THE Teoría e Historia Económica
Working Paper Series

Automation, Automatic Capital Returns, and the Functional Income Distribution

Pablo Casas and José L. Torres

WP 2020-02
May 2020

Departamento de Teoría e Historia Económica
Facultad de Ciencias Económicas y Empresariales
Universidad de Málaga
ISSN 1989-6908

Automation, Automatic Capital Returns, and the Functional Income Distribution*

Pablo Casas[a,*], José L. Torres[b]

[a] *Department of Economics, University of Huelva and UNIA, Spain*
[b] *Department of Economics, University of Málaga, Málaga, Spain*

Abstract

This paper studies the economic implications of automation. We consider that automation is affected by disruptive technologies which entail a structural change consisting in the introduction of a new physical capital input (a combination of artificial intelligence and autonomous robots), additional to "traditional" capital assets and labor. This new "automatic" physical capital is assumed to carry out production activities without the need to be combined with labor. We propose a simple production function and show that the consequences of automation depend on the combination of the automatic capital adoption rate and the elasticity of substitution between traditional and automatic technology. We find out that, if the adoption rate is below a threshold that matches the marginal productivity of automatic capital, little effects are derived from automation, independently of the elasticity of substitution of the new capital to the traditional capital and labor. However, if the automatic capital adoption rate is above the threshold level and the elasticity of substitution is higher enough, the automation process can lead to a robocalypse scenario with a total shift of both traditional capital and labor. We estimate, through the benchmark calibration of the model, that the adoption rate threshold for automatic capital is about 22.5%.

Keywords: Automatic capital; Traditional inputs; Automation; Technological change, Income distribution.

JEL Classification: O14, O33, E23, E25.

---

*We thank Emilio Congregado, Paula Fernández and Concepción Román for helpful comments. José L. Torres acknowledges financial support from project financed by the Spanish Ministry of Science and Technology ECO2016-76818-C3-2-P.

*Corresponding author: José L. Torres: e-mail: jtorres@uma.es

1. Introduction

To produce commuting services, a cab-car needs a cab-driver nowadays. Therefore, it is natural to specify an aggregate production function in which both physical capital and labor are required. Furthermore, this production function is assumed to express some complementarity between both inputs. However, current technological progress is characterized by the creation of a new type of capital (based on a combination of computers, robotics, and artificial intelligence) that can perform production activities in an autonomous way with minimal human intervention.[1] This new "self-driving taxi" is a new type of capital equipment that can substitute both the traditional manual-driving cab and the human cab-driver, and where commuting services can be produced using this new capital alone.[2] In this paper, we argue that this implies a structural change (a disruption) to the economy production technology, as a new type of capital input is incorporated into production activities. Following standard definitions in the literature (see, for instance, DeCanio, 2016), traditional capital is named just capital, whereas automatic capital is referred as robots. This technological process will result in each particular sector producing a final good using two different technologies. This action will depend on the potential automatic capital adoption rate. The question here is whether it is possible for the two technologies to coexist simultaneously in the different sectors and the economy as a whole, or, by contrast, whether the new technology will crowding-out the old one, generating the so-called robocalypse.

Literature on automation has been growing rapidly during the last decade. Nowadays, there is a wide debate about the economic implications of the automation process although this is not a new topic. The many different views in the literature about the social-economic implications of the same technological change allow to clarify the difficulty of assessing the impact of this phenomenon and past experiences regarding the introduction of new capital equipment. These considerations are of questionable value given the uncertainties about technological progress and the possibility of the technological singularity (Hanson, 2008; Brynjolfsson and McAfee, 2014; Nordhaus, 2017). The main focus have been placed on

[1] Grace *et al.* (2018) report that Artificial Intelligence (AI) researchers predict a 50% of probability of robots outperforming all human task by 2045 and substituting all human labor in 120 years. These predictions suggest that AI will outperform humans in a number of activities in the next few decades, such as translating languages (by 2024), writing high-school essays (by 2026), driving a truck (2027), working in retail (2031), writing a bestselling book (by 2049), and working as a surgeon (by 2053).

[2] See Jiang *et al.* (2015) for a discussion of the implications of the particular new disruptive capital asset (self-driving cars). We take self-driving cars just as an example of the characteristics of the new automatic capital, but it can be extended to a number of other production activities.

how this new technological progress will affect labor and labor income. Authors differ in which effect will dominate: complementary or substitution. Pessimistic visions, adopting a Luddite point of view, bet for an abruptly decline of employment and labor income (for example, Frey and Osborne, 2017) while other optimistic visions argue positive impacts for labor (for example, Ernst *et al.*, 2018). Nevertheless, the literature has not considered the change that has taken place in the composition of capital as the new capital is considered as equivalent to the old one. Indeed, the vast majority of works on automation consider robots as substitutes for workers, forgetting that they will also replace traditional capital assets which are complement of labor.[3]

Many authors have remarked the current elimination potential of labor-intensive tasks and cognitive demanding tasks (Brynjolfsson and McAfee, 2014; Ford, 2016). Within this stream of thought, Frey and Osborne (2017) argued that 47% of US employment would have been automated by 2033. However, nowadays, even these authors do not support those results (Frey, 2019). Using the same methodology, Bowles (2014) calculated that 54% of European jobs are in high risk of computerization. Other voices claimed that an increase in the robots to workers ratio reduces the employment to population ratio and the wages (Acemoglu and Restrepo, 2019). Chiacchio, Petropoulos and Pichler (2018) use the same methodology to examine the effect of industrial robots in six European countries. Autor and Salomons (2018) also follow this approach to analyze automation in 18 developed countries of the European Union, Australia, Japan, South Korea, and the United States. These authors support Acemoglu and Restrepo (2019) results. Schlog and Sumner (2018) focus on the effect of automation for workers in developing countries and their battle against what they call the "Robot Reserve Army".[4]

Nevertheless, other scholars highlight that many voices have been raised to highlight the creation of new tasks with technological progress and deny the results obtained by

[3]Acemoglu and Restrepo (2018a) collect and review various ways of modeling automation. Among them are the options to interpret this economic process as capital-augmentating or labor-augmentating technological change. Acemoglu and Restrepo (2019) offer a deep thorough vision of automation effects. Jimeno (2019) questions that robotisation and AI have the same economic implications of factor-augmenting technological progress.

[4]Estimated percentage of tasks that can be automated using the current technology in each country have been carried out by Mckinsey (2020). Their estimations suggest that the potential automatic capital adoption rate is above the 45% in every industrialized economy in the world. Manyika *et al.* (2017) concludes that technical automation potential is concentrated in countries with the largest populations and/or high wages.

other authors. In this sense, Arntz *et al.* (2016, 2017) repeated the analysis of Frey and Osborne (2017) focusing on tasks instead of occupations to conclude that only 9% of US occupations are potentially automatable. Dauth *et al.* (2017) replicate the empirical work of Acemoglu and Restrepo (2019) for the case of Germany, not finding a negative effect of robots because other sectors have absorbed the employment lost in the manufacturing industry. Bessen (2017) finds that computer technology is associated with job creation, and Graetz and Michaels (2018) affirm that robots are contributing to labor productivity growth since decades ago. Ernst *et al.* (2018) describe these opportunities regarding the increase in productivity, especially among low-skilled workers due to the tremendously reduced costs of capital. Furman and Seamans (2018) welcome the potential of AI for increased productivity growth at the same time they propose some alternative policies to mitigate AI-induced labor disruptions (universal basic income, employment subsidies and guaranteed employment). Acemoglu and Restrepo (2018b) emphasize, in a theoretical model, the labor market adjustment against automation: other sectors can reinstate labor that is not needed anymore in certain activities that are now performed by robots.[5]

The literature had adopted alternative approaches to dealing with the emergence of these new capital assets. An earlier attempt is Zeira (1998), which analyses the growth of the technological innovations that reduces labor requirements but raise capital requirements. Sachs and Kotlikoff (2012) present an overlapping generations (OLG) model in which smart machines substitute directly young unskilled workers. At the same time, these machines also complement older skilled employees.[6] Sach *et al.* (2015) contrast a robotic firm in which the only input are robots with a traditional firm with machines and labor, in a form similar to our approach. Benzell *et al.* (2017) introduce automation to represent an economy where robots are a combination of code and capital and where the code is produced by high-skilled

[5]The World Economic Forum (2018) foresees that automation will eliminate 75 million jobs across the planet by 2025, but will create 133 million newtasks. However, the fact that the capital associated to these employees will be also replaced by new technological devices is a fact that often goes unnoticed, causing us to have a partial vision of the technological change that the economy is experiencing. A computer programming device powered by AI is, of course, more productive than a programmer. The question is whether this device powered by AI is more productive than this programmer and his computer working together. If it turns out that the device powered by AI possesses a larger productivity than the worker and his associated unit of capital, this device will replace both. Thus, where we used to have a worker working with a unit of capital, we will have now a single unit of AI-powered robotic capital .

