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An economy under the digital transformation

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Abstract

During the last twenty years, we have witnessed the deep development of digital technologies. Artificial intelligence, software and algorithms have started to impact more and more frequently in our daily lives and most people didn't notice it. Recently, economists seem to have perceived that this new technological wave could have some consequences, but which one are they? Will they be positive or negative? In this paper we try to give a possible answer to these questions through an agent based computational approach; more specifically we enriched the large-scale macroeconomics model EURACE with the concept of digital technologies in order to investigate the effect that their business dynamics have at a macroeconomic level. Our preliminary results show that this productivity increase could be a double-edged sword: notwithstanding the development of the digital technologies sector can create new job opportunities, at the same time, these products could jeopardize the employment inside the traditional mass-production system.

Keywords: Intangible assets, Industry 4.0, Digital revolution, Agent-based macroeconomics

1. Introduction

During the course of history, several technological evolutions have changed and influenced the lives of human beings. In this paper we focus our attention on the impact of the digital transformation on the production systems and, as a consequence, we evaluate the potential variation of the employment rate in the long term. According to Brynjolfsson and McAfee (2014), we are facing "The Second Machine Age" that is revolutionizing our world. In particular, the authors argue that probably one of the most important technological discoveries has been the steam engine perfected by John Watt in the second half of

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the eighteenth century which allowed to produce a huge amount of mechanical energy. After that, there have been further technological developments which impacted on our production systems and, thanks to electronics and information technology, in the second half of the twentieth century the assembly lines have been largely automated. Nowadays, we are facing a new technological wave, in fact, digital technologies have been the subject of an intense improvement and the possible consequences of this productivity enhancement make economists reflect. The substantial difference between digital technologies and industrial automation is that while the latter helps human beings to overcome the limits linked to physical force, thanks to the former we can surmount the limits imposed by our mind.

At this point, a question arises spontaneously: what will be the consequences of the advent of these new digital technologies on jobs? According to Acemoglu and Restrepo (2017a,b, 2018a,b,c), AI and robotics, as automation, replace human beings in jobs that they previously performed, creating a "displacement effect". One of the most important aspects consists in the fact that, while technology until our days has impacted principally on workplaces occupied by "blue-collars" workers, now these kind of instruments probably will affect the so called "white-collars" workers.

Furthermore, it's really interesting to notice how the business dynamics related to the companies which develop and produce digital technologies are completely different compared to the economic dynamics that characterized mass-productions. As a matter of fact, Arthur (1989, 1990, 1994, 1999b) distinguishes between two different worlds: a mass-production world, characterized by diminishing returns, in which products are heavy on resources and light on knowledge and a knowledge-based world that, on the contrary, is characterized by increasing returns. In this particular reality, which regards high-tech producers, products require a deep know-how and scarce quantity of resources; in other words, this companies have high R&D fixed costs compared to their variable production costs. Furthermore, always according to Arthur, the world ruled by increasing return presents several other characteristics as network effect, path dependence, market instability, unexpectedness, winner-take-all and technological lock-in. These features are being studied in a field called Complexity Economics which, unlike the standard economic theory, emphasizes interaction among economic agents through an out-of-equilibrium approach, see Elsner et al. (2014); Arthur (1999a, 2014); Fontana (2010).

Agent-based modelling represents the best approach in order to address these aspects, see Gallegati (2018); North and Macal (2007); Hommes and LeBaron (2018), and for this reason we use this tool to conduct our analysis. In particular, we enrich a pre-existent large-scale macroeconomics model: EURACE, see Mazzocchetti et al. (2018); Ponta et al. (2018); Raberto et al. (2012); Teglio et al. (2012). The concept of innovation has already been deeply investigated through the agent based modelling, see e.g Pyka et al. (2010); Dosi et al. (2010); Caiani et al. (2018); Fanti (2018); Dawid and Reimann (2011). The EURACE model as well has been endowed with the concept of innovation, that refers to tangible capital goods, see Dawid et al. (2008). However, our research interest is different and focuses on innovation from an other perspective: the productivity increase provided by intangible digital capital goods. Software, algorithms, artificial intelligence and their developers represent the subject of our study and, as a matter of fact, we want to link the new concept of innovation to the "digital revolution", see Brynjolfsson and McAfee (2011). So, the introduction of digital technologies inside the EURACE model represents the attempt to reproduce the advent inside the economy of Industry 4.0 according to which not only the production processes are automated, but also decisions start to be subject to automation technology, see Kang et al. (2016); Parrott and Lane (2017); Cotteleer and Sniderman (2017). The new EURACE model features about the production of digital intangible Technologies are presented in Section 2. Section 3 shows our preliminary computational results. Conclusion and remarks are provided in Section 4.

