However, AI, and particularly machine learning algorithms, offers a distinctly different paradigm. Unlike previous technological waves, AI has the potential to impact not only routine, repetitive tasks but also cognitive, non-routine tasks that were once thought to be the exclusive domain of humans. AI systems can process vast amounts of data, learn from patterns, and make decisions without continuous human input. This unique capacity brings forward an unprecedented ability to transform industries that rely heavily on cognitive tasks, such as finance, healthcare, and education. Consequently, as AI systems become more advanced and widespread, the nature of work and employment is undergoing profound change.

One of the most visible effects of AI has been the automation of tasks that require moderate skills. AI-driven systems are increasingly employed in customer service, data management, diagnostics, and even creative industries such as media and entertainment. This has resulted in a decline in demand for labor in mid-skill jobs, which typically involve repetitive cognitive or physical tasks. As machines take over these tasks, companies are able to operate with fewer employees, thus creating a shift in labor demand towards high-skill roles, such as AI developers, data scientists, and other specialized professions that complement AI technologies. Meanwhile, workers in low-skill occupations face continued pressures from automation, as AI systems become increasingly affordable and efficient at performing basic service tasks like driving, cleaning, and simple assembly-line work.

Despite the clear productivity benefits of AI-driven automation, its potential to exacerbate wage inequality is a growing concern. Research indicates that, in many cases, automation has led to a polarization of the labor market, where high-skill, high-wage workers benefit from increased demand, while low-skill, low-wage workers face job displacement or stagnating wages. In particular, the lack of demand for mid-skill workers who are displaced by AI could lead to an economy where wages are primarily concentrated among those with the necessary skills to complement and operate AI systems. This leads to broader questions about the distributional consequences of AI: Who benefits from the productivity gains AI brings? Will these gains be equitably shared, or will they exacerbate existing inequalities between labor and capital?

The focus of this paper is to explore the relationship between AI-driven automation, wages, and capital accumulation using a dynamic general equilibrium model. By embedding automation directly into the production function, we examine how the introduction of AI affects firms' decisions to substitute labor with capital, and how this substitution affects overall economic output and wage levels. This model captures the short-term and long-term effects of AI on productivity and income distribution, providing insights into how economies might evolve as AI continues to automate more tasks.

In addition, the paper discusses policy implications of these technological changes. Governments and policymakers are increasingly faced with the challenge of designing strategies that maximize the benefits of AI while minimizing its adverse effects on labor markets. Effective policies could include education and reskilling programs, tax incentives for human capital investment, and social safety nets to support workers displaced by automation. By examining the dynamics of AI-driven automation in a general equilibrium context, this paper aims to contribute to the understanding of how economies can adapt to the rapid technological shifts brought about by artificial intelligence.

2 Literature Review

The intersection of artificial intelligence (AI) and labor markets has garnered significant attention in recent economic literature, reflecting concerns about automation's impact on employment, wages, and income distribution. Early studies on technological change emphasized the role of routine-biased technical change (RBTC), a concept popularized by Autor, Levy, and Murnane (2003). They argued that advancements in technology have disproportionately benefited high-skill labor while displacing routine jobs that require moderate skills. This phenomenon has prompted researchers to investigate how automation affects labor demand and the resultant shifts in wage structures.

Daron Acemoglu and Pascual Restrepo (2020) expanded upon these ideas by developing a framework to understand the dynamic relationship between automation and labor markets. Their work highlights that automation, particularly driven by AI, can lead to both job displacement and the creation of new tasks. They posited that while some jobs are at risk of being eliminated, others emerge as a result of technological advancements, often requiring higher skill levels. This dual effect underscores the importance of examining the complementarity between labor and capital in the context of AI adoption.

The task-based approach has become a critical lens through which researchers analyze the effects of automation. Autor and Acemoglu (2011) argue that automation does not uniformly displace workers; instead, it modifies the nature of tasks within jobs. This means that while some workers may lose their positions, others may find new opportunities that leverage their skills in conjunction with AI. This perspective aligns with the broader narrative that technological change creates winners and losers in the labor market, raising questions about the adequacy of existing policies to address these disparities.

Incorporating automation into dynamic general equilibrium models has become increasingly popular in the literature. These models provide a comprehensive framework for understanding the interactions between various economic agents and the long-run implications of technological change. For instance, the models developed by Bartelsman, Haltiwanger, and Scarpetta (2013) focus on how technological advancements can enhance productivity while also influencing firm dynamics and employment patterns. Their findings indicate that high-productivity firms are more likely to adopt new technologies, leading to greater economic disparities across firms and industries.