[6]Another branch of the literature on automation has focused on the relationship of this process with demography to analyze possible consequences originated by the implementation of automation with ageing people. See, for instance, Basso and Jimeno (2019).

workers, as well as both high-skilled and low-skilled workers are involved in the production of services. Acemoglu and Restrepo (2018b) develop a model in which tasks previously performed by labor can be automated but where new versions of existing tasks, in which labor has a comparative advantage, can be created. Berg *et al.* (2018) explore different views about how automation may affect the labor market, concretely they present four models reflecting diverse scenarios. In their first model, robots compete against all labor in all tasks, while in the second model, robots compete only for some tasks; the third model states that robots only substitute unskilled labor while complement skilled labor. Finally, the fourth model reduces the robots contribution to production in just one sector. Lin and Weise (2019) propose a similar model to the first one presented by Berg *et al.* (2018), in which robots constitute a labor-replacing capital. They set-up a production function where traditional capital is a complement of human labor and robot capital replaces human labor. Furthermore, they argue that the observed decline in the labor share in the U.S. is a direct consequence of robotization. Here, we depart from the existing literature by adopting a disruptive vision of automation.

This paper contributes to the literature by introducing an unconventional production function where two different and alternative technologies can be used for final output: a traditional technology, where a combination of traditional capital and labor is used, and a new technology where only automatic capital is needed for production. Traditional capital and labor are complementary and both are substitutes of the new automatic capital. Mathematically, this is represented by a CES nested in another CES function where constant return-to-scale are preserved. The aggregate technology includes two key parameters: the elasticity of substitution of the automatic capital to the combination of traditional capital and labor. It also includes the distribution parameter for both technologies which is assumed to represent the automation adoption rate. We consider that this technological function helps to a more accurate representation of the fundamental characteristics of the incoming automation process, in which traditional capital and labor are being replaced by a new autonomous input productive technology. Our aggregate technology implies that, isolated, traditional technology uses inputs which have decreasing returns. It is worthy to remark that the new technology presents constant returns (similar to an AK-type technology).

We simulate the model and compute steady states of the main macroeconomic variables for a range of values for the elasticity of substitution between the new and the traditional technologies, as a function of the new automatic capital adoption rate. The automatic capital adoption rate is assumed to be represented by the distribution parameter of the aggregate CES function. The main result of the paper consists in the finding of the existence of a threshold value for the automatic capital adoption rate. The steady state of the economy for this threshold value does not depend on the elasticity of substitution between new capital and traditional inputs, as the ratio of automatic capital to output is one. Moreover, the threshold value for the adoption rate is equal to the marginal productivity of the new capital, which is just a constant, and depends on the automatic capital depreciation rate and the discount factor. It is also the baseline for the normalization of a family of CES functions when the elasticity of substitution varies. For the benchmark calibration of the model, we find that this threshold value is about 22.5%. For an adoption rate of the new technology below that threshold value, the consequences of automation for the economy are mostly negligible, no matter how the elasticity of substitution between both technologies is. However, for an adoption rate above the threshold value, changes in the economy, as a consequence of the incorporation of the new automatic capital, are dramatic and depends on the elasticity of substitution between the two technologies. For an scenario with high elasticity of substitution between traditional production technology and an adoption rate for new capital above the threshold, we find an abrupt increase in the accumulation of the new capital and the output, as well as a sudden reduction in labor. Based of these simulations, we identify two necessary conditions for the robocalypse to occur: a high elasticity of substitution between the traditional and the automatic technology and an automatic capital adoption rate above the threshold.

In addition, we find that the functional distribution of income is not significantly affected when the adoption rate of new capital is below the threshold, although labor share slightly declines as the automatic capital adoption rate increases. However, when the new capital adoption rate is above the threshold and the elasticity of substitution between new capital and traditional technology is higher enough, labor share suddenly declines collapsing into very low values as a consequence of an intense process of labor substitution. When the net income is taken into account (see Karabarbounis and Neiman, 2014b, and Breigman, 2018) and both traditional and new capital have the same return net of depreciation, the decline in labor share has a lower magnitude. Nevertheless, it is important to remark that it would collapse for a high automatic capital adoption rate and a high elasticity of substitution between traditional and automatic technologies, since these two conditions trigger the accumulation of automatic capital, resulting in a huge amount of output.

For the sake of clarity, the rest of the paper is organized as follows. Section 2 elaborates a simple model with three inputs: labor, traditional capital and automatic capital, where the production technology is represented by a traditional CES function nested in another CES function. Section 3 presents the calibration of the model economy. Simulations from the model are presented in Section 4, which investigates the implications of the elasticity of substitution between the new capital and the traditional technology and also the automatic capital adoption rate. Section 5 focuses on the consequences for the functional distribution of income. Finally, section 6 derives the conclusions obtained from this research.

2. The model

Based on the predictions by AI researchers, the combination of AI and autonomous robots will create new types of capital assets that can perform production activities with minimal human intervention and where this new capital is expected to outperform all human tasks in the near future (Grace *et al.* 2018). This will lead automation to a new stage, where investment in new equipment will introduce a new technology that fully displaces labor in a number of tasks, contrary to more recently proposed models in the literature in which automation results in the displacement of low-skilled workers and routine tasks. Here we consider a model economy with two kinds of capital: K is the traditional capital and D represents the new automatic capital (a combination of AI and robotics). We propose a simple production function where two different technologies can coexist simultaneously: a traditional technology that requires physical capital and labor for production and a new automatic technology that employs only a new capital (hardware and artificial intelligence) for production. In order to get the model closer to economics, we consider a representative household that can freely decide labor time, consumption and investment decisions in both kinds of capital.

2.1. Technology

The aggregate production technology is a CES function for traditional technology using capital and labor nested into another CES function. In this function, new and traditional technology are substitutes. We define the following aggregate production function to represent these technological combinations:

$$Y_t = \left[\mu X_t^{\upsilon} + (1-\mu)\, {D_t}^{\upsilon}\right]^{\frac{1}{\upsilon}} \tag{1}$$

where Y_t is the final output, X_t represents traditional technology, μ is a distribution parameter for the traditional productive factors versus the new technology, D_t is the automatic capital, and υ measures the substitution between the traditional production technology and the new technology. The elasticity of substitution between traditional and automatic technologies is defined as $\sigma = 1/(1-\upsilon)$.

The traditional technology is represented by another CES function:

$$X_t = \left[\alpha K_t^{\theta} + (1-\alpha) L_t^{\theta}\right]^{\frac{1}{\theta}} \tag{2}$$

where K_t is the traditional capital, L_t is labor, α is a distribution parameter of inputs and θ measures the substitution between traditional capital and labor. The elasticity of substitution is defined as $\varepsilon = 1/(1-\theta)$. Empirical evidence suggests that $\varepsilon < 1$ (Chirinko, 2008; Eden and Gaggl, 2018), and that $\sigma > 1$ (DeCanio, 2016; Acemoglu and Restrepo, 2019; Lin and Weise, 2019). Therefore, it is assumed that $0 < \varepsilon < \sigma < \infty$. This implies higher complementarity between traditional capital and labor than between traditional technology and the automatic capital. That is, automatic capital is a substitute for both traditional capital and labor. With that specification, the elasticity of substitution between automatic capital and traditional capital and between automatic capital and labor are both equal to σ (the self-driving taxi substitute in the same proportion to both the taxi-driver and the non-self-driving car). Note that when both elasticities of substitutions are one, the aggregate production function collapse to a standard Cobb-Douglas production function with two capital assets, i.e., $Y_t = K_t^{\alpha\mu} D_t^{1-\mu} L_t^{(1-\alpha)\mu}$.

The key characteristic of that production function is that it embodies two different technologies operating simultaneously, depending on the distribution parameter between traditional and automatic technology. If $\mu = 1$, the production function collapse to the standard CES production function with physical capital and labor, where $Y_t = X_t$. If $\mu = 0$, this represents a technology with no labor and with automatic capital as the only input, with constant returns, $Y_t = D_t$. This specification seems reasonable since we assume that robots and AI do not get tired. If μ is between 0 and 1, we would have a scenario in which, presumably, not all human production activities can be substituted by the new automatic capital and the aggregate technology would be a combination of the traditional CES nested in another CES function with constant return to scale.[7]

[7] We can think about our production function in terms of the Hegelian dialectic. In the Hegelian dialectic there is always a "thesis" and its opposite, an "antithesis", and both thesis and antithesis form a "synthesis". This dialectic was conceived by Hegel as a process that is constantly repeated in life and which is perfect to study history in all its eras. In fact, Marx used his historical materialism (based on the Hegelian dialectic) to study the evolution of productive systems throughout time. There has been always a thesis, when an

