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Technologies and Labour: A Theoretical Model of Task-based Production in Labour Market with Search Frictions

David Vardanyan*

Abstract

This paper explores the effects of automation and the creation of new tasks on labour market outcomes by incorporating the task-based production of Acemoglu and Restrepo (2018a) into a modified Diamond-Mortensen-Pissarides (DMP) search and matching framework. While the effect on wages aligns with existing literature, the introduction of search frictions offers new insights regarding effects on unemployment. Automation is found to have a dual impact: it displaces workers from routine tasks but simultaneously generates productivity gains which can offset its negative effects. The net impact on unemployment and wages depends on the relative magnitude of these displacement and productivity effects which are analytically derived in the research. In contrast, the creation of new tasks has a more uniformly positive impact, as it both enhances the productivity and reinstates displaced workers, leading to lower unemployment and higher wages. The findings suggest that policies should ensure not to promote 'excessive automation', where it negatively affect the labour market. In contrast, fostering innovation and task creation can be effective ways to benefiting from technological advancements.

JEL Classification: E22, E24, J23, J24, O33

Key Words: Automation, labour market frictions, productivity, technology, unemployment

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1 Introduction

During the Great Depression, John Maynard Keynes famously predicted "technological unemployment" – a phenomenon in which the rate of labour-saving innovations exceeds the creation of new tasks for workers (Keynes, 1930). The rapid rise of artificial intelligence (AI) and robotics has sparked a growing interest towards understanding the effects of technology on the labour market. On one hand, some are alarmed by the prospects of widespread automation and significant job displacement, suggesting it will decrease the bargaining power of labour in favour of capital. Notably, Frey and Osborne (2017) projected that about 47% of American workers could be at risk of automation within two decades, while the Manyika et al. (2019) estimated that up to 30% of tasks across 60% of occupations are automatable already. Conversely, many economists look at AI and robotics through the prism of past waves of technological advances, predicting that, as before, labour productivity will increase, resulting in better labour market outcomes. Matuzeviciute et al. (2017), for example, found no significant relationship between technological innovations and unemployment using panel data from 25 European countries.

The full implications of the ongoing AI revolution remain uncertain, yet there have been multiple waves of technological innovations since the prediction made by Keynes. Therefore, there are already empirical insights into its labour market effects. According to Figure 1, the growth rate of wages has steadily declined from 1979 to 2020. While several factors may contribute to the stagnation of wages, such as the "productivity puzzle", much of the literature agrees that technological advancements are partly responsible for the reduced labour share of income.

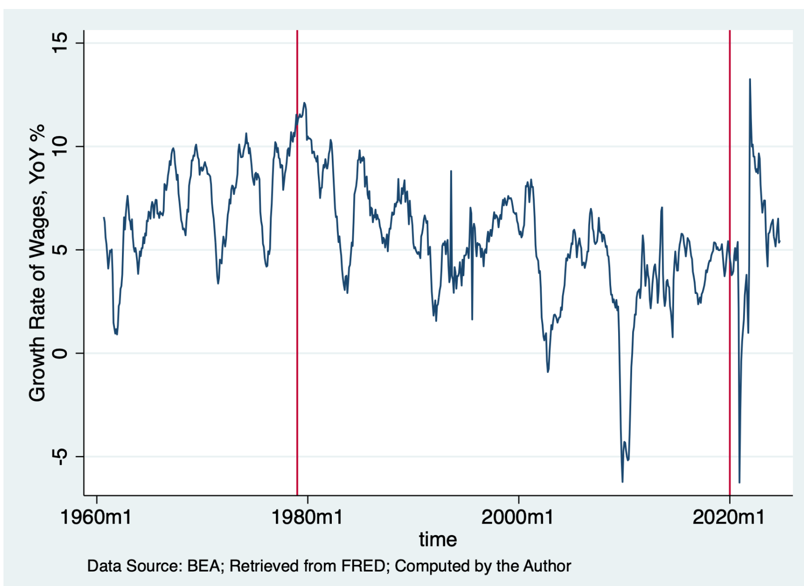

Figure 1: United States Wages Growth Rate

Meanwhile, multiple studies have found that automation led to a reduction in employment in certain industries or regions while creating new opportunities in others (Acemoglu and Restrepo, 2022; Manyika et al., 2019; Samuelson, 1989). For instance, Acemoglu and Restrepo (2022), using US Industry-Level Production data, found that workers specialised in routine tasks in industries experience rapid automation which has distressed their wages by up to 70% in the last four decades, while also significantly affecting their employment perspectives. Figure 2 illustrates that the industries that have a higher share of new job titles, that is new tasks have a higher annualised employment growth rate (Acemoglu and Restrepo, 2022). These trends occurred during unprecedented technological innovations that started in the 1980s often called the Information and Communication Technology (ICT) revolution. The ICT revolution introduced factor-augmenting and automating technologies, potentially reshaping labour market dynamics.

