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Modeling the Impact of AI-Driven Productivity Gains on Corporate Profitability, Wages, and Employment

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Abstract

Developed economies are anticipating large disruption from the emerging technology of the Artificial Intelligence sector. New tools, particularly Large Language Models with pre-training and reinforcement learning, are increasingly capable of performing the intellectual work often associated with "white-collar" jobs, posing a new risk of automating a larger percentage of the work force's professions. While this is not the first industrial revolution, historical labor shifts created demand for new cognition based jobs, while cognitive automation along with robotics threatens to displace labor across both legacy and emerging sectors. Therefore, if AI becomes capable of automating all or most tasks, it could lead to mass unemployment and a partial or total decoupling of labor and production. This paper seeks to quantify this risk by utilizing a classical simulation model to investigate an economy with a dynamic labor market and an AI capable of automating all tasks. The economy will be calibrated to a balanced state and then disrupted with the introduction of AI's "free" labor. The resilience of the system is then evaluated across various scenarios, including no intervention, minimum wages, layoff prohibitions, decreasing prices, and fiscal interventions via taxation and redistribution. This paper is primarily interested in revealing the economic impact of AI productivity increases on consumers' purchasing power and corporate profits. This paper finds that in a simplistic economy, AI generally negatively impacts employment, purchasing power, and corporate profits. Exceptions to this only occur when companies sustain demand by maintaining payrolls to employees through financial automation penalties or layoff prohibition.

Keywords
AI, Labor Productivity, Simulation.

1. Introduction
Artificial Intelligence (AI) technologies are rapidly transforming the structure of modern economies. Recent advances in machine learning, particularly Large Language Models (LLMs) trained through large-scale pretraining and reinforcement learning techniques, have significantly expanded the range of tasks that machines can perform. Unlike prior waves of industrial automation that primarily displaced manual labor, modern AI systems are increasingly capable of performing cognitive and analytical tasks traditionally associated with highly educated professions. As a result, industries including finance, software development, customer service, education, legal services, and healthcare

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along with manual tasks may experience measurable shifts in labor demand driven by AI-enabled productivity gains.

Historically, industrial revolutions have generated both disruption, displacing labor, and opportunity, providing areas of labor growth. Mechanization in the Industrial Revolution and computerization during the Information Age displaced many existing occupations like skilled textile workers while simultaneously creating new categories of employment such as those in the automotive sector. In these historical cases, labor markets, after periods of disruption, eventually adapted to the potent but measured pace of technological innovation. However, the current AI revolution presents a potentially different economic dynamic. Because AI systems increasingly substitute for cognitive and creative labor rather than merely augmenting physical productivity, the possibility exists that automation could outpace the labor market's ability to generate replacement employment opportunities and even act as an immediate substitute for human labor in the newly emerging industries. This raises concerns regarding the potential of long-term structural unemployment, widening wealth inequality, and the decoupling of labor from economic production.

Human employment plays a unique dual role within modern economies, as it functions as both a supply of labor for production and the source of consumption and demand. Therefore, large impacts to human employment have difficult to predict consequences on the general economy. In this case, increased productivity from AI adoption may substantially reduce operational costs and temporarily increase corporate profit margins; however, widespread labor displacement may simultaneously reduce aggregate consumer purchasing power and therefore total demand, which would ultimately lead to a long-run decrease in corporate profitability. Since consumer demand is a foundational driver of economic activity in developed economies, a persistent decline in labor income could destabilize broader economic systems despite increases in productive efficiency. Consequently, understanding the systemic behavior of AI-driven economies has become an increasingly urgent research problem.

Furthermore, corporations may have little optionality in choosing the degree to which they automate. Previous research has identified that AI automation causes a game theory problem for corporations reminiscent of the Prisoner's Dilemma. While it is profitable for one firm to automate their labor, lowering costs by reducing headcount, an entire economy behaving like this destroys broader demand and lowers all firms' profits beyond the savings made by automating. Regardless, the dominant strategy for any individual firm is to automate, posing an incentive-based threat to the entire market. This begs the question: In the case of an AI capable of automating all tasks, what, if any, intervention can firms or governments take to prevent poor economic outcomes due to the resulting labor disruption?

