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# Digital Innovation and its Potential Consequences: the Elasticity Augmenting Approach


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**Abstract**

Digital technologies have been experiencing in the last thirty years a considerable development which has radically changed our economy and lives. In particular, the advent of new intangible technologies, represented by software, artificial intelligence and deep learning algorithms, has deeply affected our production systems from manufacturing to services, thanks also to further improvement of tangible computational assets. Investments in digital technologies have been increasing in most of developed countries, posing the issue of forecasting potential scenarios and consequences deriving form this new technological wave. The contribution of this paper is both theoretical and related to model design. First of all we present a new production function based on the concept of organizational units. Then, we enrich the macroeconomic model Eurace integrating this new function in the production processes in order to investigate the potential effects deriving from digital technologies innovation both at the micro and macro level.



*Keywords:* Elasticity of substitution, Elasticity augmenting approach, Digital transformation, Agent-based economics, Organizational unit.


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## 1. Introduction

Since the first industrial revolution, the potential consequences deriving from new waves of technological progress have been discussed generating conflicting opinions. New technologies have always generated apprehension among the working class and even if the debate among economists is still open, most of them agree on distinguishing between short and long run effects. According to this distinction, in the short term innovation determines lower employment levels and wages, whereas in the long term the higher productivity in the production systems could determine an increase in employment and wages, see Mokyr et al. (2015). In this respect, Ricardo (1821) argued that even though the introduction of machinery is injurious to labour class, the short term displacement is only temporary: in the long run, the technological unemployment leaves room to a higher labour demand. Therefore, according to a sizable part of economists, the unemployment effect related to technological progress is not constant, but it is absorbed by the economic system itself over time. In this respect, Schumpeter (1939) affirms that economic cycles are strictly related to technological progress. The latter leads to economic expansion periods followed by recession phases characterized by supernormal unemployment. In the thought of Schumpeter, cyclical unemployment corresponds to technological unemployment and it is related to innovation process which constitutes the essence of economic system evolution.

Obviously, technological progress does not always involve the same result. In this respect, we can differentiate between two different kinds of technological innovation, i.e. product and process innovation. The positive impact on employment resulting from the former has been highlighted and underpinned by various researches, see e.g. Edquist et al. (2001); Vivarelli and Pianta (2000), whereas the latter differs in its

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labour-saving nature allowing to produce the same amount of output using less workforce. In fact, thanks to product innovation new markets can be opened leading to an increase of production and employment, while process innovation involves higher level of productivity determining a lower employment in the production system, see Pianta (2009). It is worth noting that two main analysis levels can be distinguished in order to investigate process innovation effects, namely the firm-level and the industry-level. In this regard, according to Acemoglu et al. (2020), although firms adopting automation decrease their workforce share in the production process, their overall employment increases. In other words, process innovation induces a positive employment effect at the firm-level. In fact, the adoption of automation determines a cost reduction and a consequent increase of their market shares: the lower prices linked to lower production costs determine an increase of their revenues and sizes. However, their expansion on the market occurs at the expense of their competitors and it causes a negative overall effect on employment at the industry-level: competitors which lose part of their market shares reduce the amount of workforce to cope with their lower demand of goods.

According to the so-called "Compensation Theory", the negative effects linked to labour-unfriendly process innovation are counteracted by several economic forces triggered by the technological progress itself, see Petit (1993). In this respect, Vivarelli (2014) distinguishes between six different compensation effects: the compensation mechanism "via additional employment in the capital goods sector", "via decrease in prices", "via new investments", "via decrease in wages", "via increase in incomes" and "via new products". Similarly, according to Acemoglu and Restrepo (2018a), the so-called "displacement effect" caused by the adoption of digital technologies within production processes is counteracted by four countervailing effects: the productivity effect, capital accumulation, deepening of automation and the creation of new labour-intensive tasks. In particular, for the authors the creation of new tasks and jobs in which human labour has a comparative advantage compared to capital represents the most effective force capable of balancing the replacement of workers with automated machines. According to Vermeulen and Pyka (2014), because of countervailing effects triggered by the technological progress itself, the diffusion of artificial intelligence (AI) and robots is determining a typical structural change rather than the so-called "end of work".

However, it is worth highlighting that the nature of the new digital technological wave experienced by our society is completely different compared to the previous ones. Most of innovations introduced within production systems until the end of the XXth century had the purpose to produce a huge amount of mechanical energy allowing to surmount the limits imposed by human physical force. Nowadays, according to Brynjolfsson and McAfee (2014), we are experiencing a new technological revolution called "The Second Machine Age". In this new era, through the adoption of new digital technologies such as AI, we can overcome limits imposed by our mind. In this respect, the primary objective to be pursued adopting these new digital instruments is represented by the automation of decision-making processes and this new kind of automation makes us reflect about its potential future consequences on the labour market. Furthermore, various economists and technologists contemplate the possibility that further developments in computation and artificial intelligence will lead us to a technological singularity, see Good (1966); Nordhaus (2015); Aghion et al. (2017), and the economic and social consequences of these advances could be really disruptive.

In order to forecast potential effects deriving from digital technologies innovation, it is really important to frame how these technologies affect our production systems. In this regard, literature presents several methods that have been used to evaluate the potential consequences of digital technological progress. Hanson (2001); Lankisch et al. (2019); DeCanio (2016) model AI as an input factor within production technologies. The advent of automation and AI has been represented also through the so-called factor-augmenting approach: in this case, digital technologies and their technological progress affect factors productivity. Nordhaus (2015); Graetz and Michaels (2018); Sachs and Kotlikoff (2012) model automation as a capital-augmenting technical change, whereas Bessen (2016, 2018, 2019) frame automation as labour-augmenting. Furthermore, Acemoglu and Restrepo (2018b) adopt the so-called task-based approach based on the pioneering contribution by Zeira (1998): automation, robots, AI and their evolution are represented through an increase in the number of tasks that can be performed by machines.

In this research work, to analyze long-term consequences linked to a digital transformation, we have proposed an alternative production function based on the notion of organizational unit which combines both the concept of substitutability and complementarity. This new conceptual production technology is integrated within the large-scale macroeconomic model Eurace, see Raberto et al. (2012); Teglio et al. (2012); Petrović et al. (2017); Mazzocchetti et al. (2018); Ponta et al. (2018); Teglio et al. (2019). In particular, we build on the latest version of the Eurace model, which encompasses intangible digital technologies, as presented in Bertani et al. (2020a,b), replacing the Cobb-Douglass technology, used to model the manufacturing processes in a traditional mass-production system, with a Leontief production function in which input factors are represented by organizational units. In turn, the contribution of each organization unit is given by a combination between labour and capital. Furthermore, in the new framework technological progress does not affect total factor productivity directly, but the nature of technology itself: innovation affects the elasticity of substitution between capital and labour. In other words, we propose a new alternative approach that we call elasticity-augmenting approach according to which digital technological progress increases the degree of substitutability between workforce and machines.

Through the new production function based on organizational units it is possible to represent the overall production process of firms in a more realistic way distinguishing between the various activities performed in the companies and the different education levels characterizing the workforce employed. Furthermore, the elasticity-augmenting approach represents a new consistent way to represent the technological progress, as it will be shown in the next sections. For instance, it can be considered as a valid and similar alternative to the task-based approach, especially for those models in which tasks performed by households are not heterogeneous: an increase of the elasticity of substitution can be seen as an increase in the tasks that machines can performed replacing human beings, in line with what really happened in the history of technological evolution.

Section 2 reports a brief description of the baseline version of Eurace, Section 3 presents the new Eurace extension, whereas computational results and conclusion are presented in Section 4 and 5 respectively.

## 2. The baseline Eurace model

Agent-based computational economics (ACE) is an out-of-equilibrium paradigm of simulation which represents an alternative to neoclassical economic models. In particular, ACE frames the economy as a complex evolving system composed by interacting heterogeneous agents. Being a bottom-up approach, the dynamics of the system at the macro level is given by agent interactions at the micro level that continuously change the system structure (LeBaron and Tesfatsion (2008); Dosi and Roventini (2019)).