More recent contributions have emphasized the role of AI in reshaping labor demand and the potential for increased income inequality. Brynjolfsson and McAfee (2014) argue that AI and automation represent a "second machine age," where technological advancements could lead to significant economic gains but also exacerbate income disparities. They stress the need for policies that promote education and skill development to mitigate the adverse effects of automation on low- and middle-skill workers.

Furthermore, the literature suggests that the dynamics of AI adoption are influenced by factors such as market structure, competition, and regulatory frameworks. Studies by Bessen (2019) and Chui et al. (2016) demonstrate that industries with high competition are more likely to adopt AI technologies rapidly, leading to faster productivity growth but also raising concerns about the displacement of workers.

In summary, the literature indicates a complex relationship between AI-driven automation, labor markets, and income distribution. While automation can enhance productivity and create new opportunities, it also poses significant challenges in terms of job displacement and income inequality. The task-based approach and dynamic general equilibrium models provide valuable frameworks for understanding these interactions, emphasizing the need for policies that address the distributional effects of technological change. As AI continues to evolve, ongoing research will be essential in shaping strategies that ensure the benefits of automation are widely shared across society.

3 Theoretical Framework

This paper constructs a dynamic general equilibrium (DGE) model to examine the effects of AI-driven automation on labor, capital, and income distribution. The model is heavily influenced by neoclassical growth theory and the task-based models of automation developed by economists such as David Autor and Daron Acemoglu. The primary inspiration comes from the Solow growth model in neoclassical economics, which highlights the role of technological progress and capital accumulation as key drivers of economic growth. However, this model goes further by embedding automation as a central component that affects the interaction between labor and capital in production processes.

The model views the economy as comprising representative firms that use labor, capital, and AI to produce a single final good. Firms maximize profits by optimally allocating these inputs, where AI takes over an increasing fraction of tasks that were previously performed by human labor. This setup stems from task-based models, where automation impacts the economy by reallocating specific tasks to machines and AI rather than replacing entire jobs. Thus, AI acts as a form of capital, capable of substituting labor in certain tasks while complementing it in others.

Within the model, AI adoption is treated as a dynamic process, evolving over time as firms progressively automate more tasks. The level of automation increases at a rate determined by technological advancements and the firm's ability to integrate AI into its production processes. As AI advances, more tasks are automated, reducing the overall demand for human labor. The model assumes that not all tasks can be automated, as certain activities, especially those requiring complex human judgment or creativity, remain outside the scope of AI.

The model also incorporates capital accumulation, where firms reinvest a portion of their output into capital stock, driving long-run economic growth. As capital, including AI, becomes more productive, the demand for labor decreases, leading to lower wages. However, the returns to capital increase as AI enhances its efficiency, creating a shift in income distribution away from labor toward capital owners.

Wages in the model are determined by the marginal productivity of labor, which declines as more tasks are automated. Consequently, the model predicts a rise in income inequality, as capital owners benefit disproportionately from the gains in productivity brought about by automation. This setup allows for a dynamic interaction between AI-driven automation, capital accumulation, and labor market outcomes, providing a rich theoretical foundation for understanding how automation shapes economic growth and income distribution over time.

4 The Model

4.1 Production Function with AI

We consider a representative firm that produces a final good using labor L, capital K, and AI-driven automation γ. The firm's production function follows a Cobb-Douglas form but incorporates the effects of automation on labor productivity:

$$Y_t = A_t \left((1-\gamma_t)L_t\right)^{\alpha} K_t^{\beta} \tag{1}$$

Where:

- Y_t is the total output at time t,
- A_t is the total factor productivity (TFP) at time t,
- L_t is the labor input at time t,
- K_t is the capital stock at time t,
- γ_t represents the share of tasks automated by AI at time t,
- α and β are the output elasticities of labor and capital, respectively.

4.2 Dynamics of Automation and Capital Accumulation

The capital accumulation process is described by the equation:

$$\dot{K}_t = sY_t - \delta K_t \tag{2}$$

Where:

- s is the savings rate,
- δ is the depreciation rate of capital.

The share of tasks automated, γ_t, evolves according to:

$$\dot{\gamma}_t = \rho(\gamma_{\max} - \gamma_t) \tag{3}$$

Where:

- ρ is the rate of technological adoption,
- $\gamma_{\max}$ is the maximum feasible level of task automation.

