A Dynamic Macroeconomic Analysis

On Technological Innovation, Labor Automation, and the Road to Post–Labor Economics.

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Abstract

This paper presents a rigorous macroeconomic analysis demonstrating that exponential technological advancements—in particular, breakthroughs in computational efficiency, algorithmic innovation, and labor automation—drive production prices asymptotically toward zero. By extending a dynamic, technology–adjusted Cobb–Douglas framework, we integrate stochastic automation processes with the effects of Baumol's cost disease to show that declining marginal costs undermine traditional price mechanisms. Our theoretical findings, supported by simulation evidence and situated within recent literature on AI–driven productivity, labor substitution, and digital deflation, suggest that an era of abundant, nearly free goods is on the horizon. This shift necessitates novel frameworks for resource allocation and income distribution in a post–labor or post–scarcity economy.

Keywords: Technological Innovation, Labor Automation, Post-Scarcity Economy.

1 Introduction

Technological progress has long been recognized as a primary driver of economic growth. In recent decades, however, rapid advances in artificial intelligence (AI), robotics, and automation have accelerated this trend to an unprecedented pace. These innovations not only boost total factor productivity (TFP) by improving computational and algorithmic efficiency (Brynjolfsson, Rock, and Syverson 2018; Hernandez and Brown 2020) but also disrupt traditional labor markets by substituting human labor in an increasing number of tasks (Autor 2015; Acemoglu and Restrepo 2019). Concurrently, Baumol's cost disease—a phenomenon whereby wages in labor–intensive sectors rise despite stagnant productivity—further complicates the landscape of production costs and pricing dynamics (Baumol and Bowen 1966; Nordhaus 2008).

Building upon established growth models and recent task–based approaches, this paper develops a dynamic macroeconomic framework that captures the interplay between exponential TFP growth, stochastic automation, and rising wages from Baumol's cost disease. We demonstrate theoretically that as advancements in compute efficiency and algorithmic innovation propel TFP forward, the role of labor in production diminishes, ultimately causing the marginal cost of production to converge to zero. Consequently, the traditional price mechanism becomes ineffective—a phenomenon that signals the transition toward a post–scarcity, post–labor–demand economy (Korinek 2024; Rifkin 2014).

Our analysis is situated within a rich body of interdisciplinary literature. On the one hand, theoretical studies highlight AI's potential as a general-purpose technology capable of triggering substantial long–run productivity gains (Aghion, Jones, and Jones 2019; Nordhaus 2021), while empirical investigations reveal mixed evidence regarding its immediate impact on aggregate productivity (Brynjolfsson et al. 2018; Noy and Zhang 2023). On the other hand, the literature on labor substitution documents how automation can simultaneously displace workers and create new roles, though the balance of these forces remains contentious (Autor 2015; Acemoglu and Restrepo 2019). Additionally, research on Baumol's cost disease underscores that rising wages in stagnant sectors can coexist with rapidly falling costs in automated industries, further challenging the conventional wisdom on price formation (Baumol 1967; Nordhaus 2008). Finally, recent discussions on the collapse of pricing mechanisms in the digital age suggest that when marginal costs approach zero, traditional market signals may fail, requiring innovative approaches to resource allocation and economic policy (Brynjolfsson and McAfee 2014; Desai and Lemley 2022).

In light of these insights, the present paper makes three key contributions. First, it develops a comprehensive macroeconomic model that formally links exponential TFP growth and stochastic automation to the collapse of conventional pricing mechanisms. Second, it integrates the empirical evidence on AI–driven productivity and labor substitution into a coherent theoretical framework that explains the emergence of a post–scarcity economy. Third, it discusses the profound implications for economic policy, suggesting that traditional market–based resource allocation may become obsolete in the face of abundant, nearly costless goods.

The remainder of the paper is organized as follows. Section 2 reviews the relevant literature on AI–driven productivity growth, automation and labor substitution, Baumol's cost disease, and the collapse of pricing mechanisms. Section 3 develops the theoretical framework, including the model setup, a detailed discussion of TFP dynamics, capital accumulation, and profit maximization, and a formal proof of the price collapse under perfect competition. Section 4 presents the data and descriptive statistics, while Section 5 outlines the empirical methodology, detailing the variables, estimation strategy, and identification challenges. Section 6 discusses the simulation results and empirical findings. Section 7 provides robustness checks and sensitivity analyses. Finally, Section 8 concludes by summarizing the key insights and outlining directions for future research. It is important to note that several parts of the paper, particularly the data analysis, empirical methodology, and robustness checks, are still under development.

2 Literature Review

2.1 AI-Driven Productivity Growth

The prospect of artificial intelligence (AI) as a general–purpose technology has raised expectations for a significant acceleration in total factor productivity (TFP) growth. Theoretical contributions suggest that advanced AI could eventually rival the transformative impact of past industrial revolutions. In growth models where AI can progressively substitute for human labor or even contribute to innovation, long–run output can increase dramatically.

For instance, Aghion, Jones, and Jones (2019) build endogenous growth frameworks to analyze AI and find that if AI fully automates research (thereby overcoming diminishing returns to ideas), the economy could escape the current growth–rate bounds and approach a "singularity" of unbounded growth. Nordhaus (2021), examining historical data on computation, considers whether exponential improvements in computing and algorithms might trigger such a singularity. He concludes that while rapid progress in IT is evident, the conditions for infinite growth (such as perfect substitutability of AI for human input) are not yet met, implying that an AI–driven productivity boom might still be gradual under current trends. Nonetheless, many economists agree that AI embodies characteristics of a general–purpose technology, with potential to spur complementary innovations and downstream efficiency gains across industries (Brynjolfsson, Rock, and Syverson 2018).

