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Abstract

During the last decades, we have witnessed a strong development of intangible digital technologies. Software, artificial intelligence and algorithms are increasingly affecting both production systems and our lives; economists have started to figure out the long-run complex economic implications of this new technological wave. In this paper, we address this question through the agent-based modelling approach. In particular, we enrich the macroeconomic model Eurace with the concept of intangible digital technology and investigate its effects both at the micro and macro level. Results show the emergence of the relevant stylized facts observed in the business domain, such as increasing returns, winner-take-most phenomena and market lock-in. At the macro level, our main finding is an increasing unemployment level, since the sizeable decrease of the employment rate in the mass-production system, provided by the higher productivity of digital assets, is usually not counterbalanced by the new jobs created in the digital sector.

Keywords: Intangible assets, Digital transformation, Technological unemployment, Agent-based economics

1. Introduction

During the course of history, several technological discoveries 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 revolutionising our world. In particular, the authors argue that probably one of the most important technological discovery has been the steam engine, created by John Watt in the second half of the eighteenth century, which allowed to produce a huge amount of mechanical energy. After that, there have been further technological developments that affected 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 are currently debated among economists.
The potential effects of technological transitions on the labour market have been the subject of a long debate among economists since the first industrial revolution. Potential outcomes deriving from technological progress have been distinguished between: short-term disruption and long-term benefits, see Mokyr et al. (2015). In fact, according to the "Compensation Theory", in the long-term, compensation mechanisms counterbalance the unemployment created by technological progress, see Vivarelli (2014). Along this line, the technological unemployment is only temporary: the economy experiences a structural change rather than the so-called "end of work", Vermeulen et al. (2018). However, the nature of new digital technologies is different compared to machines deriving from the steam engine and traditional automation. The substantial difference between digital technologies and traditional industrial automation is that while the latter helps

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human beings to overcome the limits linked to physical force, thanks to the former we can surmount the limits imposed by our mind. Moreover, several economists and technologists argue that artificial intelligence, thanks to significant improvements in computation, could become self-improving causing a technological singularity, see Good (1966); Nordhaus (2015); Aghion et al. (2017).

According to Acemoglu and Restrepo (2017, 2018a,b,c,d), AI and robotics, as automation, replace human beings in jobs that they previously performed, creating a "displacement effect" and this destruction of job places could only be effectively countervailed by the creation of new labour-intensive tasks. Moreover, empirical evidences show a labour market polarization: whereas technology until the end of the XX century has impacted principally on workplaces occupied by "blue-collars" workers, probably these kinds of digital instruments will mainly affect the so called "white-collars" workers performing jobs which require routine manual and cognitive skills, see Goos and Manning (2007).

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, 1996) 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, these companies have high R&D fixed costs compared to their variable production costs. Furthermore, according to Arthur, the world ruled by increasing returns presents several other characteristics as network effects, 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 (1999, 2014); Fontana (2010). Agent-based modelling represents an appropriate approach in order to address these aspects, see Gallegati (2018); North and Macal (2007); Hommes and LeBaron (2018). Out-of-equilibrium dynamics, complex interactions among economic agents and heterogeneity represent three important features that can be encompassed by agent-based modelling. Since the AI advent can be framed as a transition phase in the technological progress history, an out-of-equilibrium approach, as the agent-based one, can be an effective way to represent this structural and productive transformation. Furthermore, by capturing heterogeneity between economic agents we can distinguish between different types of productive capital: hard capital and intangible or digital capital. The need of heterogeneity to study the potential effect of a digital transformation is also reflected by labour force: workers are heterogeneous and they differ in skills. Finally, interactions drive several features of the "increasing returns" world, as for example network effects, lock-in and winner-take-most-phenomena.

In this paper, we enrich a pre-existent large-scale macroeconomics model, called Eurace (see Mazzocchetti et al. (2018); Ponta et al. (2018); Raberto et al. (2012); Teglio et al. (2012)) to tackle our research questions. The concept of innovation has already been investigated by means of agent based models (see e.g Pyka et al. (2010); Dosi et al. (2010); Caiani et al. (2019); Fanti (2018); Dawid and Reimann (2011); Vermeulen and Pyka (2014, 2018)), and also the Eurace model has been endowed with the concept of innovation, see Dawid et al. (2008); Dawid and Gemkow (2014); Dawid et al. (2014, 2018, 2019). However, we focus here on innovation from the perspective of productivity increases due to intangible digital capital goods, not only tangible ones. Software, algorithms, artificial intelligence and their developers are the subject of our study, as we want to link the concept of innovation to the one of "digital revolution", as described in Brynjolfsson and McAfee (2011). The addition of digital technologies in the Eurace model mimics the advent 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). From a macro perspective, the research work tries to address and evaluate the potential effect of a digital transformation on the economic system. Furthermore, at a micro level, our analysis aims to study the main business dynamics characterizing the digital technology producers. In this respect, the novelty of our contribution concerns the introduction of a new type of capital producer within a large-scale macroeconomic agent-based model: the intangible or digital assets developer.

The introduction of this new kind of firm, which belong to the "increasing returns world", turns out to be crucial in order to better understand and investigate the economic implication of digital technologies on business, both from a macro and micro point of view. In fact, being a bottom up approach, agent-based modelling gives us the opportunity to study not only the macroeconomic trend of the system but also the sectorial behaviours.
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. The Eurace model and the digital economy

2.1. Outline of the Eurace model

A description of the baseline version of the Eurace model that has been used in this paper can be found in Teglio et al. (2019), while Petrović et al. (2017) explain the model in more detail[1]. In this section we recall the basic features of the model that can be useful for the interpretation of the results presented in the paper.
The model includes several types of economic agents, in particular: consumption goods producers (CGPs) that manufacture a homogeneous consumption good; a capital good producer (KGP), which produces investment goods (for instance machine tools); households (HHs), that perform as workers, financial investors and consumers; and commercial banks (Bs). There are also two policy maker agents: the government (G) and the central bank (CB), responsible for fiscal and monetary policy, respectively. In order to study the impact of digital technologies on the economic system, a new economic agent, i.e., the intangible digital assets developer (DAD), has been designed and included in the model.
A graphical illustration of the Eurace model version that has been used in this paper is reported in Fig. 1. Ellipses and rectangles represent the different agents typologies, whereas arrows indicate the presence of current account monetary flows between the corresponding agents. In particular, rectangles are used when only one instance of the agent class is considered (and simulated) in the model, e.g. one government, while ellipses show the presence of multiple heterogeneous instances of that agent class, e.g. several banks. The yellow background refers to the newly introduced agent.
Agents interacts in different decentralised or centralised artificial markets. Centralised are consumption and capital goods, labour and credit markets, whereas decentralised is the financial market where firms' (or banks') stocks and government's bonds are traded. Bounded rationality, limited capabilities of computation and limited information gathering characterise agents' behavior. Finally, the Stock-Flow-consistency approach represents a distinctive feature of the Eurace model, where each agent is in fact represented as a dynamic balance sheet which includes the details regarding assets and liabilities; see Godley and Lavoie (2012); Godin and Caverzasi (2014); Ponta et al. (2018); Raberto et al. (2018).
The shorter time step in the model scheduling is the day, which is the frequency for financial market transactions, however, most agents' decisions occur at a weekly, monthly, or even yearly periodicity, and are asynchronous. Consumption budget decisions are made monthly by households but purchases are made on weekly basis; all firms' decision about production planning have a monthly asynchronous periodicity, i.e., each firm has its own activation day in the month. Finally, policy makers act on a monthly or yearly basis.

