The Productivity and Unemployment Effects of the Digital Transformation: an Empirical and Modelling Assessment

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The Productivity and Unemployment Effects of the Digital Transformation: an Empirical and Modelling Assessment

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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. The contribution of this paper is on the empirical and the modelling side. First, we present a cross-country empirical analysis assessing the correlation between intangible digital assets and different measures of productivity. Then we figure out their long-term impact on unemployment under different scenarios by means of an agent-based macro-model.

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

1. Introduction

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.

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.

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[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

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.

Building on the pioneering insights of Arthur and on the recent empirical investigation and theorizing by Haskel and Westlake (2017), the main contribution of this study is to enrich and complete the previous empirical work on the relation between different measures of productivity and intangible investments. In particular, we are considering a higher number of countries and different kinds of intangible investments, also in combination with tangible investments in information and communication technologies. In addition, we elaborate on the long-standing issue of technological unemployment, in sight of the novelty of digital automation. To this purpose, we discuss a recent contribution of the large-scale agent-based Eurace macro model to study the impact of intangible digital assets to the unemployment level and macroeconomic performance, see Bertani et al. (2019).

The paper is organized as follows. A technological unemployment literature review is presented in Section 2. The empirical analysis concerning productivities and investments is provided in Section 3. Section 4 presents the extension of the Eurace model that includes investments in intangible digital assets in order to study their effects on the economy, in particular on productivity and unemployment. Concluding remarks are shown in Section 5.

2. Technological unemployment in the digital age

Several economists divide technological progress outcomes into short and long term effects, see Mokyr et al. (2015). Technological progress is usually linked to three different outcomes[3]: product, process, organizational and marketing innovation (the latter two types are usually considered as non-technological innovations, however they are strictly influenced by technological developments and related to the other innovation kinds, see Pianta (2009); Monteiro et al. (2019)). Whereas the potential beneficial impact deriving from product innovation is underpinned by several studies, see e.g. Edquist et al. (2001); Vivarelli and Pianta (2000), process innovation presents a labour-saving nature allowing to produce the same amount of output with a reduced quantity of workforce. In the case of case product innovation new markets could be opened increasing production and employment levels, while in the case od process innovation the higher efficiency related to the introduction of new technologies determines a higher productivity which in turn can lead to lower employment, see Pianta (2009). However, according to the so-called "theory of compensation", the technological progress itself triggers different compensation mechanisms that countervail technological unemployment deriving from process innovation, see Petit (1993). As highlighted by Vivarelli (2014), six different economic forces counteracting the process innovation labour-saving effect can be distinguished, namely the compensation mechanism "via decrease in prices", "via decrease in wages", "via new investment", "via new products", "via new machines" and "via additional income". All these six mechanisms contribute to counterbalance the negative effects on employment caused by technological progress. However, not all economists have been completely optimist and confident about this compensation mechanisms, see Piva and Vivarelli (2017).

Until the end of the XXth century, most of innovations introduced within production processes allowed to produce mechanical energy, helping workers to overcome the limits imposed by physical force. Nowadays, according to Brynjolfsson and McAfee (2014), a technological revolution, called "The Second Machine Age", will radically affect the economic system. Digital technologies, represented by robotics, automation, software and artificial intelligence (AI) might be able to surmount the limits imposed by human mind.

A considerable part of economists argues that, thanks to the compensation mechanisms, digital technologies will not have a deep impact on employment. In this respect, according to Vermeulen et al. (2018), automation is determining only a typical structural change rather than the so-called "end of work". On the other hand, Acemoglu and Restrepo (2017, 2018a,b,c,d) argue that the only effective way able to counterbalance the "displacement effect" created by robotics, automation and AI is represented by the creation of new labour-intensive tasks, as the productivity effect, the capital accumulation and the deepening of automation are not able to absorb the disruptive impact of digital technologies.

Various economists and technologists hypothesized that mankind could rapidly approach a technological singularity: AI may become even self-improving, see Good (1966); Nordhaus (2015); Aghion et al. (2017). In this respect, technological unemployment target could change from "blue collars" to "white collars" workers. Empirical studies on labour market have shown a job polarization not completely consistent with the so-called "skill-biased technical change", see Goos and Manning (2007); Goos et al. (2014); Autor and Dorn (2013). Indeed, since the end of the XXth century, the advent of new digital technologies led to a decrease in the demand of mid-range workers performing routine manual and cognitive tasks and, at the same time, to an increase in demand of high salary non-routine cognitive jobs and low salary non-routine manual jobs. This phenomenon could be considered as a compensation mechanisms, and it is worth questioning if it will continue to work after the disruptive advent of enhanced-performance AI.

