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The complexity of the intangible digital economy: an agent-based model

by

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To my grandfather, **Captain Giancarlo Cidale**.

“May the wind always be at your back and the sun upon your face. And may the winds of destiny carry you aloft to dance with the stars."

- George Jacob Jung -

Declaration

I hereby declare that the contents of this dissertation are original and have not been submitted in whole or in part for consideration for any other degree or qualification in this, or any other university. This dissertation is my own work and contains nothing which is the outcome of work done in collaboration with others, except as specified in the text and Acknowledgements.

Filippo Bertani
March 2021

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First of all, I want to thank my supervisor, Prof. Marco Raberto, and the head of my research group, Prof. Silvano Cincotti, for their time and infinite patience. The few things I know about economics, I owe to them.

A special thanks goes to Prof. Andrea Teglio, Prof. Linda Ponta and Prof. Flavio Tonelli with whom I had the chance to collaborate during these years in order to realize my research work.

Obviously, a thought also goes to my parents, Daniela and Rossano, my sister, Elena, and my love, Federica, for always supporting me.

Abstract

Since the last 30 years, the economy has been undergoing a massive digital transformation. Intangible digital assets, like software solutions, web services, and more recently deep learning algorithms, artificial intelligence and digital platforms, have been increasingly adopted thanks to the diffusion and advancements of information and communication technologies. Various observers argue that we could rapidly approach a technological singularity leading to explosive economic growth. This research work as a whole is aimed at investigating potential consequences on our economy deriving from digital technological progress. In particular, the contribution of the thesis is both empirical, theoretical and related to model design. On the empirical side, I present a cross-country empirical analysis assessing the correlation between the growth rate of both tangible and intangible investments and different measures of productivity growth. The analysis results are used to inform the first of the two frameworks of the agent-based macro-model Eurace that I employ to assess the long-term impact of digital investments on economy. In particular, in the first framework, a total factor augmenting approach has been used in order to model the digital technological progress because of the significant and positive correlation between total factor productivity and ICT capital investments, composed by a combination of both tangible and intangible investments which includes ICT technologies, software and database. In the second framework, I propose a different and innovative approach in which digital technological progress influences the elasticity of substitution between capital and labour. In this way, an increase of the elasticity of substitution can be seen as an increase in the tasks that machines can perform replacing human beings. In order to develop this approach, I substitute the Cobb-Douglas production function used in the first framework with a Leontief technology in which input factors are represented by organizational units. In turn, the contribution of each unit is given by a combination of capital and labour. The second framework results to be more realistic because it allows to distinguish between the various activities performed in the companies and the different education levels characterizing the workforce employed. Computational experiments show the emergence of technological unemployment in the long-run with a high pace of intangible digital investments. However, in the elasticity augmenting framework compensation mechanisms work more effectively leading to lower unemployment levels

compared to the total factor augmenting one. Both frameworks are able to capture interesting features and empirical evidences characterizing our economic system.

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Chapter 1

Digital Transformation: an overview

1.1 Digital intangible assets: a literature review

In his 1930 lecture "Economic possibilities for our grandchildren", John Maynard Keynes predicted that in one hundred years from then, i.e. around 2030, the production problem would be solved and there would be enough for everyone but machines would cause "technological unemployment". McKinsey Global Institute in a recent report[1] stated that the increasing adoption of automation technologies, including artificial intelligence and robotics, will generate significant benefits for the economy, raising productivity and economic growth, but with a far-reaching impact on the global workforce. In particular, according to the study, around half of current work activities are subject to be technically automatable by adapting current available technologies and, by 2030, 75 million to 375 million workers will be displaced by automation with the need to change occupation to avoid unemployment.

Brian Arthur, one of the pioneers in studying the economics of the digital age, recently stated[2] that we have reached or are close to the above-mentioned "Keynes point", i.e. a new economic era where we are witnessing the "third morphing" of the digital revolution. In particular, while the first morphing in the 70s/80s was characterized by the microchip and the availability of cheap digital calculus, the second morphing in the 90s/00s by the widespread diffusion of computer networks, the third morphing is bringing intelligent machines. The combination of computers, sensors, big data and statistical learning techniques, provides machines characterized by the sort of associative intelligence typical of biological beings, then potentially able to substitute humans in a large set of activities.

[1]McKinsey Global Institute, Jobs Lost, Jobs Gained: Workforce Transitions in a Time of Automation, December 2017.

[2]Arthur (2017) Where is technology taking the economy. McKinsey Quarterly

In this respect, the higher efficiency related to the introduction of new digital technologies generally determines a higher productivity which in turn can lead to lower employment, see Pianta (2009). Furthermore, it is worth noting that while most of innovations introduced in the production process until the end of the XX century empowered workers with additional mechanical energy able to overcome the limits imposed by human physical force, “The Second Machine Age" (Brynjolfsson and McAfee (2014)) characterized by robotics, automation, software and artificial intelligence (AI) might be able to surmount also the limits imposed by human mind. Technological unemployment is then becoming the concern not only of “blue collars" but also of “white collars" workers. However, empirical studies have shown a job polarization not completely consistent with the so-called “skill-biased technical change", see Autor and Dorn (2013); Goos and Manning (2007); Goos et al. (2014). Indeed, the advent of new digital technologies has led to a decreasing demand of mid-range workers performing routine manual and cognitive tasks and, at the same time, to an increasing demand of high salary non-routine cognitive jobs and low salary non-routine manual jobs.

The key element of intelligent machines is software, i.e. the collection and combination of procedures, instructions and algorithms that set machines and computers behaviour based on environment and input. Software is an intangible good which is non-rivalrous since it is characterized by zero (or quasi zero) marginal costs. Arthur has investigated since the 80s the economic features of software and generally of intangible digital technologies as well as their effects for business and the economy as whole, see Arthur (1989, 1990, 1994, 1996). In particular, he pointed out the existence of two different economic realities: the so-called diminishing and increasing returns world. The former is represented by traditional mass-production systems whose products require a huge amount of resources and a relatively lower contribution of knowledge, whereas the latter is represented by high-tech companies such as digital technologies producers: their products are characterized by a high knowledge content and a scarce quantity of resources. Several economic features distinguish increasing returns business worlds from traditional bulk-production worlds. Arthur mentions network effects, positive feedback, path dependence, winner-takes-most/-takes-all outcomes, and then technological lock-in. In particular, positive feedbacks reinforce market position of growing companies and, at the same time, negatively affect producers with declining market share.

In the age of intelligent machines and digital automation, software, databases, artificial intelligence algorithms, and any other sort of intangible digital technologies are playing an increasingly dominant role with a far-reaching impact on the working of our economies. A recent popular book by Haskel and Westlake (2017) emphasizes the increasing weight of intangible investments in the economy and analyses its consequences. In particular, the authors point out the four main features that characterize intangible goods, the so-called four

“S": scalability, sunk costs, spillovers, synergies. Scalability is related to the non-rivalrous property of intangible goods and their zero (or quasi zero) marginal costs, see also Rifkin (2014). Usually, firms producing this type of goods face high fixed costs, generally given by research and/or development costs, compared to their variable production costs. Furthermore, most of times, intangible investments represent sunk costs. A typical example is made by software realized for specific firms and purposes; although this software represents an asset for them, in case of exit from the market, it is very difficult to recover the initial investment. Intangible investments tend to generate spillover since it may be difficult or expensive to protect new knowledge generation and other companies can benefit copying or imitating new ideas. Finally, the combination of different intangible assets together (or with hardware) spurs innovations, e.g. at organizational level, that can increase companies' profitability. In other words, synergies create value for firms and, in the “intangible economy", the willingness to increase their revenues have led to the so-called “open innovation". This fact assumes a crucial importance because, from a wider perspective, the nature of technological innovation and progress can be interpreted as based on synergies between different and existing technologies, as argued by Arthur (2009).

It is worth noting that non-rivalrous digital assets do not cover all intangible investments, which include also other relevant assets, like patents, organizational innovations, or investments in marketing and brand. However, in the era of intelligent machines and digital automation, software, databases and artificial intelligence algorithms clearly deserve the highest attention among the different kinds of intangible investments.

The increasing importance of digital technologies is also shown by digital platforms, like Amazon, Deliveroo, Glovo, Foodora and Uber, which are typical examples of non rivalrous services that have considerably affected our economic system both from employment and working condition perspective, see Kenney and Zysman (2019). The so-called “digital taylorism" has emerged, where platforms' algorithms are able to control, to evaluate and to organize labour activities. Moreover, as in the case of Foodora or Uber, some authors argue that entrepreneurial risk has been transferred from companies to workers, see Dosi and Roventini (2019).

A considerable effort has been spent during years in order to asses the impact of intangible assets on productivity both at a firm, industry and national level, see Corrado et al. (2016); Hao and Van Ark (2009); Marrocu et al. (2011), respectively. In particular, a sizeable number of researches using different estimation methods underline the positive effect that intangible assets have on labour and total factor productivity growth, see Roth (2019).

Building on the pioneering insights of Arthur and on the recent contribution by Haskel and Westlake (2017), the study presented in the next section enriches the previous empirical work on the relation between measures of productivity and intangible investments. In particular, I consider a higher number of countries and different kinds of intangible investments, also in combination with tangible investments in information and communication technologies.

The main purpose of this empirical analysis is to inform the design of the first framework of the Eurace model used to investigate potential consequences deriving from the digital technological progress. In particular, the study of the relations between different typologies of investments and productivity turns out to be crucial in order to find an effective way to model the effects of investments in digital technologies on the production processes.

Results show a significant correlation between intangible investments and both labor and total factor productivity in the period after the 2008 financial crisis. Similarly, both measures of productivity growth are correlated with a combination of both tangible and intangible investments which includes information and communication technologies and software and database. Empirical results presented in the next section have been reported in Bertani et al. (2020b).

1.2 Productivity and digital assets: an empirical assessment

Following the previous considerations about the digital transformation, the aim of this section is to provide an empirical and quantitative evidence about the impact of intangible investments on the economy, in particular on the productivity of production factors, i.e. labor and capital, taken singularly and in combination. The investigation is based on a correlation analysis between the growth rates of different measures of investments and productivity, along the line of the analysis presented in the recent book by Haskel and Westlake (2017), which I extend in many dimensions, in particular, in the number of variables considered, in the number of countries and in the length of the time period examined. The results will inform the development of the new modelling features introduced in the first framework of the agent-based macro-model Eurace concerning digital technologies. This first framework, used to address the impact of the digital transformation on the economy and in particular on the level of unemployment, will be presented in Chapter 2.

The role of intangible investments in our economy is becoming increasingly important over time. In fact, intangible investments have surpassed tangible ones in certain markets, as for example in the United Kingdom (UK), see Goodridge et al. (2012). In addition to software and databases (Soft&DB), other kinds of intangible investments are represented for example by investments in R&D, design and engineering, mineral exploration, brands and advertising, see Corrado et al. (2005); Thum-Thysen et al. (2017).

As far as digital technologies are concerned, Fig. 1.1 shows several time series representing the ratio between intangible investments in software and database and gross value added (GVA) for various countries. The ratio between investments in Soft&DB and GVA represents a relative measure which allows to compare the entity of these intangible investments between countries regardless of their size and GDP. In fact, although the bigger countries tend to invest more in absolute terms, their relative data can be lower than in some smaller countries, see the case of USA and Netherlands in Fig. 1.1(a). Except for Italy (IT) and Luxembourg (LU), see Fig. 1.1(b) and (c) respectively, these investments increased between 1995 and 2016; in particular Netherlands (NL), France (FR) and Sweden (SW) have experienced the hugest enhancement. This shows the growing importance that digital assets have in our economic system.

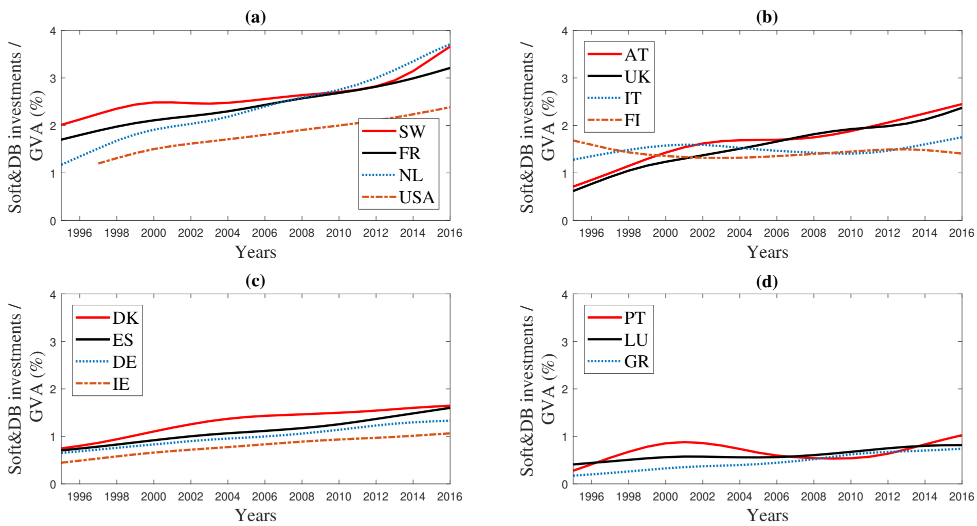

Figure 1.1: The figure shows various time series representing the trend between 1995 (1997 only for USA) and 2016 of ratio between software and database intangible investments and gross value added for several countries. Time series are author' elaboration of EU-KLEMS data (www.euklems.net) based on a Hodrick–Prescott filter with a smoothing parameter equal to 10. HP filtering has been performed to dampen excessive fluctuations and highlight the general trend. Time series are organized in sub-figure according to their values: in Fig. 1 (a) time series with highest values are displayed and in Fig. 1 (d) time series with lowest ones; in Fig. 1 (b) and (c) time series with intermediate values are reported.

Along the line of Haskel and Westlake (2017), I have carried out a correlation analysis in order to investigate the relation among different measures of productivity and types of investment. My study takes into account a larger number of countries and it is focused on a longer time period of twenty-two years, from 1995 to 2016. I split this time span in a pre and post crisis time period, i.e., from 1995 to 2007 and from 2008 to 2016. The fifteen countries considered are: Italy (IT), Germany (DE), Netherlands (NL), United Kingdom (UK), United States (USA), France (FR), Sweden (SW), Spain (ES), Denmark (DK), Portugal (PT), Austria (AT), Finland (FI), Ireland (IE), Greece (GR) and Luxembourg (LU).

Moreover, while Haskel and Westlake (2017) productivity-investments correlation analysis focused mainly on total factor productivity (TFP), I extend the analysis to different measures of productivity, namely labour productivity (P_L) and capital productivity (P_K)[3]. As for investments, I consider the following investment items:

- Total intangible investments (Tot Int): they represent the sum of R&D, software, databases, mineral exploration and artistic originals investments;
- Intangible investments in software and database (Int Soft&DB);
- Intangible investments in R&D (Int R&D);
- Total tangible investments (Tot Tang): they represent the sum of ICT equipment, transportation equipment, cultivated assets, non-residential structures, other machinery equipment and weapons investments. I do not consider investments in residential structures because the research focuses on those investments that generate productive assets.
- Tangible investments in ICT equipment (Tang ICT).
- Tangible investments in ICT equipment together with intangible investments in software and databases (ICT&Soft&DB). The combination of these investments turns out to be crucial because of the intrinsic complementarity characterizing hardware

[3]Labour productivity P_L measures how efficiently labour input is used in the production of goods and services. It can be measured as the ratio between GDP and all the persons employed in the production process or as the ratio between GDP and total hours worked. However, in the first case, the measure does not differentiate between full-time and part-time employment. Therefore, in my analysis, I consider the hours worked as labour input variable in the productivity measurement because "it bears a closer relation to the amount of productive services provided by workers than simple head counts", see OECD (2001). So, in this case, P_L represents the amount of goods and services produced in one hour.