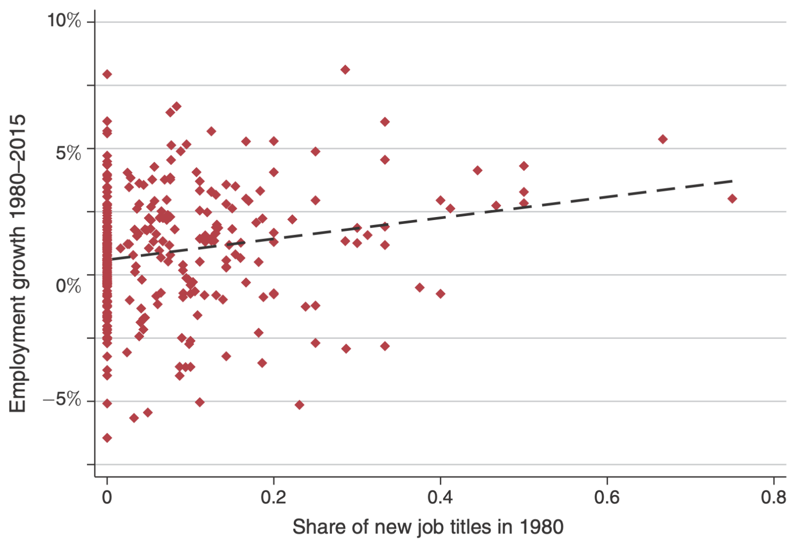

Figure 2: Employment Growth by Occupation and the Share of New Job Titles in 1980

This research contributes to the ongoing discourse by developing a labour market model based on the Diamond-Mortensen-Pissarides (DMP) search and matching framework, modified to acount for automatin and the creation of new tasks. By examining the effects of technological changes in the DMP environment we make conclusions about their effects on unemployment, which is not observed in competitive labour market models. The model features agents - workers and firms – that engage in the search for an optimal match, the efficiency of which is described by a matching function. We integrate changes in employment by altering share of tasks performed by the labour. A key component of the model is the task-based production function similar to Acemoglu and Restrepo (2018a), which determines the labour productivity. Our findings show that automation exerts both displacement and productivity effects on unemployment and wages. These effects work in opposite directions, so the overall impact depends on the differences in the magnitude between the forces. While, the displacement effect increases unemployment and suppresses wages, the productivity effect mitigates these impacts by enhancing output per worker. In contrast, the creation of new tasks generates both a productivity effect and a reinstatement effect. both of which work in the same direction to reduce unemployment and increase wages.

The paper is structured as follows: Section 2 reviews the existing literature on the impact of technology on labour market. Section 3 breaks down the entire model used in the research along with assumptions, overview of agents and the wage bargaining process. Section 4 presents and discusses the results of the relationships found, comparing with past empirical and theoretical findings. The paper concludes with Section 5.

2 Literature Review

The impact of technological advancement on the labour market is a widely debated topic. Historically, technological innovations have increased labour demand, employment, and wages (Acemoglu and Restrepo, 2019). This view is supported by the extensive historical analysis of technological revolutions and their long-term effects on employment and economic structures by Mokyr et al. (2015). Acemoglu and Restrepo (2018a) argue that any type of technological advancement creates a productivity effect which increases aggregate output. This does not necessarily result in higher wages, as technological advancement of types like labour replacement creates a displacement effect that negatively impacts wages.

As significant advancements in artificial intelligence have taken place over the past two decades, there is a growing belief that technologies could be capable of replacing labour entirely (Brynjolfsson and McAfee, 2014; Autor, 2015), though actual labour replacement depends on firms' automation choices. Contrarily, Acemoglu and Restrepo (2016) assert that technological progress is not solely a labour-replacing force but can also liberate labour from automatable tasks, leading to the creation of new, potentially more productive tasks for workers. Moreover, Autor et al. (2003) argues that computer-based technologies do not replace but rather complement humans who work on complex tasks.