Despite growing public and academic attention to AI-driven labor disruption, significant uncertainty remains regarding the long-term equilibrium behavior of economies experiencing rapid cognitive automation. Existing discussions are frequently qualitative, speculative, or focused on isolated industries rather than system-wide economic interactions. Furthermore, many current studies do not adequately model the dynamic relationships between productivity, labor displacement, wages, corporate profits, taxation, and consumer demand under varying policy conditions. There remains a need for varying quantitative simulation approaches capable of evaluating how economies may respond to different levels of AI adoption and governmental intervention.

This research seeks to address this gap by developing a classic simulation model of an industrial economy with a dynamic labor market. The simulated economy is first calibrated to a stable equilibrium state before being disrupted through the introduction of AI-generated "free" labor capable of replacing all tasks in the workforce. The model then evaluates the resilience and behavior of the economy under multiple policy scenarios, including minimum wages, layoff prohibitions, fixed/elastic pricing, and taxation with Universal Basic Income (UBI). Particular emphasis is placed on measuring the effects of AI-driven productivity gains on employment levels, consumer purchasing power, and corporate profitability.

The primary problem investigated in this paper is whether highly advanced AI-driven automation creates economically unstable conditions by weakening the relationship between human labor and production. Specifically, this study examines whether productivity growth generated through AI adoption produces sustainable economic prosperity or whether it instead accelerates labor displacement and demand-side contraction in the absence of effective policy intervention. In the case of economic disruption, the paper then investigates several policy interventions to determine what measures may be taken to mitigate the negative impacts of AI. By modeling these interactions this paper aims to contribute a quantitative framework for evaluating the economic risks and policy implications associated with large-

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scale AI adoption.

1.1 Objectives

The primary objective of this research is to quantitatively evaluate the economic impact of large-scale Artificial Intelligence (AI) adoption on labor markets, consumer purchasing power, and corporate profitability within a simulated industrial economy. This study seeks to investigate whether rapid increases in AI-driven productivity can produce stable long-term economic growth or whether they create systemic instability through widespread labor displacement and weakened aggregate demand.

To achieve this objective, the paper develops a simulation model representing a dynamic labor market and production economy. The simulation is calibrated to an initial economic equilibrium and subsequently disrupted through the introduction of AI-generated labor capable of substituting for all human work. The model is then used to evaluate the response of the economy under multiple policy and market conditions.
The specific research objectives are as follows:

1. To develop a classical, simple economic simulation framework capable of modeling AI-driven labor displacement within a dynamic industrial economy.

2. To quantify the relationship between AI productivity gains, employment levels, consumer purchasing power, wages, prices, and corporate profits during and after the process of AI adoption.

3. To analyze the effectiveness of intervention strategies, taxation of automation implementation, wage fixing, and layoff prohibition in maintaining economic stability, consumer well-being, and aggregate consumer demand.

2. Literature Review

Introduction

Technological change has historically been one of the central forces shaping economic growth, labor markets, and income distribution. Across successive industrial revolutions, innovations such as mechanization, electrification, computing, and automation have increased productivity while simultaneously reshaping the composition of employment. Although these transitions have ultimately been associated with higher aggregate welfare, they also generated significant short-term labor market disruptions, including unemployment, wage polarization, and inequality. The emergence of artificial intelligence (AI), particularly large language models (LLMs) and generative AI systems, has renewed concerns that automation may now extend beyond manual labor into cognitive and creative domains. This expansion raises important questions about macroeconomic stability, labor demand, and the adequacy of existing policy responses.

Historical Technological Change and Labor Market Adjustment

Historical research suggests that technological revolutions are characterized by both disruption and long-run adaptation. Mokyr et al. (2015) documents recurring waves of "technological anxiety," showing that fears of mass unemployment have accompanied major innovations since the Industrial Revolution. Despite these concerns, economies have historically adjusted through productivity growth and the creation of new industries and occupations.

Goldin and Katz (2008) emphasize that technological progress is closely linked to skill-biased labor demand. Their work shows that as technology advances, demand shifts toward more skilled labor, contributing to wage inequality when educational systems do not adjust at the same pace. This highlights that while technological change increases total productivity, its consequences on the marginalized can be persistent and significant. It also suggests that there is a potential level of automation that displaces all workers except those at the highest levels of skill, which could cause larger than previous labor disruptions and unemployment.

Another foundational contribution to the skill-biased view of technological change is provided by Autor et al. (2003), who show that computerization disproportionately affects routine tasks while complementing abstract and non-routine cognitive work. This framework provides the conceptual basis for understanding why automation has historically displaced certain types of labor while leaving others relatively unaffected.