As regards capital productivity P_K, it measures how efficiently capital input is used within production and it is given by the ratio between GDP and capital services. The latter “refer to the flow of productive services provided by an asset that is employed in production" and “are the appropriate measure of capital input in production analysis", see OECD (2001).

Finally, total factor productivity (or multifactor productivity) reflects how efficiently labour and capital inputs are employed together in the production process. Several factors can determine TFP variations, as for example technological progress, organizational changes, network effects and spillovers. TFP is measured as the “residual growth that cannot be explained by changes in labour and capital inputs", see OECD (2019).

and software. Hardware is useless without software and viceversa and combining these investments I can assess the real importance that digital technologies have in our society. Indeed, besides the distinction between “tangible" and “intangible" capital, another kind of common grouping is represented by “ICT" and “Non-ICT" capital (or assets), where ICT capital includes IT, CT and computerized information, namely Soft&DB, see Adarov and Stehrer (2019); Basu et al. (2004).
Software and hardware are also strictly related to each other from a technological progress point of view. In fact, according to Brynjolfsson et al. (2018), AI software and machine learning improvements are related to the creation of more powerful computer hardware (and the availability of larger database). Therefore, complementary investment in hardware turns out to be crucial in order to obtain further software developments[4].

The correlation analysis has been performed combining the EU KLEMS database[5] (https://euklems.eu), which provided information about investments, and the OECD database (https://stats.oecd.org) for information on productivity growth rates.

For each country, time averages of growth rates of different measures of productivity and investments have been calculated for each of the three time periods considered. Table 1.1 reports correlation coefficients and p-values (in brackets) between this set of country average growth rates. Asterisks points out statistically significant results[6].

Table 1.2 reports main statistical moments, i.e. mean and standard deviation σ, of investments and productivities growth rates for four representative countries among those analyzed: Greece (EL), Ireland (IE), Germany (DE), and United States (USA). These countries have been chosen according to their position in the data distribution. In particular, Greece has been chosen as the representative of the lower bound, Ireland as the representative of the upper one and Germany as median. USA is included because of its importance in the world economy. Statistical moments refer to two different time periods, namely 1997-2007

[4]Besides tangible investments in ICT assets, Brynjolfsson et al. (2018) argue that AI software needs complementary investments in other intangible assets, namely databases, human capital and organizational capital.

[5]EU KLEMS database (where KLEMS stands for capital (K), labour (L), energy (E), material (M) and service (S) inputs) collects data on industry level measures of productivity, capital formation, technological change, economic growth and employment creation for the European union members, Japan and USA. These data are meant to be used as effective inputs for policy evaluation and statistical analysis. For my research, I have gathered investments data from the EU KLEMS Release 2019, see Adarov and Stehrer (2019); Stehrer et al. (2019).

[6]Assuming a null hypothesis of non-correlation I consider three different levels of significance: a single asterisk is used when p-values are lower than 0.1 whereas two and three asterisks are used when p-values are lower than 0.05 and 0.01, respectively.

Table 1.1: The table shows the correlation coefficients and p-values (in brackets) between the sets of country time averages of different kinds of investments and productivities growth rates. Time averages refer to three different time periods, i.e. 1997-2007, 2008-2016, 1997-2016, except for IE whose averages refer to shorter time periods because of the lack of data, namely 1997-2007, 2008-2014, 1997-2014. They have been considered three types of productivity (total factor productivity (TFP), labour productivity (P_L) and capital productivity (P_K)) and four types of investment (total intangible investments, intangible investments in software and database, total tangible investments (without considering dwellings investments) and tangible investments in ICT). Significant results have been pointed out with asterisks: a single asterisk is used when p-values are lower than 0.1 whereas two and three asterisks are used when p-values are lower than 0.05 and 0.01 respectively. The analysis takes into account fifteen countries (IT, DE, NL, UK, USA, FR, SE, ES, DK, PT, AT, FI, IE, EL, LU) and it has been realized using EU-KLEMS (www.euklems.net) and OECD (www.oecd.org) data.

	1997-2007	**2008-2016**	**1997-2016**
TFP - Int tot	0,20 (0,48)	0,7025*** (0,0035)	0,40 (0,14)
P_L - Int tot	0,28 (0,31)	0,7214*** (0,0024)	0,569** (0,027)
P_K - Int tot	-0,24 (0,39)	-0,07 (0,82)	-0,43 (0,11)
TFP - Int Soft&DB	0,17 (0,54)	0,05 (0,86)	-0,02 (0,94)
P_L - Int Soft&DB	0,13 (0,64)	0,19 (0,51)	0,05 (0,87)
P_K - Int Soft&DB	0,20 (0,48)	-0,35 (0,19)	-0,17 (0,53)
TFP - Int R&D	0,19 (0,50)	0,465* (0,081)	0,28 (0,31)
P_L - Int R&D	0,32 (0,25)	0,506* (0,054)	0,495* (0,060)
P_K - Int R&D	-0,37 (0,18)	-0,13 (0,66)	-0,541** (0,037)
TFP - Tang tot	0,30 (0,28)	0,475* (0,074)	0,6494*** (0,0088)
P_L - Tang tot	0,38 (0,16)	0,32 (0,25)	0,7152*** (0,0027)
P_K - Tang tot	-0,16 (0,57)	0,22 (0,42)	-0,15 (0,59)
TFP - Tang ICT	0,17 (0,56)	0,544** (0,036)	0,36 (0,19)
P_L - Tang ICT	0,13 (0,63)	0,547** (0,035)	0,35 (0,20)
P_K - Tang ICT	0,02 (0,94)	0,02 (0,93)	0,03 (0,92)
TFP - ICT&SOFT&DB	0,19 (0,49)	0,6519*** (0,0085)	0,34 (0,22)
P_L - ICT&SOFT&DB	0,21 (0,46)	0,6460*** (0,0093)	0,40 (0,14)
P_K - ICT&SOFT&DB	0,01 (0,96)	0,06 (0,84)	-0,09 (0,75)

Table 1.2: The table shows main statistical moments, namely time average and related standard deviation (σ), of investments and productivities growth rate for Greece (EL), Ireland (IE), Germany (DE), and United States (USA). Statistical moments refer to two different time periods, namely 1997-2007 and 2008-2016, except for IE whose data refers to time intervals 1997-2007 and 2008-2014 because of the lack of data.

	Greece (EL)				**Ireland (IE)**				**Germany (DE)**				**United States (USA)**			
	1997-2007		**2008-2016**		**1997-2007**		**2008-2014**		**1997-2007**		**2008-2016**		**1997-2007**		**2008-2016**	
	Mean	σ	**Mean**	σ	**Mean**	σ	**Mean**	σ	**Mean**	σ	**Mean**	σ	**Mean**	σ	**Mean**	σ
Tot Int	6,1	7,8	-4	11	15	22	8	17	3,6	2,9	3,2	2,2	5,5	3,1	2,7	1,9
Int Soft&DB	15	18	5	31	9	16	6,0	4,9	7,3	3,9	3,7	7,2	10,1	8,6	4,3	2,8
Int R&D	8,3	6,2	-2	11	18	29	9	20	2,7	2,7	3,3	2,7	4,1	1,4	1,8	2,4
Tot Tang	8	12	-5	13	9,9	7,3	1,0	14,2	1,9	4,2	0,5	6,8	3,0	4,0	0,3	6,8
Tang ICT	9	18	-6	22	14	22	7	29	5	12	0,4	9,2	13	12	3,0	5,2
ICT&Soft&DB	10	16	-4	14	11	14	6	16	5,8	8,7	1,9	7,3	11,1	9,2	3,8	2,6
TFP	1,3	1,9	-2,1	2,3	2,0	2,1	1,1	4,5	0,92	0,62	0,4	1,9	1,29	0,61	0,41	0,70
$\mathbf{P_L}$	2,6	2,4	-1,2	1,5	3,2	2,1	2,7	4,9	1,51	0,67	0,7	1,6	2,23	0,71	1,0	1,1
$\mathbf{P_K}$	-1,8	1,4	-4,1	4,6	-1,8	2,4	-4,4	4,8	-0,5	1,1	-0,3	2,8	-1,7	1,1	-1,3	1,8

and 2008-2016, except for IE whose data refers to time intervals 1997-2007 and 2008-2014 because of the lack of data.

Significant results underline positive correlations between variables in all the cases except for the negative correlation between capital productivity and intangible R&D investments average growth rates in the 1997 – 2016 time periods. In this respect, it is worth noting that capital productivity, measured as the ratio between GDP and capital services, has been decreasing in most OECD countries for the past twenty years, see OECD (2019), and this fact may have affected the result.

In the time period 2008 – 2016 a considerable part of the results turns out to be highly significant, highlighting a positive correlation between productivity and investments. In this time period, TFP average growth rate is significantly and positively correlated with total intangible, R&D, total tangible, ICT equipment and ICT&Soft&DB investments average growth rates. Also labour productivity P_L is positively correlated with total intangible, R&D, ICT equipment and ICT&Soft&DB investments.

Even though the 1997 – 2007 time period is characterized mainly by positive relations among variables, I did not find significant results.

Fig. 1.2 show the scatter plot between TFP and total intangible investments average growth rates in the 1997 – 2007 and 2008 – 2016 time periods. The comparison of these two plots highlights an increase in the correlation between variables in the 2008 – 2016 time period, even though the growth rates tend to be lower. The same considerations hold also for R&D and ICT&Soft&DB investments average growth rates, presented in Figures 1.3 and 1.4. In 2008 – 2016 time periods, even though the positive correlation coefficient between TFP and Soft&DB intangible investments is not significant, TFP turns out to be significantly and positively correlated with the sum of Soft&DB and ICT equipment that has been called ICT&Soft&DB (the correlation coefficient is equal to 0.6519). This fact points out the complementary roles of hardware and software.

The higher correlation coefficients in the post-crisis period of 2008 – 2016 might also be explained along the lines of the cleansing effect of recessions, introduced by Caballero and Hammour (1994). According to this idea, recessions can be seen as times of "cleansing" when outdated or relatively unprofitable techniques and products are pruned out of the productive system. Therefore, after the crisis of 2007, investments in new technology induced a higher productivity growth with respect to the previous decade. Of course, many other factor might have affected this result, in particular the political response in terms of institutional reforms or economic policies. However, it is worth noting that the cleansing effect typically occurs in all countries, irrespective of their local institutional arrangement or market structure.

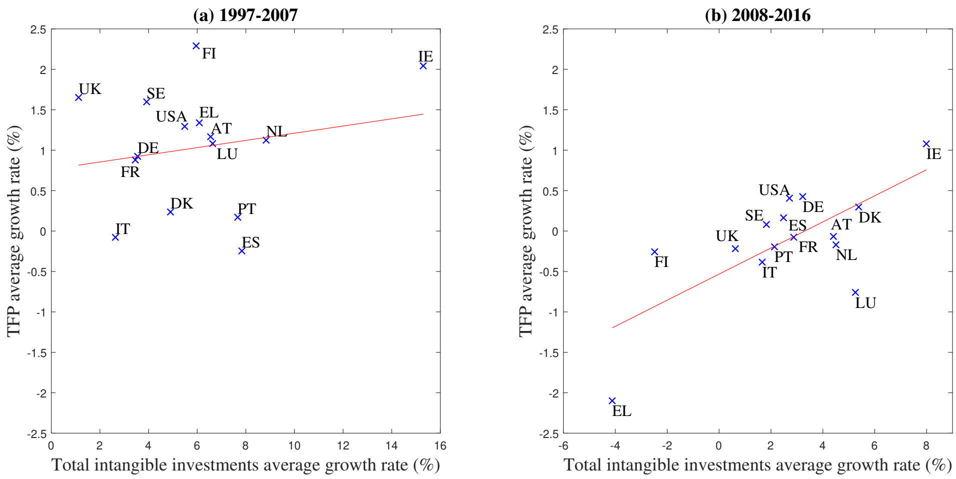

Figure 1.2: The figure shows two scatter plots between country TFP and total intangible investments average growth rates (%). Country averages are considered for two different time periods, namely 1997-2007 (a) and 2008-2016 (b), except for IE whose time average in the subplot (b) refers to a shorter interval because of the lack of data, i.e. 2008-2014. The correlation index is equal to 0.20 (a) and 0.7025 (b). Source: authors estimations based on EU-KLEMS ((https://euklems.eu)) and OECD (https://stats.oecd.org) data.

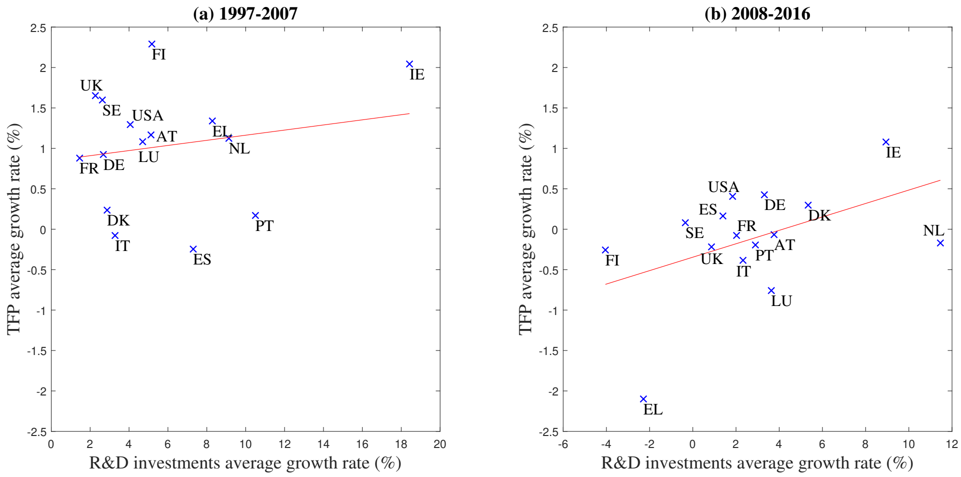

Figure 1.3: The figure shows two scatter plots between country TFP and R&D investments average growth rates (%). Country averages are considered for two different time periods, namely 1997-2007 (a) and 2008-2016 (b), except for IE whose time average in the subplot (b) refers to a shorter interval because of the lack of data, i.e. 2008-2014. The correlation index is equal to 0.19 (a) and 0.465 (b) respectively. Source: authors estimations based on EU-KLEMS ((https://euklems.eu)) and OECD (https://stats.oecd.org) data.

1.3 Digital technological progress and its potential consequences on labour market

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

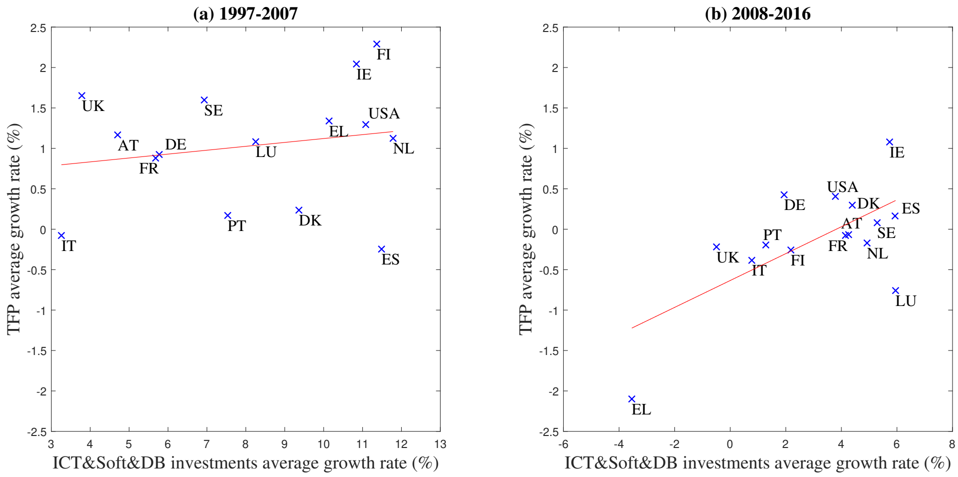

Figure 1.4: The figure shows two scatter plots between country TFP and ICT&Soft&DB investments average growth rates (%). Country averages are considered for two different time periods, namely 1997-2007 (a) and 2008-2016 (b), except for IE whose time average in the subplot (b) refers to a shorter interval because of the lack of data, i.e. 2008-2014. The correlation index is equal to 0.19 (a) and 0.6519 (b) respectively. Source: authors estimations based on EU-KLEMS ((https://euklems.eu)) and OECD (https://stats.oecd.org) data.

corresponds to technological unemployment and it is related to innovation process which constitutes the essence of economic system evolution.