[1] Petrović et al. (2017) delineate a multi-country version of the model but the description is still valid if only one country is considered, as in the present study.

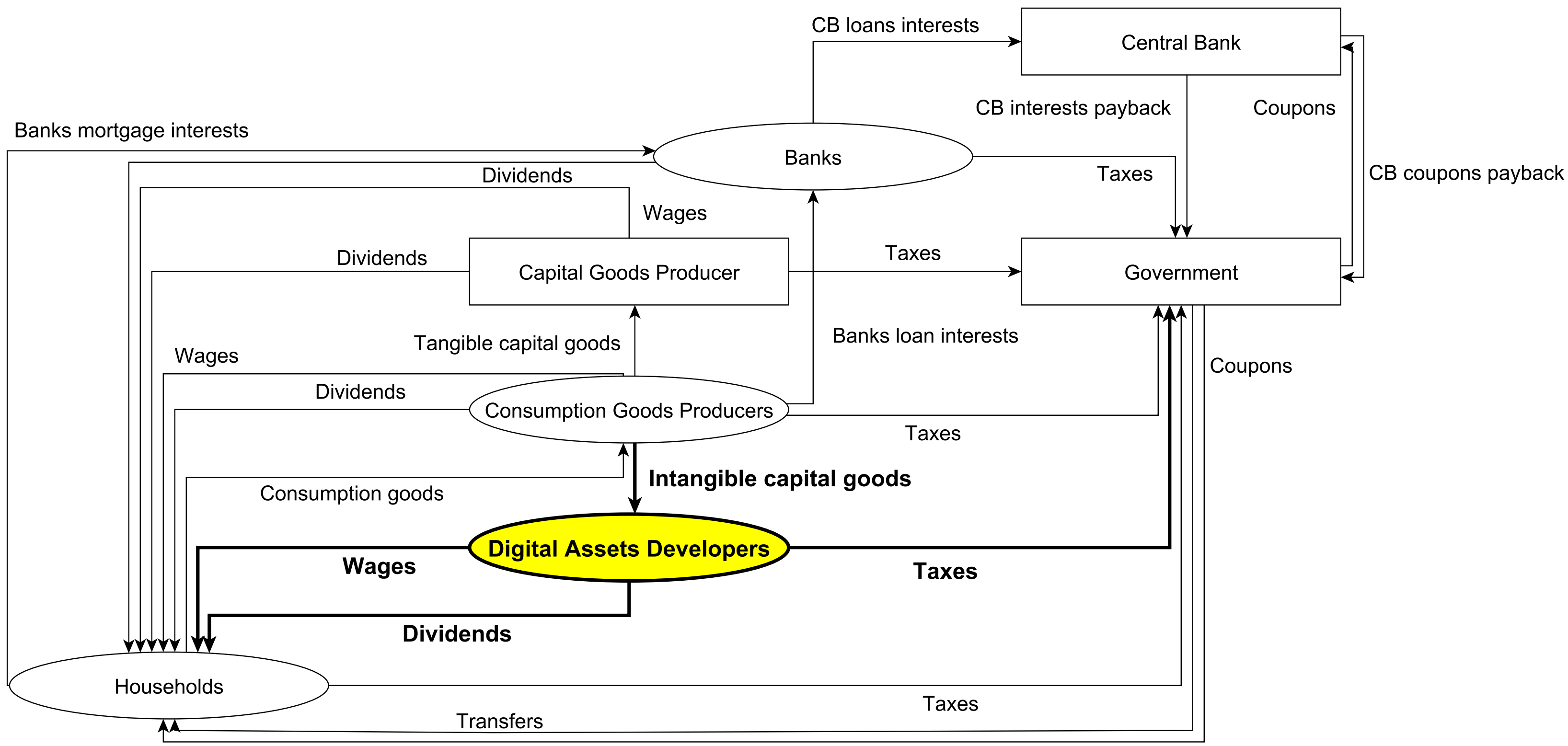

Figure 1: Graphical representation of the present Eurace model in terms of agent classes (ellipses or rectangles) and current account monetary flows (arrows). Rectangles are used when just one instance of the class in considered in the model, whereas ellipses are intended to represent the presence of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

In the following, we present a summary of the core decisions taken by main agents in the model.

Household

The household is active in the financial, labour, goods and housing markets. As a trader, it allocates its financial wealth among the available assets, which are bonds issued by the government and stock of firms and banks. As a worker, if unemployed, the household enters the labour market to evaluate pending job offers. It is randomly queued to apply to the set of available jobs with the highest wages, provided that they are higher than the reservation wage. Household receive a monthly salary, which constitutes, along with the financial returns on bonds and stocks, the total income of the household. On the basis of total income, households decide the consumption budget, according to a target wealth to income ratio, in line with the buffer-stock saving behaviour theory (Carroll (2001)). Households' decision about the product to buy is driven by purchasing probabilities based on the price.

Firm (CGP)

The firm in the Eurace model takes decision about the factors of production and how to finance them. Firms can ask credit to banks or they can issue new stocks. They distribute dividends to shareholders, which are initially all households (later it depends on financial market transactions). In particular, we present the core of the scheduling procedure for firms.

- The firm estimates the expected demand based on past sales.
- It determines the new desired production, given the level of the current inventory stock.
- It computes the needed labour force to meet the production target, determining the labour demand, and posting vacancies (if any), or firing. In particular, if the number of workers is higher than what needed by production target, CGP fires the workers in excess, otherwise it enters labour market to hire new employees. CGP sets an initial wage offer and, if it is not capable to hire all the needed workers, it increases the initial offer by a fixed parameter and starts a second round. If the target is not reached for the second time, CGP exits the labour market. However, it increases the wage offer again and this will represent the initial offer for the next monthly labour market session, see Teglio et al. (2019).
- It determines a desired level of investment by comparing the net present value of future additional cash flows with the current cost of the investment.
- The firm looks for financing, following the pecking order theory: first retained earnings, then debt, then equity.
- If rationed, the firm reduces costs in order to make the total financial needs consistent with the available resources. First, the total dividend payout is reduced up to zero, then, if still not sufficient, the investment plan is sized down and, eventually, the production plan as well.
- The firm can go bankrupt, undergoing a restructuring of its debt with a related loan write-off and a corresponding equity loss on creditor banks' balance sheets, and staying inactive for a period of time after which it enters again the market with a healthy balance sheet. Physical capital of insolvent firms is therefore not lost but remains inactive for a while.

Bank (CGP)

The bank role in the model is to provide credit to private agents; to firm in form of loans and to households in form of mortgages. When a bank receives a loan request by a firm, the request is evaluated and a loan eventually offered at a price that depends on the risk associated to the default probability of the firm. A similar procedure is used by the bank to assess the creditworthiness of households asking for mortgage loans (detail are in Ozel et al. (2019)). Bank's lending is also limited by the obligation to respect the minimum capital requirements enforced by Basel II regulation. It is worth noting that money in the model is endogenous, as new deposits are created every time a bank issues new credit.

