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# ***Exploring the interaction between ICT, innovation, and Green Productivity***

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## Acronyms and abbreviations

| | |
|---|---|
| ICT | Information Communication Technology |
| HT | High-Tech |
| GTFP | Green Total Factor Productivity |
| TFP | Total Factor Productivity |
| MLPI | Malmquist-Luenberger productivity index |
| TECH | Efficiency Change |
| TECCH | Technical Change |
| LISA | Local Indicators of Spatial Association |
| BiLISA | Bi-Local Indicators of Spatial Association |
| GPT | General purpose technology |
| SDM | Spatial Durbin Model |
| FE | Fixed Effect |
| GMM | Generalized Method of Moments |
| IV | Instrumental Variable |
| SDM | Spatial Durbin Model |
| R&D | Research and development |
| SMEs | Small and medium-sized enterprises |

## Introduction and main findings

The aim of this dissertation is to gain a deeper understanding of the relationship between the ICT sector and various aspects of economic performance, including innovation, productivity, and growth. ICT industry is a broad field of research that encompasses all technologies used to manage, collect, process, store, and transmit data and information. These technologies include computers, software, telecommunication networks, and communication devices such as mobile phones and tablets and new advancements in emerging technologies like artificial intelligence.

The ICT industry has played a significant role in economic development and industrial structure transition not only in terms of GDP, but especially in terms of information and communication infrastructure without which both modern economies and societies might not function as many essential activities today are based on technologies that belong directly or indirectly to the ICT (European Commission, 2016; Veugelers R. & Cincera M., 2010; Veugelers et al., 2012; Piatkowski, 2006).

Since the 1980s, the ICT sector has been a major driver of innovation and given the significant spillover effect on technological innovation it can be considered as a representative industry of new knowledge and new technology (van Oort & Atzema, 2004). ICT industry has been shown to drive economic growth, FDI, financial development, good governance, trade, and energy consumption. The analysis of environmental effect has also gained momentum among academicians and policymakers in recent years and the sector is recognized for its role in promoting ecological transition and reducing emissions (Niebel, 2018a).

This thesis demonstrates the significance of ICT as a source of knowledge and a tool for enhancing innovation, productivity, and growth in both regions and firms. The research also emphasizes the need to consider moderating factors, such as technological specialization, green productivity, and firm characteristics, in examining the relationship between ICT and economic performance. These findings provide valuable insights for policymakers, organizations, and researchers in the field.

In the first chapter, we analyse the innovative performance of more than 169 regions in 19 OECD countries in terms of high-tech (HT) patent applications as measured by both the extensive and intensive margin of innovation, focusing on ICT agglomeration and intra-regional technology branching dynamic. We consider patent applications in biotechnology, nanotechnology, pharmaceuticals, and medicine to be high-tech patent applications. We use data provided by the OECD on patent applications controlling for several economic indicators (GDP per capita, human capital, total R&D expenditure, different types of R&D, and technological proximity) related to OECD regions considered at TL2 level, according to the territorial OECD classification, for the period 2000 – 2015. In this chapter, our analysis is developed using two dependent variables: the extensive margin (the new technological specialization) and the intensive margin (the number of patent high-tech). To calculate the new technological specialization, we use Balassa's index on patent applications filed in the high-tech IPC class (Revealed Technological Advantages, or RTA). To measure the extensive margin of innovation, we create a dummy variable (*New_RTA*) based on the RTA. *New_RTA* is equal to 1 if the region has developed a new technological specialization in the current year that is different from the previous year, and 0 otherwise. The aim of this chapter is to contribute to the literature by identifying what elements, and how, facilitate new technological specialization, identifying ICT technologies as playing a key role in enabling regions to have a better innovative performance and to acquire new technological specializations that enable them to "survive" in present-day global competition controlling for both the aspect of technological proximity between sectors and the spatial dimension. We check for the existence of technological branching phenomena in terms of both technological and spatial proximity, to determine whether the propensity to innovate, in addition to being influenced by technological proximity, can find advantages in spatial proximity to innovative regions. We expect the ICT sector as GPT to induce a greater propensity to innovate. We also expect technological proximity to produce a greater possibility of developing new technological specializations. Another key element that facilitates knowledge diffusion and, therefore, the innovative performance of regions, is the spatial dimension of innovation, which has attracted much attention in the literature (Bottazzi & Peri, 2003; Montresor & Quatraro, 2017). In particular, when asking why some regions are more innovative than others, one of the possible answers is to be found, in addition to regional characteristics (e.g., in the endowment of specific factors), in spatial proximity to certain actors and inclusion in regional structures promoting information transfer and spillovers that lower the costs and reduce the risks associated with innovation. Hence, we test three hypotheses. The first one is that ICT agglomeration affect HT specialization at the extensive margin, but its impact is spurred by the regional technological specialization in ICT. The second one is that technological proximity affect the ability to develop high-tech patents and new technological specializations demonstrating the existence of a technological branching phenomenon. The third is that spatial proximity and innovation of neighboring regions play a significant role in the innovative performance. To test our hypotheses, we adopt several methodologies: a panel FE model as baseline, a GMM system as endogeneity check, an asymmetric check by employing the quantile regression approach for measuring the differences in the influence of ICT agglomeration on regional innovation for regions with different levels of patent activities in HT. Finally, we test for the existence of spatial effects and interregional spillovers using a spatial Durbin model. Our results show that the propensity to innovate of the regions considered is influenced at the extensive margin but not at the intensive margin by ICT agglomeration, but this positive impact is verified only when regions detain a technological specialization in ICT activities. There is a phenomenon of innovation propagation due to technological proximity between different high-tech technologies. We also find evidence of spillovers deriving from spatial proximity in ICT and branching activities.

In the second chapter, the focus is on investigating the relationship between ICT agglomeration and Green Total Factor Productivity (GTFP) growth in Europe. This chapter uses a sample of 95 large regions from 10 European countries from 2000 to 2010. The dataset was created from various sources of data, including those provided by OECD, by the EC (AMECO), and by GREECO.[1] The OECD provides information on regional R&D investment, human capital, population density, GDP, sectoral value-added, and Particulate Matter 2.5 (PM 2.5). AMECO was used to gather information on capital formation, which was used to calculate capital stock through the Perpetual Inventory Method. GREECO provided data on regional energy consumption, essential for calculating Green Total Factor Productivity. We use the Malmquist-Luenberger productivity index (MLPI) to calculate our dependent variables (D. Wang et al., 2022). The MLPI is a measure of productivity change that accounts for both efficiency change and technological change (Chung et all., 1997). As a result, our dependent variables are: Green Total Factor Productivity, Efficiency Change, and Technological Change. The study first examines the impact of ICT agglomeration on Green Total Factor Productivity (GTFP) growth, then analyses the spatial autocorrelation of both Green TFP and ICT agglomeration, and finally tests for inter-regional spillovers using a Spatial Durbin Model. To strengthen our results with fixed effects (FE), we adopt an instrumental variable approach to mitigate endogeneity or reverse causality problems.

The results of this chapter indicate that ICT agglomeration is an important indicator of a region's capacity to increase green productivity. However, the relation is non monotonic. ICT increasing economies of scale can negatively affect GTFP growth. Further analysis shows that this improvement in green total factor productivity is mainly achieved through the efficiency change in green productivity suggesting technological advancement that promotes coordinated economic growth, energy saving and emission reduction. Furthermore, the findings also suggest that GTFP growth is influenced by proximity to regions with high green productivity. This highlights the importance of promoting ICT agglomeration as a means of supporting sustainable and green economic growth in the regions.

In the third chapter the focus is on examining the contribution of R&D to the growth performance of ICT firms, considering the moderating effects of size, age, and persistence in the firms' growth process. Whereas the previous chapters were developed on macro data at regional level, this chapter differs from the others in that it uses micro enterprise data. This approach allows us to analyse ICT

[1] AMECO is the annual macro-economic database of the European Commission's Directorate General for Economic and Financial Affairs. The database is used for analysis and reports produced by the directorate general. GREECO is a project financed by ESPON. The aim of the GREECO project is to shed light on the conceptual and operational dimensions of the green economy – seen from a territorial perspective. The project aims to identify key economic areas where policy support through territorial and cohesion policies could contribute to sparking economic recovery, creating new employment opportunities, and strengthening sustainable development. The project focuses on understanding how the green economy can be integrated into various regions and territories to promote environmental sustainability and economic growth. By examining the green economy's potential impact on different areas, GREECO aims to provide valuable insights for policymakers and stakeholders to make informed decisions in fostering a greener and more resilient economy.

enterprises in depth. Hence, moving from a sample of 367 ICT firms from EU large countries (Germany, Sweden, Great Britain), for the period 2011-2019 (the resulting dataset contains 1141 observations), this paper aims to disentangle the sensitiveness of firms' performance, measured as total assets growth to R&D investments, looking at how heterogeneity in size, age and sectors have a moderating impact on R&D investment, controlling for growth persistence, capital structure, profitability and other financial variables. To strengthen our FE results, we adopt an instrumental variable approach to mitigate concerns linked to endogeneity or reverse causality issues running from firm growth to R&D investments. We further test for growth persistence adopting a dynamic model and a GMM system strategy. The results of our analysis suggest that firm-specific characteristics influence the effect of R&D investment on ICT firm growth. Indeed, there is evidence that in the ICT sector SME firms have greater growth benefits from R&D investment than larger firms. Moreover, we have evidence of a positive moderating effect of size on R&D returns to growth, with higher elasticities for SMEs than for large firms. Regarding age, investing in R&D helps younger firms that show higher returns than more mature firms (in our setting, over 40 years old). In this context, when we also consider the dynamics of persistence in this growth phenomenon, again, SMEs benefit more from R&D investments than larger companies. Even within the ICT sector itself, however, there are heterogeneous dimensions with the benefits in terms of R&D investment growth being greater in ICT service companies than in manufacturing companies. Our results are also useful to have several insights into policy issues by underlining the relevance of R&D in the growth of SMEs and suggesting that policy makers dealing with innovation-led growth should target R&D incentives to ICT firms. Our results not only underline the impressive contribution that research budgets can have in this technology sector (Bronzini & Piselli, 2016; OECD, 2015), but also suggest that current policy initiatives focused on younger firms need to be strongly supported. At the European and national level, much of the current policy interest and academic guidance is based on the observation that Europe has fewer innovative start-ups than the US, in relative terms.

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“Innovation is taking two things that already exist and putting them together in a new way.”

Tom Freston

# *Chapter 1*[2]

# Inter-sectoral and inter-regional knowledge spillovers: the role of ICT and technological branching on innovation in high-tech sectors


## *Abstract*

The aim of this paper is to examine the patenting specialization of OECD regions in high-tech (HT) domains, with a particular emphasis on the impact of information and communication technology (ICT) on innovation performance at both the extensive and intensive levels. Considering ICT as a general-purpose technology (GPT) and recognizing its influence as a knowledge driver on regional innovation, we investigate the role of ICT agglomeration in promoting HT innovation, specifically examining whether this effect is driven by regions that exhibit innovation in ICT. Additionally, we explore the inter-sectoral and inter-regional branching dynamics in HT innovation development by examining the relative proximity between HT technologies. To ensure the robustness of our findings regarding the effects of ICT agglomeration (technologically advanced) and technological proximity, we employ fixed-effects models, quantile regression, and generalized method of moments (GMM) estimators. Furthermore, we employ a Spatial Durbin Model to examine inter-regional spillover effects. Our findings indicate that the propensity for innovation at the extensive level is influenced by ICT agglomeration, but this positive impact is contingent upon regions maintaining technological specialization in ICT. Moreover, we observe inter-sectoral innovation spillovers resulting from technological proximity between technologies, as well as inter-regional spillovers stemming from spatial proximity.



**Keywords:** ICT; R&D; Smart specialization strategies, Revealed Technological Advantages; Agglomeration.
**JEL classification:** R11; R58; O31; O33.


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## 1. Introduction

The ease of access to knowledge is a crucial element that can influence the innovative performance of firms, regions, and countries. Such access can be facilitated by several factors that, by fostering knowledge flows among economic agents, even those belonging to different contexts and sectors, improve their innovative performance.

The motivations that are behind regional differences in the emerging of new technologies or growth paths have been linked by (evolutionary) economic geography to phenomena of knowledge flows and regional branching, according to which new technologies are more likely to emerge in a region when they are related to pre-existing local capabilities (Czarnitzki and Spielkamp, 2003; Frenken and Boschma, 2007; Boschma, 2017; Zhu et al. 2017; Xiao et al. 2018).

The rationale is that more related technologies and activities have higher cognitive proximity that could facilitate knowledge diffusion (Xiao and Boschma, 2022) and, in this context, a growing strand of literature emphasizes the role of General-Purpose Technologies (GPTs)[3] in positively influencing new technologies and innovation. Information and communication technologies (henceforth, ICT), which can be considered as the predominant GPTs, are a useful tool for spreading knowledge across, firms, sectors, and areas, by facilitating access to inter-regional, and inter-sectoral, knowledge flows that enables regional actors to connect and recombine competencies from sectors that seemingly lack direct connections. One of the most salient examples of this is how ICT allowed a better conversion of information into knowledge and a redesign of the innovation process in sectors like nanotechnology, biotechnology, pharmaceutical, medical products over the last two decades generating a technological convergence phenomenon of previously separated sciences (Malanowski and Compañó, 2007; Kim and Moon, 2013). However, despite the relevance of ICT in spurring future innovations and being applied in a wide range of sectors, little is known about how the technological relatedness with ICT can influence the innovation paths of regions.

Likewise, recent policy efforts, which lack theoretical foundations and unambiguous empirical evidence (Montresor and Quatraro, 2017), can be more effective if supported by a deeper knowledge of the relationship between ICTs and regional branching, providing valuable insights into the technological mechanisms driving regional development.

Such insights could also help nations and regions identify more specific roles in their policy frameworks for ICT, which is still one of the most crucial sectors for developing innovation.

When in June 2020, the European Commission announced the new European Skills Agenda, complementing the European Digital Strategy, indeed, signatories agreed that the digital ecosystem

[3] General-purpose technologies (GPTs) are technologies that have the potential to impact entire economies, typically at a national or global level. GPTs can lead to significant changes in society by influencing pre-existing economic and social structures (Bresnahan and Trajtenberg, 1995). The most iconic examples of GPTs include the steam engine, electricity, and information technology. Other examples of GPTs include the railroad, interchangeable parts, electronics, material handling, mechanization, control theory (automation), the automobile, the computer, the Internet, medicine, and artificial intelligence. These technologies are not only transformative but can also create new industries and disrupt existing ones, making them critical drivers of economic growth and social change.

is the most relevant industrial ecosystem, out of the 14 identified, in which it is necessary to upskill and reskill the workforce.[4] Registering in Europe in 2019 an annual turnover of 625 billion EUR, representing the 5.17% of EU value added, and accounting for 6.8 million workers and 1.2 million firms, the digital ecosystem is relevant by itself, but it is also at all stages of value chains and in all other ecosystems. Especially in the aftermath of COVID-19 pandemic, the firms' demand for digital technologies and infrastructure increased to remain competitive and resilient (European Commission, 2022).

However, despite the significant impact of information and communication technologies (ICTs) and other general-purpose technologies (GPTs) on various aspects of the economy, their specific role in promoting innovation and technological diversification has not received extensive attention in the existing literature. While there is a growing body of research exploring the influence of GPTs on innovation, only a few studies have specifically addressed the role of ICTs in this context.

One exception is the study conducted by Montresor and Quatraro (2017), who investigated a specific set of new generation key enabling technologies (KETs) and their potential as GPTs. However, we differentiate from their analysis considering the role of ICTs. Another contribution is the work of Xiao and Boschma (2022), which focused on GPTs and their significance as a source of knowledge for the emergence of artificial intelligence (AI). While this study sheds light on the broader impact of GPTs, it does not delve into the specific role of ICTs in promoting innovation and technological diversification in high-tech. Therefore, there is still a need for further research that specifically examines the role of ICTs as GPTs and their influence on innovation and technological diversification. By filling this gap, we aim to contribute to the existing literature and provide a more comprehensive understanding of the mechanisms through which ICTs can drive innovation and foster technological diversification in various sectors of the economy.

This paper contributes to the existing literature by examining the factors that facilitate new technological specialization and how they contribute to the introduction of radical innovations in high-tech sectors. Specifically, we identify ICTs as a key driver in enabling regions to combine existing local or global knowledge in novel ways. In addition to exploring technological complementarities between sectors, our study investigates the role of spatial proximity and inclusion in regional structures that promote information transfer and spillovers. By studying these factors, we aim to understand why certain regions exhibit higher levels of innovation compared to others. This research builds upon previous studies, which highlight the importance of regional structures in reducing innovation costs and risks associated with innovation (e.g. Feldman and Florida, 1994; Bottazzi and Peri, 2003; and Montresor and Quatraro, 2017).

[4] The digital ecosystem – including three main subsectors: ICT manufacturing, ICT services (excluding telecommunications), and telecommunications – is one of the 14 industrial "ecosystems" that the European Commission has identified in its "A New Industrial Strategy for Europe" (2021): 1. Aerospace & Defence, 2. Agri-food, 3. Construction, 4. Cultural and Creative Industries, 5. Digital, 6. Electronics, 7. Energy Intensive Industries, 8. Energy-Renewables, 9. Health, 10. Mobility-Transport-Automotive, 11. Proximity, Social Economy and Civil Security, 12. Retail, 13. Textiles, 14. Tourism. EUR-Lex - 52021DC0350.

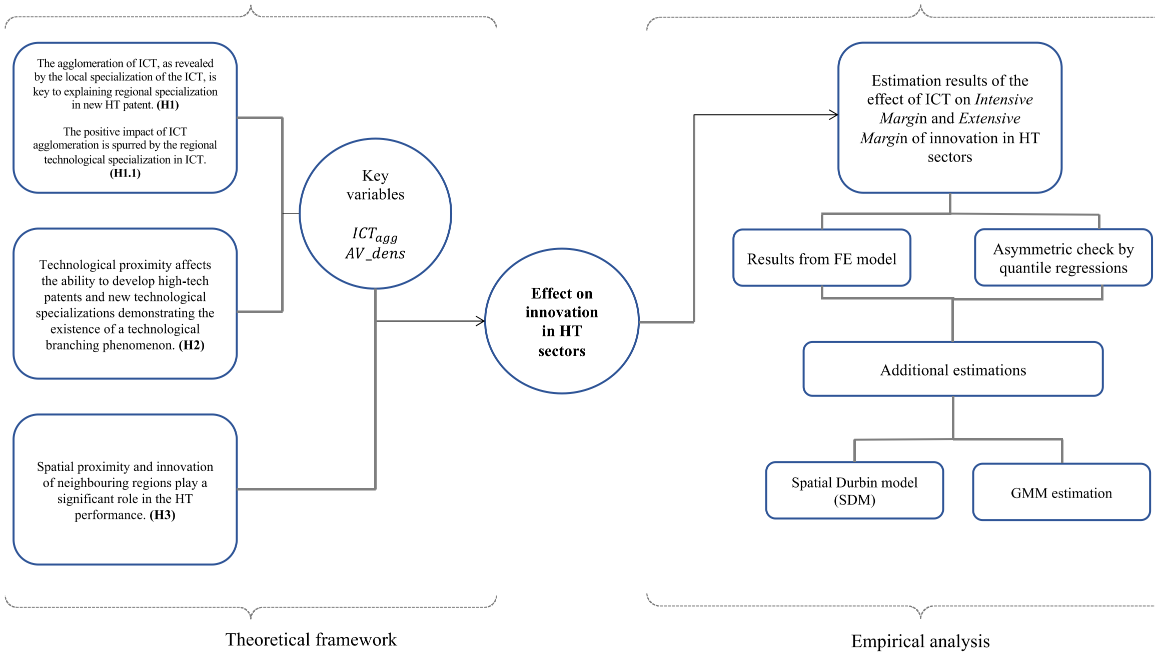
Hence, we test three hypotheses. The first one is that high concentration of ICT workers, businesses, services, and infrastructure within a specific geographical area (i.e., ICT agglomeration) affects HT specialization at the extensive and intensive margin, but its impact is spurred by the regional technological specialization in ICT. The second one is that technological proximity affect the ability to develop high-tech patents and new technological specializations demonstrating the existence of a technological branching phenomenon. The third is that spatial proximity and innovation of neighbouring regions play a significant role in the innovative performance in high tech sectors. To test our hypotheses, we adopt several methodologies: a panel fixed effects model (henceforth, FE) as baseline, a Generalized Method of Moments system (henceforth, GMM) as endogeneity check, an asymmetric check by employing the quantile regression approach for measuring the differences in the influence of ICT agglomeration on regional innovation for regions with different levels of patent activities in HT. Finally, we test for the existence of spatial effects and interregional spillovers using a Spatial Durbin Model (henceforth, SDM). The research framework is shown in Figure 1.

The analysis focuses on measuring the innovative performance of 169 regions in 19 OECD countries, over the years 2000-2015, with the latter measured by high-tech (HT) patent applications in four sectors: biotechnology, nanotechnology, pharmaceuticals, and medical. We check the existence of technological branching phenomena in terms of both technological proximity within the region and spatial proximity to innovative regions.

Our results show that the propensity to innovate of the regions considered is influenced at the extensive margin but not at the intensive margin by ICT agglomeration, but this positive impact is verified only when regions detain a technological specialization in ICT activities. There is a phenomenon of innovation propagation due to technological proximity between different technologies. We also find evidence of spillovers deriving from spatial proximity in ICT and branching activities.

The paper is structured as follows. Section 2 provides a review of the relevant literature and outlines the research hypothesis that this paper seeks to contribute to. In Section 3, we introduce the data used in our study, describe the construction of our variables of interest, and outline our estimation strategy. Section 4 presents the results of our analysis, while Section 5 discusses the findings. Finally, in Section 6, we conclude the paper.

**Fig. 1 - The research framework**




## 2. Related literature and research hypotheses

In recent years, an extensive literature has focused on the development and emergence of new technological specializations, and on the propagation mechanisms of innovation.

The presence of companies operating in some sectors more related to knowledge (for example: ICT, KIBS, KETS, etc.) has been shown to have an impact on the decision of other companies to locate in that area and determine the growth of existing companies both in terms of turnover and in terms of innovative capacity and knowledge. Therefore, as pointed out by Frenken and Boschma (2007), this results in an industrial diversification of the area that facilitates the interconnection of different industries and sectors, producing an additional innovative plug.

Crucial in this analysis are the General-purpose technologies (GPTs). The "rare properties" (Foray, 2009, 21) of GPTs lie in their wide range of applications (e.g., the widespread industrial use of ICT in nanotechnologies), and in the complementarity between inventions and applications in their development (Bresnahan, 2010). The two properties just mentioned attribute to GPTs an important function in the technological transition that recombinant innovations drive at regional level (Olsson and Frey, 2002; van den Bergh 2008; Frenken et al., 2012).

ICT sectors, being considered at the core of the category of GPTs, have the potential to drastically influence societies through their impact on pre-existing economic and social structures. However, few contributions have focused on the role of ICT technologies in the spread of new technological specialization, and on the sectoral and geographical dynamics of this technology spread.

### *2.1. Regional agglomeration and specialisation in ICT: effects on regional high-technology patents specialization*

The starting idea is that the innovation propensity and knowledge of ICT technology, as GPTs, could provide additional energy to the recombination of ideas at the local level. Thus, ICT firms could intensify their relationships with related and unrelated activities leading to an increase in the number of new technologies that the region is able to master in the area in the future.

The ICT industry has played a significant role in economic development and industrial structure transition (Piatkowski, 2006) not only in terms of GDP, but especially in terms of information and communication infrastructure without which both modern economies and societies might not function as many essential activities today are based on technologies that belong directly or indirectly to the ICT (Fransman, 2009; Veugelers, 2010; Veugelers, 2012; European Commission, 2015). The ICT sector is a highly innovative and rapidly changing area. These technologies include computing and telecommunications and encompass new developments in emerging technologies as, for example, artificial intelligence (AI). Since the 1980s, ICT has been a major driver of innovation. It led to both computers and internet access becoming commonplace in just about every home and workplace and, later on, to the integration of computers into mobile phones" (European Patent Office, 2019). ICT has a significant spillover effect on technological innovation and takes an active role in economic development insofar it can be considered as a representative industry of new knowledge and new technology (van Oort and Atzema, 2004).

Based on the discussion above, we formulate the following hypotheses:

***Hypothesis 1.a:*** *The agglomeration of ICT, as revealed by the local specialization in ICT, measured by a location quotient at regional level, is key to explaining regional specialization in new HT patents.*

***Hypothesis 1.b:*** *The positive impact of ICT agglomeration is spurred by the regional technological specialization in ICT.*

### *2.2. Technological proximity and high-tech patents*

An additional key insight is derived from the idea of proximity. Drawing on the large recent literature on economic geography of innovation we focus on the regional acquisition of new HT technologies as a process of "regional branching" i.e. the regional diversification into new technologies obtained by recombining those cognitively close to pre-existing ones (Kogler et al., 2013; Colombelli et al., 2014; Tanner, 2014; Castaldi and Frenken, 2015; Rigby, 2015; Montresor and Quatraro, 2017; Boschma et al., 2017).

The related diversification concept has arisen following the notion of smart specialisation (Foray et al., 2012; Boschma and Giannelle, 2014). This concept recommends regions to leverage their existing strengths by diversifying into technological activities related to existing one following their knowledge capabilities less risky and less costly (Balland et al., 2018). The existence of a certain past industrial structure determines to some extent what the future industrial structure will be (Boshma and Frenken, 2011). The literature suggests that economies only occasionally deviate from their past pattern of development (Boschma and Capone, 2015; Petralia et al., 2017; Pinheiro et al. 2018, 2021). Unrelated diversification is a rare and risky endeavour, it avoids lock-in (Saviotti and Frenken, 2008), but needs a profound shift in local capabilities (Neffke et al., 2018) and it is associated with radical innovation (Castaldi et al., 2015). Thus, deviating from the previous pattern may require an internal or external shock.

Crucial in this analysis is the stylized fact that innovation tends to follow cumulative and path-dependent trajectories (Dosi, 1982, 1988; Silverberg et al., 1988; Arthur 1989). Along these trajectories, the patterns of technological specialisation of firms, sectors, and countries change very slowly over time and are generally persistent. A similar phenomenon has also been detected in the context of the geography of innovation and has been qualified as "place-dependence", or "related diversification" (Boschma and Frenken, 2006; Neffke et al., 2011; Boschma, 2017; Montresor and Quatraro, 2019).

On the other hand, attention has been also paid to the unrelated (rather than related) variety of the regional knowledge-based on which breakthrough innovations would draw (Castaldi et al., 2015). In accounting for it, previous studies have mainly followed a Jacobsian perspective (Jacobs, 1969) and looked at the economic scale and metropolitan nature of regions in favoring the higher degree of knowledge variety that radical innovations would entail (Mewes, 2019; Berkes and Gaetani, 2020). In particular, firms based in regions marked by large and heterogeneous pools of knowledge, could benefit from the cross-fertilization of ideas between different industries – the so-called Jacobsian externalities (Glaser et al., 1992) – and take stock of them to innovate more radically.

Castaldi et al. (2015) use a refined version of the classical Jacobsian argument about regional variety. Following the seminal distinction proposed by Frenken et al. (2007), they suggest and find that, more than the "related" variety of the local knowledge base, the "unrelated" one matters for technological novelty. Considering radical inventions as the combination of previously unrelated fields of knowledge their introduction is retained more probably fed by a local knowledge base, whose elements are so diverse to be not related yet.