In terms of employment, Frey and Osborne (2017) forecast that almost half of US workers could be at risk of automation. Manyika et al. (2019) predicted a similar future and found industry-level empirical evidence of automation reducing employment. However, Matuzeviciute et al. (2017) found no statistically significant relationship between unemployment and technological progress at a macroeconomic level. In terms of wages, Karabarbounis and Neiman (2014) documented a decline in the labour share of income across 59 countries from 1975 to 2012, a trend often attributed to the increasing prevalence of AI, robotics, and other technologies, which may reduce wages as they compete with human tasks. However, other scholars, such as Autor et al. (2017), attribute the decline in labour share to the rise of "superstar firms". Piketty (2014), on the other hand, argues that technological advancement influences capital accumulation, which in turn causes a decline in the labour share of income in favour of capital. Acemoglu and Restrepo (2018a) further elaborate that while technologies automate some tasks, they also generate new tasks where workers hold a comparative advantage, which in turn creates a reinstatement effect that increases wages. Autor (2015) agrees with this view emphasising that the effect of automation on the labour market is not unidirectional.

In modelling technological change, many authors view it as either labour-augmenting or capital-augmenting. Factor augmenting technological advances increase output, wages and employment due to the productivity effect that they create. Our research adopts instead the task-based framework of Acemoglu and Restrepo (2018c) because it allows us to model labour replacement and creation of new tasks. Here, automation's impact on equilibrium wages is influenced by the productivity effect's magnitude relative to the displacement effect that it causes. The creation of new tasks where labour has a comparative advantage creates a reinstatement effect which works in the same direction as the productivity effect. There are also labour-augmenting and deepening automation types of technological progress, which create the same effects as the factor-augmenting technologies, and therefore will not be considered in the scope of this research. Our model also anticipates that increased automation will accelerate capital accumulation, resulting in higher output and wages.

This research aims to provide critical insights for policymakers, businesses, and workers. Using the DMP model, which accounts for search frictions, our study seeks to give nuanced results about the impacts of various technological changes on the labour market. Furthermore, the study seeks to inform policy strategies that maximise the benefits of technological advancements while mitigating their negative effects to ensure economic stability.

3 Methodology

Our model is based on the Diamond-Mortensen-Pissarides (DMP) model, a standard in the study of search and matching in labour markets. The model provides a framework for understanding how workers and firms interact to produce labour market outcomes. We incorporate the task-based production from Acemoglu and Restrepo (2018c) as well as modify the DMP model to microfound automation and creation of new tasks.

The model has an infinite-horizon, discrete-time economy with two agents Workers and Firms. Workers are infinitely living job seekers who are either employed with a probability of λ of losing their jobs or unemployed with a probability of $p(\theta)$ of finding employment. Firms have either filled jobs or vacancies which they create based on the expected profitability of hiring additional workers. After a worker gets matched with a firm, they negotiate a wage. The worker decides whether to accept job offers based on the comparison of the negotiated wage to their alternative options, which include the value of remaining unemployed. Workers aim to maximise their utility which is a function of their income and their state, while firms seek to maximise their profits which depends on the productivity of employed workers minus the costs associated with wages and vacancies. When there is an automation or creation of new tasks, it immediately affects worker employment. To simplify the incorporation of this process, the author introduces a key assumption about the workers. At any given time, there is a small proportion α of workers whose skills are distributed on the $x \in [N-1, I]$ range. These workers get immediately fired after they reveal their type after getting hired. We assume that this proportion α is independent of other variables. Therefore, if the range $x \in [N-1, I]$ decreases, the number of workers whose skills are not viable for employment decrease and therefore they get hired. If α is equal to zero, then automation or creation of new tasks does not change unemployment rate, since the workers have fully flexible skills or can learn any tasks.

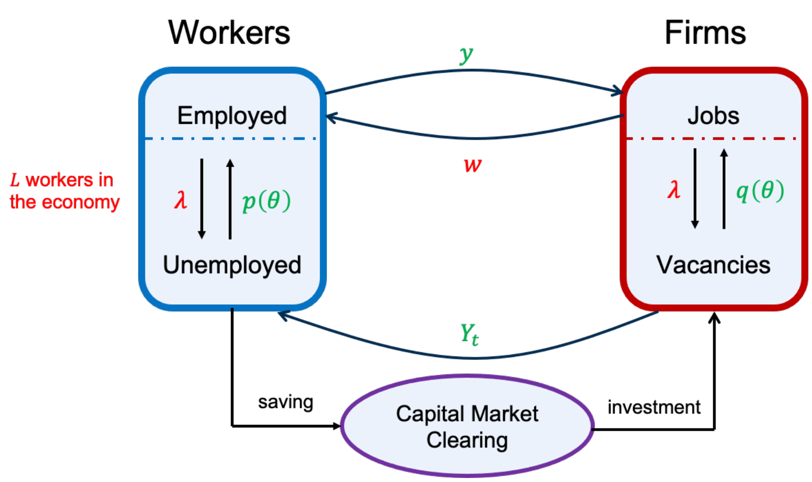

Figure 3: Agents Interactions

There is also a task-based production function inspired by Acemoglu and Restrepo (2018c) in which robots or capital does $(I - N + 1)$ proportion of the tasks while the rest of $(N - I)$ is performed by the workers. N stands for the number of tasks in the economy, while I is the number of tasks automated by capital.