From the first order conditions of the firm's profit maximization problem, we obtain the following marginal productivity of each of the three productive factors:

$$R_{k,t} = \alpha\mu Y_t^{1-v} X_t^{v-\theta} {K_t}^{\theta-1} \tag{3}$$

$$W_t = (1-\alpha)\,\mu Y_t^{1-v} X_t^{v-\theta} {L_t}^{\theta-1} \tag{4}$$

$$R_{d,t} = (1-\mu)\,Y_t^{1-v} {D_t}^{v-1} \tag{5}$$

One of the main concerns about automation is how this process will affect the functional distribution of income. From the above first order conditions, we find out that the functional distribution of gross income for the three factors resulting from our model economy is:

$$S_{l,t} = \frac{W_t L_t}{Y_t} = (1-\alpha)\,\mu Y_t^{-v} X_t^{v-\theta} {L_t}^{\theta} \tag{6}$$

$$S_{k,t} = \frac{R_{k,t} K_t}{Y_t} = \alpha\mu Y_t^{-v} X_t^{v-\theta} {K_t}^{\theta} \tag{7}$$

$$S_{d,t} = \frac{R_{d,t} D_t}{Y_t} = (1-\mu)\,Y_t^{-v} {D_t}^{v} \tag{8}$$

Notice that, at the point in which the stock of automatic capital is equal to output, the automatic capital share is equal to the rate of return to these capital assets and to the automatic capital adoption rate, represented by the distribution parameter $1-\mu$. As we will demonstrate later, this point will be key to assess the effects of automatic capital on the economy. Functional distribution of income at this point is given by:

$$S_{l,t} = (1-\alpha)\mu\frac{L_t^{\theta}}{\alpha K_t^{\theta} + (1-\alpha)L_t^{\theta}} \tag{9}$$

$$S_{k,t} = \alpha\mu\frac{K_t^{\theta}}{\alpha K_t^{\theta} + (1-\alpha)L_t^{\theta}} \tag{10}$$

$$S_{d,t} = R_{d,t} = (1-\mu) \tag{11}$$

antithesis appears and confront the preexisting thesis. Thesis and antithesis come together and form a synthesis, which become the thesis of the next stage. In this sense, regarding our production function, the traditional productive system would be a thesis, the new automatic technology the antithesis and our production function the synthesis of these two technologies. If $\mu = 1$, the synthesis between these two technologies would be equal to the previous thesis. On the contrary, if $\mu = 0$, the synthesis would be an automatic economy without labor. For any other values of $\mu \in (0,1)$ we have a synthesis in which traditional and automatic technology coexist.

2.2. Households

To keep the model as simple as possible, we assume that the utility function of our representative household is as follows:

$$U(C_t, L_t) = \gamma log(C_t) + (1-\gamma)log(1-L_t) \tag{12}$$

where C_t is total consumption and γ is a parameter reflecting the willingness to sacrifice units of consumption in favor of leisure time. The representative household satisfies the following budget constraint:

$$C_t + I_{k,t} + I_{d,t} = W_t L_t + R_{k,t} K_t + R_{d,t} D_t \tag{13}$$

where I_k is the investment in traditional capital and I_d is the investment in AI and robotics. We assume that investment decisions are specific to each capital assets due to the fact they have different characteristics. AI and robotics accumulation process would be presented in the following way:

$$D_{t+1} = (1-\delta_d)D_t + I_{d,t} \tag{14}$$

where $0 < \delta_d < 1$ is the depreciation rate of AI and robotics. Similarly, traditional capital accumulation process is as follows:

$$K_{t+1} = (1-\delta_k)K_t + I_{k,t} \tag{15}$$

where $0 < \delta_k < 1$ is the traditional capital depreciation rate. Equilibrium conditions from the household's maximization problem are,

$$\frac{1-\gamma}{\gamma}\frac{C_t}{1-L_t} = W_t \tag{16}$$

$$1 = \beta \frac{C_t}{C_{t+1}} (1 - \delta_k + R_{k,t+1}) \tag{17}$$

$$1 = \beta \frac{C_t}{C_{t+1}} (1 - \delta_d + R_{d,t+1}) \tag{18}$$

where β is the intertemporal discount factor. Notice that these equilibrium conditions establish a direct relationship between depreciation rates and returns of both traditional and automatic capital, as marginal productivities are equal, such as:

$$R_d - R_k = \delta_d - \delta_k \tag{19}$$

3. Calibration

The model is calibrated to an artificial economy where the two key parameters for studying the consequences of automation by the introduction of the new technology are kept free.[8] These parameters represent the distribution parameter in the final production CES technology, μ, and the elasticity of substitution between the automatic and the traditional technology, $\sigma = 1/(1 - \upsilon)$. Discount factor parameter, preference parameter, and technological parameters of the traditional technology are calibrated using standard values in the literature. We fix $\beta = 0.975$, $\gamma = 0.4$, $\alpha = 0.35$, $\varepsilon = 1/(1 - \theta) = 0.90$ and $\delta_k = 0.06$, using an annual basis. We choose an elasticity of substitution lower than one between traditional capital and labor, consistent with Chirinko (2008), Eden and Gaggl (2018) and Lin and Weise (2019).

The first key parameter of the model is the distribution parameter in the final production CES technology. We argue that this technological parameter can be interpreted as the adoption rate of the new technology in relation to the traditional one, where the distribution parameter for the new technology is $1 - \mu$, and where μ is the weight for the traditional technology in the aggregate CES function. This adoption rate can be defined as the percentage of tasks in the production system assumed by automatic technology. According to Manyika *et al.* (2017), the percentage of tasks that can be automated using current technology is higher than 45% for industrialized countries. This "percentage of tasks that can be automated using current technology" would be the empirical counterpart to our definition of automatic capital adoption rate. We choose a range of values for automatic capital adoption rates between 1% and 45%, so we analyze feasible scenarios according to the estimations of the percentage of tasks that can be automated using current technology, up to the value reported by Manyika *et al.* (2017). This implies that in the simulations of the model, the technological distribution parameter μ is in the range 0.55 - 0.99.

The second key parameter of the model is the elasticity of substitution between traditional technology and the automatic technology, σ. Robots and humans are assumed to have a high elasticity of substitution, although there is a lack of estimations in literature. For example, Lin and Weise (2019) states an elasticity of substitution of 5. Artuc, Bastos and Rijkers (2018) set it at 10. Acemoglu and Restrepo (2019) assume an infinite elasticity

[8] As we use the model to calculate steady states and not transition dynamics, the CES functions are not normalized in the lines suggested by de La Grandville (1989). Nevertheless, the main results in the paper indicate the basis for such normalization in the case one is interested in computing transition dynamics for a family of CES functions when the elasticity of substitution varies.

of substitution between humans and robots. DeCanio (2015) concludes that this elasticity of substitution is for sure above 2.1. However, we should bear in mind that our model does not collect implicitly the elasticity of substitution between humans and robots, but an elasticity of substitution between the automatic capital and both labor and the traditional capital of the same magnitude. The elasticity of substitution among automatic and traditional capital is even less documented than the substitution effects between humans and robots. Our model estimates that, if a robot replaces a human, it also substitutes the capital associated to this humans professional occupation. Consequently, the elasticity of substitution between automatic and traditional technology must be related to the elasticity of substitution between humans and robots. For the elasticity of substitution between the new automatic technology and the traditional technology, we explore the interval between 1 and 5, which implies that $\upsilon \in (0 : 0.8)$.

The automatic capital depreciation rate is an important additional parameter in our model economy and in assessing the economic implications of automation. Depreciation rates are expected to largely vary between the two types of capital assets in our model, where automatic capital is expected to have a higher depreciation rate. Indeed, new technological devices such as computers, telecommunications equipment and software have a higher depreciation rate than more traditional capital assets. Investment in these types of capital assets has increased the total depreciation rate for total physical capital in the economy. Automatic capital depreciation rate emerges as an important parameter driving the effects of automation. First, it introduces a difference in the returns to both types of capital. Second, the automatic capital depreciation rate is a key parameter for assessing the impact on the new technology on the economy. Graetz and Michaels (2018) consider a robots depreciation rate of ten per cent. Abeliansky and Prettner (2017), following Graetz and Michaels (2018), also assume a robotic depreciation rate of 10%. This depreciation rate would be higher than the one established by the International Federation of Robotics (2016), which sets a lifetime horizon of 12 years for robots. Lin and Weise (2019), along with Krusell *et al.* (2000), set out a quarterly depreciation of robots at 0.0515. In our case, our automatic capital is assumed to represent the most advanced technology in the economy, and, therefore, we determine $\delta_d = 0.20$, according to the depreciation rate traditionally assumed for R&D capital. This percentage is reflected in the EU KLEMS data and has been documented by numerous authors (see, for example, Hall, 2005). Table 1 summarizes the benchmark calibration of the parameters of the model and the range of values for the two parameters under investigation.

