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Forks in the Road: Modelling the Economic Prospects of Artificial Intelligence

Abstract. *The incredible velocity at which artificial intelligence (AI) is changing the economic landscape poses unprecedented challenges to decision-makers, policy advisers, and academic researchers. At this stage of development, more than offering definitive answers, economic science should be prepared to raise the right questions: will AI lead us to a utopian future of sustained economic growth, balanced income distribution, and business opportunities for all, or must we be prepared to face a dark dystopia of slow growth, sharp income inequality, and large corporations that operate virtually without the need for human labour? There are many forks in the road and the direction we will follow is, by no means, at the current stage of knowledge, completely clear. This paper puts into perspective the mentioned bifurcation paths, first through a selective literature survey and, second, by assembling a stylised model of potential substitution of human labour by AI.*

Keywords: *artificial intelligence, labour productivity, economic growth, income inequality, economic modelling.*

JEL Classification: J24, O33, O40.

1. Introduction

Artificial intelligence (AI) is transforming modern societies and economies at an astonishingly fast pace. Fed with large amounts of data, computerised systems are today capable of learning and solving a wide array of problems in a much more autonomous, fast, efficient, and reliable way than human minds. AI identifies complex structures, patterns, and regularities hidden in big data sets, and it easily adapts as new data is added to the system. Human intervention is minimal, in the sense that programming is no longer required, at least in the same terms as before. AI creates its own algorithms and rewrites them when required; this is precisely what makes these systems intelligent.

In a brief essay, Brynjolfsson and Unger (2023) approach the possible macroeconomic consequences of AI. The authors focus on three main topics of relevance for economics – productivity growth, income inequality, and market

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competition – and for each of these topics they discuss an eventual bifurcation or "fork in the road". We can either evolve to a utopic economy of fast growth, low inequality, and atomistic competition, or, oppositely, to a dystopic society in which growth is slow, income inequality rises fast, and industries become largely concentrated in a few dominant players.

Whether AI (*i*) raises obstacles to growth or boosts productivity; (*ii*) polarises jobs and wages or assists people in being better equipped to face labour market challenges; (*iii*) concentrates economic activity in a few large firms or makes knowledge widely available for small businesses to flourish, are all decisive and open questions to which currently we cannot give a definitive answer. In this paper, these three open questions are put into perspective, first through a selective literature review on state-of-the-art research about the interconnection between AI and economics; and second, from an analytical standpoint, through the presentation of a simple stylised model, in which people who are allocated to different jobs according to their productivity can be, in certain circumstances, displaced by AI.

The devised model explores different possibilities regarding the relocation of labour after a set of middle productivity / middle income jobs are lost to AI. How people adapt to changes in the labour market and in work opportunities is fundamental for determining the path of the new economy. If workers cannot adapt and a large majority of them falls to low paying jobs (or no job at all), aggregate income may even decline, and income inequality may significantly increase. If the introduction of AI signifies a boost in human capabilities and an adaptation to more sophisticated tasks (most of them required to feed AI), the economy will certainly grow, and the distribution of income may become more balanced. There is also an intimate relation between the market structure for AI and income inequality. On the one hand, if the barriers to the creation of AI are not significant, much of the population can get 'a piece of the action' and participate in a large community of small businesses, what obviously assists in lowering inequality. On the other hand, if the resources—human, technical, and financial—required to develop AI are substantive, then the number of firms engaged in it is small, and these firms will concentrate a large portion of the gains in the new economy. In this perspective, the proposed model is suitable to address the mentioned forks in the road.

The paper is organised as follows. Section 2 presents a review of the literature. Section 3 outlines the model's basic features, in this first stage in an exclusively labour economy. Section 4 introduces AI into the model and approaches the relocation of the potentially displaced labour force. Section 5 concludes.

2. AI through the lenses of economists

Although the effects of AI on economic growth are still an understudied subject (Lu and Zhou, 2021), many economists concur that artificial intelligence can increase productivity and income (Stevenson, 2019) through the enhancement and replacement of, at least a part of, human labour (Autor, 2014; Trajtenberg, 2019). Even though the intensity of replacement surely depends on factors such as the nature of work (Arntz et al., 2017; Frey and Osborne, 2017), AI is likely to replace labour even in tasks currently considered human-intensive (Agrawal et al., 2019).

In the United States, it is estimated that an additional robot (or algorithm) per thousand workers can reduce employment by 0.37 percentage points, and this effect will probably be higher in the future (Acemoglu and Restrepo, 2020). Notwithstanding, AI will eventually reduce labour demand and wages only in the case in which it is not counterbalanced by the creation of new labour-intensive activities (Autor and Dorn, 2013; Acemoglu and Restrepo, 2019). AI enables this creation, as it can substantially reduce risks related to the implementation of new jobs (Agrawal et al., 2019). Therefore, according to the mainstream literature, labour will be affected (Lu and Zhou, 2021), but its share will not be significantly reduced by AI (Aghion et al., 2019), and the competitive advantage of AI will complement that of humans (Autor, 2014, 2015). This logical argument is compatible with the evidence showing that, in the case of developed countries, technology has not been associated with a significantly higher unemployment during economic recovery (Graetz and Michaels, 2017).

In the context of rising AI capabilities, market adjustments are not necessarily automatic, even, and fair, given the underlying imperfections and imbalances. At this respect, a market imperfection recurrently highlighted in the literature is the AI implementation lag, i.e., the set of delays associated with the dissemination of the benefits of new technologies (Brynjolfsson et al., 2019). In this perspective, the best is yet to come, i.e., most of the productivity impact of AI will only be felt in the future, a few years or a few decades from now, when it is fully incorporated into production and transaction processes.