The Eurace model is composed by various types of heterogeneous economic agents, characterized by bounded rationality, that interact through centralized and decentralized markets. Moreover, each agent is endowed with a dynamic balance sheet, accounting all its assets and liabilities, see Godley and Lavoie (2012); Raberto et al. (2018) for details. In particular, the baseline Eurace model includes:

**Households (HHs)**: they perform as investors, workers and consumers. As traders, they allocate their financial wealth among available assets, namely Government bonds and stocks emitted by firms and banks. As employees, they earn a monthly wage, which, together with the financial returns on bonds and stocks forms their total income. Based on the latter, households determine their consumption budget according to a target wealth to income ratio, in line with the buffer-stock saving behaviour theory, see Carroll (2001).

**Consumption goods producers (CGPs)**: they produce and sell to households a homogeneous good and, in order to manufacture their products, they demand both labour and capital as production factors. In particular, each CGP estimates the expected demand based on past sales and determines the labour and capital demand. If the number of workers needed to fulfill the planned production is lower compared to the current employment level, the CGP fires the extra workers, otherwise it enters the labour market posting new vacancies. As regards the salary setting, the CGP sets a starting wage offer which, in case of failure in hiring the employees needed in the production process, is increased by a fixed thick in order to start a second round of hiring. If the second round is also unsuccessful, it exits the labour market. However, it increases the wage offer a second time and this will represent the initial wage offer for the next hiring session. The investments decision is also linked to the planned production and CGPs try to finance these costs following the pecking order theory: first retained earnings, then debt, then equity. In case of rationing, CGPs reduce their costs to make the total financial needs consistent with the available resources. In the event of insolvency, CGPs run into bankruptcy and undergo a restructuring process to increase the equity over debt ratio.

**Commercial banks (Bs)**: they provide credit to private agents, namely CGPs and HHs. In particular, Bs evaluate loan and mortgage requests, and eventually lend money to private agents at a price that depends on the risk associated to the default probability of the firm or on the creditworthiness of the household. The capacity of each bank of lending is not infinite. On the contrary, it is limited by the obligation to respect a capital adequacy ratio (CAR). Moreover, it is worth noting that Eurace is characterized by an endogenous money creation. In fact, new deposits are created every time a bank issues new credit.

**Capital good producer (KGP)**: it produces and sells capital goods to CGPs. In the baseline version of Eurace, these investments goods are complete means of production, including both hardware and software. In the new Eurace version presented in Bertani et al. (2020a,b) and enriched in this paper, they have to be considered as "hard" capital goods and represent the physical part of a generalized mean of production. In other words, we can consider these investment goods as the hardware part of computerized numerical control machines, robots, computer, communication equipment, etc. Obviously, these means of production need software in order to work and take part to the manufacturing process within CGPs: software and hardware must be combined together because of the intrinsic complementarity characterizing them. Therefore, each unit of "hard" capital needs to be associated with a software (or digital asset) license and, as it will be explained later, the digital assets installed on "hard" capital are develop and supply by the digital assets developers. In order to produce capital goods, the KGP hires workers performing the same labour market procedures used by CGPs and explained above.

**Government (G) and Central bank (CB)**: Policy makers are responsible for fiscal and monetary policy. In particular, G ensures a welfare system managing its income and expenditures. Total Government income derives from taxation on corporate earnings, consumption, financial and labour income. As regards Government expenditures, they include: public sector wage bills, unemployment benefits, transfers and interest payment on debt. In order to finance its activity, if in short of liquidity, G emits long-term bills, or perpetuities that pay a monthly fixed coupon. As far as CB is concerned, it provides a infinite liquidity to Bs, acting as lender of last resort. CB also sets the policy rate and the capital requirement for the banking system.

In the next section, a detailed description concerning digital assets developers and the new modelling features is reported.

## 3. Modelling the digital transformation: digital assets developers and the new production function

As mentioned above, a new extension of Eurace related to intangible digital technologies has been presented in Bertani et al. (2020a,b). In these previous research works, Eurace has been enriched with a new population of agents: the digital assets developers (DADs). These firms develop and supply a new type of productive capital, namely the intangible digital asset, which is required by consumption good producers (CGPs) in order to increase their total factor productivity (TFP). In this regard, digital technological progress has been modelled as total factor augmenting because of the high positive and significant correlation between investments in ICT capital and TFP average growth rate for a sample of 15 country during 2008-2016[1]. Digital assets differ for price and productivity level and their heterogeneity implies the existence of a new decentralized market in which DADs can potentially compete in order to sell their products to the mass production system represented by CGPs.

[1]For further details related to this correlation analysis see Bertani et al. (2020b).

The new Eurace version presented in this paper represents a step forward compared to our previous researches. In particular, digital technological progress has been modelled in a completely different way, namely using an elasticity augmenting approach. In other words, digital technologies influence the degree of substitutability between the workforce and the "hard" capital on which they are installed: the higher the technological progress, the higher the value of the elasticity of substitution $ES$. In order to implement the elasticity augmenting approach, the Cobb-Douglas function used in order to model CGPs production processes has been replaced with a Leontief production technology in which input factors are represented by organizational units (OUs). In turn, each OU contribution can be represented through the combination of labour $L$ and "hard" capital $K$ on which digital assets are integrated. Following subsections illustrate the new Eurace version in more detail.

### *3.1. Digital Assets Developers*

Along the lines of Rifkin (2014) and Haskel and Westlake (2017), digital assets are modelled as non-rivalrous goods, namely they have zero marginal production costs. According to this assumption, DADs face only fixed costs[2], given by uncertain R&D activities performed in order to develop improved versions of their digital capital assets, characterized by higher substitutability between capital $K$ and labour $L$ when employed in the manufacturing processes by CGPs. These fixed production costs are given by the wages of skilled workers employed: DADs invest a fraction of their revenue to hire only labour force characterized by a high education level[3] in order to perform their R&D activities. For each DAD agent $d$ the monthly probability $prob_d$ of developing an improved version of the digital asset is influenced by the cumulated person months $M_d$ employed since the latest version developed and it is given by the following increasing monotone function with decreasing returns to scale:

$$prob_d = 1 - \frac{1}{1 + \eta M_d} \tag{1}$$

where $\eta$ represents the shape parameter of the probability function: it determines the R&D activities likelihood of being effective. In other words, the higher the value of $\eta$, the higher the probability of developing an improved version of digital assets, for any level of cumulated person months $M_d$ employed. Another important feature related to R&D activities is their uncertainty. In fact, a successful digital assets improvement is never granted in principle because the probability is equal to 1 only asymptotically for an infinite value of person months $M_d$. Improving digital assets implies a higher degree of substitutability between input factors represented by their elasticity of substitution $ES$.

In the light of these considerations, Eurace innovation process is intrinsically linked to digital technologies and their developers. Moreover, technological progress affects the nature of technology itself. Indeed, in case of successful R&D activities, the elasticity of substitution $ES$ between labour and capital increases: digital technologies allow to replace workers with capital in the production processes in a more pervasive way. For instance, assuming the routinization level as benchmark, an enhancement of $ES$ could be seen as the capacity of digital technologies to perform tasks less and less routinary.

### *3.2. Consumption Good Producers*

#### **The New Production Technology**

[2]According to Arthur (1996) we can distinguish between two different business worlds: the diminishing returns and the increasing returns world. High-tech companies (as military, pharmaceutical and software producers) belong to the latter and they typically face very high R&D fixed costs compared to their variable production costs. Therefore, through this modelling assumption we formalize one of the most important features characterizing increasing returns business world.

[3]Households are characterized by five different education levels and this modelling feature allows to distinguish between undergraduate (the first and the second level) and graduate workers (from the third to the fifth level). The latter are employed by DADs in order to develop their digital technologies. Moreover, DADs hire graduate workers performing the same labour market procedures used by CGPs and KGP.

Companies tend to organize their structure into organizational units (OUs) in order to improve their economic performance. In particular, this organization allows to decrease costs and increase productivity. An OU is represented by a group of workers which is organized according to a specific criterion[4] and it is run by a manager.