Obviously, technological progress does not always involve the same result. In this respect, we can differentiate between two different kinds of technological innovation, i.e. product and process innovation. The positive impact on employment resulting from the former has been highlighted and underpinned by various researches, see e.g. Edquist et al. (2001); Vivarelli and Pianta (2000), whereas the latter differs in its labour-saving nature allowing to produce the same amount of output using less workforce. In fact, thanks to product innovation new markets can be opened leading to an increase of production and employment, while process innovation involves higher level of productivity determining a lower employment in the production system, see Pianta (2009). It is worth noting that two main analysis levels can be distinguished in order to investigate process innovation effects, namely the firm-level and the industry-level. In this regard, according to Acemoglu et al. (2020), although firms adopting automation decrease their workforce share in the production process, their overall employment increases. In other words, process innovation induces a positive employment effect at the firm-level. In fact, the adoption of automation determines a cost reduction and a consequent increase of their market shares. However, their expansion on the market occurs at the expense of their competitors and it causes a negative overall effect on employment at the industry-level.

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

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

In the next chapter, I am going to present the first framework of the Eurace model concerning digital technologies that has been developed in order to study potential consequences of the digital transformation. In this first framework, by virtue of the positive and significant correlation between ICT&Soft&DB and TFP, I have decided to model digital technological progress through a total factor augmenting approach.

Chapter 2

Modelling the Digital Transformation: the Total Factor Augmenting Approach in Eurace

2.1 Literature overview

The main purpose of the thesis is to study the potential effects deriving from the digital technological progress on our economy. In this regard, modelling the digital transformation turns out to be crucial in order to forecast the consequences for the economy related to the advent of new digital technologies.

The debate on how to represent the potential effects deriving from their adoption in production processes is still open. Current literature includes different methods that have been developed in order to assess unemployment, productivity change and wage inequality deriving from the digital transformation. One of these is represented by including AI within production functions as a new (production) factor, see DeCanio (2016); Hanson (2001); Lankisch et al. (2019). Moreover, as pointed out by Acemoglu and Restrepo (2018d), several researchers have modelled the introduction of automation and AI in the manufacturing sector as a factor augmenting technical change and digital transformation is represented by an increase in factor productivity, see Acemoglu (2003). For instance, Graetz and Michaels (2018); Nordhaus (2015); Sachs and Kotlikoff (2012) frame automation and AI impact as a capital-augmenting technical change, whereas Bessen (2016, 2018, 2019) represents automation as labour-augmenting.

It is worth noting that Acemoglu and Restrepo (2017, 2018a,b,c,d) point out some weaknesses of the factor augmenting approach in equilibrium models[1] and they adopt the so-called task-based approach based on the pioneering contribution by Zeira (1998): automation advent is represented as an increase in the number of tasks that can be performed by machines. Similarly, Aghion et al. (2017) develops AI through a task-based model.

2.2 The added value of agent based modelling

The criticism by Acemoglu and Restrepo holds in equilibrium models, whereas is not directly applicable to the disequilibrium approach which is the distinguishing feature of agent-based simulation models as the one presented in this chapter. In particular, differently from equilibrium models whose main purpose is to find the static vector of prices equating agents' demand and supply schedules and making their expectations self-fulfilling, agent-based computational modelling studies how agents' actions, strategies, or expectations endogenously change out-of-equilibrium and the aggregate economic patterns that this dynamic process creates, see Arthur (2006, 2010). An example of how micro-level behavior gives rise to a macro-level regularity, which is interesting in this context, is the network effect in the adoption of a technological standard, i.e. the empirically-grounded modelling feature according to whom the likelihood of adoption depends not only on the (not perfectly known) quality of the standard but also on the number of its current users. This micro choice behaviour can give rise in the long-run to a winner-take-all standard, which is not necessarily the superior one from the technological standpoint, see Arthur (1989). Furthermore, who is the winner can not be foreseen ex-ante based on agents' preferences, as in a standard equilibrium model, since the final outcome is path-dependent and small unpredictable exogenous stochastic disturbances during the dynamic selection process can give rise to different final outcomes. This macro level regularity can then be compared with the empirical evidence, see e.g. the case of software industry Arthur (1996).

Agent-based macroeconomic model arose as an alternative to neoclassical economic models, describing the economy as a complex evolving system in which macro dynamics (e.g. business cycle, long run growth) emerge out of the micro interactions among bounded rational agents, see Gallegati (2018); Hommes and LeBaron (2018); LeBaron and Tesfatsion (2008); North and Macal (2007). Differently from the structural macro models of the 70s,

[1] Acemoglu and Restrepo (2018d) argue that "factor-augmenting technologies have a limited scope to reduce the demand for labor". Another criticism made by the same authors refers to the impact of technology on labour share in national income: it is strictly related to the elasticity of substitution between production factors. Conversely, they argue that task-based approach "always reduces the labor share and it reduces labor demand and the equilibrium wage unless the productivity gains from automation are sufficiently large."

agent-based macroeconomics introduce explicit micro-foundations based on empirically observed behaviours of individuals and organizations. Agents' decisions and adaptation are embedded in a world characterised by true Knightian uncertainty and dispersed information.

Agent-based modelling represents an appropriate approach in order to address complexity and the main features characterizing the increasing returns world to which digital technology producers belong. Out-of-equilibrium dynamics, complex interactions among economic agents and heterogeneity are three important features that can be encompassed by agent-based modelling. Since the AI advent can be framed as a transition phase in the history of technological progress, an out-of-equilibrium approach, such 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 for heterogeneity to study the potential effect of a digital transformation is also reflected by the labour force: workers are heterogeneous and they differ in skills. Finally, interactions drive several features of the "increasing returns" world, such as for example network effects, lock-in and winner-take-most-phenomena. These are the reasons why I adopted this approach in order to conduct my research.

It is crucial to point out that the concept of innovation has already been investigated by means of agent based models (see e.g Caiani et al. (2019); Dawid and Reimann (2011); Dosi et al. (2010); Fanti (2018); Ponsiglione et al. (2017); Pyka et al. (2010); Rengs et al. (2020); Vermeulen and Pyka (2014, 2018)), and also the well known large-scale macroeconomic agent-based model Eurace has been endowed with the concept of innovation, see Dawid and Gemkow (2014); Dawid et al. (2008, 2019, 2014, 2018). However, this research is focused 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 my study, as I 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 are the production processes automated, but also decisions start to be subject to automation technology, see Cotteleer and Sniderman (2017); Kang et al. (2016); Parrott and Lane (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, my analysis aims to study the main business dynamics characterising digital technology producers. In this respect, the novelty of my contribution concerns the introduction of a new type of capital producer within Eurace: the intangible or digital assets developer. The introduction of this new kind of firm, which belongs 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.

2.3 The Eurace model with intangible digital assets

2.3.1 Software tools and computational framework

The baseline Eurace model and its extensions have been implemented using the Flexible Large-scale Agent Modelling Environment (FLAME). This software represents a flexible and generic agent-based modelling platform that can be used to model and simulate complex system applications in various research fields, as for example economics and biology. The FLAME software generates agent-based applications whose compilation and deployment can be performed both on laptops and high performance computers[2].

Models developed through this software are based on a specific method of computation whose name is extended finite state machines. Indeed, each agent is represented as a computational state machine which is composed of a certain number of states with transition functions between them. Agents are endowed with a memory containing variables and transition functions can read and write to these variables. Moreover, transition functions can also read and write incoming and outgoing messages used in order to achieve communication between agents. The model description is implemented in Extensible Markup Language (XML) tag structures, whereas transition functions are written used the C programming language.

FLAME is used in order to implement and simulate the Eurace model, whereas the output analysis is performed with Matlab.

2.3.2 Outline of the baseline Eurace model

Building on the empirical analysis presented in Chapter 1, which shows a clear effect of investments in ICT&Soft&DB on TFP, I have developed a new extension of Eurace, see Mazzocchetti et al. (2020, 2018); Petrović et al. (2017); Ponta et al. (2018); Raberto et al. (2012); Teglio et al. (2019, 2012). In particular, the extension presented in this chapter has been described in Bertani et al. (2020a,b).

[2]See www.flame.ac.uk for further details on FLAME.

The model includes several types of economic agents, in particular: consumption goods producers (CGPs) that manufacture homogeneous consumption goods; a capital goods 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. 2.1. Ellipses and rectangles represent the different agent 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 a newly introduced agent.

Agents interact in different decentralised or centralised artificial markets. The 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' behaviour. 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 Godin and Caverzasi (2014); Godley and Lavoie (2012); Raberto et al. (2018).

The shortest time step in the model scheduling is the day, which is the frequency for financial market transactions, however, most agents' decisions occur on a weekly, monthly, or even yearly periodicity, and are asynchronous. Consumption budget decisions are made monthly by households but purchases are made on a 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.

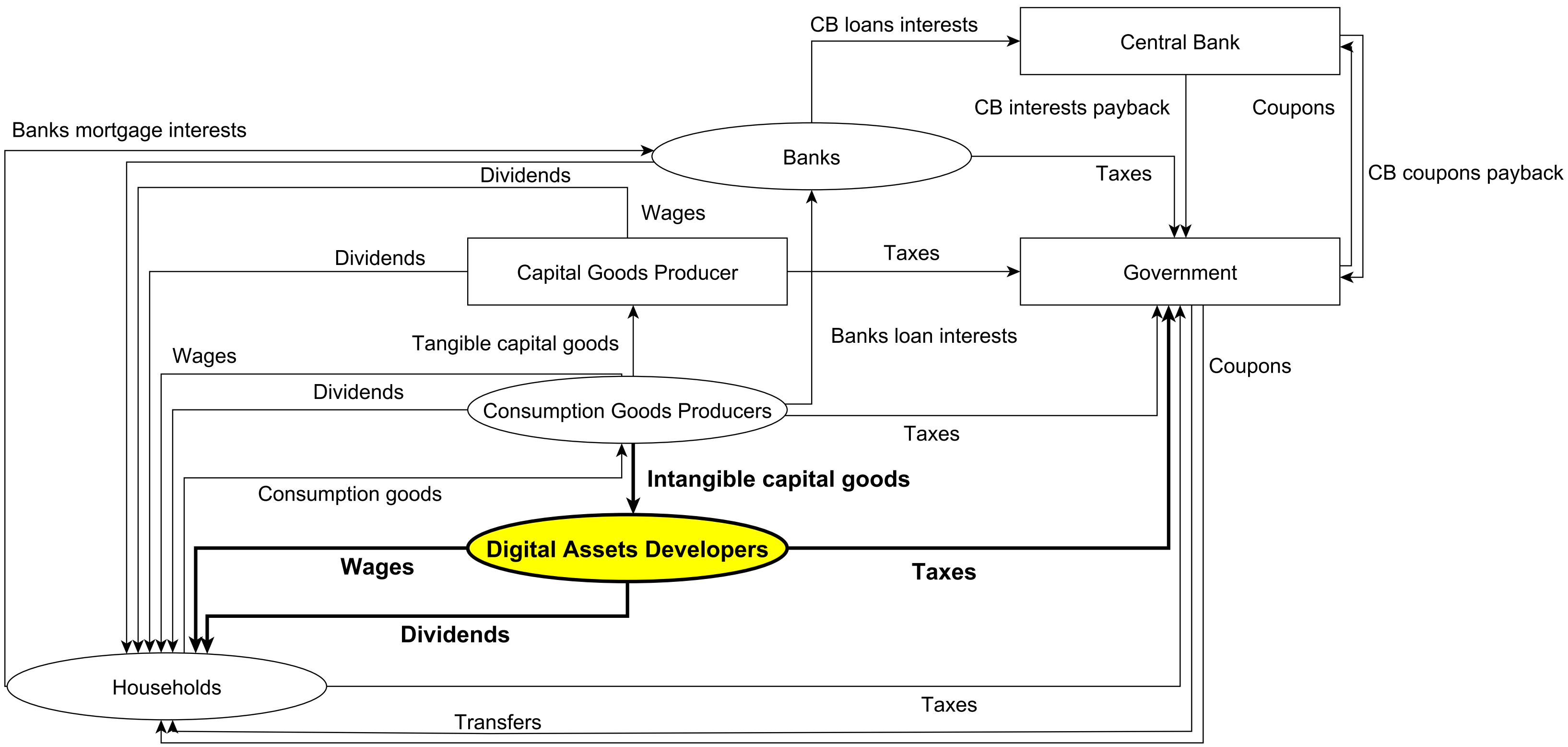

Figure 2.1: Graphical representation of the present Eurace model in terms of agent classes (ellipses or rectangles) and current account monetary flows (arrows). Rectangles are used when just one instance of the class in considered in the model, whereas ellipses are intended to represent the presence of multiple heterogeneous instances of the agent class. The yellow background refers to a newly introduced agent.

In the following, I present a summary of the core decisions taken by the 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 the 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. Households 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' decisions about the product to buy are driven by purchasing probabilities based on price.

Firm (CGP)

The firm in the Eurace model takes decisions about the factors of production and how to finance them. Firms can ask credit from banks or they can issue new shares. They distribute dividends to shareholders, which are initially all households (later it depends on financial market transactions). In particular, I 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 labour force needed 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 that needed by the production target, CGP fires the workers in excess, otherwise it enters the labour market to hire new employees. CGP sets an initial wage offer and, if it is not capable of hiring all the workers needed, 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 be 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 investment. Investment goods are produced by the capital goods producer (KGP).

- 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 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 the market again with a healthy balance sheet. Physical capital of insolvent firms is therefore not lost but remains inactive for a while.

Bank (B)

The bank role in the model is to provide credit to private agents; to firms in the form of loans and to households in the form of mortgages. When a bank receives a loan request from 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 (details 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 it is 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 initialised 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 initialised 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 at around 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 stylised facts about volatility of investments and consumption and about the correlation structure of GDP. In particular, I observed 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 lead business cycle expansion, and an anti-correlation with firms' defaults, which follow 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 researches will explore the feasibility of a full calibration of the model or of part of it, by resorting to Bayesian inference.

2.3.3 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 characterise the Eurace agents.

The stock-flow-consistent modelling approach provides a set of relevant theoretical identities to 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 2.1), that shows the asset and liability entries of each particular agent type.

The second one is the sectorial balance sheet table (Table 2.2), 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 between 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 to zero. Exceptions are: the capital goods accumulated by firms; inventories; housing units and equity shares[3] owned by households.

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

The third table is the cash flow matrix (Table 2.3), which shows 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, determine the liquidity change of a sector.