2. Modeling the digital economy

2.1. Outline of the basic EURACE model

The base version of the stock-flow consistent EURACE model includes several agent populations, in particular it incorporates: consumption goods producers (CGPs), that manufacture a homogeneous consumption good; a capital good producer (KGP), which produces means of production (for instance machine tools); households (HHs), that perform as workers, financial investors and consumers; commercial banks (Bs) and two policy makers: the government (G) and the central bank (CB), responsible for fiscal and monetary policy, respectively. To address the issue of the consequences of the new technological wave on the economy the intangible digital assets developers (DADs) agents have been included in the model.

The graphical representation of the present EURACE model in terms of agent classes (ellipses or rectangles) and current account monetary flows (arrows) is shown in Fig. 1. Rectangles are used when just one instance of the class is considered in the model, whereas ellipses are intended to represent the presence of multiple heterogeneous instances of the agent class. The yellow background refers to the newly introduced agent. The arrows represent the current account flows.

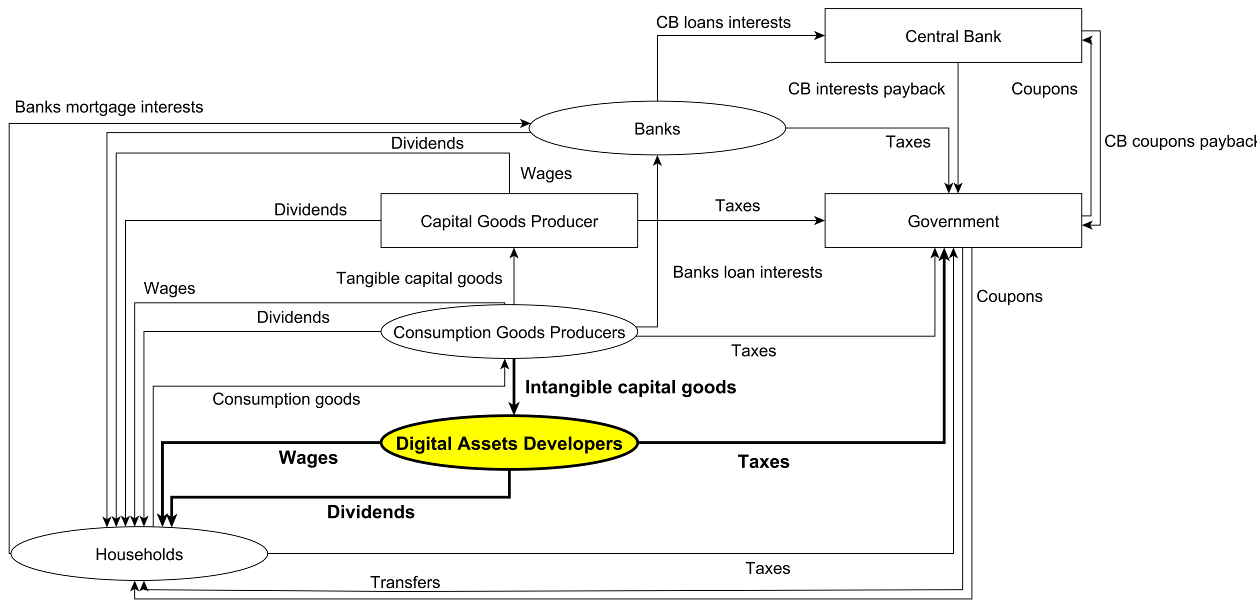

Figure 1: Graphical representation of the present EURACE model in terms of agent classes (ellipses or rectangles) and current account monetary flows (arrows). Rectangles are used when just one instance of the class is considered in the model, whereas ellipses are intended to represent the presence of multiple heterogeneous instances of the agent class. The yellow background refers to newly introduced agent.

The agents interacts through different decentralized and centralized artificial markets; the former for consumption and capital goods, labor, housing and credit, whereas the latter for firms (or banks) stocks and government bonds. Bounded rationality and limited capabilities of computation and information gathering characterize agents' behaviour; see Teglio et al. (2017); Ozel et al. (2019); Raberto et al. (2018) for a detailed description concerning markets and comportment of agents. Furthermore, as underlined in Ponta et al. (2018) the Stock-Flow-consistency represents a distinctive feature of the EURACE model; in fact each agent has its own balance sheet which includes the details regarding assets and liabilities, see Godley and Lavoie (2016); Godin and Caverzasi (2014); Ponta et al. (2018).