Therefore, the production of a company is given by the interaction between complementary OUs and firm complexity is given by the number of units: the higher the number of OUs, the higher the company complexity as the number of necessary interactions increases. Being OUs not substitutable[5], a Leontief production technology can represent the macro production within a generic firm composed by $n$ OUs:

$$Y = min[\gamma_1 Y_{OU_1}, \gamma_2 Y_{OU_2}, ....., \gamma_n Y_{OU_n}], \tag{2}$$

where $Y_{OU_i}$ represents the contribution provided by the i-th OU to $Y$ and $\gamma_i$ is the coefficient of production of the OU considered. Each OU takes part in the production process requiring inputs, namely different kinds of "hard" capital $K_i$ and workers $L_i$, and its contribution in productive term can be improved, for example through technological innovation.

The debate among economists on the value of $ES$ between $K$ and $L$ is still open, see Arrow et al. (1961); Douglas (1976); Kalt (1978); Piketty and Goldhammer (2014); Mućk (2017); Gechert et al. (2019). However, regardless of the substitutability grade between $K$ and $L$, it is possible to represent the contribution $Y_{OU_i}$ of the i-th OU through a constant $ES$ (CES) production technology with constant returns to scale, see Arrow et al. (1961):

$$Y_{OU_i} = [\alpha_i K_i^{-\rho_i} + (1-\alpha_i) L_i^{-\rho_i}]^{-1/\rho_i} \tag{3}$$

where $\alpha_i$ is the distribution parameter and $\rho_i$ represents the substitution parameter and it is a transform of the $ES$ $\sigma_i$:

$$\sigma_i = \frac{1}{1+\rho_i} \tag{4}$$

The coefficient of production $\gamma_i$ results to be crucial because it defines the optimal contribution of the specific organizational unit in order to produce a certain amount of goods $\hat{Y}$. In this regard, the optimal contribution $\hat{Y}_{OU_i}$ of each organizational unit $OU_i$ is given by the ratio between the target production $\widetilde{Y}$ and the coefficient of production $\gamma_i$:

$$\hat{Y}_{OU_i} = \frac{\widetilde{Y}}{\gamma_i} \tag{5}$$

After determining the quantity of consumption goods to be produced $\widetilde{Y}$ and then the optimal contribution of each organizational unit $OU_i$, a potential way to define the optimal demands of input factors inside the different $OU_i$, i.e. $\hat{K}_i$ and $\hat{L}_i$, is represented by the mathematical optimization methods of Lagrange multipliers. In this respect, the following relation represents the Lagrangian function used for the calculation of these input factors in each organizational units $OU_i$ in Eurace:

$$\mathcal{L}(L_i, K_i, \Lambda) = C(L_i, K_i) + \Lambda g(L_i, K_i) = w_{OU_i} L_i + r_i(c_{K_i} K_i) + \Lambda\{Y_{OU_i} - [\alpha_i K_i^{-\rho_i} + (1-\alpha_i) L_i^{-\rho_i}]^{-1/\rho_i}\} \tag{6}$$

where $C(L_i, K_i)$ represents the cost function to be minimized and $g(L_i, K_i)$ is the production technology constraint. Moreover, $w_{OU_i}$ represents the average cost of labour or mean wage[6], $r_i$ and $c_{K_i}$ are the rental

[4] We can distinguish between two general criteria to group positions in order to create an OU at the first hierarchical level, namely the functional and the divisional one, see Mintzberg (1979). According to the former, human resources are grouped by knowledge, skill, work process or work function, whereas the divisionalized form is based on market grouping.

[5] The reasoning behind this logic assumption is linked to the irreplaceable nature of OUs tasks: the function performed by the human resources OU can not be performed by the manufacturing or R&D unit. This is why OUs are considered complementary.

[6] For the sake of simplicity, firms consider the average wage paid to their employees working in that specific organizational unit $w_{OU_i}$ as the labour cost. In fact, households differ in education level and each of these refers to a different wage. Therefore, the mean wage of the organizational unit $OU_i$ represents an appropriate measure of the labour cost which is, in fact, heterogeneous.

rate proxied by the corporate loan rate and the unit cost of the "hard" capital, respectively. Multiplying $K_i$, which represents the physical stock of "hard" capital, by $c_{K_i}$ we obtain its monetary value. In this way, we can evaluate the rental cost of the capital stock $K_i$ multiplying it by $r_i$.

Starting from $\mathcal{L}(L_i, K_i, \Lambda)$, the Lagrange multipliers methods leads CGPs to formulate the demands of production factors reported below for each $OU$. As regards the optimal amount of labour $\hat{L}_i$, it is given by this equation:

$$\hat{L}_i = \hat{Y}_{OU_i}\Big[\alpha_i(\beta_i r_i c_{K_i})^{\frac{\rho_i}{\rho_i+1}} + \beta_i(w_{OU_i}\alpha_i)^{\frac{\rho_i}{\rho_i+1}}\Big]^{\frac{1}{\rho_i}} \frac{1}{(w_{OU_i}\alpha_i)^{\frac{1}{\rho_i+1}}} \tag{7}$$

where $\beta_i = 1 - \alpha_i$. The optimal amount of capital $\hat{K}_i$ is givenby the following equation:

$$\hat{K}_i = \hat{Y}_{OU_i}\Big[\alpha_i(\beta_i r_i c_{K_i})^{\frac{\rho_i}{\rho_i+1}} + \beta_i(w_{OU_i}\alpha_i)^{\frac{\rho_i}{\rho_i+1}}\Big]^{\frac{1}{\rho_i}} \frac{1}{(\beta_i r_i c_{K_i})^{\frac{1}{\rho_i+1}}} \tag{8}$$

**Integrating the New Production Technology in Eurace**

For the sake of simplicity, each CGP is organized according to a functional structure with two complementary OUs grouped by skills and knowledge.

The first unit $OU_1$ is representative of the manufacturing process inside the company and it only includes undergraduate workers characterized by a low educational level. In order to produce consumption goods, this OU is endowed with "hard" capital represented by machine tools, robots and automated machines that can be improved through the integration of technologically advanced digital assets. High-skilled workers characterized by a high education level are grouped in a second unit $OU_2$ performing all the intellectual tasks, e.g. engineering, human resources and marketing. We assume that graduate workers do not need machines in order to work. Therefore, we do not consider the presence of capital, both tangible and intangible, within $OU_2$, focusing our technological progress study on the pure manufacturing process.

According to our modelling assumption, CGPs production technology are represented by the following function:

$$Y = min[\gamma_1 Y_{OU_1}, \gamma_2 Y_{OU_2}] = min\Big\{\gamma_1[\alpha K^{-\rho_d} + (1-\alpha)L_u^{-\rho_d}]^{-1/\rho_d}, \gamma_2 L_g\Big\} \tag{9}$$

where $L_u$ and $L_g$ represent undergraduate and graduate work force respectively.

This distinction between graduate and undergraduate workforce implies a more specific labour demand compared to the previous Eurace versions. Indeed, CGPs no longer require indiscriminate workforce but, on the contrary, they evaluate both the graduate and undergraduate workers needed in order to reach the production target and try to hire them in the proportion imposed by the production technology. It is also worth noting that a potential lack of graduate workers can not be compensated by undergraduates and consequently this determines a production reduction.

As mentioned above, technological progress affects ES $\sigma_d$ modifying the isoquant curve and redefining the optimal demand of production factors[7], i.e capital $K$ and labour $L_u$, within $OU_1$. In particular, a successful R&D activity performed by the reference DAD $d$ is followed by an update of the digital technology adopted by the CGP and the value of $\sigma_d$ between $K$ and $L_K$ into $OU_1$ increases by a fixed tick equal to $\delta_\sigma$ following the relation below:

$$\sigma_{d_t} = \sigma_{d_{t-1}} + \delta_\sigma \tag{10}$$

[7] The optimal demand of $K$ and $L_u$ is determined considering both the input factor variable in the short-term.