Policy makers

The central bank provides liquidity in infinite supply to banks, acting as lender of last resort. It also sets the policy rate according to a dual mandate rule, i.e., low unemployment and stable prices.

The government ensures a welfare system through fiscal policy. Taxes come from corporate earnings, consumption (VAT), financial income and labour income. Government expenditures include the public sector wage bill, unemployment benefits, transfers, and interest payment on debt. On a monthly basis, if in short of liquidity, the government issues new bonds, which are perpetuities that pay a monthly fixed coupon.

The model has not been calibrated to any specific real-world economy; however, it is worth noting that all agents' balance sheet variables have been initialized in a consistent way and with relative ratios derived from the literature or from the empirical evidence observed in advanced economies. For instance, the initial debt-to-equity ratio of firms is set to 2, which is a realistic value for companies in the industrial sector; banks' equity to risk-weighted assets ratio is initialized to 20%. Furthermore, the initial value of public debt is set to a value that, assuming a 10% unemployment rate and the initial productive capacity of firms, would set the debt-to-GDP ratio around to 100%, which is in line with the average Eurozone value. As for empirical validation, it is worth noting that the simulated time series generated by the model match the main stylized facts about volatility of investments and consumption and about the correlation structure of GDP. In particular, we observe that GDP is positively correlated with investments and consumption, and it is anti-correlated with the unemployment rate. GDP also shows a positive correlation with firms' loans, which are leading the business cycle expansion, and an anti-correlation with firms' defaults, which are following a contraction of the economy. For further details about the validation and calibration of the model, see Teglio et al. (2019).

As pointed out by Platt (2019), further developments of agent-based model calibration techniques are required in order to definitively calibrate large-scale models, like Eurace; however, future research will explore the feasibility of a full calibration of the model or of part of it, by resorting to Bayesian inference.

2.2. Eurace: a stock-flow-consistent model

Following Godley and Lavoie (2012) and Godin and Caverzasi (2014), a compact description of the stock-flow-consistent Eurace model is presented through the following tables that outline the stocks (balance sheet entries) and flows (income statement entries) that characterize the Eurace agents. The stock-flow-consistent modelling approach provides a set of relevant theoretical identities at the agent, sector, and aggregate level, whose subsistence need to be numerically verified during the simulation, thus providing a very important diagnostic and validation tool for the model and its implementation. The first table presented is the agent class balance sheet table (Table 1), that shows the asset and liability entries of each particular agent type.

The second one is the sectorial balance sheet table (Table 2), that presents the assets and liabilities aggregated over a sector (all agents belonging to the same class). Columns report the aggregated balance sheet of each sector, whereas rows identify the relations among sectors by spotting the liabilities (with minus sign) in one sector and the corresponding claims, i.e. assets (with plus sign), in another sector, thus generally summing up to zero. Exceptions are: the capital goods accumulated by firms; inventories; housing units and equity shares[2] owned by households.

The third table is the cash flow matrix (Table 3), that show the monetary flows among sectors, both in the current and capital account. The current account reports aggregate revenues (plus sign) and payments (minus sign) among sectors, therefore summing to zero along the rows. The capital account reports the endogenous money creation / destruction operations by means of borrowing/debt repayment by private agents with banks. These operations, along with the current account net cash flows, determines the liquidity change of a sector.

Finally, the fourth is the revaluation matrix (Table 4) that provides the information about changes in sectors' net worth (equity) between periods. In particular, agents' net worth dynamics depends on net cash flows in

[2] We assume that equity shares in households' portfolio do not sum up to zero with the corresponding equity counterpart in the issuer balance sheet because of the usual difference between market price and book value.

the current account, physical capital depreciation and price changes in financial (stocks and bonds) and real (housing units, capital goods and inventories of consumption goods) assets.

Table 1: Balance sheets of any agent class characterizing the Eurace economy. Balance sheet entries in the table have a subscript character, that is the index of an agent in the class to which the variable refers. In some cases, we can find two subscript characters, where the second one refers to the index of an agent in another class where there is the balance-sheet counterpart. For instance, D_f refers to the total debt of firm f, i.e. a liability, and $\mathcal{L}_b$ refers to the aggregate loans of bank b, i.e. an asset. $\ell_{f,b}$ (or $\ell_{b,f}$) refer to the loans granted by banks b to firms f. Of course, $\sum_b \mathcal{L}_b = \sum_f \ell_{b,f}$ represents an aggregate balance sheet identity, that is verified along the entire simulation. $n_{E_{h,x}}$ represent the number of outstanding equity shares of agents x held by households h. The market price of the equity shares is given by p_{E_x}. The stock portfolio's value of household h is then computed as: $\sum_x n_{E_{h,x}} p_{E_x}$. Government bonds' number and market price are given by n_G and p_G, respectively.

Agent class	**Assets**	**Liabilities**
Household *abbrev.*: HH *index*: $h = 1, \dots, N_{Hous}$	Liquidity: M_h Stock portfolio: $\Sigma_b n_{E_{h,b}} p_{E_b}+$ $\Sigma_f n_{E_{h,f}} p_{E_f}+$ $n_{E_{h,K}} p_{E_K}$ + $\Sigma_d n_{E_{h,d}} p_{E_d}$ + Gov Bonds: $n_{h,G}\ p_G$ Housing units: X_h	Mortgages: U_h Equity: E_h
Consumption Goods Producer *abbrev.*: CGP *index*: $f = 1, \dots, N_{Firm}$	Liquidity: M_f Capital goods: K_f Inventories: I_f	Debt: $D_f = \sum_b \ell_{f,b}$ Equity: E_f
Capital Goods Producer *abbrev.*: KGP	Liquidity: M_K Inventories: I_K	Equity: E_K
Digital Assets Developers *abbrev.*: DAD *index*: $d = 1, \dots, N_{DADs}$	Liquidity: M_d Licences: $n_{l,d}$	Equity: E_d
Bank *abbrev.*: B *index*: $b = 1, \dots, N_{Bank}$	Liquidity: M_b Loans: $\mathcal{L}_b = \sum_f \ell_{b,f}$ Mortgages: $U_b = \sum_h U_{b,h}$	Deposits : $\mathcal{D}_b = \sum_h M_{b,h} + \sum_f M_{b,f} + M_{b,K}$ CB standing facility: $D_b = \ell_{b,CB}$ Equity: E_b
Government *abbrev.*: G	Liquidity: M_G	Outstanding government bonds value : $D_G = n_G\ p_G$ Equity: E_G
Central Bank *abbrev.*: CB	Liquidity: M_{CB} Loans to banks: $\mathcal{L}_{CB} = \sum_b \ell_{CB,b}$ Gov Bonds: $n_{CB,G}\ p_G$	Outstanding fiat money: Fiat_{CB} Deposits: $\mathcal{D}_{CB} = \sum_b M_b + M_G$ Equity: E_{CB}

Table 2: Sectorial balance sheet matrix. Subscripts represent the index of the agent or of the sector (i.e. the set of all agents of the same class) to which the stock refers. Uppercase indexes are used when the stock refers to the whole sector, e.g. F refers to the sector of all CGPs and to the aggregate value of a particular stock in the sector, whereas lowercase subscripts are used when it refers to the single agent (for instance in the case of sums). Finally, superscript characters are introduced in the case of government bonds units n_G, i.e. n_G^H and n_G^{CB}, and $Loans_B$, i.e. $Loans_B^F$ and $Loans_B^{RP}$, because the balance sheet counterpart (in the asset side) is hold by two sectors, i.e. households and central bank in the case of government bonds units and consumption good producers and renewable power producer in the case of loans.