Finally, the fourth is the revaluation matrix (Table 2.4) that provides information about changes in sectors' net worth (equity) between periods. In particular, agents' net worth dynamics depends on net cash flows in 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 2.1: Balance sheets of any agent class characterising the Eurace economy. Balance sheet entries in the table have a subscript character, which 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 a firm f, i.e. a liability, and $\mathscr{L}_b$ refers to the aggregate loans of a 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, $\sum_b \mathscr{L}_b = \sum_f \ell_{b,f}$ represents an aggregate balance sheet identity, that is verified throughout 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 bond numbers 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: $\mathscr{L}_b = \sum_f \ell_{b,f}$ Mortgages: $U_b = \sum_h U_{b,h}$	Deposits : $\mathscr{D}_b = \sum_h M_{b,h} + \sum_f M_{b,f} + M_{b,K}$ 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: $\mathscr{L}_{CB} = \sum_b \ell_{CB,b}$ Gov Bonds: $n_{CB,G}\ p_G$	Outstanding fiat money: Fiat_{CB} Deposits: $\mathscr{D}_{CB} = \sum_b M_b + M_G$ Equity: E_{CB}

Table 2.2: 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 bond 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 held by two sectors, i.e. households and central bank in the case of government bond units and consumption goods producers and renewable power producers 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		$+I_F\ p_C$	$+I_K\ p_K$					$+I_F\ p_C + I_K\ p_K$
					$+D_F$			
Debt(-) / Credit(+)	$-U_H$	$-D_F$			$+U_H$		$+\ell_{CB}$	0
					$-\ell_{CB}$			
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 (-)	$+\Sigma_f n_{E_f} p_{E_f}$	$-E_F$						$+\Sigma_f n_{E_f} p_{E_f} - E_F$
	$+n_{E_k} p_{E_k}$		$-E_K$					$+n_{E_k} p_{E_k} - E_K$
	$+\Sigma_d n_{E_{DAD,d}} p_{E_{DAD,d}}$			$-E_{DAD}$				$\Sigma_d n_{E_{DAD,d}} p_{E_{DAD,d}} - E_{DAD}$
	$+\Sigma_b n_{E_b} p_{E_b}$				$-E_B$			$+\Sigma_b n_{E_b} p_{E_b} - E_B$
	$-E_H$					$-E_G$	$-E_{CB}$	$-E_H - E_G - E_{CB}$
Σ	0	0	0	0	0	0	0	0

Table 2.3: Sectorial transaction flow matrix of agents populating the EURACE economy. Note that HH stands for 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
Current Account	Consumption goods	−	+						0
	Investment goods		−	+					0
	Licences		−		+				0
	Training courses		−		+				0
	Wages	+	−	−	−		−		0
	Transfers	+					−		0
	Taxes	−	−	−	−	−	+		0
	Dividends	+	−	−	−	−			0
	Coupons	+					−	+	0
	CB coupon payback						+	−	0
	Banks loan interest		−			+			0
	Banks mortgage interest	−				+			0
	CB loan interest					−		+	0
	CB interest payback						+	−	0
		=	=	=	=	=	=	=	
	Net cash flow	Savings	Profits	Profits	Profits	Profits	Surplus	Seignoirage	0
Capital Account	Net cash flow	+Savings	+Profits	+Profits	+Profits	+Profits	+Surplus	+Seignoirage	0
	Δ Loans		$+\Delta D_F$			$-\Delta D_F$ $+\mathscr{L}_{CB}$		$-\Delta\mathscr{L}_{CB}$	0
	Δ Mortgages	$+U_H$				$-U_H$			0
	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 2.4: 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		$E_{H,t}$	$E_{F,t}$	$E_{K,t}$	$E_{DAD,t}$	$E_{B,t}$	$E_{G,t}$	$E_{CB,t}$	$E_{TOT,t}$

2.3.4 Supply side

In this study, the Eurace model is enriched with a new class of productive capital, which is represented by intangible digital assets, say software or any other digitized 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 raising their 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.

In line with the literature on intangible capital, see e.g. Haskel and Westlake (2017), it is assumed that intangible digital assets are non-rivalrous, i.e., they are characterised by zero marginal production costs. In particular, production costs are actually given only by the R&D costs, which are determined by the cumulated labour costs of the skilled labour 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 characterised 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:

$$prob_d = 1 - \frac{1}{1 + \eta M_d} \tag{2.1}$$

where η is a shape parameter, homogeneous across all DAD agents, setting the development speed, i.e., the higher η is, the higher the probability to develop an improved version of digital assets is, for any level of cumulated person months M_d employed. The rationale behind Eq. 2.1 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 workforce needed is set so that the wage bill is a fixed fraction of the DAD's 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 characterising the economy. Basically, DADs embodie the essence of Schumpeterian entrepreneurship: they represent the engine of innovation and technological progress within the Eurace macroeconomic system.

Concerning the hiring process, DADs enter the labour market and perform exactly the same procedures as CGPs with whom they compete for the labour force. However, there is an important difference: while CGPs hire households from the highest (fifth level) to the lowest (first) education level indistinctly, yet prioritising highly educated workers, DADs employ only workers with a high degree of education (from the third level upwards) to employ them in research activities and then develop new intangible digital assets.

2.3.5 Demand side

Intangible digital assets are demanded by CGPs which pay a user licence to DADs for their utilisation. In particular, digital assets, namely software, are integrated within “hard" capital purchased by the KGP. “Hard" capital shall be considered as a generalized mean of production which represents the physical part of: machine tools, computerized numerical control machines, robots, computing equipment (or computer hardware), communications equipment, etc. These means of production need software in order to work; in this regard, it is assumed that each unit of “hard" capital needs to be associated with a digital asset license. The modelling assumptions of integrating digital assets with “hard" capital in the consumption goods production process and associating them with productivity are grounded on the empirical analysis presented in the previous chapter, where I found a positive correlation between ICT equipment (hard capital) and Soft&DB (digital assets) investments with total factor productivity. This modeling assumption embodies the concept of complementarity between hardware and software. 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 digital technology employed sets the TFP of the CGP. In particular, along the lines of Teglio et al. (2019), I consider the labour 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.,

$$q_{C_f} = \gamma_f N_f^{\alpha} K_f^{\beta} = \gamma_f N_f^{\alpha} K_f^{1-\alpha} \tag{2.2}$$

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 no longer a 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 other words, according to the empirical findings reported in the previous chapter, in particular to the positive correlation between TFP and both R&D and ICT&Soft&DB investments, the impact of digital assets innovation on production processes is modelled as total factor augmenting, namely as increasing the value of TFP. Moreover, also the empirical analysis made by Haskel and Westlake (2017) shows a high correlation between total factor productivity and intangible investments. Therefore, a total factor augmenting approach can be considered as a suitable modelling choice to capture a key empirical fact connected to the digital transformation of the economy.

Furthermore, 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. 2.2. Although 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 my choice to adopt the Cobb-Douglas production technology with constant return to scale to model the introduction of digital intangible innovation, see Doraszelski and Jaumandreu (2018); Kalt (1978); Solow (1957).

The TFP γ_f is modelled as follows:

$$\gamma_f = \exp(1 + \eta_\gamma \kappa_d) \tag{2.3}$$

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:

$$\kappa_{d_t} = \kappa_{d_{t-1}} + \delta_\kappa \tag{2.4}$$

The TFP growth has been formulated as exponential in order to model a strong and significant impact of digital technological progress on the economy. In particular, an exponential growth trend allows to consider an increasing relevance of digital technologies on the production process and then on the labour market. Moreover, growth rates productivity data provided by OECD suggests a long-term exponential trend of TFP, albeit with a declining rate, and this further justifies my modelling assumption.

It is worth noting that, while in the baseline Eurace version total factor productivity also depends on the workforce's specific skills[1], in this extension it is assumed 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 licence 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 I 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 licences depends on the number of computers where it is installed. For the sake of simplicity, it is stated that this dependence is linear and that the DAD agent simply charges a unit licence cost p_{D_d} multiplied by the size of physical capital, say computers, or more generally physical machines that can be automatised and therefore more productive, due to 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 of computing the net present value (NPV) of expected net future cash flows that the CGP would get with the switch, as follows:

$$NPV_{d^*} = \frac{p_{C_f}(q^*_{C_f} - q_{C_f})}{r_D} + \frac{(p_{D_d} - p_{D_{d^*}})K_f}{r_D} - w\hat{N}_f\,, \tag{2.5}$$

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 licence 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. 2.5 takes into account that the difference in productivity between the two technologies (see Eq. 2.3) generates a different expected production level, given the present endowment of production factors, according to Eq. 2.2, and therefore different expected future revenues[2]. The second term of Eq. 2.5 takes into account the difference in the user licence bill. In this respect, the CGP usually faces a

[1]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.

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

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 licence price, as outlined in the next subsection.

2.3.6 Digital asset price dynamics

On a monthly basis, each CGP transfers to its reference DAD d a money amount to pay the licence fee, which is equal to the unit licence price P_{D_d} times the number of licences held by the consumption goods producer.

The unit licence 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 licence price P_{D_d} over time, whereas in the competitive case, each DAD adapts the licence price independently according to the dynamics of licence sales, with the purpose of getting market shares. In both cases, the licence price is 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 of labour costs, i.e. wages.

The user licence unit price p_{D_d} for each DAD in case of “collusive pricing" follows this relation:

$$p_{D_d} = \lambda w \tag{2.6}$$

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 rule of thumb based on past sales. If the DAD increases the number of licences sold , it also increases the mark-up by a fixed tick equal to δ_λ, otherwise it reduces prices by the same amount:

$$\begin{cases} \lambda_{t+1} = \lambda_t + \delta_\lambda & \text{if } Q_t > Q_{t-1} \\ \lambda_{t+1} = \lambda_t - \delta_\lambda & \text{if } Q_t \leq Q_{t-1} \end{cases} \tag{2.7}$$

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 characterised 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. 2.5, the user licence unit price could determine the transition from certain digital technologies to cheaper ones. Furthermore, through this pricing behavioural assumption, DADs can exploit expansion phases of their sales, thereby increasing their profits by raising mark-up.

Therefore, in case of “competitive pricing", λ assumes a heterogeneous and variable connotation.

2.3.7 Employees’ digital technologies skills

The third term of the Eq. 2.5 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’s 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 licences and 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 characterising the macroeconomic system. The lower these switching costs, the higher the probability of adopting a new kind of digital asset. In fact, with this particular micro-assumption, I 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, Belleflamme and Peitz (2018); Farrell and Klemperer (2007); Heinrich. Indeed, companies virtually benefit from the "digital technologies" skill of their workers and this precisely happens when they are assessing a possible digital asset 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 2.5. 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 of selling 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 one technology to another by reducing switching costs. In this respect, it is worth noting that, on a monthly basis, a fraction of workers resigns to find better job opportunities or is fired by CGPs. This continuous turnover characterising the Eurace labour market helps the diffusion among CGPs of the predominant digital technologies reflected in 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 or 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 a CGP’s production is not affected by digital technologies skills, each worker must be trained to manage the digital asset adopted in order to start the process.

2.4 Computational results

2.4.1 Design of experiments

The new features of the model allow to analyse different scenarios. In particular, I consider two digital asset pricing scenarios. In the first one, named “collusive pricing", DADs sell their licences at the same price, determined as a fixed share of the nominal wage. In the second one, henceforth “competitive pricing" scenario, I endowed the firm with the possibility of independently raising or decreasing their licence 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, I explore the two cases previously described with six different values of η, the parameter which controls the probability of developing an improved version of the digital asset, see Eq. 2.1; in this way I obtain twelve different scenarios.

The methodology of this 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 the 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-year-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. In order to give a complete overview of the model response, I also plot the time series of the most important variables of interest, so as to show the trend during the entire twenty-year-long simulation; all time series considered refer to a specific seed.

This analysis aims to investigate the behaviour of DADs at a micro level in order to verify the possible existence of phenomena that characterise the increasing-returns world, see Arthur (1996), and at the macro level to assess the impact of this new industrial sector on the economic dynamics.

Furthermore, I enrich the study focusing the analysis on the "competitive pricing" scenarios, comparing them with a case characterized by the absence of digital technological progress and digital assets. In this way, it is possible to understand in a deeper way the potential implications related to technological progress. In this respect, ensemble averages over twenty seeds, along with related standard errors, of time averages over a twenty-years-long period of the most relevant economic variables are presented.

2.4.2 "Competitive pricing" and "collusive pricing" business dynamics analysis

As we can see in Fig.2.2(a), "competitive pricing" scenarios are characterised by higher values of TFP (γ_f) compared to "collusive pricing" ones, independently of the value of the innovation probability function shape parameter η; this is due to the higher unit user licence price p_{D_d} (whose distribution is reported in Fig.2.2(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, I link the cost structure to the revenues structure through the average wage w, see Eq. 2.6. 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. 2.7. In presence of "competitive pricing", the average value of the mark-up λ results to be higher, see Fig.2.4(b), and this fact leads to higher employment in the DADs industrial sector (see Fig. 2.2(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 probability function, see Eq. 2.1. 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 licences 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 consumption goods 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

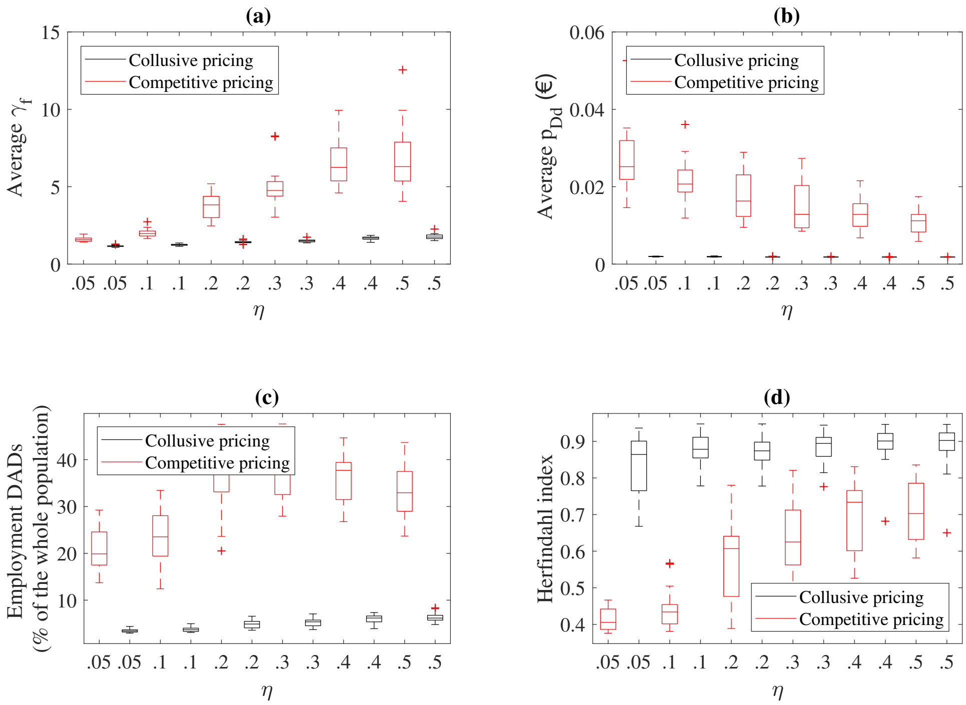

Figure 2.2: The figure shows a series of boxplots representing, for any values of η and for any pricing scenario considered, the distribution of: the average total factor productivity γ_f (a), the average unit user licence price p_{D_d} (b), the employment in the DADs industrial sector (c), the Herfindahl market power index (d). Each boxplot reports the distribution of the time averages over a twenty-year time period for each one of the twenty seeds considered.

productivity for their digital assets. Furthermore, the competition between DADs established by “competitive pricing" is accentuated by η; indeed the unit licence price p_{D_d} decreases as the innovation probability function shape parameter η enhances. At the same time, although the average price decreases in case of high values of η, the market concentration increases[3], as is visible in Fig.2.2(d). This emerging phenomenon, that I call the “converse concentration effect" appears in contradiction with 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 characterises the “Increasing-returns World" in which, by exploiting the right wave, a firm can become the market leader. What stimulates the emergence of a product over others, and consequently the birth of market concentration, is competitiveness; after acquiring the highest market share, the leader company can afford

[3]To represent the market concentration I use a standard measure: the Herfindahl index, see Kwoka (1985)

to raise its price but always in agreement with the value perceived by the customer (related to productivity and price). At the same time other competitors, in order to gain market shares, tend to decrease their product prices. The result is a reduction of the average price. Therefore, the digital assets market turns out to be very susceptible to unit licence price p_{D_d} variations and the result is the absence of price overshoot effects, see also Fig. 2.5 (c).