Being $\rho_d$ a transform of $\sigma_d$, technological transition affects its value according to the following relation derived from Eq. 4:

$$\rho_d = \frac{1 - \sigma_d}{\sigma_d} \tag{11}$$

Alternatively, the firm can increase the ES $\sigma_d$ by adopting more technologically advanced digital assets. In this respect, each CGP can adopt only one kind of intangible digital asset at a time, namely its digital assets in use are supplied by only one DAD. On a monthly basis, it has a given exogenous probability to change its reference DAD. In order to evaluate a potential switching, the CGP performs a costs and benefits analysis through the computing of a net present value for each alternative digital technologies:

$$NPV = \Big[max(0, \hat{K} - \hat{K}^*)c_K + \frac{w\hat{L}_u - w\hat{L}_u{}^*}{r}\Big] + \frac{p_l\hat{K} - p_l{}^*\hat{K}^*}{r} - c_d N_{L_K} \tag{12}$$

where asterisks point out variables referring to the new digital technologies under financial evaluation and hats indicate optimal quantities of production factors. Moreover, $c_K$ is the hard capital unit cost, $r$ represents the rental rate of capital proxied by the corporate loan rate and $w$ is the average wage within the $OU_1$. The NPV first term refers to the production cost saving linked to the use of the new digital technology. In fact, if the elasticity of substitution of the new technologies is different, the optimal quantities of labour $\hat{L}_u$ and capital $\hat{K}$ change determining different optimal costs. As concerning NPV second term, it refers to the difference between the licence unit price $p_l$ of the digital technology currently in adoption and the one under consideration $p_l^*$. These two prices are multiplied by the two optimal quantities of capital related to elasticities of substitution of the different digital technologies. The third and final term takes into account the training costs that the firm would face to train its employees to manage the new digital technology: $c_d$ is the training cost per workers whereas $N_{L_u}$ represents the number of employees that are not able to manage the new digital technology under financial evaluation.

In this regard, HHs have been endowed with a set of digital technology skills that represent their ability to manage the various digital assets on the market. If a worker does not have the required skill or, in other words, he is not able to use the digital asset adopted, he must be trained to take part to the production process; these training courses are provided by DADs. Therefore, this is why the training costs are taken into account in the costs and benefits analysis: if a company decides to change digital asset, it must evaluate also potential costs associated to workers training. From a certain point of view, these expenditures can be considered as intangible investments in formation: firms enhance their human resources paying for their "digital education".

The presence of this set of digital technology allows us to model an indirect network effect according to which economic benefits arise indirectly from the interaction of different groups (Farrell and Klemperer (2007); Belleflamme and Peitz (2018)). In fact, both CGPs and DADs can benefit from these digital skills. As regards CGPs, the higher the number of workers with that skill, the lower the transition costs to the digital technology under evaluation, while regarding DADs, the higher the number of workers able to manage their digital assets, the higher the probability to sell their technology.

Obviously, CGPs could also face training costs following a hiring session. This is why CGPs hire workers prioritizing those able to manage the digital technology adopted in that specific moment.

### *3.3. The dynamics of digital assets prices*

On a monthly base, each CGP pays a certain amount of money $M$ proportional to its capital endowment to the reference DAD:

$$M = p_l K \tag{13}$$

Along with training costs, license costs represent one of the DADs incomes and, in order to compete on the digital technologies market, DADs vary their licence unit price $p_l$. In fact, according to the second term of Eq. 12, a lower value of $p_l$ could determine the switch to another digital technology. In this regard, it is also worth noting that any technological unevenness could be compensated by a lower price. $p_l$ is given by the following formula:

$$p_l = \lambda w \tag{14}$$

where $w$ is the average salary characterizing the economic system and $\lambda$ represents the mark-up. The latter is varied over time according to the past sales trend in order to handle market uncertainties characterizing the economy. Indeed, if the DAD finds an increase in sales $Q$, it decides to increase the mark-up by a fixed tick equal to $\delta_\lambda$, otherwise it opts for a price reduction by the same amount trying to increase its market share:

$$\begin{cases} \lambda_{t+1} = \lambda_t + \delta_\lambda & \text{if } Q_t > Q_{t-1} \\ \lambda_{t+1} = \lambda_t - \delta_\lambda & \text{if } Q_t \leq Q_{t-1} \end{cases} \tag{15}$$

## 4. Computational results

### *4.1. Design of experiments*

In order to evaluate the potential consequences related to digital technological progress on the economic system, we investigate our model with four different level of $\eta$, namely the shape parameter of the innovation probability function, see Eq. 9. The parameter $\eta$ results to be crucial because it influences the endogenous rate of technological progress within economy. Indeed, as mentioned above, the higher the value of $\eta$, the higher the probability of developing an improved version of the digital asset. Furthermore, we consider also a "no intangible investments" scenario in which intangible investments and technological progress do not exist, for a total of five scenarios.

We base the methodology of our research on Monte Carlo computational experiments: each scenario is simulated with twenty different seeds of the pseudorandom number generator. Therefore, we consider a total number of 100 simulations to conduct our analysis. According to the study methodology, most of results are presented in the form of boxplots. Each boxplot represents the distribution of time averages of relevant variables over a twenty-year-long time period, including the twenty simulations characterised by different seeds. In particular, boxes enclose values from the first to the third quartile. The horizontal segments within boxes represent the median, while the green diamond is the mean value of the distribution. Boxes include also whiskers representing the minimum and maximum values of the distributions which are not considered outliers. The latter are represented by red plus signs.

In order to give a complete overview of our model, we present also yearly averages across 20 seeds (with the related standard error) and several time series related to the most important variables of interest, so we can show the trend of the system during the entire twenty-year-long simulation; all time series considered refer to a specific seed.

### *4.2. The dynamics of the system: a macroeconomic perspective*

Fig. 1 (a) shows an increase with $\eta$ of the average elasticity of substitution $\sigma$ between input factors in the manufacturing organizational unit $OU_1$. In fact, high values of $\eta$ determine high rates of endogenous technological progress and consequently high value of $\sigma$. In this respect, the higher the technological progress level, the wider the range of tasks that can be performed by the "hard" capital on which technologically advanced digital technologies are installed. According to Eq. 7 and 8, different values of $\rho$, which is a transform of $\sigma$, imply different optimum quantities of input factors. The latter are determined considering respective costs of inputs in order to increase the economic efficiency of the manufacturing process and the adoption of capital appears cheaper compared to human beings. Therefore, higher values of the elasticity $\sigma$ determine a substitution of labour with capital in the CGPs industrial sector. The process innovation within CGPs turns out to be detrimental for workers that are replaced by technologically advanced machines. As a matter of fact, Fig. 1 (b) and (c) show a decrease in the employment level and an increase of the total stock of capital within CGPs with $\eta$, respectively. Therefore, the higher the digital technological progress (which is strictly influenced by $\eta$), the lower the employment level within CGPs.

It is worth highlighting that this substitution of labour with capital determines an increase in the labour productivity $P_L$ in the CGPs, which is calculated through the ratio between CGPs output, i.e. the sold quantity of consumption goods in terms of units, and number of workers employed, see Fig. 1 (d).

The substitution between labour and capital results in an increase of the general unemployment rate, see Fig. 2 (a): the economic system is not able to absorb the job destruction (or displacement effect)

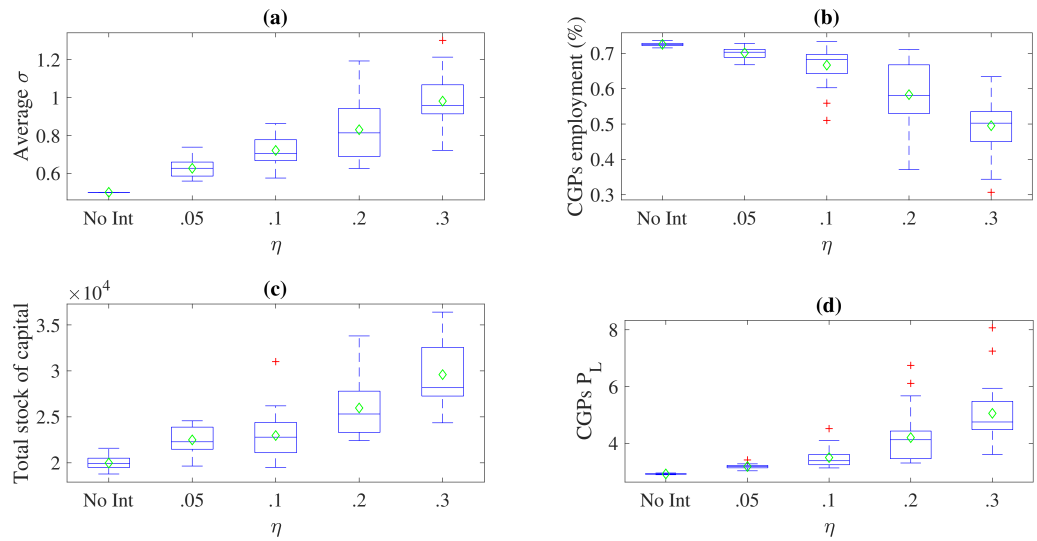


Figure 1: The figure shows a series of boxplots representing, for any scenario considered, the distribution of: the average elasticity of substitution $\sigma$ characterizing the economy (a), the employment level within CGPs (b), the total units of capital (c), the labour productivity within CGPs (d). Each boxplot reports the distribution of the time averages over a twenty-year time period for each one of the twenty seeds considered.