	Sectors							
	Non-Financial Private Agents (NFPAs)				Banks	Policy Makers		Σ
	HHs	**CGPs**	**KGP**	**DADs**	**Bs**	**G**	**CB**	
Tangible Capital	$+X_H\ p_X$	$+K_F\ p_K$						$+X_h\ p_X\ +K_F\ p_K$
Inventories		$+I_F\ p_C$	$+I_K\ p_K$					$+I_F\ p_C\ +I_K\ p_K$
Debt(-) / Credit(+)	$-U_H$	$-D_F$			$+D_F$ $+U_H$ $-\ell_{CB}$		$+\ell_{CB}$	0
Liquidity:								
NFPA	$+M_H$	$+M_F$	$+M_K$	$+M_{DAD}$	-D_B			0
Banks/Gov					$+M_B$	$+M_G$	- D_{CB}	0
Central Bank							$+\mathrm{M}_{CB}$ $-\mathrm{Fiat}_{CB}$	$+\mathrm{M}_{CB,0}$
Gov Bonds	$+n_G^H\ p_G$					$-n_G\ p_G$	$+n_G^{CB}\ p_G$	0
Equity Shares (+) / Net worth (-)	$+\Sigma_f n_{E_f} p_{E_f}$ $+n_{E_k} p_{E_k}$ $+\Sigma_d n_{E_{DAD,d}} p_{E_{DAD,d}}$ $+\Sigma_b n_{E_b} p_{E_b}$ $-E_H$	$-E_F$	$-E_K$	$-E_{DAD}$	$-E_B$	$-E_G$	$-E_{CB}$	$+\Sigma_f n_{E_f} p_{E_f} - E_F$ $+n_{E_k} p_{E_k} - E_K$ $\Sigma_d n_{E_d} p_{E_d} - E_{DAD}$ $+\Sigma_b n_{E_b} p_{E_b} - E_B$ $-E_H - E_G - E_{CB}$
Σ	0	0	0	0	0	0	0	0

Table 3: **Sectorial transaction flow matrix of agents populating the EURACE economy**. Note that HH stands fo Households, CGP stands for Consumption Goods Producer, KGP stands for Capital Goods Producer, DAD stands for Digital Assets Developers, Gov stands for Government and CB stands for Central Bank.

		HHs	**CGPs**	**KGP**	**DAD**	**Bs**	**G**	**CB**	Σ
	Consumption goods	$-$	$+$						0
	Investment goods		$-$	$+$					0
	Licences		$-$		$+$				0
	Training courses		$-$		$+$				0
Current Account	Wages	$+$	$-$	$-$	$-$		$-$		0
	Transfers	$+$					$-$		0
	Taxes	$-$	$-$	$-$	$-$	$-$	$+$		0
	Dividends	$+$	$-$	$-$	$-$	$-$			0
	Coupons	$+$					$-$	$+$	0
	CB coupons payback						$+$	$-$	0
	Banks loan interests		$-$			$+$			0
	Banks mortgage interests	$-$				$+$			0
	CB loans interests					$-$		$+$	0
	CB interests payback						$+$	$-$	0
		=	=	=	=	=	=	=	
	Net cash flow	Savings	Profits	Profits	Profits	Profits	Surplus	Seignoirage	0
	Net cash flow	+Savings	+Profits	+Profits	+Profits	+Profits	+Surplus	+Seignoirage	0
	Δ Loans		$+\Delta D_F$			$-\Delta D_F$ $+\mathcal{L}_{CB}$		$-\Delta\mathcal{L}_{CB}$	0
	Δ Mortgages	$+U_H$				$- U_H$			0
Capital Account	Δ Issue of new shares / bonds	$-\Sigma_f p_{E_f} \Delta n_{E_f}$ $-p_G \Delta n_G$	$+\Sigma_f p_{E_f} \Delta n_{E_f}$				$+p_G \Delta n_G$		0
	Δ Quantitative easing	$+p_G \Delta n_G^{QE}$						$-p_G \Delta n_G^{QE}$	0
	Δ Private Liquidity & Δ Banks' deposits	$-\Delta\ M_H$	$-\Delta\ M_F$	$-\Delta\ M_K$	$-\Delta\ M_{DAD}$	$+\Delta\ D_B$			0
	Δ Banks / Public Liquidity & Δ Central bank deposits					$-\Delta\ M_B$	$-\Delta\ M_G$	$+\Delta\ D_{CB}$	0
	Δ CB Liquidity / Δ Fiat Money							$-\Delta\ M_{CB}$ $+\Delta\ \text{Fiat}_{CB}$	0
	Σ	0	0	0	0	0	0	0	

Table 4: Sectorial revaluation matrix. The matrix provides information about changes in sectors' net worth (equity) between periods. Net worth changes depend on net cash flows in the current account, physical capital depreciation (at rate ξ_K) and price changes in real and financial assets. It is worth noting that net worth of the issuers of financial assets (firms and the government) are not subject to asset price changes.

		HHs	**CGPs**	**KGP**	**DADs**	**Bs**	**G**	**CB**	**Σ**
Equity$_{t-1}$		$E_{H,t-1}$	$E_{F,t-1}$	$E_{K,t-1}$	$E_{DAD,t-1}$	$E_{B,t-1}$	$E_{G,t-1}$	$E_{CB,t-1}$	$E_{TOT,t-1}$
Net cash flow		+Savings	+Profits	+Profits	+Profits	+Profits	+Surplus	+Seignoirage	0
Revaluations/ Devaluations									
	Housing units	$+\Sigma_h X_h \Delta p_X$							$+\Sigma_h X_h \Delta p_X$
	Capital		$+\Sigma_f K_f \Delta p_K$ $-\Sigma_f \xi_K K_f p_K$						$+\Sigma_f K_f \Delta p_K$ $-\Sigma_f \xi_K K_f p_K$
	Inventories		$+\Sigma_f I_f \Delta p_c$	$+I_K \Delta p_K$					$+\Sigma_f I_f \Delta p_c$ $+I_K \Delta p_K$
	Equity shares	$+\Sigma_f n_{E_f} \Delta p_{E_f}$ $+\Sigma_b n_{E_b} \Delta p_{E_b}$ $+n_{E_K} \Delta p_{E_K}$ $+\Sigma_d n_{E_{DAD}} \Delta p_{E_{DAD}}$							$+\Sigma_f n_{E_f} \Delta p_{E_f}$ $+\Sigma_b n_{E_b} \Delta p_{E_b}$ $+n_{E_K} \Delta p_{E_K}$ $+\Sigma_d n_{E_d} \Delta p_{E_d}$
	Bonds	$+n_G^H \Delta p_G$						$+n_G^{CB} \Delta p_G$	$+n_G^H \Delta p_G$ $+n_G^{CB} \Delta p_G$
		=	=	=	=	=	=	=	=
Equity		$E_{H,t}$	$E_{F,t}$	$E_{K,t}$	$E_{DAD,t}$	$E_{B,t}$	$E_{G,t}$	$E_{CB,t}$	$E_{TOT,t}$

2.3. Intangible digital assets

As said above, in the present study, the Eurace model is enriched 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 (TFP). 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.