2.2. Intangible digital assets

As said above, in the present study, the EURACE model is characterized by a new class of productive capital which is represented by intangible digital assets, say software or any other digitalized knowledge-based assets, e.g., algorithms, advanced routines, instructions. These new capital assets are developed and supplied by a new class of agents, namely the intangible digital assets developer (DAD), and are employed in the production process by CGPs with the purpose of rising total factor productivity. Intangible digital assets are heterogeneous among the different DADs active in the economy, depending on their accumulated digital knowledge, which increases over time based on the R&D investments made. Obviously, this new type of asset implies the existence of a novel digital market, in which DADs can potentially compete.

2.3. Supply side

In line with the literature on intangible capital, see e.g. Haskel and Westlake (2017), we assume that intangible digital assets are non-rivalrous, i.e., they are characterized by zero marginal production costs. In particular, production costs are actually given only by the R&D costs, which are determined by the cumulated labor costs of the skilled labor force employed at any DAD agent.
On a monthly basis, each DAD agent d has a chance to develop a new version of its digital capital asset which is characterized by higher knowledge content, then more productivity when employed in the production process by CGPs. The probability $prob_d$ of a successful completion of development of the new digital asset version is set to depend on the cumulated person months M_d employed by the DAD since the latest version development, as follows:

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

where η is a shape parameter, homogeneous across all DAD agents, setting the development speed, i.e., the higher is η, the higher is the probability to develop an improved version of digital assets, for any level of cumulated person months

M_d employed. The rationale behind the shape of Eq. 1 is to set the probability as an increasing monotone function of cumulated human efforts devoted to R&D but with decreasing returns to scale. It is also worth noting that R&D is modelled here as an uncertain activity whose positive outcome, i.e., a higher level of knowledge reached by the DAD, then leading to an improved version of its produced digital asset, is never granted in principle, since the probability is equal to 1 only asymptotically for an infinite number of person months. DADs determine the number of employees monthly according to their revenues, precisely the hiring of workers represents a fraction of the DADs monthly turnover. Obviously, this means that the number of employees in the DADs sector is influenced not only by revenues, but also by the average wage characterizing the economy.

2.4. Demand side

Intangible digital assets are demanded by CGPs which pay a user license to DADs for their utilization. According to the model design, every CGP adopts one intangible digital technology at a time, i.e., its digital assets in use are supplied by only one DAD. The knowledge level of the employed digital technology sets the total factor productivity of the CGP. In particular, along the lines of Teglio et al. (2017), we consider the labor force N_f, employed at any CGP f, and its physical capital endowment K_f, as the production factors employed for the production of consumption goods q_{C_f}, according to a Cobb-Douglas technology, i.e.,

$$q_{C_f} = \gamma_f N_f^{\alpha} K_f^{\beta} \,, \tag{2}$$

where α and β are the production elasticity parameters and γ_f is the total factor productivity. An important novelty with respect to the baseline EURACE model is that γ_f is not anymore an homogeneous constant across all the CGPs but a variable, specific to each CGP, which increases over time based on the knowledge content κ_d of the digital asset adopted by each CGP, i.e., the digital knowledge level reached by its supplying DAD agent. In particular, total factor productivity γ_f is modelled as follows:

$$\gamma_f = \exp(1 + \eta_\gamma \kappa_d) \tag{3}$$

where the knowledge level κ_d is an integer variable whereas η_γ is a scale parameter, homogeneous across all CGPs.

For the right of use of its intangible digital technology, a DAD agent d charges CGP f a monthly amount of money proportional to the level of capital endowment K_f of CGP f, i.e., an amount equal to $p_{D_d} K_f$, where p_{D_d}, set by the *DAD* agent, could be considered as a user license unit price. The rationale of this modelling feature is that, even if intangible digital assets are non-rivalrous, then replicable many times at no additional cost irrespective of the size of the CGP's capital, the related services of installation, maintenance, and assistance, which we assume are provided by DADs as well, are an increasing monotone function of the size of capital stock. For instance, often the price of software

licenses depends on the number of computers where it is installed. For the sake of simplicity, we state that this dependence is linear and that the DAD agent simply charges a unit license cost p_{D_d} multiplied by the size of physical capital, say computers, or more generally physical machines that can be automatized and then made more productive by means of intangible digital technology.
On a monthly basis, the CGP has a given exogenous probability $prob_f$ to consider the adoption of a different digital technology, i.e., to assess costs and benefits of switching from the present digital supplier d to another one d^*. In particular, the cost-benefit analysis consists in computing the net present value (NPV) of expected net future cash flows that the CGP would get with the switch, as follows:

$$NPV_{d^*} = \frac{p_{C_f}(q^*_{C_f} - q_{C_f})}{r_D} + \frac{(p_{D_d} - p_{D_{d^*}})\,K_f}{r_D} - w\hat{N}_f\,, \tag{4}$$

where the first term gives the present value of the gain (loss) in future revenues, the second addend is given by difference between the user license unit price of the new digital technology under consideration and the one currently in adoption, the third and final term takes into account the training costs that the firm would face for its personnel to manage the new digital technology. In particular, the first addend of Eq. 4 is intended to take into account that the difference in productivity between the two technologies, see Eq. 3, implies an expected different production level, given the present endowment of production factors, labor and capital, according to Eq. 2, then different expected future revenues[1]. In addition, the second term of Eq. 4 takes into account the difference in the user license equation bill. In this respect, the CGP usually faces a trade-off between expected higher (lower) future revenues due to a more (less) productive alternative digital technology and higher (lower) costs for the digital services provided by the DAD, since higher (lower) productivity of the digital asset are usually accompanied with higher (lower) unit user license price, as outlined in the next section.

2.5. Digital asset price dynamics

CGPs pay monthly the unit license price to the reference DAD. In order to endow DADs with a competitive comportment, we implement an active pricing mechanism which can possibly be turned off. Consequently, the absence or presence of this dynamics allows us to evaluate two different situations: a case of price collusion, in which DADs jointly decide to adopt the same user unit license price p_{D_d}, that we call “Passive pricing” case, and a price war scenario characterized by aggressive and competitive behaviours which we call “Active pricing” case. In both cases, the license price is proportional to the average wage w which characterized the macroeconomic system. This modelling choice

[1] The implicit assumption made here is that all consumption goods will be sold at the present price p_{C_f}

is related to the R&D activity performed by the various digital firms; as a matter of fact, in order to develop and produce their products, they need to hire researchers whose wages will constitute the costs incurred by them. So, for this reason, we link the cost structure to the revenue structure. Moreover, for the same reason, we assume that the training cost per worker is equal to w, see Eq. 4. The user license unit price p_{D_d} for every DAD in case of "Passive pricing" follows this relation:

$$p_{D_d} = \lambda w \tag{5}$$

where λ, in case of "Passive pricing", is an exogenous and homogeneous parameter , while in the other case it can increase or decrease over time according to an exogenous parameter δ; the positive or negative contribution of the latter depends on the number of sold licenses: if the DAD finds an increase in sales, it decides to enhance the price, otherwise it opts for a price reduction in order to assume a better market position. In fact, as shown in the Eq. 4, the user license unit price could determine the transition from a certain digital technologies to a cheaper one. So, in case of "Active pricing", λ assumes a heterogeneous and variable connotation.

2.6. Employees digital technologies skills

As regards the employees, the third term of the Eq. 4 is related to the training costs which a company should support in order to make workers operational with the alternative digital technologies. Every worker is endowed with a set of "digital technologies" skills, that can be as large as the number of DADs present in the economy. These skills represent the employee ability to handle the different types of digital assets and the possibility to expand this set is linked to the training courses provided by the DADs; so, from a financial perspective the gain for DADs comes from two different activities: the selling of licenses and the training courses. From a modelling point of view, the training costs for the company are given by the number of workers without the "digital technologies" skill taken into account ($\hat{N}_f$) multiplied by the training cost per worker (w). The lower these costs, the higher the probability to adopt a new kind of digital assets. As a matter of fact, with this particular micro-assumption, we want to model the presence inside EURACE macro-economy of a network effect related to the transition from digital technologies less widespread to others more diffused. In fact, companies virtually benefit from the "digital technologies" skill of their workers and this precisely happens when they are valuing a possible digital assets change: higher the number of workers with that particular skill, lower the transition costs to that alternative digital technologies which could be cheaper or more productive.

The continuous turnover characterizing the EURACE labour market helps the diffusion of the predominant digital technologies reflected on the long term inside the economy by the number of workers with that "digital technologies" skill. Obviously, not only companies can benefit from the skills acquired by their workers in case of a digital technology transition but, at the same time, DADs can profit from employees skills: the higher the number of workers able to use their digital assets, the higher the probability to sell their products.