There is a Solow model like capital market clearing, as a result of which capital and output converge to their equilibrium levels. Figure 3 shows the interactions between the two agents.

3.1 Model setup and Agents Problems

3.1.1 Bellman Equations

Both agents discount the future using the interest rate δ. Value of being employed to the worker is the wage, w, minus the excess value from being employed relative to unemployed with probability of $\lambda + \alpha(I - N + 1)$:

$$\delta W = w - \Big[\lambda + \alpha(I - N + 1)\Big](W - U) \tag{1}$$

The value of being unemployed to the worker is the unemployment benefits, b, plus the additional value from becoming employed with probability p:

$$\delta U = b + p(W - U) \tag{2}$$

The value of a job filled by worker to the firm is the labour productivity, y, minus the wage and the excess value from being having a job relative to a vacancy with the same probability of a worker losing their job:

$$\delta J = y - w - \Big[\lambda + \alpha(I - N + 1)\Big](J - V) \tag{3}$$

The value of a vacancy to be filled by worker to the firm is the cost of keeping a vacancy, which can include advertising plus the additional value from becoming a filled job with probability q:

$$\delta V = -f + q(J - V) \tag{4}$$

3.1.2 Matching Technology

A critical component of any DMP model is the matching function, which describes how unemployed workers and vacancies come together to create new employment matches. We have a Cobb-Douglas matching function which depends on the efficiency of the matching function B, number of vacancies v, the number of unemployed workers u, and the weight of unemployment for the matching function relative to the number of vacancies μ:

$$m = Bu^{\mu}v^{1-\mu}$$

The matching function's efficiency can be influenced by various factors, including the methods used by firms and workers to find each other and the overall state of the economy. The matching function derives the following:

$$p = \frac{m}{u} = B\theta^{1-\mu} \equiv p(\theta) \tag{5}$$

$$q = \frac{m}{v} = B\theta^{-\mu} \equiv q(\theta) \tag{6}$$

where θ is the labour market tightness,

$$\theta = \frac{v}{u}$$

3.1.3 Wage Bargaining

The surplus of a match measures how much better off a worker and firm are together as opposed to when separate:

$$S = W - U + J - V$$

Wage bargaining for worker using the assumption of generalised Nash Bargaining:

$$\frac{W-U}{\beta} = \frac{J-V}{1-\beta} \tag{7}$$

where β is the proportion of the total surplus that goes to the workers, while $(1-\beta)$ goes to the firms.

3.1.4 Free Entry

The assumption of free entry is applied to vacancies,

$$V = 0 \tag{8}$$

If $V > 0$, firms post more vacancies, making it harder to fill vacancies and thus reducing their value. If $V < 0$, firms close down vacancies, making it easier to fill other vacancies and thus increasing their value.

3.1.5 Unemployment Rate

The change in the number of unemployed is given by the Law of Motion described as the difference between job destruction and job creation

$$u_{t+1} - u_t = \text{Job Destruction} - \text{Job Creation}$$

Unemployment rate of worker

$$u_{t+1} = u_t + \Big[\lambda + \alpha(I - N + 1)\Big](1 - u_t) - p(\theta)u_t \tag{9}$$

3.1.6 Production Function

We begin by using a simplified version of the task-based approach which was presented in Acemoglu and Restrepo (2018b). Aggregate output is generated by integrating the services from a set of tasks $x \in [N-1, N]$, using a Cobb-Douglas aggregator:

$$\ln Y = \int_{N-1}^{N} \ln y(x) dx \tag{10}$$

since the tasks are run between $[N-1, N]$, we can consider the effect of changing the range of tasks without changing the total amount of tasks.

Tasks in $x \in [0, I]$ can be produced either by labour or capital, while the tasks in $x \in (I, N]$ can only be produced by workers:

$$y(x) = \begin{cases} A^L(x)\ell(x) + A^K(x)k(x) & \text{if } x \in [0, I] \\ A^L(x)\ell(x) & \text{if } x \in (I, N] \end{cases} \tag{11}$$

The firm's profit maximisation problem is as follows

$$\max_{\ell(x),k(x)} \ln Y - r\int_{N-1}^{I} y(x)dx - w\int_{I}^{N} y(x)dx \tag{12}$$

There are four different types of technological changes in the task-based framework.