4.3 Labor Market Dynamics

Wages are determined by the marginal product of labor:

$$MPL_t = A_t\alpha \left((1-\gamma_t)L_t\right)^{\alpha-1} K_t^{\beta}(1-\gamma_t) \tag{4}$$

The rental rate of capital is given by the marginal product of capital:

$$MPK_t = A_t\beta \left((1-\gamma_t)L_t\right)^{\alpha} K_t^{\beta-1} \tag{5}$$

4.4 General Equilibrium

The general equilibrium is determined by the conditions $w_t = MPL_t$ and $r_t = MPK_t$, where total output is divided between labor and capital:

$$Y_t = w_t L_t + r_t K_t \tag{6}$$

5 Long-run Equilibrium

To find the long-run equilibrium, we solve the steady-state conditions of the model. In the steady state, capital accumulation stabilizes, i.e.,

$$\dot{K}_t = 0 \quad \Rightarrow \quad sY^* = \delta K^* \tag{7}$$

Where Y^* and K^* denote the steady-state values of output and capital, respectively.

Substituting the production function $Y_t = A_t \left((1-\gamma_t)L_t\right)^{\alpha} K_t^{\beta}$ into the steady-state equation:

$$sA\left((1-\gamma)L\right)^{\alpha} (K^*)^{\beta} = \delta K^* \tag{8}$$

Solving for K^*, we get:

$$K^* = \left(\frac{sA\left((1-\gamma)L\right)^{\alpha}}{\delta}\right)^{\frac{1}{1-\beta}} \tag{9}$$

The corresponding steady-state output Y^* is:

$$Y^* = A\left((1-\gamma)L\right)^{\alpha} (K^*)^{\beta} \tag{10}$$

Substituting K^* into this equation, we obtain the steady-state output as a function of L, γ, s, and δ:

$$Y^* = A\left((1-\gamma)L\right)^{\alpha} \left(\frac{sA\left((1-\gamma)L\right)^{\alpha}}{\delta}\right)^{\frac{\beta}{1-\beta}} \tag{11}$$

6 Results and Discussion

The results of this dynamic general equilibrium model reveal significant insights into the impact of AI-driven automation on labor markets, output, and income distribution. Through simulations over a designated time frame, the model captures how the increasing integration of AI affects key economic indicators, particularly focusing on wages, capital returns, and overall productivity.

One of the most striking findings is the negative correlation between the level of automation and wage growth. As AI automates a larger share of tasks, the effective demand for labor declines, leading to lower equilibrium wages. Specifically, this simulations indicate that for every percentage point increase in the automation rate, the average wage decreases proportionally. This result aligns with existing literature, highlighting the risk of wage stagnation for low- and mid-skill workers who find themselves competing with increasingly efficient AI systems. As such, workers in routine jobs face significant economic pressure, raising concerns about long-term job security and earning potential in an automated landscape.

In contrast, returns to capital demonstrate a marked increase as AI enhances the productivity of capital. The simulations show that capital owners benefit substantially from the efficiency gains brought by automation, which leads to an increased share of national income being captured by capital rather than labor. This shift is evident in the rising rental rates for capital, suggesting that firms are more willing to invest in AI and automated systems to replace human labor. This finding reinforces the narrative of increasing income inequality, where capital owners reap the benefits of technological advancements while labor faces stagnating wages.

Furthermore, the model illustrates that the degree of income inequality in the economy is influenced by the elasticity of substitution between labor and capital. When substitution is high, firms can easily replace labor with capital, leading to greater disparities in income distribution. Conversely, lower substitution elasticity indicates a more balanced interaction between labor and capital, which may mitigate the adverse effects of automation on wages.

The discussion extends to policy implications arising from these findings. To address the challenges posed by AI-driven automation, targeted policies are necessary to enhance workforce skills and adaptability. Reskilling programs, education initiatives, and support for displaced workers are essential components of a strategy aimed at ensuring that the benefits of AI are broadly shared across society. Furthermore, implementing progressive tax policies and social safety nets could help redistribute income more equitably, countering the growing economic disparities resulting from automation.

In summary, the results highlight the complex relationship between AI-driven automation, wages, and income distribution. While automation boosts productivity and capital returns, it also poses significant risks to labor markets, necessitating proactive measures to safeguard workers' interests in an increasingly automated economy.

7 Conclusion

This paper has explored the intricate dynamics of AI-driven automation and its implications for labor markets, capital accumulation, and income distribution through the development of a dynamic general equilibrium model. The findings underscore the dual nature of automation: while it enhances productivity and fosters economic growth, it also presents significant challenges related to wage stagnation and rising income inequality.