2.4. 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, and therefore higher productivity when employed in the production process by CGPs. The probability $prob_d$ of a successful completion of the new digital asset version depends on the cumulated person months M_d employed by the DAD since the latest version developed, 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 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, 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 needed workforce is set so that the wage bill is a fixed fraction of the DADs monthly turnover. Obviously, this means that the number of employees in the DADs sector is inuenced not only by revenues, but also by the average wage characterizing the economy. Concerning the hiring process, DADs enter the labor market and perform exactly same procedures of CGPs with whom they compete for the labor force. However, there is an important difference: while CGPs hire households from the highest (fifth level) to the lowest (first) education level indistinctly, yet prioritizing highly educated workers, DADs employ only workers with a high degree of education (from the third level upwards) to be employ them in the research activities and then develop new intangible digital assets.

2.5. 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 TFP of the CGP. In particular, along the lines of Teglio et al. (2019), we consider the labor force N_f, employed at any CGP f, and its physical capital endowment K_f, as the production factors used for the production of consumption goods q_{C_f}, according to a Cobb-Douglas technology with constant returns to scale, i.e.,

$$q_{C_f} = \gamma_f N_f^{\alpha} K_f^{\beta} = \gamma_f N_f^{\alpha} K_f^{1-\alpha} \tag{2}$$

where α and β are the production elasticity parameters and γ_f is the TFP. 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. Through this assumption, we model a total factor augmenting technological progress[1]. In particular, the TFP γ_f is modelled as follows:

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

where η_γ is a scale parameter homogeneous across all CGPs whereas κ_d represents the knowledge level of the digital asset adopted. In case of a successful R&D activity, the latter increases by a fixed tick equal to δ_κ according to the following relation:

$$\kappa_{d_t} = \kappa_{d_{t-1}} + \delta_\kappa \tag{4}$$

It is worth noting that, while in the baseline Eurace version total factor productivity depends as well on the workforce' specific skills[2], in this extension we assume that TFP γ_f is only influenced by the digital technological progress.

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 therefore more productive, due to the 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:

$$NPV_{d^*} = \frac{p_{C_f} (q^*_{C_f} - q_{C_f})}{r_D} + \frac{(p_{D_d} - p_{D_{d^*}})\, K_f}{r_D} - w\hat{N}_f\,, \tag{5}$$

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. The variable r_D represents the weighted average cost of capital proxied by the corporate loan rate. In particular, the first addend of Eq. 5 takes into account that the difference in productivity between the two technologies (see Eq. 3) generates a different expected production level, given the present endowment of production factors, according to Eq. 2, and therefore

[1] A total factor augmenting approach shall be considered as a suitable modelling choice to capture a key empirical fact connected to the digital transformation of the economy. Indeed, empirical evidences show a high correlation between total factor productivity and intangible investments, see Haskel and Westlake (2017). Moreover, according to Uzawa (1961), a technological progress is both Hicks and Harrod neutral (labour-augmenting) if and only if the production function is in the form of Eq. 2. Notwithstanding the debate concerning the average trend of technological progress is still open among economists, the literature regarding empirical analysis leans towards Hicks and Harrod neutrality. This tendency underpins our choice to adopt the Cobb-Douglass production technology with constant return to scale to model the introduction of digital intangible innovation, see Solow (1957); Doraszelski and Jaumandreu (2018); Kalt (1978).

[2] Households are endowed with a specific skill which varies according to their labour activity: the longer their job career the higher the specific skill value.

different expected future revenues[3]. The second term of Eq. 5 takes into account the difference in the user license 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.

2.6. Digital asset price dynamics

On a monthly basis, each CGP transfers to its reference DAD d a money amount to pay for the license fee, which is equal to the unit license price P_{D_d} times the number of licences held by the consumption goods producer.
The unit license price is set by the DAD. To study the behaviour of the economic system under two different competitive scenarios, two different pricing mechanisms have been considered, namely "price collusion" and "price competition" regimes. Under the "price collusion" regime, all DADs adopt the same unit license price P_{D_d} over time, whereas in the competitive case, each DAD adapts the licence price independently according to the dynamics of license sales, with the purpose to get market shares. In both cases, the license price is be proportional to the average wage w in the economy. The rationale of this modelling choice is to relate the dynamics of revenues of digital firms (DADs) to the one of costs, which consist only in labour costs, i.e. wages.
The user license unit price p_{D_d} for each DAD in case of "collusive pricing" follows this relation:

$$p_{D_d} = \lambda w \tag{6}$$

where the mark-up λ, in case of "collusive pricing", is an exogenous and homogeneous parameter , while in the "competitive" case the price can increase or decrease over time according to a simple thumb rule based on past sales. If the DAD increased the number of sold licences, it also increases the mark-up by a fixed tick equal to δ_λ, otherwise it reduces price by the same amount:

$$\begin{cases} \lambda_{t+1} = \lambda_t + \delta_\lambda & \text{if } Q_t > Q_{t-1} \\ \lambda_{t+1} = \lambda_t - \delta_\lambda & \text{if } Q_t \leq Q_{t-1} \end{cases} \tag{7}$$

This variable mark-up policy allows DADs to manage the fluctuations of sales by means of a trade-off between mark-up and market shares, see Fraser (1985); Goldstein (1986a,b). In fact, DADs perform their business activities in an economic environment characterized by uncertainty and, in case of sales contractions, a lower price could determine higher revenues by gaining market shares at the expense of competitors. In this respect, as shown in Eq. 5, the user license unit price could determine the transition from a certain digital technologies to a cheaper one. Furthermore, through this pricing behavioural assumption, DADs can exploit expansion phases of their sales, then increasing then increasing their profits by raising mark-up.
Therefore, in case of "competitive pricing", λ assumes a heterogeneous and variable connotation.

2.7. Employees digital technologies skills

The third term of the Eq. 5 is related to the training costs which a company should bear in order to train workers 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, which can be augmented by means of training courses provided by the DADs. Therefore, revenues of DADs come 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 ($\hat{N}_f$) that are still not trained with the "digital technologies", multiplied by the training cost per worker (w) which is equal to the average wage characterizing the macroeconomic system. The lower these switching costs, the higher the probability to adopt a new kind of digital assets. In fact,

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

with this particular micro-assumption, we want to model the presence inside Eurace macro-economy of 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); Heinrich (2018). 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: the higher the number of workers with that particular skill, the lower the transition costs to that alternative digital technologies which could be cheaper or more productive, see 5. 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.

The diffusion of these skills among workers increases competitiveness lowering the switching costs between digital technologies. In fact, skills propagation inside the model allows CGPs to pass more easily from a technology to another one by reducing switching costs. In this respect, it is worth noting that, on a monthly base, a fraction of workers resigns to find better job opportunities or it is fired by CGPs. This continuous turnover characterizing the Eurace labour market helps the diffusion among CGPs of the predominant digital technologies reflected on the long term inside the economy by the number of workers with that "digital technologies" skill.