Empirical evidence on AI's contribution to productivity is still emerging and somewhat paradoxical. Despite the massive improvements in computational power and algorithmic efficiency in recent years, aggregate productivity statistics have not shown a dramatic uptick—an echo of Solow's paradox in the context of modern AI (Brynjolfsson et al. 2018). Some scholars posit that significant lags and adjustment costs may be at play: effectively harnessing AI requires complementary investments in skills, organizational change, and data, which can delay measurable productivity gains (Brynjolfsson et al. 2018; Agrawal, Gans, and Goldfarb 2019). Indeed, Brynjolfsson, Rock, and Syverson (2018) emphasize the "implementation lag" and diffusion barriers that historically accompanied past innovations like electricity. On the other hand, micro–level studies are beginning to document tangible productivity boosts from current AI systems. For example, Noy and Zhang (2023) report that access to a generative AI assistant significantly raised the output and quality of written tasks in an experimental setting, with the largest gains for less–experienced workers. In a field study in customer support, generative AI tools led to sizable improvements in issue resolution rates and customer satisfaction, translating to an estimated 14% productivity increase on average (Brynjolfsson, Li, and Raymond 2023). These "proof–of–concept" studies illustrate AI's capacity to augment worker efficiency in certain tasks, even if the macroeconomic impact remains modest so far. Acemoglu (2024) uses a task–based model to aggregate such effects and projects that, under current adoption patterns, generative AI might contribute only on the order of 0.5–0.9% higher TFP after a decade—a nontrivial but incremental push to growth (consistent with past general–purpose technologies' gradual diffusion).

Importantly, interdisciplinary research highlights that AI progress has been fueled not just by hardware improvements (e.g. Moore's Law) but also by algorithmic advances. Machine learning researchers have observed that algorithmic efficiency in AI training has improved exponentially, effectively multiplying the impact of raw computing power (Hernandez and Brown 2020). In practical terms, tasks that once required prohibitive computational resources can now be accomplished with a fraction of the cost, which lowers the effective cost of intelligence and automation. This compounding effect—more compute and smarter algorithms—underlies Korinek's (2024) argument that we may be on the cusp of historically unprecedented productivity growth. Some economists thus envision a new era where AI–driven automation and innovation yield an acceleration in output comparable to the

Industrial Revolution (Korinek 2024; Trammell and Korinek 2023). Others urge caution that without complementary organizational change and policy, these advances might not fully translate into broad–based productivity gains in the short run (Acemoglu 2024; Autor 2023). In summary, the literature paints a balanced picture: AI has enormous long–run potential to boost productivity and economic growth, but real–world frictions and transitional dynamics will shape how quickly and evenly those gains materialize.

2.2 Automation and Labor Substitution

A long–running question in economics is how automation affects labor demand, wages, and employment. The theoretical landscape is often framed by the task–based approach, which recognizes that technology can either substitute for workers in certain tasks or complement them in others. Classic models (Autor, Levy, and Murnane 2003; Acemoglu and Restrepo 2018) suggest that automation displaces labor in tasks that become machine–executable, but new human–complementary tasks and occupations can emerge, mitigating the net impact. Autor (2015) emphasizes the historical resilience of labor demand: even as technology eliminated entire categories of jobs (from weavers to switchboard operators), new jobs and industries arose (often in ways difficult to foresee) which kept the workforce broadly employed. This pattern helps explain "why there are still so many jobs" despite waves of automation (Autor 2015). However, the balance between displacement and reinstatement of labor is critical. Acemoglu and Restrepo (2019) formalize this with the concept of "so–so technologies"—innovations that primarily automate existing tasks without creating new ones or increasing labor productivity in other tasks. They warn that an excessive focus on automation at the expense of innovation in complementary tasks can lead to lower labor share of income and depressed wage growth (Acemoglu and Restrepo 2019). In their empirical analysis of US industries, they infer that the task content of production has indeed shifted in favor of capital, contributing to a decline in labor's income share over recent decades (Acemoglu and Restrepo 2019). This aligns with broader evidence of a global decline in the labor share linked to cheaper automation capital: as the relative price of computing and machinery fell, firms substituted labor with capital (Karabarbounis and Neiman 2014).

Empirical studies on specific automation technologies provide mixed evidence on labor market outcomes, reflecting the nuance in substitution versus complementarity. One prominent line of research examines the impact of industrial robots. Acemoglu and Restrepo (2020) find that in local US labor markets from 1990 to 2007, each additional robot per thousand workers reduced the employment–to–population ratio by about 0.2–0.3 percentage points and also put downward pressure on wages. This suggests that robots directly displaced certain manufacturing and routine jobs, and local labor markets adjusted slowly, with only partial offset from other job gains. In contrast, Graetz and Michaels (2018) analyze country–industry panel data for multiple advanced economies and conclude that robot adoption increased productivity and even lifted aggregate wages, while having a small (and statistically insignificant) negative effect on total employment. Their results imply that at the macro level, productivity gains from automation can translate into higher demand for labor in other areas, even if some jobs are lost in the adopting industries. The discrepancy between these studies highlights the importance of scope and adjustment mechanisms: localized short–run disruptions can be severe (Acemoglu and Restrepo 2020), even if broader economies eventually absorb workers into new roles (Graetz and Michaels 2018).