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 Virgillito

[3]https://www.oecd.org/site/innovationstrategy/defininginnovation.htm

(2019).

3. The impact on productivity: an empirical assessment

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). Besides software and databases, other kinds of intangible investments are represented for example by investments in R&D, design and engineering, mineral exploration, brands and advertising, see Thum-Thysen et al. (2017); Corrado et al. (2005).

As far as digital technologies are concerned, Fig. 1 shows several time series[4] representing the ratio between intangible investments in software and database and gross value added (GVA) for various countries. Except for Italy (IT) and Luxembourg (LU), see Fig. 1(b) and (c) respectively, these investments increased between 1997 and 2014; 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.

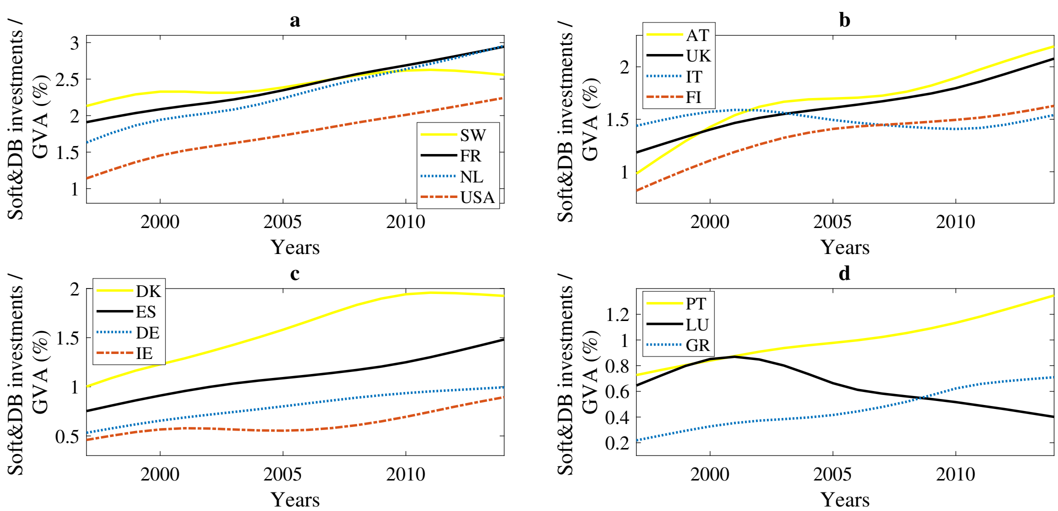

Figure 1: The figure shows various time series representing the trend between 1997 and 2014 of ratio between software and database intangible investments and gross value added for several countries. Time series have been elaborated by authors using EU-KLEMS data and they are organized in sub-figure according 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. The analysis has been made by authors using EU-KLEMS data (www.euklems.net).

Along the line of Haskel and Westlake (2017), we have carried out a correlation analysis in order to investigate the relation among different measures of productivity and types of investment. Our study takes into account a larger number of countries and it is focused on a longer time period of eighteen years, from 1997 to 2014. We split this time span in a pre and post crisis time period, i.e., from 1997 to 2007 and from 2008 to 2014. 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), we extend the analysis to different measures of productivity, namely labour productivity P_L (measured as GDP per hour worked) and capital productivity P_K (measured as the ratio between GDP and capital services). As for investments, we consider the following investment items:

[4] Time series are made by authors using EU-KLEMS data (www.euklems.net) and have been filtered through a Hodrick–Prescott filter with a smoothing parameter equal to 10.

- 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. We 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 and software. In fact, hardware is useless without software and viceversa. Therefore, combining these investments we can assess the real importance that digital technologies have in our society.

The correlation analysis has been performed combining the EU-KLEMS (www.euklems.net) database, which provided information about investment, and the OECD (www.oecd.org) database for information on productivity.

Table 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: 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, SW, ES, DK, PT, AT, FI, IE, GR, LU) and it has been realized using EU-KLEMS (www.euklems.net) and OECD (www.oecd.org) data.