All in all, technological developments, both related and unrelated with respect to the production system, have been shown to play a major role on regional innovation and the emergence of new industrial specializations (Kogler et al., 2013; Boschma et al., 2014; Colombelli et al., 2014; Tanner 2016; Backman and Lööf, 2015; Boschma et al., 2015; Castaldi, et al., 2015; Rigby 2015).[5] A deeper

[5] On the mechanisms underlying this type of regional branching, see Tanner (2014).

understanding of the diversification strategies that can optimally balance the development of related and unrelated activities is provided by Alshamsi et al. (2018). The researchers developed algorithms to identify the optimal activities to target at each time step for diversifying an economy. Their findings suggest that the strategies that minimize the total time needed to diversify an economy are those that target highly connected activities during a specific time window. However, the regional factors that could help the process of knowledge recombination, following a Schumpeterian perspective, appear still neglected. The Weitzman's concept (1998) of recombined innovation and its regional declination can be crucial in the view of industrial branching at the regional level (Quatraro, 2010; Castaldi et al., 2015). In other words, a broad and various portfolio of companies influences the diversity of their knowledge base and helps create a fertile field of ideas that generates Jacobean spillover (Jacobs, 1969) as well as innovations that recombine knowledge and innovations from multiple sectors. The relatedness degree of these heterogeneous activities makes it easier to innovate by recombining ideas and technologies at the regional level (Montresor and Quatraro, 2017). We expect these to be the salient effects that ICT have on the creation of technological novelty. In contributing to fill this gap, the second aim of this paper is to investigate the role that local technologies marked by knowledge combinatorial properties can have in driving regional technological novelty.

Based on the two opposing views in the literature described above, we will test the following second hypothesis:

***Hypothesis 2:*** *Technological proximity affects the ability to develop high-tech patents and new technological specializations demonstrating the existence of a technological branching phenomenon.*

### *2.3. Spatial proximity and interregional spillovers of innovation of neighboring regions*

Another important argument is that a region does not branch its activities in isolation from other regions and the technological effects that ICT can exert in the regional knowledge base may extend beyond a region's geographic boundaries and make the knowledge/specialization of that region significant for the development of new technological specializations in neighbouring ones. As has been widely shown by the literature on interregional spillovers (e.g., Maruseth and Verspagen, 2002; Bottazzi and Peri, 2003; Kalapouti and Varsakelis, 2015), spatial proximity allows knowledge to flow from one region to another in different ways (e.g., through technology transfer, research collaboration, and labor mobility). Cross-regional spillovers may concern ICTs especially if we consider the explicit nature of their knowledge base. Boschma (2005) argues that geographical proximity per se is neither a necessary nor a sufficient condition for propagation to take place. However, it facilitates interactive learning and propagation. Montresor and Quatraro (2017) emphasize the existence of geographic spillovers in the propagation of innovation. On the other hand, diversification is often characterized as an endogenous process inherently conditioned by geography as capabilities are embedded in actors based in countries, regions, or cities (Boschma, 2017). Accordingly, we can expect that the benefits that ICT have for regional innovation could be gained even by regions lagging in their development like peripheral regions, if they are closer to leader regions in the same respect, typically, core regions. Building on the literature examined, we will test the following hypothesis in the paper:

***Hypothesis 3***: *Spatial proximity and innovation of neighboring regions play a significant role in the HT performance.*

## 3. Data, Variable Construction, and Empirical Estimation Strategy

In this section, we provide an overview of the data, variable construction, and empirical estimation strategy employed in our study. We begin by discussing the data on high-tech innovation in Section 3.1, focusing on the relevant indicators and sources used to capture this phenomenon. Next, in Section 3.2, we delve into the extensive margin of high-tech innovation, exploring how we measure and define this crucial aspect of technological advancement. Section 3.3 examines ICT agglomeration, shedding light on its significance and the specific measures utilized to capture its effects. Furthermore, Section 3.4 delves into the concept of technological proximity and its role in fostering innovation. Finally, in Section 3.5, we outline our estimation strategy employed to analyze the relationships between the variables of interest.

### *3.1. Data on innovation high-tech*

The data on innovation have been extracted from the OECD Patents and Innovation Indicators by extrapolating the information to the large region (TL2) level.[6] Our final sample consists of more than 169 different regions located in 19 OECD countries over the period 2000-2015. We used patent data (IPC applications), primarily, as a proxy for the region's ability to expand into new technologies by looking at technological specializations proxied by an indicator of Revealed Technology Advantage in high-tech sectors. We follow the OECD by including in this category patents in five different sectors: nanotech, biotech, pharmaceutical, medical, ICT.

Moreover, studying the innovation in biotechnology, nanotechnology, pharmaceuticals, and medicine is important because they involve highly intensive R&D activities that produce high-tech

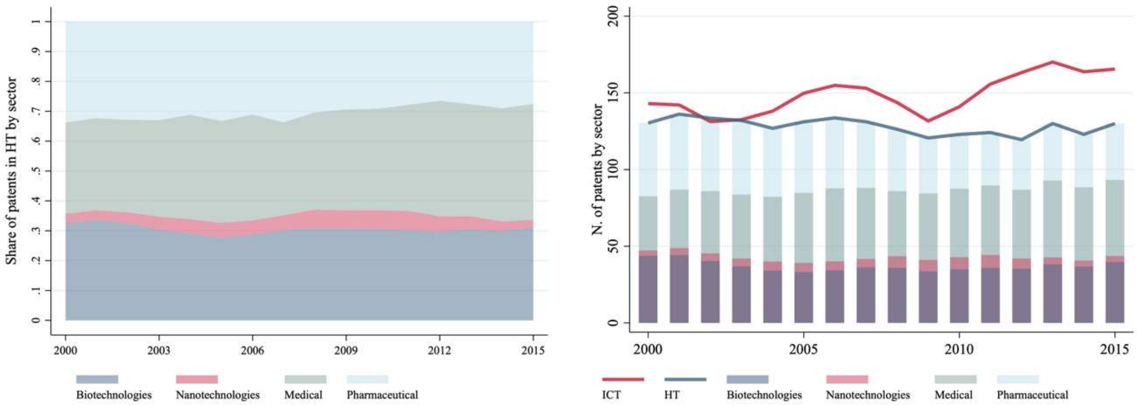
[6] Regions in OECD Member Countries have been classified according to two territorial levels (TL2 and TL3). This classification - which, for European countries, is largely consistent with the Eurostat Nomenclature of Territorial Units for Statistics (NUTS) - facilitates greater comparability of regions at the same territorial level. The differences with the NUTS classification concern Belgium, Greece, and the Netherlands where the NUTS 2 level correspond to the OECD TL3 and Germany where the NUTS1 corresponds to the OECD TL2 and the OECD TL3 corresponds to 97 spatial planning regions (Groups of Kreise). For the United Kingdom, the Eurostat NUTS1 corresponds to the OECD TL2. The countries in our final sample are Austria (5 regions), Belgium (3), Canada (4), Czech Republic (6), Denmark (2), Finland (4), France (12), Germany (16), Greece (1), Hungary (6), Italy (18), Norway (2), Portugal (3), Slovakia (2), Slovenia (2), Spain (14), Sweden (6), United Kingdom (12), and United States (51).

patents. These interdisciplinary fields have a significant impact on society and are believed to be connected in some way to ICT technologies due to their high level of interdisciplinarity. They require innovative solutions to complex problems, resulting in technically demanding patents that are of strategic importance for national and regional economies and have high commercialization potential. These sectors rely heavily on research and development activities and interdisciplinary applications, which require significant investments in terms of time, money, and resources. As a result, companies and researchers in these fields are continually seeking innovative solutions to complex problems, leading to the creation of high-tech patents. Moreover, the impact of these sectors on society in areas such as health, energy, and the environment contribute to the strategic importance of patents produced in these areas. Measuring the innovative performance of a region in terms of high-tech patents, as we do in this study, can offer valuable insights into its technological and economic competitiveness.

Patent statistics are often used by policymakers to measure research and development (R&D) output and innovation (European Commission, 2020). A weakness of using patent data is that innovation is defined narrowly: patents are only considered product or process innovations if they are commercialized. This approach excludes innovations related to changes in organizational structure or new marketing methods, as defined in the Oslo Manual (OECD, 1997, 2005). However, a strength of using patents as an indicator of innovation is that the commercialization of a patent automatically implies the introduction of a technological innovation, since patents are only granted for novelties and inventions (Svensson, 2021).

In Fig. 2.a, we present the share of each sector in the category of HT over the period 2000-2015. Among the sectors analysed, biotechnologies (0.31), medical (0.37) and pharmaceuticals (0.35) all contribute, in our sample, on average by about one third of the total performance in the HT sectors, with peaks around 0.37 for the medical sector. This is different for the nanotechnology sector, whose innovation is less important in relative terms in the high-tech patent category, with an average share of 0.06 (showing the higher value in 2011 and lower in 2000, with 0.08 and 0.03 respectively). Fig. 2.b, instead, shows the evolution, on average, of the number of patents in HT sectors and ICT. While patents in both categories follow a similar pattern, the innovation in ICTs shows an increase after 2009, confirming the relevance of the sector.

**Fig. 2 – Share of patents by sector in HT**

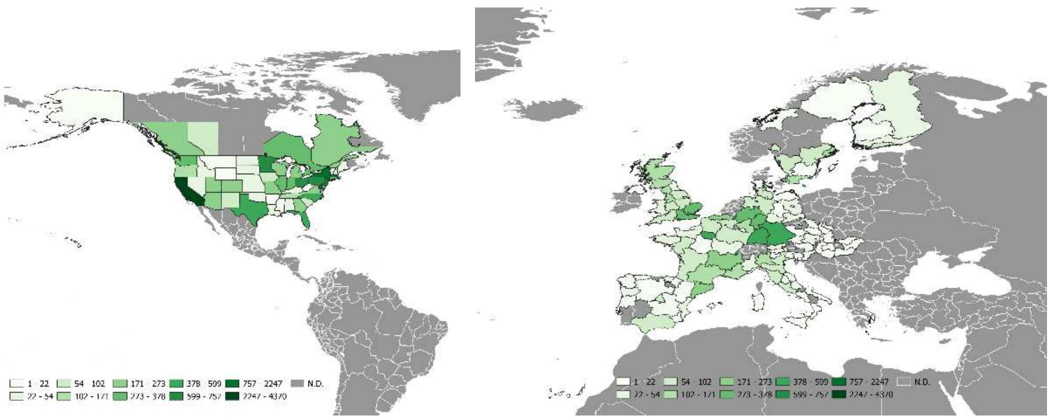



(a) (b)

Notes: The figure in panel (a) plots the average share of patents filled in each of the four corresponding IPC high-tech classes we include in the HT sectors (Biotechnologies, Nanotechnologies, Medical, Pharmaceutical). The figure in panel (b) shows the average evolution of the number of patents in HT sectors (Biotechnologies, Nanotechnologies, Medical, Pharmaceutical) and in ICT sector.
Source: Authors' elaboration on OECD data.

As said, in our work we use patent data (IPC applications) in HT sectors, primarily, as a proxy of the innovative performance of regions. To have a clear idea of the geographical distribution of HT patents, Fig. 3 plots the number of patents in HT in the last year of our sample. As expected, the most innovative large regions are located mainly in the US (California (US06) with 4,369.942 HT patent applications in 2015; Massachusetts (US25) 2,247.177, and New York (US36) 916.8459). As far as Europe is concerned, the most innovative regions are Île-de-France (FR1) in France (550.468), and Bavaria (DE2) (541.1). In Europe, the role of the European manufacturing core (Germany, France, the United Kingdom, northern Italy) is still alive as the engine of the interconnected development.

**Fig. 3 - Geographical distribution of HT patents**



*(a)* *(b)*

Notes: The figure plots the regions' number of patents applications filled in the HT sectors (nanotech, biotech, pharmaceutical, medical) in 2015. Panel (a) shows the levels of HT patents for regions located in Canada, and United States. Panel (b) shows the levels of HT patents for regions located in Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Italy, Norway, Portugal, Slovakia, Slovenia, Spain, Sweden, United Kingdom. The regions in grey are not included in the sample.
Source: Authors' elaboration on OECD data.

From OECD database we also derive our control variables to check for region-specific economic characteristics that could influence regional innovation performance. We extract at regional level GDP at constant 2015 prices, the number of workers with tertiary education (HC), regional total R&D expenditure share over GDP. We are also able to distinguish between private R&D expenditures done in the business sector ($R\&D_{it}^{bus}$), the government sector ($R\&D_{it}^{gov}$), and the higher education sector ($R\&D_{it}^{he}$). As pointed out by Content et al. (2021), the latter two could represent a proxy for public R&D expenditure.

In Table A.2 the variables used in the main text are explained in detail. In Table A.3 the descriptive statistics give us a general overview of the data we have available. It is interesting to note that 68% of the R&D expenditure of the regions in our dataset comes from private investments, while only 13% comes from government investments and 18% from investments in high education.[7] In terms of patents, on average about 70 per cent of high-tech patents come from the medical and pharmaceutical area. The biotech area is also very productive. About $New\_RTA_{i,t}^{HT}$, our dataset captures 886 new specialisations out of a total of 1,631 observations. On average, there is a 50% chance of a new specialization emerging per year in each region within our dataset.

In Fig. A.1. we describe the evolution of high-tech and ICT patents over time for each country in the sample. It is clear the leadership of the United States which has the highest concentration of patents in both high-tech and ICT, with over 2000 patent applications per million inhabitants. Europe also has considerable levels of patent applications, with Western and Northern Europe reaching levels of around 800 patents per million inhabitants. Remarkable results also emerge for Italy, Spain, and Canada, with around 200 patents per million inhabitants in each country. It is worth noting that in historically more innovative countries, the number of ICT patents per million inhabitants tends to be higher than the number of high-tech patents. This trend is observed in the US, all of Western Europe, as well as Sweden, Norway, and Finland.

### *3.2. Extensive margin of high-tech innovation*

Moving from data on patents, to check the role of ICT in promoting innovation in HT sectors, we follow the literature on the emergence of new productive activities (Boschma et al., 2013; Colombelli et al., 2014; Montresor and Quatraro, 2017), by computing the new technological specialization in sector s in the region i at time t ($\text{New\_RTA}_{ist}$) moving from the RTA (Revealed Technological Advantages). We apply Balassa's index to patent applications filed in the corresponding IPC class ($Pat_{ist}$) (Soete, 1987):

[7] A further 1% comes from private non-profit investments.

$$\mathrm{RTA}_{ist} = \frac{\frac{\mathrm{Pat}_{ist}}{\sum_{i=1}^{n} \mathrm{Pat}_{ist}}}{\frac{\sum_{s=1}^{m} \mathrm{Pat}_{ist}}{\sum_{i=1}^{n} \sum_{i=1}^{m} \mathrm{Pat}_{ist}}} \tag{1}$$

where the RTA for the region $i$ (out of n) at time $t$ is greater than 1 ($\mathrm{RTA}_{ist} > 1$) if the region is specialized in the implementation of patents in each sector s (out of m) at time t, otherwise it is not specialized. $Pat_{ist}$ is the number of patents filled in the corresponding IPC class.[8] To obtain our measure of extensive margin of innovation, we build a dummy variable $\mathrm{New\_RTA_{ist}}$ based on $\mathrm{RTA}_{ist}$ which is greater than 1 if the region i has developed a new technological specialization in t that is different from the eventual technological specialization in t-1; $\mathrm{New\_RTA_{ist}}$ is equal to zero in the other cases.

$$New\_RTA_{ist} = \begin{cases} 1\ if\ RTA_{ist} > 1\ and\ RTA_{i,s,t-1} \leq 1 \\ 0\ otherwise \end{cases} \tag{2}$$

This measure allows us to identify regions that have developed new technological specializations in HT sectors over time, which we use to investigate the role of ICT in promoting innovation in these sectors.

### *3.3. ICT agglomeration*

To test our H1 (see section 2.1), we measure the ICT agglomeration following the location entropy method based on the number of employees in a region (Liu et al., 2021; Zhao et al., 2021a). It is calculated as follows:

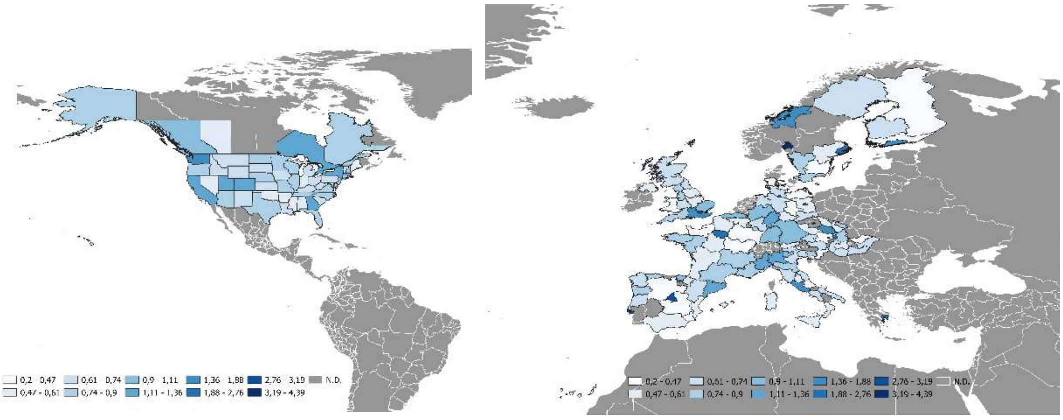
$$\mathrm{ICT\_agg}_{it} = \frac{ICT\_empl_{it} / \sum_{i}^{c} ICT\_empl_{it}}{empl_{it} / \sum_{i}^{c} empl_{it}} \tag{3}$$

Where $ICT\_empl_{it}$ is the number of employees in ICT sector[9] in region *i* at time *t* in country *c* where the region is located, and $empl_{it}$ is the total number of employees in all sectors in region *i* at time *t*. Figure 4 plots the spatial distribution of the indicator of ICT agglomeration, where – looking at in Panel (a) - the regions where the employment in ICT activities is higher are in US (District of Columbia (US11) showing a location quotient of 2.19, Washington (US53) 1.52, and New York (US36) 1.36). In Canada, instead, the regions with higher values of ICT agglomeration are Ontario (CA35) with 1.14, British Columbia (CA59) 1.085, and Quebec (CA24) 0.876.

[8] In our specifications, when we consider the new specialization in HT sectors, we denote the new specialization as $New\_RTA_{i,t}^{HT}$ with the apex denoting the HT sector. See also Table A.2 for variable description.

[9] In section A.1 in Appendix A, we introduce the Classifications and description of ICT sector and in Table A.1, we describe the NACE v.2 ICT Industry classification adopted. The sectoral coverage of ICT follows the assignment of the NACE code economic activity sectors according to the official OECD definition.

**Fig. 4 – Geographical distribution of ICT agglomeration**




*(a)* *(b)*

Notes: The figure plots the regions' level of ICT agglomeration in 2015. Panel (a) shows the levels of ICT agglomeration for regions located in Canada, and United States. Panel (b) shows the levels of ICT agglomeration for regions located in Austria, Belgium, Czech Republic, Denmark, Finland, France, Germany, Greece, Hungary, Italy, Norway, Portugal, Slovakia, Slovenia, Spain, Sweden, United Kingdom. The regions in grey are not included in the sample.
Source: Authors' elaboration on OECD data.

If we look at European countries – Panel (b) – the regions with higher ICT agglomeration in 2015 are located in Norway (Oslo and Akershus (NO01) 4.39), Czech Republic (Prague (CZ01) 4.05), Portugal (Metropolitan area of Lisbon (PT17) 3.19), and Spain (Madrid (ES30) 3.11). In general, capital regions in Europe and beyond tend to have higher levels of ICT agglomeration than other regions. This is probably since the national bureaucratic machine needs quality ICT services, but in general these areas are also densely populated and characterised by a higher level of concentration of service-related activities.

### *3.4. Technological proximity*

The literature on proximity is extensive; however, it is mainly related to economic geography (Boschma, 2005). Nevertheless, starting from the idea of geographic proximity it is possible to imagine a non-geographical space separating different technologies thanks to the properties of conditional probability and on the idea of technological and cognitive proximity (see Hidalgo et al., 2007; Kogler et al., 2013; Colombelli et al., 2014; Essletzbichler, 2015; Rigby, 2015). Using RTA as an indicator of technological specialization, following Montresor and Quatraro (2017), we define the concept of proximity between two technologies s and z at time t. By benefitting from the properties of conditional probability:

$$\varphi_{s,z,t} = \min\{P(RTA_{s,t}|RTA_{z,t}), P(RTA_{z,t}|RTA_{s,t})\} \quad (4)$$

the higher the number of specializations occurring at the same time the higher the probability of both events occurring; consequently, the proximity between the two technologies also increases (Montresor and Quatraro, 2017). For each focal technology z, we then calculate the (weighted) average proximity with respect to it of the different s technologies in which region i has gained a new revealed technological advantage at time t:

$$\mathrm{WAD}_{izt-1} = \frac{\sum_{s\neq z} \varphi_{szt-1}\,\mathrm{New\_RTA}_{ist}}{\sum_{s\neq z} \varphi_{szt-1}} \tag{5}$$

Finally, for each region i, we calculated the average proximity at time t-1, by weighting them with the RTA that the region has gained at time t:

$$\mathrm{AV\_dens}_{it} = \sum_{s\#z} \mathrm{WAD}_{izt-1} \frac{\mathrm{New\_RTA}_{ist}}{\sum_{z\neq s} \mathrm{New}_{\mathrm{RTA}_{ist}}} \tag{6}$$

Hence, $AV\_dens$ is a proxy for the extent to which the new technological advantages that a region gains at time t are on average close in the year preceding the new technological specialization. The objective is to define whether the technological distance in the year immediately preceding the new specialization tends to narrow and if so whether this is statistically significant. The higher the number of specializations happening at the same time the higher the probability of both events occurring, consequently the proximity between the two technologies also increases (Montresor and Quatraro, 2017). Technological proximity was calculated across all the different technology specialisations: biotech, nanotech, pharmaceutical, medical, and ICT. In this way, we obtained a measure of the proximity between all these different technologies.

### *3.5. Estimation strategy*

As said, the aim of this paper is to measure the effect of ICT agglomeration, ICT innovation performance and the role of spatial proximity in the innovation performance in HT sectors. To do so, our estimation strategy relies on different complementary steps that we describe in this section.
We move from the following equation, in which we measure the innovation performance by using both the number of patents in HT sectors - to test the impact of ICT on the intensive margin of innovation - and the emerging of new specializations in HT sectors as indicator of the extensive margin of innovation as dependent variables. Then, we progressively include other controls to refine the analysis. The starting equation is the following:

$$Y_{i,t} = b_1(Y_{i,t-1}) + b_2(X_{i,t-1}) + b_3(ICT\_agg_{i,t-1}) + b_4(AV\_dens_{i,t}) + \chi_i + \phi_t + \varepsilon \tag{7}$$

Where $Y_{i,t}$ can be alternatively our measure of intensive ($Patents_{i,t}^{HT}$) and extensive ($New\_RTA_{i,t}^{HT}$) margin of innovation calculated as in Eq. 2. To check some persistency in innovation performance, we also include the t-1 lag of our dependent variable. Furthermore, to test our hypotheses 1 and 2, our variables of main interest are represented by the employment agglomeration in ICT ($ICT\_agg_{i,t-1}$), and the proximity between technologies ($AV\_dens_{i,t}$). Based on previous research, $X_{i,t-1}$ is a vector of regional controls (in logs) including: $GDP_{\mathrm{pc}_{i,t-1}}$ , the gross domestic product per capita for region $i$, at time $t$-1, to control for the level of economic development of regions that could influence their innovation performance; $R\&D_{i,t-1}$ , the share of R&D investment over GDP, to control for the relevance of the investment in R&D; $HC_{i,t-1}$ , the number of workers with tertiary education, to control for the level of human capital of the regions. We include in our model both region ($\chi_i$) and year ($\phi_t$) fixed effects to control for unobserved characteristics and time trends that could influence the innovation performance.

As said, since we consider the ICT as a GPT that could help to spread knowledge across sectors, we test also if the concentration of ICT itself has an impact on innovation in HT or if it should be also accompanied by innovative specialisation in ICT itself for being an efficient driver of knowledge.

To this aim, we also include the interaction, at t-1, between the level concentration of ICT in region and the technological advance in ICT of the same region ($RTA_{i,t}^{ICT}$), measured with a dummy variable that equals 1 if region *i* has an $RTA^{ict}$>1 in *t-1* and 0 otherwise. Therefore, we augment the Eq. 8 as follows[10]:

$$Y_{i,t} = b_1\left(Y_{i,t-1}\right) + b_2(X_{i,t-1}) + b_3\left(ICT\_agg_{i,t-1}\right) + b_4\left(RTA_{i,t-1}\right) + b_5\left(ICT\_agg_{i,t-1} \times RTA_{i,t-1}^{ICT}\right) + b_4\left(AV\_dens_{i,t-1}\right) + \chi_i + \phi_t + \varepsilon \tag{8}$$

Where the interaction term represents the reinforcing effect that specialization in ICT has on agglomeration and we expect $b_5$ being positive if ICT agglomeration per se is not sufficient, but it should be also innovative.

We use different methodologies. First, a baseline fixed effect model analysis. Next, we adopt a GMM system as endogeneity check for all the variables of our model. Further, we use a quantile regression approach for measuring the differences in the influence of ICT agglomeration on regional innovation for regions with different levels of patent activities in HT. Finally, we use a spatial model to test for the existence of a spatial innovation propagation phenomenon. This model should be able to appreciate both the effects of the dependent variable with spatial lag and time-spatial lag[11].

[10] We know that our sample exhibit high heterogeneity in terms of their degree of innovativeness. To reduce this heterogeneity and establish a common basis for comparison, we have decided to utilize the Global Innovation Index (2015) as a benchmark to merge our regions. By using this index, we can categorize, and group countries based on their innovation performance (Table C.3).

[11] See Section B for the Spatial Matrix (W).

## 4. Results

### *4.1. How ICT Agglomeration and Technological Proximity Drive High-Tech Innovation*

In Table 1 and 2 we present the results of our estimation of Eq. 7 for the intensive margin and the extensive margin respectively, by adding controls (column 1) to our dynamic specification, then by estimating the effect of technological proximity and ICT agglomeration (columns 2-4). Furthermore, in column 5, we estimate the interacting effect of ICT agglomeration and ICT specialization to look at the relevance of being not only concentrated in ICT, but also innovative (as per Eq. 8). Finally, we look at the heterogeneity in R&D by considering different sources of R&D investments, both coming from private sector ($R\&D_{i,t-1}^{bus}$) and public sector ($R\&D_{i,t-1}^{gov}$ and $R\&D_{i,t-1}^{he}$) (column 6).

In the first step of our analysis, we use a panel fixed effects (FE) model that includes both region and time FE. This approach allows us to control for unobserved heterogeneity across regions and time-specific effects, and to estimate the fixed effects of each region and time period. This is important because it helps us to identify the unique characteristics of each region and time period that affect the dependent variables, while holding constant all other time-varying variables that could be driving the results.

**Intensive margin –** When considering the intensive margin, measured as the total number of patents in the HT sectors, the results in Table 1 show that past innovation, as expected, has a positive effect on current innovation performance, as regions with higher levels of patent applications at time *t-1* appear to be more innovative at the time *t*. The controls in the equation have a positive (and statistically significant) correlation with innovation performance, except for GDP per capita, whose coefficient is not significant, albeit positive, across all our different specifications.