Implementation lags and an uneven distribution of gains are associated with a series of misalignments and specific features of AI markets. On the one hand, AI is intimately intertwined with the use of big data as a production input, an input whose ownership is strongly concentrated (Babina et al., 2024). Concentration of ownership implies concentration of earnings, what has relevant implications concerning the value of the aggregate propensity to consume and, thus, of aggregate demand (they will both shrink), meaning that an important obstacle to sustained economic growth can, effectively, in this way, arise.

On the other hand, there are significant discrepancies between the current state of educational systems and the development of competencies they should stimulate in the novel AI economy, namely concerning the need for a stronger focus on analytical, creative, and emotional skills (Trajtenberg, 2019). Long-term policies should emphasise the acquisition of such essential skills (Autor, 2014), without neglecting the fact that people are heterogeneous and, therefore, that different individuals should pursue different paths to achieve their full potential in a challenging new and constantly mutating labour market (Webster and Ivanov, 2020).

A further fundamental point to consider in the context of the AI economy is the employment and wage polarisation between routine and non-routine jobs (Autor et al., 2017; Cavaglia and Etheridge, 2020; Jaimovich and Siu, 2020). Job polarisation brings a variety of challenges to the organisation of socio-economic relations:

beyond the obvious issues associated with income inequality and unemployment, one should also regard the social exclusion and disillusionment of a large portion of the population that eventually emerges and goes hand-in-hand with a world of increasingly fascinating technical wonders and fast-growing potential to generate unprecedented material wealth.

AI implementation can also increase inequality levels within as well as between countries or regions, especially to the disadvantage of those that have their comparative advantages based on labour, and particularly unskilled labour (Korinek and Stiglitz, 2021). To face the redistribution challenges, it is necessary to establish policies to regulate sharing benefits between the different stakeholders (Ernst et al., 2019).

Regarding how companies work, it should be noted that advanced technologies can optimise firms' prediction capabilities, and decision making processes of firms, which can lead to economic polarisation within and between sectors (Agrawal et al., 2019). The strength of this polarisation effect will depend on factors such as labour productivity (Autor and Dorn, 2013; Autor et al., 2017), and production costs and their relationship with economies of scale (Varian, 2019). Recent studies present evidence that AI generally occurs in large companies and that, consequently, it promotes higher industry concentration (Babina et al., 2024) and the formation of natural monopolies (Korinek and Stiglitz, 2021). On the other hand, AI adoption is an enabler of imitation processes and, consequently, it can reduce future innovation development (Aghion et al., 2019).

Many of the above briefly discussed concerns are incorporated, in the next sections, into a stylised model of labour heterogeneity and AI penetration, with the explicit purpose of discussing further the 'forks in the road' argument.

3. A framework of heterogeneous labour productivity and jobs

Consider an economy in which labour is the single input in production. Later, this input will potentially be replaced by AI in certain jobs; however, as a baseline framework, take for now an AI free economy. Assume that workers are heterogeneous regarding their productivity levels and that they spread over a productivity distribution of labour. Let $x \geq 0$ represent productivity levels and assume an exponential distribution. The corresponding probability density function (PDF) is as follows:

$$f(x) = \lambda e^{-\lambda x}, \qquad \lambda > 0 \tag{1}$$

In equation (1), $f(x)$ represents the density of agents endowed with labour productivity x; λ is a scale parameter such that $f(0) = \lambda$. With the adopted specification of the productivity distribution, we are assuming that the population of workers is normalised to 1,

$$L = \int_0^{+\infty} f(x)dx = 1 \tag{2}$$

Workers endowed with productivity x can execute any job requiring a productivity equal to or lower than x, choosing to perform the activity that allows them to make the best possible use of their skills. Consider that there are n jobs in the economy, denoted by $\#1, \#2, \dots, \#n$. To execute job $\#i,\ i = 1,2,..,n$, a minimum productivity level $x(\#i)$ is required, and jobs are ordered by increasing productivity: $x(\#1) < x(\#2) < \cdots < x(\#n)$. As a simplifying assumption, consider that $x(\#i) = i$. In this setting, the share of workers executing job $\#i$ is

$$L(\#i) = \int_i^{i+1} f(x)dx = e^{-\lambda i} - e^{-\lambda(i+1)} \tag{3}$$

The exception to the above general expression is the share of labour for job $\#n$ which includes every worker with a productivity equal to or higher than n,

$$L(\#n) = \int_n^{+\infty} f(x)dx = e^{-\lambda n} \tag{4}$$

There is also a share of workers who remain jobless, because they do not possess the level of productivity required to perform the least demanding job (their productivity is lower than 1); this share is:

$$L(\#0) = \int_0^1 f(x)dx = 1 - e^{-\lambda} \tag{5}$$

Employed workers amount to $\sum_{i=1}^{n} L(\#i) = 1 - L(\#0) = e^{-\lambda}$.