Task-Based Models and Empirical Automation Effects

The modern economic analysis of automation is strongly grounded in the framework developed by Acemoglu and Restrepo (2018), which uses a task-based model while distinguishing between the displacement effect of automation and the counteracting productivity and reinstatement effects. Automation reduces labor demand by substituting machines for human labor, but may also increase output and create new tasks that restore labor demand. In a later paper, Acemoglu and Restrepo (2020) also find that exposure to industrial robots in U.S. labor markets has led to significant reductions in employment and wages in affected regions. These findings suggest that adjustment processes may be incomplete or that labor markets do not always fully offset displacement through new job creation. Also implied is that limited reinstatement effects along with targeted automation on specific tasks create long-run, uneven effects on broader labor markets.

Building on this, Autor (2015) also argues that automation replaces tasks rather than entire occupations, affecting many but allowing labor markets to adjust through task reallocation. Displaced workers often transition into new roles that emerge as a result of technological progress. However both the productivity effects and the displacement may appear slower than anticipated as Brynjolfsson et al. (2017) note that productivity gains from new technologies such as computerization or AI may be delayed due to institutional and organizational frictions. Neugart (2023) extend this literature by developing dynamic models of task reallocation under automation. Their work shows that automation can generate structural changes in industry composition and labor demand over time, with uneven adjustment across sectors. This reinforces the idea that task-based automations cause labor market responses that are structural, gradual, and heterogeneous.

Artificial Intelligence and Labor Market Exposure

The emergence of artificial intelligence has significantly expanded the range of tasks that can be automated. With capabilities including professional level writing, image generation, and even growing mathematical understanding, large language models are a novel automation technology. Eloundou et al. (2023) show that large language models have high exposure across a wide range of occupations, particularly in cognitive, language-intensive, and administrative tasks. Unlike earlier waves of automation that primarily affected routine manual labor, AI systems increasingly impact knowledge-based occupations which had previously operated as the roles to which displaced labor reintegrated into.

Dominski and Lee (2025) provide empirical evidence that these theoretical concerns are already materializing. Their findings indicate that occupations with higher AI exposure experience reductions in employment and working hours, suggesting early-stage labor market adjustments to AI adoption. Additionally, Hampole et al. (2025) further analyze firm-level responses to AI adoption and show that labor demand effects vary depending on task structure and substitutability between AI systems and human labor. While some reallocation toward complementary tasks occurs, overall labor demand declines in highly exposed occupations, indicating partial but incomplete adjustment.

Macroeconomic Models and Simulation-Based Evidence

Recent literature increasingly focuses on macroeconomic and simulation-based approaches to evaluating the impact of AI. Acemoglu (2024) argues that the macroeconomic effects of AI may be more limited than commonly assumed. In his framework, AI primarily leads to task reallocation rather than large-scale labor displacement. If one assumes that only a subset of tasks can be automated, aggregate effects on employment and output may be more moderate than predicted by more extreme scenarios.

In contrast, Wang and Wong (2025) develop a labor-search model of AI adoption that produces multiple equilibrium outcomes. Their simulations suggest that under certain parameters, AI can generate substantial unemployment due to rapid labor substitution and insufficient creation of new tasks. This introduces the possibility of nonlinear labor market responses and multiple stable economic outcomes. Korinek and Suh (2024) extend this analysis to long-run scenarios involving advanced AI systems. Their results suggest that if AI becomes a near-complete substitute for human labor, traditional wage-based income distribution may break down, potentially resulting in persistent unemployment and structural inequality.

Systemic Risk and the AI Layoff Trap

Another central concern in recent literature is whether AI could generate systemic macroeconomic instability through

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aggregate demand effects. Falk and Tsoukalas (2026) introduce the concept of the "AI Layoff Trap," a game theory concept similar to the Prisoner's Dilemma in which firms individually benefit from automation through cost reductions but collectively reduce aggregate demand by lowering labor income. Because workers are also consumers, widespread automation reduces consumption demand, creating a feedback loop that may slow economic growth and reduce profits.

In this framework, firms are trapped in an automation arms race: even if automation reduces overall welfare, competitive pressures force firms to continue substituting labor with AI. This mechanism differs from traditional models of technological change, which assume that displaced workers are eventually reabsorbed into new sectors of the economy.