caused by digital technologies within CGPs. However, Eurace is able to capture two different compensation mechanisms that counteract this technological unemployment, namely the compensation mechanism "via decrease in price" and "via additional employment in the capital good sector". The innovation process within manufacturing organizational unit $OU_1$ allows CGPs to save money linked to replaced workforce. This cost reduction leads to a unit price decrease as it is visible in Fig. 2 (b): high values of $\eta$ and high level of technological progress determine low price levels. In turn, this price decrease determines an increase in the real sales of consumption goods, see Fig. 2 (c). Obviously, lower consumption good price levels are related to higher real average wage, see Fig. 2 (d).

Fig. 3 shows the trend of the consumption goods (CGs) prices level over time. In the case without tangible investments prices increases over time, whereas for $\eta = 0.1$; 0.2 and 0.3 prices tend to decrease in the long term reflecting technological progress and this trend is the representation of the compensation mechanism "via decrease in price" cited above. In the case characterized by $\eta = 0.05$, although the CGs price level is lower compared to the case without intangible investments, it continues to growth with a lower rate: the technological progress determines a slowdown of CGs price level growth instead of a decrease.

Fig. 4 (a) shows that the unemployment level increases over time in every scenario considered except for the "No Intangible Investments" case in which it remains constant. It is worth highlighting that for the first ten years, the unemployment levels are quite similar in all the scenarios and acceptable. In particular, for $\eta =$ 0.05 and 0.1 the percentage of unemployment is equal to the case characterized by the absence of intangible investments. After the first ten years the trajectories tend to separate and this separation intensifies over time.

Obviously, the unemployment trends are strictly related to the technological progress within the economic system. Fig 4 (b) shows the average elasticity of substitution $\sigma$ characterizing the economy. In the "No Intangible Investments" case it remains constant, whereas in the other cases it increases during the time. In the first ten years, the values assumed by $\sigma$ do not involve mass unemployment because the system is able to counteract quite effectively the job destruction within the CGPs industrial sector also for high values of $\eta$ (namely 0.2 and 0.3). After ten years, $\sigma$ assumes values significantly higher than one for high values of $\eta$ and this fact leads to critical levels of unemployment at the end of the period. In this scenarios, the

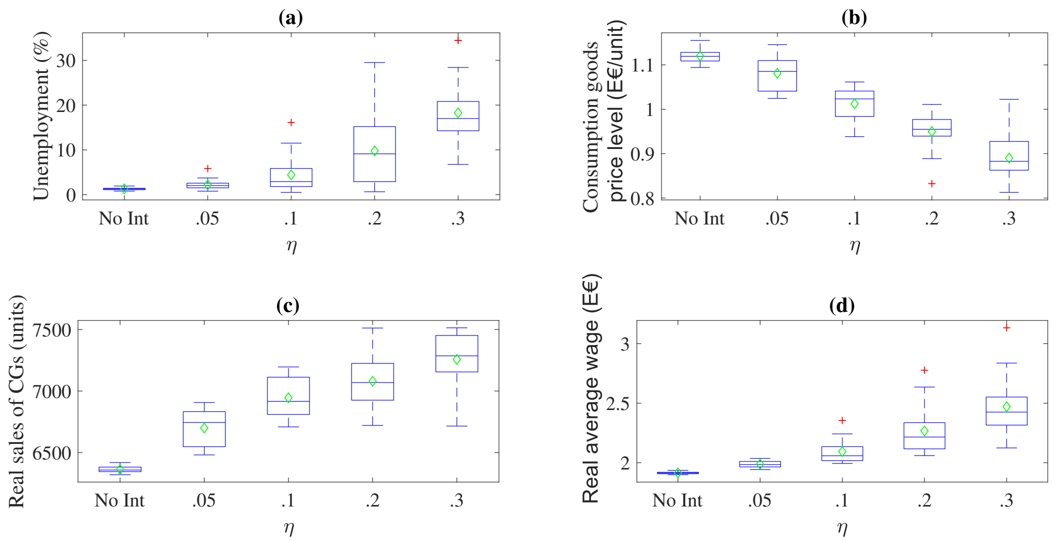


Figure 2: The figure shows a series of boxplots representing, for any scenario, the distribution of: the unemployment level (a), the consumption goods price level (b), the real sales of consumption goods (CGs) (c), the real average wage (d). Each boxplot reports the distribution of the time averages over a twenty-year time period for each one of the twenty seeds considered.

compensation mechanisms are not capable to counteract innovation process within CGPs. In fact, Fig. 4 (c) and (d) show a decrease in the CGPs employment and an increase of their capital endowment, respectively. In other words, machines replace human beings in the jobs that they used to perform within CGPs and this tendency is amplified as technological progress increases. The unemployment level remains acceptable in the long term only for $\eta = 0.05$. Indeed, it remains quite constant as in the case without digital technological progress.

Fig. 5 (a) and (b) show the increase of the labour productivity $P_L$ and the decrease of the capital productivity $P_K$ over time. The former reflects the unemployment trend displayed by Fig. 4 (a) and the latter reflects the evolution of the stock of capital within the system shown by Fig. 4 (d). In particular, as regards $P_L$, it remains constant in the case without digital investments whereas in the other ones it increases over time proportionally to the technological progress itself. As far as $P_K$ is concerned, after a transitory phase in which trajectories are almost the same, it decreases over time proportionally to the technological progress.

The massive unemployment affects also CGPs sales: beyond a certain limit, technological progress turns out to be a double-edged sword. As a matter of fact, while CGs real sales increases over time for $\eta = 0.05; 0.1; 0.2$, for $\eta = 0.3$ they reach a plateau after the fourteenth year. In this regard, it is worth noting that, after fourteen years the stock of capital decreases for $\eta = 0.3$ , see Fig. 4 (d). Although there is a decrease in the CGPs capital endowment, the sales are stable in the long term, as just noted. This fact is linked to an increase of the market concentration, see Fig. 5 (d). As a matter of fact, for $\eta = 0.3$, the market concentration increases over time in a significant way. Therefore, firms that experience a reduction of their sales stop to invest in machines and the depreciation process determines a decrease in their capital endowment. At the same time, firms that experience an increase of market share tend to maintain or increase their capital stock. Even in the case without intangible investments, the market concentration doubles, causing the emergence of a group of larger companies on the market. However, the technological progress amplifies market concentration: the first firms that adopt technologically advanced digital assets are able to manufacture their products with lower costs acquiring higher market shares. In other words, process innovation helps firm to be more competitive and increase their revenues.