Labour productivity coincides, in this interpretation of the economy, with workers' income; hence, job $\#i$ generates an income equal to the product between the number of workers associated with the job and the job's rank, i.e.,

$$y(\#i) = L(\#i) \times i, \ \ i = 1, \dots, n \tag{6}$$

Aggregate income is, then, straightforward to compute:

$$Y = \sum_{i=1}^{n} y(\#i) = \sum_{i=1}^{n} e^{-\lambda i} = \frac{1 - e^{-\lambda n}}{e^{\lambda} - 1} \tag{7}$$

To illustrate the above reasoning, consider a simple example, with $\lambda = 0.25$ and $n = 25$. Figures 1 and 2 represent, respectively, the share of workers assigned to each job and the income generated by each job. In the proposed setting, low-productivity jobs have many associated workers, but each of them generates a low level of income; high-productivity jobs give rise to high levels of income, but because these jobs have attached a small number of workers, the corresponding $y(\#i)$ is low.

For the mentioned values of parameters, unemployment amounts to $L(\#0) = 0.2212$ and aggregate income is, according with (7), $Y = 3.5140$.

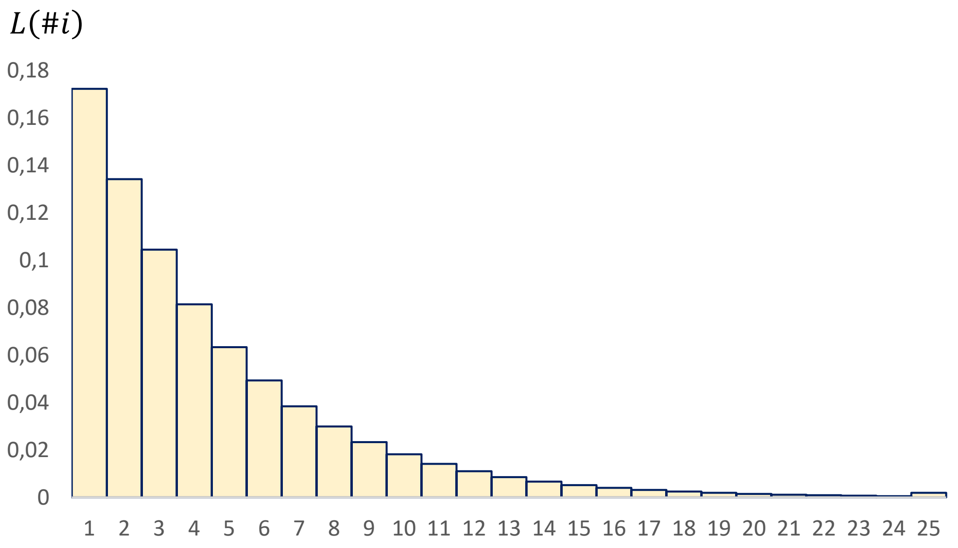

Figure 1. Workers per job

Source: authors' calculations on model simulation.

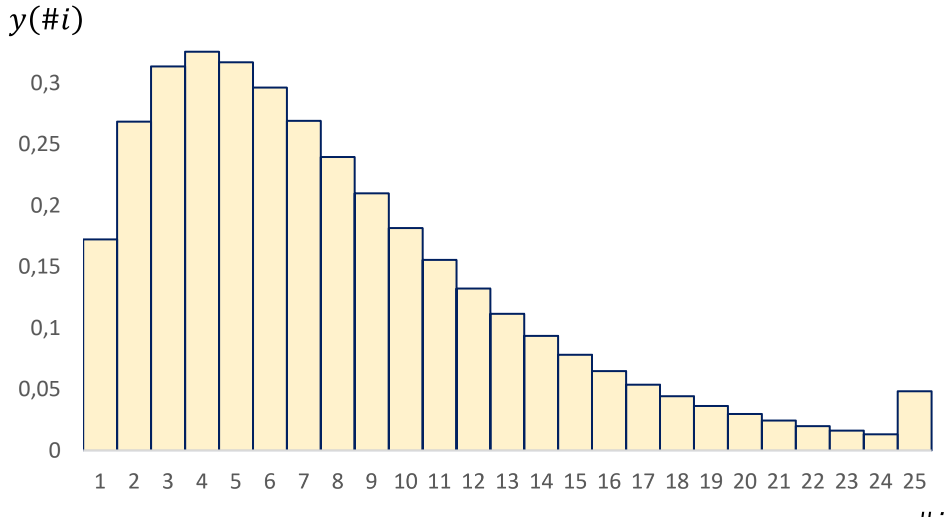

Figure 2. Income per job

Source: authors' calculations on model simulation.

In addition to measuring aggregate income, we are also interested in evaluating income inequality. For such a purpose, one can compute the Gini coefficient. This coefficient assumes values between zero (full equality) and 1 (complete inequality).

The coefficient can be obtained using the following formula:

$$G = \frac{1}{2Y}\sum_{i=0}^{n}\sum_{j=0}^{n} L(\#i)L(\#j)|i-j| \tag{8}$$

For the above considered numerical example: $G = 0.5613$.

4. Replacing humans by AI

4.1 AI efficiency and AI implementation costs

In the characterized economic setting, AI developers emerge as the agents who engage in the conception and implementation of automated processes, with the explicit purpose of profitably replacing human labour force in production (i.e., in the execution of each existing job). Recall that $y(\#i)$ represents the labour income for job $\#i$. The rule for replacing workers by AI in job $\#i$ is, then, $y_{AI}(\#i) > y(\#i)$, with $y_{AI}(\#i)$ the net income of adopting AI in activity $\#i$. This net income is modelled as follows. First, assume that in the absence of costs associated with the development of AI, the respective return is, for any of the jobs, a constant value $\Omega > 0$; this parameter can be interpreted as a measure of AI efficiency.