Table 1: **Calibrated parameters**

	Parameter	Definition	Value
Preferences	β	Discount factor	0.975
	γ	Consumption-leisure preference parameter	0.40
Technology	α	Capital share in the traditional technology	0.35
	δ_k	Traditional capital depreciation rate	0.06
	δ_d	Automatic capital depreciation rate	0.20
	ε	Traditional capital-labor elasticity	0.90
	σ	Traditional-automatic technologies elasticity	[1-5]
	μ	Technologies distribution parameter	[0.55-0.95]

Given the calibrated model, we investigate steady states resulting from combinations of different values for the two key parameters: the elasticity of substitution among traditional and automatic technologies and the automatic capital adoption rate. This is why we solve the following system of 10 equations for ten unknown quantities, where variables without a time index represent steady state values:

$$R_d = \frac{1}{\beta} - 1 + \delta_d \tag{20}$$

$$R_k = \frac{1}{\beta} - 1 + \delta_k \tag{21}$$

$$I_d = \delta_d D \tag{22}$$

$$I_k = \delta_k K \tag{23}$$

$$W = \frac{1-\gamma}{\gamma}\frac{C}{1-L} \tag{24}$$

$$Y = \left[\mu\, X^{\upsilon} + (1-\mu)\ D^{\upsilon}\right]^{\frac{1}{\upsilon}} \tag{25}$$

$$C = Y - I_d - I_k \tag{26}$$

$$L = \left[\frac{Y^{1-\upsilon}\,(1-\alpha)\,\mu X^{\upsilon-\theta}}{W}\right]^{\frac{1}{1-\theta}} \tag{27}$$

$$K = \left[\frac{Y^{1-\upsilon}\alpha\mu X^{\upsilon-\theta}}{R_k}\right]^{\frac{1}{1-\theta}} \tag{28}$$

$$D = Y\left[\frac{(1-\mu)}{R_d}\right]^{\frac{1}{1-\upsilon}} \tag{29}$$

4. Traditional versus automatic technology and the adoption rate

In this section, we explore the parametric space of the model economy and compute steady states depending on the values of the two fundamental parameters of the proposed technology: the elasticity of substitution between the traditional and the automatic technology, and the distribution parameter representing automatic capital adoption rate. We present the results for three values of the elasticity of substitution between traditional and automatic technology: 1, 1.5, 2 and 5.

We find a particular value for the automatic capital adoption rate for which any steady state value depends on the elasticity of substitution between the traditional and the automatic technology. This is equivalent to the baseline point for a family of normalized CES functions. This occurs because, in this particular steady state, the ratio of automatic capital to output is one. This threshold value for the adoption rate of automatic capital is just equal to the marginal productivity of this new type of capital ($1-\mu = R_d$), which remains a constant and depends on the automatic capital depreciation rate and the discount factor. For the benchmark calibration of the model we find that this threshold value is about 22.5%. This value is essential for assessing the effects of automation on the main variables of the economy. For an adoption rate of the new technology below that threshold value, the consequences of automation are almost insignificant regardless of the elasticity of substitution between both technologies. However, for an adoption rate above the threshold value, changes in the economy provoked by the new capital could be dramatic, depending on the elasticity of substitution between the two technologies. Another property of the threshold is that the stock of automatic capital and the output level are equal at this point $D = Y$. Therefore, we can clearly identify which parameters influence the threshold, as it is collected in equation (20).

The threshold point is equivalent to the baseline point for the normalization of a family of CES functions for different elasticities of substitution. As shown by de La Grandville (2016), the distribution parameter of a normalized CES function (interpreted here as the adoption rate of the automatic capital) is the geometric mean of the capital share and the interest rate such as $1-\mu = S_d^{(1-v)} R_d^v$. In our model, the baseline point for the normalization of the CES functions implies that the distribution parameter is equal to the interest rate, and hence, in the threshold point the automatic capital share is equal to:

$$S_d = 1 - \mu = R_d = \frac{1}{\beta} - 1 + \delta_d \tag{30}$$

Figure 1 reflects the steady state values for output, labor, traditional capital, and automatic capital as a function of the adoption rate of automatic capital and for the four selected values of the elasticities of substitution. We find that, for the low values of the adoption rate of automatic capital, the new technology has little effect on the main macroeconomic variables. As we observe in Figure 1, steady state values of labor, output and automatic and traditional capital are almost the same for any elasticity of substitution between the traditional and the automatic technology.

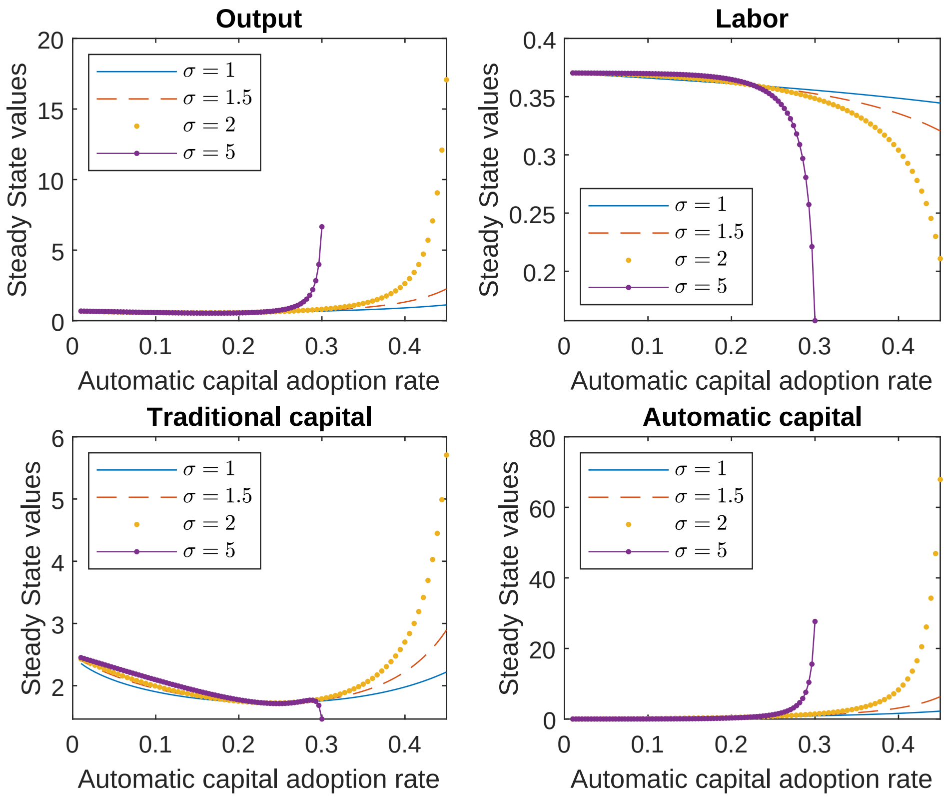

Figure 1: Steady state values for output, traditional capital, labor, and automatic capital as function of the automatic capital adoption rate and the elasticity of substitution between traditional technology and automatic technology.

At the threshold, steady state values are the same for any elasticity of substitution since the family of CES functions for any value of the elasticity of substitution intersect at this point. For values above the threshold, the elasticity of substitution is crucial. For a scenario with high elasticity of substitution between traditional production technology and an adoption rate for new capital far above the threshold, we find an abruptly increase in the accumulation of the new capital and output, and a sudden reduction in labor. Based on these simulations, we find two necessary conditions for the so-called robocalypse to occur: a high elasticity of substitution between the traditional and the automatic technology and an automatic capital adoption rate above the threshold.

In a scenario where the automatic capital adoption rate is very high (say more than 0.5), no matter how the elasticity of substitution between both technologies is, the automatic capital will dominate, increasing output to spectacular values and reducing traditional inputs to minimum quantities. For a high elasticity of substitution between the new and the traditional technology (i.e., $\sigma = 5$), it is observed a dramatic and sudden fall in labor while automatic capital and output increase exponentially when the automatic capital adoption rate is above the threshold. We find that the lower the elasticity of substitution, the lower the effect provoked by the introduction of the automatic technology is, once the threshold level has been surpassed. In fact, when the elasticity of substitution is, for instance, of a magnitude of 1, it is observed a slight fall in labor time together with a slight increase of automatic capital and output, but it does not take place an abrupt change. However, the effects of the new technology increase for higher values of the elasticity of substitution.

As it can be observed, traditional capital falls softly as the automatic capital adoption rate augments until the threshold. For automatic capital adoption rates above the threshold, we estimate that, initially, the stock of traditional capital increases as the adoption rates increases, as shown in the bottom left of Figure 1. This positive effect on traditional capital is provoked by the rise of returns of traditional capital when the distribution parameter of the CES function is above the threshold. However, when the adoption rate of the new technology reach a certain level, it is observed a sudden drop in the stock of traditional capital. Indeed, if the elasticity of substitution is large, say of a magnitude of 5, it is observed that this sudden drop occurs for an adoption rate around 25%. For lower values of the elasticity of substitution, the adoption rate must be large enough (higher than the range shown in the Figures) for this effect to be observed.

A different behavior is found in terms of labor, in spite that the elasticity of substitution between the new technology and traditional capital and between new technology and labor are both the same. First, working time remains almost constant for automatic capital adoption rates below the threshold independently of the elasticity of substitution between traditional and new technology. When automatic capital adoption rate is above the threshold, labor starts to be very sensitive to the introduction of the new capital depending on the elasticity of substitution. We observe a dramatic decline in labor for values of σ larger than 2.

In sum, we find the existence of a relatively large range of plausible values of the automatic capital adoption rate for which the irruption of the automatic capital has little consequences on the economy, independently of the elasticity of substitution between traditional and automatic technology. This applies if the adoption rate of automatic capital is below the threshold. In addition, it is clear from these results that the elasticity of substitution of AI and robotics concerning the traditional productive factors can vary from sector to sector, task to task, and so on. Therefore, it is relevant to analyze the possible impact of Industry 4.0 technology in an economy depending on the adoption rate of this technology and the elasticity of substitution regarding the rest of productive inputs. One could think about a scenario where the automatic capital adoption rates are higher than 45%, as this is a potential adoption rate for current technology estimated in some studies. Our model considerably illustrates the consequences of this situation. According to the benchmark calibration applied to it, this scenario corresponds to an economy well above the threshold value. The threshold value is increasing with the depreciation rate of automatic capital. For the threshold to be around 45%, the depreciation rate should be around 0.425, a value much higher than the depreciation rate for any existing capital assets (although not different from the allowed depreciation rates for computers in taxing schemes). The most eye-catching scenario is one of high substitution effect that represents the exponential growth of the automatic technology. Curiously, the most striking one would be the vision more accepted by literature.[9]

From previous results, it is clear that the identified threshold value is key for assessing the consequences of automation through automatic capital. The value of this threshold is just the marginal productivity of automatic capital. In steady state, it depends only on the discount factor and on the depreciation rate of automatic capital. In practice, the range of variation of values for the discount factor is small, so the depreciation rate of automatic capital would be the most influential parameter determining the threshold.