1. **Automation**
   This is the technological progress that occurs at the *extensive margin*, that is an increase in the range of tasks that can be performed by capital. In the model it corresponds to an increase in I. Figure 4 shows that an when I increases to I' the proportion of tasks done by capital increases, while the one by labour decreases. In this type of Automation the range of tasks used in the production in the economy stays the same.

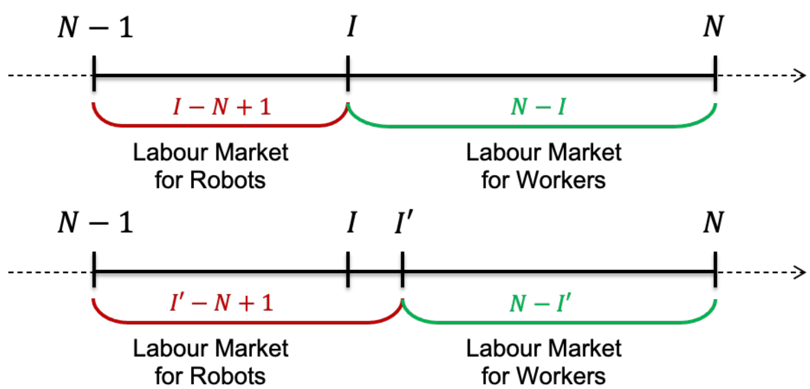

Figure 4: Visualising Automation

2. **Creation of new tasks**
   Those are the technological advances that create new tasks in which labour has a comparative advantage, as noted by the assumption above. In the model it corresponds to an increase in N. Figure 5 illustrates how this type of automation increases the labour share of tasks as well as shifts the range of tasks produced.

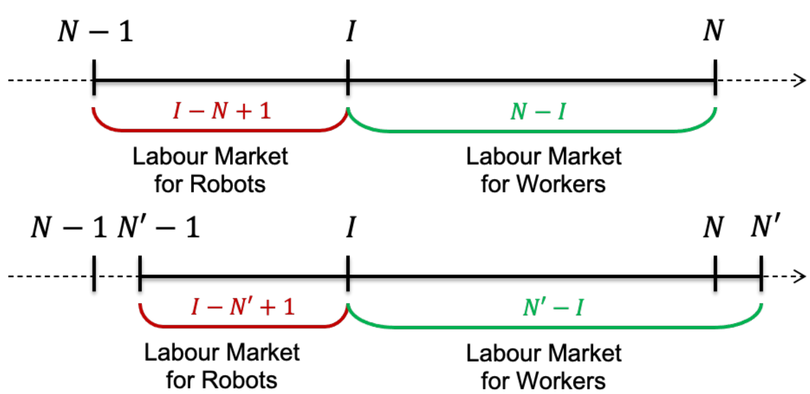

Figure 5: Visualising Creation of New Tasks

3. **Labour-augmenting technological advancement**

Those are the technological advances that increase labour productivity. In the model it corresponds to an increase in A^L.

4. **Deepening of Automation**
   Those are the automation that occur at the *intensive margin*, that is an capital becomes more productive in the tasks that it can already do. In the model it corresponds to an increase in A^K.

3.2 Equilibrium

3.2.1 Demand Equation

The Demand Equation we obtained in the appendix is

$$S = \frac{y-b}{\delta + \lambda + \alpha(I-N+1) + \beta p(\theta)} \tag{13}$$

This demand curve is downward sloping: $\theta \uparrow \Rightarrow p(\theta) = B\theta^{1-\mu} \uparrow \Rightarrow S \downarrow$
This equation describes the idea that workers/firms value jobs more if they are harder to find/generate.

3.2.2 Supply Equations

The supply function we obtained in the appendix is

$$f = (1-\beta)q(\theta)S \tag{14}$$

This supply curve is upwards sloping: $S \uparrow \Rightarrow q(\theta) = B\theta^{-u} \downarrow \Rightarrow \theta \uparrow$
This equation describes the idea that firms post more vacancies if having a filled job is more profitable.