However, AI has associated costs. These costs are attached to two types of obstacles faced when creating automated solutions: the costs of adapting AI to activities requiring basic human contact, which are higher for non-sophisticated jobs; and the costs linked to the adaptation of AI to activities demanding a high degree of creativity and ingenuity, which increase with the sophistication of jobs. These ideas translate the well-known notion of job polarisation, according to which jobs which are easier to automate are those located at the middle of the productivity and income scale; jobs in the extremes are difficult to transfer to AI given the highlighted reasons (see Section 2 and the references therein).

The above logic can be analytically translated into two simple functions. The first represents the costs of AI development in closing the gap with human touch; the second represents the costs of AI development in replicating human creativity:

$$c_{AI,ht}(\#i) = e^{-(\omega i)^{\beta}} \tag{9}$$

$$c_{AI,hc}(\#i) = 1 - e^{-[\omega(i-1)]^{\beta}} \tag{10}$$

In equations (9) and (10), $\omega > 0, \beta > 1, i = 1, \ldots, n$. Equation (10) suggests that the most basic activity, $\#i = 1$, does not require any creativity, and therefore there are no associated creativity costs, $c_{AI,hc}(1) = 0$. This same job has high costs of AI generation associated with human touch, $c_{AI,ht}(1) = e^{-\omega^{\beta}}$, which is a value close to 1 (these are costs per efficiency unit and, thus, measured in a 0-1 scale). As we progress along the job productivity line, the costs attached to human touch adaptation decrease, while the costs associated with human creativity adaptation increase.

Figure 3 shows the two cost components, for the range of assumed jobs. The figure reveals the polarisation character of AI: lower overall costs of AI implementation are found in the jobs at intermediate levels of the scale. On the extremities (i.e., low productivity and high productivity jobs), the adaptation to human touch, on the one hand, and the adaptation to human creativity, on the other hand, significantly increase the underlying costs of AI research (to draw the figure, it was assumed $\omega = 0.1$, $\beta = 2.5$ and, as before, $\lambda = 0.25$ and $n = 25$). The visualisation of the graphic allows to confirm that adopting AI for jobs in the middle of the productivity scale has relatively low costs, but the cost increases sharply as one departs, to one way or the other, from the intermediate positions.

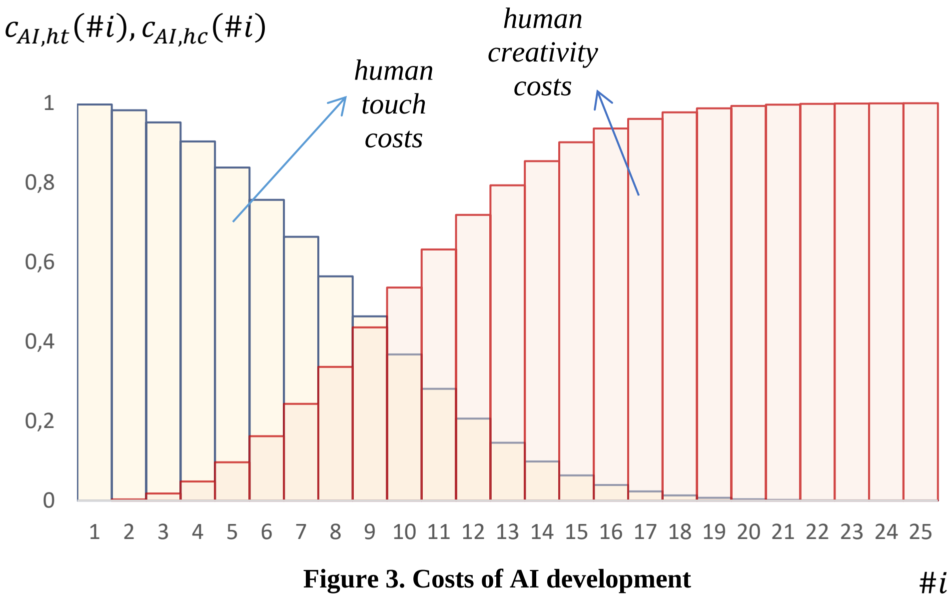

Figure 3. Costs of AI development
Source: authors' calculations on model simulation.

4.2 Turning jobs obsolete through advantageous AI solutions

The potential income that AI can generate, for each activity, is expressed in equation (11). This equation takes into consideration the two types of costs that were mentioned above,

$$y_{AI}(\#i) = \Omega\{1 - [c_{AI,ht}(\#i) + c_{AI,hc}(\#i)]\} = \Omega\left\{e^{-[\omega(i-1)]^{\beta}} - e^{-(\omega i)^{\beta}}\right\} \quad (11)$$

All jobs for which *i* satisfies condition $y_{AI}(\#i) > y(\#i)$ are jobs for which there is an advantage in replacing human labour by AI. In the case of the numerical example, reconsidering the already taken parameter values and assuming $\Omega = 3$, one draws Figure 4, with the purpose of visualizing for which jobs labour is replaced by more cost-efficient AI processes. The graphic reveals that in this 25-jobs economy, jobs #7 to #16 generate a higher return if executed by AI rather than by humans. It is, in fact, the middle-skill – middle-income jobs that are lost. There is an evident polarisation of jobs.