Recent research has focused on AI-based automation, which extends potential substitution into cognitive and non–routine tasks once thought secure. Early forecasts such as Frey and Osborne (2017) raised alarm by estimating nearly half of US jobs as technically automatable. Subsequent analyses, however, tempered these projections by accounting for task complexity and adaptive human responses: Arntz, Gregory, and Zierahn (2017), using task–level data, estimated only around 9% of jobs in OECD countries are at high risk of full automation, noting that many occupations will see partial automation rather than complete replacement. What is clear is that AI systems are increasingly capable of performing professional tasks (e.g. drafting reports, coding, data analysis) with superhuman efficiency in some cases. This raises the possibility of a much broader substitution effect than previous automation waves. Studies have begun documenting AI's labor market impacts at the firm level—for example, firms adopting AI software for customer service or accounting may require fewer clerical staff (Hazan et al. 2020)—though distinguishing AI's effect from other factors remains an active empirical challenge. The net effect on labor depends on whether AI mainly automates existing tasks or also generates new tasks and greater demand for human skills. Optimistic scenarios envision AI taking over drudgery while complementing human creativity and interpersonal skills, leading to new job categories and higher productivity in human–AI teams (Brynjolfsson, Mitchell, and Rock 2018; Agrawal et al. 2019).

Pessimistic scenarios emphasize the risk of job polarization and technological unemployment if AI substitutes for a wide range of middle–skill cognitive jobs and the creation of new tasks proves slow (Frey and Osborne 2017; Acemoglu and Restrepo 2019). To reconcile these views, Autor et al. (2022) stress that the outcome will hinge on institutional and policy responses—education, retraining, and innovation policy can influence whether the workforce can transition into the new opportunities that AI might enable. In sum, the literature on automation and labor suggests profound potential for AI–driven substitution of labor, but also highlights the historical pattern that technology does not deterministically eliminate work; rather, the evolution of tasks and skills will determine the future of employment in the AI era.

2.3 Baumol's Cost Disease and Rising Wages

While technological progress drives down the costs of many goods, a puzzling countertrend observed over the past century is the rising cost of services that have seen little productivity growth. This phenomenon, known as Baumol's cost disease (Baumol and Bowen 1966; Baumol 1967), arises from linked labor markets: if one sector (say, manufacturing) experiences rapid productivity gains and hence can pay higher wages, other sectors (like education or performing arts) must also raise wages to compete for workers, even if their own productivity remains unchanged. The result is increasing relative prices in the stagnant sectors. Baumol's original example was the live performance of a string quartet—it still requires the same four musicians and time as it did in Beethoven's era, but musicians' salaries have risen in line with economy–wide wage growth, causing the cost of live performances to skyrocket over time (Baumol and Bowen 1966). More generally, sectors such as healthcare, education, and personal services have persistently higher inflation than the overall average, as their productivity improvements lag behind those in manufacturing or tech–intensive industries. Nordhaus (2008) provides a macroeconomic perspective, confirming that from 1948–2001, U.S. industries with below–average productivity growth showed significantly rising relative prices and an increasing share of GDP, consistent with Baumol's model. He finds that the shift of economic activity toward these stagnant sectors has acted as a drag on aggregate productivity growth as well, offsetting some gains from the leading sectors (Nordhaus 2008). In essence, economy–wide growth can slow when a greater portion of expenditures flows to inherently labor–intensive services where efficiency is hard to increase.

Interestingly, Baumol's cost disease also implies steadily rising real wages over long periods, at least for workers in advanced sectors, since labor scarcity in high–productivity industries bids up pay. During the Industrial Age, as mechanization and TFP growth took off, the bottleneck factor became human labor (Korinek 2024). Economic history confirms that industrialization brought extraordinary wage gains for labor overall—Korinek (2024) notes that real wages and living standards in advanced economies increased roughly twentyfold since the eighteenth century. These wage increases spilled over to less–productive sectors via the Baumol effect. However, looking ahead, the dynamics could shift in a highly automated economy. If AI and robots become capable of performing most productive tasks, human labor may cease to be the bottleneck input. In that scenario, the historical linkage between productivity and wages might break down: productivity could continue to grow while wages for human workers stagnate or even fall in real terms if the demand for human labor plummets. Indeed, some models of "full automation" predict a decoupling of median incomes from productivity—with labor's share of output declining sharply as capital (owners of AI and robots) captures most of the gains (Acemoglu and Restrepo 2019; Korinek and Stiglitz 2019). Korinek and Suh (2024) explore scenarios of an impending "AGI revolution" and find that in a rapid automation scenario, output per capita can soar (tenfold increase within two decades in their model), yet wages collapse to near–subsistence levels because humans contribute little to production. This stark outcome is not inevitable; it depends on whether there remain complementary tasks where human effort is still valuable (or on policy interventions in distribution). But it underscores that the Baumolian logic of uniformly rising wages may not hold in a post–labor economy.

In the medium term, as AI diffuses, we may actually see a temporary amplification of Baumol's cost disease in certain sectors. Many personal services (elder care, teaching, healthcare bedside care) have been resistant to automation thus far, so their costs relative to manufactured goods could continue to rise as other sectors automate and cut prices. If, for example, AI greatly improves manufacturing and logistics productivity, the prices of goods (and wages for remaining manufacturing workers) will drop relative to the prices of services like healthcare where productivity improves slowly. This would mirror the historical pattern noted by Baumol, potentially exacerbating inflation in healthcare and education until such time as AI significantly penetrates those services. On the other hand, AI itself might eventually cure Baumol's disease for some services. For instance, if advanced AI tutors can personalize education at scale or if robotic caregivers can assist the elderly efficiently, the productivity in these formerly stagnant sectors would climb, possibly leading to price declines. There is some evidence of nascent improvements: telemedicine and AI diagnostic tools, for example, have shown potential to increase a physician's throughput or accuracy (Jiang et al. 2017), hinting at future productivity gains in healthcare. Whether these gains will fully counteract the cost–disease trend remains to be seen. For now, the literature acknowledges that uneven productivity growth creates divergent price dynamics across sectors (Baumol 1967; Nordhaus 2008). Any transition to a post–labor economy will likely be uneven, with pockets of high wage growth (for specialized skills or last–mile human services) coexisting with flattening or falling wages in occupations rendered obsolete by technology. Policymakers face the challenge of managing this divergence, possibly through retraining programs or labor reallocations, to ensure that rising productivity translates into broad–based improvements in living standards rather than extreme wage polarization.