3. Computational results

3.1. Design of experiments

The new EURACE model features allow us to analyze various scenarios. In particular, we consider two different digital assets pricing scenarios: in the first named "passive pricing", DADs sell their licenses at the same price, determined as a fixed share of the nominal wage; in the second, henceforth "active pricing" scenario, we endowed the firm with the possibility to raise or decrease independently their license prices; the choice between these two options depends on the market share owned by them: the bigger the share, the higher the price and vice versa, as outlined in the previous section. In order to conduct an in-depth analysis, we explore the two cases previously described with six different values of η, the parameter which controls the probability to develop an improved version of the digital asset, see Eq. 1; in this way we obtain twelve different scenarios. The methodology of our study is based on Monte Carlo computational experiments: each scenario is simulated with twenty different seeds of the pseudo random number generator. So, a total of 240 simulations has been considered in order to conduct our investigation. Obviously, all the parameters are identical across the different scenarios except for η. The computational results shown in the following subsections, in accordance with the methodology used, are presented in the form of boxplots, an ordinary mode to present data distribution. In particular, each boxplot shows the distribution of the time averages of relevant variables over twenty years long time interval, concerning the twenty simulations characterized by different seeds. Boxes enclose the values from the first to the third quartile; they also comprehend whiskers that extend up to minimum and the maximum data points not considered outliers; the horizontal segments inside boxes represent the median of the distribution. Moreover, in order to give a complete overview of the model response, we plot also the time series of the most important variables of interest, so to show the trend during the entire twenty years long simulation; all time series considered refer to a specific seed. Our analysis aims to investigate the behavior of DADs at a micro level in order to verify the possible existence of the phenomena that characterize the "Increasing-returns World"; at the same time, it leads us also to asses the impact of this new industrial sector at the macro level.

3.2. "Active pricing" and "Passive pricing" business dynamics analysis

As we can see in Fig. 2(a), "active pricing" scenarios are characterized by higher values of total factor productivity (γ_f) compared to the "passive pricing" ones, independently of the value of η; this is due to the higher unit user license price p_{D_d} (whose distribution is reported in Fig. 2(b)), that in case of "active pricing" can be managed by the DADs in order to increase their revenues. Higher turnover does not necessarily involve higher R&D intensity, represented by the person months employed by the DAD, because, as already explained in the previous section, we link the cost structure to the revenues structure through the average wage w, see Eq. 5. So, the variable that effectively affects the R&D intensity is λ, which in case of "passive pricing" is fixed throughout the simulation, while in the other case varies according to the DAD pricing strategy. In presence of "active pricing", the average value of λ results to be higher, see Fig. 4(b), and this fact leads to a higher employment inside the DADs industrial sector (see Fig. 2(c)), and as a consequence to a greater average γ_f. At the same time, obviously γ_f increases with η which sets the

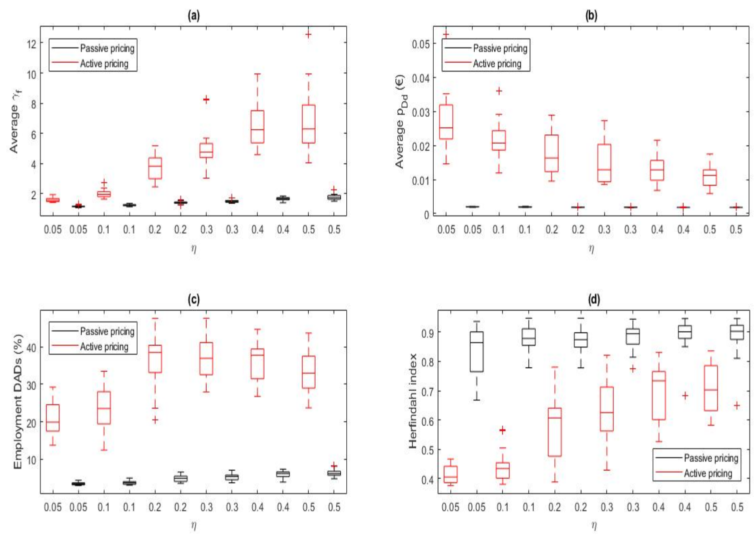

Figure 2: The figure shows a series of boxplots representing, for any values of η and for any pricing scenario considered, the distribution of: the average total factor productivity γ_f (a), the average unit user license price p_{D_d} (b), the employment in the DADs industrial sector (c), the Herfindahl market power index (d). Each boxplot reports the distribution of the time averages over twenty years long time period for each one of the twenty seeds considered.