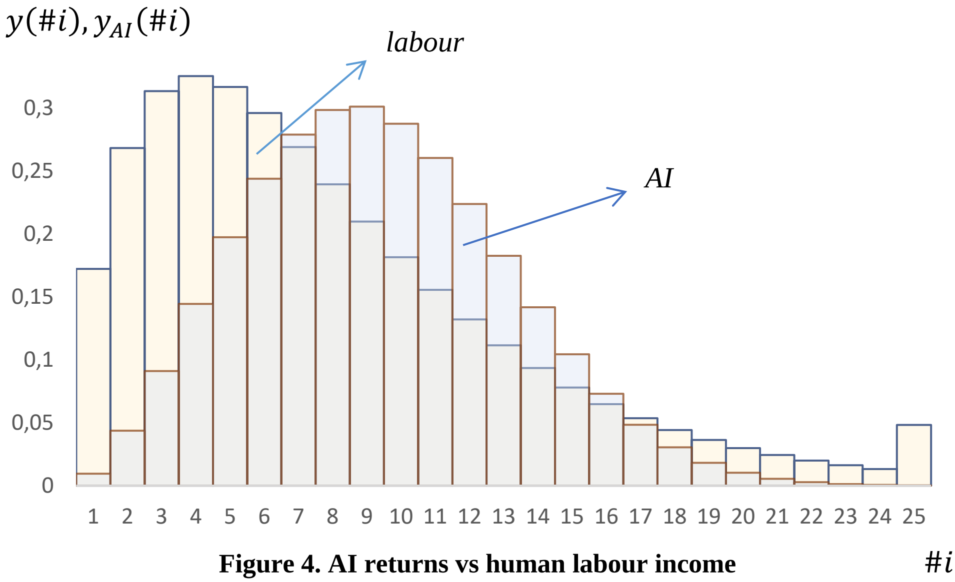

Figure 4. AI returns vs human labour income

Source: authors' calculations on model simulation.

Following the established reasoning, one should expect AI to turn obsolete jobs $\#k$ $(k \geq 1)$ to $\#l$ $(k < l \leq n)$. Thus, in generic form, the share of workers replaced by AI amounts to

$$\int_{k}^{l+1} \lambda e^{-\lambda x} dx = e^{-\lambda k} - e^{-\lambda(l+1)} \tag{12}$$

Under the numerical example, the share of displaced workers is $\int_{7}^{17} 0.25e^{-0.25x} dx = e^{-0.25\times 7} - e^{-0.25\times 17} = 0.1595$ (i.e., 15.95% of the population of workers are no longer assigned to the activities that they could best perform). The lost jobs have correspondence in a loss of income,

$$\sum_{i=k}^{l} y(\#i) = \sum_{i=k}^{l} \left[e^{-\lambda i} - e^{-\lambda(i+1)}\right] i \tag{13}$$

The new AI activities give rise to the following additional income:

$$\sum_{i=k}^{l} y_{AI}(\#i) = \sum_{i=k}^{l} \Omega \left\{e^{-[\omega(i-1)]^{\beta}} - e^{-(\omega i)^{\beta}}\right\} \tag{14}$$

According to the set-out logic, (14) must be a value larger than (13), because this is what justifies replacing human labour by AI. In the case of the numerical example: $\sum_{i=7}^{16} y(\#i) = 1.5355$ and $\sum_{i=7}^{16} y_{AI}(\#i) = 2.1522$.

One can generalise the numerical illustration by attributing different values to the AI productivity parameter Ω. For Ω <1.7717, no job is replaced by AI and we are back at the initially characterised labour economy. As the value of the AI efficiency parameter increases, the number of extinguished human jobs also increases. Table 1 provides information on the jobs lost to AI, the corresponding missing income, and the AI generated returns, in each case, for some entire values of Ω above 1. Obviously, $\sum_{i=k}^{l} y_{AI}(\#i) > \sum_{i=k}^{l} y(\#i)$ holds for every selected Ω.

Table 1. AI efficiency and job replacement

	Activities transferred to AI	Income lost (human jobs)	Income gained (AI)
$\Omega = 2$	#10-#14	0.6743	0.7308
$\Omega = 3$	#7-#16	1.5355	2.1522
$\Omega = 4$	#6-#17	1.8853	3.2595
$\Omega = 5$	#5-#18	2.2464	4.4541
$\Omega = 6$	#5-#18	2.2464	5.3449
$\Omega = 7$	#4-#19	2.6083	6.6150

Source: authors' calculations on model simulation.

4.3 Where do displaced workers go?

So far, the analysis appears to provide an unequivocally positive aggregate result for the economy. The work that was previously developed by human labour is now more efficiently performed by AI technologies that dispense human intervention. Even if these workers are not relocated to other jobs, the economy as a whole benefits, and part of the gains might be redistributed by those who are penalised, through public policies or other redistributive mechanisms. In what follows, we argue that the aggregate gain is not a sure result, because the displacement of workers might lead to a reorganisation of productive activities, which may change the configuration of the productivity distribution.