[9] Lin and Weise (2019), Eden and Gaggl (2018), Acemoglu and Restrepo (2019), DeCannio (2016), and Artuc, Ethar and Rijkers (2018), who, among others, assume high substitution effect of AI and robotics.

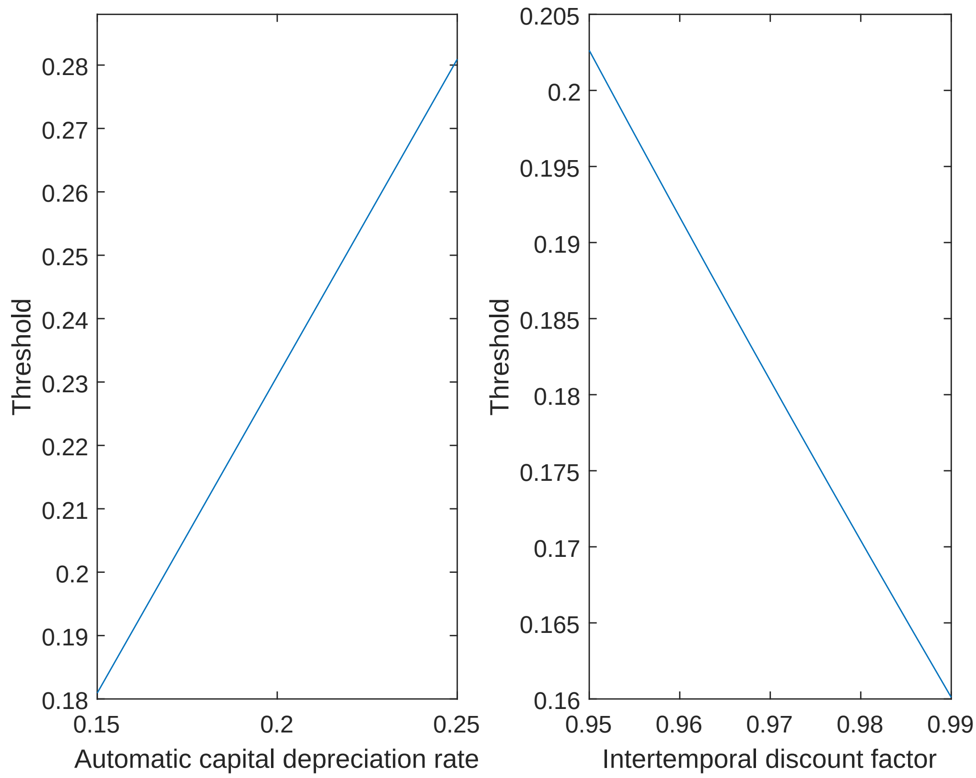

Figure 2: Automatic capital adoption rate threshold as a function of automatic capital depreciation rate and intertemporal discount factor.

Figure 2 depicts the threshold value as a function of δ_d and β. Given the benchmark depreciation rate, the threshold value varies from 16% to around 20% for a range of values of the discount factor between 0.99 and 0.95. The most influential parameter is the depreciation rate of automatic capital. For a depreciation rate of 0.15, the threshold value is approximately 0.18, whereas for a depreciation rate of 0.25, the threshold increases to 0.28, as the relationship between both variables is linear. In short, given that the threshold depends directly on the robots' depreciation rate, the higher the automatic capital depreciation rate, the lower impact the process of automatic capital adoption will have in the economy.

Figure 3 plots steady state for labor as a function of the elasticity of substitution between new and traditional technology for different values of the automatic capital adoption rate. The case for which labor is a constant for any value of the elasticity of substitution corresponds to an adoption rate equals to the threshold. For adoptions rates below the threshold, we find that the response of labor is almost constant for any value of the elasticity of substitution and even positive as the elasticity of substitution increases. However, for values of the adoption rate above the threshold, the response of labor is negative and dramatically depends on the elasticity of substitution. If the elasticity of substitution is low enough, little effects of the new technology on labor are observed. However, as the elasticity of substitution increases, the negative impact on hours is exacerbated.

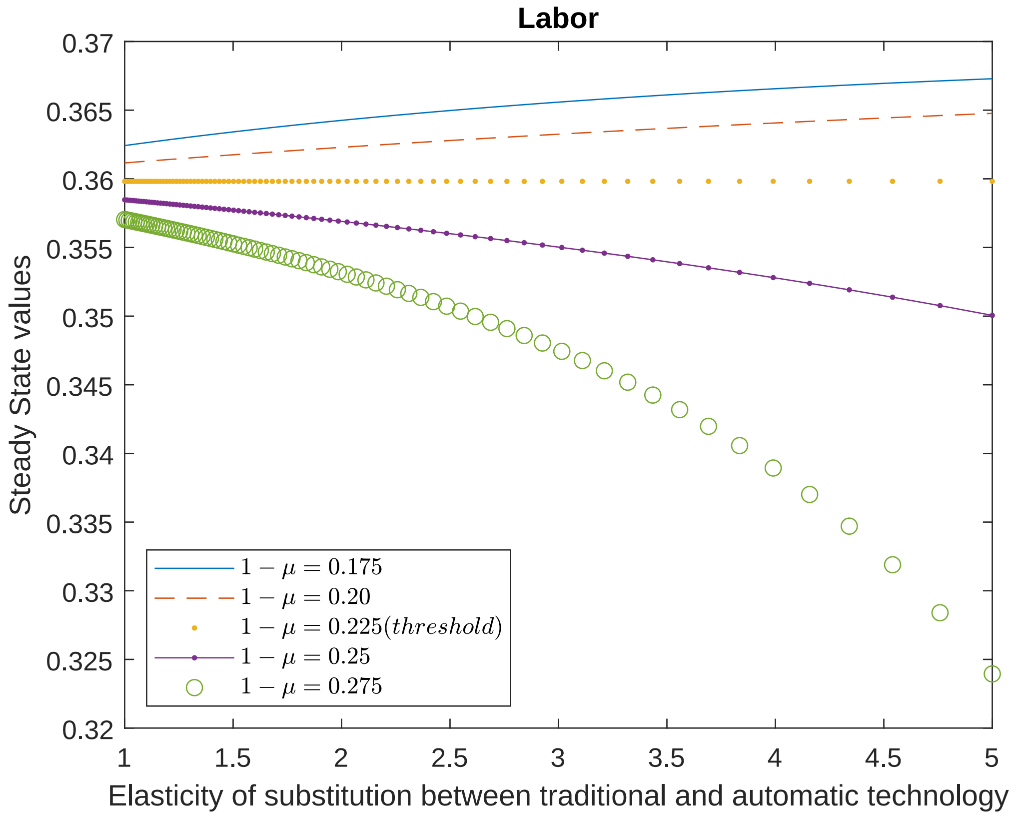

Figure 3: Evolution of labor time regarding the elasticity of substitution between traditional and automatic technology for automatic capital adoption rates below and above the 22.5% threshold.

Some important implications can be derived from previous results. The model indicates the existence of threshold conditions that divide the economy in two different worlds. Thus, this threshold value reflects an economic singularity if the elasticity of substitution between the traditional and the automatic technology is large enough. On the one hand, in a world where the automatic capital adoption rate is below the threshold, the new technology does not provoke significant changes in the main macroeconomic variables, independently of the elasticity of substitution between the traditional and the automatic technology. On the other hand, in a world where the automatic capital adoption rate is above the threshold, this technology represents a structural change and its impact in the economy relies on the elasticity of substitution between the traditional and the automatic technology.

Although the model represents an economy at an aggregate level, we can extract some considerations at a sectoral level. In the economy, it should be expected that sectors would have different adoption rates for automatic capital. Whereas the adoption rate of automatic capital can be large in some sectors, in others, the adoption rate could be lower. Automatic technology would have no effects on employment in those sectors with a low adoption rate of the new technology. We find that, in sectors where the presence of AI and robotics represents less than the estimated value of 22.5%, labor and traditional capital increase with the elasticity of substitution while AI and robotics decrease. In sectors where the presence of AI and robotics represents more than 22.5% of the total productive factors, labor falls when the elasticity of substitution rises while traditional capital, AI and robotics augment. Then, we can conclude that AI and robotics are destined to dominate those sectors in which their capacity for implementation is higher than this threshold. This technology, in the long run, will not settle down in those sectors in which they have no capacity to represent more than 22.5% of the productive factors.

