Nova Aetas Distributed Systems Intelligence

Greypaper

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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.

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.

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.

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:

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

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.

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.

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:

$$P_t\beta(1-\phi_t)K_t^{\alpha(1-\eta)}L_t^{\beta(1-\phi_t)-1}A_t = W_0e^{\kappa t}.$$

As $t \to \infty$, $A_t = A_0e^{c_{\text{total}}t}$ 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_tL_t, negligible relative to the exponentially increasing output.

Conditions for Labor Cost Negligibility

To illustrate how W_tL_t can become negligible, suppose L_t decreases exponentially at rate κ', with $\kappa' > \kappa$. Then $W_tL_t = W_0e^{\kappa t} \cdot e^{-\kappa' t} = W_0e^{(\kappa-\kappa')t} \to 0$ 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.

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

$$\lim_{t\to\infty} MC_t = 0,$$

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.

Summary of Conditions and Dynamics

1. TFP grows due to both computational efficiency (doubling every 2 years) and algorithmic efficiency (doubling every 1.3 years), combining into an exponential growth with rate $c = \nu \frac{\ln(2)}{2} + \theta \frac{\ln(2)}{1.3}$.

2. Automation progresses in stochastic jumps, pushing $\phi_t \to 1$ over time, reducing labor's role in production.

3. Baumol's cost disease ensures W_t grows at a rate κ, but the automation–driven reduction in labor demand can dominate.

4. As $t \to \infty$, if $W_t L_t$ and $R_t K_t / O_t$ become negligible due to exponential TFP growth and diminishing labor input, marginal cost MC_t and hence P_t tend to zero.

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.

Author's Note

One of the primary challenges presented by this economic paradigm shift arises due to the collapse of the price mechanism. To put it very simply, how the fuck do we allocate resources in capitalist markets of supply and demand if we have no price mechanism? I staunchly reject the communist economic philosophies underlying its current marketing euphemisms, Universal Basic Income (UBI) and Computational Communism, which would without a doubt doom humanity's fate down a dystopian path towards authoritarianism, where our social, political, and economic systems are dictated by a government–operated AI centralized planner. I will not allow that future to become a reality on my watch.

With that, I hope this paper has effectively conveyed the motivations behind my work in designing and building alternative economic frameworks. My highest aspiration in taking on this work is to participate in building a future for humanity that promotes individual liberty and accelerates human agency through the Universal Basic Compute framework and the AI Agent Network Market–Mimicry framework. My dedicated efforts with Nova Aetas Distributed Systems Intelligence are focused on developing and implementing these paradigms to advance this mission. Together, these technology frameworks collide to create a future liberated by technological sovereignty, leveraging decentralized and distributed systems to elevate humanity's social, economic, and governance structures to the next stage of civilization.