If jobs $\#k$ to $\#l$ are no longer in the hands of workers, all workers with productivity larger than k and lower than $l+1$ are displaced from their current jobs (recall that job $\#l$ demands a productivity level such that $l \leq x < l+1$). Assume the following scenario: all workers formerly involved in the extinguished jobs are unable to acquire new competencies and are pushed back to low-skill activities.[1] This scenario will imply a reorganisation of low-skill activities such that a new exponential distribution of productivities is formed to the left of the AI interval. The new distribution of workers is such that:

$$\int_0^k \hat{\lambda} e^{-\hat{\lambda} x} dx + \int_{l+1}^{+\infty} \lambda e^{-\lambda x} dx = 1 \qquad (15)$$

In equation (15), the distribution of workers to the right of $l+1$ remains in the same position as before; however, the distribution to the left of k is reconfigured, and its position now depends on a new scale parameter $\hat{\lambda}$. The value of this parameter

[1] Nuances to this assumption are straightforward to introduce: some of the workers might eventually acquire new competences and shift onto the right-hand-side of the distribution; this does not change significantly the argument one wants to point out.

is easily computable by solving the integrals in (15), and it amounts to: $\hat{\lambda} = \lambda \frac{l+1}{k}$; this is a value higher than λ. Figure 5 illustrates the changes for the assumed numerical example. In this example, $\hat{\lambda} = 0.6071$.

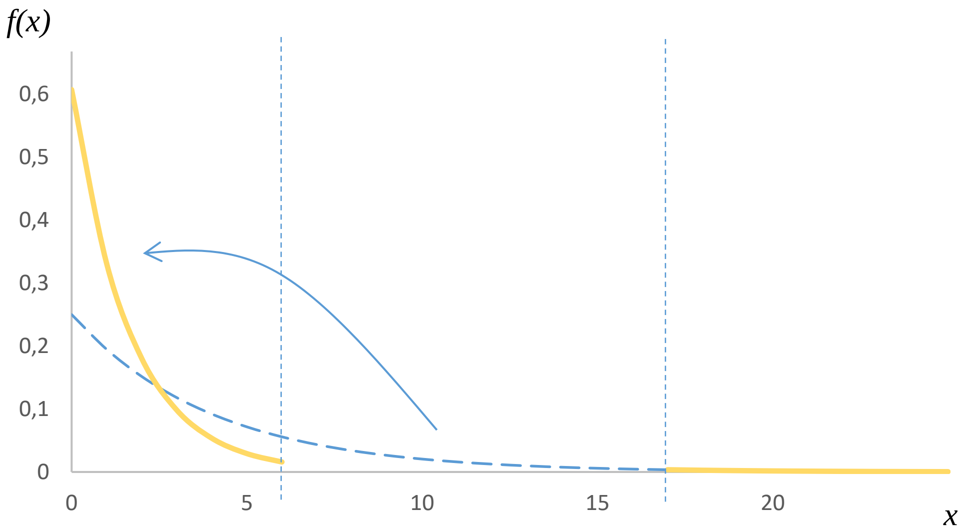

Figure 5. Labour-replacing AI and the relocation of labour
Source: authors' calculations on model simulation.

The figure shows how the introduction of AI allegedly disturbs the economy: the original distribution subsists only for the high-skilled segment to the right of the AI interval. To the left of this interval, the arrival of a large quantity of workers eventually reshapes the distribution pulling workers to more unskilled jobs than previously (there are adaptation and restructuring costs that may pull workers already developing some of these activities further behind in the skill scale). This reshaping of jobs and skills may prevent the economy from benefiting on the aggregate: regardless of the direct positive effect of AI, there is a possible negative effect concerning the organisation of work. Moreover, observe that many workers are pushed into the no job zone, i.e., to levels of productivity such that $x < 1$.

Figure 6 represents aggregate income with AI against aggregate income with no AI, for the same values of the AI efficiency parameter as in Table 1. The graphic indicates that if AI is not particularly efficient, then it will not penetrate significantly in available jobs, and it will generate lower returns in the activities it effectively penetrates. Thus, AI may not boost overall productivity and growth, if Ω is relatively low (below the value in the benchmark example, i.e., $\Omega = 3$). On the contrary, relatively high values of Ω lead to a superior outcome under AI adoption. This is our first fork in the road: one should expect the replacement of workers by AI to boost income, but this may not occur if the contribution of AI to productivity is weak and, simultaneously, the required reorganisation of work leads to more people engaged in no productive activity or in activities with low value added.

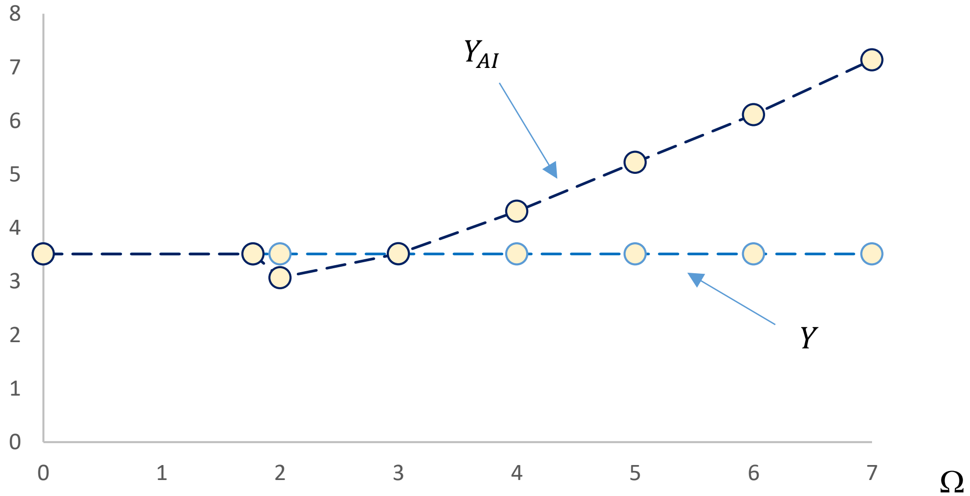

Figure 6. Aggregate income with and without AI
Source: authors' calculations on model simulation.