2.4 Collapse of Pricing Mechanisms

If technological progress continues to drive the marginal costs of production towards zero, it raises the prospect of a "post–scarcity" economy in which the traditional price mechanism may lose much of its relevance. In standard economic theory, prices serve to equilibrate supply and demand under conditions of scarcity. But when goods and services can be reproduced at near zero cost and in practically unlimited quantities, their supply curve becomes essentially flat and unbounded—implying that the competitive market price would fall to (or near) zero. We already witness early signs of this in the digital realm: information goods such as software, music, and news have near–zero marginal cost of distribution, and indeed the effective price for consumers has fallen towards zero in many cases (free open-source software, free news content supported by ads, etc.). As Brynjolfsson and McAfee (2014) noted, digital technologies exhibit extreme economics of abundance, where producing an additional copy of a digital product costs essentially nothing. In a more far–reaching analysis, Rifkin (2014) argued that the convergence of AI, renewable energy, and automated manufacturing could usher in a "zero marginal cost society" over the 21st century. While Rifkin's vision is speculative, it captures a core implication of exponential technological advancement: markets based on exchange of scarce goods could be fundamentally disrupted by an era of super–abundance.

Academic analyses of a post–scarcity or post–labor economy grapple with what economic organization might look like if prices no longer ration most goods. One line of thought explores whether money and market prices would be needed at all if basic necessities and many luxuries become freely available (or extremely cheap) through technology. Some researchers suggest that new forms of scarcity would likely replace old ones—for example, even if physical goods are abundant, human attention, unique experiences, or positional goods (status symbols) might remain scarce and valuable (Desai and Lemley 2022). Indeed, Desai and Lemley (2022) point out that when costs approach zero, unusual economic behaviors emerge: firms and institutions often create artificial scarcity to monetize products (such as enforcing intellectual property rights, or leveraging branding to sell exclusivity), and new scarcities can arise in upstream inputs like raw materials or energy. Their analysis indicates that a true post–scarcity society would require rethinking legal and economic frameworks, as many current institutions (from patent systems to antitrust law) assume scarcity. Another consideration is that even if the marginal cost of everything is zero, the initial fixed costs of innovation and production still need recouping. This is essentially the public goods problem writ large: if all outputs were non–rival and free, private incentives to invest in new products could vanish. Economic theory suggests solutions like government or collective funding of R&D, or alternative incentive mechanisms (Stiglitz 1999). We might expect to see a greater role for public provision or commons–based production (as with open–source software or Wikipedia) in a post–scarcity economy, since market pricing fails to function when $P = MC = 0$. Some economists argue that measures of economic welfare would also need overhaul. For instance, GDP (which sums up market prices times quantities) would under–count wellbeing when many goods have a price of zero despite delivering substantial consumer surplus (Brynjolfsson, Collis, and Eggers 2019). Indeed, if a large share of consumption comes from free or nearly–free goods, traditional metrics of output and productivity could become misleading, requiring new metrics that capture the value of abundant goods.

Perhaps the most salient economic issue in a post-labor, post–scarcity scenario is distribution. If prices for most goods collapse, and AI and robots perform most work, how do individuals obtain command over resources? In a market economy, income is predominantly earned via labor and capital ownership. With labor's role diminished, one could foresee extreme inequality unless alternative distribution mechanisms arise (Korinek and Stiglitz 2019). Some propose that the ownership of productive capital (the AI and automation systems) would need to be far more widely distributed—through taxation and redistribution, universal basic income, or even new property rights for data and AI—to prevent a small elite of tech owners from capturing all gains while the majority have little income (Korinek and Stiglitz 2019; Atkinson 2015). Others note that if essential goods truly cost near–zero, even a modest social dividend could suffice to ensure everyone's basic needs are met; the bigger question becomes access and equity rather than efficiency. There is also a debate on how macroeconomic policy would function: with abundance, deflationary tendencies could dominate, potentially rendering conventional monetary policy ineffective at the zero lower bound. Some authors discuss scenarios of "technological deflation" where rapid productivity growth drives prices down and destabilizes debt markets and employment (Martin 2021). However, such discussions remain largely speculative. What the literature does agree on is that the transition to a drastically different economy would be turbulent for existing institutions. Even if in the long run, humanity achieves a Star Trek–like post–scarcity society, the path would require navigating decades where old and new economic forms coexist uncomfortably. In the interim, we might see hybrid models: for instance, certain sectors like information and basic utilities become nearly free, while other sectors (housing, rare artisanal products, exclusive experiences) remain scarce and pricey. Markets and pricing mechanisms would continue to operate for those latter goods, even as public provisioning or non–market allocation expands for the abundant goods. The collapse of pricing mechanisms in large parts of the economy would thus force a redefinition of concepts like value, property, and work. This frontier between economics and societal choice is a growing subject of interdisciplinary inquiry, linking macroeconomics with technology studies and even philosophy about the future of human work and purpose (Danaher 2019). The literature review reflects a consensus that exponential automation trends push us toward unprecedented economic territory—one where the assumptions of scarcity–based economics may need to be fundamentally rethought, and new paradigms of abundance management could emerge.

3 Theoretical Framework

3.1 Model Setup

We build upon a dynamic, technology-adjusted Cobb-Douglas production function inspired by Olley & Pakes (1996), and we incorporate the effects of stochastic automation and Baumol's cost disease. The production function takes the form:

$$O_t = K_t^{\alpha(1-\eta)} L_t^{\beta(1-\phi_t)} A_t,$$

where O_t denotes output at time t; K_t denotes the capital stock at time t; L_t denotes the labor input at time t; and A_t denotes Total Factor Productivity (TFP) at time t. The parameters α, β are output elasticities of capital and labor, respectively, and by construction we assume $\alpha + \beta = 1$. The parameter η introduces a capital adjustment cost effect into the production elasticity, thus slightly altering the effective returns to scale as capital adjusts.