It is worth noting that productivity (which represents the digital asset quality inside the model) and the “right price" combined together are the key to a 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. 2.1 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 a 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 DADs. This behaviour is clearly visible in Fig. 2.3 (a) and (b) where the employment concerning the DADs industrial sector increases over time, while CGPs hire fewer and fewer employees because of high digital asset productivity (or TFP γ_f). As a matter of fact, it represents the so-called compensation mechanism “via additional employment in the capital goods sector": the higher demand for labour from the digital technologies industrial sector contrasts the “displacement effect" generated by the digital transformation of the economy, see Vivarelli (2014). Despite 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. 2.4(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. 2.2(a). As shown in Fig. 2.4 (c), the total number of licences 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, the trend of TFP γ_f, in case of “collusive pricing" the number of licences is higher compared to the “competitive pricing" case.

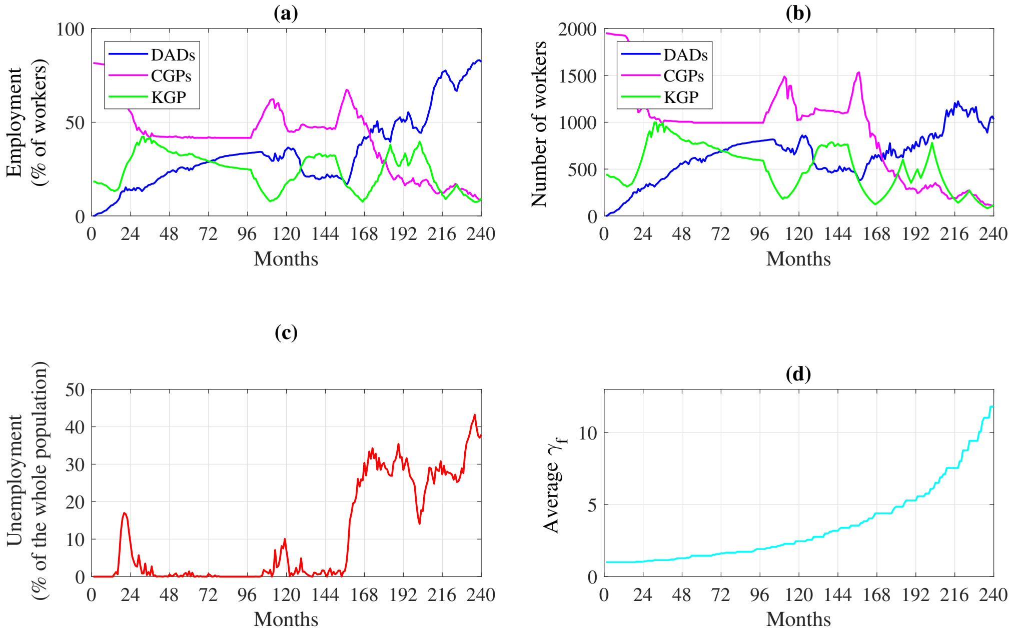

Figure 2.3: The figure displays various time series in case of "competitive pricing" and $\eta = 0.3$; in particular it shows: the percentage (a) and number of employees (b) in the various industrial sectors: consumption goods producers (CGPs), capital goods producers (KGPs), digital asset developers (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 $\eta = 0.3$.

2.4.3 Competitiveness in the "competitive pricing" case

In this subsection, I present a micro-analysis concerning the competitive dynamics involving the digital assets industrial sector in the "competitive pricing" case. Fig. 2.5 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 market leading position; the emergence of this DAD over others is due to successful *R&D* activities, which allows it to develop technologies with 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. 2.1. The cumulated person months M_d is influenced by revenue, therefore, the 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 licence prices, in the long-term the leader DAD improves its product

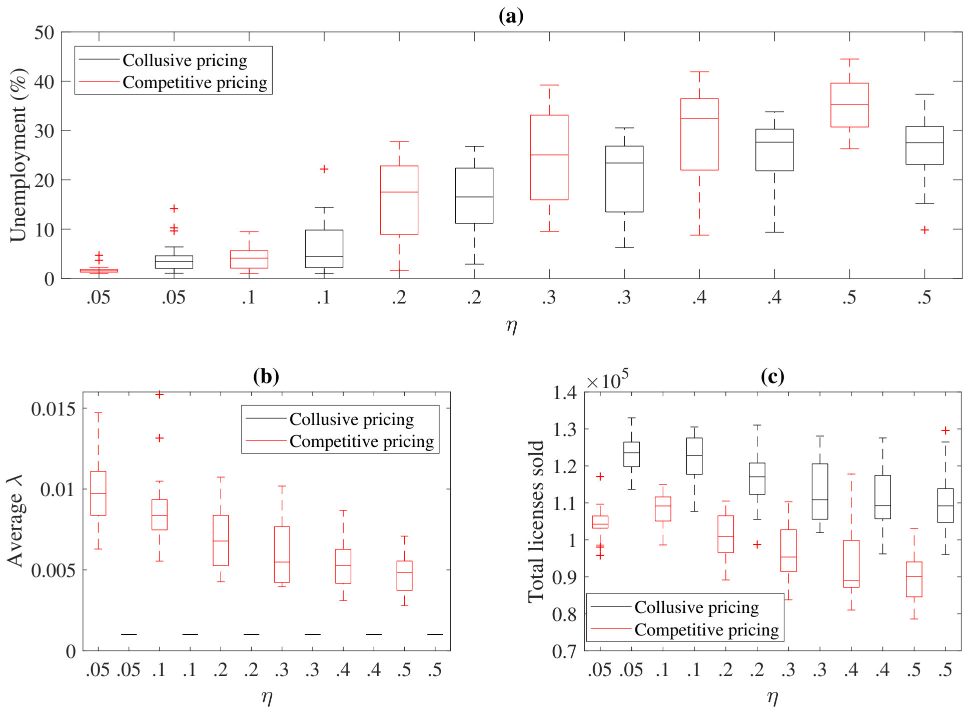

Figure 2.4: The figure shows a series of boxplots representing, for any value of η and for any pricing scenario considered, the distribution of: unemployment (%) (a), average mark-up λ (b) and total number of licences in the economy (c). Each boxplot reports the distribution of the time averages over a twenty-year time period for each one of the twenty seeds considered.

and the higher productivity of its digital assets covers the price difference with respect to product competitors. 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. 2.5 shows that, even if the *DAD*2 has a higher number of users (that are CGPs) compared to *DAD*3, the latter has sold (or renewed) a higher number of licences in the middle of the simulation (around time 96), because licences are proportional to the capital shares of user companies. This is what seems to make the difference because revenues depend on licences 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

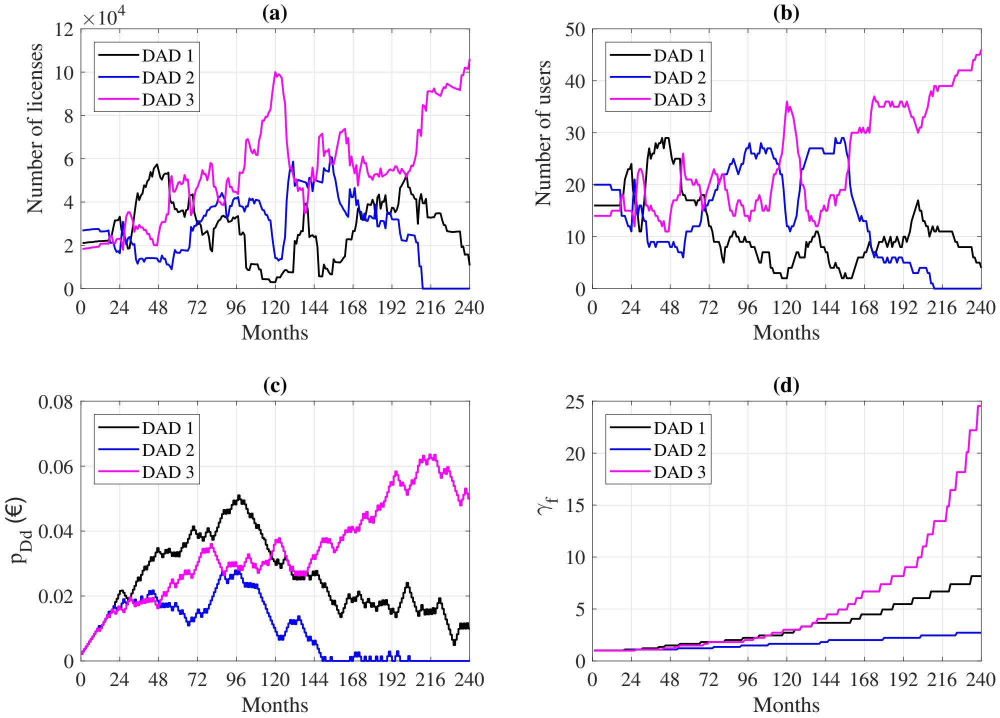

Figure 2.5: The figure displays various time series in case of "competitive pricing" and $\eta = 0.3$; in particular it shows: number of licences (a), number of users (b), unit user licence price p_{D_d} (c) and total factor productivity γ_f (d) of the three different digital assets developers. All time series refer to a specific replication which is representative of the system average trend in case of "competitive pricing" and $\eta = 0.3$.

productive and competitive, need digital assets. The interaction between these two industrial sectors highlights the complexity of the intangible digital economy.

2.4.4 The digital economy from a macroeconomic perspective

As shown in Fig. 2.6(d), in both pricing cases, the consumption goods 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 latter allows one to save both capital and labour force, as we can see from the higher unemployment, see Fig. 2.4 (a). In other words, higher values of TFP determine a decrease in production costs. In this respect, the lower average unit user licence price p_{D_d} has a positive impact on the price of consumption goods, as shown in Fig. 2.2 (b). In fact, CGPs follow a mark-up pricing rule on unit costs, where costs are represented by: wages, debt interests, licences and training courses, see Fabiani et al. (2006); Plott and Sunder (1982).

Fig. 2.6 (c) shows a slight decrease of the average nominal wage characterising the economy which influences the consumption goods price level. Moreover, Fig. 2.6 (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 a lower unit user licence price p_{D_d} and average wage w, see Fig. 2.2(b) and Fig. 2.6(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. However, the higher level of real sales is not only determined by the higher average nominal wage, but also by the lower consumption goods price level. In other words, Eurace is able to capture the so-called compensation mechanism “via decrease in price": the costs reduction leads to a prices decrease which in turn determines a higher demand of goods. However, this compensation mechanism together with the “via additional employment in the capital good sector" one is not able to balance effectively all the technological unemployment in the CGPs industrial sector.

The decrease of the central bank interest rate with the enhancement of η shows the intent of the policy maker to increase employment fostering new investments, see Fig. 2.6 (a).

2.4.5 The “competitive pricing" case: a deeper investigation

In this subsection, a deeper analysis concerning the “competitive pricing" case is presented. In particular, the various “competitive pricing" scenarios are compared with a base scenario, in which digital technologies and their technological progress are not considered.

Tables 2.5 and 2.6 display ensemble averages over twenty seeds, along with related standard errors, of time averages over a twenty-years-long period of the most relevant economic variables. These data confirm all the considerations developed in the previous subsections.

As reported in Table 2.5, in case of no intangible investments, the unemployment level tends to be higher compared to the case $\eta = 0.05$. This is related to the interaction between the “displacement effect" and the compensation mechanism “via additional employment in the (digital) capital goods sector" as mentioned above. For the lowest value of η, this compensation mechanism is able to absorb effectively the unemployment generated by digital technologies in CGPs creating also additional job places, while for higher value of η, “displacement effect" takes over on it leading in certain case to mass unemployment. Moreover, it is possible to affirm that for $\eta = 0.1$ the unemployment level is acceptable. As a matter of fact, besides the compensation mechanism “via additional employment in the

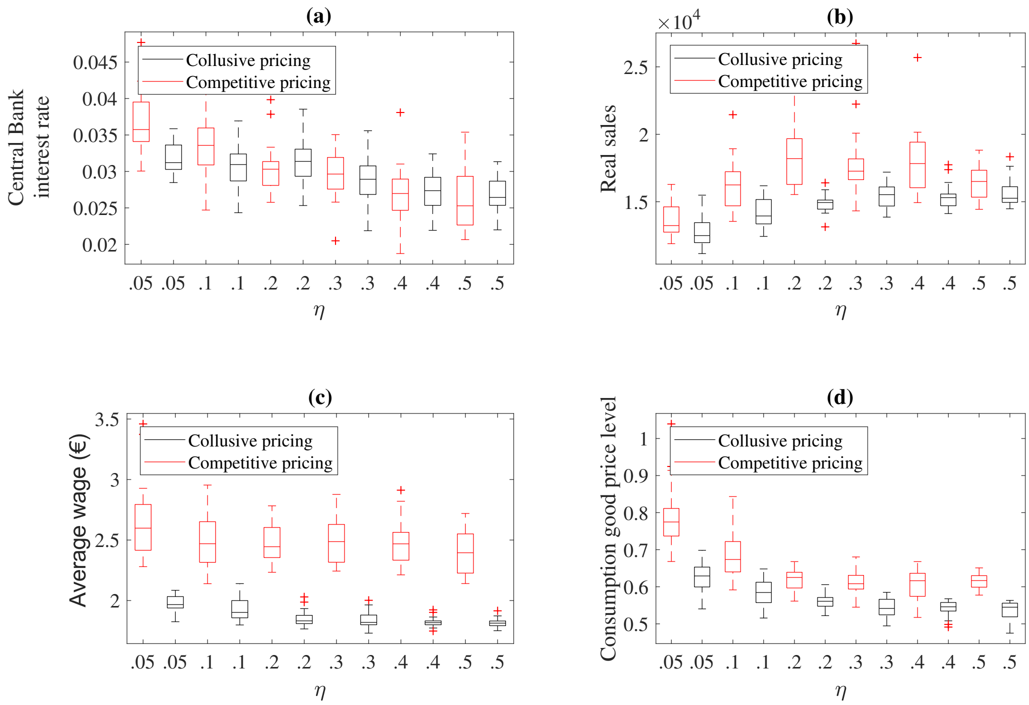

Figure 2.6: The figure shows a series of boxplots representing, for any values of η and for any pricing scenario considered, the distribution of: Central bank interest rate (a), real sales (b), average wage (c), consumption goods price level (d). Each boxplot reports the distribution of the time averages over a twenty-year time period for each one of the twenty seeds considered.

capital goods sector", also the “via decrease in price" one emerges[4]; for this value of η, the join effect of this two compensation mechanisms is able to counteract effectively the technological unemployment.

For high values of η, i.e. $\eta = 0.4; 0.5$, the economic system is strongly affected by digital technological progress whose impact results to be very significant also because of the exponential TFP growth shape. Fig. 2.7 shows that for high η values the “displacement effect" caused by digital technologies increases dramatically over time: digital assets substitute workers in jobs that they previously performed in the mass production industrial sector

[4]The consumption goods price level is lower for $\eta = 0.1$ compared to the case without intangible investments. This fact is strictly related to the higher TFP γ_f which has doubled because of technological progress. This fact allows firms to produce the same amount of output using less input factors.

Table 2.5: For each variable and scenario considered, the table shows ensemble average (and related standard error in brackets) of time averages distributions over a twenty-years-long time period. The variables reported are: average TFP (γ_f), unemployment level (%), average real wage (€), consumption goods sold quantity. The analysis takes into account six different values of η and the case characterized by the absence of intangible investments.