	1997-2007	**2008-2014**	**1997-2014**
TFP - Tot Int	0.082 (0.77)	0.81*** (0.0003)	0.46* (0.081)
P_L - Tot Int	0.21 (0.45)	0.79*** (0.0006)	0.67*** (0.0065)
P_K - Tot Int	-0.44 (0.1)	0.17 (0.54)	-0.37 (0.18)
TFP - Int Soft&DB	0.44 (0.11)	0.018 (0.95)	0.29 (0.29)
P_L - Int Soft&DB	0.47* (0.079)	0.22 (0.43)	0.5* (0.058)
P_K - Int Soft&DB	0.11 (0.68)	-0.38 (0.16)	-0.29 (0.29)
TFP - Int R&D	0.041 (0.89)	0.62** (0.014)	0.3 (0.28)
P_L - Int R&D	0.2 (0.47)	0.6** (0.019)	0.59** (0.02)
P_K - Int R&D	-0.53** (0.043)	0.07 (0.81)	-0.58** (0.025)
TFP - Tot Tang	0.26 (0.35)	0.54** (0.037)	0.53** (0.044)
P_L - Tot Tang	0.31 (0.26)	0.32 (0.24)	0.51* (0.05)
P_K - Tot Tang	-0.042 (0.88)	0.41 (0.13)	0.087 (0.76)
TFP - Tang ICT	0.31 (0.27)	0.63** (0.012)	0.34 (0.22)
P_L - Tang ICT	0.2 (0.48)	0.43 (0.109)	0.22 (0.44)
P_K - Tang ICT	0.25 (0.38)	0.48* (0.071)	0.21 (0.45)
TFP - ICT&Soft&DB	0.34 (0.21)	0.81*** (0.00026)	0.51* (0.054)
P_L - ICT&Soft&DB	0.31 (0.26)	0.62** (0.015)	0.48* (0.071)
P_K - ICT&Soft&DB	0.11 (0.71)	0.5* (0.058)	0.097 (0.73)

For each country, time averages of different productivities and investments growth rates have been calculated for each of the three periods considered. Table 1 reports correlation coefficients and p-values (in brackets) between the sets of investments and productivities time averages referred to all countries considered[5]. Asterisks points out statistically significant results[6].

Significant results underline mostly positive correlations between variables. In particular, in the time period $2008-2014$ the majority 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 highly and positively correlated with total intangible, R&D and ICT&Soft&DB investments.

Even though the $1997-2007$ time period is characterized mainly by positive relations among variables, we did not find significant results except for the negative correlation between capital productivity and intangible R&D investments average growth rates. 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.

Fig. 2 show the correlation between TFP and total intangible investments average growth rates in the $1997-2007$ and $2008-2014$ time periods. The comparison of these two plots highlights an increase in the correlation between variables in the $2008-2014$ time period, even though the growth rates tend to be lower. These considerations are true also for R&D and ICT&Soft&DB investments average growth rates, presented in Figures 3 and 4. In $2008-2014$ 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 0.81). This fact points out the complementary roles of hardware and software.

The higher correlation coefficients in the post-crisis period of $2008-2014$ might 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.

4. Modelling the digital transformation

4.1. Literature overview

Formalizing the digital transformation involving our society through a modelling approach turns out to be crucial in order to forecast potential future consequences related to the advent of digital technologies. In this respect, the debate on how to represent the potential effects deriving from their adoption in production processes is still open. Current literature comprehends different methods that have been developed in order to assess unemployment, productivity change and wage inequality deriving from digital transformation. One of these is represented by including AI within production functions as a new (production) factor, see Hanson (2001); Lankisch et al. (2019); DeCanio (2016).

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: digital transformation is represented by an increase in factor productivities, see Acemoglu (2003). In this respect, Nordhaus (2015); Graetz and Michaels (2018); 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.

Conversely, Acemoglu and Restrepo (2017, 2018a,b,c,d) point out some weaknesses of the factor augmenting approach in equilibrium models[7] and they adopt the so-called task-based approach based on the

[5]Time series stationarity has been verified through a KPSS test.

[6]Assuming a null hypothesis of non-correlation we 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.