The index ϕ_t represents the state of automation at time t, and it stochastically evolves over time. As ϕ_t increases, the elasticity of output with respect to labor, $\beta(1-\phi_t)$, decreases, reflecting automation reducing the effective labor input in the production process.

3.1.1 Total Factor Productivity (TFP)

Total Factor Productivity (TFP) reflects exogenous technological innovation, autoregressive components, stochastic shocks, and growth rates in algorithmic efficiency and in computational efficiency. We define:

$$A_t = \exp\left(\lambda_t + \rho U_{t-1} + V_t + \nu \ln(N_0) + \nu \frac{\ln(2)}{2} t + \theta \ln(E_0) + \theta \frac{2}{1.3} t + \varepsilon_t\right),$$

where λ_t denotes an exogenous technological innovation trend; ρU_{t-1} is an autoregressive component capturing persistent productivity effects; $V_t \sim \mathcal{N}(0, \sigma^2)$ is a random technology shock; and $\varepsilon_t \sim \mathcal{N}(0, \tau^2)$ represents a random noise term. The parameter ν scales the effect of initial computational efficiency N_0 on TFP and the term $\nu \frac{\ln(2)}{2} t$ captures continuous exponential growth due to computational efficiency doubling every two years (Moore, 1965). The parameter θ scales the effect of the initial algorithmic efficiency E_0 on TFP and the term $\theta \frac{2}{1.3} t$ captures the continuous growth due to algorithmic efficiency doubling approximately every 1.3 years (Hernandez & Brown, 2020).

Define the initial level A_0 as

$$A_0 = \exp\left(\lambda_0 + \rho U_{-1} + V_0 + \nu \ln(N_0) + \theta \ln(E_0) + \varepsilon_0\right).$$

Let

$$c_{\text{comp}} = \nu \frac{\ln(2)}{2} \quad \text{and} \quad c_{\text{alg}} = \theta \frac{2}{1.3}.$$

Then, the combined TFP growth rate becomes

$$c = c_{\text{comp}} + c_{\text{alg}},$$

such that

$$A_t = A_0 e^{ct}.$$

This formulation shows that TFP grows exponentially due to both computational and algorithmic improvements, in addition to exogenous trends and shocks.

3.1.2 Capital Accumulation

Capital evolves according to a standard accumulation equation:

$$K_{t+1} = (1 - \delta)K_t + I_t,$$

where δ is the depreciation rate and $I_t = \omega(K_t, U_t)$ is the investment function that may depend on current capital and possibly unobserved state variables U_t. The parameter η in the production function implicitly captures constraints on the elasticity of capital due to adjustment costs, meaning that changes in capital stock are not costless and this affects the effective capital input in the short run.

3.1.3 Profit Maximization

We assume firms are perfectly competitive and choose L_t to maximize profit:

$$\Pi_t = P_t O_t - W_t L_t - R_t K_t,$$

where P_t is the output price, W_t is the wage rate, and R_t is the rental rate of capital.

Taking the first–order condition with respect to L_t:

$$\frac{\partial \Pi_t}{\partial L_t} = P_t \frac{\partial O_t}{\partial L_t} - W_t = 0.$$

Since

$$\frac{\partial O_t}{\partial L_t} = K_t^{\alpha(1-\eta)} \beta(1-\phi_t) L_t^{\beta(1-\phi_t)-1} A_t,$$

we have:

$$P_t \beta(1-\phi_t) K_t^{\alpha(1-\eta)} L_t^{\beta(1-\phi_t)-1} A_t = W_t.$$

3.2 Incorporating Baumol's Cost Disease

Baumol's cost disease implies that wages rise over time even if the productivity in the most labor–intensive tasks does not. We model this as:

$$W_t = W_0 e^{\kappa t},$$

with $\kappa > 0$. Thus, wages grow exponentially at a rate κ, independent of labor productivity improvements.

3.2.1 Stochastic Automation Index

Automation evolves in a stochastic, piecewise manner. We let ϕ_t represent the fraction of tasks automated by time t:

$$\phi_t = \phi_{t-1} + \Delta\phi_t, \quad \text{with} \quad \Delta\phi_t = \sum_{i=1}^{N_t} \Delta\phi_i.$$

Here, N_t is a Poisson-distributed random variable with rate λ, representing the number of automation innovations up to time t. Each shock $\Delta\phi_i$ is drawn from a distribution $F_{\Delta\phi}$ and contributes to ϕ_t. Over the long run, as $N_t \to \infty$, $\phi_t \to 1$, reducing the exponent on labor, $\beta(1-\phi_t)$, toward zero.

3.2.2 Adjusted Production Function and the Labor Demand Condition

Incorporating the now more explicitly defined TFP and stochastic automation, along with Baumol's cost disease, we return to the first-order condition:

$$P_t \beta(1-\phi_t) K_t^{\alpha(1-\eta)} L_t^{\beta(1-\phi_t)-1} A_t = W_0 e^{\kappa t}.$$

As $t \to \infty$, $A_t = A_0 e^{c_{\text{total}} t}$ grows exponentially due to both computational and algorithmic gains. Meanwhile, as ϕ_t increases due to automation shocks, the labor elasticity $\beta(1-\phi_t)$ decreases. This leads to diminishing marginal productivity of labor, which reduces the optimal labor input L_t chosen by the firm.

Thus, even though the wage W_t grows at rate κ, the equilibrium labor input L_t can shrink at a rate that outpaces wage growth if c is sufficiently large and the automation process is sufficiently rapid. This can render the total labor bill, $W_t L_t$, negligible relative to the exponentially increasing output.