Moreover, these skills do not influence CGPs production processes and employment sessions. In fact, in this version of the model, firms are willing to bear training courses costs: their hiring preference is oriented to education levels. Even though CGPs production is not affected by digital technologies skills, each worker must be trained to manage the adopted digital asset in order to start the process.

3. Computational results

3.1. Design of experiments

The new features of the model allow us to analyse different scenarios. In particular, we consider two digital assets pricing scenarios. In the first one, named "collusive pricing", DADs sell their licenses at the same price, determined as a fixed share of the nominal wage. In the second one, henceforth "competitive 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 pseudorandom number generator. So, a total of 240 simulations has been considered in order to conduct our investigation. 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, a practical way to present data distribution. In particular, each boxplot shows the distribution of the time averages of relevant variables over a twenty years long time interval, including the twenty simulations characterised by different seeds. Boxes enclose the values from the first to the third quartile, and include whiskers, which extend up to the minimum and maximum data points that are not considered outliers. The horizontal segments inside the 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 phenomena that characterize the "Increasing-returns World", see Arthur (1996), and at the macro level to asses the impact of this new industrial sector on the economic dynamics.

3.2. "Competitive pricing" and "collusive pricing" business dynamics analysis

As we can see in Fig.2(a), "competitive pricing" scenarios are characterized by higher values of TFP (γ_f) compared to the "collusive pricing" ones, independently of the value of the innovation probability function shape parameter 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 "competitive 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. 6. So, the variable that effectively affects the R&D intensity is the mark-up λ, which in case of "collusive pricing" is fixed throughout the simulation, while in the other case varies according to the DAD pricing strategy, see Eq. 6. In presence of "competitive pricing", the average value of the mark-up λ results to be higher, see Fig.4(b), and this fact leads to higher employment in the DADs industrial sector (see Fig. 2(c)), and as a consequence to a greater average TFP γ_f. At the same time, obviously the TFP γ_f increases with η which determines the shape of the innovation

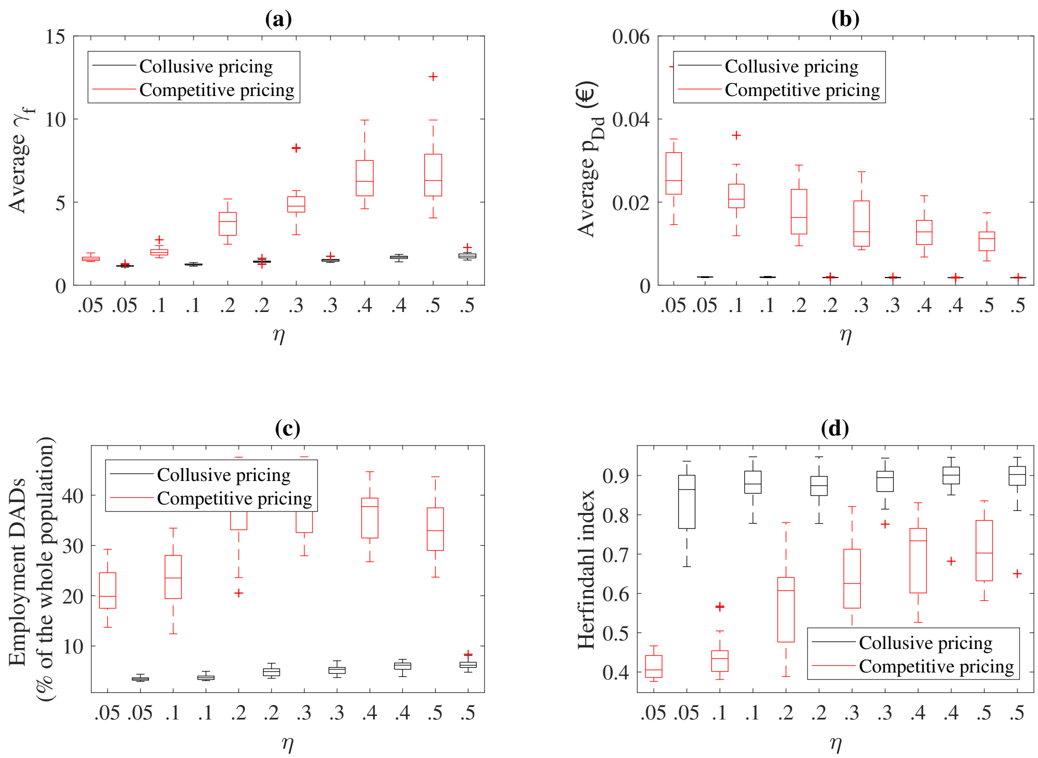

Figure 2: The figure shows a series of boxplots representing, for any values of η and for any pricing scenario considered, the distribution of: the average total factor productivity γ_f (a), the average unit user license price p_{D_d} (b), the employment in the DADs industrial sector (c), the Herfindahl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

probability function, see 1. The parameter η sets the likelihood that cumulated R&D activities may have an actual impact. In this respect, R&D intensity is linked to the mark-up λ. 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 "collusive 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 the TFP γ_f. In fact, in the "collusive pricing" case, DADs are limited in hiring new researchers because of their lower mark-up λ and obviously this fact implies a lower productivity for their digital assets. Furthermore, the competition between DADs established by the "competitive pricing" is accentuated by η; indeed the unit license price p_{D_d} decreases as the innovation probability function shape parameter η enhances. At the same time, notwithstanding the average price decreases in case of high values of η, the market concentration increases[4], as it is visible in Fig.2(d). This emerging phenomenon, that we call "converse concentration effect" appears in contradiction with the standard wisdom, according to which competitive markets, characterised by lower prices, are not concentrated. In this case, the competition represented by lower prices and consequently by lower values of mark-up 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 become the leader 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 other competitors, in order to gain market shares, tend to decrease their product prices. The results is a reduction of the average price. Therefore, digital assets market turns out to be very susceptible to unit license prices p_{D_d} variations and the result is the absence of price overshoot effects, see also Fig. 5 (c).

It is worth noting 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 "collusive pricing" scenario, the Herfindahl index turns out to be high for each value of η; this happens because only "fortune" leads to the emergence of a market leader and not a decision-making strategy. In particular, "fortune" is represented by the randomness related to Eq. 1 which is not counterbalanced by any "competitive pricing" strategy.

Going further with the analysis, the high employment in the digital technologies sector, in case of "competitive 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 behaviour 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 TFP 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 TFP 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 the innovation probability function shape parameter 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 "collusive pricing"; this is related to the fact that up to these values, in case of "competitive 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 shown in Fig. 4 (c), the total number of licenses sold decreases with η both in case of "competitive" and collusive "pricing"; logically, this is due to the higher value of TFP γ_f which involves a lower stock of capital goods for the same output. Accordingly to the trend of TFP γ_f, in case of "collusive pricing" the number of licenses is higher compared to the "competitive pricing" case.