[7]Acemoglu and Restrepo (2018d) argue that "factor-augmenting technologies have a limited scope to reduce the demand for labor". Another criticism made by authors refers to the impact of technology on labour share in national income: it is strictly

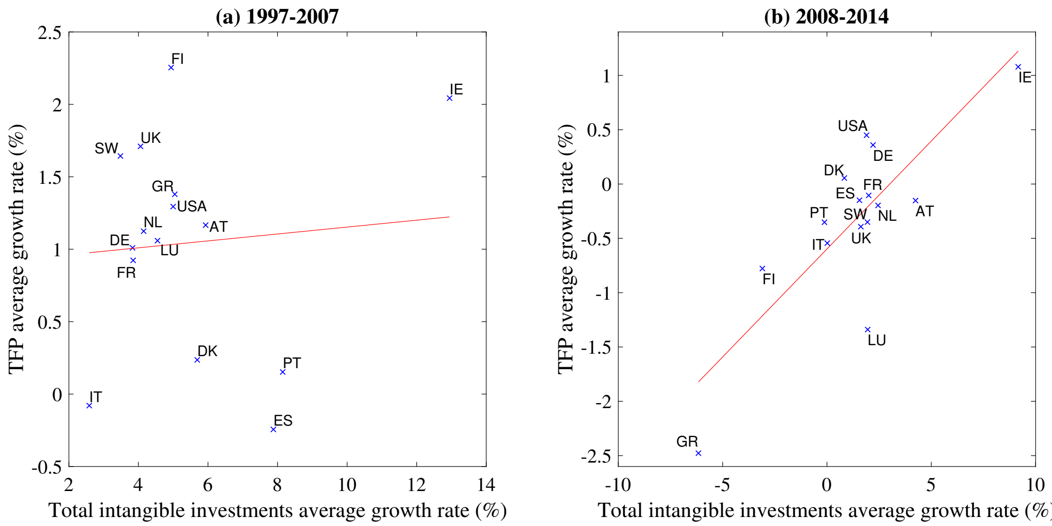

Figure 2: The figure shows two scatter plots representing for countries under investigation two regressions between country average TFP and total intangible investments growth rates (%). Country averages are considered for two different time periods: 1997-2007 (a) and 2008-2014 (b). The correlation index is equal to 0.082 (a) and 0.81 (b). Source: authors estimations based on EU-KLEMS (www.euklems.net) and OECD (www.oecd.org) data.

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.

It is worth noting however that the criticism by Acemoglu and Restrepo holds in equilibrium models. Building on the empirical analysis presented in the previous section showing a clear effect of investments in ICT&Soft&DB on TFP, we have then developed a new extension of the well known large-scale macroeconomic model Eurace, see Raberto et al. (2012); Teglio et al. (2012); Petrovic et al. (2017); Mazzocchetti et al. (2018); Ponta et al. (2018); Teglio et al. (2019); Bertani et al. (2019). The disequilibrium hypothesis which is the foundation of the agent-based modelling approach makes the caveat made by Acemoglu and Restrepo not applicable to our model.

4.2. The Eurace model with intangible assets

The Eurace model is populated by several types of economic agents, characterised by limited capabilities of computation and information gathering, which interact through different markets. Each agent is represented as a dynamic balance sheet which contains the details regarding its assets and liabilities; see Godley and Lavoie (2012); Raberto et al. (2018) for details. Most agents' decisions occur at a weekly, monthly, quarterly, or yearly periodicity, and are asynchronous.

The household (HH) operates in the financial market, labour market, goods market and housing market. As a trader, it allocates its financial wealth among the available assets, which are bonds issued by the government and stocks issued by firms and banks. As a worker, it receives 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, see Carroll (2001). Households' decision about the product to buy is driven by purchasing probabilities based on the price.

related to the elasticity of substitution between production factors. Conversely, task-based approach adopted by them "always reduces the labor share and it reduces labor demand and the equilibrium wage unless the productivity gains from automation are sufficiently large."