Policy Responses and Institutional Design

The literature identifies several potential policy responses aimed at mitigating the labor market consequences of AI. Korinek and Stiglitz (2021) argue that policy should focus on steering technological progress rather than relying solely on redistribution after displacement occurs. They emphasize that market incentives may lead firms to overinvest in labor-replacing technologies, creating socially inefficient outcomes. Falk and Tsoukalas (2026) focus instead on different governmental interventions, and argue that the Pigouvian tax, a tax on negative behaviors similar to penalties for pollution, is the only effective countermeasure against their "AI Layoff Trap." They notably discard universal basic income and other popular concepts as ineffective in preventing aggregate demand freefall.

Training and reskilling programs remain a traditional policy tool for managing technological transitions. However, their effectiveness depends on the availability of new employment opportunities. If AI is capable of automating both cognitive and manual tasks, then new opportunities arising from AI may recursively also be automated. In this case, retraining alone will not be sufficient in mitigating negative employment and demand effects.

Summary

The literature on technological change and artificial intelligence presents a complex and evolving picture of labor market dynamics. Historical evidence suggests that technological revolutions ultimately generate productivity gains and new employment opportunities, although often accompanied by significant transitional disruptions. Task-based models emphasize that automation replaces tasks rather than entire jobs, allowing partial labor reallocation over time, leaving a moderate and uneven impact on labor markets.

However, recent AI-focused research suggests that generative AI may represent a broader structural shift by automating cognitive and professional tasks in addition to routine labor. Empirical evidence indicates that labor market effects are already emerging in exposed occupations, while macroeconomic models present divergent predictions ranging from moderate adjustment (Acemoglu 2024) to significant unemployment and systemic instability (Wang and Wong 2025; Falk and Tsoukalas 2026). Policy literature highlights the difficulty of addressing these challenges using traditional tools such as retraining and redistribution alone.

Overall, the literature suggests that AI represents both a continuation of historical technological trends and a potential structural break due to its scale, speed, and cognitive reach. The ultimate economic impact will depend on the interaction between technological capabilities, labor market adjustment mechanisms, and institutional policy responses.

3. Methods

A simplified dynamic macroeconomic model was constructed to simulate an economy with multiple firms, a labor market, paid wages, material costs, demand, and profits. This established a productive, profitable base model economy with high employment and demand satisfaction.

To represent the emergence of Artificial Intelligence, a productivity factor representing AI's cheap and scalable task replacement was introduced. Several separate scenarios regarding wages, prices, and corporate/governmental interventions were then simulated by adjusting this base model's parameters and assumptions.

3.1 Assumptions

Like all models, this simulation is limited by constraints and assumptions to simplify the global economy into an understandable framework. These are listed below.

- The Artificial Intelligence introduced to the economy is task agnostic and capable of automating all work in a production process.

- Since all tasks, including new jobs, can be automated, employee redistribution is not a factor.
- Total available labor stays constant. No immigration or emigration to this economy.
- The internal industry studied employs individuals to meet only the demands of the economy, and lays off excess employees. No overproduction.
- All available employees are initially employed.
- All labor, both external and internal, receive the same wages.
- The internal industry and external industries experience automation at the same rate.
- Demand represents a "maximum want" and not a "minimum need" for individuals.
- There exists a maximum saturated demand for the internal industry's product past which individuals will not purchase any more.
- Profits earned are distributed to owners and shareholders, not reinvested into the economy.

3.2 Constructing the Base Model

The base model consists of several core, simple economic trends and behaviors. The labor market, for example, is represented by two pools of individuals: 100 individuals are employed by the "internal" industry of firms represented in the financial calculations, and another 100 individuals are employed by an outside industry also undergoing automation. These individuals remain employed by their firms so long as the demand and output of the firms' products justify the current level of employment. Productivity for a given period is defined as the amount of product that can be produced per employed person. Employment of the internal and external firms, product output, and productivity in a given period are governed by equations 1,2, 3, and 4 below.

$$(1)\ Demand_t = (Internal\ Employment_t + External\ Employment_t) * Min(Demand\ Per\ Person, \frac{Wages_t}{Price_t})$$

$$(2)\ Product\ Output_t = Min(Demand_t, Internal\ Employment_t * Productivity_t)$$

$$(3)\ Internal\ Employment_{t+1} = \frac{Product\ Output_t}{Productivity_t}$$

$$(4)\ Productivity_{t+1} = Productivity_t * (1 + Productivity\ Factor)$$

Demand per person, price, and productivity factor are all parameters. In the base model, the productivity factor is equal to zero, so product output, employment, and productivity remain constant throughout. Equations 2 and 4 show that when the productivity factor is above zero, product output (which is upper bounded by demand) becomes increasingly dependent on productivity instead of employment. Equation 3 then translates this change in employment value by decreasing employment in subsequent periods.