Next, we approach income inequality. In a first moment, let us concentrate solely on the inequality among workers, thus disregarding the information about who reaps the gains of AI. In Table 2, the Gini coefficient is presented for the same values of Ω used so far in the numerical illustrations. Recall that different values of the AI efficiency parameter trigger different processes of relocation of labour, given the number of activities that are transferred to AI, thus provoking different reconfigurations of the left-hand-side of the productivity distribution. As a result, the distribution of income across workers changes as well, and one should expect inequality to rise as individuals are pushed away to less qualified jobs or to no jobs at all. Therefore, the results should reflect an increase in inequality as the efficiency of AI improves. Table 2 confirms this intuition.

Table 2. Gini coefficient (workers' income)

	Activities transferred to AI	$\hat{\lambda}$	Gini coefficient
$\Omega = 2$	#10-#14	0.375	0.6160
$\Omega = 3$	#7-#16	0.6071	0.6893
$\Omega = 4$	#6-#17	0.75	0.7252
$\Omega = 5$	#5-#18	0.95	0.7701
$\Omega = 6$	#5-#18	0.95	0.7701
$\Omega = 7$	#4-#19	1.25	0.8277

Source: authors' calculations on model simulation.

Table 2 uncovers the evidence that the Gini coefficient increases as workers are relocated. Hence, not only do workers lose income for AI owners, but they also see their income becoming less evenly distributed among them. As AI penetrates the economy, the level of inequality rises as a significant part of the population of workers is pushed to low-paying jobs, while others keep their high-paying jobs (in the right-hand-side of the productivity distribution, beyond the activities lost to AI).

In the scenario depicted in Table 2, the introduction of AI penalises the economy regarding the goal of attaining or maintaining an equitable distribution of income. The question we should now pose is whether and how may AI eventually contribute to lower inequality instead of intensifying it? The answer requires speculating about who reaps the gains of AI, a discussion that follows in the next subsection.

4.4 Who owns AI?

The above highlighted increase in income inequality originates on the fact that only the income of workers has been taken into consideration, and, thus, the returns of the owners of AI have been overlooked. Taking these returns into consideration, it is not only possible to find a different result concerning inequality, but one can also briefly address the third fork in the road, namely market concentration.

To keep the analysis tractable, assume two extreme cases, one in which AI is open source, available to everyone who wants to develop it; the other extreme case puts AI in the hands of an elite of resourceful individuals. In the context of our framework, we consider that the first scenario allows every worker to share the financial gains of AI, while the second setting implies that only workers at the n^{th} job benefit from AI activities. These assumptions allow for recomputing the inequality index, in order to understand in which conditions AI eventually conducts to lower inequality or, on the contrary, intensifies income inequalities even further. It appears to be obvious that industry concentration goes hand in hand with stronger inequality in the current setting, in which concentration does not affect aggregate income (it only redistributes it).

Table 3 presents the value of the Gini coefficient for the already assumed values of the AI efficiency parameter. The inequality index is now calculated for pervasive distribution of AI gains and for the concentrated distribution of AI benefits. The results are compared with the scenario in which AI income is not assigned to workers, and to the initial scenario with no AI. Results are obvious: if AI means of production are accessible to all, this reduces inequality; if they are concentrated on an elite, the Gini coefficient exhibits a higher value.

Table 3. Gini coefficient (different scenarios)

	G **no AI**	***G*** **AI (only workers)**	***G*** **AI (uniform distribution of AI gains)**	***G*** **AI (AI gains restricted to the** n^{th} **group)**
$\Omega = 2$	0.5613	0.6160	0.4927	0.7070
$\Omega = 3$	0.5613	0.6893	0.3943	0.8781
$\Omega = 4$	0.5613	0.7252	0.3873	0.9315

	G no AI	G AI (only workers)	G AI (uniform distribution of AI gains)	G AI (AI gains restricted to the n^{th} group)
$\Omega = 5$	0.5613	0.7701	0.4342	0.9645
$\Omega = 6$	0.5613	0.7701	0.4257	0.9694
$\Omega = 7$	0.5613	0.8277	0.5325	0.9856

Source: authors' calculations on model simulation.

The values in the table allow us to interpret the second fork in the road. Inequality can be reduced if the gains of AI are evenly distributed by all. It can increase sharply if gains are retained by a small fraction of the population. This is associated with the concentration of economic activity; i.e., AI developers can be a large part of the population or only a few individuals or corporations endowed with resources that are only accessible to an elite of agents in the economy.

5. Conclusions

The undertaken analysis modelled the impact of AI through a simple framework of heterogeneous labour productivity and AI penetration. As workers are replaced by AI in some of the intermediate jobs in the productivity line, aggregate income increases, and, thus, the economy allegedly grows. However, workers are relocated to other activities, and some of them may even lose the possibility of having a job; in this case, AI may have an overall negative impact on growth, leading to lower levels of income. AI also raises inequality among workers if these do not benefit from the gains of AI. If the gains of AI are distributed by the population of workers, inequality may be reduced (if such gains are distributed evenly) or it may increase (if only a small subset of agents benefit from AI), a result that depends on the path followed with regard to industry concentration; AI may signify strong economies of scale and concentration; it may also signify a democratisation in the access to means of production and increased competition.