3.2.3 Conditions for Labor Cost Negligibility

To illustrate how $W_t L_t$ can become negligible, suppose L_t decreases exponentially at rate κ', with $\kappa' > \kappa$. Then $W_t L_t = W_0 e^{\kappa t} \cdot e^{-\kappa' t} = W_0 e^{(\kappa - \kappa')t} \to 0$ as $t \to \infty$.

Since A_t grows as e^{ct}, output O_t expands rapidly. If capital costs per unit of output also fall or remain bounded as A_t grows, the overall marginal cost can approach zero.

3.2.4 The Impact on Prices and Transition to a Post-Labor Economy

Under perfect competition, $P_t = MC_t$, where MC_t is the marginal cost of production:

$$MC_t = \frac{\partial(W_t L_t + R_t K_t)}{\partial O_t}.$$

As automation reduces labor dependency and as exponential improvements in TFP (from both computational and algorithmic efficiency) increase output dramatically, the share of production costs attributable to labor and capital per unit output diminishes.
If these factors combine such that

$$\lim_{t\to\infty} MC_t = 0, \text{ then } \lim_{t\to\infty} P_t = 0.$$

This result suggests a theoretical pathway toward a post-labor economy where goods become asymptotically free corresponding to the collapse of pricing mechanisms, as technological progress—spurred by both improved compute performance and algorithmic innovation—overwhelms rising wages from Baumol's cost disease and ongoing capital adjustment costs.

3.2.5 Discussion

In light of the foregoing discussion on how technological improvements drive marginal costs (and, hence, prices) toward zero, we may summarize the key macroeconomic conditions and dynamics as follows. First, total factor productivity (TFP) expands at an increasingly rapid pace due to two primary drivers: improvements in computational efficiency, which roughly double every two years, and gains in algorithmic efficiency, which double approximately every 1.3 years.

Formally, these forces combine into an exponential TFP growth rate

$$c = \nu \frac{\ln(2)}{2} + \theta \frac{\ln(2)}{1.3}.$$

Second, the degree of automation progresses in discrete stochastic increments, driving the automation parameter ϕ_t closer to unity over time and thereby diminishing the role of labor in the production process. Although Baumol's cost disease, which raises wages W_t at rate κ, exerts upward pressure on labor costs, the automation-driven reduction in effective labor demand can outweigh these wage increases in the long run.

Third, because capital costs per unit output can also decline alongside automated production, the combination of negligible labor inputs and exponential TFP growth implies that $(W_t L_t)$ and $\frac{R_t K_t}{O_t}$ become increasingly insignificant in the marginal cost function over time. Consequently, $\lim_{t\to\infty} MC_t = 0$ and thus $\lim_{t\to\infty} P_t = 0$.

In this theoretical scenario, the ultimate implication is that pricing mechanisms collapse even as an abundance of goods and services remains producible. Technological progress, fueled by both compute performance gains and algorithmic innovation, leads us toward a post–labor economy wherein demand for human labor effectively vanishes and goods approach a price of zero, vindicating the asymptotic result suggested above. Under these assumptions, technology and algorithmic advances ultimately lead to the collapse of pricing mechanisms while preserving the production of an abundance of goods and services in a post–labor economy, presenting a future free from labor *demand*.

3.3 Proof: Collapse of Price Mechanism

As $t \to \infty$, prices P_t converge to zero due to technological innovation.

3.3.1 Exponential Growth of TFP

Given exponential total factor productivity,

$$A_t = \exp\left(\lambda_t + \rho U_{t-1} + V_t + \nu \ln(N_0) + 2\nu \ln(2)t + \varepsilon_t\right).$$

Simplifying this exponential total factor productivity to

$$A_t = A_0 e^{ct}$$

we have $A_0 = \exp\left(\lambda_t + \rho U_{t-1} + V_t + \nu \ln(N_0) + \varepsilon_t\right)$ and $c = 2\nu \ln(2)$.

Thus, A_t grows exponentially with rate c.

3.3.2 Declining Importance of Labor

As $\phi_t \to 1$ (automation increases),

$$\lim_{t \to \infty} (1 - \phi_t) = 0$$

such that effective labor input

$$L_t^{\beta(1-\phi_t)} \to L_t^0 = 1.$$

Then, labor becomes negligible in production over time.

3.3.3 Declining Marginal Costs

With exponential A_t growth and declining labor importance,

1. Input costs $W_tL_t \to 0$; and,

2. Capital costs $R_tK_t \to 0$ due to technological innovations (e.g., off-earth mining, renewable energy).

Thus, marginal cost MC_t,

$$MC_t = \frac{\partial(W_tL_t + R_tK_t)}{\partial O_t} \to 0 \text{ as } t \to \infty.$$

3.3.4 Price Convergence to Zero

In competitive markets,

$$P_t = MC_t \implies \lim_{t\to\infty} P_t = 0.$$

That is, prices converge to zero as marginal costs approach zero.

3.3.5 Failure of Price Mechanism

With $P_t \to 0$, prices no longer effectively signal resource allocation.