To simulate that other industries are also automating their tasks, equation 5 imposes the same rate of change to external employment as is present for internal employment.

$$(5)\ \frac{External\ Employment_t}{Initial\ External\ Employment} = \frac{Internal\ Employment\ Rate_t}{Initial\ Internal\ Employment}$$

The remainder of the model uses classical accounting formulas to simulate sales, revenues, expenses, and profits. Since product output is upper bounded by demand, sales always equals the product output. Material costs and labor costs both contribute to expenses, with cost per material and wages being parameters (wages are made variable in later models). Equations governing these factors are below.

$$(6)\ Sales_t = Product\ Output_t$$

$$(7)\ Expenses_t = Material\ Unit\ Cost * Product\ Output_t + Internal\ Employment_t * Wages$$

$$(8)\ Revenues_t = Sales_t * Price$$

$$(9)\ Profits_t = Revenues_t - Expenses_t$$

In this base model, wages, prices, and productivity are all fixed, which results in a deterministic, consistently profitable model. Parameter values for the base model can be seen in the Table 1 below:

Table 1. Base Model Parameters (Constant Wage, Constant Price)

Initial Internal Employment	100
Outside Population	100
Initial Productivity	5
Productivity Improvement Factor	0
Wage Rate	5
Materials Cost Per Unit	0.5
Demand per person	3
Initial Price	2

The next models introduce variation in these parameters which simulate the introduction of Artificial Intelligence and disrupt the simplistic economy.

3.3 Introducing Artificial Intelligence through Productivity Factors

Artificial Intelligence, if capable of automating many or all tasks, can be seen as a productivity increasing factor that reduces the need for employment to meet market demands. As seen by the current Large Language Models offered to corporations, both the capability and adoption of AI tools take time to improve. Development of AI tools are also facilitated by the tools themselves, which may cause a positive feedback loop in improvement. Because of this, diffusion of increased productivity is likely to take on an exponential growth pattern, starting slowly and growing faster. Equation 4 shows that this is modeled by raising productivity to the same factor repeatedly. To simulate the introduction of Artificial Intelligence, the productivity factor is then set to a small positive number of 0.01, which allows for productivity to grow gradually and then rapidly in the simulated economy. In the initial model, wages and prices remain fixed for simplicity, but this can also be interpreted as price controls and minimum wages being present in the system.

3.4 Fixed Price Decreasing Wages Model

If unemployment rises due to rising productivity, a surplus of labor will arise in the labor market. This will create a situation in which more individuals compete for a shrinking number of jobs. Ultimately, due to the lack of scarcity, this should depress wages over time. A model was created to reflect this in which wages are no longer fixed but are instead decreasing with time along with employment. Equation 10 below shows this behavior.

$$(10)\ Wage_{t+1} = Wages_t * Employment\ Rate_t$$

This creates a pattern where wages decrease proportionally to the increase in unemployment over time. All other factors of the base model remain intact for this model.

3.5 Fixed Price Increasing Wages Model

A counterclaim to the argument just stated is that the massive increase in productivity from the introduction of AI will drive wages higher because of the abundance of goods. To model this, the following relationship was established between wages and productivity in Equation 11.

$$(11)\ Wage_{t+1} = Wages_t * (1 + Productivity\ Factor)$$

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This creates a pattern where wages increase proportionally to the increase in productivity over time. All other factors of the base model remain intact for this model.

3.6 Fixed Wages Decreasing Price Model

The next model introduces variable pricing with maintained wages (which can represent minimum wage policies). Since production is becoming cheaper, goods are more abundant, and competition forcing competitive pricing, prices are expected to decrease. This is modeled by equation 12 below, where prices decrease proportionally with the increase in productivity.

$$(12)\ Price_{t+1} = \frac{Price_t}{(1 + Productivity\ Factor)}$$

3.7 Decreasing Wages and Decreasing Price Model

A more complete model should combine the effects of both decreasing wages and prices, as productivity is increasing while employment is decreasing. This model implements this by again utilizing equations 10 and 12 to govern this change.