The developed analysis intended to illustrate the various paths AI can lead us, regarding macroeconomic outcomes, namely, with respect to growth and income distribution. The analytical model is admittedly unsophisticated, pursuing just a comparative static analysis and neglecting relevant elements of dynamics. Dynamics can be introduced, for instance, by assuming that every time AI increases its penetration in the economy, the number of qualified jobs increases as well, meaning that a process of sustained growth through AI may emerge.

Nevertheless, despite its shortcomings, the framework is sufficiently rich to offer a baseline structure to think about relevant topics in the new AI economy, such as job polarisation, the reconversion of labour markets, the access to opportunities in the AI industries, and the distribution of AI gains.

References

[1] Acemoglu, D., Restrepo, P. (2019), *Artificial Intelligence, Automation and Work.* In A. Agrawal *et al.* (eds.), *The Economics of Artificial Intelligence: an Agenda*, NBER conference report series, Chicago: CUP, chapter 8, 197-236.

[2] Acemoglu, D., Restrepo, P. (2020), *Robots and Jobs: Evidence from US Labor Markets. Journal of Political Economy*, 128(6), 2188-2244.

[3] Aghion, P., Jones, B.F., Jones, C.I. (2019), *Artificial Intelligence and Economic Growth*. In A. Agrawal *et al.* (eds.), *The Economics of Artificial Intelligence: an Agenda*, NBER conference report series, Chicago: CUP, chapter 9, 237-282.

[4] Agrawal, A., Gans, J., Goldfarb, A. (2019), *Artificial Intelligence: the Ambiguous Labor Market Impact of Automating Prediction. Journal of Economic Perspectives*, 33(2), 31-50.

[5] Arntz, M., Gregory, T., Zierahn, U. (2017), *Revisiting the Risk of Automation*. *Economics Letters*, 159, 157-160.

[6] Autor, D.H. (2014), *Polanyi's Paradox and the Shape of Employment Growth*. NBER working paper nº 20485.

[7] Autor, D.H. (2015), *Why Are There Still So Many Jobs? The History and Future of Workplace Automation. Journal of Economic Perspectives*, 29(3), 3-30.

[8] Autor, D.H., Dorn, D. (2013), *The Growth of Low-skill Service Jobs and the Polarization of the US Labour Market. American Economic Review*, 103(5), 1553-1597.

[9] Autor, D.H., Dorn, D., Katz, L.F., Patterson, C., Van Reenen, J. (2017), *Concentrating on the Fall of the Labour Share*. *American Economic Review Papers and Proceedings*, 107(5), 180-185.

[10] Babina, T., Fedyk, A., He, A., Hodson, J. (2024), *Artificial Intelligence, Firm Growth, and Product Innovation. Journal of Financial Economics*, 151, article 103745.

[11] Brynjolfsson, E., Unger, G. (2023), *The Macroeconomics of Artificial Intelligence. Finance & Development, International Monetary Fund*, 20-25.

[12] Brynjolfsson, E., Rock, D., Syverson, C. (2019), *Artificial Intelligence and the Modern Productivity Paradox: a Clash of Expectations and Statistics. In A. Agrawal et al. (eds.), The Economics of Artificial Intelligence: an Agenda, NBER conference report series*, Chicago: CUP, chapter 1, 23-60.

[13] Cavaglia, C., Etheridge, B. (2020), *Job Polarization and the Declining Quality of Knowledge Workers: Evidence from the UK and Germany. Labour Economics*, 66, article 101884.

[14] Ernst, E., Merola, R., Daniel, S. (2019), *Economics of Artificial Intelligence: Implications for the Future of Work. IZA Journal of Labor Policy*, 9(1).

[15] Frey, C.B., Osborne, M.A. (2017), *The Future of Employment: How Susceptible are Jobs to Computerisation? Technological Forecasting and Social Change*, 114, 254-280.

[16] Graetz, G., Michaels, G. (2017), *Is Modern Technology Responsible for Jobless Recoveries? American Economic Review*, 107(5), 168-173.

[17] Jaimovich, N., Siu, H.E. (2020), *Job Polarization and Jobless Recoveries. Review of Economics and Statistics*, 102(1), 129-147.

[18] Korinek, A., Stiglitz, J.E. (2021), *Artificial Intelligence, Globalization, and Strategies for Economic Development*. NBER working paper nº 28453.

[19] Lu, Y., Zhou, Y. (2021), *A Review on the Economics of Artificial Intelligence. Journal of Economic Surveys*, 35(4), 1045-1072.

[20] Stevenson, B. (2019), *Artificial Intelligence, Income, Employment, and Meaning. In A. Agrawal et al. (eds.), The Economics of Artificial Intelligence: an Agenda, NBER conference report series*, Chicago: CUP, chapter 7, 189-196.

[21] Trajtenberg, M. (2019), *Artificial Intelligence as the Next GPT: a Political-Economy Perspective. In A. Agrawal et al. (eds.), The Economics of Artificial Intelligence: an Agenda, NBER conference report series*, Chicago: CUP, chapter 6, 175-186.

[22] Varian, H. (2019), *Artificial Intelligence, Economics, and Industrial Organization. In A. Agrawal et al. (eds.), The Economics of Artificial Intelligence: an Agenda, NBER conference report series*, Chicago: CUP, chapter 16, 399-422.

[23] Webster, C., Ivanov, S. (2020), *Robotics, Artificial Intelligence, and the Evolving Nature of Work. In B. George and J. Paul (eds.), Digital Transformation in Business and Society: Theory and Cases*, chapter 8, 127-143, Cham, Switzerland: Palgrave Macmillan.