As far as the compensation mechanism “via additional employment in the capital good sector” is con-

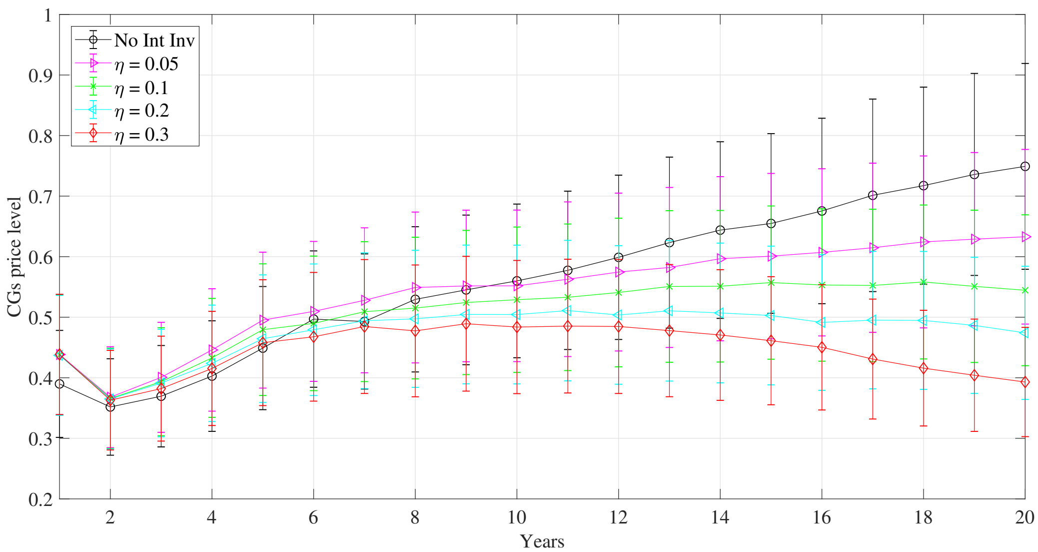


Figure 3: For each scenario considered, the figure displays for each year the mean across 20 seeds (with the related standard error) of the yearly time averages of the CGs price level.

cerned, it is related to the increase of employment in the capital good sector. In fact, the substitution of the workforce with capital determines a higher demand of capital, both "hard" and digital, which increases with $\eta$. As mentioned above, the two kinds of capital are complementary: each unit of "hard" capital is associated with a digital asset license. Therefore, the employment level within DADs and the KGP increases with $\eta$, see Fig. 6 (a) and (b).

The two compensation mechanisms are not able to counterbalance effectively the technological unemployment caused by technologically advanced digital assets in the CGPs. This is why the system experiences high levels of unemployment for high values of $\eta$.

It is worth noting that other compensation mechanisms do not emerge or do not have been modelled in Eurace, e.g. the "via new products" one. This fact may have influenced the unemployment levels displayed by the model, making them higher compared to the potential levels achievable in case of high technological progress. However, the coexistence of all the compensation mechanisms is not possible. For instance, the compensation mechanism "via increase in incomes" is not compatible with the "via decrease in wages" one, as reported by Vivarelli (2014).

The increase of the capital stock in production processes determines a decrease of the capital productivity $P_K$, which is defined through the ratio between the CGPs output and the capital endowment, see Fig. 6 (c). In this Eurace framework, technological progress does not affect the total factor productivity as in Bertani et al. (2020a,b), but it influences the elasticity of substitution $\sigma$. Therefore, technological progress allows CGPs to produce the same amount of output using a different optimal combination of production factors characterized by a reduction of the most expensive input and an increase in the cheapest one. In this regard, it is worth highlighting that a decrease in the adoption of an input is always compensated by an increase in the other one. Since capital is the least expensive, CGPs tend to adopt more capital in the production process instead of workers[8]. This is why the capital productivity $P_K$ decreases with $\eta$. Empirical evidences

[8]It is worth noting that an increase of the elasticity of substitution $\sigma$ could also determined exactly the opposite, namely an increase in the number of workers and a decrease in the stock of capital. However, the use of capital turns out to be less expensive compared to the workforce and the optimization leads to an increase in the capital endowment. In fact, for any value of the elasticity of substitution, the cost of the capital required to produce a unit of consumption good tend to be lower compared to the labour one.

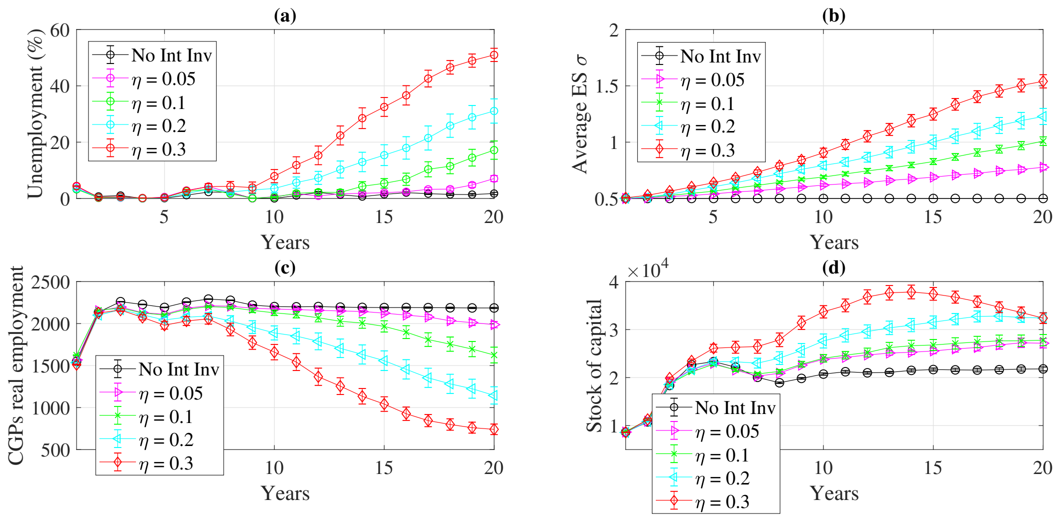


Figure 4: For each scenario considered, the figure displays for each year the mean across 20 seeds (with the related standard error) of the yearly time averages of: the unemployment level(%) (a), the average elasticity of substitution ES $\sigma$ (b), the number of workers within CGPs (c) and the stock of capital (d).

show that $P_K$ has been decreasing in most of OECD countries for the past twenty years. On the contrary, even if faintly, the labour productivity has been growing for the past twenty years in OECD countries, see OECD (2019).

According to our model, besides decreasing costs of using capital, a potential explanation of this phenomenon could be found in an increase of the elasticity of substitution $\sigma$. In fact, the model shows that an increase of $\sigma$ leads to an increase of $P_L$ and a decrease of $P_K$. From a financial perspective, it is logic to adopt to a large extent (or completely) the cheapest input factors in the production process. However, there must be also the technological possibility to do this: input factors must be replaceable in a high range of tasks. Therefore, the adoption of an input factors is not only determined by the costs, but it depends also on technology.

Although the level of unemployment increases with $\eta$, the economy experiences also high values of real GDP for high values of $\eta$, see Fig. 6 (d). Obviously, these high real GDP levels are linked to low prices and also to the Government which ensures a welfare system through fiscal policy that guarantees an economic subsidy to unemployed households. This subsidy allows unemployed to perform a basic subsistence consumption.

It is worth underlying the different employment levels related to the various education degrees characterizing households. In fact, workers can be distinguished in five groups based on their education levels. The various kinds of firms demand different types of workforce according to the tasks that they have to perform and in order to develop and produce their products: DADs hire only workers from the third up to perform R&D activities; CGPs hire undergraduate workers (from the first to the third education level) to employ in the manufacturing organizational unit $OU_1$ and graduate workers (fourth and fifth education level) in order to use them in the organizational unit $OU_2$ in which the various intellectual tasks are performed; KGP hire workers disregarding their education level to produce "hard" capital. According to our modelling assumptions, the digital technological progress affects the manufacturing unit increasing the elasticity of substitution $\sigma$ between labour and capital. Therefore, workforce characterized by low education levels is directly influenced by process innovation. For each value of $\eta$ considered, Fig. 7 shows the trend of the employment levels related to the various education degrees characterizing households. In the "No intangible investment" case (see Fig. 7 (a)) for each education level the number of workers is constant over time. As regards the other cases, workers with education level equal to 4 and 5 remain constant over time, whereas those with an educational level equal to 1,2 and 3 decrease over time and this fact reflects the technological progress within the economy. As a matter of fact, as pointed out above, technological progress increases over