Felten *et al.* (2018) provide a measure of the AI capacity of penetration in different sectors by identifying AI advances at the occupation level, indicating how AI changes occupations' characteristics. Fossen and Sorgner (2019) build on Felten *et al.* (2018) and Frey and Osborne (2017) to bring a vision of the transforming and destructive effects of AI and robotics. They identify the occupations with low destructive effect (those with less than a 70% of computerization probability in Frey and Osborne, 2017) and high transformer effect (more than a 3 in the scale of advances in AI provided by Felten *et al.,* 2018) as the "rising stars". However, occupations in the "human terrain" represent a very low number if we compare them with the other groups and most of them have a probability of computerization higher than 0.5. Therefore, we can argue that almost none occupation is saved from being transformed or eliminated by AI and robotics. Taking into account current and potential productivity and capacity of these technologies to spare human labor, it is clear that the occupations affected by the so-call "transformation" by AI advances will experience a decrease in labor needs. This decrease can lead to a working day reduction or labor demand contraction and it will mainly depend on the regulation imposed from labor market institutions.

The message of this paper is rather optimistic regarding the impact of automation on the economy. For automation to have dramatic effects, the adoption rate of the new technology must be above a threshold value equivalent to the marginal productivity of the new automatic capital. The depreciation rate of new capital assets is increasing, and therefore, the depreciation rate of automatic capital is expected to be high, augmenting the threshold point, and hence, preventing a disruptive effect by the new technology. Even in the case, the automatic capital adoption rate would be above the threshold, robocalypse also requires a high elasticity of substitution between the new automatic technology and traditional technology.

5. Automatic capital and the functional distribution of income

One of the most important concerns regarding automation is how this process affects labor share and labor income. In this section, we use the model to investigate the effects of the new automatic technology on the functional distribution of income. A large and increasing body of the literature has focused on the implications of automation for labor compensation and inequality, suggesting also that automation is one of the factors originating the decline in labor share over the last decades (Graetz and Michaels, 2018; Charalampidis, 2020). Indeed, the searching for an explanation on this issue remains one of the fundamental macroeconomic topics nowadays. Karabarbounis and Neiman (2014a) argue that the decrease in the relative price of investment goods induced firms to replace labor inputs for capital inputs. Karabarbounis and Neiman (2014a) argue that half of this decline is explained because of the lower price of investment goods. Farmer and Lafond (2016) analyze the predictability of a technological change stating that many technologies follow a generalized version of Moore's law since their costs tend to drop exponentially. Following this idea, the decline of the labor share could be justified by technological change.

We depart from the existing literature by arguing that the cause of the observed decline in labor share does not only rely on the lower price of investment goods but also on the changing character in the new investment goods and to the productivity increase in technologies such as AI and robotics, that is, new automatic capital deepening. Interestingly, Eden and Gaggl (2018) identify the decline in the labor share with a decline in routine occupations. At the beginning of the nineties, routine occupations exceeded non-routine ones but in the middle of the decade, a shift was produced and non-routine occupations exceeded routine ones. In our model economy, total income not only is distributed between labor and traditional capital, but also another fraction is earned by the new automatic capital. The key difference is that, whereas a complementary relationship between traditional capital and labor exits, these two inputs have a substitution relationship with the automatic capital input.

Capital depreciation rate is not only a key variable for assessing the impact of the new technology on main aggregate variables but also is an important factor determining capital consumption. Given the high values of depreciation for the new capital assets, the effects on inequality should be studied once capital consumption is taken into account. However, most of the analysis of labor share and income inequality ignores the distinction between gross and net income due to capital consumption. Karabarbounis and Neiman (2014b) highlight the importance of the physical capital depreciation rate, often neglected, for the study of income distribution and inequality. Bridgman (2018) shows that depreciation and production taxes are important determinants of the labor share, as they are included in total output, and hence, a fall in labor share may not imply a gaining in capital income. He shows that gross labor share has been falling since 1970s, but this net labor share shows a more stable path. We follow Karabarbounis and Neiman (2014b) and Bridgman (2018) analyses that account for capital depreciation in separating gross and net labor shares.

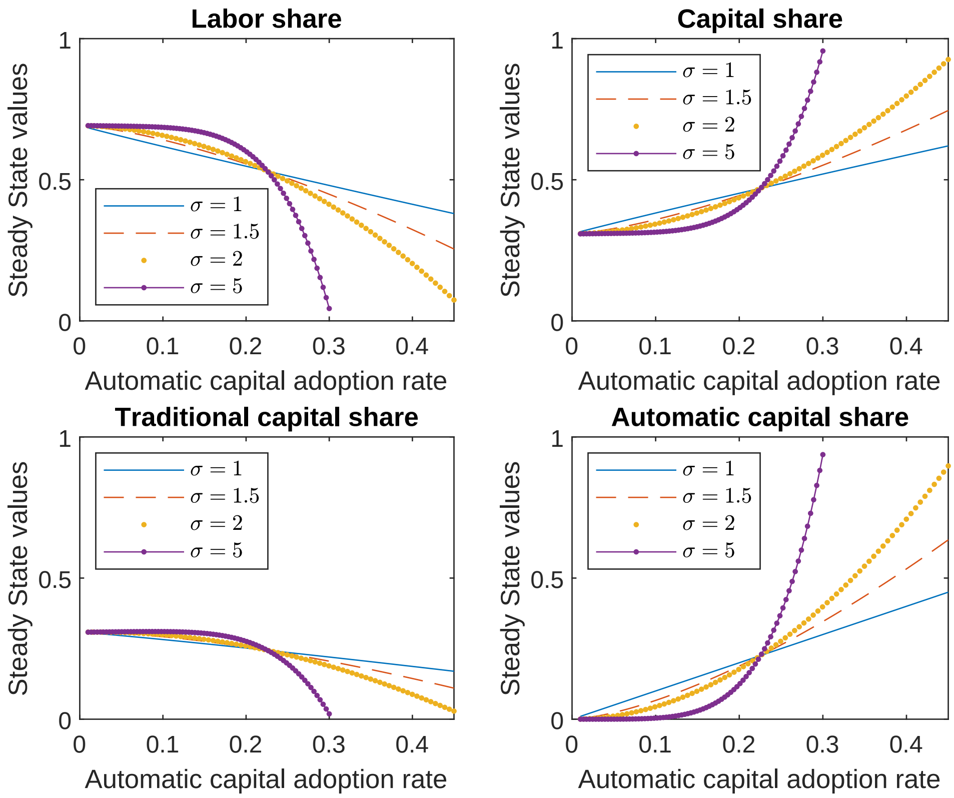

Figure 4: The functional distribution of income, Automatic capital adoption rate and the elasticity of substitution between traditional and automatic technology. Gross income.

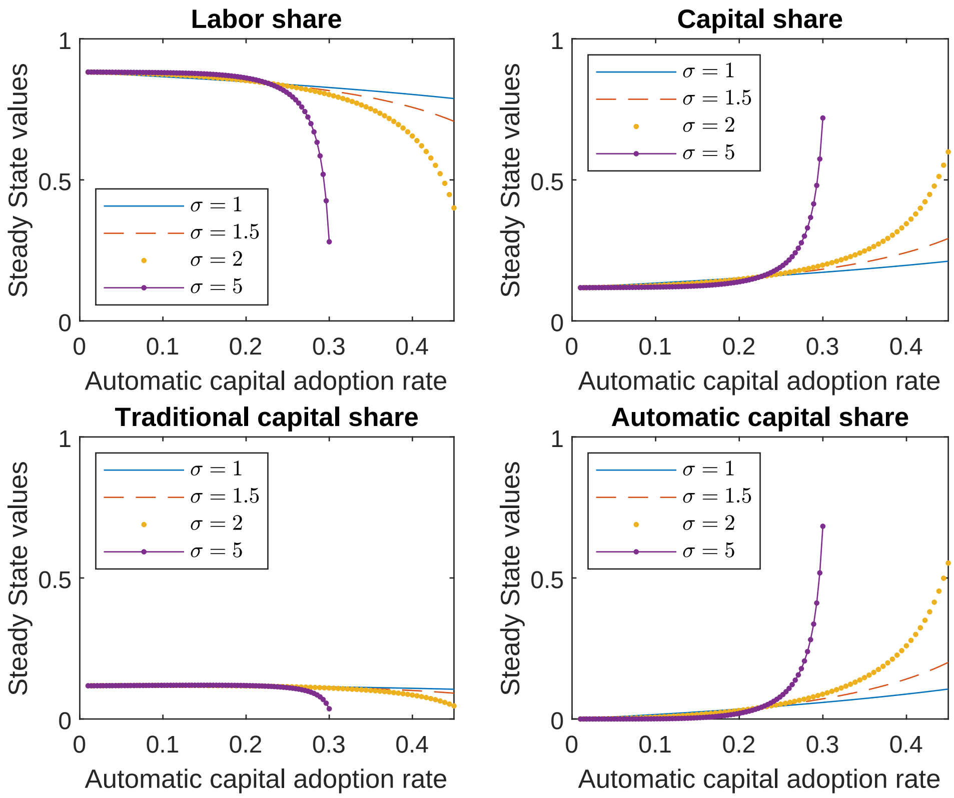

Figure 5: The functional distribution of income, Automatic Capital adoption rate and the elasticity of substitution between traditional and automatic technology. Net income.