About the other controls, HC seems to have a positive effect on the propensity to patent in our sample, since high-skilled workers are naturally connected to the innovation process, as does R&D expenditure. In particular, the results on R&D holds also when we split the R&D investments, between private sector ($R\&D_{it-1}^{bus}$) and public sector ($R\&D_{it-1}^{gov}$, $R\&D_{it-1}^{he}$).

Coming to our variables of main interest, the role of ICT agglomeration, technological specialization in ICT and the interaction between them, is positively associated with the growth of high-tech patents, but the coefficient is not significant (columns 2, and 4-6). Differently, the technological proximity between technologies seems to play a role. From our preferred specification (column 6), an increase of one percentage point in the proximity linkages that each technology in region *i* at time *t* has with respect to other regions, would increase the number of patents in HT by the 0.02%. This positive correlation confirms the hypothesis of regional branching process, supporting the role of the accumulation of technological expertise in similar or complementary technologies in the innovation performance (Montresor and Quatraro, 2017; Perez, 2010).

**Table 1 - FE Model - ICT and technological branching: Intensive margin ($\boldsymbol{Patents^{HT}_{i,t}}$)**

| VARIABLES | (1)<br>FE | (2)<br>FE | (3)<br>FE | (4)<br>FE | (5)<br>FE | (6)<br>FE |
|---|---|---|---|---|---|---|
| $Patents^{HT}_{i,t-1}$ | 0.273*** | 0.273*** | 0.270*** | 0.270*** | 0.268*** | 0.267*** |
| | (0.0441) | (0.0441) | (0.0441) | (0.0442) | (0.0440) | (0.0457) |
| $GDP_{\mathrm{pc}_{i,t-1}}$ | 0.334 | 0.331 | 0.300 | 0.297 | 0.302 | 0.193 |
| | (0.255) | (0.256) | (0.257) | (0.259) | (0.258) | (0.266) |
| $R\&D_{i,t-1}$ | 0.382*** | 0.382*** | 0.382*** | 0.381*** | 0.380*** | |
| | (0.0764) | (0.0766) | (0.0760) | (0.0762) | (0.0762) | |
| $HC_{i,t-1}$ | 0.529*** | 0.511*** | 0.545*** | 0.519*** | 0.513*** | 0.474*** |
| | (0.149) | (0.164) | (0.146) | (0.162) | (0.161) | (0.168) |
| $AV\_dens_{i,t}$ | | | 0.194*** | 0.194*** | 0.209*** | 0.213*** |
| | | | (0.0471) | (0.0473) | (0.0479) | (0.0486) |
| $ICT\_agg_{i,t-1}$ | | 0.0333 | | 0.0507 | 0.00606 | -0.00474 |
| | | (0.123) | | (0.128) | (0.132) | (0.134) |
| $RTA^{ICT}_{i,t-1}$ | | | | | 0.0384 | 0.0325 |
| | | | | | (0.0316) | (0.0307) |
| $ICT\_agg_{i,t-1} \times RTA^{ICT}_{i,t-1}$ | | | | | 0.107 | 0.113 |
| | | | | | (0.0756) | (0.0744) |
| $R\&D^{bus}_{i,t-1}$ | | | | | | 0.176*** |
| | | | | | | (0.0457) |
| $R\&D^{gov}_{i,t-1}$ | | | | | | 0.0404* |
| | | | | | | (0.0241) |
| $R\&D^{he}_{i,t-1}$ | | | | | | 0.112*** |
| | | | | | | (0.0321) |
| Constant | -2.432 | -2.342 | -1.604 | -1.464 | -1.478 | 0.240 |
| | (2.784) | (2.849) | (2.850) | (2.923) | (2.920) | (3.019) |
| Obs. | 1,631 | 1,631 | 1,631 | 1,631 | 1,631 | 1,631 |
| No. of regions | 169 | 169 | 169 | 169 | 169 | 169 |
| R-squared | 0.974 | 0.974 | 0.975 | 0.975 | 0.975 | 0.975 |
| Region FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: Clustered standard errors at the regional level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

**Extensive margin –** As far as the extensive margin is concerned, also in this case the results in Table 2 show that new specializations could be determined in a sensitive way by previous new specialization. The results on the controls are in line with the ones from Table 1.

**Table 2 - FE Model - ICT and technological branching: Extensive margin ($New\_RTA^{HT}$)**

| VARIABLES | (1) FE | (2) FE | (3) FE | (4) FE | (5) FE | (6) FE |
|---|---|---|---|---|---|---|
| $New\_RTA_{i,t-1}^{HT}$ | 0.0945** | 0.0941** | 0.0991** | 0.0985** | 0.0972** | 0.0990** |
| | (0.0406) | (0.0408) | (0.0400) | (0.0402) | (0.0398) | (0.0398) |
| $GDP_{\mathrm{pc}_{it-1}}$ | 0.359 | 0.356 | 0.303 | 0.298 | 0.309 | 0.222 |
| | (0.274) | (0.275) | (0.278) | (0.279) | (0.273) | (0.277) |
| $R\&D_{i,t-1}$ | 0.219*** | 0.219*** | 0.215*** | 0.214*** | 0.211*** | |
| | (0.0822) | (0.0820) | (0.0800) | (0.0797) | (0.0799) | |
| $HC_{i,t-1}$ | 0.536*** | 0.515** | 0.555*** | 0.520*** | 0.516*** | 0.483** |
| | (0.178) | (0.200) | (0.178) | (0.196) | (0.193) | (0.192) |
| $AV\_dens_{i,t}$ | | | 0.317*** | 0.317*** | 0.340*** | 0.341*** |
| | | | (0.0570) | (0.0570) | (0.0582) | (0.0583) |
| $ICT\_agg_{i,t-1}$ | | 0.0398 | | 0.0673 | -0.0244 | -0.0325 |
| | | (0.136) | | (0.131) | (0.131) | (0.134) |
| $RTA_{i,t-1}^{ICT}$ | | | | | 0.0442 | 0.0414 |
| | | | | | (0.0529) | (0.0529) |
| $ICT\_agg_{i,t-1} \times RTA_{i,t-1}^{ICT}$ | | | | | 0.245** | 0.245** |
| | | | | | (0.104) | (0.104) |
| $R\&D_{i,t-1}^{bus}$ | | | | | | 0.112** |
| | | | | | | (0.0479) |
| $R\&D_{i,t-1}^{gov}$ | | | | | | -0.00441 |
| | | | | | | (0.0320) |
| $R\&D_{i,t-1}^{he}$ | | | | | | 0.0462 |
| | | | | | | (0.0337) |
| Constant | -5.205* | -5.096 | -3.838 | -3.651 | -3.719 | -2.526 |
| | (3.068) | (3.098) | (3.150) | (3.168) | (3.106) | (3.158) |
| Obs. | 1,631 | 1,631 | 1,631 | 1,631 | 1,631 | 1,631 |
| No. of regions | 169 | 169 | 169 | 169 | 169 | 169 |
| R-squared | 0.625 | 0.625 | 0.638 | 0.638 | 0.640 | 0.640 |
| Region FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: Clustered standard errors at the regional level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Also in this case, HC and R&D play, as expected, a positive role in the probability of gaining new technological specialization. Concerning the latter, going more in detail, the positive role of investments in R&D is confirmed when we look at heterogeneity in R&D, with the investments coming from the private sector ($R\&D_{it-1}^{bus}$) having a positive correlation with new specialization performance (column 6). Also in this case, our variables of main interest are the ICT agglomeration and the technological proximity. The former seems to be positively correlated with the introduction of new technological specializations only if the agglomeration is characterized by a technological advantage in ICT. Therefore, it does not seem to be sufficient to have a high concentration of firms in ICT if this is not accompanied by considerable innovation in the sector that makes it possible to be on the technological frontier and thus facilitate the dissemination of knowledge. In short, a behind-the-scenes role for ICT in the processes leading to the development of new technologies equally decisive which is amplified by the presence of ICT specialization in the region. Finally, the positive coefficient of technological proximity supports, also in this case, the hypothesis of regional branching process.

We further develop a FE model borrowed from the baseline, but at sector level: we then obtain the results for both extensive and intensive margin on a sector-by-sector basis. The intensive margin (Table C.1) confirms the results exposed in the baseline for pharmaceutical and medical, whereas it appears that the interaction between agglomeration and ICT specialisation is particularly effective for biotech and nanotech. This aspect should be analysed in more detail in future work, but this evidence probably stems from the increased interaction of the two sectors with ICT. The results for technological proximity are also confirmed in the sectoral estimates for three of the four sectors that make up the HT macro-sector of our analysis excluding the patents pertaining to the medical area which seem to be too distant from other HT-technologies and ICT.

The results for the extensive margin (Table C.2) confirm our expectations of the lagged dependent variable: specialising in a high-tech technology accelerates an innovation process involving the nearest sectors – and this explains the positive effects of $New\_RTA_{i,t-1}^{HT}$ in the baseline – but does not lead to incremental growth of the old specialisation. Technological proximity has the same behaviour as discussed for the intensive margin: we can say that its effect is positive for high-tech except for medical patenting. Returning to ICT, the impact of ICT specialization on the development of new specializations is positive in the pharmaceutical sector but negative in the medical sector, whereas agglomeration does not show a significant effect in either technological specialization. Interestingly, the result that emerges from the interaction – $ICT\_agg_{i,t-1} \times RTA_{i,t-1}^{ICT}$ – is only significant and positive for nanotech.

### *4.2. Quantile Regression Analysis: ICT Agglomeration and Asymmetric Innovation Effects*

To check for any asymmetry in the results, we conduct an asymmetric check by employing the quantile regression approach for measuring the differences in the influence of ICT agglomeration on regional innovation for regions with different levels of patent activities in HT. Following the estimation framework of Coad and Rao (2006) and Kang et al. (2021), the regression model is constructed in such a way that the dependent variable $Y_i$ is the $\tau^{th}$ distribution quantile of patent HT and the coefficients are estimated at quantile $\tau$.

This approach is important because it allows us to identify any difference in the effects of the independent variables across different quantiles of the dependent variable. This information can help us to identify whether there are threshold effects, nonlinearities or other complex relationships between the variables that are not captured by the traditional linear models.

The coefficients of ICT agglomeration interacted with RTA_ICT are positive but not significant at the lower quantile (i.e., 10th), and at the highest (above $90^{th}$), but they become both positive and significant at the higher quantiles (i.e., 25th, 50th, and 75th) according to the results presented in Table 3. This implies that ICT agglomeration can significantly increase patents in regions with patent in HT not in the extreme values. As for regions with these levels of patent, ICT agglomeration interacted with specialization in ICT promotes patent in HT. In addition, the coefficient of $ICT\_agg_{i,t-1} \times RTA_{i,t-1}^{ICT}$ at the 25th quantile is the highest, indicating that regions with low patents above a certain threshold, have the most prominent promotion effect, suggesting that more efficient measure in this direction should be considered to increase innovation activity. The potential explanation for the above results is that cities with low patent level usually have relatively too weak economic development level to benefit from ICT agglomeration. However, regions above this low level will lead to rapid technological growth and resource saving dividend. Conversely, regions with higher patents already have wider diffusion of ICT industry, so technological innovation brought by ICT agglomeration is less effective in promoting patent in HT up to become insignificant. For the control variables, the coefficients related to the effects of R&D are significant at the middle quantiles. In the high-quantile regions (i.e., 75th), government and university expenditure have no significant impact in promoting patent in HT.

**Table 3 - Quantile analysis: Intensive margin ($Patents^{HT}$)**

| VARIABLES | (1) Q10 | (2) Q25 | (3) Q50 | (4) Q75 | (5) Q90 |
|---|---|---|---|---|---|
| $Patents^{HT}_{i,t-1}$ | 0.230*** | 0.211*** | 0.186*** | 0.161*** | 0.144*** |
| | (0.0489) | (0.0351) | (0.0258) | (0.0339) | (0.0460) |
| $GDP_{\mathrm{pc}_{it-1}}$ | -0.319 | -0.267 | -0.198 | -0.131 | -0.0833 |
| | (0.233) | (0.167) | (0.123) | (0.162) | (0.220) |
| $R\&D^{bus}_{i,t-1}$ | 0.0743 | 0.0657 | 0.0545 | 0.0434 | 0.0356 |
| | (0.0645) | (0.0463) | (0.0340) | (0.0447) | (0.0607) |
| $R\&D^{gov}_{i,t-1}$ | 0.0663* | 0.0500* | 0.0285 | 0.00751 | -0.00743 |
| | (0.0356) | (0.0256) | (0.0188) | (0.0247) | (0.0335) |
| $R\&D^{he}_{i,t-1}$ | 0.0737 | 0.0703* | 0.0658** | 0.0614* | 0.0582 |
| | (0.0524) | (0.0376) | (0.0276) | (0.0363) | (0.0494) |
| $HC_{i,t-1}$ | 0.0197 | 0.0536 | 0.0980 | 0.142 | 0.172 |
| | (0.145) | (0.104) | (0.0762) | (0.100) | (0.136) |
| $AV\_dens_{i,t}$ | 0.216*** | 0.221*** | 0.228*** | 0.235*** | 0.239*** |
| | (0.0731) | (0.0525) | (0.0385) | (0.0507) | (0.0688) |
| $ICT\_agg_{i,t-1}$ | -0.119 | -0.0964 | -0.0663 | -0.0367 | -0.0158 |
| | (0.112) | (0.0802) | (0.0588) | (0.0774) | (0.105) |
| $RTA^{ICT}_{i,t-1}$ | 0.0165 | 0.0303 | 0.0486 | 0.0664* | 0.0791 |
| | (0.0566) | (0.0407) | (0.0299) | (0.0393) | (0.0534) |
| $ICT\_agg_{i,t-1} \times RTA^{ICT}_{i,t-1}$ | 0.194 | 0.185** | 0.172*** | 0.160* | 0.151 |
| | (0.118) | (0.0851) | (0.0624) | (0.0821) | (0.112) |
| Obs. | 1,741 | 1,741 | 1,741 | 1,741 | 1,741 |

Notes: Standard errors in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

### *4.3. GMM Results: Legacy, Branching, and Agglomeration Effects in Regional Innovation*

Up to this point, we have considered our FE model, which by construction regresses the dependent variable at time t against its lagged value. This type of setting introduces an element of dynamics, which requires an econometric strategy capable of minimizing possible bias in the estimates, such as a GMM (Generalized Method of Moments) model.

This approach is important because it addresses potential endogeneity concerns that may arise due to omitted variables or reverse causality. GMM is a popular estimation method that uses moment conditions to identify the parameters of the model. This method is different from the previous ones because it relies on a set of moment conditions to estimate the parameters, rather than using the data to estimate the model directly.

In this Section, we employ a GMM (Generalized Method of Moments) model to address potential endogeneity concerns that may arise due to omitted variables or reverse causality.

Specifically, the GMM estimator we implemented is based on the approach originally proposed by Arellano and Bond (1991), known for its efficiency in the presence of arbitrary heteroscedasticity and its ability to account for the structure of residuals in generating consistent estimates. To further enhance the efficiency of our estimates, we utilize the GMM System (GMM-SYS) estimator, as suggested by Arellano and Bover (1995) and Blundell and Bond (1998). This estimator instruments the time-varying variables with lagged first-differenced terms, resulting in improved performance compared to the usual first difference GMM estimator.

Importantly, we treat the time-varying variables as potentially endogenous and generate GMM-like instruments for them using available lags. We follow the rule of thumb suggested by Roodman (2009a, 2009b), which recommends having a number of instruments greater than the number of endogenous variables but not exceeding the number of units used in the analysis (Arellano and Bover, 1995; Blundell and Bond, 1998). To ensure the reliability of our results, we conducted specification tests to assess the presence of second-order serial correlation. The results indicate that our models do not suffer from second-order serial correlation, providing further support for the validity of our estimates. Additionally, both the Hansen and Sargan test results confirm that the instruments used are not over-identified.

Overall, our GMM estimation results (as presented in Table 4) are consistent with our previous findings, further reinforcing the robustness of our analysis. First, as anticipated, we observe that past advancements in new technological domains positively contribute to further gains in subsequent periods, both in terms of the intensive and extensive margins of high-tech (HT) innovation. Regions that have previously ventured into new technological fields (extensive margin) or exhibited higher levels of HT innovation (intensive margin) have demonstrated a persistent ability to do so. These findings confirm the presence of a legacy effect, which aligns with previous empirical studies (Colombelli et al., 2014; Montresor and Quatraro, 2017). Consistent with the existing literature, the coefficients of $Patents_{i,t-1}^{HT}$ and $New\_RTA_{i,t-1}^{HT}$ while statistically different from zero, are less than one. This suggests a dynamic process wherein the prospects for developing new technological specializations may diminish over time, rendering the assumption of exponential growth in these domains implausible. Moreover, the construction of $New\_RTA_{i,t-1}^{HT}$ unveils an intriguing characteristic associated with regional branching processes.

**Table 4 - GMM-SYS System Estimator: estimating the effect of ICT and technological branching on HT innovation (1-3) and new specializations HT (4-6)**

| | $Patents_{i,t}^{HT}$ | | | $New\_RTA_{i,t}^{HT}$ | | |
|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
| $Patents_{i,t-1}^{HT}$ | 0.970*** | 0.971*** | 0.949*** | | | |
| | (0.0193) | (0.0194) | (0.0313) | | | |
| $New\_RTA_{i,t-1}^{HT}$ | | | | 0.492*** | 0.497*** | 0.432*** |
| | | | | (0.121) | (0.134) | (0.143) |
| $GDP_{\mathrm{pc}_{it-1}}$ | -0.175 | -0.171 | 0.113 | -0.324 | -0.226 | -0.239 |
| | (0.117) | (0.108) | (0.136) | (0.236) | (0.284) | (0.247) |
| $R\&D_{i,t-1}$ | 0.0410 | 0.0397 | | 0.0612 | 0.0512 | |
| | (0.0461) | (0.0415) | | (0.114) | (0.126) | |
| $HC_{i,t-1}$ | 0.0860 | 0.0734 | -0.0158 | 0.654*** | 0.617*** | 0.653*** |
| | (0.0660) | (0.0622) | (0.0720) | (0.177) | (0.180) | (0.239) |
| $AV\_dens_{i,t}$ | 0.261** | 0.276** | 0.186* | 0.497** | 0.525*** | 0.368** |
| | (0.105) | (0.110) | (0.110) | (0.198) | (0.196) | (0.173) |
| $ICT\_agg_{i,t-1}$ | 0.0487 | 0.0360 | -0.0108 | 0.0637 | 0.00791 | 0.00180 |
| | (0.0408) | (0.0434) | (0.0530) | (0.0890) | (0.113) | (0.102) |
| $RTA_{i,t-1}^{ICT}$ | | 0.0276 | 0.0301 | | -0.0326 | 0.00241 |
| | | (0.0249) | (0.0286) | | (0.0584) | (0.0578) |
| $ICT\_agg_{i,t-1} \times RTA_{i,t-1}^{ICT}$ | | 0.0462 | 0.0130 | | 0.249** | 0.183* |
| | | (0.0379) | (0.0478) | | (0.0976) | (0.105) |
| $R\&D_{i,t-1}^{bus}$ | | | 0.0254 | | | -0.0438 |
| | | | (0.0436) | | | (0.0775) |
| $R\&D_{i,t-1}^{gov}$ | | | -0.0244 | | | -0.00665 |
| | | | (0.0174) | | | (0.0395) |
| $R\&D_{i,t-1}^{he}$ | | | 0.0287 | | | 0.0169 |
| | | | (0.0459) | | | (0.179) |
| Obs. | 1,631 | 1,631 | 1,631 | 1,631 | 1,631 | 1,631 |
| No. of regions | 169 | 169 | 169 | 169 | 169 | 169 |
| No. of instruments | 176 | 178 | 133 | 57 | 59 | 50 |
| ar1p | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| ar2p | 0.395 | 0.390 | 0.634 | 0.102 | 0.114 | 0.162 |
| Sargan-p | 0.122 | 0.129 | 0.706 | 0.807 | 0.737 | 0.935 |
| Hansen-p | 0.647 | 0.650 | 0.367 | 0.360 | 0.386 | 0.499 |

Notes: Standard errors in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

The variable of technological proximity ($\mathrm{AV\_dens}_{it}$) is positively correlated with both the intensive and extensive margin. In line with previous literature, this supports the branching hypothesis, testifying that not only does the correlated variety help regions diversify their technological base in the intensive margin, but also increases their ability to diversify and branch out in the extensive margin by increasing the set of newly acquired technologies.

Turning to the ICT dimensions, the results confirm what we already found in the FE model. In particular, the agglomeration seems to play a relevant role in enhancing the emerging of new HT specializations and the effect is spurred if the agglomeration is in regions showing ICT technological advantage in the previous period. For sectors where a given region is already innovative, instead, the role of ICT seems not to be crucial for increasing the number of patent applications, while it is relevant the technology proximity between them.

### *4.4. Spatial analysis: Innovation as a Borderless Phenomenon*

The evidence discussed so far provides solid support for the role of ICT in the emergence of new HT technology specializations in regional contexts. In this section, we present an additional battery of estimates conducted to test whether our previous results were robust to a more explicit consideration of spatial aspects.

In this section, we propose a study of the dynamics of geographical propagation of patents high-tech through Spatial Durbin Model (SDM). In addition, we maintain the same fixed-effects structure as previous estimates.[12]

This approach is important because it allows us to control for spatial autocorrelation, which can arise when observations in neighboring regions are more similar to each other than to observations further away. Spatial dependence can lead to biased estimates and incorrect standard errors if not accounted for. The Spatial Durbin model is different from the other models that we apply until now because it explicitly accounts for the spatial relationship between observations in the analysis.

In Table 5, we show the results from the SDM estimation for both the intensive margin (columns 1-3) and the extensive margin (columns 4-6). For both dependent variables, we use both the temporally and spatially lagged dependent variable. Rho is always significant and positive (except in column 6), which suggests that spatial effects are present both in the dynamics leading to new technological specializations and in the branching of innovation across regional boundaries.[13]

The SDM also confirms the good results shown so far. In particular, previous gains of new technological specializations contribute to a positive climate for innovation and the development of further technological specializations (Colombelli et al., 2014; Montresor and Quatraro, 2017). However, in the SDM we can refer not only to past innovations in region I, but also to innovations in neighbouring regions. The spatially lagged dependent ($wPatents_{i,t}^{HT}$) variable, albeit is only

[12] In our estimate we both add the time-lagged and space-time-lagged dependent variables.

[13] The number of observations in the SDM estimate is higher than in other estimates due to the interpolation of missing values. The SDM requires a strongly balanced panel of data to work effectively, so missing values are often interpolated to maintain balance.

significant in the first column, suggests the presence of a spatial effect on HT innovation. Technological proximity is also confirmed in this estimate as a particularly important variable in the diffusion of HT technologies and new specializations. $AV\_dens_{i,t}$ captures an intrinsic link between patents belonging to different tectological fields, but which may have common matrices, and may develop together or in parallel. Thus, technological proximity may result in increased regional innovative capacity. However, the latter does not play a key role in diffusion across regional boundaries. Turning to the ICT dimension, our results confirm the relevance of the ICT agglomeration if interacted with the ICT technological advantage. In fact, the interaction between them seems to play a relevant role in improving the emerging of new HT specializations.

About the results of the spatially lagged variables, it appears that proximity to regions with a high level of per capita income may not be driving forces but rather act as gravitational centers attracting the most innovative minds and companies, effectively preventing the technological development of less innovative regions. The human capital ($wHC$) also plays a similar role; regions with high earning capacity are often also regions with high levels of education, so the reading of this result is a function of the combination of $HC$ and $GDP_{\mathrm{pc}}$. On the other hand, R&D from neighboring regions is indeed involved in the process of innovation diffusion, this finding seems consistent with the idea that regional authorities ($wR\&D^{gov}$), companies ($wR\&D^{bus}$) and universities ($wR\&D^{he}$) from different regions cooperate with each other in the search for innovative solutions and development.

Regarding the choice of Durbin spatial model (SDM), recent appreciation of this model in the literature considers it significantly superior to other spatial models (Elhorst, 2014). To gain further support for our choice, we follow Belotti et al. (2016) and perform two post-estimation estimation tests, which allow us to test whether SDM is the most appropriate choice. Test 1 is a linear null hypothesis test that tests whether the coefficient of the spatially lagged repressor is equal to zero. Test 2 is a nonlinear hypothesis, in which the null hypothesis is that the coefficient of the spatially lagged repressor is equal to the product of the coefficient of the same non-spatially lagged repressor and the coefficient of the spatially lagged dependent variable.[14] The bottom of Table 5 shows the results of these tests.

[14] For this estimation, we referred to the work of Belotti et al. (2017), using Stata's xsmle command. In order to proceed with the estimation, we balanced our sample with regions present for more than one year and interpolating missing values.