size of R&D intensity inside the DADs. It is very important to note that the competition between DADs, related to the possibility of freely managing the price of their licenses leads to an increase in the average price itself compared to the "passive pricing" case, but, at the same time, it involves a higher quality of digital capital assets for the consumption good producers, which is reflected by γ_f. In fact, in the "passive pricing" case, DADs are limited in hiring new researchers because of their lower λ and obviously this fact implies a lower productivity for their digital assets. Furthermore, the competition between DADs established by the "active pricing" is accentuated by η; indeed the user license unit price (p_{D_d}) decreases as η enhances. At the same time, notwithstanding the average price decreases in case of high values of η, the market concentration increases[2], as it is visible in Fig. 2(d). This emerging phenomenon, that we call

[2]to represent the market concentration we use a standard measure: the Herfindahl index, see Kwoka (1985)

"converse concentration effect" appears in contradiction with the standard wisdom, according to which competitive markets, characterized by lower prices, are not concentrated. In this case, the competition represented by lower prices and consequently by lower values of λ, arises in order to contrast the market concentration that characterize the "Increasing-returns World" in which, by exploiting the right wave, a firm can lock-in the market. What stimulates the emergence of a product on others, and consequently the birth of market concentration, is competitiveness; after acquiring the highest market share, the leader company can afford to raise its price but always in agreement with the value perceived by the customer (related to the productivity and price). At the same time the other competitors, in order to gain market shares, tend to decrease their product prices. The results is a reduction of the average price. It is very important to note that the productivity (which represents the digital asset quality inside the model) and the "right price" combined together are the key to the company's success. On the other hand, in the "passive pricing" scenario, the Herfindahl index turns out to be high for each value of η; it happens because in this case only the "fortune" leads to a market lock-in and not a decision-making strategy. In particular, the "fortune" is represented by the randomness related to Eq. 1 which is not counterbalanced by any "active pricing" strategy. Going further with the analysis, the high employment in the digital technologies sector, in case of "active pricing", seems to represent the transition from a mass-production economy to an high-tech services economy. The "Displacement effect" in the consumption goods industrial sector, due to the enhancement of productivity of the digital assets, is contrasted by the creation of new jobs in the sector of the DADs. This behavior is clearly visible in Fig. 3 (a) and (b) where the employment concerning the DADs industrial sector increases over time, while CGPs hire less and less employees because of the high digital assets productivity (or Total factor productivity γ_f). As a matter of fact, it represents what Acemoglu calls the "Productivity effect": the higher demand for labor from the digital technologies industrial sector contrasts the "Displacement effect" generated by the digital transformation of the economy. Notwithstanding the creation of these new job opportunities, at the same time, for high level of γ_f DADs are not able to absorb all the unemployment created by their digital assets; Fig. 4(a) shows an increase of unemployment caused by the enhancement of η over time in both cases. It is interesting to note that for the first two values of η (0.05 and 0.1) the unemployment is higher in case of "passive pricing"; this is related to the fact that until these values, in case of "active pricing", DADs can absorb the unemployment caused by their digital assets. Beyond those values, the "displacement effect" is too high; in fact, we can see a significant difference between average productivity in the two cases, see Fig. 2(a). As we can see in Fig. 4 (c), the total number of licenses sold decreases with η both in case of "active" and passive "pricing"; logically, this is due to the higher value of γ_f which involves a lower stock of capital goods for the same output. Accordingly to the trend of γ_f, in case of "passive pricing" the number of licenses is higher compared to the "active pricing" case.

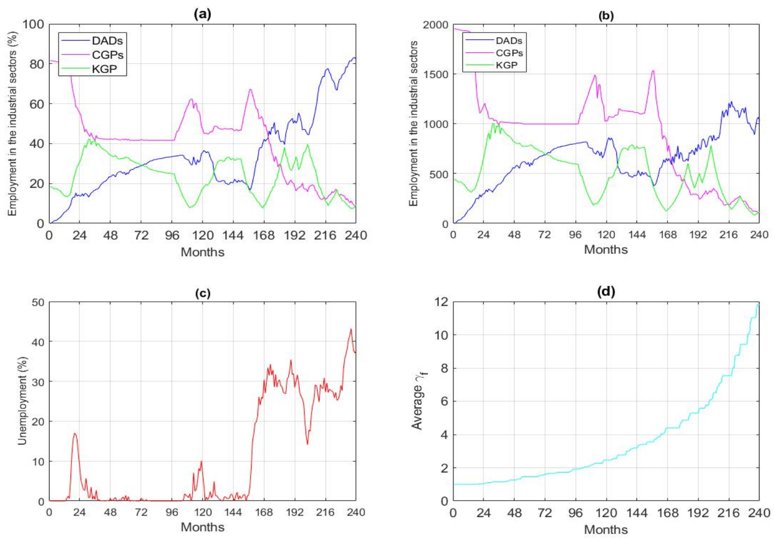

Figure 3: The figure displays various time series in case of "active pricing" and $\eta = 0.3$; in particular it shows: the percentage (a) and number of employees (b) in the various industrial sectors: consumption good producers (CGPs), capital good producer (KGP), digital assets developers (DADs); total unemployment (c) and average Total factor productivity (d). All time series refer to a specific seed.