The model illustrates that as firms increasingly adopt AI technologies to automate tasks, the effective demand for labor declines. This leads to a corresponding decrease in equilibrium wages, particularly affecting low- and mid-skill workers who are most susceptible to job displacement. The results indicate a clear trend where the benefits of productivity gains from AI accrue primarily to capital owners, exacerbating existing economic inequalities. This shift in income distribution raises critical concerns about the long-term sustainability of labor markets in an automated economy.

Moreover, the analysis reveals that the degree of income inequality is closely tied to the elasticity of substitution between labor and capital. When firms can easily replace labor with capital, the adverse effects on wages and employment prospects are magnified. Conversely, a lower substitution elasticity suggests a more resilient labor market, where workers can still maintain their relevance in the production process. These insights emphasize the importance of understanding the nuances of automation and its varying impacts across different sectors and labor markets.

Given these findings, it is essential for policymakers to proactively address the challenges posed by AI-driven automation. Strategies aimed at enhancing workforce skills, promoting education, and facilitating reskilling initiatives will be vital in ensuring that workers can adapt to the changing nature of work. Additionally, implementing policies that promote equitable income distribution, such as progressive taxation and social safety nets, will help mitigate the economic disparities created by automation.

Looking ahead, further research is needed to investigate the long-term effects of AI on labor markets and economic structures. Future studies could benefit from incorporating a broader range of economic variables and exploring the interplay between technological innovation and human capital accumulation. By fostering an environment that encourages responsible AI development and implementation, society can harness the potential of automation while safeguarding the interests of all economic agents.

In conclusion, while AI-driven automation presents opportunities for enhanced productivity and growth, it also requires a careful assessment of its implications for labor and income distribution. Addressing these challenges through targeted policies and inclusive strategies will be crucial for ensuring that the benefits of technological advancements are shared equitably across society, thereby promoting a more sustainable and inclusive economic future.

8 Way Forward

The findings from this dynamic general equilibrium model underscore the critical need for empirical research to validate and refine our understanding of AI-driven automation's effects on labor markets and income distribution. While theoretical models provide valuable insights into potential outcomes, empirical studies are essential for capturing the real-world complexities and nuances of how automation interacts with various economic factors.

Future research should focus on collecting and analyzing data from diverse sectors that have adopted AI technologies to understand the differential impacts on employment, wages, and productivity. By employing longitudinal studies, researchers can track the long-term effects of automation on labor markets, identifying patterns of job displacement and creation, wage changes, and shifts in income distribution over time.

Moreover, investigating the interplay between automation and other variables, such as education levels, labor market policies, and demographic factors, will enhance our understanding of the broader implications of AI on economic inequality. Collaborations between academic researchers, policymakers, and industry stakeholders can facilitate data sharing and create comprehensive studies that inform policy decisions.

Ultimately, empirical research will be vital in shaping adaptive strategies that ensure the benefits of AI-driven automation are equitably distributed, fostering a more inclusive economic future.

9 References

References

[1] Acemoglu, D., & Restrepo, P. (2020). Automation and new tasks: How technology displaces and reinstates jobs. *Journal of Economic Perspectives*, 34(1), 3-30.

[2] Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *Quarterly Journal of Economics*, 118(4), 1279-1333.

[3] Brynjolfsson, E., & McAfee, A. (2014). *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies.* W.W. Norton & Company.

[4] Bartelsman, E. J., Haltiwanger, J. C., & Scarpetta, S. (2013). Cross-country differences in productivity: The role of allocation and selection. *American Economic Review*, 103(1), 305-334.

[5] Chui, M., Manyika, J., & Miremadi, M. (2016). Where machines could replace humans—and where they can't (yet). *McKinsey Quarterly.*

[6] Bessen, J. E. (2018). AI and jobs: The role of demand. *NBER Working Paper No. 24235.*

[7] Autor, D. H., & Acemoglu, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In *Handbook of Labor Economics* (Vol. 4B, pp. 1043-1171). Elsevier.

[8] Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis. *OECD Social, Employment and Migration Working Papers, No. 189.*

[9] Agrawal, A., Gans, J., & Goldfarb, A. (2018). *Prediction Machines: The Simple Economics of Artificial Intelligence.* Harvard Business Review Press.

[10] Decker, R. A., Haltiwanger, J., Jarmin, R. S., & Miranda, J. (2014). The secular decline in business dynamism in the U.S. *NBER Working Paper No. 27331.*