**Table 5 - Spatial Durbin Model (SDM)**

| | $Patents^{HT}_{i,t}$ | | | $New\_RTA^{HT}_{i,t}$ | | |
|---|---|---|---|---|---|---|
| VARIABLES | (1) | (2) | (3) | (4) | (5) | (6) |
| **MAIN** | | | | | | |
| $Patents^{HT}_{i,t-1}$ | 0.255*** | 0.252*** | 0.250*** | | | |
| | (0.0475) | (0.0471) | (0.0457) | | | |
| $New\_RTA^{HT}_{i,t-1}$ | | | | 0.189*** | 0.186*** | 0.183*** |
| | | | | (0.0352) | (0.0350) | (0.0345) |
| $GDP_{\text{pc}_{it}}$ | 0.165 | 0.159 | 0.175 | -0.111 | -0.132 | -0.137 |
| | (0.299) | (0.298) | (0.301) | (0.178) | (0.180) | (0.174) |
| $ICT\_agg_{i,t}$ | -0.110 | -0.120 | -0.130 | 0.0673 | 0.0436 | 0.0178 |
| | (0.142) | (0.142) | (0.141) | (0.111) | (0.110) | (0.112) |
| $AV\_dens_{i,t}$ | 0.128*** | 0.137** | 0.151*** | 0.234*** | 0.312*** | 0.319*** |
| | (0.0415) | (0.0533) | (0.0533) | (0.0448) | (0.0610) | (0.0619) |
| $R\&D_{i,t}$ | 0.199** | 0.201** | | -0.0194 | -0.0312 | |
| | (0.0910) | (0.0889) | | (0.0569) | (0.0578) | |
| $HC_{i,t}$ | 0.633*** | 0.643*** | 0.612*** | 0.357*** | 0.363*** | 0.364*** |
| | (0.192) | (0.193) | (0.195) | (0.137) | (0.138) | (0.137) |
| $R\&D^{bus}_{i,t}$ | | | 0.0721 | | | -0.0809* |
| | | | (0.0662) | | | (0.0441) |
| $R\&D^{gov}_{i,t}$ | | | 0.0663* | | | 0.00389 |
| | | | (0.0353) | | | (0.0213) |
| $R\&D^{he}_{i,t}$ | | | 0.0946 | | | 0.0687* |
| | | | (0.0746) | | | (0.0372) |
| $RTA^{ICT}_{i,t}$ | | 0.00759 | 0.00478 | | 0.119*** | 0.117*** |
| | | (0.0443) | (0.0450) | | (0.0430) | (0.0436) |
| $ICT\_agg_{i,t} \times RTA^{ICT}_{i,t}$ | | 0.0996 | 0.113* | | 0.0921* | 0.105** |
| | | (0.0620) | (0.0623) | | (0.0495) | (0.0499) |
| **SPATIAL** | | | | | | |
| rho | 0.261** | 0.234** | 0.0961 | 0.330*** | 0.356*** | 0.371*** |
| | (0.118) | (0.116) | (0.119) | (0.116) | (0.119) | (0.122) |
| **VARIANCE** | | | | | | |
| sigma2_e | 0.128*** | 0.127*** | 0.126*** | 0.112*** | 0.111*** | 0.111*** |
| | (0.014) | (0.014) | (0.015) | (0.007) | (0.007) | (0.007) |
| **W** | | | | | | |
| $wPatents^{HT}_{i,t}$ | 0.622* | 0.502 | 0.380 | | | |
| | (0.368) | (0.362) | (0.353) | | | |
| $wNew\_RTA^{HT}_{i,t}$ | | | | -0.0816 | -0.157 | -0.136 |
| | | | | (0.343) | (0.331) | (0.343) |
| $wGDP_{\text{pc}_{it}}$ | -4.200* | -3.983 | -4.432* | -3.254 | -2.741 | -2.393 |
| | (2.431) | (2.423) | (2.533) | (2.090) | (2.120) | (2.145) |
| $wICT\_agg_{i,t}$ | 0.524 | 0.238 | 0.168 | -0.139 | -0.355 | -0.116 |
| | (1.103) | (1.087) | (1.087) | (0.957) | (0.973) | (0.973) |
| $wAV\_dens_{i,t}$ | -0.293 | -0.197 | 0.627 | 0.465 | 0.851 | 0.892 |
| | (0.626) | (0.772) | (0.750) | (0.648) | (0.829) | (0.832) |
| $wR\&D_{i,t}$ | 2.406*** | 2.413*** | | 0.230 | 0.0843 | |
| | (0.772) | (0.785) | | (0.714) | (0.720) | |
| $wHC_{i,t}$ | -3.934*** | -3.725*** | -3.023*** | -1.011 | -0.878 | -0.500 |
| | (1.440) | (1.426) | (1.435) | (1.087) | (1.103) | (1.057) |
| $wR\&D^{bus}_{i,t}$ | | 0.0415 | 1.396*** | | 0.579 | 0.648 |
| | | (0.713) | (0.5061) | | (0.733) | (0.737) |
| $wR\&D^{gov}_{i,t}$ | | 1.310 | 0.4901** | | 0.735 | 1.004 |
| | | (1.126) | (0.2061) | | (0.761) | (0.804) |
| $wR\&D^{he}_{i,t}$ | | | 0.669** | | | -0.165 |
| | | | (0.3465) | | | (0.400) |
| $wRTA^{ICT}_{i,t}$ | | | 0.7625 | | | 0.6484 |
| | | | (0.7039) | | | (0.7372) |
| $wICT\_agg_{i,t} \times RTA^{ICT}_{i,t}$ | | | 1.804 | | | 1.004 |
| | | | (1.200) | | | (0.8039) |
| Observations | 2,505 | 2,505 | 2,505 | 2,505 | 2,505 | 2,505 |
| No. of regions | 167 | 167 | 167 | 167 | 167 | 167 |
| Region FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| AIC | 1873.45 | 1875.65 | 1861.39 | 1553.49 | 1545.66 | 1541.38 |
| BIC | 2118.15 | 2143.65 | 2152.69 | 1798.19 | 1813.66 | 1832.68 |
| Test 1 | 14.62*** | 13.28*** | 17.94*** | 4.28*** | 4.17*** | 9.70*** |
| Test 2 | 14.72*** | 13.38*** | 18.48*** | 4.38*** | 4.40*** | 9.96*** |

Notes: Standard errors in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

## 5. Discussion

The results obtained from the econometric models used in our analysis provide insights into the dynamics of technological specialization in HT, the focal role of ICT and the various factors also shaping this specialisation (such as past innovation). Overall, we find strong evidence that past technological advantages and correlation with other technologies are important drivers of further technological specialization, both in terms of depth of specialization within existing fields (intensive margin) and expansion into new fields (extensive margin).

Specifically, the interaction between ICT agglomeration ($ICT\_agg$) and technological specialization in ICT ($RTA^{ICT}$) is significant and positive for the extensive margin analysis of new RTA in HT. In regions specialized in ICT with high agglomeration of ICT firms benefit from an important advantage compared to other regions in terms of their ability to develop new technological specializations.

However, the impact on the intensive margin in terms of number of high-tech patents is less clear. Nevertheless, the analysis at the intensive margin, conducted using a quantile approach for the number of patents in HT, provides evidence that ICT agglomeration, when interacted with technology specialization in ICT, promotes patents in HT for regions with patent levels that are not in the extreme quantile values (i.e., between the 25th and 90th percentiles). This suggests that more efficient measures in this direction should be considered to increase innovation activity. Therefore, regions that produce fewer patent applications appear to benefit more significantly from both technological specialization in ICT and ICT agglomeration.

A second relevant result concerns proximity, which emphasizes the importance of technological branching. Technological proximity consistently plays a decisive role in the dynamics leading to new technological specializations and the production of new patents. Innovation also results from the recombination of resources through specific forms of technological branching. Specifically, technological proximity has been decisive in all our estimates, suggesting that these five technologies (ICT, biotech, nanotech, pharma, medical) are strongly interconnected. The development of one of these technologies enables the regional branching capacity of the same, increasing the possibility of developing new technological specializations. Moreover, the economic environment also tends to improve, becoming more fertile and attractive.

Another point we focused on was the spatial analysis. It is also clear from this analysis that there is a regional effect in the propagation of both technological specializations and patents. The results suggest that high-tech innovation is spatially transmitted; proximity to an innovative region may therefore facilitate the approach towards these technologies. Cross-regional spillovers enable regions to exploit a strategy complementary to the regional development of HT leading to technological diversification: they have the opportunity of absorbing their knowledge from the outside through mechanisms like interregional technology transfer and cooperation agreements. Therefore, there is also a phenomenon of geographical branching of technologies. In conclusion, our results confirm our hypotheses.

In particular, in relation to the existing literature, our results confirm critical mechanisms of regional diversification. A first evidence is that having entered new technological fields in the past (extensive margin) - or having better performance in HT innovation in the past (intensive margin) - regions develop the ability to do so persistently, confirming the evidence of legacy already found by some previous studies (Colombelli et al., 2014; Montresor and Quatraro, 2017). Furthermore, our analysis, extending the analysis to the ICT, confirms the critical role of GPTs emphasised in previous studies for other GPTs such as KETS (Montresor and Quatraro, 2017). In particular, the role of ICT technologies as GPTs, given their pervasive nature and high applicability in different sectors, penetrate every part of the economy and entail changes even to the techno-economic paradigm of the whole economy (Perez, 2010). This is in line with theoretical assumptions stemming from the seminal work of Schumpeter (1934), which concerns the so-called "recombination process" and the ability to recombine and modify existing capabilities (Weitzman, 1998). A third relevant result we get confirms that the diffusion of knowledge is strongly attached to technological relatedness between sectors which represents the cognitive dimension of proximity, which, along with other dimensions such as geographic or institutional proximity, is found in recent studies able to facilitate knowledge transmission and spillovers by promoting interactive learning (Montresor and Quatraro, 2017: Xiao and Boschma, 2022).

## 6. Concluding remarks

The ICT agglomeration and technological specialization in ICT have a positive impact on the development of new specializations in high-tech. In particular, the ICT agglomeration seems to have the ability to attract new resources, technologies, and innovative capacities that determine the development of new technological specializations at the regional level.

As said, our results confirm that ICTs have a dual importance that makes them crucial for the development of new technologies: first, they provide a knowledge base that gives regions digital capabilities and infrastructure to innovate (Xiao and Boschma, 2022). Second, ICTs play an important role behind their own domain. Indeed, ICT is a GPT that shares similarities with past innovations and has vast potential applications and complementarities with other technologies. The invention of the microprocessor, a key component of ICT, has spurred further innovation and productivity gains in ICT-producing industries. In addition, ICT has unleashed innovation potential in sectors beyond ICT production, such as through organisational restructuring, business process reengineering and new product development (van der Wiel et al., 2004).

Furthermore, our findings suggest policy recommendations aimed at promoting ICT agglomeration and technological specialization in ICT to stimulate the development of new technological specializations in high-tech. Regions specialized in ICT with high agglomeration of ICT firms should be prioritized in terms of support for innovation activities. Additionally, effective measures should be introduced to boost innovation activity in regions that produce fewer patent applications, particularly in those with low patents above a specific threshold. Another crucial policy recommendation is to foster proximity and encourage technological branching. Regional development strategies should concentrate on creating strong connections between various high-tech industries and promoting the development of new technologies that are related to pre-existing ones. This can be achieved by promoting interregional technology transfer and cooperation agreements. Moreover, policies that promote cross-regional spillovers should be implemented to facilitate the approach towards high-tech industries. This can assist regions in leveraging a complementary strategy to regional development, resulting in technological diversification. Finally, the phenomenon of geographical branching of technologies should be considered while developing policies to promote innovation and regional development.

Future development can be followed in many directions as there is a set of region-specific characteristics, and of possible interactions among regions that could influence knowledge diffusion. First, future developments could also include the role of mobility of people across regions, as people could act as natural driver of knowledge by carrying knowledge about the know-how of origin regions and transfer to the destination region by being employed in crucial sector for regions' innovation performance (Wang et al., 2022). Moreover, there are location-specific characteristics that can enhance innovators' performance in terms of innovation. The extensive literature on urban agglomeration highlights how strong urbanization phenomena can lead to varying levels of innovation performance across different regions (Bettencourt et al., 2007; Dong et al., 2017).[15] Finally, more evidence about the differences between peripherical and non-peripherical regions could be needed to understand whether there are differences in terms of technology absorption capacity.

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# Appendix

## Section A – Classifications and variables description

In this section of the Appendix, we provide information regarding the variables used in the analysis. It is divided into two subsections: Section A.1, in which we present the ICT sector classification; Section A.2, in which detailed description of the variables is provided.

### Section A.1 – Classifications and description of ICT sector and HT sectors

The sectoral coverage of ICT follows the assignment of the NACE code economic activity sectors according to the official OECD definition: “The output (goods and services) of a candidate industry must be primarily intended to perform or enable the function of processing and communicating information by electronic means, including transmission and display”.

The codes of the relevant economic activities that meet the official definition of the ICT sector are detailed in Table A.1 below. They can be grouped into three aggregates: “ICT Sector – Total,” “ICT Manufacturing” and “ICT Services”.

“More than a third of the 165 000 applications received by the EPO in 2017 concerned ICT directly or indirectly. The EPO recognizes the growing importance of ICT to industry, society and the economy while believing that high-quality patents are critical to encouraging, promoting, and protecting innovation in ICT. As such, the Office has created an ICT technical sector within the office, bringing together the EPO's examination competence and specialization in telecommunications, computers, and related areas” (European Patent Office, 2019).

**Table A.1 - NACE v.2 ICT Industry classification**

| | | | |
|---|---|---|---|
| ICT Sector | ICT Manufacturing | 26.1 | Manufacture of electronic components and boards |
| | | 26.2 | Manufacture of computers and peripheral equipment |
| | | 26.3 | Manufacture of communication equipment |
| | | 26.4 | Manufacture of consumer electronics |
| | | 26.8 | Manufacture of magnetic and optical media |
| | ICT Services | 46.5 | Wholesale of information and communication equipment |
| | | 58.2 | Software publishing |
| | | 61 | Telecommunication |
| | | 62 | Computer programming, consultancy, and related activities |
| | | 63.1 | Data processing, hosting, and related activities; web portals |
| | | 95.1 | Repair of computers and communication equipment |

## Section A.2 – Variables description and statistics

**Table A.2 - Variables description**

| Variable | Description | Unit |
|---|---|---|
| $GDP_{pc_{i,t}}$ * | Gross domestic product per capita (constant price 2015). | Absolute |
| $R\&D_{i,t}$ * | Total expenditure in R&D. | % of GDP |
| $R\&D_{i,t}^{bus}$ * | Business expenditure in R&D. | % of GDP |
| $R\&D_{i,t}^{gov}$ * | Government expenditure in R&D. | % of GDP |
| $R\&D_{i,t}^{he}$ * | R&D expenditure in Higher Education. | % of GDP |
| $HC_{i,t}$ * | Population aged 25 to 64 with tertiary education. | % |
| $Patents_{i,t}^{HT}$ * | $Pat_{ist}$ number of patents applications filled in the corresponding IPC high tech class in region i at time t. | Absolute |
| $Patents_{i,t}^{bio}$ * | N° of patent applications in biotech. | Absolute |
| $Patents_{i,t}^{med}$ * | N° of patent applications in medical. | Absolute |
| $Patents_{i,t}^{nano}$ * | N° of patent applications in nanotech. | Absolute |
| $Patents_{i,t}^{pharma}$ * | N° of patent applications in pharmaceutical. | Absolute |
| $Patents_{i,t}^{ICT}$ * | N° of patent applications in ICT. | Absolute |
| $RTA_{i,t}^{bio}$ ** | Specialization in patent biotech. | Dummy |
| $RTA_{i,t}^{med}$ ** | Specialization in patent medical. | Dummy |
| $RTA_{i,t}^{nano}$ ** | Specialization in patent nanotech. | Dummy |
| $RTA_{i,t}^{pharma}$ ** | Specialization in patent pharma. | Dummy |
| $RTA_{i,t}^{ICT}$ ** | Specialization in patent ICT. | Dummy |
| $New\_RTA_{i,t}^{HT}$ ** | New technological specializations in HT sectors of region i, which were observed at time t but not at time t-1. | Dummy |
| $ICT\_empl_{it}$ ** | Total employment in the information and communication sector. | Absolute |
| $empl_{it}$ * | Total employment in all sectors. | Absolute |
| $ICTAGG_{it}$ ** | ICT agglomeration based on the number of employees in ICT as per Eq. 3. | % |
| $AV\_dens_{i,t}$ ** | Proximity between patents high tech – Regional average value of the density of the proximity linkages that each technology observed at time t in region i reveals with respect to HT technologies observed in the same region at time t-1. (Montresor & Quatraro, 2017). | % |

Notes: The subscripts *i* for regions and *t* for time.

Sources: * OECD data; ** Authors' elaboration on OECD REGPat Database (2022)

**Table A.3 - Descriptive statistics**

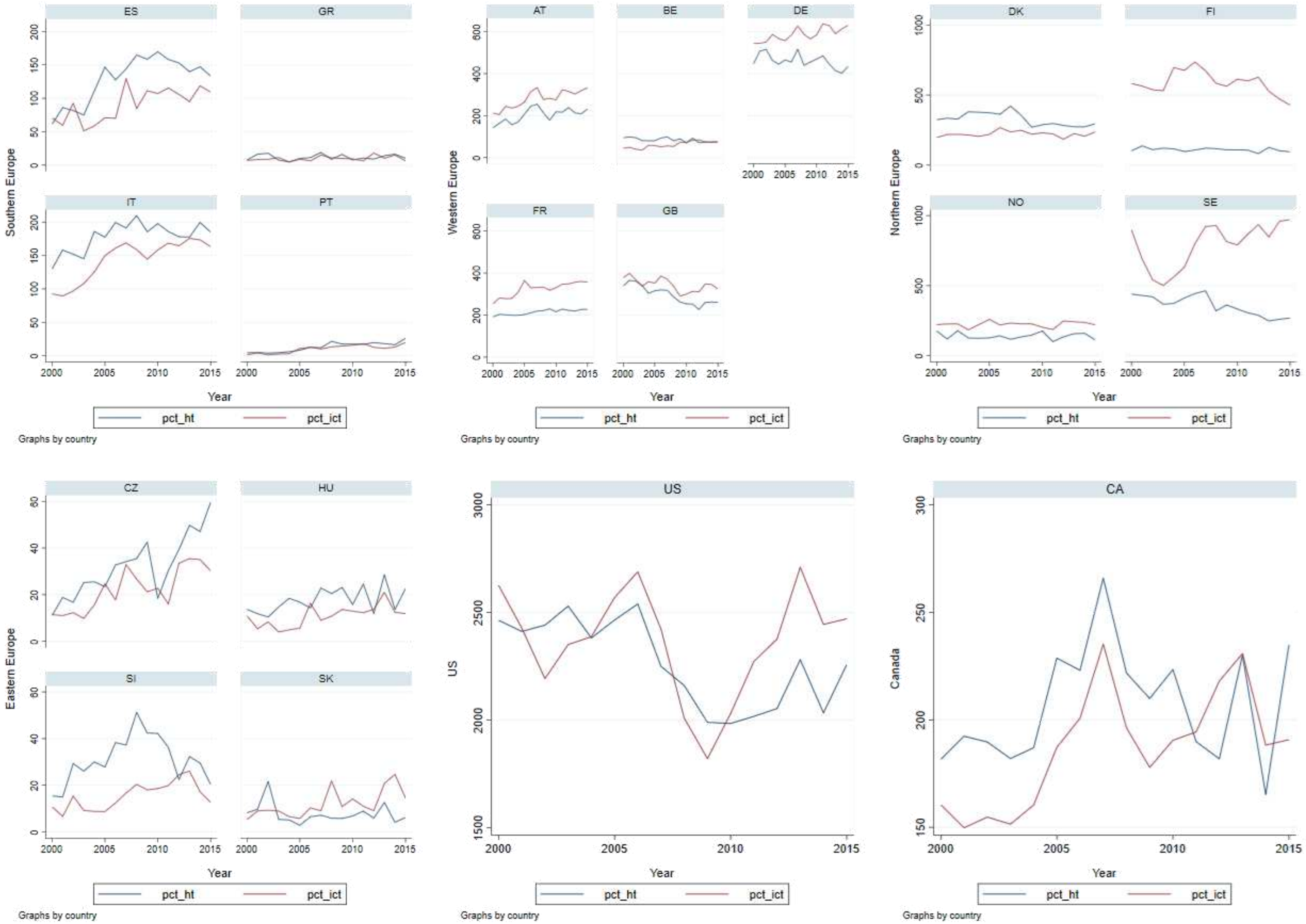
| Variable | Obs. | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| $GDP_{{pc}_{i,t}}$ | 1631 | 44781.775 | 17483.46 | 12692.732 | 190831.19 |
| $R\&D_{i,t}$ | 1631 | 1.724 | 1.272 | 0 | 8.08 |
| $R\&D_{i,t}^{bus}$ | 1430 | 1.168 | .938 | 0 | 5.13 |
| $R\&D_{i,t}^{gov}$ | 1513 | .288 | .646 | 0 | 6.97 |
| $R\&D_{i,t}^{he}$ | 1512 | .382 | .195 | .03 | 3.32 |
| $HC_{i,t}$ | 1627 | 30.803 | 10.804 | 7.2 | 62 |
| $Patents_{i,t}^{HT}$ | 1631 | 200.799 | 448.434 | .417 | 4369.942 |
| $Patents_{i,t}^{bio}$ | 1631 | 60.082 | 144.713 | 0 | 1730.9 |
| $Patents_{i,t}^{med}$ | 1631 | 68.054 | 156.783 | .047 | 1841.43 |
| $Patents_{i,t}^{nano}$ | 1631 | 8.07 | 18.771 | 0 | 239.662 |
| $Patents_{i,t}^{pharma}$ | 1631 | 64.594 | 144.913 | .022 | 1420.45 |
| $Patents_{i,t}^{ICT}$ | 1631 | 248.199 | 729.038 | 0 | 9993.82 |
| $RTA_{i,t}^{bio}$ | 1631 | .546 | .498 | 0 | 1 |
| $RTA_{i,t}^{med}$ | 1631 | .476 | .5 | 0 | 1 |
| $RTA_{i,t}^{nano}$ | 1631 | .443 | .497 | 0 | 1 |
| $RTA_{i,t}^{pharma}$ | 1631 | .514 | .5 | 0 | 1 |
| $RTA_{i,t}^{ICT}$ | 1631 | .224 | .417 | 0 | 1 |
| $New\_RTA_{i,t}^{HT}$ | 1631 | .543 | .498 | 0 | 1 |
| $ICT\_empl_{it}$ | 1631 | 63034.147 | 83705.272 | 2900 | 629281 |
| $empl_{it}$ | 1631 | 2271125.6 | 2344017.7 | 200400 | 17815000 |
| $ICTAGG_{it}$ | 1631 | .949 | .601 | .186 | 4.741 |
| $AV\_dens_{i,t}$ | 1631 | .074 | .032 | .034 | .38 |

**Table A.4 – Correlation among variables**

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) $Patents^{HT}_{i,t}$ | 1.000 | | | | | | | | | | | |
| (2) $ICT\_agg_{it}$ | 0.130*** | 1.000 | | | | | | | | | | |
| (3) $RTA^{ICT}_{i,t}$ | 0.217*** | 0.217*** | 1.000 | | | | | | | | | |
| (4) $Patents^{ICT}_{i,t}$ | 0.900*** | 0.130*** | 0.298*** | 1.000 | | | | | | | | |
| (5) $GDP_{pc_{i,t}}$ | 0.228*** | 0.616*** | 0.253*** | 0.180*** | 1.000 | | | | | | | |
| (6) $R\&D_{i,t}$ | 0.336*** | 0.189*** | 0.297*** | 0.250*** | 0.329*** | 1.000 | | | | | | |
| (7) $R\&D^{bus}_{i,t}$ | 0.470*** | 0.079*** | 0.272*** | 0.398*** | 0.236*** | 0.779*** | 1.000 | | | | | |
| (8) $R\&D^{gov}_{i,t}$ | 0.016 | 0.218*** | 0.229*** | -0.003 | 0.323*** | 0.570*** | -0.026 | 1.000 | | | | |
| (9) $R\&D^{he}_{i,t}$ | 0.022 | 0.112*** | 0.046* | -0.016 | 0.009 | 0.365*** | 0.159*** | 0.184*** | 1.000 | | | |
| (10) $AV\_dens_{i,t}$ | -0.148*** | -0.090*** | -0.274*** | -0.122*** | -0.161*** | -0.217*** | -0.252*** | -0.086*** | -0.085*** | 1.000 | | |
| (11) $HC_{i,t}$ | 0.305*** | 0.332*** | 0.321*** | 0.223*** | 0.582*** | 0.455*** | 0.490*** | 0.185*** | 0.140*** | -0.259*** | 1.000 | |
| (12) $New\_RTA^{HT}_{i,t}$ | 0.207*** | 0.156*** | 0.098*** | 0.100*** | 0.184*** | 0.229*** | 0.108*** | 0.169*** | 0.136*** | -0.017 | 0.362*** | 1.000 |

**** p<0.01, ** p<0.05, * p<0.1*

**Fig. A.1 - Evolution of high-tech and ICT patents over time for each country**



## Section B – Spatial matrix (W)

We obtain a row-normalized inverse distance-weighting matrix, with respect to the latitude and longitude coordinates of the relevant regions. As can be seen in Table B.1, the imported spatial matrix consists of 167 cross-sectional. The regional coordinates were extracted via the Google Maps API Key using the geocode command in the statistical software RStudio. Regional coordinates extracted from Google Maps represent approximate regional geographic centres as specified on Google Maps Developers Platform.

**Table B.1 - Summary of spatial-weighting object W**

| | | |
|---|---|---|
| *Matrix* | *Dimensions* | *167 x 167* |
| | *Stored as* | *167 x 167* |
| *Values* | *min* | *0.000* |
| | *mean* | *0.002* |
| | *max* | *0.190* |

## Section C – Additional checks – FE results by technology

In this Section, we present additional analyses to explore the relationship between ICT and technological branching across different high-tech sectors. Specifically, we examine the intensive and extensive margins of this relationship.

Table C.1 presents the fixed effects model results focusing on the intensive margin of the relationship between ICT and technological branching across various high-tech sectors. In Table C.2, we present the fixed effects model results concerning the extensive margin of the ICT and technological branching relationship.

The results of these analyses are discussed in the main text.

**Table C.1 - FE Model - ICT and technological branching: Intensive margin for different high-tech sectors**

| VARIABLES | $Patents_{i,t}^{BIO}$ FE | $Patents_{i,t}^{NANO}$ FE | $Patents_{i,t}^{PHARMA}$ FE | $Patents_{i,t}^{MED}$ FE |
|---|---|---|---|---|
| $Dep.Var._{i,t-1}$ | 0.154*** | 0.109** | 0.117** | 0.128** |
| | (0.0516) | (0.0489) | (0.0459) | (0.0498) |
| $GDP_{\mathrm{pc}_{i,t-1}}$ | 0.140 | -0.318 | 0.336 | 0.0298 |
| | (0.361) | (0.689) | (0.364) | (0.370) |
| $R\&D_{i,t-1}^{bus}$ | 0.0444 | -0.0231 | 0.400*** | 0.187*** |
| | (0.0680) | (0.104) | (0.0754) | (0.0631) |
| $R\&D_{i,t-1}^{gov}$ | 0.0647* | 0.0562 | 0.0378 | 0.0800*** |
| | (0.0331) | (0.0576) | (0.0370) | (0.0256) |
| $R\&D_{i,t-1}^{he}$ | 0.174*** | 0.0696 | 0.132 | 0.178*** |
| | (0.0474) | (0.0845) | (0.0877) | (0.0542) |
| $HC_{i,t-1}$ | 0.795*** | 0.853* | 0.530** | 0.366 |
| | (0.291) | (0.432) | (0.247) | (0.243) |
| $AV\_dens_{i,t}$ | 0.482*** | 0.793*** | 0.604*** | -0.371*** |
| | (0.0881) | (0.136) | (0.0722) | (0.0650) |
| $ICTAGG_{i,t-1}$ | -0.110 | 0.0657 | -0.0472 | 0.149 |
| | (0.197) | (0.442) | (0.231) | (0.209) |
| $RTA_{i,t-1}^{ICT}$ | 0.0440 | 0.192* | 0.0864 | -0.0323 |
| | (0.0516) | (0.0983) | (0.0529) | (0.0389) |
| $ICTAGG_{i,t-1} \times RTA_{i,t-1}^{ICT}$ | 0.258** | 0.352* | 0.158 | -0.0220 |
| | (0.115) | (0.213) | (0.105) | (0.129) |
| Constant | -0.0201 | 3.986 | -0.866 | 0.556 |
| | (4.243) | (7.955) | (4.115) | (4.237) |
| Observations | 1,580 | 1,275 | 1,613 | 1,584 |
| R-squared | 0.940 | 0.813 | 0.936 | 0.947 |
| Region FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |

Notes: Clustered standard errors at the regional level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

**Table C.2 - FE Model - ICT and technological branching: Extensive margin for different specialization in high tech sectors**

| VARIABLES | $New\_RTA_{i,t}^{BIO}$ FE | $New\_RTA_{i,t}^{NANO}$ FE | $New\_RTA_{i,t}^{PHARMA}$ FE | $New\_RTA_{i,t}^{MED}$ FE |
|---|---|---|---|---|
| $Dep.Var._{i,t-1}$ | -0.229*** | -0.300*** | -0.261*** | -0.247*** |
| | (0.0180) | (0.0178) | (0.0219) | (0.0165) |
| $GDP_{\mathrm{pc}_{i,t-1}}$ | 0.0309 | 0.613** | -0.221 | -0.255 |
| | (0.192) | (0.290) | (0.226) | (0.175) |
| $R\&D_{i,t-1}^{bus}$ | -0.0508 | -0.0398 | 0.0247 | 0.0641 |
| | (0.0368) | (0.0600) | (0.0368) | (0.0518) |
| $R\&D_{i,t-1}^{gov}$ | 0.0114 | -0.0173 | 0.00644 | 0.00376 |
| | (0.0219) | (0.0285) | (0.0166) | (0.0203) |
| $R\&D_{i,t-1}^{he}$ | 0.0566 | -0.0182 | -0.00357 | 0.0246 |
| | (0.0406) | (0.0437) | (0.0301) | (0.0346) |
| $HC_{i,t-1}$ | 0.190 | 0.224 | -0.226 | 0.276* |
| | (0.147) | (0.255) | (0.155) | (0.157) |
| $AV\_dens_{i,t}$ | 0.287*** | 0.416*** | 0.433*** | -0.235*** |
| | (0.0546) | (0.0719) | (0.0501) | (0.0496) |
| $ICTAGG_{i,t-1}$ | -0.171 | -0.0872 | 0.0478 | 0.0803 |
| | (0.112) | (0.156) | (0.124) | (0.123) |
| $RTA_{i,t-1}^{ICT}$ | 0.0218 | 0.0103 | 0.0908** | -0.0634* |
| | (0.0426) | (0.0436) | (0.0363) | (0.0339) |
| $ICTAGG_{i,t-1} \times RTA_{i,t-1}^{ICT}$ | 0.0660 | 0.334*** | 0.108 | -0.116 |
| | (0.0831) | (0.118) | (0.0855) | (0.0732) |
| Constant | -0.0372 | -6.045* | 4.382* | 1.361 |
| | (2.282) | (3.372) | (2.557) | (2.012) |
| Observations | 1,580 | 1,275 | 1,613 | 1,584 |
| R-squared | 0.223 | 0.229 | 0.262 | 0.226 |
| Region FE | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ |

Notes: Clustered standard errors at the regional level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

## Section C.1 – Additional checks – Global Innovation Index

The countries under consideration exhibit high heterogeneity in terms of their degree of innovativeness. To reduce this heterogeneity and establish a common basis for comparison, we have decided to utilize the Global Innovation Index[16] (2015) as a benchmark to merge our regions. By using this index, we can categorize, and group countries based on their innovation performance, thereby facilitating a more homogeneous analysis. The sample of countries can be divided into three categories based on the Global Innovation Index (GII), which ranks countries according to their level

[16] The Global Innovation Index (GII) is an annual report that measures and ranks the innovation performance of countries worldwide. It provides a comprehensive assessment of various indicators related to innovation, including inputs (such as institutions, human capital, infrastructure, and market sophistication) and outputs (such as knowledge creation, technology transfer, and creative outputs). The GII is a collaborative effort of several organizations, including Cornell University, INSEAD, and the World Intellectual Property Organization (WIPO).

of innovation. The categories are as follows:[17]

1. Most Innovative (1): This category includes countries that exhibit the highest level of innovation according to the GII. These countries are particularly successful in developing new technological specializations.
2. In-Between (2): This category consists of countries that fall between the most and least innovative groups. While they may not be at the forefront of innovation, they experience a significant positive effect in terms of developed patents. The presence of ICT companies and technological specialization in ICT plays a crucial role in their innovation process.
3. Least Innovative (3): This category comprises countries that are considered the least innovative based on the GII. Unlike the first two categories, these countries do not benefit significantly from either the presence of ICT companies or technological specialization in the ICT sector.

