On Artificial Intelligence

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Preferring a search for objective reality over revelation is another way of satisfying religious hunger... It aims to save the spirit, not by surrender but by the liberation of the human mind. Its central tenet, as Einstein knew, is the unification of knowledge. When we have unified enough certain knowledge, we will understand who we are and why we are here.

Edward O. Wilson, *Consilience* (1998, p. 7)

1 Motivation

In this paper we focus in the modeling aspects of factor oriented labor augmenting technologies that favor high skilled workers. We exposit Acemonglu and Restrepo's (2020a) model which describes in a rigorous, analytical, and thought-provoking way, the process of worker displacement through automation, and the creation of new tasks for workers to perform, as a result of this automation. The models contained herein show how inequality is exacerbated by automation. However, they also explain how new tasks can create jobs for either skilled or unskilled workers, depending on the nature of the tasks which are created. New technologies are constantly being invented which augment physical and human capital, and at the same time replace workers stuck in the middle between jobs that will not be automated, and jobs that cannot be automated (Autor, et al 2015). In fact, robots can be thought of as competing against workers for jobs, and in the end, if humans cannot find work to do, we may be overtaken by the machines in certain physical and mental tasks (Restrepo and Acemoglu 2019). For now these automated tasks are primarily clunky, rule based tasks and processes (Autor, et al 2003) however, as we learn more about ourselves, we are training our machines to act and think more and more like us.

In section two we discuss a basic definition of automation and go on to model the changes in the demand for skills. In section three we present a different, more analytical model for the way that wages and labor demand change in the presence of automation technologies. Section four concludes with a short summary and a few words on the the importance of economic systems modeling in a AI driven world.

2 A Basic Model of Automation

Definition 1 *Automation: Changes that enable capital to be used in tasks that were previously performed by labor or increase the productivity of capital in said tasks.*

One of the main assumptions of this model is that technological based change is biased in favor of high skilled labor, and yet automation will increase the real wages of workers across the spectrum of income and skill. Consider changes in the demand for skills can be modeled as

$$d\left(\frac{w_H}{w_L}\right) = -\frac{1}{\sigma} d\ln\left(\frac{H}{L}\right) + \frac{\sigma-1}{\sigma} d\ln\left(\frac{A_H}{A_L}\right). \tag{1}$$

where $\frac{w_H}{w_L}$ is the ratio of the skill premium, $\frac{H}{L}$ is the relative ratio of the supply of skills, σ is the elasticity of substitution between skilled and unskilled workers and A_L and A_H are factor-augmenting technologies for unskilled and skilled workers respectively. Goods are produced from a mass, M of tasks $x \in \mathcal{T}$, combined by a constant elasticity of substitution aggregator given by

$$Y = \left(\frac{1}{M} \int_{\mathcal{T}} (My(x))^{\frac{\lambda-1}{\lambda}} dx\right)^{\frac{\lambda}{\lambda-1}}. \tag{2}$$

Here $\lambda \geq 0$ is the elasticity of substitution between tasks. In the model, tasks are performed by unskilled labor $l(x)$, skilled labor $h(x)$, or capital $k(x)$. And

$$y(x) = \psi_L(x)l(x) + \psi_H(x)h(x) + \psi_K(x)k(x). \tag{3}$$

$\psi(x) \equiv A_j \cdot \gamma_j(x)$ for $j \in \{L, H, K\}$ denotes the productivity of factor j at task x. γ is some function of the task and essentially is a way to measure the efficiency of production. The market clearing conditions are

$$L = \int_{\mathcal{T}} l(x)dx \qquad \text{and} \qquad H = \int_{\mathcal{T}} h(x)dx$$

Because the change in the factor augmenting technologies, ceterius paribus does not change the allocation of tasks to these factors and has no impact on Γ_H/Γ_L. These Γ_j are called "share parameters" by Acemoglu and Restrepo (2020), and they represent the *range* of tasks that are able to be performed by the two types of labor. Because of this, we can write Γ_H/Γ_L as a function of the factor augmenting technologies ratio, $A_H H/A_L L$ and other technologies, denoted as the vector θ :

$$\ln\left(\frac{\Gamma_H}{\Gamma_L}\right) = \Gamma\left(\frac{A_H H}{A_L L}, \theta\right).$$

From Equation (1) we can also write

$$d\ln\left(\frac{w_H}{w_L}\right) = -\frac{1}{\sigma}d\ln\left(\frac{H}{L}\right) + \frac{\sigma-1}{\sigma}d\ln\left(\frac{A_H}{A_L}\right) + \frac{1}{\lambda}d\ln\left(\frac{\Gamma_H}{\Gamma_L}\right)\bigg|_{\frac{A_H H}{A_L L}} \tag{4}$$