	Average γ_f	**Unempl. (%)**	**Aver. real wage (E€)**	**Real consumption**	**CGs price level**
No Int Inv	1 (0)	2.76 (0.27)	2.681 (0.013)	9768 (75)	0.7433 (0.0050)
η= **0.05**	1.610 (0.035)	1.79 (0.20)	3.539 (0.062)	13657 (289)	0.792 (0.020)
η= **0.1**	2.006 (0.058)	4.31 (0.55)	3.965 (0.073)	16290 (426)	0.684 (0.015)
η= **0.2**	3.79 (0.20)	15.84 (1.84)	4.384 (0.098)	18391 (531)	0.6191 (0.0068)
η= **0.3**	5.02 (0.29)	25.2 (2.3)	4.36 (0.13)	17974 (590)	0.6127 (0.0074)
η= **0.4**	6.51 (0.32)	30.0 (2.1)	4.34 (0.11)	17997 (567)	0.6043 (0.0097)
η= **0.5**	6.76 (0.46)	35.2 (1.3)	4.040 (0.072)	16499 (297)	0.6152 (0.0047)

Table 2.6: For each variable and scenario considered, the table shows ensemble average (and related standard error in brackets) of time averages distributions over a twenty-years-long time period. The variables reported are: CGPs employment level (%), DADs employment level (%), KGP employment level (%) and total capital stock owned by CGPs. The analysis takes into account six different values of η and the case characterized by the absence of intangible investments.

	CGPs empl. (%)	**DADs empl. (%)**	**KGP empl. (%)**	**CGPs total capital stock**
No Int Inv	52.16 (0.31)	0 (0)	24.79 (0.44)	117346 (1407)
η= **0.05**	44.31 (0.92)	16.42 (0.76)	17.18 (0.41)	95691 (925)
η= **0.1**	39.1 (1.2)	17.89 (0.87)	18.42 (0.34)	99209 (816)
η= **0.2**	27.5 (1.4)	21.37 (0.93)	14.99 (0.56)	92094 (1252)
η= **0.3**	22.31 (0.92)	19.4 (1.2)	12.77 (0.53)	87821 (1705)
η= **0.4**	20.18 (0.77)	18.03 (0.93)	11.51 (0.61)	84920 (1941)
η= **0.5**	18.64 (0.48)	15.29 (0.73)	10.59 (0.36)	81568 (1345)

represented in the model by consumption good producers (CGPs)[5]. However, for η = 0.1 the unemployment level is not extremely high and does not assume critical value.

Obviously, as mentioned above, the unemployment trend reflects the technological progress within the economy. In this regard, Fig. 2.8 shows a significant increase of the average TFP γ_f for high values of η. This increase determine a collapse of the economic system.

Furthermore, Fig. 2.8 shows that in the long-term the average TFP γ_f is higher for η = 0.4 compared to η = 0.5; this fact witnesses a decrease of R&D activities related to a very high endogenous rate of technological change which determines in the long-term a lower capital level and in turn lower revenues in the DADs sector for η = 0.5. Indeed, the average productivity level is higher in this case until the 19th year, than the curve flattens. This fact highlights the complexity characterizing the digital economy in which the various industrial sectors are interrelated with each other.

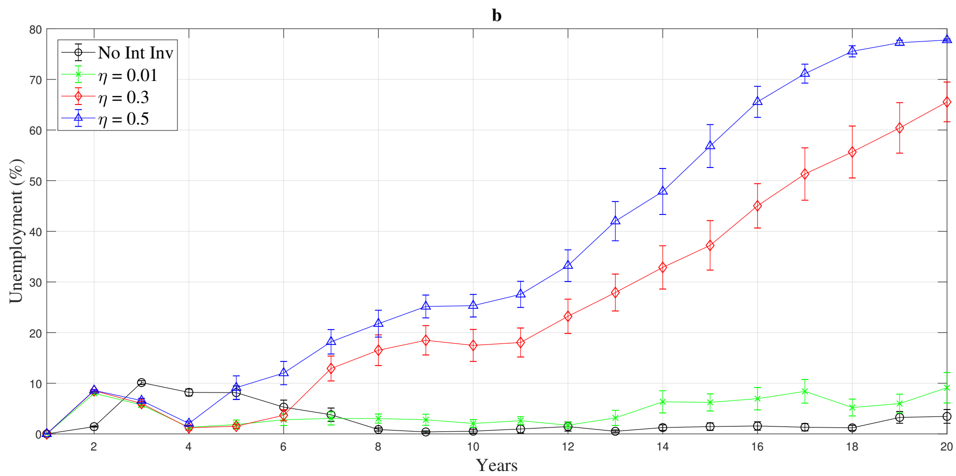

Figure 2.7: For η = 0.01; 0.2; 0.5 and the no intangible investments case, the figure displays for each year the average across 20 seeds (with the related standard error) of the yearly means of the unemployment level.

It results to be difficult to imagine a future characterized by such high unemployment levels. However, since we do not have a perfect ability to foresee the future, considering high values of η gives us a complete overview of the long-term possible scenarios even if they seem to be unrealistic or catastrophic. Moreover, testing a large range of values gives us the possibility to verify the functioning and validity of my model.

[5]For the sake of clarity, I did not include in Fig. 2.7 all the scenarios considered converning the "competitive pricing" case. However, Table 2.5 completes the analysis adding information related to the missing scenarios.

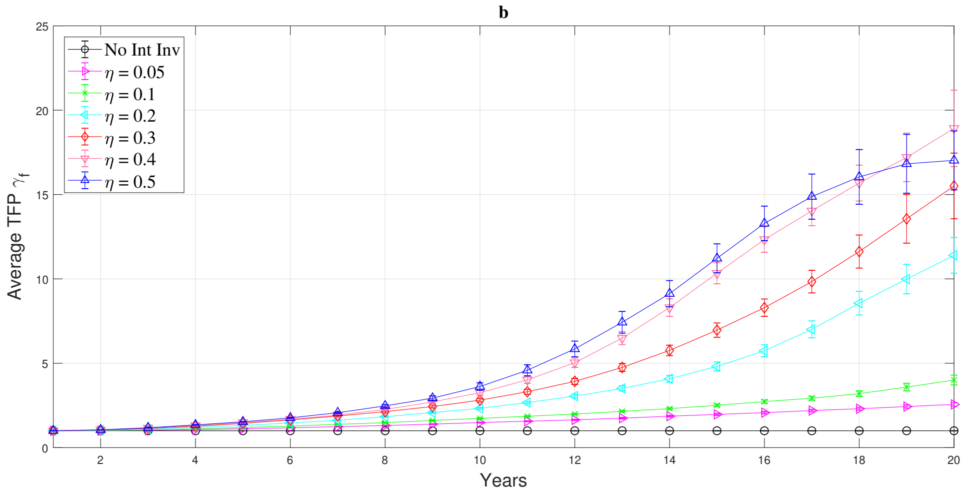

Figure 2.8: For each scenario (i.e., value of η considered), the figure displays for each year the average across 20 seeds (with the related standard error) of the yearly means of the average productivity or TFP of digital assets.

These strong negative effects on the economy are partly related to the lack of other compensation mechanisms, as for example the introduction of new products in the market. In this respect, the compensation mechanism “via new products" represents one of the most effective counterbalancing effects to process innovation. In fact, literature highlights a positive relationship between product innovation and employment, see Pianta (2009). However, being the consumption goods homogeneous, this type of compensation mechanism can not be modelled in Eurace at the current state.

It is worth noting that not all the compensation mechanisms can coexist together and can be captured by a model at the same time. For example, the compensation mechanism “via increase in incomes" is in clear contrast with the "via decrease in wages" one, as highlighted by Vivarelli (2014).

Obviously, all these results are strictly linked to the modelling assumption influenced by the empirical analysis: the total factor augmenting technological progress. As explained above, the positive and significant correlations between TFP - ICT&Soft&DB and TFP - R&D has leaded me to assume a positive effect of these investments on the TFP. Therefore, in Eurace technological progress affects input factors, namely capital and labour, increasing their marginal productivity in the same proportion.

Chapter 3

Modelling the Digital Transformation: the Elasticity Augmenting Approach

3.1 The elasticity augmenting framework: a short introduction

In this chapter, in order to analyze long-term consequences linked to a digital transformation, I have proposed an alternative production function based on the notion of organizational unit which combines both the concept of substitutability and complementarity. This new conceptual production technology is integrated within the large-scale macroeconomic model Eurace. In particular, I build on the latest version of the Eurace model presented in Chapter 2 and in Bertani et al. (2020a,b), which encompasses intangible digital technologies, replacing the Cobb-Douglas technology, used to model the manufacturing processes in a traditional mass-production system, with a Leontief production function in which input factors are represented by organizational units. In turn, the contribution of each organization unit is given by a combination between labour and capital. Furthermore, in this new framework, technological progress does not affect total factor productivity directly, but the nature of technology itself: innovation affects the elasticity of substitution between capital and labour. In other words, I propose a new alternative approach that I call elasticity-augmenting approach according to which digital technological progress increases the degree of substitutability between workforce and machines.

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

Except for the features described in the next sections, the second framework of the Eurace model presents the same modelling assumption described in the previous chapter. Moreover, the research contribution exposed below has been reported in Bertani et al. (2021).

3.2 The new production technology

Companies tend to organize their structure into organizational units (OUs) in order to improve their economic performance. In particular, this organization allows to decrease costs and increase productivity. An OU is represented by a group of workers which is organized according to a specific criterion[1] and it is run by a manager.

Therefore, the production of a company is given by the interaction between complementary OUs and firm complexity is given by the number of units: the higher the number of OUs, the higher the company complexity as the number of necessary interactions increases. Being OUs not substitutable[2], a Leontief production technology can represent the macro production within a generic firm composed by n OUs:

$$Y = min[\gamma_1 Y_{OU_1}, \gamma_2 Y_{OU_2}, ..., \gamma_n Y_{OU_n}] \tag{3.1}$$

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

The debate among economists on the value of ES between K and L is still open, see Arrow et al. (1961); Douglas (1976); Gechert et al. (2019); Kalt (1978); Mućk (2017); Piketty and Goldhammer (2014). However, regardless of the substitutability grade between K and L,

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

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

it is possible to represent the contribution Y_{OU_i} of the i-th OU through a constant ES (CES) production technology with constant returns to scale, see Arrow et al. (1961):

$$Y_{OU_i} = [\alpha_i K_i^{-\rho_i} + (1-\alpha_i) L_i^{-\rho_i}]^{-1/\rho_i} \tag{3.2}$$

where α_i is the distribution parameter and ρ_i represents the substitution parameter and it is a transform of the ES σ_i:

$$\sigma_i = \frac{1}{1+\rho_i} \tag{3.3}$$

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

$$\hat{Y}_{OU_i} = \frac{\widetilde{Y}}{\gamma_i} \tag{3.4}$$

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

$$\mathscr{L}(L_i,K_i,\Lambda) = C(L_i,K_i) + \Lambda g(L_i,K_i) = w_{OU_i} L_i + r_i(c_{K_i} K_i) + \Lambda\{Y_{OU_i} - [\alpha_i K_i^{-\rho_i} + (1-\alpha_i) L_i^{-\rho_i}]^{-1/\rho_i}\} \tag{3.5}$$

where $C(L_i,K_i)$ represents the cost function to be minimized and $g(L_i,K_i)$ is the production technology constraint. Moreover, w_{OU_i} represents the average cost of labour or mean wage[3], r_i and c_{K_i} are the rental rate proxied by the corporate loan rate and the unit cost of the “hard" capital, respectively. Multiplying K_i, which represents the physical stock of “hard" capital, by c_{K_i} we obtain its monetary value. In this way, I can evaluate the rental cost of the capital stock K_i multiplying it by r_i.

Starting from $\mathscr{L}(L_i,K_i,\Lambda)$, the Lagrange multipliers methods leads CGPs to formulate the demands of production factors reported below for each OU. As regards the optimal

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

amount of labour $\hat{L}_i$, it is given by this equation:

$$\hat{L}_i = \hat{Y}_{OU_i} \left[\alpha_i (\beta_i r_i c_{K_i})^{\frac{\rho_i}{\rho_i+1}} + \beta_i (w_{OU_i} \alpha_i)^{\frac{\rho_i}{\rho_i+1}} \right]^{\frac{1}{\rho_i}} \frac{1}{(w_{OU_i} \alpha_i)^{\frac{1}{\rho_i+1}}} \tag{3.6}$$

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

$$\hat{K}_i = \hat{Y}_{OU_i} \left[\alpha_i (\beta_i r_i c_{K_i})^{\frac{\rho_i}{\rho_i+1}} + \beta_i (w_{OU_i} \alpha_i)^{\frac{\rho_i}{\rho_i+1}} \right]^{\frac{1}{\rho_i}} \frac{1}{(\beta_i r_i c_{K_i})^{\frac{1}{\rho_i+1}}} \tag{3.7}$$

3.2.1 Integrating the new production technology in the Eurace model

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

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

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

$$Y = min[\gamma_1 Y_{OU_1}, \gamma_2 Y_{OU_2}] = min\left\{ \gamma_1 [\alpha K^{-\rho_d} + (1-\alpha) L_u^{-\rho_d}]^{-1/\rho_d}, \gamma_2 L_g \right\} \tag{3.8}$$

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

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

As mentioned above, technological progress affects ES σ_d modifying the isoquant curve and redefining the optimal demand of production factors[4], i.e capital K and labour L_u, within OU_1. In particular, a successful R&D activity performed by the reference DAD d is followed by an update of the digital technology adopted by the CGP and the value of σ_d between K and L_K into OU_1 increases by a fixed tick equal to δ_σ following the relation below:

$$\sigma_{d_t} = \sigma_{d_{t-1}} + \delta_\sigma \tag{3.9}$$

Being ρ_d a transform of σ_d, technological transition affects its value according to the following relation derived from Eq. 3.3:

$$\rho_d = \frac{1-\sigma_d}{\sigma_d} \tag{3.10}$$

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

$$NPV = \left[max(0, \hat{K} - \hat{K}^*)c_K + \frac{w\hat{L}_u - w\hat{L}_u{}^*}{r}\right] + \frac{p_l\hat{K} - p_l{}^*\hat{K}^*}{r} - c_d N_{L_K} \tag{3.11}$$

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

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

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

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

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

3.3 Computational results

3.3.1 Design of experiments

In order to evaluate the potential consequences related to digital technological progress on the economic system, I investigate the Eurace model with four different level of η, namely the shape parameter of the innovation probability function presented in the previous chapter (see Eq. 2.1 in Chapter 2). The parameter η results to be crucial because it influences the endogenous rate of technological progress within economy. Indeed, as mentioned in the previous chapter, the higher the value of η, the higher the probability of developing an improved version of the digital asset. Furthermore, I consider also a “no intangible investments" scenario in which intangible investments and technological progress do not exist, for a total of five scenarios.

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

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

3.3.2 The dynamics of the system: a macroeconomic perspective

Fig. 3.1 (a) shows an increase with η of the average elasticity of substitution σ between input factors in the manufacturing organizational unit OU_1. In fact, high values of η determine high rates of endogenous technological progress and consequently high value of σ. In this respect, the higher the technological progress level, the wider the range of tasks that can be performed by the “hard" capital on which technologically advanced digital technologies are installed. According to Eq. 3.6 and 3.7, different values of ρ, which is a transform of σ, imply different optimum quantities of input factors. The latter are determined considering respective costs of inputs in order to increase the economic efficiency of the manufacturing process and the adoption of capital appears cheaper compared to human beings. Therefore, higher values of the elasticity σ determine a substitution of labour with capital in the CGPs industrial sector. The process innovation within CGPs turns out to be detrimental for workers that are replaced by technologically advanced machines. As a matter of fact, Fig. 3.1 (b) and (c) show a decrease in the employment level and an increase of the total stock of capital within CGPs with η, respectively. Therefore, the higher the digital technological progress (which is strictly influenced by η), the lower the employment level within CGPs.

It is worth highlighting that this substitution of labour with capital determines an increase in the labour productivity P_L in the CGPs, which is calculated through the ratio between CGPs output, i.e. the sold quantity of consumption goods in terms of units, and number of workers employed, see Fig. 3.1 (d).