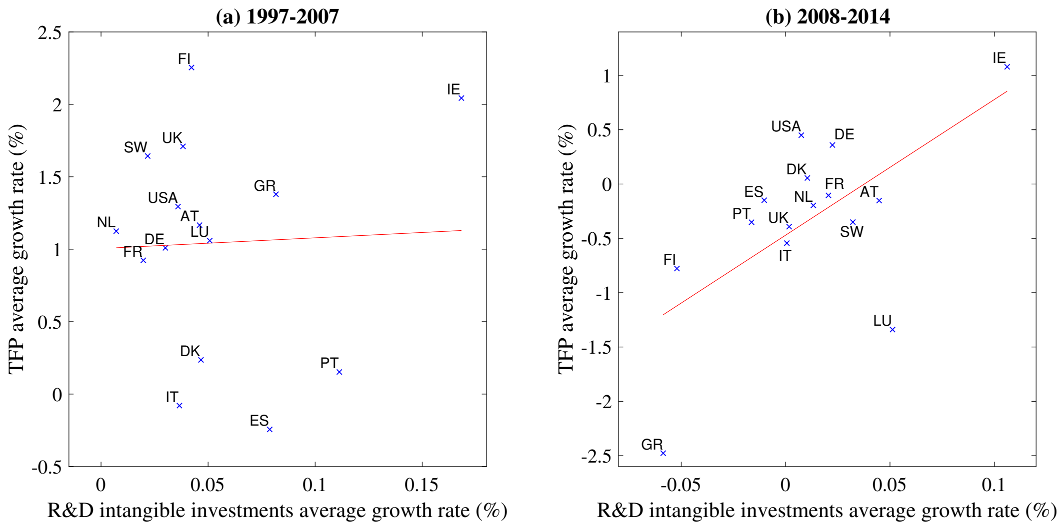

Figure 3: The figure shows two scatter plots representing for countries under investigation two regressions between country average TFP and R&D investments growth rates (%). Country averages are considered for two different time periods: 1997-2007 (a) and 2008-2014 (b). The correlation index is equal to 0.041 (a) and 0.62 (b) respectively. Source: authors estimations based on EU-KLEMS (www.euklems.net) and OECD (www.oecd.org) data.

The consumption good producer (CGP) produces and sells an homogeneous good, taking decisions about the factors of production and how to finance them. In brief, once the CGP has estimated the expected demand based on past sales, it determines the labour demand (posting new vacancies or firing) and the investment level, by comparing the net present value of future additional cash flows with the current cost of the investment. The CGP tries to finance these costs according to the pecking order theory: first retained earnings, then debt, then equity. If rationed, the CGP reduces costs in order to make the total financial needs consistent with the available resources. If insolvent, the CGP defaults and undergoes a restructuring process to increase the equity over debt ratio.

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

The other main agents in the model are the capital good producer (KGP), which produces investment goods and sells them to CGPs, and the policy maker agents, which are in charge of economic policy and regulation. In particular, the government (G) ensures a welfare system through fiscal policy. Taxes come from corporate earnings, consumption (VAT), financial income and labour income. Government expenditures include the public sector wage bill, unemployment benefits, transfers, and interest payment on debt. On a monthly basis, if in short of liquidity, the government issues new bonds, which are perpetuities that pay a monthly fixed coupon. The central bank (CB) 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, and the capital requirement for banking regulation.

Intangible digital assets consist in software or in any other digitalized knowledge-based assets, e.g., algorithms, advanced routines, instructions, which can support the production process. Intangible digital assets are developed and supplied by a specific agent, namely the intangible digital assets developer (DAD), and are employed by CGPs with the purpose of rising total factor productivity. Intangible digital assets are heterogeneous among the different DADs, depending on their accumulated digital knowledge, which increases