Figures 4 and 5 plot the steady state functional distribution of income for gross and net income resulting from simulations of the model. We find that the introduction of automatic technology is associated with labor share decline (capital-deepening effect). This labor share fall is higher as higher the automatic capital adoption rate is, and its deepening depends on the elasticity of substitution between the traditional and the automatic technology. For adoption rates below the threshold, little change in labor share is observed as consequence of the introduction of the new technology. However, above the threshold, changes are dramatic.

The estimated functional distribution of income suggests that the mere introduction of automatic capital as an additional input for production implies a decline of the labor share, as little substitution of traditional capital share by the new automatic capital returns is observed. Additionally, this decline is accentuated by the value of the elasticity of substitution between the new automatic technology and traditional technology. That is, the crowding-out of traditional capital by the new automatic capital is not complete as to offset the effects on labor income. The negative slope curvature of the labor share steady state values, as a function of the automatic capital adoption rate, gets more pronounced as the substitution effect gets higher. Not only labor share declines with the introduction of the automatic capital but also the traditional capital income share. By contrast, the automatic capital income share increases as its adoption rate does. Therefore, automatic capital is not only absorbing the decline in the labor share but also the decline in the traditional capital income share. Again, the overall effects will depend on whether the automatic capital adoption rate is above or below the threshold. Comparing Figure 4 and Figure 5, we observe how the net income labor share decline is moderate when the automatic capital adoption rate is below the threshold, or in a situation above the threshold when the elasticity of substitution is low enough. That is, with the exception of a robocalypse scenario (high adoption rate and high elasticity of substitution), the new technology has a moderate impact on labor share.

As we can observe in the bottom right plot of Figure 4, if the elasticity of substitution among traditional and automatic technology is equal to our lower limit ($\sigma = 1$), the automatic capital share grows in parallel with the adoption rate. That is to say, in this scenario capital share matches always the adoption rate: $1 - \mu = R_d D/Y$. For low elasticity of substitution, there is a linear function that relates robot income share with robots adoption rate. In this scenario, shares are higher with respect to higher elasticities of substitution scenarios for adoption rates below the threshold, while we find the opposite dynamics when we have adoption rates above the threshold. Acemoglu and Restrepo (2019) study the effects of a robot density increase in the labor market, and they conclude that one more robot per a thousand worker reduces wages by 0.25-0.5 percent and the employment to population ratio by 0.18-0.24. Then, we know for sure that it also reduces labor compensation, and therefore, the labor share.[10]

Charalampidis (2020) remarks the counter-cyclical character of the U.S. labor share.[11] They justify the causes of its fluctuations with the following elements and proportions: automation (54%), workers' market power (24%) investment efficiency (6%), and the relative price of investment account (4%). For Prettner (2019), automation only explains the 14% of the observed decline of the labor share over the last decades in the United States, while Aum *et al.* (2018) argue that computerization during the 1990s gives a rationale for most of the

[10]We should bear in mind that the study analyzes data from 1990 to 2007, so it puts the focus on a period with low robotization and we have already observed that its effects on the economy for automatic capital adoption rates lower than 22.5% are not remarkable. In fact, Charalampidis (2020) highlights that automation shocks are the main cause of the post-2007 cyclical labor share drop.

[11]Leduc and Liu (2019) also find a countercyclical character in it. Their explanation for this fact is that automation improves labor productivity while muting wage increases.

decline in the labor share between 1980 and 2010 (4 out of 5 percentage points). Guerriero (2019) ascertains the global decline of the labor share, taking into account 151 economies in a panel data analysis and concluding that labor share varies significantly among economies and it has decreased over time especially since 1980. In the case of Europe, Dao *et al.* (2017) analyzes the decrease in the labor income share distinguishing between advanced economies and emerging markets. They discover that half of the overall decline in advanced economy is due to the technological progress and varying exposure to routine occupations.

In the literature, several authors have drawn a very negative picture for future labor share, as well as a horizon of hyper inequality originated by technological progress. For instance, Piketty (2014) argues that capital returns grow more than economic growth itself and this causes inequity. Consequently, under this scenario, it seems clear that the intervention of the government is needed to deal beforehand about what could be a major problem in the forthcoming decades. This is why numerous authors remark the necessity of a robot tax (Guerreiro *et al.,* 2017; Thuemmel, 2018), or an Universal Basic Income (Hoynes and Rothstein, 2019), which could be interpreted as reminiscent of Luddite thought. However, other authors adopt a more optimistic view of predicting a soft transition without dramatic losses in worker earnings. Bongers and Molinari (2020) study trends in average working time from the Industrial Revolution and argue that automation represents a new technological revolution that can have an important impact in the reduction of average working time while increasing compensation to employees level. Our analysis reflect both pessimistic and optimistic views; only under certain conditions (high automatic capital adoption rate and high elasticity of substitution between new capital and traditional technology), working time is going to experiment a great fall. However, for low values of the elasticity of substitution between new and traditional technology and low adoption rate of the new technology, little negative effects on labor are predicted. As a consequence, only in the scenario where the automatic capital adoption rate is higher enough, some kind of redistribution policies must be implemented.

6. Conclusions

This paper develops a simple macroeconomic general equilibrium model to analyze how the introduction of new automatic technology can affect the economy. The main hypothesis is the consideration of a new type of capital (i.e., automatic capital) that can produce final goods in a stand-alone fashion. This new technology directly competes with the traditional one. The example of the combination of a cab-car with a cab-driver in front of a self-driving cab is highly illustrative in order to better understand the implications of this technological change process. The model is simulated and the steady states are computed depending on the new automatic capital adoption rate, which we assume equivalent to the distribution technological parameter of a CES combining both technologies, and on the elasticity of substitution between the traditional and the new technology. From this analysis we draw some important conclusions and key issues that can be worth noting in helping us to consider the potential impact of this new technology.

The most important result of the paper is the identification of a threshold value for the automatic capital adoption rate which leads to the possibility of two totally different scenarios. The threshold value for new capital adoption rate has a simple interpretation, being equal to the marginal productivity of the new capital in steady state. This allows us to easily identify its determinants: the discount factor and the depreciation rate of the new capital. For the benchmark calibration of the model, where the annual discount factor is 0.975 and automatic depreciation rate is 20%, the threshold value for the new capital adoption rate is around 22.5%. At this threshold, the stock of automatic capital equals the output. For adoption rates below the threshold, where the elasticity of substitution between the traditional and the automatic technology is not a relevant variable, we do not observe significant changes in the main variables of the economy. However, things are completely different when the adoption rate is above the threshold because the elasticity of substitution between both technologies becomes an important variable. In a scenario with an automatic capital adoption rate below the threshold, labor time slightly increases as higher is the substitution effect of the new automatic technology.On the contrary, in an scenario with an automatic capital adoption rate above the threshold, we find the opposite process, since labor falls abruptly.

The introduction of the new automatic technology can provoke a radical fall on both labor time and labor share, but for this to happen a high substitution effect between the traditional and the automatic technology and a high presence of the new automatic technology are needed. We study the relationship between this new automatic capital and the functional distribution of income with the aim of shedding some light on the decline of the labor share, and we find that the mere introduction of the automatic technology implicitly causes a decline in labor share. The dimensions of this decline depend directly on the elasticity of substitution between technologies and the adoption rate. This decline is almost the same for any elasticity of substitution until the automatic capital adoption rate matches the threshold. Consequently, the elasticity of substitution plays a crucial role in augmenting the decline of the labor share.

From the previous results, we can establish the necessary conditions for the so-called robocalypse to occur. The introduction of the automatic capital does not imply a great fall in labor demand. For an abrupt decline of labor time, it is necessary a high substitution effect between technologies and an automatic capital adoption rate above the threshold. These would be the two necessary requirements for the robocalypse to take place: a high adoption rate of automatic technology and a high substitution elasticity between new and traditional technologies. In any other scenario, automatic technology can perfectly coexist with traditional technology having a minimal impact on the labor market.

Empirical evidence about robots adoption rates estimates that potential AI and autonomous robot penetration is relatively high (above 45%), a value well above our estimated threshold. Additionally, empirical evidence also affirms that the elasticity of substitution between new and traditional technologies could be also of high magnitude. The combination of that empirical evidence moves the economy to our robocalypse scenario, where labor collapses. The threat of an unprecedented increase in inequality under this scenario can be clearly observed in our analysis of the functional distribution of income. Nevertheless, the high depreciation rate of new equipment (and the increasing depreciation rate over time for computers, telecommunication equipment, software), implies that the threshold adoption rate can be also increasing in the future, reducing the risk of robocalypse, even for the case of high elasticity of substitution between both technologies. Thus, our paper opens the possibility that the robocalypse scenario could be avoided, as the threshold for the adoption rate will increase at the same proportion than the depreciation rate of new automatic capital assets.

References

[1] Abeliansky, A., and Prettner, K. (2017). Automation and demographic change. *CEGE Discussion Papers*, No. 310, University of Göttingen, Center for European, Governance and Economic Development Research (CEGE), Göttingen.

[2] Acemoglu, D. and Restrepo, P. (2018a). Modeling Automation. *NBER* Working Paper n. 24321.