3.8 Decreasing Wages and Decreasing Price Model with Layoffs Prohibited

One intervention that a rational government may try to implement is prohibiting layoffs due to AI adoption. This model explores this possibility by removing the relationship established in equation 3 and maintaining fixed employment across time. Wages and prices still decrease according to equations 10 and 12.

3.10 Decreasing Wages and Decreasing Prices Model with Fixed Markup

If AI is implemented to reduce labor costs, prices may decrease in a variety of ways depending on corporate strategies. Equation 12 previously shows the possibility of price decreasing with productivity, but this allows for circumstances where companies sell products for less than their value, which rationally should not happen. To adjust, equations 13 and 14 were implemented to maintain a constant markup for price.

$$(13)\ Unit\ Cost_t = \frac{(Wages_t * Internal\ Employment_t\ +\ Material\ Cost\ *\ Sales_t)}{Sales_t}$$

$$(14)\ Price_t = \ Unit\ Cost_t\ + (Initial\ Price\ -\ Initial\ Unit\ Cost)$$

This maintains the same per unit profit as established in the first period.

3.11 Decreasing Wages and Decreasing Prices Model with Fixed Margins

Another potential pricing choice would be to maintain a consistent profit margin across all periods. In this case, equation 13 is combined with equation 15 below.

$$(15)\ Price_t\ =\ Unit\ Cost_t\ * \frac{Initial\ Price}{Initial\ Unit\ Cost}$$

This maintains the same overall profit margin established in the first period.

3.12 Decreasing Wages and Decreasing Price Model with Unemployment Tax

This model attempts to intervene in the economic outcome of the model in 3.11 by implementing a tax on unemployment in the system. The tax revenues are then redistributed into the economy in the form of demand. Equations 16 and 17 show the tax and adjusted demand formulas.

$$(16)\ Automation\ Tax_t = Profits_t\ * Unemployment\ Rate_t$$

$$(17)\ Demand_t = \ Min(\frac{Automation\ Tax_t}{Price_t}, Demand\ Per\ Person\ *\ Unemployed\ Persons_t)$$

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$$+(Internal\ Employment_t +\ External\ Employment_t) * Min(Demand\ Per\ Person, \frac{Wages_t}{Price_t})$$

This structure creates a reinforcing cycle whereby demand is supplemented by taxation on automation efforts. This supplementation is upper bounded by the amount of funds necessary to satisfy unemployed public demand.

3.13 Decreasing Wages and Decreasing Price Model with Payroll Tax

This model replaces the unemployment tax from 3.12 with a Payroll tax, which attempts to penalize automation efforts at a more specified level. Instead of a sweeping percentage tax on profits, this tax directly taxes companies the difference between their initial employment costs and their current labor costs. This disincentivizes automation to some extent, as it guarantees constant labor costs, but still allows for the benefits of increased productivity. Equation 17 remains the rule for demand, and equation 18 shows the formula used for automation tax.

$$(18)\ Automation\ Tax_t = ((Internal\ Employment_1 + External\ Employment_1) * Wages_1) - ((Internal\ Employment_t + External\ Employment_t) * Wages_t)$$

3.14 Fixed Wages and Layoff Prohibitions with Fixed Margins

The final investigates what may happen if workers were to effectively organize into unions powerful enough to prevent wage decline and unemployment. In this case, wages and employment are fixed, while prices are allowed to vary and AI is introduced into the economy.

4. Results and Discussions

4.1 Numerical Results

Table 2 shows the collective numerical results of the 12 models constructed. The results of each model can be interpreted according to how (1) owners of businesses, (2) the broader labor market, and (3) individual employees fare in the simulated economies. Owners mandate high profits for their businesses, the labor market seeks high employment, and individuals desire purchasing power capable of maximally fulfilling their demand for goods.