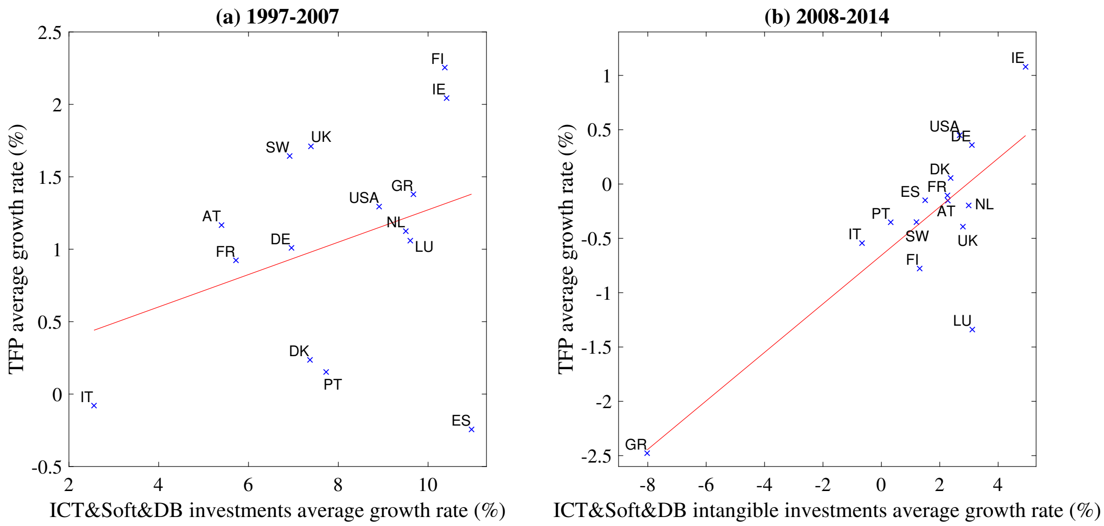

Figure 4: The figure shows two scatter plots representing for countries under investigation two regressions between country average TFP and ICT&Soft&DB investments growth rates (%). Country averages are considered for two different time periods: 1997-2007 (a) and 2008-2014 (b). The correlation index is equal to 0.34 (a) and 0.81 (b) respectively. Source: authors estimations based on EU-KLEMS (www.euklems.net) and OECD (www.oecd.org) data.

over time based on the R&D investments made. DADs compete among each other for providing firms with new digital technology.

Intangible digital assets are assumed non-rivalrous, i.e., characterized by zero marginal production costs, see e.g. Haskel and Westlake (2017). Production costs are given only by the R&D costs, which are determined by the cumulated labor costs of the skilled labor force employed at any DAD agent. On a monthly basis, each DAD has a chance to develop a new version of its digital asset, endowed with higher productivity when employed in the production process by CGPs. The probability $prob_d$ of a successful completion of the new digital asset version depends on the cumulated person months M_d employed by the DAD since the latest version developed, as follows:

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

where η is a shape parameter setting the development speed, i.e., the higher is η, the higher is the probability to develop an improved version of digital assets, for any level of cumulated person months M_d employed. The rationale behind Eq. 1 is to set the probability as an increasing monotone function of the 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 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 the DADs monthly turnover. This means that the number of employees in the DADs sector is influenced not only by revenues, but also by the average wage in the economy.

Consumption good producers (CGPs) require digital assets in order to increase their productivity. The production processes of the various companies have been modelled through a Cobb-Douglass production function with constant return to scale as follows:

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

where N_f and K_f are the labour force employed and the capital endowment owned by a generic firm f, respectively, whereas γ_f represents the heterogeneous TFP. As reported in the previous section, our empirical analysis shows that TFP is positively and significantly correlated with R&D and ICT&Soft&DB investments and, according to these findings, we model the impact of digital assets innovation on production processes as total factor augmenting, namely increasing TFP value. Indeed, in our model the digital innovation is determined by R&D activities performed by DADs and the high correlation characterizing TFP and R&D investments growth rates leads us to hypothesize a total factor augmenting influence of these investments on the mass production sector represented by CGPs. In particular, TFP γ_f of a generic firm f has been modelled as follows:

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

where η_γ is a scale parameter homogeneous across all CGPs while κ_d represents the digital asset adopted productivity level. Each CGP can adopt only one kind of digital asset at a time and if the R&D activity of the reference DAD is successful, κ_d will be increase by a fixed tick equal to δ_κ as reported in the following relation:

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

The quantity of digital assets licenses required by CGPs is equal to the amount of capital units owned by firms themselves. In other words, each capital unit is associated with a digital asset license. See Bertani et al. (2019) for a more detailed description of the intangible Eurace extension.

4.3. Computational results

In order to evaluate the potential effects of digital assets technological progress on the economic system and, in particular, on the labour market, we explore six different values of η, which is the innovation probability function shape parameter. It is worth noting that η sets the success probability of R&D activity performed by DADs: the higher the η value, the higher the probability to develop an improved version of digital technology. Moreover, we consider also a “no intangible investments” case characterized by no digital technologies innovation in order to have a wider perspective for analysis: it can be considered as the Eurace baseline scenario. The methodology is based on Montecarlo computational experiments: we run twenty simulations for each of the seven scenarios under investigation. Therefore, a total number of 140 simulations has been considered in our analysis. According to the study methodology, we present ensemble averages (and related standard errors) of time averages distributions over a twenty-years-long period of most relevant variables for the seven scenarios investigated, see Table 2; furthermore, we plot some time series to provide a more clear overview of the trajectories of relevant economic variables.