In this equation,

$$\Gamma_j = \frac{\frac{1}{M}\int_{\tau_j}\gamma_j(x)^{\lambda-1}dx}{1-\frac{1}{M}\int_{\tau_K}\left(\frac{\psi_K(x)}{q(x)}\right)^{\lambda-1}dx} \text{ for } j \in \{L, H\}. \tag{5}$$

We can now derive the change in $\ln\left(\frac{\Gamma_H}{\Gamma_L}\right)$ as

$$d\ln\left(\frac{\Gamma_H}{\Gamma_L}\right) = \frac{\partial\ln\left(\frac{\Gamma_H}{\Gamma_L}\right)}{\partial\ln\left(\frac{A_H H}{A_L L}\right)} \cdot d\ln\left(\frac{A_H H}{A_L L}\right) + d\ln\left(\frac{\Gamma_H}{\Gamma_L}\right)\bigg|_{\frac{A_H H}{A_L L}}.$$

by the definition of a total derivative. The final term in this expression means changes in Γ_H and Γ_L due to technology, holding the ratio of factor augmenting technologies, $\frac{A_H H}{A_L L}$ constant.

Now we bring in the first proposition from Acemoglu and Restrepo (2020).

Theorem 1 *If there is an improvement in automation such that the productivity of capital in a set of tasks $\mathcal{A} \subset \mathcal{T}_L$ increases to $\psi_K(x) > 0$. Then the skill premium's increase is given by*

$$dln\left(\frac{w_H}{w_L}\right) = \frac{1}{\sigma}\frac{\int_{\mathcal{A}}\gamma_L^{\lambda-1}dx}{\int_{\tau_L}\gamma_L^{\lambda-1}dx}. \tag{6}$$

Here, w_H increases, and w_L may either increase or decrease. Total Factor Productivity (TFP) increases by

$$dlnTFP_{\mathcal{A}} = \frac{1}{M}\int_{\mathcal{A}}\frac{\left(\frac{w_L}{\psi_L(x)}\right)^{1-\lambda} - \left(\frac{q(x)}{\psi_K(x)}\right)^{1-\lambda}}{1-\lambda}dx \quad > 0$$

and the labor share decreases by

$$ds = -\frac{1}{M}\int_{\mathcal{A}}\left(\frac{\psi_K(x)}{q(x)}\right)^{\lambda-1}dx$$

Proof: Here we derive the change in the skill premium only. The rest is left as an exercise for the reader. We begin by defining the function

$$\tilde{\Gamma}(w_H/w_L;\theta) = \frac{\int_{w_H/\psi_H(x)\leq w_L/\psi_L(x),\gamma_K(x)=0}\psi_H(x)^{\lambda-1}dx}{\int_{w_H/\psi_H(x)\leq w_L/\psi_L(x),\gamma_K(x)=0}\psi_L(x)^{\lambda-1}dx}$$

Our equilibrium condition is that $\tilde{\Gamma}(w_H/w_L;\theta) = \Gamma(A_H H/A_L L;\theta)$. Here the skill premium satisfies

$$\frac{w_H}{w_L} = \tilde{\Gamma}(w_H/w_L;\theta)^{\frac{1}{\lambda}}\cdot\left(\frac{A_H}{A_L}\right)^{\frac{\lambda-1}{\lambda}}\left(\frac{H}{L}\right)^{-\frac{1}{\lambda}}. \tag{7}$$

A change in $\ln H/L$ reduces the skill premium by

$$\frac{\partial \ln w_H/w_L}{\partial \ln H/L} = -\frac{1}{\sigma}.$$

Now, using equation 7, we can write this function as

$$\frac{\partial \ln w_H/w_L}{\partial \ln H/L} = \frac{1}{\lambda}\frac{\partial \ln\tilde{\Gamma}}{\partial \ln w_H/w_L}\frac{\ln w_H/w_L}{\partial \ln H/L} - \frac{1}{\lambda},$$

and so by some simple algebra,

$$\frac{\partial \ln w_H/w_L}{\partial \ln H/L} = -\frac{\frac{1}{\lambda}}{1-\frac{1}{\lambda}\frac{\ln\tilde{\Gamma}}{\partial \ln w_H/w_L}}.$$