3.3. Competitiveness in the "active pricing" case

In this subsection, we present a micro-analysis concerning the competitive dynamics involving the digital assets industrial sector in the "Active pricing" case. Fig. 5 displays the trend of the most important variables related to the DADs already mentioned above. It is very interesting to notice that a company assumes a leading market position; the emergence of this DAD on others is due to its chance to innovate, which allows it to develop technologies with a higher productivity. Despite the attempt of other DADs to regain the market shares lost, which becomes increasingly considerable, through a decrease of their license prices, on the long-term the leader DAD has deeply improved its product and this means that the higher productivity of its digital assets covers the price difference with other products. Furthermore, Fig. 5 shows that, notwithstanding $DAD2$ has a higher number of users (that are CGPs) compared to $DAD3$, this latter has sold (or renewed) a higher number of licenses in the middle of the simulation, which is linked directly to the capital stocks of user companies; this is what really makes the difference because revenues depend on licenses and not on users in general. This fact underlines the importance to have stable customers and also that a possible growth of them, from an economic perspective, could determine a growth of the high-tech producer itself. So the model shows an interdependence between the two different industrial sectors. This means that a potential slowing-down in the CGPs economic activity could determine

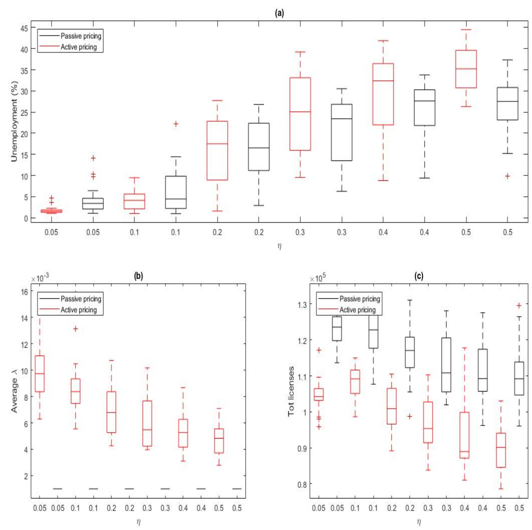

Figure 4: The figure shows a series of boxplots representing, for any values of η and for any pricing scenario considered, the distribution of: unemployment (%) (a), average λ (b) and total number of licenses in the economy (c). Each boxplot reports the distribution of the time averages over twenty years long time period for each one of the twenty seeds considered.

accordingly a deceleration in the DADs activity and this fact highlights, in a certain way, the vulnerability of the digital technologies sector. In other words, CGPs sustain DADs helping them to innovate their products and, at the same time, CGPs, in order to be more productive and competitive, need digital assets. The interaction between these two industrial sectors highlights the complexity of the intangible digital economy.

3.4. The digital economy from a macroeconomic perspective

As shown in Fig. 6(d), the consumption good price level decreases with high values of η; this trend is related to the augmentation with η of the average total factor productivity γ_f which saves both capital and labor force, as we can see from the higher unemployment and from the lower number of licenses sold (see Fig. 4 (a) and (c)). Moreover, a positive impact on consumption goods price is made by lower average unit user license price p_{D_d}, as it is shown in Fig. 2 (b); the average wage, which influences the consumption goods price, notwithstanding shows a diminution, does not appear to be significantly affected by η, see Fig. 6 (c). At the same time, the figure shows an important difference between the two cases considered, in fact the average wage is much higher in case of "active pricing". In agreement with the several variables of interest, the passive pricing case shows lower consumption goods prices. In accordance with this last variable behavior, which determine an enhancement of households purchasing