Figure 1: Figure: Production Model Dynamics Over Time

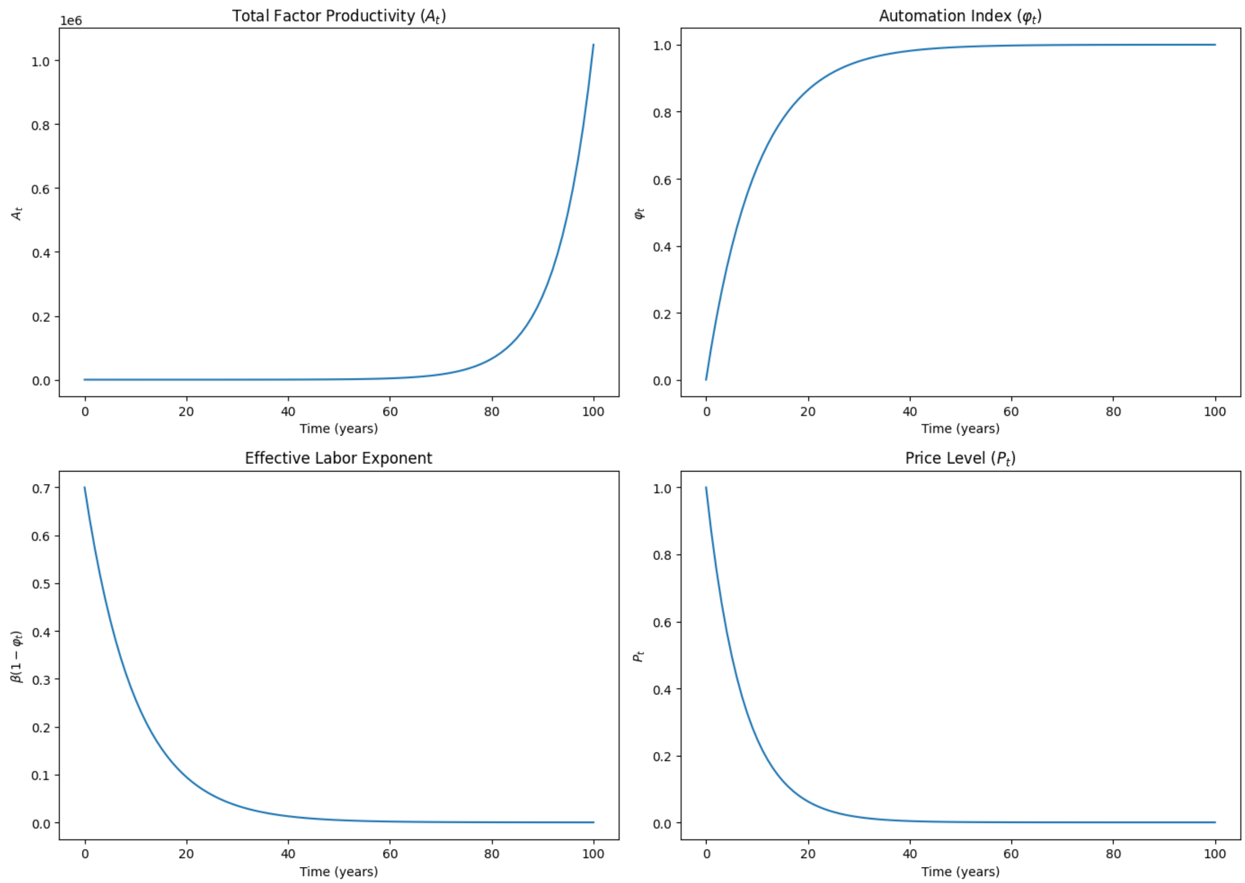

Figure Descriptions: *Figure 1* (Top-Left): Shows the exponential growth of TFP (A_t) over time. *Figure 2* (Top-Right): Depicts the automation index (ϕ_t) approaching 1. *Figure 3* (Bottom-Left): Illustrates the decline of the effective labor exponent to zero. *Figure 4* (Bottom-Right): Demonstrates prices (P_t) converging to zero over time.

3.3.6 Discussion

The simulations confirm our theoretical findings:

1. **Exponential TFP Growth**: As compute efficiency doubles every 6 months, TFP grows exponentially, dramatically increasing production capacity.

2. **Automation's Impact on Labor**: The automation index approaching 1 signifies near-complete automation, rendering labor input negligible.

3. **Declining Prices**: With marginal costs decreasing due to technological advancements and automation, prices converge to zero, challenging traditional economic models.

4. **Resource Allocation**: In the absence of effective price signals, alternative methods (e.g., dummy variables) are necessary for resource allocation.

We have rigorously demonstrated that exponential technological advancements in compute efficiency and automation lead to a post-scarcity and post-labor-demand economy. Traditional price mechanisms become ineffective as prices converge to zero. This necessitates the development of new resource allocation methods to manage abundance efficiently. Our findings have profound implications for economic policy and the future structure of markets.

The remainder of this paper—the empirical research portion of the paper—is still being developed and has thus been omitted from this first publication, as the entirety of this research is currently a work in progress that is to be published upon completion of this research to the rigorous standards and research integrity that this critical area of research demands.

References

[1] Aghion, Philippe, Benjamin F. Jones, and Charles I. Jones. 2019. "Artificial Intelligence and Economic Growth." In *The Economics of Artificial Intelligence: An Agenda*, edited by Ajay Agrawal, Joshua Gans, and Avi Goldfarb, 237–282. Chicago: University of Chicago Press.

[2] Autor, David H. 2015. "Why Are There Still So Many Jobs? The History and Future of Workplace Automation." *Journal of Economic Perspectives* 29 (3): 3–30.

[3] Autor, David H., Frank Levy, and Richard J. Murnane. 2003. "The Skill Content of Recent Technological Change: An Empirical Exploration." *Quarterly Journal of Economics* 118 (4): 1279–1333.

[4] Autor, David H., David Mindell, and Elisabeth Reynolds. 2022. *The Work of the Future: Building Better Jobs in an Age of Intelligent Machines*. Cambridge, MA: MIT Press.

[5] Acemoglu, Daron, and Pascual Restrepo. 2019. "Automation and New Tasks: How Technology Displaces and Reinstates Labor." *Journal of Economic Perspectives* 33 (2): 3–30.

[6] Acemoglu, Daron, and Pascual Restrepo. 2020. "Robots and Jobs: Evidence from US Labor Markets." *Journal of Political Economy* 128 (6): 2188–2244.