Because of this relation, we know that $\tilde{\Gamma}$ satisfies

$$\frac{1}{\sigma} = \frac{\frac{1}{\lambda}}{1-\frac{1}{\lambda}\frac{\ln\tilde{\Gamma}}{\partial \ln w_H/w_L}}$$

Now we take the log derivative of (7) to get

$$dln\left(\frac{w_H}{w_L}\right) = \frac{1}{\lambda}\frac{\partial \ln\tilde{\Gamma}}{\partial \ln w_H/w_L} dlnln\left(\frac{w_H}{w_L}\right) + \frac{1}{\lambda}\frac{\int_{\mathcal{A}} \gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L} \gamma_L^{\lambda-1}dx}$$

Finally we solve for $dln\left(\frac{w_H}{w_L}\right)$ to get our result, equation (6).

$$dln\left(\frac{w_H}{w_L}\right) = \frac{\frac{1}{\lambda}}{1-\frac{1}{\lambda}\frac{\partial \ln\tilde{\Gamma}}{\partial \ln w_H/w_L}}\frac{\int_{\mathcal{A}} \gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L} \gamma_L^{\lambda-1}dx} = \frac{1}{\sigma}\frac{\int_{\mathcal{A}} \gamma_L^{\lambda-1}dx}{\int_{\mathcal{T}_L} \gamma_L^{\lambda-1}dx}.$$

This derivation is essentially showing that the changes in the so called skill premium are driven by the jobs lost by low skill workers. We now move on to the more comprehensive, global model of balanced growth.

3 A Balanced Growth Model

This model is very different that the one in the previous section, and as such the variables and constants are defined to be different. It is slightly more complex, however may be more indicative of the forces changing labor demand and supply in the global economy today.

We begin with some basic assumptions and regularity conditions which will provide a basis for our model in this section. First we purport that there exists $I \in [N-1, N]$ such that tasks $i \leq I$ are automated, and $i > I$ are produced with labor. Per Acemoglu and Restrepo's 2017 paper

$$y(i) = \bar{B}(\zeta)\left[\eta^{\frac{1}{\zeta}}q(i)^{\frac{\zeta-1}{\zeta}} + (1-\eta)^{\frac{1}{\zeta}}(\gamma(i)l(i))^{\frac{\zeta-1}{\zeta}}\right]^{\frac{\zeta}{\zeta-1}}$$

In this production function, $\gamma(i)$ is the productivity of labor in task i, $\zeta \in (0, \infty)$ is the elasticity of substitution between intermediates (read automation technologies) and labor, $\eta \in (0,1)$ is the share parameter of the CES production function. When $\zeta = 1, \bar{B}(\zeta) = \psi^{\eta}(1-\eta)^{\eta-1}\eta^{-\eta}$, and 1 otherwise. For tasks $i \leq I$, which can be produced by labor or capital and in their respective production function, this is represented as such

$$y(i) = \bar{B}(\zeta)\left[\eta^{\frac{1}{\zeta}}q(i)^{\frac{\zeta-1}{\zeta}} + (1-\eta)^{\frac{1}{\zeta}}(k(i)+\gamma(i)l(i))^{\frac{\zeta-1}{\zeta}}\right]^{\frac{\zeta}{\zeta-1}}.$$

Here we must make an assumption.

Assumption 1: $\gamma(i)$ *is strictly increasing.*

Furthermore, we give an important demand equation which will be used in the analysis of household utility yet to come

$$u(C, L) = \frac{(Ce^{-v(L)})^{1-\theta} - 1}{1-\theta}.$$

Here C is consumption, L denotes the labor supply of the average household, and $v(L)$ is the utility cost of labor supply which is continuously differentiable, increasing, and convex. $U(C, L)$ itself is concave. θ is the inverse of the intertemporal elasticity of substitution. Now the setup is complete.

Theoretical Model of the Economy: The household's dymanic preferences are given by

$$\int_0^\infty e^{-\rho t}u(C(t), L(t))dt,$$

where ρ is the discount rate. We must now make assumption one stronger to continue with the model.

Assumption 1a: ($\gamma(i)$ satisfies

$$\gamma(i) = e^{Ai} \quad \text{and} \quad A > 0.$$

Furthermore, we have an additional assumption which we will use in our model.

Assumption 2: One of the following two conditions holds

1. $\eta \to 0$, or

2. $\zeta = 1$.

This ensures that the demand for labor and capital is homothetic.

Definition 2 *Balanced Growth Path: a trajectory path for the economy such that output and capital grow at a constant rate determined by the rate of technological change.*

Here we will introduce a very simplified version of Proposition 4 of Acemoglu and Restrepo's 2017 paper, The Race between Man and Machine.