[3] Acemoglu, D. and Restrepo, P. (2018b). The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares and Employment. *American Economic Review*, 108(6), 1488-1542.

[4] Acemoglu, D. and Restrepo, P. (2019). Robots and Jobs: Evidence from US Labor Markets. *Journal of Political Economy* (Forthcoming).

[5] Arntz, M., Gregory, T., and Zierahn, U. (2016). The Risk of Automation for Jobs in OECD Countries: a Comparative Analysis, Social, Employment and Migration. *Working Paper* 189, Paris: Organisation for Economic Co-operation and Development.

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

[7] Artuc, E., Bastos, P. S. R. and Rijkers, B. (2018). Robots, Tasks and Trade," *Policy Research Working Paper* n. 8674, The World Bank.

[8] Aum, S., Lee, S. Y., and Shin, Y. (2018). Computerizing industries and routinizing jobs: Explaining trends in aggregate productivity. *Journal of Monetary Economics*, 97(1), 1-21.

[9] Autor, D. and Salomons, A. (2018). Is Automation Labor-Displacing? Productivity Growth, Employment, and the Labor Share. *NBER Working Paper* n. 24871.

[10] Basso, H. S. and Jimeno, J. F. (2019). From Secular Stagnation to Robocalypse? Implications of Demographic and Technological Changes. *CEPR Discussion Paper* n. DP14092.

[11] Benzell, S.G., Kotlikoff, L.J., Lagarda, G. and Sachs, J.D. (2017). Robots are us: Some economics of human replacement. *IDB Working Paper* n. IBD-WP-785.

[12] Berg, A., Buffie, E. F. and Zanna, L-F. (2018). Should we fear the robot revolution? (The correct answer is yes). *Journal of Monetary Economics*, 97(1), 117-148.

[13] Bernard, A. B., Fort, T. C., Smeets, V., and Warzynski, F. (2018). Heterogeneous Globalization: Offshoring and Reorganization. Technical report, Dartmouth College.

[14] Bessen, J. E. (2017). Automation and Jobs: When Technology Boosts Employment. Boston University School of Law, *Law and Economics Research Paper* n. 17-09.

[15] Brynjolfsson, E., and McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. (First edition.). New York: W.W. Norton & Company.

[16] Bongers, A. and Molinari, B. (2020). Economic growth, technological progress, and employment. In: Leal Filho W., Azul A., Brandli L., Özuyar P., Wall T. (eds). Decent Work and Economic Growth. Encyclopedia of the UN Sustainable Development Goals. Springer.

[17] Bowles, J. (2014). "The Computerisation of European Jobs", blog, 24 July, Bruegel, http://bruegel.org/2014/07/the-computerisation-of-europeanjobs/.

[18] Charalampidis, N. (2020). The U.S. Labor Income Share And Automation Shocks. *Economic Inquiry*, 58(1), 294-318.

[19] Chiacchio, F., Petropoulos, G. and Pichler, D. (2018). The impact of industrial robots on EU employment and wages: A local labour market approach. *Working Papers* n. 25186, Bruegel.

[20] Chirinko, R.S. (2008). Sigma: The long and short of it. *Journal of Macroeconomics*, 30, 671-686.

[21] Dauth, W., S. Findeisen, J. Sudekum and N. Woessner (2017). German Robots: the Impact of Industrial Robots on Workers. *CEPR Discussion Paper* n. DP12306.

[22] de La Grandville, O., (1989). In quest of the Slutsky Diamond. *American Economic Review* 79, 468-481.

[23] DeCanio, Stephen J., (2016). Robots and humans- complements or substitutes? *Journal of Macroeconomics*, 49(2), 280-291.

[24] Eden, M., and Gaggl, P. (2018). On the Welfare Implications of Automation. *Review of Economic Dynamics*, 29, 15-43.

[25] Ernst, E., Merola, R., and Samaan, D. (2018). The economics of artificial intelligence: Implications for the future of work. 10.13140/RG.2.2.29802.57283.

[26] Farmer, J., and Lafond, F. (2016). How predictable is technological progress? *Research Policy*, vol. 45(3), 647-665

[27] Felten, E.W., Raj, M., and Seamans,R. (2018). A Method to Link Advances in Artificial Intelligence to Occupational Abilities. *AEA Papers and Proceedings*, 108, 54-57.

[28] Ford, M. (2015). *The Rise of the Robots: Technology and the Threat of Mass Unemployment.* London: Oneworld Publications.

[29] Fossen F., and Sorgner A. (2019). Mapping the Future of Occupations: Transformative and Destructive Effects of New Digital Technologies on Jobs. *Foresight and STI Governance*, 13(2), 10-18.

[30] Freeman, R. B. (2015). Who owns the robots rules the world. IZA World of Labor.

[31] Frey, C. B. (2019). *The Technology Trap: Capital, Labor, and Power in the Age of Automation.* Princenton: Princeton University Press.

[32] Frey, C. B., and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation?. *Technological Forecasting and Social Change*, 114(2), 254-280.

[33] Furman, J., and Seamans, R. (2018). AI and the Economy. NBER Chapters, in *Innovation Policy and the Economy*, 19, 161-191.

[34] Grace, K., Salvatier, J., Dafoe, A., Zhang, B. and Evans, O. (2018). When will AI exceed human performance? Evidence from AI experts. *Journal of Artificial Intelligence Research*, 62, 729-754.

[35] Graetz, G. and Michaels, G. (2018). Robots at Work.*Review of Economics and Statistics*, 100(5), 753-768.

[36] Guerriero, M. (2019). The Labor Share of Income Around the World: Evidence from a Panel Dataset. *ADBI Working Paper* 920. Tokyo: Asian Development Bank Institute.

[37] Guerreiro, J., Rebelo, S. and Teles, P. (2017). Should Robots Be Taxed? *NBER Working Paper* n. 23806.

[38] Hanson, R. (2008). Economics of the singularity. *IEEE Spectrum*, 45(6), 45-50.

[39] Hall, Bronwyn H. (2005). Measuring the Returns to R&D: the Depreciation Problem. *Annals of Economics and Statistics*, 79-80, 341-381.

[40] Hoynes, H.W. and Rothstein, J. (2019). Universal Basic Income in the US and Advanced Countries. *NBER Working Paper* n. 25538.

[41] International Federation of Robotics (2016). World Robotics Industrial Robots 2016.

[42] Jiang, T., Petrovic, S., Ayyer, U., Tolani, A., and Husain, S. (2015). Self-driving cars: Disruptive or incremental. *Applied Innovation Review*, 1, 3-22.

[43] Karabarbounis, L. and Neiman, B. (2014a). The Global Decline of the Labor Share. *Quarterly Journal of Economics*, 129 (1), 61-103.

[44] Karabarbounis, L. and Neiman, B. (2014b). Capital depreciation and labor shares around the world: measurement and implications. *NBER Working Paper* n. 20606.

[45] Koh, D., Santaeulia-Llopis, R. and Zheng, Y. (2016). Labor Share Decline and Intellectual Property Products Capital, *Working Papers* n. 927, Barcelona Graduate School of Economics.

[46] Krusell, P., Ohanian, L. E., Ríos-Rull, J. V. and Violante, G. L. (2000). Capital-skill Complementarity and Inequality: A Macroeconomic Analysis. *Econometrica*, 68, 1029-1053.

[47] Leduc, S. and Liu, Z. (2019). Robots or Workers? A Macro Analysis of Automation and Labor Markets. *Federal Reserve Bank of San Francisco Working Paper* n. 2019-17.

[48] Lin, T. T. and Weise, C. L. (2019). A New Keynesian model with robots: Implications for business cycles and monetary policy. *Atlantic Economic Journal*, 47, 81-101.

[49] Manyika, J., Chui, M., Miremadi, M., Bughin, J., George, K., Willmott, P. and Dewhurst, M. (2017). *A Future That Works: Automation, Employment and Productivity*. Chicago: McKinsey Global Institute.

[50] Nordhaus, W.D. (2017). Are we approaching an economic singularity? Information technology and the future of economic growth. *NBER Working Paper* n. 21547.

[51] Piketty, T. (2014). *Capital in the Twenty-First Century*. Cambridge Massachusetts: The Belknap Press of Harvard University Press.

[52] Prettner, K. (2019). A note on the implications of automation for economic growth and the labor share. *Macroeconomic Dynamics*, 23(3),1294-1301.

[53] Sachs, J. D., Benzell, S. G. and LaGarda, G. (2015). "Robots: Curse or Blessing? A Basic Framework. *NBER Working Papers* n. 21091.

[54] Sachs, J. D., and Kotlikoff, L. J. (2012). Smart machines and long-term misery. Techn. Rep. n. 18629, NBER.

[55] Schlogl, L., and A. Sumner (2018). The Rise of the Robot Reserve Army: Automation and the Future of Economic Development, Work, and Wages in Developing Countries. *Working Papers* n. 487, Center for Global Development.

[56] Thuemmel, U. (2018). Optimal Taxation of Robots. *CESifo Working Papers*, n. 7317.

[57] World Economic Forum (2018). *The Future of Jobs Report*. World Economic Forum.

[58] Zeira, J. (1998). Workers, machines, and economic growth. *Quarterly Journal of Economics*, 113(4), 1091-1117.