The substitution between labour and capital results in an increase of the general unemployment rate, see Fig. 3.2 (a): the economic system is not able to absorb the job destruction (or displacement effect) caused by digital technologies within CGPs. However, Eurace is able to capture two different compensation mechanisms that counteract this technological

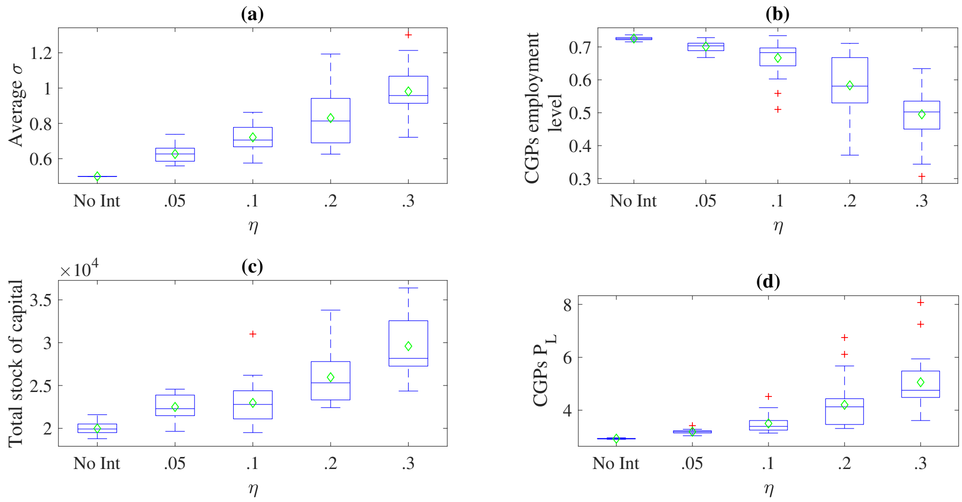

Figure 3.1: The figure shows a series of boxplots representing, for any scenario considered, the distribution of: the average elasticity of substitution σ characterizing the economy (a), the employment level within CGPs (b), the total units of capital (c), the labour productivity within CGPs (d). Each boxplot reports the distribution of the time averages over a twenty-year time period for each one of the twenty seeds considered.

unemployment, namely the compensation mechanism “via decrease in price" and “via additional employment in the capital good sector". The innovation process within manufacturing organizational unit OU_1 allows CGPs to save money linked to replaced workforce. This cost reduction leads to a unit price decrease as it is visible in Fig. 3.2 (b): high values of η and high level of technological progress determine low price levels. In turn, this price decrease determines an increase in the real sales of consumption goods, see Fig. 3.2 (c). Obviously, lower consumption good price levels are related to higher real average wage, see Fig. 3.2 (d).

Fig. 3.3 shows the trend of the consumption goods (CGs) prices level over time. In the case without tangible investments prices increases over time, whereas for $\eta = 0.1$; 0.2 and 0.3 prices tend to decrease in the long term reflecting technological progress and this trend is the representation of the compensation mechanism “via decrease in price" cited above. In the case characterized by $\eta = 0.05$, although the CGs price level is lower compared to the case without intangible investments, it continues to growth with a lower rate: the technological progress determines a slowdown of CGs price level growth instead of a decrease.

Fig. 3.4 (a) shows that the unemployment level increases over time in every scenario considered except for the “No Intangible Investments" case in which it remains constant. It is worth highlighting that for the first ten years, the unemployment levels are quite similar in all the scenarios and acceptable. In particular, for $\eta = 0.05$ and 0.1 the percentage of

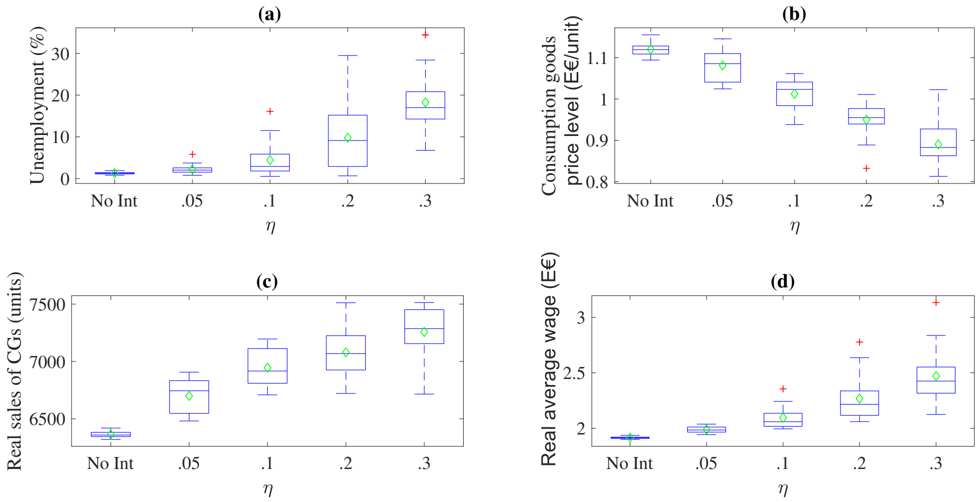

Figure 3.2: The figure shows a series of boxplots representing, for any scenario, the distribution of: the unemployment level (a), the consumption goods price level (b), the real sales of consumption goods (CGs) (c), the real average wage (d). Each boxplot reports the distribution of the time averages over a twenty-year time period for each one of the twenty seeds considered.

unemployment is equal to the case characterized by the absence of intangible investments. After the first ten years the trajectories tend to separate and this separation intensifies over time.

Obviously, the unemployment trends are strictly related to the technological progress within the economic system. Fig 3.4 (b) shows the average elasticity of substitution σ characterizing the economy. In the “No Intangible Investments" case it remains constant, whereas in the other cases it increases during the time. In the first ten years, the values assumed by σ do not involve mass unemployment because the system is able to counteract quite effectively the job destruction within the CGPs industrial sector also for high values of η (namely 0.2 and 0.3). After ten years, σ assumes values significantly higher than one for high values of η and this fact leads to critical levels of unemployment at the end of the period. In this scenarios, the compensation mechanisms are not capable to counteract innovation process within CGPs. In fact, Fig. 3.4 (c) and (d) show a decrease in the CGPs employment and an increase of their capital endowment, respectively. In other words, machines replace human beings in the jobs that they used to perform within CGPs and this tendency is amplified as technological progress increases. The unemployment level remains acceptable in the long term only for $\eta = 0.05$. Indeed, it remains quite constant as in the case without digital technological progress.

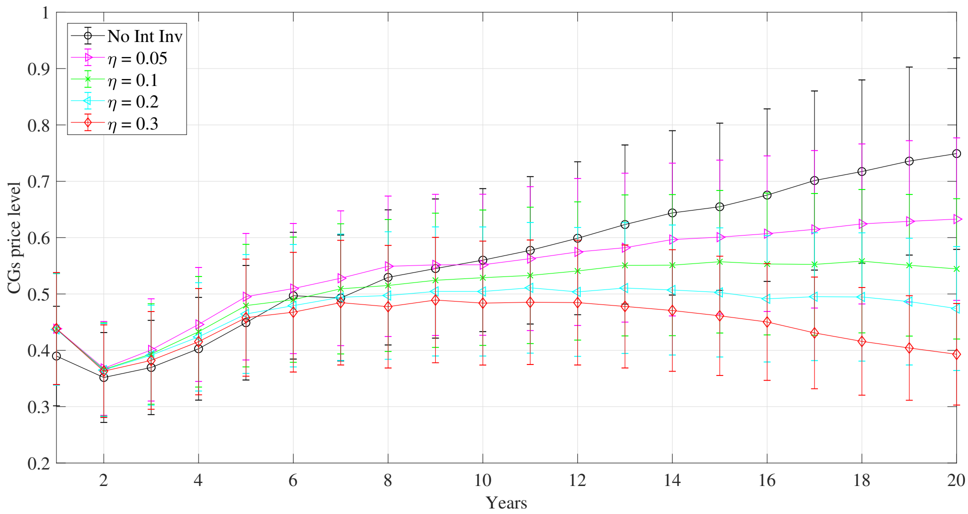

Figure 3.3: For each scenario considered, the figure displays for each year the mean across 20 seeds (with the related standard error) of the yearly time averages of the CGs price level.

Fig. 3.5 (a) and (b) show the increase of the labour productivity P_L and the decrease of the capital productivity P_K over time. The former reflects the unemployment trend displayed by Fig. 3.4 (a) and the latter reflects the evolution of the stock of capital within the system shown by Fig. 3.4 (d). In particular, as regards P_L, it remains constant in the case without digital investments whereas in the other ones it increases over time proportionally to the technological progress itself. As far as P_K is concerned, after a transitory phase in which trajectories are almost the same, it decreases over time proportionally to the technological progress.

The massive unemployment affects also CGPs sales: beyond a certain limit, technological progress turns out to be a double-edged sword. As a matter of fact, while CGs real sales increases over time for $\eta = 0.05; 0.1; 0.2$, for $\eta = 0.3$ they reach a plateau after the fourteenth year. In this regard, it is worth noting that, after fourteen years the stock of capital decreases for $\eta = 0.3$, see Fig. 3.4 (d). Although there is a decrease in the CGPs capital endowment, the sales are stable in the long term, as just noted. This fact is linked to an increase of the market concentration, see Fig. 3.5 (d). As a matter of fact, for $\eta = 0.3$, the market concentration increases over time in a significant way. Therefore, firms that experience a reduction of their sales stop to invest in machines and the depreciation process determines a decrease in their capital endowment. At the same time, firms that experience an increase of market share tend to maintain or increase their capital stock. Even in the case without intangible investments, the market concentration doubles, causing the emergence of a group of larger companies on the market. However, the technological progress amplifies market concentration: the first firms that adopt technologically advanced digital assets are able to manufacture their products with lower costs acquiring higher market shares. In other words, process innovation helps firm to be more competitive and increase their revenues.

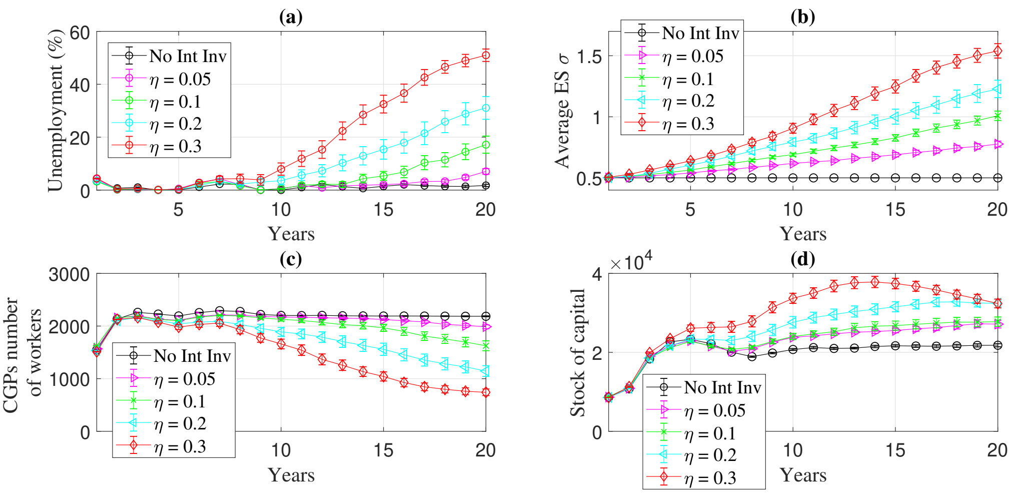

Figure 3.4: For each scenario considered, the figure displays for each year the mean across 20 seeds (with the related standard error) of the yearly time averages of: the unemployment level(%) (a), the average elasticity of substitution ES σ (b), the number of workers within CGPs (c) and the stock of capital (d).

As far as the compensation mechanism “via additional employment in the capital good sector" is concerned, it is related to the increase of employment in the capital good sector. In fact, the substitution of the workforce with capital determines a higher demand of capital, both “hard" and digital, which increases with η. As mentioned above, the two kinds of capital are complementary: each unit of “hard" capital is associated with a digital asset license. Therefore, the employment level within DADs and the KGP increases with η, see Fig. 3.6 (a) and (b).

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

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

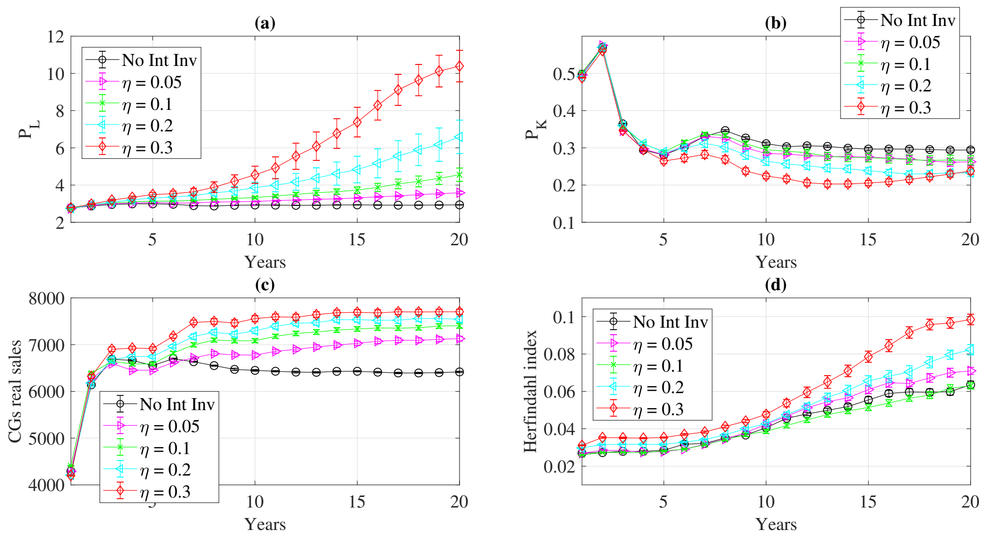

Figure 3.5: For each scenario considered, the figure displays for each year the mean across 20 seeds (with the related standard error) of the yearly time averages of: the labour productivity P_L (a), the capital productivity P_K (b), the CGs real sales (c) and the stock of capital (d).

The increase of the capital stock in production processes determines a decrease of the capital productivity P_K, which is defined through the ratio between the CGPs output and the capital endowment, see Fig. 3.6 (c). In this Eurace framework, technological progress does not affect the total factor productivity as in Bertani et al. (2020a,b), but it influences the elasticity of substitution σ. Therefore, technological progress allows CGPs to produce the same amount of output using a different optimal combination of production factors characterized by a reduction of the most expensive input and an increase in the cheapest one. In this regard, it is worth highlighting that a decrease in the adoption of an input is always compensated by an increase in the other one. Since capital is the least expensive, CGPs tend to adopt more capital in the production process instead of workers[5]. This is why the capital productivity P_K decreases with η. Empirical evidences show that P_K has been decreasing in most of OECD countries for the past twenty years. On the contrary, even if faintly, the labour productivity has been growing for the past twenty years in OECD countries, see OECD (2019).

According to our model, besides decreasing costs of using capital, a potential explanation of this phenomenon could be found in an increase of the elasticity of substitution σ. In fact,

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

the model shows that an increase of σ leads to an increase of P_L and a decrease of P_K. From a financial perspective, it is logic to adopt to a large extent (or completely) the cheapest input factors in the production process. However, there must be also the technological possibility to do this: input factors must be replaceable in a high range of tasks. Therefore, the adoption of an input factors is not only determined by the costs, but it depends also on technology.

Although the level of unemployment increases with η, the economy experiences also high values of real GDP for high values of η, see Fig. 3.6 (d). Obviously, these high real GDP levels are linked to low prices and also to the Government which ensures a welfare system through fiscal policy that guarantees an economic subsidy to unemployed households. This subsidy allows unemployed to perform a basic subsistence consumption.