Proposition: Suppose that Assumptions 1a and 2 hold. The economy has a Balanced Growth Path (BGP) with positive growth if and only if we are in one of these situations:

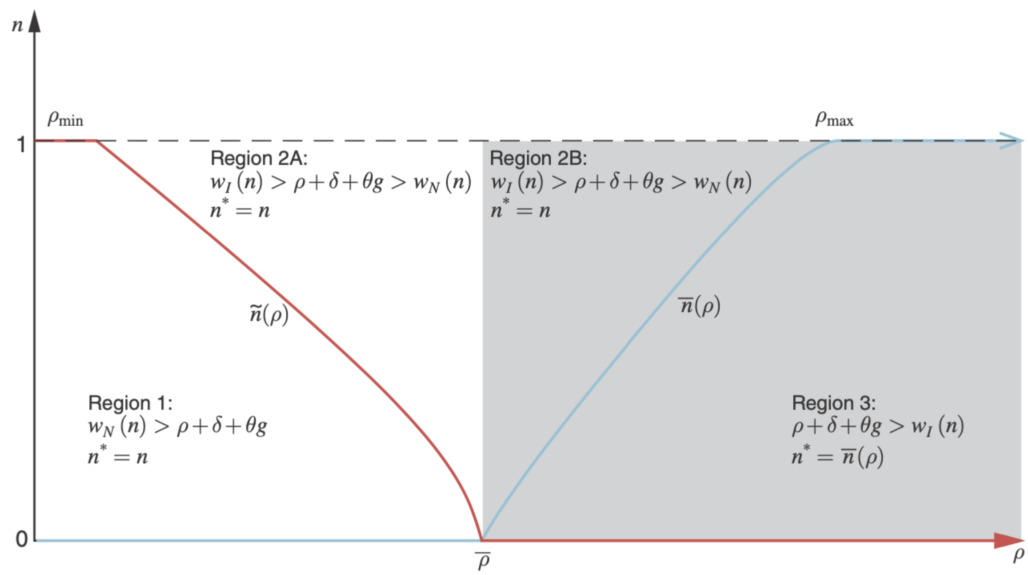

Figure 1: Behavior of Factor Prices for Labor in Different Parts of the Parameter Space

1. **Full Automation:** $\rho < \bar{\rho}$, $N(t) = I(t)$, and $B > \delta + \rho > \frac{1-\theta}{\theta}(B - \delta - \rho) + \delta$ because of the transversality condition. This leads us to a unique and globally stable Balanced Growth Path where $n^*(t) = 0$, meaning that all tasks are produced with capital and the labor share is zero. Here, $n^*(t)$ is a summary measure of the state of technology used in equilibrium, I is the threshold task automation, and N is the number of tasks to be automated. In additon, $\bar{\rho}$ is defined as $\bar{\rho} = B - \delta - \theta g$.

2. **Interior BGP with Immediate Automation:** $\rho \in (\rho_{min}, \rho_{max}), \dot{N}(t) = \dot{I}(t) = \Delta$, and $n(t) = n > max\{\bar{n}(\rho), \tilde{n}(\rho)\}$, where we have the following conditions on $n, \tilde{n}$, and $\bar{n}$:

    (a) For $n < \tilde{n}(\rho)$, new tasks would reduce aggregate output ans so are not adopted.

    (b) For $n > \tilde{n}(\rho)$, new tasks raise aggregate output and so are immediately produced with labor.

    (c) For $n > \bar{n}(\rho)$, automated tasks raise aggregate output and so are immediately produced with capital.

    (d) Finally, for $n < \bar{n}(\rho)$, additonal automation would reduce aggregate output, so small changes in automation technology do not affect n^* and other equilibrium objects.

3. **Interior BGP with Eventual Automation:** $\rho > \bar{\rho}$, $\dot{N}(t) = \Delta$ with $\dot{I}(t) \geq \Delta$ and $n(t) < \bar{n}(\rho)$, and $\rho + (\theta - 1)A\Delta > 0$ to ensure the transversality condition. This is a unique and globally stable BGP such that $n^*(t) = \bar{n}(\rho)$ and $I^*(t) = \tilde{I}(t) > I(t)$. The following figure is necessary to depict the differences in notation for various types of labor shifts.

4. **No Automation:** $\rho > \rho_{max}$, $\dot{N}(t) = \Delta$, and $\rho + (\theta - 1)A\Delta > 0$ per the transversality condition. So there is a unique and globally stable balanced growth path. Here, $n^*(t) = 1$, therefore all tasks are produced with labor and the capital share is zero.