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Table 2. Numerical Results of 12 Classical Simulations of AI Impacts on a Simplified Economy

	Productivity	Wages	Prices	Employment	Profit Rules	Taxes	Long Run Employment Rate	Long Run Unit Sales	Long Run Profits Per Period
1	No AI	Declining	Falling	Layoffs			100%	400	100
2	AI	Mandated	Controlled	Layoffs			0%	0	0
3	AI	Declining	Controlled	Layoffs			0%	0	0
4	AI	Increasing	Controlled	Layoffs			0%	0	0
5	AI	Mandated	Falling	Layoffs			0%	0	0
6	AI	Declining	Falling	Layoffs			0%	0	0
7	AI	Declining	Falling	Layoffs Prohibited			100%	600	-800
8	AI	Declining	Falling	Layoffs	Fixed Markup		0%	0	0
9	AI	Declining	Falling	Layoffs	Fixed Margin		0%	0	0
10	AI	Declining	Falling	Layoffs	Fixed Margin	Unemployment Tax	0%	0	0
11	AI	Declining	Falling	Layoffs	Fixed Margin	Payroll Tax	0%	600	114.3
12	AI	Fixed	Falling	Layoffs Prohibited	Fixed Margin		100%	600	125

Blue columns in Table 2 show each model type with its values across several parameters. The original case without AI introduction achieves all three of the objectives (in green) in a perpetual steady state. However the majority of models in which AI is introduced show all three of these objectives are unmet regardless of differences in wage, price, and employment strategies. In these cases, the automation of labor first causes high unemployment and/or low wages, which causes lower demand/sales from employees, and then finally destroys profits as no one is able to purchase the goods produced.

Outliers to this result include models with layoff prohibitions. In model 7, employment remains high, and employees therefore have some purchasing power while wages still decline. Prices are allowed to fall at the rate of increased productivity, so employees are also still able to purchase goods. However, this scenario is unrealistic, as profits become negative since material expenses remain stable while prices fall to zero. The model which is arguably most realistic is the fixed margin model, where wages, prices, and employment all decrease while companies maintain a fixed profit margin to avoid incurring losses on sales. This case, like most others, results in widespread unemployment, minimal sales, and minimal profits. The unemployment tax model is similarly ineffective in preventing this outcome, as it taxes profits, which approach zero over time, essentially taxing a diminishing source and failing to redistribute capital sufficiently enough to stimulate the economy.

Only two interventions have a significant positive impact. The first is the payroll automation tax, which taxes companies the exact amount of labor cost that they have avoided through automation. In this case, prices, wages, and employment all fall, but companies maintain profits and employees are able to satisfy demand through the redistributed tax income. This matches intuition, as costs are arbitrarily designed to stay constant, and wages are proportionally replaced by the redistribution of the Payroll tax. The second positive outcome occurs when layoffs are prohibited and wages are maintained (theoretically through government or union regulation). In effect, this has the exact same outcome as the Payroll tax, as in both scenarios employees maintain their salary through payments through the companies yet provide no labor to the production process. Both cases allow for the economy to leverage the advantages of higher productivity while maintaining the same amount of purchasing demand as in the original state.

4.2 Graphical Results

The various models are contrasted in terms of company profitability in Figure 1 with the legend numbers corresponding the rows in Table 2. Starting at the top, the baseline case represents the profitability in the absence of AI. The lack of productivity improvement leaves wages, prices, and employment level unchanged. The second case shows the effect of fixing wages and prices. This shows an increase in profitability as AI induced productivity improvement allows the company to meet previously unmet demand and layoff unneeded workers. However, these productivity improvements soon lead to layoffs and a declining of purchasing power where demand and profits quickly fall to zero. The third case of productivity eroded wages with fixed prices shows an identical increase, but an even quicker fall as declining wages and layoffs collapse purchasing power, demand, and profits.

The fourth case shows the result of AI enhanced productivity by directly increasing wages. Firm profits rise steadily over a longer period of time to a lower peak of approximately $150 per period before gradually falling to zero. The fifth case of fixed wages and falling prices shows a gradual decline of profitability until excess capacity leads to layoffs which results in a rapid drop into the red before neutralizing to zero profitability. The sixth case of declining wages and prices shows the same trajectory, but a shallower dip into the red and a brief rebound back into profitability before converging to zero profitability. The closely related case seven of falling wages and prices with prohibited layoffs starts with the same trajectory, but with a much more significant fall into steady-state losses of $800 per period (Figure 1).