This classification aligns with the findings from the quantile regression analysis, indicating that the interaction between ICT agglomeration and technological specialization contributes to the evolution of production systems, fostering innovation.

[17] Our list of countries categorized according to their Global Innovation Index (GII) scores (2015):
GII = 1 (Higher than 60 points): Sweden, United Kingdom, United States of America, Finland, Denmark.
GII = 2 (Between 50 and 60 points): Germany, Norway, Finland, Denmark, France, Austria, Belgium, Canada, Czech Republic.
GII = 3 (Between 40 and 50 points): Italy, Portugal, Spain, Greece, Hungary, Slovakia, Slovenia.

**Table C.3: FE Model - ICT and technological branching: Global Innovation Index (2015)**

| | (1) | | (2) | | (3) | |
|---|---|---|---|---|---|---|
| VARIABLES | FE | FE | FE | FE | FE | FE |
| $Patents_{i,t-1}^{HT}$ | 0.449*** | | 0.0268 | | 0.115** | |
| | (0.0826) | | (0.0526) | | (0.0548) | |
| $New\_RTA_{i,t-1}^{HT}$ | | 0.0915* | | 0.116 | | 0.0497 |
| | | (0.0536) | | (0.0957) | | (0.0582) |
| $GDP_{\mathrm{pc}_{i,t-1}}$ | 0.274 | 0.0685 | -0.706 | 0.160 | 0.567 | 0.774 |
| | (0.302) | (0.410) | (0.526) | (0.462) | (0.821) | (0.751) |
| $R\&D_{i,t-1}^{bus}$ | 0.0484 | 0.0162 | 0.155 | 0.0379 | 0.410*** | 0.223* |
| | (0.0419) | (0.0485) | (0.132) | (0.177) | (0.132) | (0.125) |
| $R\&D_{i,t-1}^{gov}$ | 0.00538 | -0.0393 | -0.197** | -0.182** | 0.186*** | 0.0723 |
| | (0.0148) | (0.0364) | (0.0822) | (0.0729) | (0.0591) | (0.0705) |
| $R\&D_{i,t-1}^{he}$ | 0.0242 | -0.0451 | 0.471** | -0.0545 | -0.0911 | 0.169** |
| | (0.0338) | (0.0437) | (0.178) | (0.161) | (0.0676) | (0.0778) |
| $HC_{i,t-1}$ | 0.144 | 0.611 | 0.120 | -0.0227 | -1.327*** | -0.363 |
| | (0.180) | (0.372) | (0.279) | (0.385) | (0.443) | (0.304) |
| $AV\_dens_{i,t}$ | 0.104** | 0.209*** | 0.285*** | 0.511*** | 0.401*** | 0.554*** |
| | (0.0420) | (0.0676) | (0.0726) | (0.126) | (0.139) | (0.138) |
| $ICT\_agg_{i,t-1}$ | -0.177 | -0.227 | -0.0714 | 0.420 | 0.667* | -0.153 |
| | (0.111) | (0.223) | (0.235) | (0.305) | (0.380) | (0.240) |
| $RTA_{i,t-1}^{ICT}$ | -0.0349 | 0.0664 | -0.146** | -0.0184 | 0.0607 | -0.0902 |
| | (0.0296) | (0.0621) | (0.0611) | (0.200) | (0.107) | (0.108) |
| $ICT\_agg_{i,t-1} \times RTA_{i,t-1}^{ICT}$ | 0.0778 | 0.432** | 0.131* | 0.222 | 0.0148 | 0.275 |
| | (0.0870) | (0.163) | (0.0759) | (0.226) | (0.175) | (0.188) |
| Constant | -0.499 | -1.935 | 11.78* | -0.271 | 2.320 | -4.707 |
| | (3.429) | (4.506) | (6.002) | (5.315) | (8.919) | (8.003) |
| Observations | 870 | 870 | 379 | 379 | 382 | 382 |
| R-squared | 0.983 | 0.621 | 0.978 | 0.627 | 0.940 | 0.622 |
| Region FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |

Notes: Clustered standard errors at the regional level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

“Environment is no one’s property to destroy; it’s everyone’s responsibility to protect.”

Mohith Agadi

# *Chapter 2*

# The impact of ICT agglomeration on Green TFP in Europe


## *Abstract*

This paper analyses the relationship between the concentration of the Information and Communication Technology (ICT) Industry and the growth of Green Total Factor Productivity (GTFP). The study employs the Malmquist-Luenberger productivity index to analyze the impact of ICT agglomeration on environmentally sustainable economic growth in a selected sample of European regions from 2000 to 2010. The analysis explores the mechanisms through which ICT concentration affects growth promotion, energy conservation, and emission reduction. By estimating GTFP growth, the study considers the potential for energy conservation and the reduction of pollutants resulting from the concentration of investments in the ICT industry, as well as the improved utilization of capital, energy, and labor inputs. The ICT sector, as a driver of knowledge and innovation in European regions, is likely to facilitate the adoption of cleaner technologies, thereby reducing negative environmental impacts associated with economic growth. The study adopts an output-oriented approach to estimate GTFP growth and utilizes the Malmquist-Luenberger productivity index to decompose GTFP into two components: efficiency change and technological change. Additionally, the analysis controls for key variables such as GDP per capita, human capital, R&D expenditure, and population density using a panel model that incorporates regional and time fixed effects. Spatial autocorrelation analysis is conducted on both GTFP and ICT agglomeration, and the existence of inter-regional spillover effects is tested using a Spatial Durbin Model (SDM). The findings of the study indicate that ICT agglomeration serves as an important indicator of a region's capacity to enhance green productivity. However, the relationship is non-monotonic, as the economies of scale resulting from ICT concentration may negatively impact GTFP growth. Further analysis reveals that the improvement in green total factor productivity is primarily driven by efficiency changes in green productivity, suggesting technological advancements that promote coordinated economic growth, energy savings, and emission reductions. Moreover, the results highlight the influence of proximity to regions with high green productivity on GTFP growth, underscoring the significance of promoting ICT agglomeration as a means to support sustainable and environmentally friendly economic growth in regions.



**Keywords**: ICT agglomeration; Green TFP; Sustainability; Green economy.

**JEL Codes:** R11; L86; O44; Q55; C31.

# 1. Introduction

The importance of the information and communication technologies (ICT) sector for productivity has been a topic of research interest since the 1980s, triggered by Robert Solow's statement that "you can see the computer age everywhere but in the productivity statistics". This remark initiated the academic debate on the impact of ICT and digital technologies in general on productivity (Biagi, 2013). Subsequent literature has confirmed the role of ICT in boosting productivity (Biagi, 2013; Jorgenson et al., 2008; Van Ark et al., 2008; Veugelers et al., 2012). However, research on the environmental impacts of ICT is limited, with most studies focusing on China and other emerging economies (Wang et al., 2022; Dong et al. 2022; Husman et al., 2022). Surprisingly, the literature has largely overlooked the issue of green total factor productivity (GTFP) in the context of the impact of ICT on productivity.

In recent years, the traditional focus of economists on GDP growth and productivity as the sole indicators of economic success has been challenged. The negative environmental consequences of uncontrolled economic growth have become increasingly apparent, leading economists to adopt a more holistic view of economic success that includes environmental sustainability (Kahn, 2015). Concepts such as 'green productivity', 'green growth' and the 'circular economy' have emerged, incorporating environmental considerations into traditional productivity and growth models. Furthermore, some economists argue that prioritizing sustainable economic growth can foster a more inclusive and equitable society (Kahn, 2015). However, this area of research remains relatively under-researched, with numerous perspectives and opinions on the trade-offs between economic growth, productivity and environmental sustainability still being debated.

In contrast, the increasing severity of pollution and the criticism of an unsustainable production method characterized by a "pollute first, treat later" approach (Zhao et al., 2021; Wang et al., 2020) cannot be ignored. The European Environmental Agency (EEA) highlights that air quality standards are consistently exceeded across the EU, with pollutant concentrations far exceeding the latest World Health Organization (WHO) recommendations.[18] A significant proportion of the urban population is, indeed, exposed to elevated levels of fine particulate matter (PM 2.5), with 96% exceeding the latest WHO health-based guidelines (World Health Organization, 2021). Environmental concerns go beyond the economic and social relevance to include potential impacts on the climate, oceans, fauna, and flora. Scientists worldwide are warning of the imminent threat of mass extinction (Barnosky et al., 2011). In response, the European Union (EU), as part of the Green Deal's Zero Pollution Action Plan, has set an ambitious target to reduce PM2.5 levels by at least 55% from 2005 levels by 2030.

[18] The WHO Air quality guidelines recommend levels and interim targets for common air pollutants: PM2.5, O3, NO2, and SO2. They recommend aiming for annual mean concentrations of PM2.5 not exceeding 5 µg /m$^3$, O3 non exceeding 60 µg /m$^3$ during the peak season, and NO2 not exceeding 10 µg /m$^3$, and the peak season mean 8-hr ozone concentration not exceeding 60 µg /m$^3$. (µg = microgram)

[19] The EU is also introducing stricter requirements to tackle air pollution at source, including agriculture, industry, transport, buildings, and energy supply (European Environment Agency, 2022). The ICT industry has the potential to contribute significantly to sustainable low-carbon development and given the increasing global emphasis on addressing climate change has generated an increasing attention in the economic literature (Dong et al., 2021; Wang et al., 2021; Lahouel et al., 2021). However, the diffusion of ICT faces barriers in rural or less developed regions, including technical requirements (Lee et al., 2017) and educational disparities (Fong, 2009), resulting in a concentration mainly in developed areas, which is associated with economic growth and environmental impacts (Liu et al., 2021). Furthermore, ICT agglomeration can lead to an unbalanced regional industrial structure, resulting in wasted resources and increased emissions (Fang et al., 2020; Li et al., 2017). In addition, the attractiveness of areas with high levels of ICT activity contributes to additional energy consumption and subsequent emissions (Wu et al., 2021). Nevertheless, the ICT industry exhibits characteristics of industrial convergence and knowledge spillovers, which promote technological progress and low-carbon development across the industry (Moyer & Hughes, 2012). The impact of ICT agglomeration on carbon emissions remains mixed and poses challenges for policy makers. While numerous studies have examined the impact of industrial agglomeration on carbon emissions, few have specifically analysed the impact of ICT agglomeration. Despite the potential for the ICT industry to reduce emissions (Haini, 2021; Lu, 2018), the direct impact of ICT agglomeration on emissions reduction may be limited. However, it can promote green productivity through its ability to facilitate knowledge transfer between different technologies.

Therefore, this study aims to fill a significant gap in the existing literature by providing new insights into the potential relationship between ICT agglomeration and growth in GTFP. Understanding the phenomenon of ICT agglomeration and its impact on green productivity growth is crucial for understanding how information technology can contribute to building a sustainable and resilient economy.

ICT agglomeration can promote economic prosperity without compromising environmental integrity: companies operating in the ICT sector have the potential to drive green productivity growth by implementing innovative solutions for energy and resource management. In addition, ICT agglomeration can facilitate the diffusion of knowledge and skills related to environmental sustainability, foster synergies between different economic activities and create new business opportunities aligned with environmental sustainability goals. Furthermore, ICT agglomeration can play an important role in creating green jobs and facilitating the training of a workforce specialised in environmental sustainability, thereby facilitating the transition to a more sustainable and resilient economy.

[19] To achieve this goal, the Commission is revising the ambient air quality directives to align them more closely with WHO recommendations.

This paper uses Slacks Based Model-Data Envelopment Analysis (SBM-DEA) to analyse the impact mechanism of ICT agglomeration on green economic growth from two perspectives: growth promotion and energy conservation/emissions reduction. The analysis uses a selected sample of 95 European regions for the period 2000-2010 obtained from the OECD database, AMECO, and GREECO. The estimation of GTFP growth considers the potential energy savings and emission reductions resulting from the concentration of investment in the ICT industry, as well as the more efficient use of capital, energy, and labour inputs.

The study suggests that the ICT sector, acting as a knowledge driver and influencing the innovative performance of European regions, should have a greater capacity to adopt cleaner technologies, thereby reducing the negative environmental impacts associated with growth. The results show that ICT agglomeration serves as a critical indicator of a region's ability to increase green productivity. However, the relationship is not monotonic, as the economies of scale resulting from ICT agglomeration can have a negative impact on GTFP growth. Further analysis shows that the observed improvement in green GTFP is mainly due to efficiency changes in green productivity, suggesting technological advances that promote coordinated economic growth, energy savings and emission reductions. In addition, the results show that GTFP growth is influenced by proximity to regions with high levels of green productivity, highlighting the importance of promoting ICT agglomeration as a means of fostering sustainable and green economic growth within regions.

The paper is organized as follows. In Section 2, we review the related literature to which this paper aims to contribute. Section 3 describes our theoretical framework and our research hypothesis, while Section 4 describes our data. Section 5 explains our estimation strategy. In Section 6, we discuss the results. Finally, Section 7 concludes the paper.

## 2. Literature review

This research aims to fill an important gap in the literature by providing new insights into the potential link between ICT agglomeration and Green Total Factor Productivity (GTFP) growth. The study addresses two distinct strands of literature: the impact of ICT agglomeration on productivity and the broader relationship between ICT and the environment.

**ICT and Environment:** ICT tools have become essential in today's business and social environments (Cardona et al., 2013; Dogan & Aslan, 2017). The significant decrease in the cost of ICT has facilitated significant investment in ICT, leading to economic restructuring and integration into our daily lives (Cardona et al., 2013). ICT plays an important role in various aspects such as economic growth, education, foreign direct investment, financial development, trade, good governance, and energy consumption (Appiah-Otoo et al., 2022; Appiah-Otoo & Song, 2021). As a result, the environmental impacts of ICTs have received increasing attention from scholars and policy makers.

Scholars have presented different perspectives on the environmental impact of ICTs. Some argue that ICTs contribute to improving environmental quality, as evidenced by a negative correlation between ICTs and carbon dioxide emissions (CO2E) in 13 G-20 countries (Ahmed et al., 2021; Chien et al., 2020, and Nguyen et al., 2020). However, other studies suggest that ICTs have a negative impact on the environment (Salahuddin et al., 2016). For example, Yang et al. (2016) found a positive correlation between ICT and PM2.5 emissions, both in terms of production and consumption. Fuel combustion, especially in the power generation and manufacturing sectors, is the main source of direct CO2 and PM2.5 emissions. Shabani & Shahnazi (2019) also found that ICTs contribute to CO2E in the industrial sector, while the opposite effect is observed in the transport sector.

Many factors have been examined in the literature to understand the moderating influences on the relationship between ICT and the environment. The stage of development of a country plays an important role. Danish et al. (2018) highlights the role of the stage of development, finding that ICTs degrade the environment in high-income emerging economies. Conversely, ICTs have no discernible effect on CO2E in high-income developing countries but contribute to environmental sustainability in low-income developing countries (N'dri et al., 2021). However, an important recent study has challenged the assumption that the level of CO2E (high, medium, or low) determines the environmental impact of ICTs, showing that ICTs degrade the environment in countries across the CO2E spectrum (Alataş, 2021).

Furthermore, the quality of a country's ICT infrastructure acts as an additional conditional determinant. Appiah-Otoo et al. (2022) found that the relationship between ICT and environmental sustainability is complex and varies according to the quality of ICT infrastructure. In countries with high quality ICT infrastructure, ICTs are associated with positive environmental impacts, whereas in countries with moderate and low ICT quality, ICTs can have negative environmental impacts due to increased energy demand associated with the installation of ICT equipment. Conversely, better ICT infrastructure allows easier access to the Internet for various activities such as banking, education, e-commerce, entertainment, healthcare, and remote working, thereby increasing energy efficiency and improving environmental quality. In addition, countries with high-quality ICT tend to have advanced e-government systems, which can help reduce corruption and red tape and increase transparency, ultimately improving environmental conditions.

Finally, the overall impact of ICTs on the environment can be decomposed into three different partial effects, and it is uncertain which effect will prevail. According to Higón et al. (2017) and Shabani & Shahnazi (2019), the effect of ICTs could have three different impact on the environment: (a) a substitution effect, (b) a use effect, and (c) a cost effect.

The substitution effect suggests that ICTs contribute to improving environmental quality by reducing energy consumption and CO2 emissions through various means, such as the use of email, e-books, intelligent transport systems, sharing economy platforms, traffic control cameras, smart cities, e-government, e-commerce, online education, and online communication. By enabling these alternative methods, ICTs can potentially reduce the environmental impacts associated with traditional practices.

However, ICTs can also have a negative impact on the environment through their lifecycle stages, including production, processing, distribution, and disposal. These stages contribute to increased energy consumption and $CO_2$ emissions, known as the *use effect*. The rapid consumption of ICTs also leads to lower prices for goods and services, resulting in increased product demand, energy consumption and $CO_2$ emissions, known as the cost effect.

Furthermore, Wang et al. (2022) show that ICT agglomeration has a positive direct effect on carbon emissions. However, this effect can be mitigated indirectly through the promotion of technological innovation, which can lead to the development and adoption of more environmentally friendly practices and solutions.

In summary, the environmental impact of ICTs is complex and multifaceted. While ICTs offer potential benefits through the substitution effect, their use and associated life cycle stages can have negative environmental impacts. The overall outcome depends on the interaction of these partial effects, making it difficult to draw a definitive conclusion.

**ICT agglomeration and environment:** Despite the growing importance of ICT industry agglomeration and development, there is limited research on its specific impact on carbon emissions. The internal mechanisms underlying the relationship between ICT agglomeration and carbon emissions remain unclear. Existing studies present an ambiguous picture, with some suggesting that ICTs improve environmental quality (Ahmed et al., 2021; Chien et al., 2020; Nguyen et al., 2020; Wang et al., 2022), while others highlight the negative impact of ICTs on the environment (Salahuddin et al., 2016; Yang et al., 2016; Shabani & Shahnazi, 2019).

However, further research on the relationship between ICT agglomeration and carbon emissions is crucial for policymakers and academics in formulating future industrial plans. The process of urbanisation and the effects of industrial agglomeration have gained significant importance due to global economic growth. Industrial agglomeration promotes economic development, increases social welfare, and reduces income inequality, but also leads to increased energy consumption. The environmental concerns associated with industrial agglomeration have gained further attention following the COVID-19 pandemic. Research has focused on the impact of industrial agglomeration on energy use and carbon emissions, with $CO_2$ emissions being the primary greenhouse gas of interest.

Studies have examined the impact of different industrial sectors on carbon emissions, with manufacturing, known for its energy-intensive nature, having a significant impact on the environment (Y. Wang et al., 2018). Research by Lan et al. (2021) has also highlighted the impact of manufacturing agglomeration on $CO_2$ emissions in China. In addition, research on producer services and high-tech industries has shown that their agglomeration can potentially reduce carbon emissions (J. Zhao et al., 2021a; R. Zhao & Zhao, 2020).

In summary, while researchers have explored the impact of ICT agglomeration on regional economic growth and innovation, limited attention has been paid to its environmental impact, particularly in terms of carbon emissions. The focus has been primarily on the role of ICT in regional economic integration and its demonstrated enhancement of firms' innovation capabilities (Awoleye et al., 2020; Kuchiki, 2021). The analysis of ICT's impact on productivity, considering its complex relationship with emissions, as explored in some studies, remains largely absent.

## 3. Theoretical framework and research hypotheses

Through the review of the literature, we find that the nexus between industrial agglomeration and carbon emissions has much evidence, but the research on the influence between ICT agglomeration and carbon emissions is still scant. First, the agglomeration and development of the ICT industry has become an inevitable trend in the era of digital transformation and the information revolution, and studies on industrial agglomeration have gradually increased but still few scholars have paid attention to ICT agglomeration (Kuchiki, 2021; Raspe & Van Oort, 2004). Second, most scholars are concerned about the economic and social impact of ICT agglomeration, while few scholars have paid attention to its effect on pollution (Lee et al., 2022). Third, it is missing the analysis of the internal impact mechanism between ICT agglomeration and pollution (Wang et al., 2022). Fourth, to our knowledge, there is no previous research on the potential link between ICT agglomeration and green productivity growth.

We differ from the studies illustrated above in the following ways. This study aims to provide new insights into how ICT contributes to green growth in the European context. Indeed, we know that the role of ICT on economic growth and productivity is well argued (Niebel, 2018), yet its impact on green growth is less studied. On the other hand, as a crucial facilitator of innovation and technology transfer, ICT plays a significant role in decreasing energy consumption and GHG emissions (Niebel, 2018). Hence, ICT holds great promise for boosting economic growth, reducing poverty, and combating climate change. There is hope that ICT may have the potential to separate economic growth from CO2 emissions (Plepys, 2002). The study aims to provide evidence on this relationship and contribute to the understanding of how ICT can support green productivity growth in the European context. The traditional focus of economists on GDP growth and productivity as the primary indicators of economic success has been challenged in recent years as the negative impact of economic growth on the environment have become increasingly apparent. The study takes into consideration the negative impacts of economic growth on the environment and the need for a more holistic view of economic success that incorporates environmental sustainability. The results of this research could have important policy implications for decision-makers and stakeholders looking to promote green productivity growth in Europe through the development of ICT clusters. The literature has confirmed the role of ICT on productivity (Biagi, 2013; Jorgenson et al., 2008; van Ark et al., 2008), but there is less research on the importance of ICT for green productivity. Hence, the first research hypothesis is that there is a relationship between ICT agglomeration and Green Total Factor Productivity (GTFP) growth in Europe:

***Hypothesis 1:*** *ICT agglomeration impacts on total green productivity growth in Europe.*

The second hypothesis suggests that neighboring regions are spatially correlated in terms of their Green TFP and the ICT agglomeration. This correlation is due to the fact that regions tend to influence each other in policymaking and problem-solving, which leads to the formation of spatial clusters in both GTFP and *ICTAGG*.
Moreover, the hypothesis suggests that proximity to regions with a high level of ICT agglomeration can potentially stimulate the growth of GTFP, leading to greater economic prosperity.

***Hypothesis 2:*** *There are regional clusters of ICT agglomeration and Green TFP.*

The third hypothesis is based on the idea that ICT industries have a strong potential for eco-innovation and can contribute to the development of more sustainable production processes and products (Wang et al., 2022). Furthermore, the clustering of ICT companies in certain regions can lead to increased knowledge sharing, collaboration, and competition, which can further drive productivity growth and eco-innovation. Additionally, the spillover effects from these leading regions can result in the adoption of new technologies and best practices in neighbouring regions, leading to a positive impact on their GTFP growth as well. In order to test this hypothesis, a spatial econometric analysis will be conducted using data on ICT agglomeration and green productivity. Hence, we propose the following hypothesis.

***Hypothesis 3:*** *There are regional spillover effects of ICT agglomeration on Green Total Factor Productivity Growth in Europe.*

# 4. Data

### *3.1. Data and variable selection*

This study uses a sample of 95 large regions from 10 countries located in the European area[20,21], covering an eleven-year period from 2000 to 2010. The reference database was provided by the OECD, which offers information at the regional level and provides several key indicators for the

[20] Country: Austria, Belgium, Denmark, France, Germany, Italy, Norway, Portugal, Spain, and Sweden.
[21] The following countries are members of the EU: Austria, Belgium, Denmark, France, Germany, Italy, Portugal, Spain, and Sweden. Norway is not a member of the EU, although it is part of the European Economic Area (EEA) and the Schengen Area, which allows free movement of people, goods, and services between European countries.

study such as PM 2.5, R&D investment, human capital, population density, GDP, and value added produced by different sectors. The Annual Macro-Economic Database (AMECO)[22] from the European Commission is also used to retrieve information on capital formation, which is then used to calculate the capital stock via the PIM (Perpetual Inventory Method). Furthermore, data on total energy consumed at the regional level is retrieved from the Territorial Potentials for a Greener Economy (GREECO)[23] project database[24], which is crucial for calculating the Green TFP.[25]

As control variables, the study considers: R&D investment that could have an impact on GDP production and air pollution; the percentage of the population with tertiary education that could have a positive effect in terms of actual development of green technologies and also awareness of the pollution phenomenon and therefore behaviours; the population density and industrial structure could influence both air pollution and GDP production.[26] Table 1 describes the variables used.

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[22] AMECO is the annual macro-economic database of the European Commission's Directorate General for Economic and Financial Affairs. The database is used for analysis and reports produced by the directorate general.