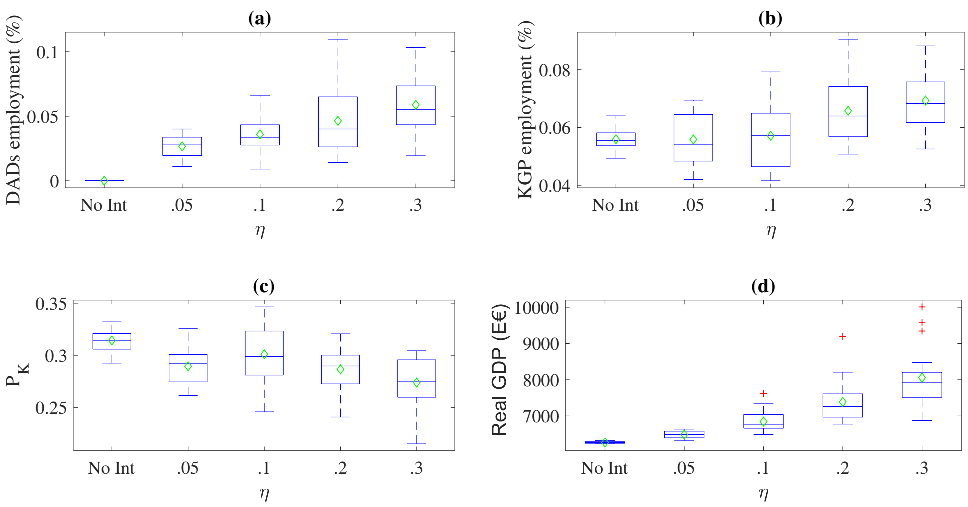

Figure 3.6: The figure shows a series of boxplots representing, for any scenario considered, the distribution of: the employment level within DADs (a), the employment level within KGP (b), the capital productivity P_K (c), the real GDP (d). Each boxplot reports the distribution of the time averages over a twenty-year time period for each one of the twenty seeds considered.

It is worth underlying the different employment levels related to the various education degrees characterizing households. In fact, workers can be distinguished in five groups based on their education levels. The various kinds of firms demand different types of workforce according to the tasks that they have to perform and in order to develop and produce their products: DADs hire only workers from the third up to perform R&D activities; CGPs hire undergraduate workers (from the first to the third education level) to employ in the manufacturing organizational unit OU_1 and graduate workers (fourth and fifth education level) in order to use them in the organizational unit OU_2 in which the various intellectual tasks are performed; KGP hire workers disregarding their education level to produce “hard" capital. According to our modelling assumptions, the digital technological progress affects the manufacturing unit increasing the elasticity of substitution σ between labour and capital. Therefore, workforce characterized by low education levels is directly influenced by process innovation. For each value of η considered, Fig. 3.7 shows the trend of the employment levels related to the various education degrees characterizing households. In the "No intangible investment" case (see Fig. 3.7 (a)) for each education level the number of workers is constant over time. As regards the other cases, workers with education level equal to 4 and 5 remain constant over time, whereas those with an educational level equal to 1,2 and 3 decrease over time and this fact reflects the technological progress within the economy. As a matter of fact, as pointed out above, technological progress increases over time determining the replacement of labour with capital within the manufacturing organization units and this tendency increases with η.

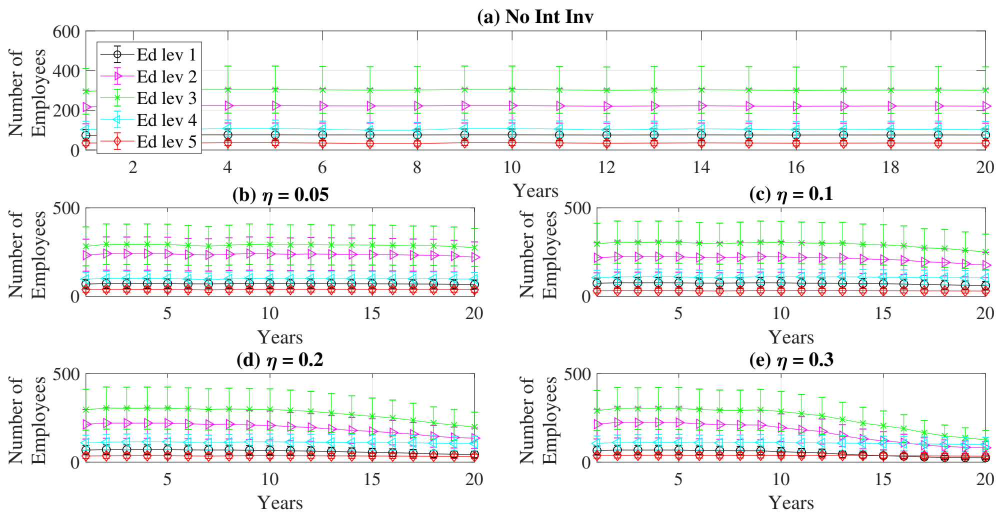

Figure 3.7: For each scenario considered, the figure displays several subplots representing for each education level and for each year the mean across 20 seeds (with the related standard error) of the yearly time averages of the number of workers within the economic system.

3.3.3 The competitive dynamics between DADs

In this subsection, I explore the competitive behaviour showed by DADs within digital technologies market. It is worth highlighting that also the Eurace framework described in Bertani et al. (2020a,b) presents the same business dynamics. As mentioned above, DADs compete in order to increase their market share trying to improve their products and varying their license unit cost. In fact, according to Eq. 3.11, a higher value of σ (linked to a successful R&D activity) or a lower price can determine the switch between digital assets.

Fig. 3.8 (a) shows the emergence of a market leader in the long term on the digital assets market: a DAD acquires almost all of the digital technologies market. In other words, it emerges one of the most important features related to the increasing returns world, namely the winner-take-all phenomenon.

The emergence of a market leader results to be the consequences of an intense competition between DADs. Fig. 3.8 (a) shows that the market shares of digital technologies producers vary over time; they lose and gain market shares continuously before the ascent of a definitive market leader, namely $DAD1$, which detains most of the digital market. Although other DADs, i.e. $DAD2$ and $DAD3$, try to contrast the rise of $DAD1$ decreasing their prices and giving also their licenses for free in certain periods, they are not able to recover their lost market shares; the higher revenues deriving from the higher number of licenses sold allow $DAD1$ to increase its R&D intensity and develop improved version of digital assets (see 3.8 (b)) and its competitors can not compensate the increasing technological gap with lower prices, see 3.8 (c). In this regard, digital assets produced by $DAD1$ allow CGPs to replace workers with capital in a wider range of tasks compared to the other digital technologies on the market and this fact determines a significant cost reductions. In fact, $DAD1$ can also increase significantly its license unit price once it has technologically surpassed other DADs. Using other terms, these digital assets increase the production process efficiency allowing to produce the same amount of goods using less financial resources. From this perspective, the elasticity of substitution σ can be considered as an efficiency parameter as argued by de La Grandville (1997).

3.3.4 Elasticity augmenting approach and total factor augmenting approach: a technological unemployment comparison

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

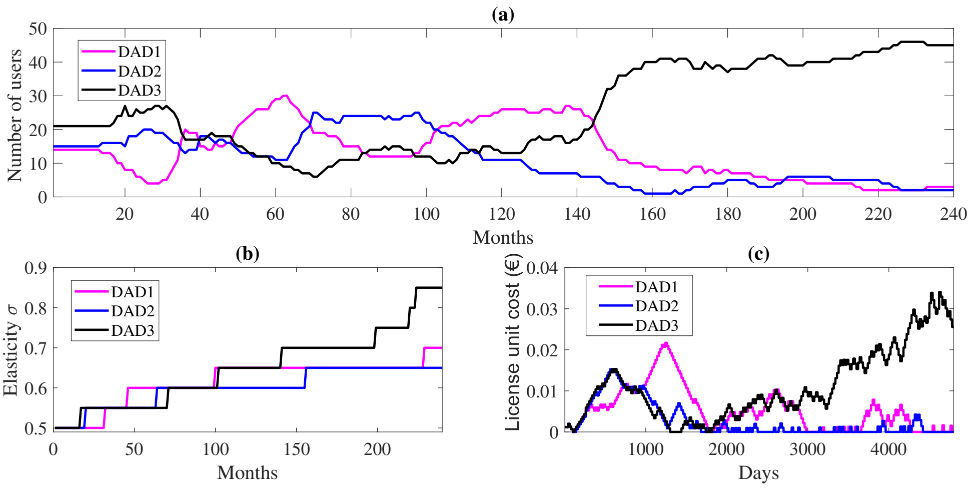

Figure 3.8: The figure displays various time series in case of $\eta = 0.2$; in particular it shows: number of users (a), Elasticity of substitution ES σ (b) and license unit cost (€) (c) of the three different digital assets developers. All time series refer to a specific replication which is representative of the system average trend in case of $\eta = 0.2$.

One sensible comparison can concern the technological unemployment within the economic system. Fig. 3.9 shows that for low values of η (to which low technological progress rates correspond) the unemployment level within the economy are similar. At the same time for high values of η the unemployment level is significantly higher in the total factor augmenting framework. This difference is strictly linked to the compensation mechanism "via additional employment in the capital goods sector". In the total factor augmenting version, digital technological progress influences in the same way capital and labour, determining a decrease of both input factor demands. On the other hand, in the elasticity augmenting framework, digital technological progress affects the elasticity of substitution between labour and capital. This leads to a replacement of labour with capital. Therefore, the compensation mechanism "via additional employment in the capital goods sector" is more effective because it works not only in the DADs industrial sector but also in the KGP.

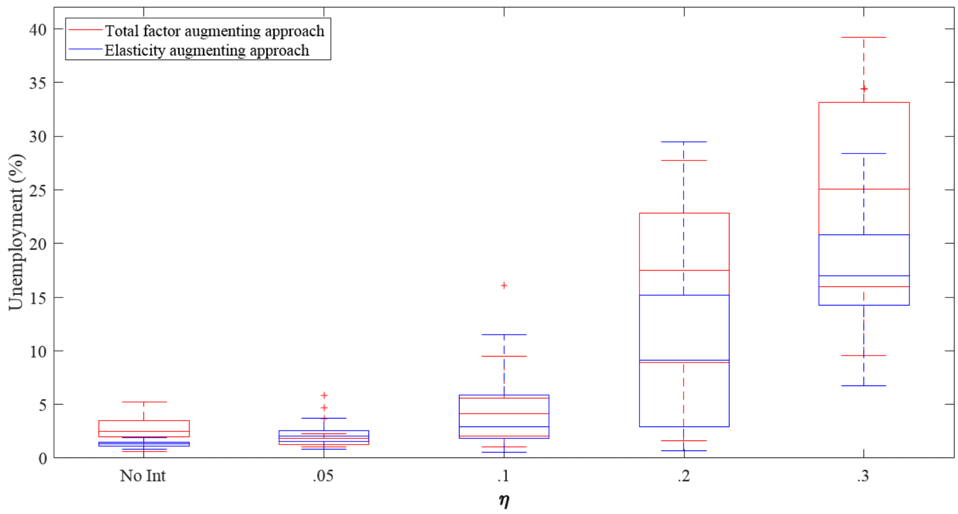

Figure 3.9: The figure shows a series of boxplots representing, for any scenario and Eurace version considered, the distribution of the unemployment level (%). Each boxplot reports the distribution of the time averages over a twenty-year time period for each one of the twenty seeds considered.

Conclusion

A synthesis of the research work and main findings

The main purpose of this research is to provide a scientific contribution to the open debate concerning the potential consequences of the digital technological progress.

First, I performed an empirical analysis taking into account various European countries and USA data in order to asses the relation between productivity and different kinds of tangible and intangible investments. This analysis shows a high positive and significant correlation between total factor productivity and two key investment typologies: the sum between tangible ICT equipment, software and database investments, and R&D investments.

According to these main empirical findings, I have modelled a new framework of the Eurace agent-based model that includes new intangible digital investment assets as well as new agents in charge of their development, say digital assets developers (DADs). By virtue of the complementarity between hardware and software, consumption goods producers (CGPs) install these digital technologies within “hard" capital in order to increase their total factor productivity.

DADs invest a fixed fraction of their revenues in R&D activities that have a likelihood to bring to light a smarter version of the digital asset with an increased impact on the total factor productivity of its users, i.e. the CGPs. R&D activities performed by DADs then lead to an innovation process inside the economic system, whose speed, that I control through an exogenous parameter, turns out to be crucial in order to understand the potential implications of intangible digital technology adoption on the economy and the labour market. In this respect, I observe that in case of a moderate rate of innovation, compensation mechanisms (“via decrease in price" and via “additional employment in the capital goods sector") counteract the displacement effect caused by digital technologies in the traditional mass production system represented by consumption goods producers. Conversely, for high rate of technological progress, the unemployment increases dramatically. Furthermore, the increasing employment level within DADs in case of higher rates of technological progress highlights a clear labour market transformation: the economic system experiences a transition from a mass production economy to a digital services one.

In the third and final phase of my research, starting from the concept of organizational unit, I have implemented a new production function which replaces the Cobb-Douglas technology used in the total factor augmenting framework. In particular, this production technology is represented by a Leontief function in which the input factors are organizational units. In turn, the contribution of these units is given by the combination between labour and capital or only by labour. In order to evaluate the potential consequences of digital technological progress on the economy, I have proposed an alternative approach, namely the elasticity augmenting approach. According to this modelling assumption, the technological progress affects the elasticity of substitution between capital and labour within the manufacturing process; as in the total factor augmenting framework, the engine of the technological progress is represented by the DADs. Through this approach, I want to represent the evolution of digital technologies over time which are able to replace human beings in an ever wider set of tasks.

Similarly to the first framework developed, the elasticity augmenting one shows the significant influence that digital technological progress has on the labour market. Also in this case, high rates of technological progress could lead to a long term mass technological unemployment: compensation mechanisms captured by Eurace are not able to counteract effectively the replacement of human workers with technologically advanced machines.

Comparing the elasticity augmenting approach with the total factor augmenting one, the former results to be more realistic because it is able to capture a decreasing capital productivity and an increasing labour productivity in line with what it is experienced by the economy. By influencing the elasticity of substitution, the technological progress determines a replacement of labour with machines, whereas, in a total factor augmenting framework, it determines a decrease of the demand of both production factors.

The research work has highlighted the growing importance of intangible digital investments in the economy. Although both approaches lead to critical unemployment levels for high rates of technological progress, in case of low or intermediate rates, the economy does not experience negative long-term consequences. Therefore, according to the Eurace model, experienceable future scenarios will depend on the rate of technological progress.

Limitations

It is worth highlighting that results are also influenced by the absence of specific policies, e.g. a robot tax, aimed at reducing and counteracting the technological unemployment caused by digital assets. Besides a robot tax, an excessive displacement effect could also be countered through a reform of the education system in order to train the future generations of “digital workers", thus helping the match between supply and demand on the evolving labour market.

Moreover, results are also influenced by the absence of other compensation mechanisms, as for example the product innovation. In particular, the latter could provide a relevant contribution of new jobs related to the opening of new markets. The co-presence of all mechanisms highlighted by compensation theory nevertheless turns out to be impossible because, in some cases, they are not compatible.

In the total factor augmenting framework, the massive unemployment is also related to the exponential shape of the total factor productivity growth. Through this modelling assumption, the impact of digital technological progress turns out to be significant on the labour market. However, it is worth noting that empirical data suggests long term exponential growth of total factor productivity.

Direction for further research

I will focus my future research on the role of Government in the digital transformation, trying to find effective policy mixes aimed at contrasting displacement effect and, at the same time, fostering technological progress. Indeed, besides organizational improvements, technological progress represents the only effective stimulus that can guarantee an economic growth for our system. For this reason, it should not be hindered.

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