3.2.3 Combining demand and supply equations

Combining (13) and (14), we get

$$f\Big[\delta + \lambda + \alpha(I-N+1) + \beta p\Big] = (1-\beta)q(y-b)$$

Substituting (5) and (6),

$$f\Big[\delta + \lambda + \alpha(I-N+1) + \beta B\theta^{1-\mu}\Big] = (1-\beta)B\theta^{-\mu}(y-b) \tag{15}$$

3.2.4 Wage Curve

The wage curve we obtained in the appendix is

$$w = y - (1-\beta)\Big[\delta + \lambda + \alpha(I-N+1)\Big]\frac{y-b}{\delta + \lambda + \alpha(I-N+1) + \beta p(\theta)} \tag{16}$$

3.2.5 Steady-state Unemployment Rate

The steady-state unemployment rate, $\overline{u}$, we obtained in the appendix is

$$\overline{u} = \frac{\lambda + \alpha(I-N+1)}{\lambda + \alpha(I-N+1) + p(\theta)} \tag{17}$$

3.2.6 Production Function

There are several assumptions that we need to make for the task-based production function to work as intended. These assumptions have the same objectives as the ones made by Acemoglu and Restrepo (2018c):

Assumption 1: Labour has a *comparative advantage* in higher-indexed tasks, i.e. the ratio $A^L(x)/A^K(x)$ is increasing in x.

$$\frac{\mathrm{d}A^L(x)}{\mathrm{d}A^K(x)} > 0 \qquad \forall x$$

Assumption 2: All tasks in the range $[N-1, I]$ will be produced using capital (machines),

$$\frac{w}{r} > \frac{A^L(I)}{A^K(I)}$$

Assumption 3: Creation of new tasks, an increase in N, will increase aggregate output,

$$\frac{A^L(N)}{A^K(N-1)} > \frac{w}{r}$$

Instead of deriving the same exact equilibrium conditions in the appendix as in Acemoglu and Restrepo (2018c), we will rather explain the process and provide the main steady-states that they got.

The equilibrium rental rate and wages, obtained through firm profit maximisation, solving (12):

$$r = \frac{Y}{K}(I-N+1) \qquad\qquad w = \frac{Y}{L}(N-I) \tag{18}$$

Note: The market for robots is perfectly competitive, meaning it does not have any rigidity. While, the labour market is not perfectly competitive and will has search frictions as we already showed. Therefore, the equation above is about the matched labour.

Then we compute the steady-state capital level through Solow-like capital accumulation and substitute it into the aggregate output function, obtaining the equilibrium output of

$$Y = D\left(\frac{K}{I-N+1}\right)^{I-N+1}\left(\frac{L}{N-I}\right)^{N-I} \tag{19}$$

where

$$D = \exp\left(\int_{N-1}^{I} \ln A^K(x)dx + \int_{I}^{N} \ln A^L(x)dx\right) \tag{20}$$

The equilibrium aggregate output is derived from the allocation of the capital and labour to tasks.

Equilibrium output per worker is,

$$Y/L = D\left(\frac{K}{L(I-N+1)}\right)^{I-N+1}\left(\frac{1}{N-I}\right)^{N-I} \tag{21}$$

4 Results & Discussion

As DMP model is highly suitable for studying long-run labour market dynamics, we are only examining the stochastic steady states and do not go forward with dynamic equilibria. Future papers can indeed extend the model here to a DSGE studying dynamic solutions. Our analytical findings are summarised in the table below.

Variable	Automation	Creation of New Tasks
Unemployment	**Uncertain** Displacement Effect = + Productivity Effect = −	**Positive** Reinstatement Effect = − Productivity Effect = −
Wages	**Uncertain** Displacement Effect = − Productivity Effect = +	**Positive** Reinstatement Effect = + Productivity Effect = +

Table 1: Steady State Summary

4.1 The Impact of Automation on Labour Market Outcomes

First, we will assess how automation affects labour productivity or output per worker in our case. We take the natural logarithm of the equilibrium output per worker and then take the first derivative with respect to I. As a result we obtain,

$$\frac{\mathrm{d}\ln(Y/L)}{\mathrm{d}I} = \ln[A^K(I)] - \ln[A^L(I)] + \ln K - \ln L - \ln(I - N + 1) + \ln(N - I) \tag{22}$$

After rearranging and substituting the equilibrium rental rate and wages we get,

$$\frac{\mathrm{d}\ln(Y/L)}{\mathrm{d}I} = \underbrace{\ln\left(\frac{w}{A^L(I)}\right) - \ln\left(\frac{r}{A^K(I)}\right)}_{\text{productivity effect } >0} \tag{23}$$

According to **Assumption 2**, the relationship we obtained above is positive. Therefore, automation creates an increase in productivity.