[23] GREECO is a project financed by ESPON. The aim of the GREECO project is to shed light on the conceptual and operational dimensions of the green economy – seen from a territorial perspective. The project aims to identify key economic areas where policy support through territorial and cohesion policies could contribute to sparking economic recovery, creating new employment opportunities, and strengthening sustainable development. The project focuses on understanding how the green economy can be integrated into various regions and territories to promote environmental sustainability and economic growth. By examining the green economy's potential impact on different areas, GREECO aims to provide valuable insights for policymakers and stakeholders to make informed decisions in fostering a greener and more resilient economy.

[24] Total Energy consumed at the regional level is only available from 2000 to 2010.

[25] The data from AMECO and GREECO were originally aggregated at the NUTS2 level, but there were some discrepancies between NUTS2 and LR2 in some countries in the sample. The incompatibility between OECD large regions (TL2) and NUTS-2 geographical classifications was present for a short list of countries (Belgium, France, Germany, and United Kingdom), where the NUTS 2 level corresponds to the OECD TL3 provincial classification. To resolve this issue, the information was re-aggregated from the NUTS2 level to the LR2 level.

[26] The industrial structure is calculated as the ratio of value added produced by the service sector to total value added.

**Table 1 - Variable description**

| Variable | Description | Data | Unit |
|---|---|---|---|
| $\boldsymbol{GTFP_{it}}$ | Green Total Factor Productivity | Authors' elaboration | Index |
| $\boldsymbol{TECH_{it}}$ | Technical efficiency change | Authors' elaboration | Index |
| $\boldsymbol{TECCH_{it}}$ | Technological change | Authors' elaboration | Index |
| $\boldsymbol{GDPC_{it}}$ | Gross domestic product per capita (constant price 2015). | OECD | Absolute |
| $\boldsymbol{R\&D_{it}}$ * | Total expenditure in R&D. | OECD | % of GDP |
| $\boldsymbol{EDU_{it}}$ * | Population aged 25 to 64 with tertiary education | OECD | % |
| $\boldsymbol{POP\_DENS_{it}}$ * | Population density | OECD | Pop/m$^2$ |
| $\boldsymbol{ECST_{it}}$ | Share of service Gross value added (GVA) on the total GVA | Authors' elaboration | % |
| $\boldsymbol{ICTAGG_{it}}$ | ICT agglomeration based on the number of employees in ICT as per Eq. 4. | Authors' elaboration | Index |
| $\boldsymbol{EMP_{it}}$ * | Total employment in all sectors. | OECD | Absolute |
| $\boldsymbol{EMPICT_{it}}$ * | Total employment in ICT sector | OECD | Absolute |
| $\boldsymbol{CAPITAL_{it}}$ *** | Stock of Capital Formation | Authors' elaboration | In millions of $ |
| $\boldsymbol{ENERGY_{it}}$ ** | Total Energy consumed | GREECO | TJ |
| $\boldsymbol{GDP_{it}}$ | Gross domestic product (constant price 2015). | OECD | In millions of $ |
| $\boldsymbol{AIRPOL_{it}}$ * | PM2.5 refers to tiny particles or droplets in the air that are two- and one-half micrometres or less in width. | OECD | ug/m3" |

### *4.2. Dependent variables*

We use the Malmquist-Luenberger productivity index (MLPI)[27] to calculate our three dependent variables: green total factor productivity, technical efficiency change, technological change (Wang et al., 2022). The MLPI is a measure of productivity change that takes into account both efficiency change and technological change. The traditional approach to measuring productivity change focuses on measuring marketable outputs relative to paid factors of production, but this can result in biased measures due to the ignoring of by-products such as pollution. To address this issue, Chung and Färe (1997) introduced the Malmquist-Luenberger productivity index, which considers the reduction of undesirable outputs (e.g., pollution) while crediting increases in desirable outputs. The index is based on a radial directional distance function (DDF) measure and is defined as the output-oriented Malmquist-Luenberger productivity index with undesirable outputs, considering two adjacent periods (s and t). The MLPI is a useful tool for measuring productivity change over time and comparing the productivity of different firms or industries. It can also be used to identify areas for improvement and to inform productivity-enhancing policies.[28]

[27] The models introduced here is based on the DEA. Thus, it is part of the DEA-based Malmquist models.
[28] A brief summary of the literature using the MP is available in the Appendix B.1.

As shown in Table 2, the inputs utilized to compute our MLPI include the number of workers employed (*EMPLOYEES*), the stock of capital formation (*STOCK VALUE*), and the total energy consumed (*FEC TOT*). We chose to include energy as a factor of production, not only due to its critical role in modern economies, but also because of its effects on emissions. Managing energy usage is of paramount importance to reduce our society's gas emissions to decrease environmental hazards. The outputs used in our calculations are GDP as a measure of desirable output, and PM2.5 as a measure of undesirable output. By imposing these inputs and outputs, the result of the MLPI is the Green Total Factor Productivity (GTFP) change.

**Table 2 - The index system for evaluating green total factor productivity**

| Type | Variable | Data |
|---|---|---|
| Input | EMPLOYEES (L) | Employees |
| Input | STOCK VALUE (K) | Stock of Capital Formation |
| Input | FEC TOT (E) | Final Electricity consumption |
| Desirable output | GDP (Y) | Real GDP (2015) |
| Undesirable output | PM2.5 (-Y) | Pollution in terms of PM 2.5 |

The output-oriented Malmquist-Luenberger productivity index with undesirable outputs is defined as:[29]

$$MLPI = \left[\frac{1 + D_r^t(x^s, y^s, b^s;\ g)}{1 + D_r^t(x^t, y^t, b^t;\ g)} x \frac{1 + D_r^s(x^s, y^s, b^s;\ g)}{1 + D_r^s(x^t, y^t, b^t;\ g)}\right]^{1/2} \tag{1}$$

To avoid an arbitrary choice between base years, a geometric mean of the fraction-based Malmquist-Luenberger productivity index has been taken in base years t (first fraction) and s (second fraction). The MLPI index indicates improvements in productivity if its value is greater than one and decreases in productivity if its value is less than one. It can be decomposed into two components (Chung et al., 1997), one measuring efficiency change (*TECH*) and one measuring technological change (*TECCH*):

$$TECH = \left[\frac{1 + D_r^t(x^s, y^s, b^s;\ g)}{1 + D_r^t(x^t, y^t, b^t;\ g)}\right] \tag{2}$$

$$TECCH = \left[\frac{1 + D_r^t(x^s, y^s, b^s;\ g)}{1 + D_r^t(x^s, y^s, b^s;\ g)} x \frac{1 + D_r^t(x^t, y^t, b^t;\ g)}{1 + D_r^s(x^t, y^t, b^t;\ g)}\right]^{1/2} \tag{3}$$

[29] The inputs are represented by x, the desirable outputs by y, the undesirable outputs by b, and the direction is denoted by g. Dr represents our directional distance function (Wang et al., 2022). The direction g is defined as (0, y, -b), where y represents the desirable direction, and -b represents the undesirable direction.

Therefore, our study will investigate the relationship on MLPI and the two components resulting from the MLPI$_p$: $TECH_p$ and $TECCH_p$. Hence, our three dependent variables are the MLPI, which represents our measure of Green Total Factor Productivity (*GTFP*), the Efficiency Change (*TECH*) component, which captures technological progress, and the Technical Change (*TECCH*) component, which captures the rate of change in technology over time. Together, these three variables provide a comprehensive understanding of the productivity dynamics of a given region.

Our measure of productivity can take the following values:

- $MLPI > 1\ demostrates\ progress\ in\ productivity;$
- $MLPI = 1\ demostrates\ no\ change\ in\ productivity;$
- $MLPI < 1\ demostrates\ a\ decrease\ in\ productivity.$

The Efficiency Change (*TECH*) and Technical Change (*TECCH*) assume the same values as the Malmquist-Luenberger productivity index, with the same logic. Specifically, values greater than 1 indicate progress in TECH (*TECCH*), values equal to 1 indicate no change in TECH (*TECCH*), and values less than 1 indicate a decrease in TECH (*TECCH*).

Fig. 1 shows the average values of the *GTFP, TECH*, and *TECCH* indices between 2000 and 2010. To summarize, the average value of the total green factor productivity of our sample suggests that the GTFP was above 1 in only a few years of our sample period, indicating a decrease in green productivity overall. During the analysed period, the national green development policy was not well implemented, resulting in an increase in GDP that was followed by a more than proportional increase in PM 2.5 emissions. *TECCH* also experienced a similar trend. The case of *TECH* is slightly different, as it remained close to 1 throughout the period. Basically, in the years analysed, there is no evidence of either green technological change or green technological progress.

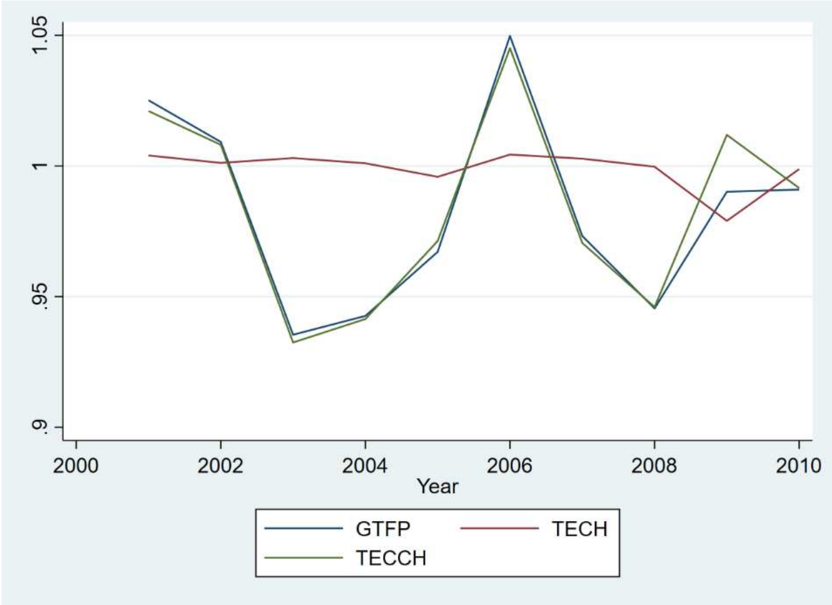
When comparing different European regions (Fig. 2), we observe that the trend is similar across all areas. As expected, Northern Europe is the best performing region in terms of green productivity, although the trend remains bearish even in this area.[30]

Figure 3 shows the distribution map of Green TFP in the regions of our sample for the year 2010. The regions where the GTFP is higher are Vienna with an average value of 1.011, Saxony with 1.005, Île-de-France with 1.002, and Campania with 1.001.

[30] According to the United Nations geoscheme for subregions of Europe, the following countries are categorized into the following subregions:

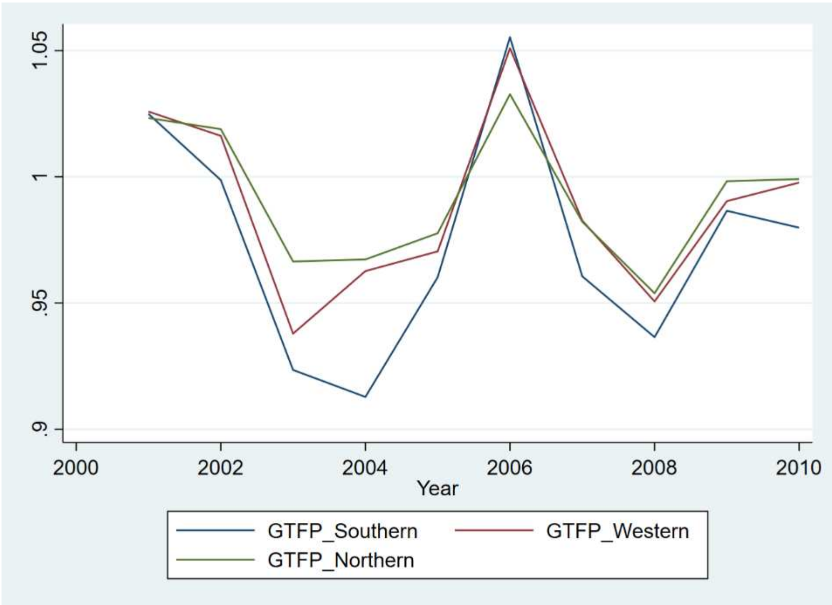
- Southern Europe: Italy, Spain, Portugal.
- Western Europe: France, Germany, Austria, Belgium.
- Northern Europe: Sweden, Denmark, Norway.

**Fig. 1 - Malmquist-Luenberger productivity index**



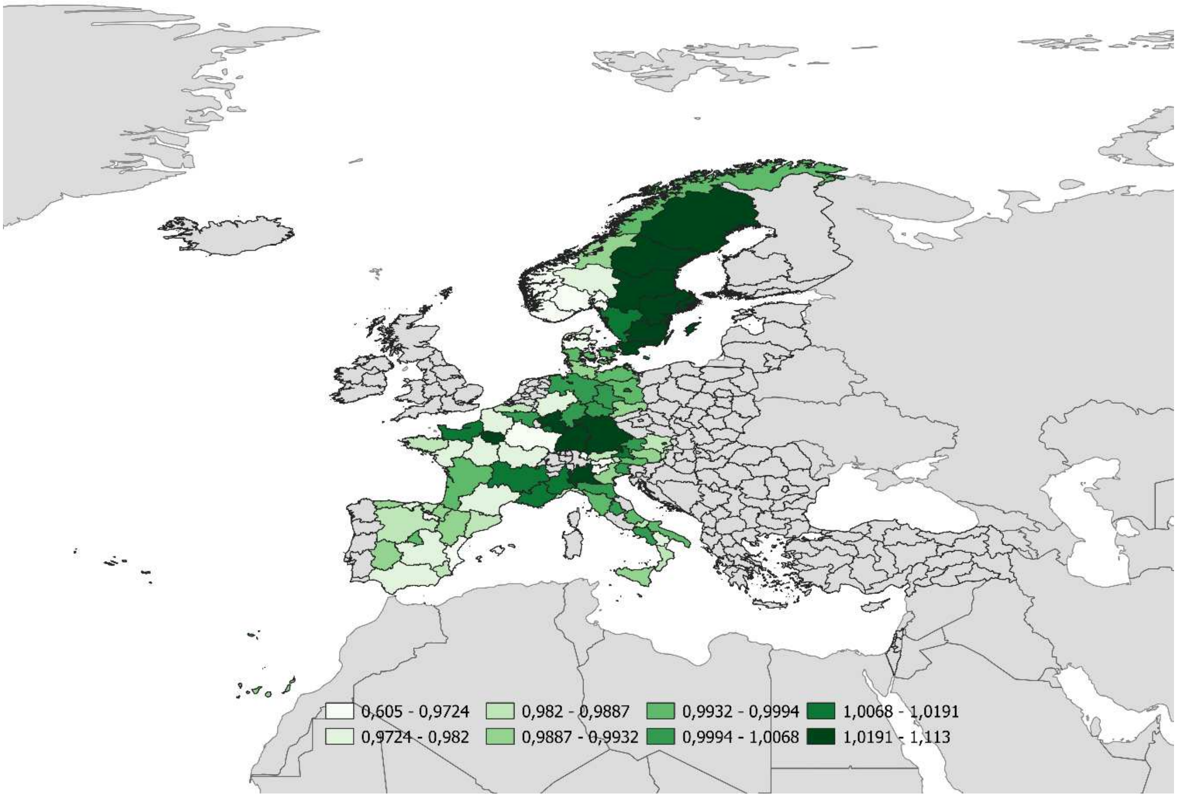

Note: Evolution of the Malmquist-Luenberger productivity index, and its subcomponents, between 2000 and 2010.
Resource: Authors' elaboration.

**Fig. 2 - GTFP Growth in southern, northern, and western Europe from 2000 to 2010**




Note: Development of the Malmquist-Luenberger productivity index between 2000 and 2010 in the four European geographical areas.
Resource: Authors' elaboration.

**Fig. 3 - Geographical distribution of Green TFP (2010)**




Notes: The figure shows the levels of GTFP in 2010 for regions located in Austria, Belgium, Denmark, France, Germany, Italy, Norway, Portugal, Spain, Sweden.
Source: Author' elaboration.

### *4.3. Explanatory variable*

To test our three hypothesis (see section 3), we measure the ICT agglomeration following the location entropy method based on the number of employees in a region (Liu et al., 2021; J. Zhao, Dong, et al., 2021a). It is calculated as follows:

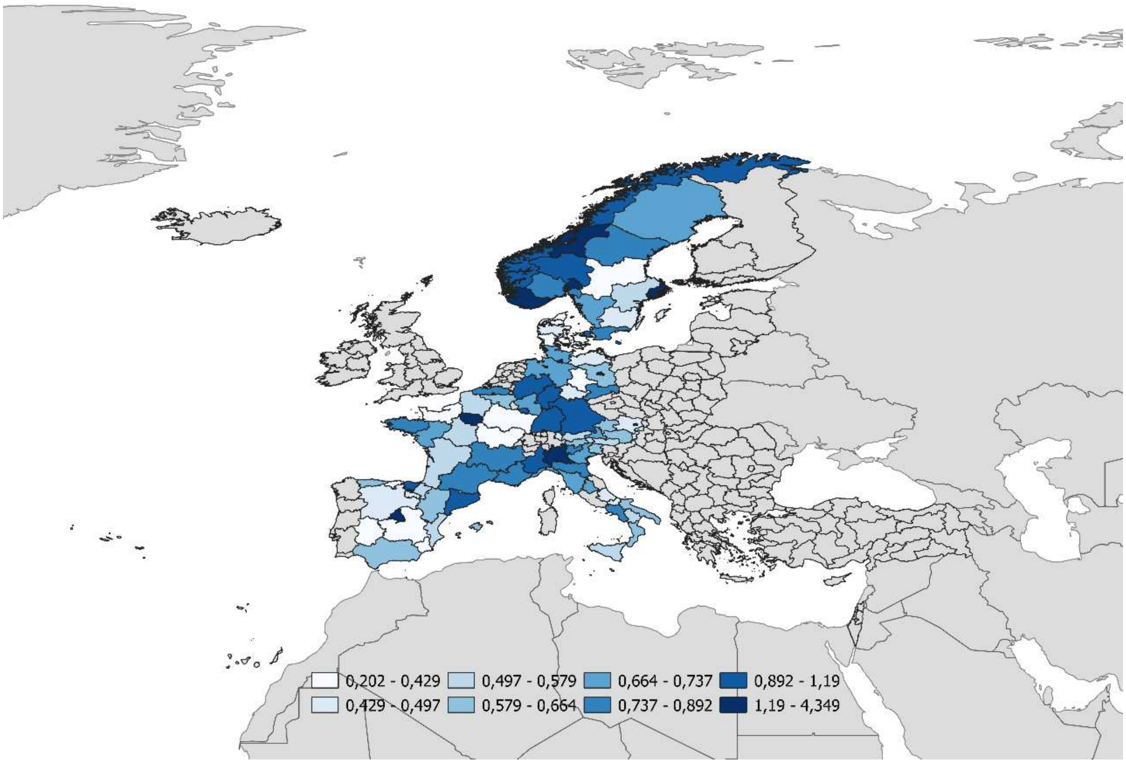
$$\mathrm{ICTAGG}_{it} = \frac{ICT\_empl_{it}/\sum_i^c ICT\_empl_{it}}{empl_{it}/\sum_i^c empl_{it}} \tag{4}$$

Where $EMP\,ICT_{it}$ is the number of employees in ICT sector[31] in region *i* at time *t* in country *c* where the region is located, and $EMPLOYEES\ _{it}$ is the total number of employees in all sectors in region *i* at time *t*. Fig. 4 plots the spatial distribution of the indicator of ICT agglomeration, the regions where the employment in ICT activities is higher are Brussels Capital Region with an average value of 3.78, Île-de-France with 2.61, Madrid with 2.54, Lombardy with 1.37, Piedmont with 1.16, and Catalonia

[31] In section A.1 in Appendix A, we introduce the Classifications and description of ICT sector and in Table A.1, we describe the NACE v.2 ICT Industry classification adopted. The sectoral coverage of ICT follows the assignment of the NACE code economic activity sectors according to the official OECD definition**.**

with 1.14. In general, capital regions in Europe tend to have higher levels of ICT agglomeration than other regions. This is probably since the national bureaucratic machine needs quality ICT services, but in general these areas are also densely populated and characterised by a higher level of concentration of service-related activities.

**Fig. 4 - Spatial distribution of ICT agglomeration (2010)**




Notes: The figure shows the levels of ICT agglomeration in 2010 for regions located in Austria, Belgium, Denmark, France, Germany, Italy, Norway, Portugal, Spain, Sweden.
Source: Author' elaboration.

### *4.4. Descriptive statistics*

In this section, we present descriptive statistics and data visualizations to analyze the data used for this study.

Table 3 presents the descriptive statistics, including the mean, standard deviation, minimum and maximum values for each variable.

The variable $GTFP_{it}$, which stands for Green Total Factor Productivity, serves as a measure of green economic efficiency and productivity, and has an average value of 0.979, indicating a declining trend in economic efficiency and green productivity in the regions studied. With a standard deviation of 0.053 and a range of variation between 0.605 and 1.136, there appears to be an uneven distribution of $GTFP_{it}$ across regions.

Further analysis decomposes the $GTFP_{it}$ index into two components: technological efficiency $TECH_{it}$ and scale progress ($TECCH_{it}$), as shown in equation (2). The mean of $TECH_{it}$ is 0.997, with a standard deviation of 0.02 and a range between 0.898 and 1.088. These results suggest that the regions in the sample did not experience significant improvements in technological efficiency. As for $TECCH_{it}$, the mean is 0.983, with a standard deviation of 0.052 and a range between 0.605 and 1.136. It is noteworthy that Figure 1 shows a very similar behavior between $GTFP_{it}$ and $TECCH_{it}$, indicating similar descriptive statistics.

Regarding ICT agglomeration ($ICTAGG_{it}$), the mean is 0.829, accompanied by a standard deviation of 0.61 and a range between 0.196 and 4.818. These results indicate different levels of concentration of ICT industries in the regions studied, with some regions having relatively high levels of concentration and others having lower levels.

The descriptive statistics show a mean of 15.41 ug/m3 and a standard deviation of 4.80 for air pollution ($AIRPOL_{it}$). The minimum and maximum values are 5 ug/$m^3$ and 35.67 ug/$m^3$ respectively.[32] These results indicate that there is a considerable variation in air pollution levels between regions, with some areas experiencing relatively low levels of pollution and others experiencing higher levels.

The variable $ENERGY_{it}$ represents the total energy consumption of each region. In the table provided, the mean of $ENERGY_{it}$ is reported as 340000TJ, with a standard deviation of 361000TJ and a range between 12328.762 and 2350000TJ. This suggests that energy consumption varies between regions, with some areas having relatively high levels of energy consumption and others having lower levels.

Finally, $CAPITAL_{it}$ refers to the stock of capital formation in each region. The mean value of the stock in dollars is reported as $314000, with a range between $15152.02 and $2470000. These results highlight the profound differences in terms of capital stock between the regions of Europe.

[32] ug/m3 stands for micrograms per cubic meter and it's a way to express the concentration of PM2.5 particles in the air.

**Table 3 - Descriptive statistics**

| Variables | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| $GTFP_{it}$ | 667 | .979 | .053 | .605 | 1.136 |
| $TECH_{it}$ | 667 | .997 | .021 | .898 | 1.088 |
| $TECCH_{it}$ | 667 | .983 | .052 | .605 | 1.136 |
| $GDPC_{it}$ | 667 | 38688.14 | 10870.392 | 21230.111 | 86201.492 |
| $R\&D_{it}$ | 667 | 1.394 | .916 | .21 | 5.52 |
| $EDU_{it}$ | 667 | 21.651 | 8.725 | 4.3 | 47.9 |
| $POP\_DENS_{it}$ | 667 | 325.813 | 872.766 | 3.34 | 6725.54 |
| $ECST_{it}$ | 667 | .707 | .075 | .517 | .969 |
| $ICTAGG_{it}$ | 667 | .829 | .61 | .196 | 4.818 |
| $EMP_{it}$ | 667 | 1270000 | 1240000 | 90200 | 8005700 |
| $EMPICT_{it}$ | 667 | 35057.961 | 59289.718 | 660 | 414690 |
| $CAPITAL_{it}$ | 667 | 314000 | 353000 | 15152.026 | 2470000 |
| $ENERGY_{it}$ | 667 | 340000 | 361000 | 12328.762 | 2350000 |
| $GDP_{it}$ | 667 | 121000 | 135000 | 5911.51 | 791638 |
| $AIRPOL_{it}$ | 667 | 15.412 | 4.807 | 5 | 35.67 |

## 5. Estimation strategy

We adopt an output-oriented approach to estimate $GTFP_{it}$ growth and utilize the Malmquist-Luenberger productivity index methods. We incorporate both desirable output ($GDP_{it}$) and undesirable output ($AIRPOL_{it}$) into our calculations. This approach also allows us to understand the impact channels by decomposing the $GTFP_{it}$ into two components: efficiency change and technological change. Furthermore, we estimate the role of ICT agglomeration while controlling for key variables such as GDP per capita, human capital, R&D, and population density. We also analyse the spatial autocorrelation of both $GTFP_{it}$ and ICT agglomeration and test for the existence of inter-regional spillover effects using a Spatial Durbin Model (SDM).

### *5.1. Baseline*

In order to test the hypotheses outlined in the previous sections and to measure the impact of ICT agglomeration on green TFP growth, we use the following baseline equation:

$$Y_{i,t} = \beta_0 + \beta_1 GDPC_{it} + \beta_2 POP\_DENS_{it} + \beta_3 R\&D_{it} + \beta_4 EDU_{it} + \beta_5 ECST_{it} + b_6 ICTAGG_{it} + b_7 ICTAGG^2{}_{it} + \lambda_f + \phi_s + \varepsilon_{it} \tag{5}$$

where the subscripts *i* and *t* refer to region and year respectively. We use three different $Y_{i,t}$ variables within the same model: $GTFP_{it}$ and its two different components, $TECH_{it}$ and $TECCH_{it}$. In addition, we include a set of control variables that could potentially influence our three dependent variables: $GDPC_{it}$, representing gross domestic product per capita; $POP\_DENS_{it}$ as a measure of population density; $R\&D_{it}$ as a percentage of GDP to capture regional innovation capacity; $EDU_{it}$ to capture human capital; and $ECST_{it}$, which indicates the share of gross value added produced in the service sector relative to total GVA, to control for economic structure. Finally, we include our main explanatory variables $ICTAGG_{it}$ and $ICTAGG^2{}_{it}$ as well as country-specific fixed effects $\lambda_f$ and year fixed effects $\phi_s$.

To further investigate the spatial dependence between ICT agglomeration and green productivity, we use the Spatial Durbin Model to test for spatial dependence in the relationship between ICT agglomeration and green productivity.

Finally, the spatial autocorrelation analysis will allow us to investigate whether the values of our dependent variables tend to be similar for regions that are geographically close to each other. Overall, the combination of the baseline equation and the SDM model and spatial autocorrelation analysis provides a comprehensive approach for investigating the relationship between ICT agglomeration and green productivity.[33]

### *5.2. Instrumental variables approach*

The fixed effects specification of Eq. 5 may be subject to estimation bias due to the choice of endogenous inputs. In our case, the use of IV is important because the variable of interest, ICT agglomeration, may be correlated with unobserved factors that affect green productivity and its two components, leading to endogeneity issues. By using IV, this study attempts to address this issue by finding an instrument that is correlated with ICT agglomeration but not with the error term in the regression. The use of IV can provide more reliable estimates of the causal effect of ICT agglomeration on productivity and technological change.