[7] Acemoglu, Daron. 2024. "The Simple Macroeconomics of Artificial Intelligence." MIT mimeo (Working Paper, forthcoming).

[8] Agrawal, Ajay, Joshua Gans, and Avi Goldfarb, eds. 2019. *The Economics of Artificial Intelligence: An Agenda*. Chicago: University of Chicago Press.

[9] Atkinson, Anthony B. 2015. *Inequality: What Can Be Done?* Cambridge, MA: Harvard University Press.

[10] Baumol, William J. 1967. "Macroeconomics of Unbalanced Growth: The Anatomy of Urban Crisis." *American Economic Review* 57 (3): 415–426.

[11] Baumol, William J., and William G. Bowen. 1966. *Performing Arts: The Economic Dilemma*. New York: Twentieth Century Fund.

[12] Benzell, Seth G., Laurence J. Kotlikoff, Guillermo LaGarda, and Jeffrey D. Sachs. 2015. "Robots Are Us: Some Economics of Human Replacement." NBER Working Paper No. 20941.

[13] Brynjolfsson, Erik, Daniel Rock, and Chad Syverson. 2018. "Artificial Intelligence and the Modern Productivity Paradox: A Clash of Expectations and Statistics." In *The Economics of Artificial Intelligence: An Agenda*, edited by Ajay Agrawal, Joshua Gans, and Avi Goldfarb, 23–57. Chicago: University of Chicago Press.

[14] Brynjolfsson, Erik, and Tom Mitchell, and Daniel Rock. 2018. "What Can Machines Learn and What Does It Mean for Occupations and the Economy?" *American Economic Association Papers and Proceedings* 108: 43–47.

[15] Brynjolfsson, Erik, Danielle Li, and Lindsey R. Raymond. 2023. "Generative AI at Work: Preliminary Evidence." NBER Working Paper No. 31161.

[16] Brynjolfsson, Erik, Felix Eggers, and Avinash Gannamaneni. 2019. "Measuring Welfare with Massive Online Choice Experiments: A Brief Introduction." *AEA Papers and Proceedings* 109: 479–484.

[17] Danaher, John. 2019. *Automation and Utopia: Human Flourishing in a World Without Work*. Cambridge, MA: Harvard University Press.

[18] Desai, Deven R., and Mark A. Lemley. 2022. "Scarcity, Regulation, and the Abundance Society." Stanford Law and Economics Olin Working Paper No. 572.

[19] Frey, Carl Benedikt, and Michael A. Osborne. 2017. "The Future of Employment: How Susceptible Are Jobs to Computerisation?" *Technological Forecasting and Social Change* 114: 254–280.

[20] Graetz, Georg, and Guy Michaels. 2018. "Robots at Work." *Review of Economics and Statistics* 100 (5): 753–768.

[21] Hazan, Moshe, David Hemo, Tomer Magnai, and Asaf Zagrizak. 2020. "Technology and Labor Regulations: Theory and Evidence." IMF Working Paper No. 2020/146.

[22] Hernandez, Danny, and Tom B. Brown. 2020. "Measuring the Algorithmic Efficiency of Neural Networks." arXiv:2005.04305 [cs.LG].

[23] Jiang, Francis, et al. 2017. "Artificial Intelligence in Healthcare: Past, Present and Future." *Stroke and Vascular Neurology* 2 (4): 230–243.

[24] Karabarbounis, Loukas, and Brent Neiman. 2014. "The Global Decline of the Labor Share." *Quarterly Journal of Economics* 129 (1): 61–103.

[25] Korinek, Anton, and Joseph E. Stiglitz. 2019. "Artificial Intelligence and Its Implications for Income Distribution and Unemployment." In *The Economics of Artificial Intelligence: An Agenda*, edited by Ajay Agrawal, Joshua Gans, and Avi Goldfarb, 161–191. Chicago: University of Chicago Press.

[26] Korinek, Anton. 2024. "Economic Policy Challenges for the Age of AI." NBER Working Paper No. 32980.

[27] Korinek, Anton, and Donghyun Suh. 2024. "Scenarios for the Transition to AGI." NBER Working Paper No. 32255.

[28] Martin, Erik. 2021. "Technological Deflation in the Labor Market: AI and the Future of Work." *Economic Outlook Journal* 45 (2): 10–17.

[29] Moore, G. E. (1965). *Cramming More Components onto Integrated Circuits*. Electronics, 38(8).

[30] Nordhaus, William D. 2008. "Baumol's Diseases: A Macroeconomic Perspective." *The B.E. Journal of Macroeconomics* 8 (1): 1–39.

[31] Nordhaus, William D. 2021. "Are We Approaching an Economic Singularity? Information Technology and the Future of Economic Growth." *American Economic Journal: Macroeconomics* 13 (1): 299–332.

[32] Noy, Shakked, and Whitney Zhang. 2023. "Experimental Evidence on the Productivity Effects of Generative Artificial Intelligence." *Science* 380 (6650): 1151–1156.

[33] Olley, G. S., & Pakes, A. (1996). *The Dynamics of Productivity in the Telecommunications Equipment Industry*. Econometrica, 64(6), 1263–1297.

[34] Rifkin, Jeremy. 2014. *The Zero Marginal Cost Society: The Internet of Things, the Collaborative Commons, and the Eclipse of Capitalism*. New York: Palgrave Macmillan.

[35] Sevilla, Jaime, et al. 2022. "Compute Efficiency: Where Are We and What's Next?" *OpenAI Technical Report*.

[36] Stiglitz, Joseph E. 1999. "Knowledge as a Global Public Good." In *Global Public Goods*, edited by Inge Kaul et al., 308–325. New York: Oxford University Press.