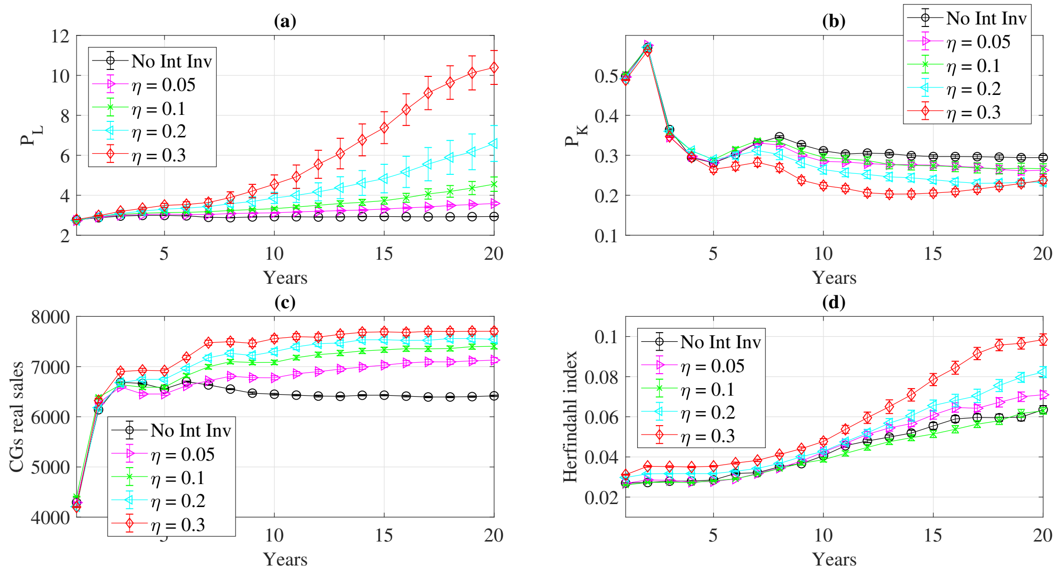


Figure 5: For each scenario considered, the figure displays for each year the mean across 20 seeds (with the related standard error) of the yearly time averages of: the labour productivity $P_L$ (a), the capital productivity $P_K$ (b), the CGs real sales (c) and the stock of capital (d).

time determining the replacement of labour with capital within the manufacturing organization units and this tendency increases with $\eta$.

### *4.3. The competitive dynamics between DADs*

In this subsection, we explore the competitive behaviour showed by DADs within digital technologies market. It is worth highlighting that also the Eurace framework described in Bertani et al. (2020a,b) presents the same business dynamics. As mentioned above, DADs compete in order to increase their market share trying to improve their products and varying their license unit cost. In fact, according to Eq. 12, a higher value of $\sigma$ (linked to a successful R&D activity) or a lower price can determine the switch between digital assets.

Fig. 8 (a) shows the emergence of a market leader in the long term on the digital assets market: a DAD acquires almost all of the digital technologies market. In other words, it emerges one of the most important features related to the increasing returns world, namely the winner-take-all phenomenon.

The emergence of a market leader results to be the consequences of an intense competition between DADs. Fig. 8 (a) shows that the market shares of digital technologies producers vary over time; they lose and gain market shares continuously before the ascent of a definitive market leader, namely $DAD1$, which detains most of the digital market. Although other DADs, i.e. $DAD2$ and $DAD3$, try to contrast the rise of $DAD1$ decreasing their prices and giving also their licenses for free in certain periods, they are not able to recover their lost market shares; the higher revenues deriving from the higher number of licenses sold allow $DAD1$ to increase its R&D intensity and develop improved version of digital assets (see 8 (b)) and its competitors can not compensate the increasing technological gap with lower prices, see 8 (c). In this regard, digital assets produced by $DAD1$ allow CGPs to replace workers with capital in a wider range of tasks compared to the other digital technologies on the market and this fact determines a significant cost reductions. In fact, $DAD1$ can also increase significantly its license unit price once it has technologically surpassed other DADs. Using other terms, these digital assets increase the production process efficiency allowing to produce the same amount of goods using less financial resources. From this perspective, the elasticity of substitution $\sigma$ can be considered as an efficiency parameter as argued by de La Grandville (1997).

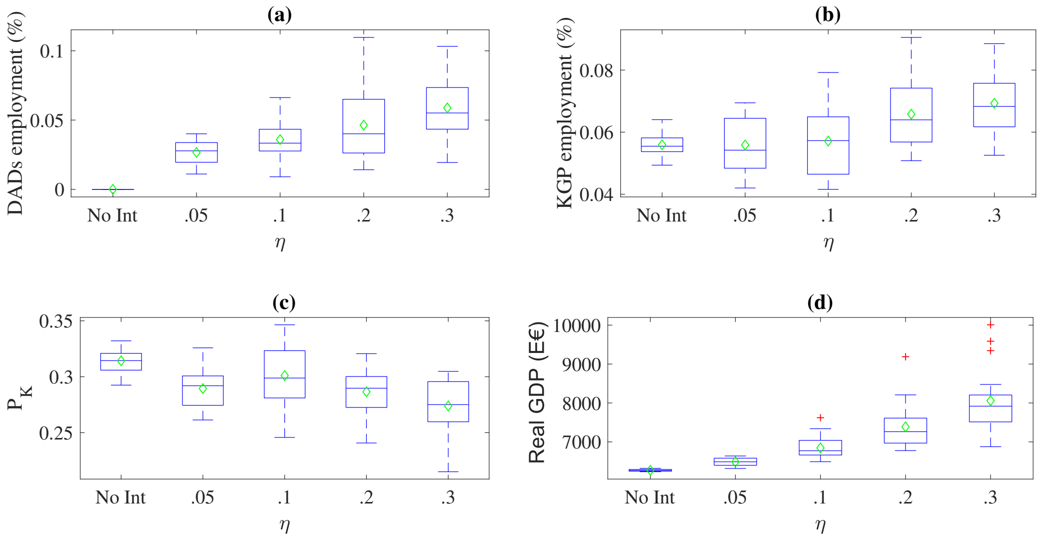


Figure 6: The figure shows a series of boxplots representing, for any scenario considered, the distribution of: the employment level within DADs (a), the employment level within KGP (b), the capital productivity $P_K$ (c), the real GDP (d). Each boxplot reports the distribution of the time averages over a twenty-year time period for each one of the twenty seeds considered.

### *4.4. Elasticity augmenting approach and total factor augmenting approach: a technological unemployment comparison*

We present here a comparison between the total factor augmenting approach in Bertani et al. (2020a,b) and the elasticity augmenting approach of this paper. It is worth noting that the two Eurace versions under analysis are characterized by different production technologies. In the total factor augmenting framework, the production processes of CGPs are modelled through the constant returns to scale Cobb-Douglas production function which has always been used in the Eurace research works. In this new research, we adopt a Leontief production function based on the concept of organizational units. Therefore, being production technologies different, a punctual analysis showing differences between each variables results to be not significant and effective.

One sensible comparison can concern the technological unemployment within the economic system. Fig. 9 shows that for low values of $\eta$ (to which low technological progress rates correspond) the unemployment level within the economy are similar. At the same time for high values of $\eta$ the unemployment level is significantly higher in the total factor augmenting framework. This difference is strictly linked to the compensation mechanism "via additional employment in the capital goods sector". In the total factor augmenting version, digital technological progress influences in the same way capital and labour, determining a decrease of both input factor demands. On the other hand, in the elasticity augmenting framework, digital technological progress affects the elasticity of substitution between labour and capital. This leads to a replacement of labour with capital. Therefore, the compensation mechanism "via additional employment in the capital goods sector" is more effective because it works not only in the DADs industrial sector but also in the KGP.