Table 2: 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 (€)	Real consumption	CGs price level
No Int Inv	1 (0)	2.76 (0.27)	2.68 (0.013)	9768 (75)	0.74 (0.005)
$\eta = 0.05$	1.61 (0.04)	1.79 (0.2)	3.54 (0.062)	13657 (289)	0.79 (0.02)
$\eta = 0.1$	2.0065 (0.058)	4.32 (0.56)	3.97 (0.073)	16290 (426)	0.68 (0.015)
$\eta = 0.2$	3.79 (0.2)	15.84 (1.84)	4.38 (0.098)	18391 (531)	0.62 (0.0068)
$\eta = 0.3$	5.016 (0.29)	25.18 (2.28)	4.36 (0.13)	17974 (590)	0.61 (0.0074)
$\eta = 0.4$	6.51 (0.32)	29.98 (2.096)	4.34 (0.11)	17997 (567)	0.6 (0.0097)
$\eta = 0.5$	6.76 (0.46)	35.18 (1.25)	4.04 (0.072)	16499 (297)	0.62 (0.0047)

Table 2 shows that digital assets average productivity (γ_f) increases with η: the higher the value of η the higher the endogenous rate of technological progress in the model, see also Fig. 5. Furthermore, this higher digital assets productivity for high values of η leads to higher unemployment level in the economic system. In fact, Fig. 6 shows that for high η values the “displacement effect” caused by digital technologies increases dramatically: digital assets substitute workers in jobs that they previously performed in the mass production industrial sector represented in the model by consumption good producers (CGPs). However, for low η values (i.e. 0.05 and 0.1) the unemployment level is not extremely high.

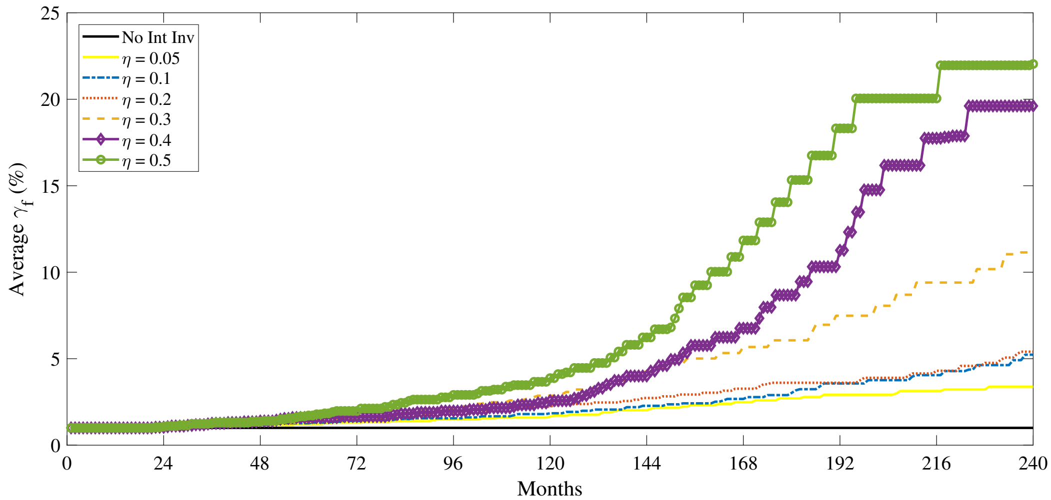

Figure 5: The figure shows various time series representing the digital assets average productivity or TFP (γ_f) trend for each scenario considered. All time series are representative of a typical trend and refer to the same seed of the pseudorandom number generator.

It is worth noting that, as reported in Table 2, 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 of two different effects: the "displacement effect" and the compensation mechanism "via additional employment in the (digital) capital goods sector", see Acemoglu and Restrepo (2018a); Vivarelli (2014). The former refers to the destruction of job places in the CGPs industrial sector, whereas the latter is related to the creation of new job opportunities in the DADs industrial sector, see Table 3. For the lowest value of η, the 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.

Table 3: 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)
$\eta = 0.05$	44.31 (0.92)	16.42 (0.76)	17.18 (0.41)	95691 (925)
$\eta = 0.1$	39.073 (1.22)	17.89 (0.87)	18.42 (0.34)	99209 (816)
$\eta = 0.2$	27.5 (1.41)	21.37 (0.93)	14.99 (0.56)	92094 (1252)
$\eta = 0.3$	22.31 (0.92)	19.44 (1.23)	12.77 (0.53)	87821 (1705)
$\eta = 0.4$	20.18 (0.77)	18.033 (0.93)	11.51 (0.61)	84920 (1941)
$\eta = 0.5$	18.64 (0.48)	15.29 (0.73)	10.6 (0.36)	81568 (1345)