The proof of this statement is omitted due to the relative brevity of this paper. The interested reader can find the details in Appendix A of Acemoglu and Restrepo's 2017 paper, The Race between Man and Machine.

This proposition is highly technical, however its importance lies in the simplicity with which it models an economy. The statement renders explicit boundaries and conditions with which to measure the condition or state of the economy and the health of the labor force.

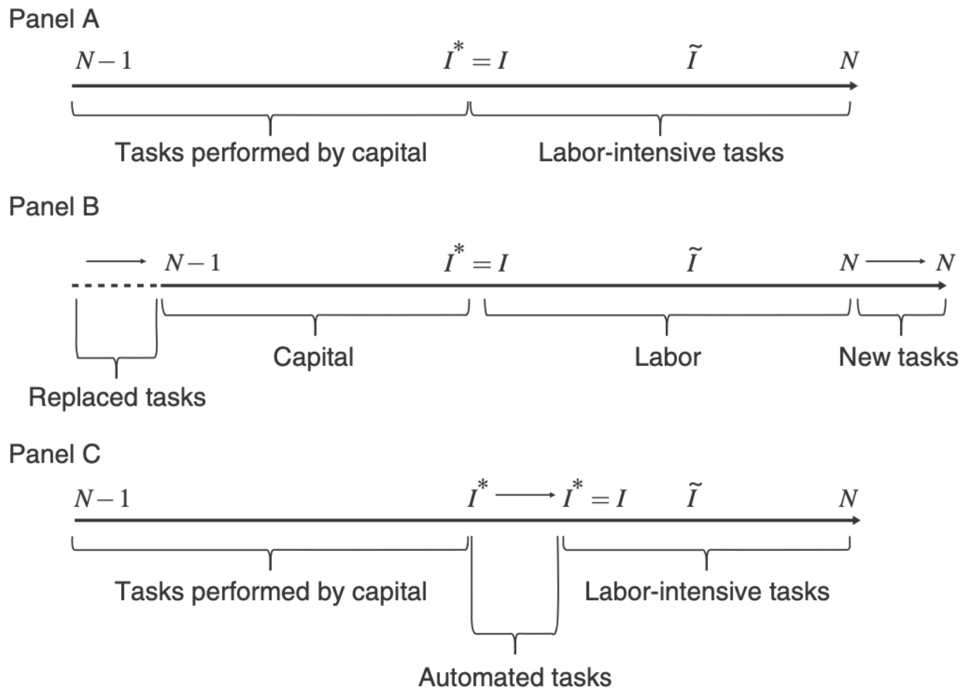

Figure 2: Scales for Shifting Labor Automation Technologies

While Figure 1 shows a drawing of the boundaries in a two dimensional plane, Figure 2 shows these boundaries in a way that is much easier to understand. The main difference to note in this figure is the abstraction between panels B and C. Panel B shows a healthy, robust economy experiencing technological advancement and growth. Old tasks are replaced with new tasks, and while there may still be a need for retraining, there are new jobs being created which drives a spirited demand for labor. Meanwhile, panel C tells a much scarier story. Labor intensive tasks are being replaced with automated tasks, and no new tasks are appearing. While this economy may be experiencing growth, it is of an artificial nature. In this scenario, more and more people are falling out of the labor force because there is simply nothing for them to do. This could be a potentially dangerous situation for humanity to be in should it ever occur. While this part of the paper did not bring any new models, or provide an explicit contribution, I believe it is nonetheless important to understand all aspects of the situation we are in. Anecdotal evidence has implored policymakers time and time again; what should we do to help those whose jobs have been automated? In order to answer that question, we must first fully understand the problem.

4 Concluding Remarks

This review of the recent technical literature surrounding technological, skill and task based automation provides a good foundation to study the impacts of artificial intelligence on the workforce. Based on this theoretical modeling, we can 'drill down' to the root causes and forces shaping the changes in labor market that are yet to come. While the math is a little distant from anecdotal evidence, it is nevertheless just as accurate a depiction of reality, merely from a different perspective. The literature surrounding artificial intelligence as a field is highly technical, and so as economists, if we are to understand this so called 'black box' technology, we too must look inside the black box of our own economy in the most rigorous way possible in order to get a grasp of the changes occurring. I believe that the next 5-10 years are going to be incredibly important, not only for us to innovate when it comes to AI, but also for us to manage the (sometimes unequal) impact that our technology can have on a vulnerable and constantly shifting workforce.

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