4.1.1 The Impact on Unemployment

The relationship between automation and unemployment rate is derived in the appendix, while here we only present the final result:

$$\begin{aligned}\frac{\mathrm{d}\ln(\overline{u})}{\mathrm{d}I} = {} & \frac{\alpha}{\lambda + \alpha(I - N + 1)} - \frac{\alpha}{\lambda + \alpha(I - N + 1) + p(\theta)} - \frac{p(\theta)}{\lambda + \alpha(I - N + 1) + p(\theta)} \\ & \left[(1-\mu)\frac{\delta + \lambda + \alpha(I - N + 1) + \beta p(\theta)}{\mu\big[\delta + \lambda + \alpha(I - N + 1)\big] + \beta p(\theta)}\frac{y}{y - b}\frac{\mathrm{d}\ln y}{\mathrm{d}I} - \frac{\alpha(1-\mu)}{\mu\big[\delta + \lambda + \alpha(I - N + 1)\big] + \beta p(\theta)}\right]\end{aligned} \tag{24}$$

where $\frac{\mathrm{d}\ln y}{\mathrm{d}I} > 0$ as was shown before.

From the equation above we can conclude that automation affects unemployment through two counteracting forces, displacement and productivity.

$$\frac{\mathrm{d}\ln(\overline{u})}{\mathrm{d}I} = \text{Displacement Effect} \; + \; \text{Productivity Effect}$$

The displacement effect is positive if $\alpha \neq 0$, that is, it results in higher unemployment. Workers are being replaced due to the changes in the proportion of tasks that are performed by them.

The productivity effect is negative driven by an increase in output per worker that occurs during automation. Meaning the unemployment decreases due to increases in output per worker. Here,

$$\text{Displacement Effect} = \underbrace{\frac{\alpha}{\lambda + \alpha(I - N + 1)} - \frac{\alpha}{\lambda + \alpha(I - N + 1) + p(\theta)}}_{\text{Displacement Effect}>0}$$

On the other hand, productivity decreases the unemployment rate, given by the rest of the terms in $\frac{\mathrm{d}\overline{u}}{\mathrm{d}I}$

4.1.2 The Impact on Wages

Similar to the findings by Acemoglu and Restrepo (2018c), automation affects wages through two channels: positively via productivity effect and negatively via the displacement effect.

$$\frac{\mathrm{d}\ln(\overline{w})}{\mathrm{d}I} = \text{Displacement Effect} \; + \; \text{Productivity Effect}$$

In the equation below, the blue coloured part is the productivity effect, while the red coloured one is the displacement effect.

$$\begin{aligned}\frac{\mathrm{d}w}{\mathrm{d}I} = {} & \frac{\mathrm{d}y}{\mathrm{d}I} + (1-\beta)\frac{(y-b)\left(\alpha + \beta\frac{\mathrm{d}p(\theta)}{\mathrm{d}I}\right)\Big[\delta + \lambda + \alpha(I - N + 1)\Big]}{\big[\delta + \lambda + \alpha(I - N + 1) + \beta p(\theta)\big]^2} \\ & -(1-\beta)\frac{\alpha(y-b)}{\delta + \lambda + \alpha(I - N + 1) + \beta p(\theta)} - (1-\beta)\frac{\delta + \lambda + \alpha(I - N + 1)}{\delta + \lambda + \alpha(I - N + 1) + \beta p(\theta)}\frac{\mathrm{d}y}{\mathrm{d}I}\end{aligned}$$

4.2 The Impact of Creation of New Tasks on Labour Market Outcomes

We begin by considering how creation of new tasks affects output per worker. We take the first order derivative of the natural logarithm of labour productivity with respect to the number of tasks in the economy, N:

$$\frac{\mathrm{d}\ln(Y/L)}{\mathrm{d}N} = -\ln[A^K(N-1)] + \ln[A^L(N)] - \ln K + \ln L + \ln(I - N + 1) - \ln(N - I) \tag{25}$$

After rearranging and substituting the equilibrium rental rate and wages, we get

$$\frac{\mathrm{d}\ln(Y/L)}{\mathrm{d}N} = \underbrace{\ln\left(\frac{r}{A^K(N-1)}\right) - \ln\left(\frac{w}{A^L(N)}\right)}_{\text{productivity effect }>0} \tag{26}$$

According to **Assumption 3**, the productivity effect we obtained above is positive.