Table 3 shows a decrease in the CGPs employment level with the increase of η, and this is true also for the capital good producer (KGP). In this respect, the higher digital assets productivity implies not only a lower level of employment, but also a lower level of (hard) capital in the production processes and this is why the KGP employment decreases with η, whose increase determines a higher endogenous technological progress rate. As regards the DADs employment, it increases until $\eta = 0.2$, after that it starts to decrease. This trend is related to the high average digital assets productivity which characterizes the economy for high value of η. In fact, the number of licences sold by DADs is strictly related to the capital level inside

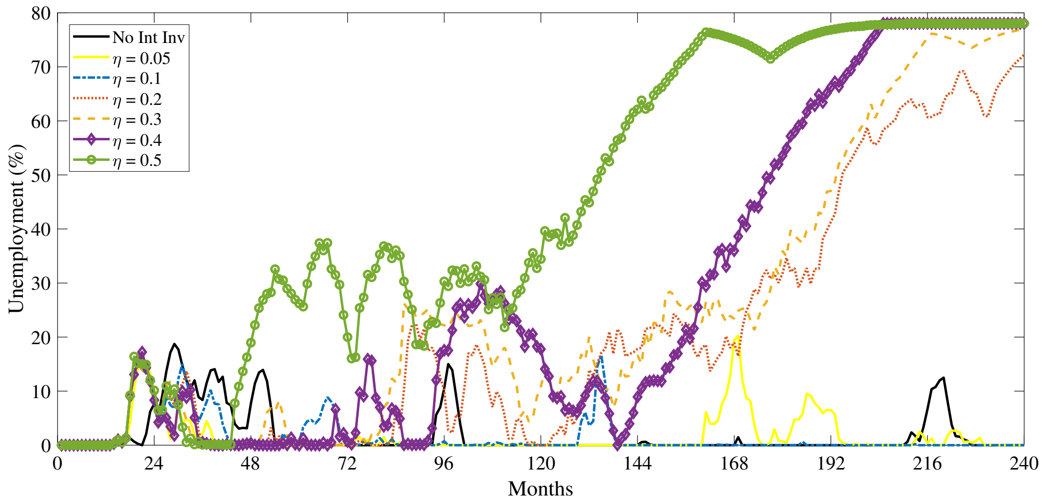

Figure 6: The figure shows various time series representing the unemployment level trend for each scenario considered. All time series are representative of a typical trend and refer to the same seed of the pseudorandom number generator.

the CGPs: the higher the productivity the lower the capital level inside CGPs and the lower the licenses sold because each unit of capital is associated to a license, see Table 3. Therefore, for high value of η, the technological progress affects negatively also the DADs. This fact highlights the complexity characterizing the digital economy in which the various industrial sectors are interrelated with each other.

Table 2 shows an increase of the average real wage until $\eta = 0.2$, after that it starts to decrease slightly. This increase in the real wage is strictly related to a decrease in the consumption goods price level. In fact, firms set their prices through a mark-up pricing rule on unit costs and the higher productivity related to digital technological progress allows CGPs to hire less workers reducing production costs. 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 is not able to counteract effectively the displacement effect in the CGPs industrial sector related to the higher average TFP. Therefore, the lower consumption goods price level determines a higher CGPs sold quantity, see Table 2, and comparing η scenarios, it emerges a strong relation between these two variables.

5. Concluding remarks

The research work has highlighted the growing importance that intangible digital investments are assuming in our economic system. First of all, we performed an empirical analysis taking into account various European countries and USA data in order to asses the relationships between productivities (TFP, P_L and P_K) and different kinds of tangible and intangible investments. This analysis shows a high positive and significant correlation between TFP and two key investment kinds: ICT&Soft&DB and R&D.

According to these main empirical findings, we have presented a new Eurace extension in which investments in digital technologies affects TFP. This new version of Eurace is characterized by a new population of agents: the digital assets developers (DADs). These new companies develop and supply a new type of digital productive capital, which is required by CGPs in order to increase their TFP. R&D activities performed each month by DADs lead to an innovation process inside the economic system, whose intensity turns out to be crucial in order to understand the potential implications of digital technologies on labour market. In this respect, even though compensation mechanisms counteract the displacement effect caused by digital technologies in the traditional mass production system represented by CGPs, for high rate of technological progress the unemployment increases dramatically. Going further with the model results analysis, the increasing DADs employment level with higher levels 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.

Both modelling and empirical results make us reflect on potential future scenarios deriving from this intense digital transformation experienced by our society.

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