## 5. Conclusion

Starting from the concept of organizational unit, we have implemented a new production function within the macroeconomic agent-based model Eurace. In particular, this production technology is represented by a Leontief function in which the macro input factors are organizational units. In turn, the contribution of these units is given by the combination between labour and capital or only by labour. In order to evaluate the potential consequences of digital technological progress on the economy, we have proposed an alternative

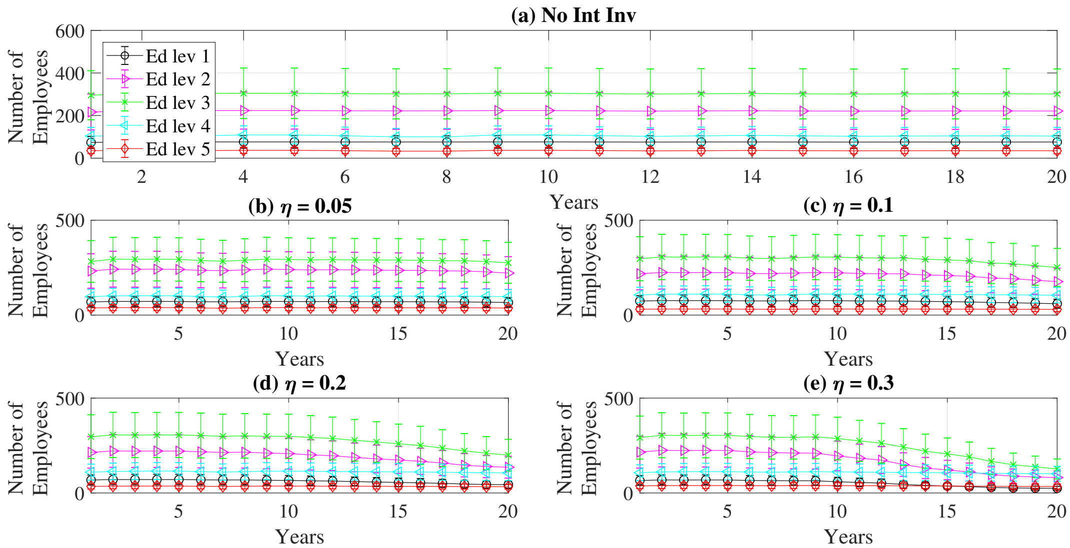


Figure 7: For each scenario considered, the figure displays several subplots representing for each education level and for each year the mean across 20 seeds (with the related standard error) of the yearly time averages of the number of workers within the economic system.

approach, namely the elasticity augmenting approach. According to this modelling assumption, the technological progress affects the elasticity of substitution between capital and labour within the manufacturing process. Through this approach, we want to represent the evolution of digital technologies over time which are able to replace human beings in an ever wider set of tasks.

The engine of the technological progress in Eurace model is represented by the so-called digital assets developers. In fact, these agents invest a fixed fraction of their revenues in order to perform R&D activities to improve their products. Digital assets, e.g. software, artificial intelligence, etc., are required by CGPs to perform their production activities: by virtue of the complementarity between hardware and software, they install these digital technologies within "hard" capital in order to produce consumption goods.

The research work underlines the growing importance of digital technologies and their technological progress in our economy. In particular, it shows the significant influence that digital technological progress has on the labour market. It is worth noting that the potential future consequences and scenarios linked to digital innovation that we could experience in the future are strictly influenced by the rate of the technological progress itself. According to our computational results, high rates of technological progress could lead to a long term mass technological unemployment. This outcome is due to the ineffectiveness of the economic system to absorb all the technological unemployment caused by digital assets: compensation mechanisms captured by Eurace are not able to counteract effectively the replacement of human workers with technologically advanced machines.

However, results are also affected by the absence of other compensation mechanisms, e.g. the "via new products" one, and specific policies aimed at countervail the negative effects of process innovation, e.g. the introduction of a robot tax or a reduction of working hours. In this respect, it is worth noting that the coexistence of all compensation mechanisms described in literature is not possible because some of these are in clear contradiction with each other. As regards potential policy measures in order to stem and prevent critical level of unemployment, they will be the object of our future researches.

Comparing the elasticity augmenting approach with the total factor augmenting one (which has been used in the previous Eurace extension concerning digital technological progress), the former results to be more realistic because it is able to capture a decreasing capital productivity and an increasing labour productivity in line with what it is experienced by the economy. By influencing the elasticity of substitution,

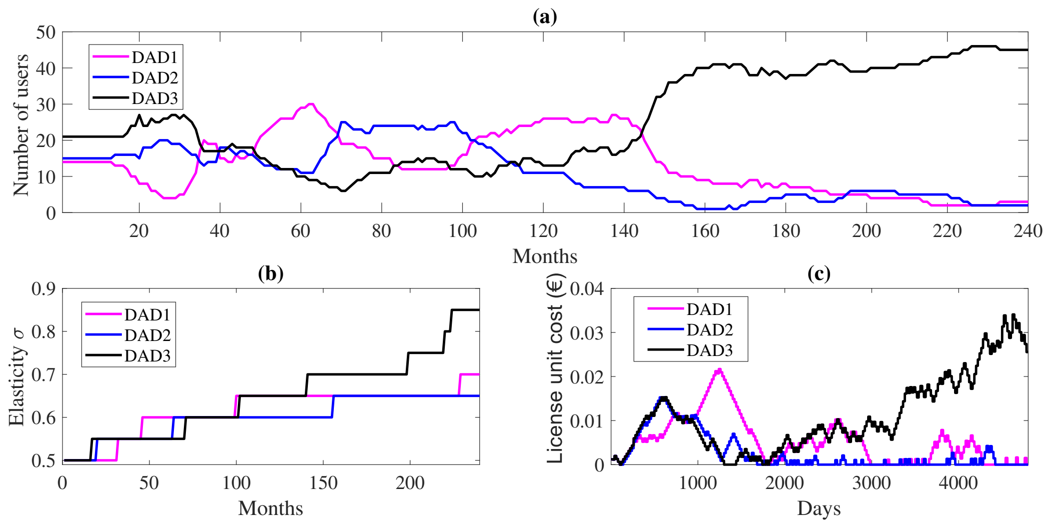


Figure 8: The figure displays various time series in case of $\eta = 0.2$; in particular it shows: number of users (a), Elasticity of substitution ES $\sigma$ (b) and license unit cost (€) (c) of the three different digital assets developers. All time series refer to a specific replication which is representative of the system average trend in case $\eta = 0.2$.

the technological progress determines a replacement of labour with machines, whereas, in a total factor augmenting framework, it determines a decrease of the demand of both production factors.

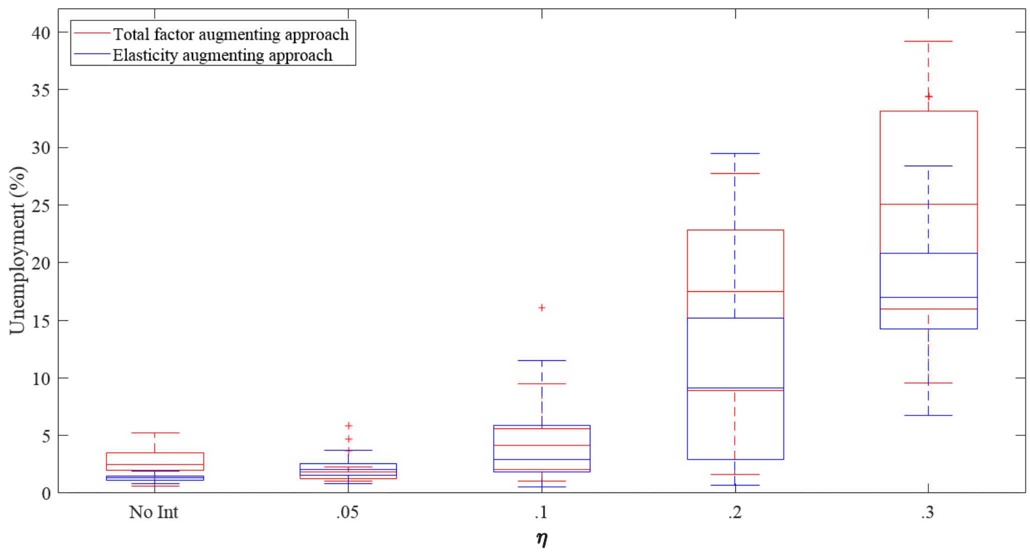


Figure 9: The figure shows a series of boxplots representing, for any scenario and Eurace version considered, the distribution of the unemployment level (%). Each boxplot reports the distribution of the time averages over a twenty-year time period for each one of the twenty seeds considered.

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