To assess the possibility of reverse causality from Green TFP growth and ICT agglomeration, we implement an IV strategy by predicting in a zero-stage regression the *ICTAGG*, including a number of fixed effects: a) time FE ($\phi_t$) that capture unobserved time-varying characteristics and b) regional FE ($\lambda_i$) interacted with a dummy variable for the *dotcom* bubble period (2000-2002) to help us capture the difficulties that our countries faced during the big stock bubble in the ICT sector.

$$ICTAGG\_hat_{it} = \alpha + \phi_t + \lambda_i * dotcom_{i,t} + \varepsilon \tag{6}$$

[33] In Table E.1, we employ the logarithm of ICT agglomeration (ICTAGG) and utilize a classical non-linear regression approach. In addition, we incorporated quantile regression (Table E.2) to examine the relationship's trend across different quartiles of the dependent variable. Finally, we know that our sample exhibit high heterogeneity in terms of their degree of innovativeness. To reduce this heterogeneity and establish a common basis for comparison, we have decided to utilize the Global Innovation Index (2015) as a benchmark to merge our regions. By using this index, we can categorize, and group countries based on their innovation performance (Table E.3).

Hence, we predict the regional level of *ICTAGG* by using the estimated coefficients from Eq. 6. We then take the predicted instrument and insert it into a normal IV estimate. The predicted value of *ICTAGG* correlates with actual *ICTAGG* values very significantly.[34]
This tool could be particularly valuable because the high-tech sectors, including ICT, may have been impacted differently by the bursting of the speculative bubble in the early 2000s across the regions in our sample. This sudden downturn in the high-tech sectors may have hindered the implementation of new technologies, mainly due to the mistrust that the bursting of the speculative bubble had caused. These factors could potentially create endogeneity issues and impact the relationship between technology specialization and green productivity in your study.

### 5.3. Spatial autocorrelation

To verify whether there is spatial dependence in ICT agglomeration and green economic growth, we use global and local Moran's *I* to test spatial autocorrelation.

$$\text{Global Moran's I: I} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}(X_i - \bar{X})(X_j - \bar{X})}{S^2 \sum_{i=1}^{n}\sum_{j=1}^{n} W_{ij}} \tag{7}$$

$$Local\ Moran's\ I: I = I_i(d) = Z_i \sum_{i \neq 1}^{j} W'_{ij} Z_j \tag{8}$$

Where $S^2 = \frac{\sum_{i=1}^{n}(X_i - \bar{X})^2}{n}$, $X_i$ is the sample observation value of region i, and n is the total number of regions considered in this study $Z_i = \frac{X_i - \bar{X}}{\sigma}$ , $\sum_{i \neq 1}^{j} W'_{ij} Z_j$ is the spatial lag vector – which represents the weighted average deviation of green economic growth index in adjacent areas –, $W_{ij}$ is the spatial weight matrix, which is determined in this paper by geographical distances.
Finally, we develop also the bivariate Local Moran's I. The treatment of the bivariate Local Moran's I closely follow that of its global counterpart (Anselin L. et al., 2002). In essence it captures the relationship between the value for $GTFP_{it}$at location i and the average of the neighboring value *ICTAGG* $x_i$, and its spatial lag $\sum_j w_{ij}\, y_j$.

$$I_i^B = c x_i \sum_j w_{ij}\, y_j \tag{9}$$

[34] We provide zero-stage results in Appendix D.1.

Where $w_{ij}$ are the elements of the spatial weights' matrix.

### *5.4. Spatial Durbin Model*

The next step after the spatial autocorrelation analysis is the implementation of a spatial model, our choice fell on the Spatial Durbin Model. The SDM is a statistical model commonly used in spatial econometrics to analyze the relationship between a dependent variable and its spatially lagged and contemporaneous independent variables. It extends the standard Durbin model by incorporating spatial dependencies into the regression framework. In the SDM, the dependent variable is influenced not only by its own past values and the contemporaneous values of independent variables but also by the spatially lagged values of both the dependent and independent variables. This allows for capturing spatial spillover effects or interactions among neighboring observations.

In Eq. 10, we include the same variables as in Eq. 5, but replace all control variables with $(X_{it})$. Additionally, we introduce the lagged dependent variable $(Y_{it-1})$ and spatially lagged independent variables $W(X_{it})$ ,$W(ICTAGG_{it})$ and $W(ICTAGG^2{}_{it})$. We also include country $\lambda_f$ and year $\phi_s$ fixed effects.

$$Y_{i,t} = \beta_0 + b_1 Y_{it-1} + \beta_2 X_{it} + \beta_3 W(X_{it}) + \beta_4 ICTAGG_{it} + \beta_5 W(ICTAGG_{it}) + \beta_6 W(ICTAGG^2{}_{it}) + \lambda_f + \phi_s + \varepsilon_{it} \quad (10)$$

## 6. Results

### *6.1. The basic results of ICT agglomeration on Green TFP, TECH and TECCH*

Table 4 presents the results of our estimation of Eq. 5. The first three columns show the results of our $GTFP_{it}$ estimation. The next three columns (4, 5, and 6) use $TECH_{it}$ as the dependent variable, while the final three columns (7, 8, and 9) use $TECCH_{it}$ as the dependent variable. The first column of each dependent variable (columns 1, 4, and 7) represents the control variables. In the second column of each dependent variable, we added our focal variables $ICTAGG$, and in the third column, we added $ICTAGG_{it}$ squared to detect any quadratic relationship with our focal variable.

The results show that $ICTAGG$ has a positive and significant effect on $GTFP_{it}$ in columns 2 and 3, with the coefficient increasing from 0.0309 to 0.0675 when $ICTAGG$ squared is added. In columns 5 and 6, $ICTAGG$ has a positive and significant effect on $TECH_{it}$, while in columns 8 and 9, it has a positive but insignificant effect on $TECCH_{it}$. The coefficient estimates for $ICTAGG$ squared are negative and significant in columns 3 and 6, but non-significant in column 9. This suggests that there is a non-linear quadratic relationship between our dependent variable and the independent variable, which is captured by our model. If the linear term $(ICTAGG_{it})$ is positive and significant and the quadratic

($ICTAGG$) term is negative and significant, it indicates that the relationship between the independent variable and the dependent variable is non-linear and presents an inverted U-shaped curve. This means that after a certain point, an increase in ICT agglomeration starts to have a negative effect on the dependent variable. In other words, this may indicate that an excessively high concentration of the $ICTAGG$ may have beneficial effects up to a certain point. However, beyond that point, it may begin to reduce the benefits or even become detrimental to the dependent variable.

Among the control variables, it is noteworthy to examine the result of the structural change variable. In columns 5 and 6, the percentage of added value of services over the regional total ($ECST_{it}$) is found to be significant and negative, indicating that a service-based economy hinders the improvement of technologies used. However, in the following columns (7, 8 and 9), this variable suggests that a radical change of technologies is favoured by an economic structure that is particularly skewed towards services. In addition, the results indicate that the logarithm of GDP per capita ($GDPC_{it}$) has a positive and significant impact on all dependent variables, except for columns 8 and 9. However, the other control variables used in the analysis are rarely significant.

Our results indicate that the models have a relatively high R-squared value, indicating that they explain a substantial amount of variation in the outcome of interest. Additionally, the models control for region and year fixed effects (FE), meaning that the coefficients reflect the differences in the outcome of interest between countries and across time, holding other factors constant. The standard errors are clustered at the regional level, so that the model accounts for the possibility of correlation between the errors of different observations within the same regions.

**Table 4 - The baseline results of ICT agglomeration on GTFP, TECH and TECCH**

| VARIABLES | (1) FE GTFP | (2) FE GTFP | (3) FE GTFP | (4) FE TECH | (5) FE TECH | (6) FE TECH | (7) FE TECCH | (8) FE TECCH | (9) FE TECCH |
|---|---|---|---|---|---|---|---|---|---|
| $ICTAGG_{it}$ | | 0.0309** | 0.0675*** | | 0.0130* | 0.0342** | | 0.0174 | 0.0319 |
| | | (0.0145) | (0.0204) | | (0.00706) | (0.0167) | | (0.0107) | (0.0215) |
| $ICTAGG_{it}^{2}$ | | | -0.00690** | | | -0.00401* | | | -0.00274 |
| | | | (0.00287) | | | (0.00224) | | | (0.00303) |
| $R\&D_{it}$ | -0.00360 | -0.00165 | -0.000389 | 0.00315 | 0.00396 | 0.00469 | -0.00633 | -0.00523 | -0.00473 |
| | (0.00741) | (0.00718) | (0.00695) | (0.00387) | (0.00379) | (0.00373) | (0.00606) | (0.00598) | (0.00597) |
| $EDU_{it}$ | -0.000453 | -0.000580 | -0.000720 | -0.000789 | -0.000842 | -0.000923 | 0.000299 | 0.000227 | 0.000172 |
| | (0.00101) | (0.00101) | (0.000991) | (0.000753) | (0.000744) | (0.000731) | (0.000998) | (0.000996) | (0.000977) |
| $POP\_DENS_{it}$ | 0.00820 | 0.0315 | 0.0454 | 0.0605 | 0.0703 | 0.0783* | -0.0501 | -0.0370 | -0.0315 |
| | (0.102) | (0.100) | (0.0975) | (0.0432) | (0.0430) | (0.0424) | (0.112) | (0.112) | (0.110) |
| $ECST_{it}$ | 0.0106 | -0.00999 | 0.0315 | -0.194** | -0.202** | -0.178* | 0.213* | 0.201* | 0.218* |
| | (0.115) | (0.120) | (0.116) | (0.0874) | (0.0901) | (0.0905) | (0.114) | (0.116) | (0.118) |
| $GDPC_{it}$ | 0.101** | 0.102** | 0.107*** | 0.0652** | 0.0653** | 0.0682** | 0.0390 | 0.0392 | 0.0412 |
| | (0.0417) | (0.0399) | (0.0395) | (0.0269) | (0.0267) | (0.0266) | (0.0407) | (0.0400) | (0.0404) |
| Constant | -0.121 | -0.250 | -0.422 | 0.165 | 0.111 | 0.0111 | 0.668 | 0.596 | 0.528 |
| | (0.526) | (0.477) | (0.473) | (0.373) | (0.367) | (0.365) | (0.482) | (0.463) | (0.472) |
| Observations | 667 | 667 | 667 | 667 | 667 | 667 | 667 | 667 | 667 |
| R2 | 0.720 | 0.722 | 0.723 | 0.342 | 0.345 | 0.346 | 0.719 | 0.720 | 0.720 |
| N_clust | 95 | 95 | 95 | 95 | 95 | 95 | 95 | 95 | 95 |
| Region FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES | YES | YES | YES |

Notes: Clustered standard errors at the regional level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

### *6.2. Robustness check: instrumental variable approach*

Up to this point, we have considered our FE model (Eq.5), but to check our results, we decided to use the instrumental variables approach (IV). The IV approach reduces causal relationships between variables in situations where traditional regression techniques may produce biased results due to endogeneity issues. In our case, the use of IV is important because the variable of interest, ICT agglomeration, may be correlated with unobserved factors that affect green productivity and green technological change, leading to endogeneity issues.

Our IV estimates confirm the results of our FE model (Table 5). Specifically, in columns (1) and (2), we find that $ICTAGG$ has a positive and significant effect on $GTFP_{it}$, suggesting that regions with higher ICT agglomeration have higher $GTFP_{it}$ growth. Additionally, in columns (3) and (4), we find that ICT agglomeration is positive and significant only for $TECH_{it}$, indicating that regions with higher ICT agglomeration are more likely to adopt new technologies and experience higher growth in high-tech industries. The IV estimates also confirm the presence of a quadratic relationship between the dependent variable and $ICTAGG$, as found in the previous estimation.

Regarding the control variables, the log of GDP per capita ($GDPC_{it}$) has a positive and significant effect across columns 1 to 4, indicating that richer regions tend to experience higher green productivity growth and adopt new technologies more quickly. However, the other control variables, including R&D expenditure, demographic characteristics, and economic structure, have mixed effects and are generally not significant across different columns.

It is important to note that the validity of IV estimates depends on the strength of the instrument used. We report the rank of the first-stage F-statistic (RKF), which is a measure of the strength of the instrument. In general, a higher RKF value indicates a strong instrument and increases confidence in the validity of the IV estimates. In our case, the reported RKF values are relatively high, suggesting that the IV estimates may be reliable.

**Table 5 - The IV results of ICT agglomeration on GTFP, TECH and TECCH**

| VARIABLES | (1)<br>IV<br>GTFP | (2)<br>IV<br>GTFP | (3)<br>IV<br>TECH | (4)<br>IV<br>TECH | (5)<br>IV<br>TECCH | (6)<br>IV<br>TECCH |
|---|---|---|---|---|---|---|
| $ICTAGG_{it}$ | 0.0928** | 0.155** | 0.0374* | 0.0636** | 0.0555 | 0.0923 |
| | (0.0442) | (0.0669) | (0.0191) | (0.0290) | (0.0356) | (0.0603) |
| $ICTAGG_{it}^2$ | | -0.0202** | | -0.00845* | | -0.0119 |
| | | (0.00987) | | (0.00428) | | (0.00908) |
| $R\&D_{it}$ | 0.00226 | 0.00312 | 0.00551 | 0.00587 | -0.00283 | -0.00232 |
| | (0.00755) | (0.00765) | (0.00404) | (0.00402) | (0.00639) | (0.00659) |
| $EDU_{it}$ | -0.000835 | -0.00106 | -0.000943 | -0.00104 | 7.02e-05 | -6.19e-05 |
| | (0.00101) | (0.00102) | (0.000745) | (0.000744) | (0.000972) | (0.000966) |
| $POP\_DENS_{it}$ | 0.0782 | 0.0850 | 0.0887* | 0.0915** | -0.00816 | -0.00418 |
| | (0.103) | (0.0834) | (0.0491) | (0.0451) | (0.101) | (0.0922) |
| $ECST_{it}$ | -0.0512 | 0.0998 | -0.219** | -0.155 | 0.176 | 0.265* |
| | (0.153) | (0.146) | (0.0973) | (0.0971) | (0.127) | (0.141) |
| $GDPC_{it}$ | 0.102** | 0.117*** | 0.0655** | 0.0716*** | 0.0396 | 0.0481 |
| | (0.0405) | (0.0422) | (0.0273) | (0.0271) | (0.0398) | (0.0423) |
| Observations | 667 | 667 | 667 | 667 | 667 | 667 |
| Region FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| N_clust | 95 | 95 | 95 | 95 | 95 | 95 |
| rkf | 264.9 | 25.28 | 264.9 | 25.28 | 264.9 | 25.28 |

Notes: Clustered standard errors at the regional level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

### *6.3. Spatial Autocorrelation*

The Table 6 presents the results of a global Moran's I analysis for four variables, $GTFP_{it}$, $TECH_{it}$, $TECCH_{it}$and $ICTAGG$ for the years 2001 to 2010. The I column shows the value of the Moran's I statistic, which measures spatial autocorrelation. The "p-value" column shows the significance level of the Moran's I statistic. The global Moran's I test provides important information about the relationship between spatial variables. A positive Moran's I value indicates that similar values tend to be located near each other, while a negative value indicates that dissimilar values tend to be located near each other.

The results show that total GTFP has a positive and highly significant spatial autocorrelation in almost all years examined - the same is also true for, $TECH_{it}$ and $TECCH_{it}$- while ICT agglomeration has a negative and not statistically significant spatial autocorrelation for all years. The highly significant positive spatial autocorrelation of $GTFP_{it}$, $TECH_{it}$ and $TECCH_{it}$ suggest that areas with high levels of this variable are probably surrounded by other areas with high levels. There is therefore a spatial correlation of green productivity. On the other hand, the negative, non-statistically significant spatial autocorrelation of ICT agglomeration suggests that there is no clear pattern in the distribution of this variable in the study area.

**Table 6 - Global Moran's I index values of GTFP, TECH, TECCH and ICTAGG from 2001 to 2010**

| | GTFP | | TECH | | TECCH | | ICTAGG | |
|---|---|---|---|---|---|---|---|---|
| Year | I | p-value | I | p-value | I | p-value | I | p-value |
| 2001 | 0.065*** | 0.000 | 0.000 | 0.236 | 0.110*** | 0.000 | -0.022 | 0.206 |
| 2002 | 0.015** | 0.016 | 0.070*** | 0.000 | 0.022*** | 0.002 | -0.024 | 0.171 |
| 2003 | 0.111*** | 0.000 | 0.044*** | 0.000 | 0.099*** | 0.000 | -0.023 | 0.199 |
| 2004 | 0.100*** | 0.000 | 0.094*** | 0.000 | 0.073*** | 0.000 | -0.021 | 0.235 |
| 2005 | 0.046*** | 0.000 | -0.008 | 0.435 | 0.067*** | 0.000 | -0.021 | 0.234 |
| 2006 | 0.072*** | 0.000 | 0.057*** | 0.000 | 0.098*** | 0.000 | -0.021 | 0.238 |
| 2007 | 0.063*** | 0.000 | 0.072*** | 0.000 | 0.042*** | 0.000 | -0.018 | 0.293 |
| 2008 | 0.040*** | 0.000 | 0.042*** | 0.000 | 0.060*** | 0.000 | -0.018 | 0.300 |
| 2009 | -0.008 | 0.410 | 0.018** | 0.027 | 0.013** | 0.025 | -0.018 | 0.304 |
| 2010 | 0.020*** | 0.003 | 0.030*** | 0.003 | 0.013*** | 0.001 | -0.018 | 0.306 |

Notes: Clustered standard errors at the regional level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

### *6.3.1. Local Moran's I*

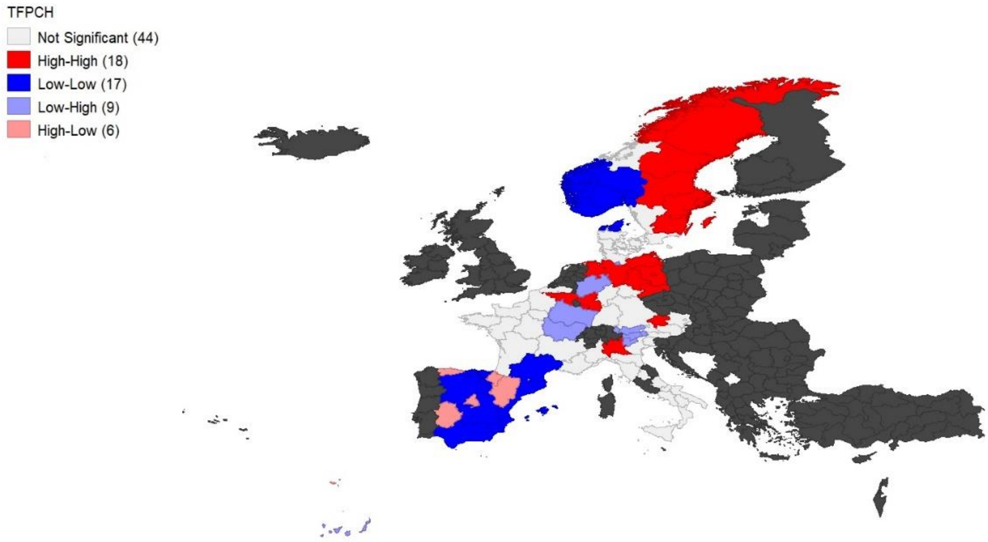
To investigate the spatial distribution of green economic growth and ICT agglomeration, we calculated the local Moran's I index for both $GTFP_{it}$ and *ICTAGG.* The resulting scatter plot is divided into four quadrants, and the spatial correlation analysis is presented in Figg. 4 and 5. The cluster map shows the type of influence at the spatial level based on the position of the value and its spatial lag in the Moran scatter plot, with a significance level of 0.25%. This methodology, named LISA (Local Indicators of Spatial Association), is seen as having two important characteristics. First, it provides a statistic for each location with an assessment of significance. Second, it establishes a proportional relationship between the sum of the local statistics and a corresponding global statistic. Figures 5 and 6 depict all four categories by using LISA (Anselin, 2010):

- High-High clusters are shown in red, indicating regions with high green productivity (high ICT agglomeration) that are geographically close to other regions with high green productivity (high ICT agglomeration).
- Low-Low clusters are shown in blue, indicating regions with low green productivity growth (low ICT agglomeration) that are geographically close to other regions with low green productivity growth (low ICT agglomeration).

- Low-High spatial outliers are also shown in blue, representing regions with low green productivity growth (low ICT agglomeration) that are surrounded by regions with high green productivity growth (high ICT agglomeration).
- High-Low spatial outliers are shown in pink, representing regions with high green productivity growth (high ICT agglomeration) that are surrounded by regions with low green productivity growth (low ICT agglomeration).

Fig. 5 suggests that there is a spatial correlation of Green TFP where regions with a high growth rate of $GTFP_{it}$ tend to be agglomerated in nearby areas, but the same is also true for regions with a low growth rate of $GTFP_{it}$. On the other hand, Fig. 6 suggests a less clear picture, where regions with low ICT agglomeration are often close to regions with high ICT concentration (L-H). However, we can still identify a good number of H-H and L-L clusters.

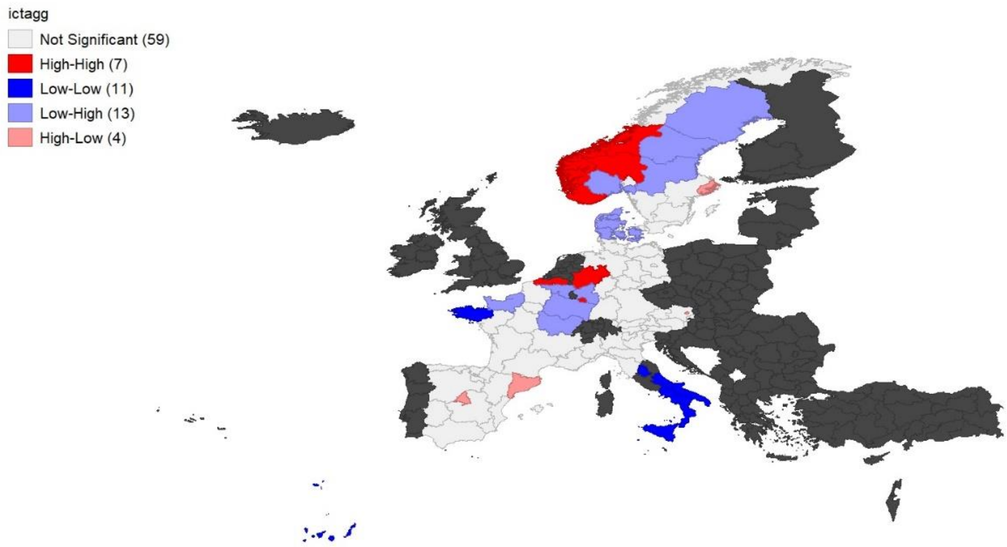
**Fig. 5 - LISA cluster map of Green TFP in 2010**




Notes: The cluster map GTFP shows the influence at the spatial level based on the position of the value and its spatial lag in the Moran scatter plot, with a significance level of 0.25%.

Source: Authors' elaboration.

**Fig. 6 - LISA cluster map of ICT agglomeration in 2010**



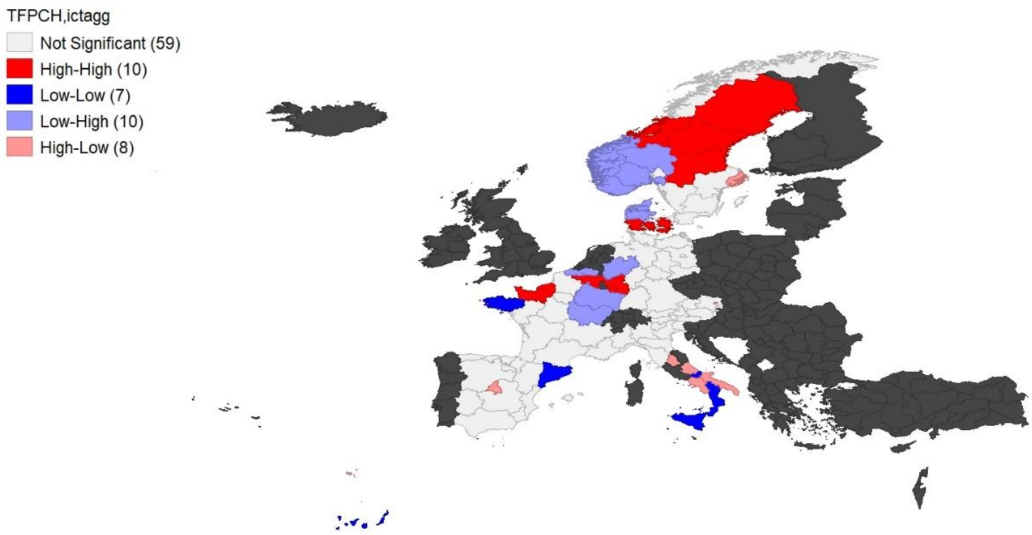

Notes: The cluster map ICT Agglomeration shows the influence at the spatial level based on the position of the value and its spatial lag in the Moran scatter plot, with a significance level of 0.25%.

Source: Authors' elaboration.

### *6.3.3. Bivariate Local Moran's I*

Fig. 7 shows the results of our bivariate Local Moran's I analysis. While the interpretation of this analysis is not straightforward, we can infer that high Green TFP growth is often accompanied by proximity to regions with high ICT agglomeration. We deduce this from the presence of 10 High-High (H-H) regions, as well as 10 regions with low $GTFP_{it}$ that are close to regions with high ICT agglomeration (L-H). In contrast, there are only a few regions (5) with high $GTFP_{it}$ close to regions with low ICT agglomeration. Finally, there are only 3 regions with low values of both Green TFP and ICT agglomeration (L-L). In conclusion, it appears that there is a positive relationship between ICT agglomeration and Green TFP, as there are more regions with high values of both variables (10 H-H) than there are regions with low values of both variables (L-L). Additionally, there are more regions with high ICT agglomeration values but low Green TFP values (10 L-H) than there are regions with high Green TFP values but low ICT agglomeration values (5 H-L), which suggests that ICT agglomeration may be more important for achieving high Green TFP growth values than vice versa.

**Fig. 7 - BiLISA cluster map: GTFP growth and ICT agglomeration in 2010**




Notes: The cluster map ICT Agglomeration shows the influence at the spatial level based on the position of the value and its spatial lag in the Moran scatter plot, with a significance level of 0.25%.
Source: Authors' elaboration.

### *6.4. Spatial Durbin model*

The evidence discussed so far provides important insights into the role ICT agglomeration can play in terms of green productivity growth. However, in this section we want to go a step further to interpret the spatial relationships between $ICTAGG$, $GTFP_{it}$, $TECH_{it}$ and $TECCH_{it}$. Hence, in this section we propose a study of the dynamics of geographical propagation of patents Green TFP growth through Spatial Durbin Model (SDM). In addition, we maintain regional fixed effects in columns 1, 3 and 5 and regional and annual fixed effects in columns 2, 4 and 6. In Table 7, we show the results from the SDM estimation on our three dependent variables. The estimates used in the SDM consider the quadratic structure. We use the spatially lagged dependent variable ($wY$). Rho is always significant and positive, which suggests that spatial effects are present both in the dynamics leading to new technological specializations and in the branching of innovation across regional boundaries. This confirms the findings of our Global Moran I (Table 6).