3.3. Competitiveness in the "competitive pricing" case

In this subsection, we present a micro-analysis concerning the competitive dynamics involving the digital assets industrial sector in the "competitive pricing" case. Fig. 5 displays the trend of the most important variables related to 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 successful *R&D* activities, which allows it to develop technologies with a higher productivity. Besides the innovation probability function shape parameter η, *R&D* activities are influenced by the cumulated person months M_d employed since the latest improvement: the higher the value of M_d, the higher the probability to develop an improved version of digital asset, see Eq. 1. The cumulated person months M_d is influenced by the revenue, therefore, the

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

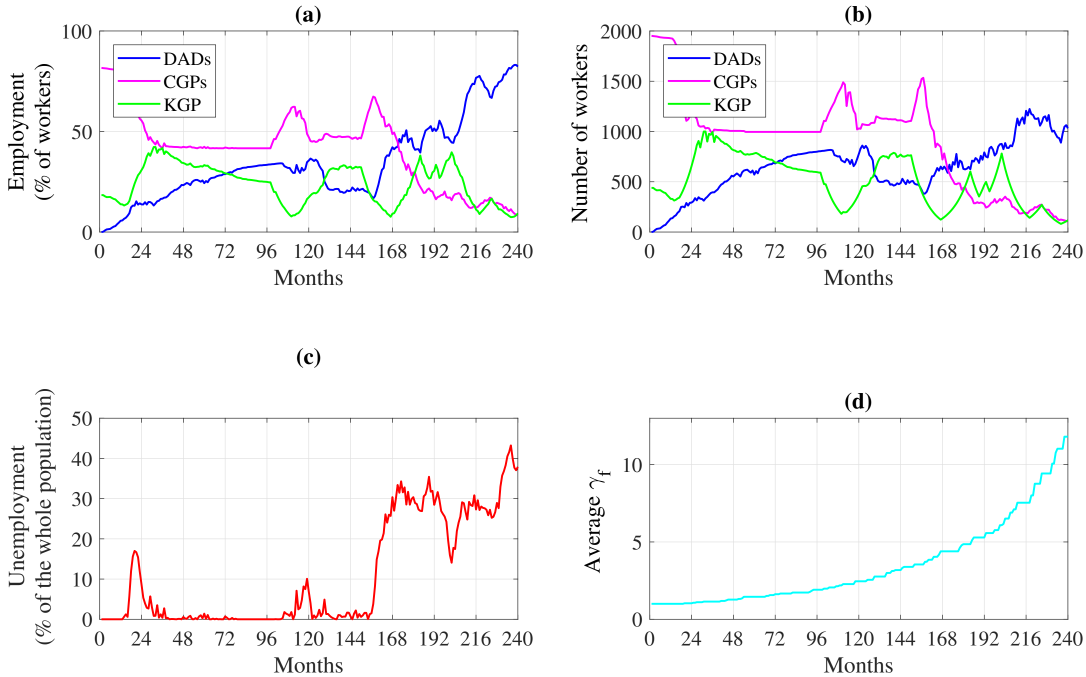

Figure 3: The figure displays various time series in case of "competitive pricing" and $\eta = 0.3$; in particular it shows: the percentage (a) and number of employees (b) in the various industrial sectors: consumption good producers (CGPs), capital good producer (KGP), digital assets developers (DADs);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

DAD with the highest market share performs the highest $R\&D$. Despite the attempt of other DADs to recover the lost market shares, through a decrease of their license prices, on the long-term the leader DAD improves its product and the higher productivity of its digital assets covers the price difference with respect to products competitor. This trend could be considered as a representation of Arthur theory concerning the economy of "increasing returns", according to which, thanks to its ability and strategy, a company could lock-in the market. Furthermore, Fig. 5 shows that, even if the $DAD2$ has a higher number of users (that are CGPs) compared to $DAD3$, the latter has sold (or renewed) a higher number of licenses in the middle of the simulation (around time 96), because licences are proportional to the capital stocks of user companies. This is what seems to make the difference because revenues depend on licenses and not on users in general. This result underlines the importance for the DAD to have stable customers and to possibly guarantee their growth, because this could determine a growth of the high-tech producer itself. Therefore, the model highlights an interdependence between the two different industrial sectors, showing how a potential slowing-down in the CGPs economic activity could determine a deceleration in the DADs activity. 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), in both pricing cases, the consumption good price level decreases with high values of the innovation probability function shape parameter η, due to the increase of the average TFP γ_f. The

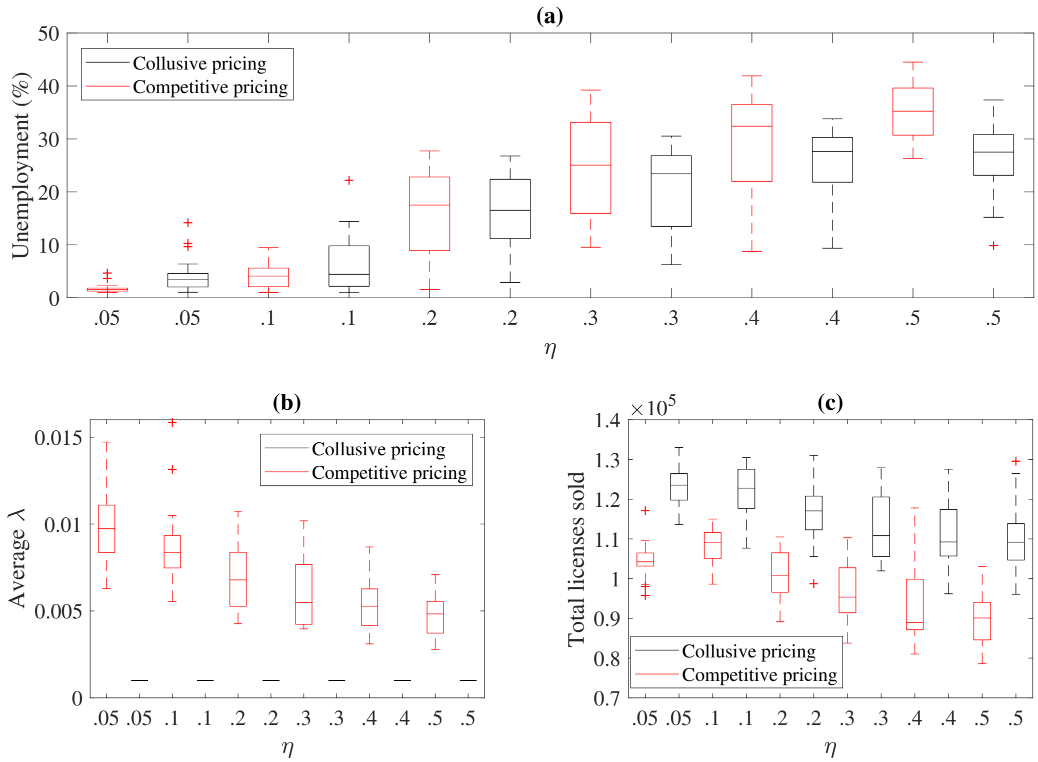

Figure 4: The figure shows a series of boxplots representing, for any values of η and for any pricing scenario considered, the distribution of: unemployment (%) (a), average mark-up λ (b) and total number of licenses in the economy (c). Each boxplot reports the distribution of the time averages over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

latter allows to save both capital and labor force, as we can see from the higher unemployment, see Fig. 4 (a). In other words, higher values of TFP determine a decrease in the production costs. In this respect, the lower average unit user license price p_{D_d} have a positive impact on the price of consumption goods, as it is shown in Fig. 2 (b). In fact, CGPs follow a mark-up pricing rule on unit costs, where costs are represented by: wages, debt interests, licenses and training courses, see Plott and Sunder (1982); Fabiani et al. (2006). Fig. 6 (c) shows a slight decrease of the average wage characterizing the economy which influences the consumption good price level. Moreover, Fig. 6 (c) shows an important difference between the two market scenarios: the average wage is much higher in case of "competitive pricing". According to the mark-up pricing-rule on unit costs, the "collusive pricing" case shows lower consumption goods prices because of lower average wage w and unit user license price p_{D_d}, see Fig. 2(b) and Fig. 6(c) respectively. In case of "competitive pricing", the higher average wage w, representative of a greater purchasing power, determines higher real sales compared to the "collusive pricing" case for any value of η. 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