4.2.1 The Impact on Unemployment

New tasks impact unemployment through reinstatement and productivity forces which work in the same direction and both reduce unemployment.

$$\frac{\mathrm{d}\ln(\overline{u})}{\mathrm{d}N} = \text{Reinstatement Effect} + \text{ Productivity Effect}$$

Reinstatement effect is coloured blue, while the productivity effect is red. Both of them are negative, that is unemployment decreases when technological advancement creates new tasks.

$$\begin{aligned}\frac{\mathrm{d}\ln(\overline{u})}{\mathrm{d}N} = &-\frac{\alpha}{\lambda+\alpha(I-N+1)} + \frac{\alpha}{\lambda+\alpha(I-N+1)+p(\theta)} - \frac{p(\theta)}{\lambda+\alpha(I-N+1)+p(\theta)} \\ &\left[(1-\mu)\frac{\delta+\lambda+\alpha(I-N+1)+\beta p(\theta)}{\mu\big[\delta+\lambda+\alpha(I-N+1)\big]+\beta p(\theta)}\frac{y}{y-b}\frac{\mathrm{d}\ln y}{\mathrm{d}N} + \frac{\alpha(1-\mu)}{\mu\big[\delta+\lambda+\alpha(I-N+1)\big]+\beta p(\theta)}\right]\end{aligned} \tag{27}$$

4.2.2 The Impact on Wages

New tasks impact wages through reinstatement and productivity forces similar to findings of Acemoglu and Restrepo (2018c), where these forces also work in the same direction and increase wages.

$$\frac{\mathrm{d}\ln(\overline{w})}{\mathrm{d}N} = \text{Reinstatement Effect} + \text{ Productivity Effect}$$

Reinstatement effect is coloured blue, while the productivity effect is red. Both of them are positive, that is an increase in N increases wages.

$$\begin{aligned}\frac{\mathrm{d}w}{\mathrm{d}I} = &\frac{\mathrm{d}y}{\mathrm{d}I} + (1-\beta)\frac{(y-b)\left(\beta\frac{\mathrm{d}p(\theta)-\alpha}{\mathrm{d}I}\right)\Big[\delta+\lambda+\alpha(I-N+1)\Big]}{\big[\delta+\lambda+\alpha(I-N+1)+\beta p(\theta)\big]^2} \\ &+(1-\beta)\frac{\alpha(y-b)}{\delta+\lambda+\alpha(I-N+1)+\beta p(\theta)} - (1-\beta)\frac{\delta+\lambda+\alpha(I-N+1)}{\delta+\lambda+\alpha(I-N+1)+\beta p(\theta)}\frac{\mathrm{d}y}{\mathrm{d}I}\end{aligned}$$

4.3 Evaluation and Possible Extensions

We have analytically derived theoretical results but we did not run any simulations for this research. The reason behind that, was the difficulty to adequately reason the calibration methods. To the best of author's knowledge the task-based approach developed by Acemoglu and Restrepo (2018c) is purely theoretical and has not been simulated in any other research. Therefore, as we did not want to just come up with calibrated parameters and functions, we decided to rather stick to analytically deriving the relationships between the variables in the model. Additionally, as the author coined a new parameter α which they did not see anywhere in the literature, making assumptions about its approximate value for simulation reasons would not have been the best practice. Nevertheless, the research drew new insights regarding the impact of technological innovations on unemployment which does not exclude the possibility of the predicted 'technological unemployment'. On the other hand, the findings regarding the impact of technologies on wages are consistent with the results from Acemoglu and Restrepo (2018a).

Future research could be extended through DSGE-style model that builds up on the DMP model developed in the paper. Moreover, a modification of the model could be interesting where the newly developed term α would not just be a fixed parameter but rather a variable that depends on the tasks performed by labour. The model in this paper serves as a framework for future research on the relationship between technologies and labour market.

5 Conclusion

This paper has explored the intricate effects of technological advancements, particularly automation and task creation, on labour market outcomes using a modified DMP model. Our findings reveal that automation has a dual impact: it displaces workers from routine tasks but also creates productivity gains that can mitigate unemployment and raise wages for those able to transition into new roles. The extent of these effects depends on the relative strengths of the productivity and displacement effects. While automation generally improves output per worker, its impact on wages and employment remains uncertain and hinges on how efficiently new tasks are created and how adaptable the labour force is to these changes.

The creation of new tasks, by contrast, tends to have a more uniformly positive effect, both reducing unemployment and increasing wages through the reinstatement effect. This suggests that fostering innovation in areas where labour holds a comparative advantage could be key to ensuring positive labour market outcomes as technology continues to advance.

Ultimately, our research highlights the importance of policy interventions that support workers in adapting to technological changes. Policymakers should consider strategies that facilitate retraining and upskilling to ensure that workers can benefit from new technological developments. By striking a balance between automation's disruptive potential and the creation of new employment opportunities, we can harness technological progress to improve both productivity and living standards across the economy.

Future work could extend this analysis by simulating dynamic equilibria or by incorporating more detailed data on specific industries and worker skill sets. Such extensions would offer valuable insights for policymakers, businesses, and workers navigating the ongoing technological revolution.

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