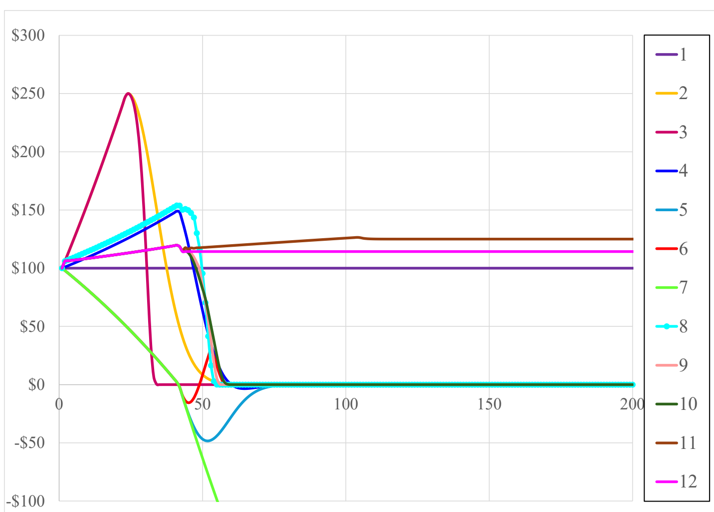

Figure 1. Profit by Time Period for Each Model

The eighth case of falling wages and prices with a fixed price markup shows a trajectory very similar to the fourth case peaking at $153 per period, but with a slightly higher raise and faster fall, before profits fall to zero. The nearly identical ninth case with a fixed percent margin rather than a fixed absolute price markup shows a more modest increase to about $114 before plummeting to zero. The tenth case of imposing an unemployment tax on the previous case results in a nearly identical result.

The eleventh case of imposing a payroll tax where all lost wages are taxed 100%, put into production, redistributed to the unemployed resulted in the best steady-state solution with a sustained profitability of $125 profit per period. The efficacy of this type of perfectly efficient tax in reality is quite questionable. The final twelfth case of having wages and employment frozen allows for price stabilization with sustained production of 600 units per period and a profit of approximately $114 per period. This case is also quite unrealistic in that this completely sustained employment comes in spite of the fact that the AI productivity enhancement has eventually completely negates the need for any labor at all.

4.3 Proposed Improvements

Limitations to the simulation include (1) limited complexity to the number of firms and products represented, (2) the assumption of homogenous tasks that are equally automated by AI, and (3) the total assumption that all future labor sectors will be automated. Because of this, obvious improvements to the model may include expanding the scope of firms represented, adding in limitations and complexity into the tasks that can be automated, and including some redistribution of labor to sectors like healthcare or customer service where humans may be irreplaceable.

4.4 Validation

The results of this paper use a different modeling technique from the previous literature but yield similar results to other attempts to model AI layoffs. Falk and Tsoulakas' working paper titled "The AI Layoff Trap" uses a competitive task-based model and also concludes that increasing AI productivity results in negative financial impacts on both workers and firm owners while acknowledging the beneficial impacts of a penalty automation tax like the Payroll tax. Wang and Wong's paper "Artificial intelligence and technological unemployment" also uses a labor-search model and demonstrates a relationship between the increased productivity of AI and increased unemployment.

5. Conclusion

All three objectives of this paper were met, as a model simulating a simplified economy was developed, AI was introduced to that model as a disruption, and interventions were tested as remedies to the negative effects of the implementation. The results of these simulations indicate that AI, if capable of automating all human labor tasks, poses a significant risk to both corporate and individual well-being in a simplified economic model.

Regardless of wage or price increase/decrease, the introduction of AI into this model as a total replacement to human labor harms both corporate profits and individuals' ability to meet their own demands without intervention. Whether or not this effect remains in cases of partial or heterogeneous automation is not observable with these models. Additionally this result assumes that new jobs created by AI will be insufficient to replace the quantity lost or immediately automated as well. These models do not make claims regarding the likelihood of AI's ability to become advanced enough to automate all tasks.

This result adds a unique contribution to the literature by adding a simple classical model to often speculative or mathematical investigations of the AI labor effect. These models demonstrate intuitive effects of decoupling labor and production that show the potential negative outcomes of rapid and unregulated AI implementation. The results of the interventions suggest that the key to preventing negative economic outcomes is maintaining consumer spending power. This can be achieved by halting AI progress (as in the base case), by preventing wage decreases and layoffs through regulation, or by supplementing consumer purchasing with a redistributed Payroll tax on corporations.

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