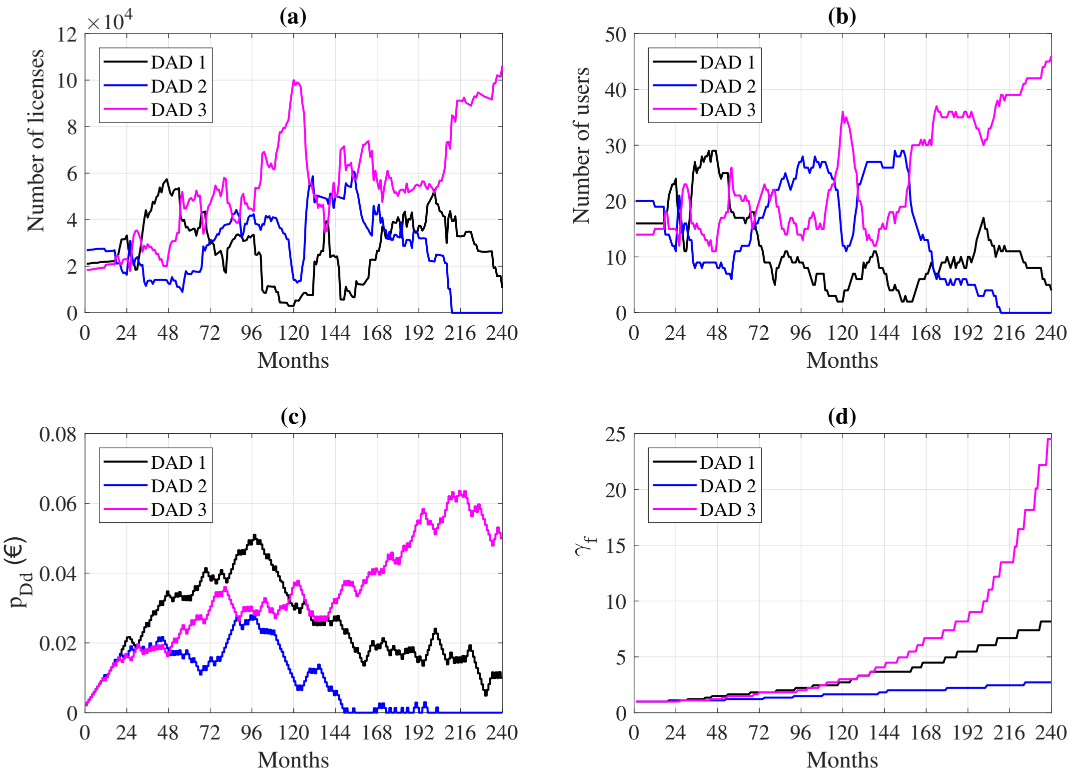

Figure 5: The figure displays various time series in case of "competitive pricing" and $\eta = 0.3$; in particular it shows: number of licenses (a), number of users (b), unit user license price p_{D_d} (c) and total factor productivity γ_f (d) of the three different digital assets developers. All time series refer to a specific replication which is representative of the system average trend in case of "competitive pricing" and $\eta = 0.3$.

levels. The existing differences between competitive and collusive pricing point out very interesting aspects. Both cases lead to the success of a company with respect to competitors but, in case of "competitive pricing", competitiveness stimulates the development of more productive digital assets and a higher employment in 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, in particular from an employment perspective. In case of "competitive 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.

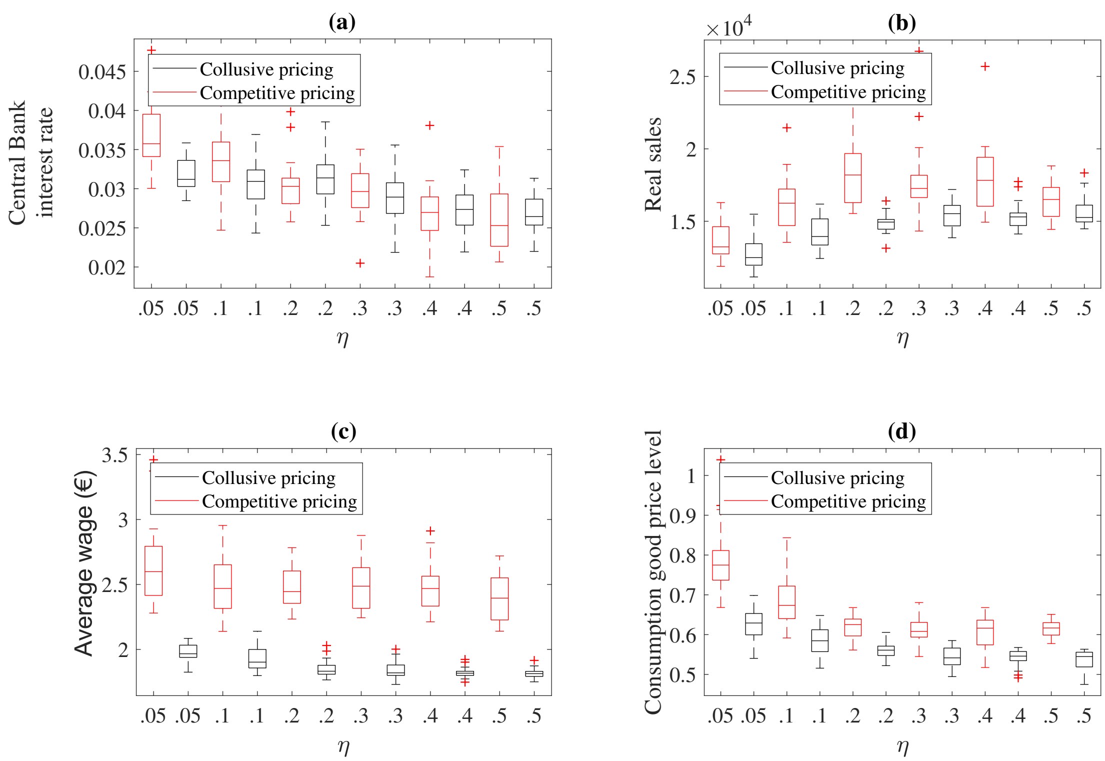

Figure 6: The figure shows a series of boxplots representing, for any values of η and for any pricing scenario considered, the distribution of: Central bank interest rate (a), real sales (b), average wage (c), consumption good price level (d). Each boxplot reports the distribution of the time averages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

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