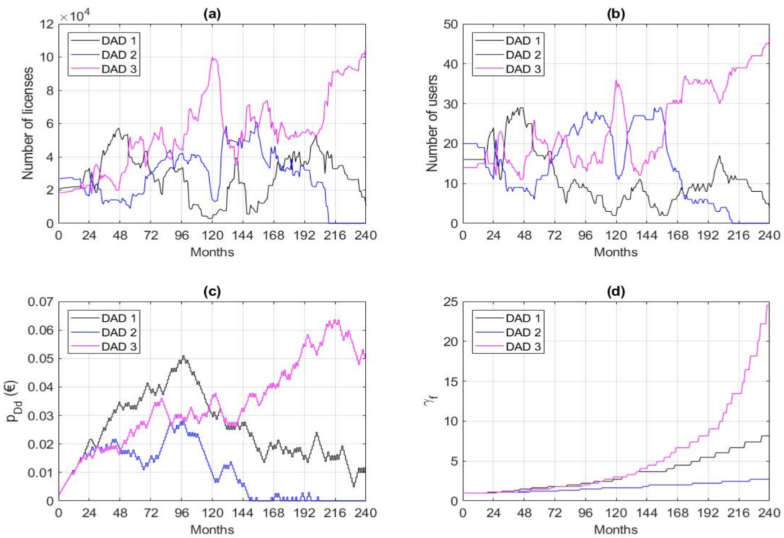

Figure 5: The figure displays various time series in case of "active pricing" and $\eta = 0.3$; in particular it shows: number of licenses (a), number of users (b), unit user license price p_{D_d} (c) and total factor productivity γ_f (d) of the three different digital assets developers

power, the real sales increase with η; the greater average wage causes, in case of "active pricing", higher real sales compared to the other case, see Fig. 6(b). The decrease of the central bank interest rate with the enhancement of η shows the intent of the policy maker to increase the employment, see Fig. 6 (a).

4. Conclusion

The computational results presented in the paper are able to capture the essence related to the new digital technologies world and the stylized facts that characterize the existing literature. Furthermore, the economic dynamics emerged from the simulations shows interesting properties both at the micro and at the macro levels, which can be a valid food for thought. The existing differences between active and passive pricing point out very interesting aspects. Both cases lead to the success of a company with respect to competitors but, in case of "active pricing", competitiveness stimulates the development of more productive digital assets and a higher employment inside the industrial sector of digital assets producers. The "converse concentration effect" shows that very concentrated markets present lower average license prices due to "aggressive" decision-making strategies. In other words, this phenomenon leads to "competitive concentrations" in the digital world. The effect of digital technologies on the labour market seems to be crucial about the real possible consequences of this new technological wave which could transform considerably the economy,

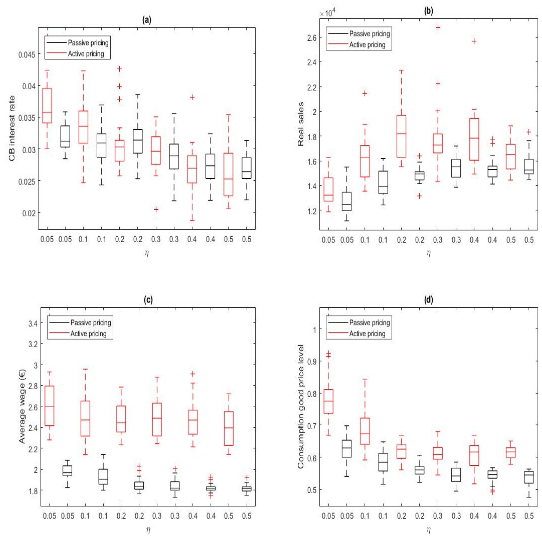

Figure 6: The figure shows a series of boxplots representing, for any values of η and for any pricing scenario considered, the distribution of: Central bank interest rate (a), real sales (b), average wage (c), consumption good price level (d). Each boxplot reports the distribution of the time averages over twenty years long time period for each one of the twenty seeds considered.

in particular from an employment perspective. In case of "Active pricing" the model highlights a clear economic transformation in which the industrial sector of mass-production replaces workers with increasingly productive technologies, while the digital assets producers hire workers in order to develop and improve these technologies. Nevertheless, the unemployment increases in the long-term within the model because of the increasing digital assets productivity. Probably, we should see these results as a warning for our society, that, in order to maintain a social stability, must be prepared to this new technological wave, whose impact is not yet well assessable. The education system will play a crucial role because it will have the task of forming the new generation of "digital workers". This could ensure in the future a smoother transition towards the "real" digital revolution which probably we're just experiencing; in this way people will be prepared to new job position in digital services and manufacturing. Our next research will focus on the study of government policies, concerning social welfare and education, which could facilitate and promote the transition to the future digital world.

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