The SDM confirms the results shown so far. In particular, the results suggest that $ICTAGG$ seems to have an important role to increase the $GTFP_{it}$ and its components. On the other hand, respect to the previous estimation (FE and IV), the SDM underline the important role of $ICTAGG_{it}$ also for $TECCH_{it}$. Furthermore, it seems that ICT agglomeration has an important role in helping green growth between neighboring regions ($wICTAGG_{it}$ and $wICTAGG_{it}^2$), thus facilitating knowledge transfer (see columns 1, 2, 5 and 6). In addition, the growth of green productivity and its components also seems to play an important role in terms of the spread of the phenomenon among neighboring regions.

Among the control variables, also into the SDM emerge the interesting result of the structural change variable. In this case, $ECST_{it}$ seems to influence in a significative way our $GTFP_{it}$ and $TECCH_{it}$. These results suggest that both $GTFP_{it}$ and $TECCH_{it}$ are favored by an economic structure that is particularly skewed towards services. In addition, the results indicate that the logarithm of GDP per capita ($GDPC_{it}$) has a positive and significant impact on all dependent variables.

Regarding the selection of the Durbin spatial model (SDM), recent studies in the literature have widely acknowledged its superiority over other spatial models (Elhorst, 2014). In order to reinforce our decision, we adopt the approach of Belotti et al. (2017) and conduct two post-estimation tests. These tests will enable us to ascertain if the SDM is indeed the most suitable and appropriate choice for our analysis. Test 1 is a linear null hypothesis test that tests whether the coefficient of the spatially lagged repressor is equal to zero. Test 2 is a nonlinear hypothesis, in which the null hypothesis is that the coefficient of the spatially lagged repressor is equal to the product of the coefficient of the same non-spatially lagged regressor and the coefficient of the spatially lagged dependent variable. The bottom of Table 7 shows the results of these tests which refuse both hypotheses.

**Table 7 - Spatial Durbin Model results**

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| VARIABLES | SDM | SDM | SDM | SDM | SDM | SDM |
| **Main** | | | | | | |
| $ICTAGG_{it}$ | 0.0957*** | 0.0847*** | 0.0366*** | 0.0297** | 0.0572*** | 0.0550*** |
| | (0.0240) | (0.0249) | (0.0134) | (0.0122) | (0.0182) | (0.0204) |
| $ICTAGG_{it}^{2}$ | -0.0110*** | -0.00914*** | -0.00564*** | -0.00403** | -0.00501** | -0.00494* |
| | (0.00292) | (0.00325) | (0.00166) | (0.00187) | (0.00234) | (0.00263) |
| $R\&D_{it}$ | 0.0108** | 0.0111** | 0.00518 | 0.00399 | 0.00602 | 0.00655 |
| | (0.00551) | (0.00551) | (0.00350) | (0.00341) | (0.00422) | (0.00425) |
| $EDU_{it}$ | -0.000142 | 2.90e-05 | -0.000497 | 0.000119 | 0.000360 | -8.77e-05 |
| | (0.000829) | (0.000886) | (0.000540) | (0.000565) | (0.000642) | (0.000730) |
| $POP\_DENS_{it}$ | -0.0677 | -0.0265 | -0.0436 | -0.00679 | -0.0203 | -0.0224 |
| | (0.0627) | (0.0601) | (0.0540) | (0.0539) | (0.0668) | (0.0650) |
| $ECST_{it}$ | 0.238** | 0.247** | -0.0613 | -0.0571 | 0.300*** | 0.305*** |
| | (0.118) | (0.117) | (0.0891) | (0.0856) | (0.0604) | (0.0656) |
| $GDPC_{it}$ | 0.139*** | 0.169*** | 0.0647** | 0.0767*** | 0.0730*** | 0.0926*** |
| | (0.0364) | (0.0377) | (0.0288) | (0.0285) | (0.0283) | (0.0312) |
| **W** | | | | | | |
| $wY$ | 0.0655* | 0.244* | -0.0873 | 0.520* | 0.0606*** | 0.314*** |
| | (0.0394) | (0.145) | (0.125) | (0.306) | (0.0230) | (0.0720 |
| $wICTAGG_{it}$ | 0.945*** | 1.114*** | -0.0281 | -0.0173 | 0.966*** | 1.150*** |
| | (0.235) | (0.297) | (0.148) | (0.171) | (0.230) | (0.319) |
| $wICTAGG_{it}^{2}$ | -0.0955*** | -0.114*** | 0.0101 | 0.0120 | -0.105*** | -0.127*** |
| | (0.0265) | (0.0333) | (0.0162) | (0.0188) | (0.0262) | (0.0352) |
| $wR\&D_{it}$ | 0.00831 | 0.0694 | 0.0204 | 0.0286 | -0.0207 | 0.0251 |
| | (0.0367) | (0.0707) | (0.0187) | (0.0444) | (0.0286) | (0.0504) |
| $wEDU_{it}$ | 0.00486 | 0.00471 | -0.00177 | 0.00198 | 0.00550** | 0.00658 |
| | (0.00394) | (0.00738) | (0.00189) | (0.00373) | (0.00279) | (0.00576) |
| $wGDPC_{it}$ | -0.0461 | 0.00713 | -0.0135 | 0.192 | 0.0264 | -0.196 |
| | (0.0959) | (0.157) | (0.0725) | (0.133) | (0.0636) | (0.148) |
| **Spatial** | | | | | | |
| rho | 1.225*** | 1.148*** | 1.061*** | 1.010*** | 1.241*** | 1.113*** |
| | (0.0457) | (0.0715) | (0.0522) | (0.0739) | (0.0464) | (0.141) |
| **Variance** | | | | | | |
| sigma2_e | 0.000981*** | 0.000946*** | 0.000310*** | 0.000303*** | 0.000805*** | 0.000762*** |
| | (0.000119) | (0.000125) | (2.93e-05) | (2.81e-05) | (0.000125) | (0.000124) |
| | | | | | | |
| Observations | 950 | 950 | 950 | 950 | 950 | 950 |
| Number of id_reg | 95 | 95 | 95 | 95 | 95 | 95 |
| Region FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | | ✓ | | ✓ | | ✓ |
| depvar | GTFP | GTFP | TECH | TECH | TECCH | TECCH |
| AIC | -3908.147 | 3949.684 | -5017.275 | -5029.308 | -4093.953 | -4128.96 |
| BIC | -3835.3 | -3876.837 | -4944.428 | -4956.461 | -4021.106 | -4056.113 |
| Test 1 | 35.54*** | 29.46*** | 18.79*** | 34.19*** | 22.53*** | 17.79*** |
| Test 2 | 31,17*** | 22.92*** | 14.32*** | 30.09*** | 22.17*** | 18.33*** |

Notes: Clustered standard errors at the regional level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

## 7. Conclusions and policy implications

As shown in previous studies (Niebel, 2018b; Wang et al., 2022), ICT agglomeration is likely to lead to an overall reduction in emissions and energy consumption, as well as an increase in productivity. On the other hand, efficiency changes play an important role, as ICT agglomeration could lead to better exploitation of increasing economies of scale and generate an unbalanced concentration of activities in core locations, with ambiguous results in terms of growth-related pollution.

In our results, ICT agglomeration shows a positive impact on both the growth of Green TFP and its two components, the growth of technical development ($TECH_{it}$) and the growth of technological change ($TECCH_{it}$). In particular, the results suggest that the ICT agglomeration is particularly effective for the development of existing technologies - this result is consistent across all analyses conducted - while radical development of new technologies seems to be favored by the ICT agglomeration only in the Spatial Durbin Model. Overall, the global effect on Green TFP growth is evident in all our specifications. In particular, the results that emerged from the Global and (bi)Local Moran's I are interesting. Green TFP growth seems to be related to the presence of spatial clusters that appear to facilitate the development of green technologies, while the ICT agglomeration seems to be less related to the presence of spatial clusters. Instead, the results that emerged from the BiLISA cluster map suggest that the presence of ICT clusters also helps Green TFP growth. This last result is also confirmed by the SDM in which ICT agglomeration is significant and positive with all dependent variables used.

In terms of policy implications, the positive impact of the ICT agglomeration on green total factor productivity ($GTFP_{it}$) suggests that there may be potential benefits in promoting further development in this sector. Furthermore, as demonstrated by previous studies (Niebel, 2018b; J. Wang et al., 2022), it is likely that the ICT agglomeration leads to a reduction in emissions and energy consumption, as well as an increase in productivity. Since the results suggest a strong relationship between the ICT agglomeration and Green TFP, policymakers may want to consider these factors when developing strategies to promote sustainable economic growth.

These results could be of fundamental importance for policy makers who should take these factors into account when developing strategies to promote sustainable economic growth and reduce the negative environmental impacts of industrial activities, by orienting their strategies towards a stronger role of ICT in their economies and also towards attracting foreign investment in this sector. More specifically, if the results show that ICT agglomeration has a significant positive effect on green economic growth, and if spatial factors are at work and show that an increasing level of ICT agglomeration significantly promotes green economic growth in the surrounding areas, the results suggest the positive effect of technological progress that promotes the coordinated development of economic growth, energy saving and emission reduction.

Finally, it is necessary to encourage institutions to innovatively develop new ICT tools, such as green finance, digital commerce and e-business activities, and other ICT-related service activities to stimulate the vitality of the ICT services market. On the other hand, it is important for institutions to continue their investment role in terms of capital allocation developed for the purpose of environmental protection, while slowing down the approval process for high-polluting and high-input industries and strengthening the green transformation of enterprises by several channels: reducing the waste of resources in the process of promoting the agglomeration of ICT industries, promoting the agglomeration of ICT activities and economic factors by following standards and norms for ICT agglomeration in the future, guiding local enterprises to introduce the ICT industry in an orderly manner, and realizing the rational use of resources are other basic policy goals. In addition, from the perspective of the distribution characteristic of ICT agglomeration, the phenomenon of ICT agglomeration in core regions may exacerbate regional disparities. Mutual promotion and development of ICT industries and regional cooperation in environmental governance among countries are very urgent. The government should pay attention to the technological spillovers caused by ICT agglomeration, strengthen the convergence of the ICT industry and traditional industries, and provide the necessary technical and financial support. However, at this stage, the emission reduction capability of technological innovation needs to be stronger than the indirect promotion of carbon emissions through economies of scale.

Therefore, the government can bridge the technology gap by introducing foreign capital, opening the market, and realizing the reduction of carbon emissions through ICT agglomeration. For example, governments should establish the ICT industry cooperation zone, improve the resource sharing of local ICT industries, complement advantages, and further promote the efficient use of resources and rapid technological progress.

Finally, if asymmetric results emerge from the analysis, showing that ICT agglomeration has a significant emission reduction effect in countries with lower carbon emissions, but the opposite effect in countries with severe greenhouse effect, governments need to control the phenomenon of ICT agglomeration to avoid energy waste and inefficient resource allocation for cities with higher carbon emissions, and the convergence of the ICT industry into a high-energy-consuming and high-polluting industry should be controlled. At the same time, governments should promote the improvement of local scientific and technological level while building ICT agglomeration. For example, pilot projects for industrial agglomeration should be established in cities with relatively advanced technology and in cities supported by representative ICT industries and service activities.

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# Appendix

## Section A – ICT classifications and correlation

In this section, we will present two parts: A.1 - the ICT sector classification, and A.2 - the correlation of variables in our sample.

### Section A.1 – Classifications and description of ICT sector

The sectoral coverage of ICT follows the assignment of the NACE code economic activity sectors according to the official OECD definition: "The output (goods and services) of a candidate industry must be primarily intended to perform or enable the function of processing and communicating information by electronic means, including transmission and display".

The codes of the relevant economic activities that meet the official definition of the ICT sector are detailed in Table A.1 below. They can be grouped into three aggregates: "ICT Sector – Total," "ICT Manufacturing" and "ICT Services".

"More than a third of the 165 000 applications received by the EPO in 2017 concerned ICT directly or indirectly. The EPO recognizes the growing importance of ICT to industry, society and the economy while believing that high-quality patents are critical to encouraging, promoting, and protecting innovation in ICT. As such, the Office has created an ICT technical sector within the office, bringing together the EPO's examination competence and specialization in telecommunications, computers, and related areas" (European Patent Office, 2019).

**Table A.1 - NACE v.2 ICT Industry classification**

| | | | |
|---|---|---|---|
| ICT Sector | ICT Manufacturing | 26.1 | Manufacture of electronic components and boards |
| | | 26.2 | Manufacture of computers and peripheral equipment |
| | | 26.3 | Manufacture of communication equipment |
| | | 26.4 | Manufacture of consumer electronics |
| | | 26.8 | Manufacture of magnetic and optical media |
| | ICT Services | 46.5 | Wholesale of information and communication equipment |
| | | 58.2 | Software publishing |
| | | 61 | Telecommunication |
| | | 62 | Computer programming, consultancy, and related activities |
| | | 63.1 | Data processing, hosting, and related activities; web portals |
| | | 95.1 | Repair of computers and communication equipment |

## Section A.2 – Correlation

The Table A.2 shows pairwise correlations.

**Table A.2 - Pairwise correlations**

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) $GTFP_{it}$ | 1.000 | | | | | | | | | | | | | | |
| (2) $TECH_{it}$ | 0.264*** | 1.000 | | | | | | | | | | | | | |
| (3) $TECCH_{it}$ | 0.923*** | -0.128*** | 1.000 | | | | | | | | | | | | |
| (4) $GDPC_{it}$ | 0.016 | -0.001 | 0.018 | 1.000 | | | | | | | | | | | |
| (5) $R\&D_{it}$ | 0.093** | 0.041 | 0.079** | 0.381*** | 1.000 | | | | | | | | | | |
| (6) $EDU_{it}$ | -0.023 | -0.039 | -0.007 | 0.297*** | 0.483*** | 1.000 | | | | | | | | | |
| (7) $POP\_DENS_{it}$ | 0.047 | 0.037 | 0.033 | 0.605*** | 0.188*** | 0.295*** | 1.000 | | | | | | | | |
| (8) $ECST_{it}$ | 0.099** | 0.004 | 0.100*** | 0.296*** | 0.165*** | 0.030 | 0.513*** | 1.000 | | | | | | | |
| (9) $ICTAGG_{it}$ | 0.076** | 0.024 | 0.069* | 0.766*** | 0.352*** | 0.398*** | 0.752*** | 0.530*** | 1.000 | | | | | | |
| (10) $EMP_{it}$ | 0.062* | 0.011 | 0.058 | 0.171*** | 0.332*** | 0.178*** | 0.014 | 0.133*** | 0.278*** | 1.000 | | | | | |
| (11) $EMPICT_{it}$ | 0.087** | 0.027 | 0.077** | 0.409*** | 0.397*** | 0.270*** | 0.168*** | 0.275*** | 0.561*** | 0.828*** | 1.000 | | | | |
| (12) $CAPITAL_{it}$ | 0.075* | -0.012 | 0.080** | 0.284*** | 0.385*** | 0.192*** | 0.081** | 0.218*** | 0.348*** | 0.926*** | 0.876*** | 1.000 | | | |
| (13) $ENERGY_{it}$ | 0.055 | 0.033 | 0.042 | 0.202*** | 0.347*** | 0.200*** | 0.032 | 0.113*** | 0.254*** | 0.922*** | 0.835*** | 0.915*** | 1.000 | | |
| (14) $GDP_{it}$ | 0.079** | 0.023 | 0.070* | 0.314*** | 0.352*** | 0.183*** | 0.092** | 0.197*** | 0.405*** | 0.969*** | 0.921*** | 0.958*** | 0.933*** | 1.000 | |
| (15) $AIRPOL_{it}$ | 0.042 | 0.030 | 0.030 | 0.313*** | -0.010 | -0.301*** | 0.223*** | 0.040 | 0.265*** | 0.356*** | 0.286*** | 0.336*** | 0.335*** | 0.398*** | 1.000 |

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

## Section B – Malmquist-Luenberger productivity index and the relationship between ICT and productivity

### *Section B.1 – DEA-based Malmquist productivity index*

The Malmquist productivity index (MPI) is a measure of productivity change that combines both technical efficiency change (TECCH) and technological change (TECH) into a single index. Data Envelopment Analysis (DEA) is a method used to measure TEC, which is the change in efficiency over time, by comparing the relative efficiency of a set of decision-making units (DMUs). The DEA-based Malmquist productivity index uses DEA to measure TEC, and then combines it with TC to obtain the MPI. In other words, DEA is a tool used to measure one of the components (TEC) of the MPI, and the MPI is a measure of overall productivity change that incorporates both TEC and TC.

#### *Section B.1.1 – A brief review of the literature on Malmquist productivity*

Recently, several studies have been conducted using the Malmquist productivity index approach and the DEA method to investigate productivity change. Fernández et al. (2018) applied the DEA-based Malmquist Productivity Index to evaluate the performance of air separation units, while Li et al. (2017)used the radial version of DEA models in their analysis. RRahman & Salim (2013) used the SBM Network DEA model to measure environmental performance of Chinese industrial systems, and Zhang & Brümmer (2011) studied the impact of policy reform on Chinese agriculture and the productivity change.[35] Khoshroo et al. (2022) apply they study to agriculture sector but using DEA-based Malmquist models to determine the green productivity. Khoshroo et al. (2022), studied the productivity changes in chickpea farms in 16 provinces of Iran from 2007-2015 using energy inputs like human labor, machinery, seed, and fertilizers.[36] Based on the results obtained, four categories were identified to classify the 16 chickpea-producing provinces. Different plans to improve productivity were proposed for each category. According to the results, the category 'machinery' had the highest percentage of total energy savings and thus the highest effect on energy saving and pollution reduction. Mulwa et al. (2012)measured the total factor productivity of sugarcane farming in Kenya by considering the role of undesirable pollutant outputs. They examined differences between the usual indicators of the Malmquist index while not adjusting for the environmental variable. However, they employed conventional radial models and also considered an optimistic viewpoint for measuring performance over time. RRahman & Rahman (2013) studied the total factor productivity in maize cultivation in Bangladesh and found that policies such as investing in soil

[35] DEA is one of the most popular approaches used by managers to measure the performance of agricultural companies.

[36] This research proposed three new Malmquist productivity index (MPI) approaches that simultaneously evaluate the productivity changes over time based on optimistic, pessimistic, and general viewpoints. By using the concept of double frontier, the research proposed a method that provides a comprehensive and realistic assessment of productivity changes compared to conventional MPI.

conservation and irrigation, developing climate-resistant species, and increasing corn prices would increase corn cultivation and create a sustainable production technology. However, their study using stochastic frontier models did not consider undesirable outputs. Another study of Iranian agriculture showed a negative relationship between TFP growth and energy consumption, possibly due to cheap and inappropriate use of energy in the area. This study used conventional data envelopment analysis models and only considered desirable data, not undesirable data (Moghaddasi & Pour, 2016). Finally, Qian et al. (2022) analyses the impact of financial agglomeration on green economic growth in China from 2008 to 2017. The authors, using the Malmquist productivity index, find that financial agglomeration has a significant positive effect on green economic growth, specifically that a 1% increase in the degree of financial agglomeration causes China's green total factor productivity to rise by 0.1837%.[37] This paper is crucial for our study not only because they use the same approach for the analysis but also because there is a strong link between the financial sector and the ICT sector. In fact, the financial sector is traditionally ICT-intensive (Asongu & Moulin, 2016; Chien et al., 2020).

## Section B.2 – The relationship between ICT and productivity

A majority of researchers agree that ICT played a significant role in the US growth resurgence observed from 1995 to 2006. Jorgenson et al. (2008) estimate that the share of growth attributed to ICT increased from 43% during the 1971-1995 period to 59% during the 1995-2000 period. The contribution from increased investment in ICT capital almost doubled, and there was a more than twofold increase in Total Factor Productivity (both inside and outside the ICT producing sector). However, for the post-2000 period, Jorgenson et al. (2008) found that the contribution of investment in ICT capital to growth fell and TFP growth in the ICT producing sector decreased. On the other hand, the role of TFP outside the ICT producing sector (and hence in ICT-using sectors) increased. Overall, it is estimated that ICTs accounted for about 38% of the US output growth during the 2000-2006 period.

The period 1996-2006, the rise in the EU-US labour productivity gap is mainly due to three factors, all of which are related to ICTs. First, the US experienced a higher productivity growth rate in the ICT producing sector, largely due to the impressive technological improvement characterizing this sector (twice as high in the US as it has been in the EU) and to its size, which is relatively larger in the US (significant exceptions are Finland and Sweden). Second, investment in ICT capital (i.e., ICT capital deepening) has been higher in the US than in the EU. Third, Total Factor Productivity (TFP) in the service sector, and especially in wholesale and retail trade and finance, which are heavy ICT users, has been rising much faster in the US than in the EU (with some exceptions, like the Netherlands and the UK). When looking at the contribution of ICTs to labour productivity growth in

[37] This paper is crucial for our study, as the financial sector is traditionally ICT-intensive.

the EU and the US, Bart van Ark (2008) found that in the EU it went from 1.3 percentage points for 1980-1995 to 0.9 for 1995-2004, while in the US, it went from 1 in the former period to 2.2 in the latter, with the largest increase arising from TFP growth. This clearly indicates that ICTs were becoming less of a growth driver in the EU during a period in which the US-EU labour productivity gap was increasing.

However, some researchers argue that ICTs may not generate the same long-term and sustainable innovation drive as General Purpose Technologies (GPTs) did in the past. This is due to the slowdown in productivity and economic growth in the last decade and the decline in their contribution to growth observed in the US (Biagi F., 2013). Despite this, the view that the lower presence of ICT companies, particularly young ICT companies, in Europe is responsible for the growing productivity gap between the US and the EU is supported by more recent research (Veugelers R., 2012; Veugelers & Cincera, 2010; Veugelers R. & Cincera M., 2010; Veugelers et al., 2012).

## Section C – Spatial matrix (W)

We obtain a row-normalized inverse distance weighting matrix, with respect to the latitude and longitude coordinates of the relevant regions. As can be seen in Table C.1, the imported spatial matrix consists of 138 cross-sectional. The regional coordinates were extracted via the Google Maps API Key using the geocode command in the statistical software RStudio. Regional coordinates extracted from Google Maps represent approximate regional geographic centers as specified on Google Maps Developers Platform. We encountered some problems in the construction of our set of coordinates: in fact, some regions were not tracked by Google Maps and in many cases the coordinates of the country were returned. In these cases, we had to correct these errors manually.

**Table C.1 - Summary of spatial-weighting object W**

| | | |
|---|---|---|
| *Matrix* | *Dimensions* | *95 x 95* |
| | *Stored as* | *95 x 95* |
| *Values* | *min* | *0.00* |
| | *mean* | *0.01* |
| | *max* | *0.19* |

## Section D – Zero Stage Result

In Table D.1, we show the results of the zero-stage in which we regress $ICTAGG$ on the predicted ones estimated as in Eq. 6., as well as on the control variables and fixed effects we use in the second stage, as in Eq. 5. The results show nice correlation of the predicted $ICTAGG$ with the observed ones, with coefficient being very strongly correlated with the actual ones.

**Table D.1 - Zero-Stage**

| VARIABLES | ICTAGG |
|---|---|
| $IC\widehat{TAGG}\_hat_{it}$ | 0.710*** |
| | (0.0436) |
| $R\&D_{it}$ | -0.0503** |
| | (0.0224) |
| $EDU_{it}$ | 0.00558* |
| | (0.00304) |
| $POP\_DENS_{it}$ | -0.600 |
| | (0.483) |
| $ECST_{it}$ | 0.581 |
| | (1.083) |
| $GDPC_{it}$ | 0.0390 |
| | (0.179) |
| Constant | 2.311 |
| | (3.686) |
| Observations | 667 |
| R-squared | 0.984 |
| Region x dotcom FE | ✓ |
| Year FE | ✓ |
| N_clust | 95 |

Notes: Clustered standard errors at the firm level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

## Section E – Additional results

### *Section E.1 - The linear results using the logarithm of ICT agglomeration on GTFP, TECH and TECCH*

In the section explaining the results, we emphasize the existence of an inverted U-shaped relationship between ICT agglomeration and green TFP growth. We acknowledge that the peak point of the effect is often higher than the maximum value of ICT agglomeration and highlight the need for caution when interpreting out-of-sample predictions in a quadratic specification, particularly when extreme values are present. To enhance the reliability of our findings, we have conducted two additional estimations.

In Table E.1, we employ the logarithm of ICT agglomeration (ictagg) and utilize a classical non-linear regression approach. The results confirm our earlier findings, indicating a strong and robust relationship between our dependent variables and ictagg.

In addition, we incorporated quantile regression (Table E.2) to examine the relationship's trend across different quartiles of the dependent variable. We observed that the significance remains high for all quantiles, except the last one; however, the coefficient tends to decrease. Notably, the coefficient is highest for the first quantile (Q10) in our analysis, indicating a strong relationship between ICT agglomeration and GTFP when GTFP is low. As GTFP increases, the importance of ICT agglomeration in promoting greener outcomes diminishes, as evidenced by the declining coefficient trend.

**Table E.1 – Robustness check: ln($ICTAGG_{it}$)**

| VARIABLES | (1)<br>FE | (2)<br>IV | (3)<br>FE | (4)<br>IV | (5)<br>FE | (6)<br>IV |
|---|---|---|---|---|---|---|
| $ln(ICTAGG_{it})$ | 0.0364** | 0.110*** | 0.0198** | 0.0453** | 0.0158 | 0.0656* |
| | (0.0156) | (0.0355) | (0.00986) | (0.0213) | (0.0155) | (0.0331) |
| $R\&D_{it}$ | -0.000821 | 0.00481 | 0.00466 | 0.00660 | -0.00513 | -0.00133 |
| | (0.00696) | (0.00761) | (0.00377) | (0.00430) | (0.00595) | (0.00655) |
| $EDU_{it}$ | -0.000735 | -0.00131 | -0.000942 | -0.00114 | 0.000177 | -0.000209 |
| | (0.00101) | (0.00110) | (0.000732) | (0.000769) | (0.000982) | (0.000986) |
| $POP\_DENS_{it}$ | 0.0511 | 0.138 | 0.0838* | 0.114** | -0.0315 | 0.0273 |
| | (0.105) | (0.0910) | (0.0427) | (0.0498) | (0.116) | (0.0951) |
| $ECST_{it}$ | 0.0549 | 0.145 | -0.170* | -0.139 | 0.232** | 0.293** |
| | (0.114) | (0.148) | (0.0856) | (0.0954) | (0.114) | (0.137) |
| $GDPC_{it}$ | 0.112*** | 0.133*** | 0.0708*** | 0.0782*** | 0.0436 | 0.0579 |
| | (0.0397) | (0.0458) | (0.0266) | (0.0280) | (0.0406) | (0.0438) |
| Constant | -0.458 | | -0.0181 | | 0.522 | |
| | (0.518) | | (0.365) | | (0.519) | |
| Observations | 667 | 667 | 667 | 667 | 667 | 667 |
| R-squared | 0.722 | -0.014 | 0.346 | 0.022 | 0.720 | -0.004 |
| Region FE | YES | YES | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES | YES | YES |
| N_clust | 95 | 95 | 95 | 95 | 95 | 95 |
| depvar | TFPCH | TFPCH | TECH | TECH | TECCH | TECCH |
| rkf | | 60.02 | | 60.02 | | 60.02 |

Notes: Clustered standard errors at the regional level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

**Table E.2 – Quantile regression**

| VARIABLES | (1) Q10 | (2) Q25 | (3) Q50 | (4) Q75 | (5) Q90 |
|---|---|---|---|---|---|
| $ICTAGG_{it}$v | 0.227* | 0.213** | 0.189*** | 0.168* | 0.151 |
| | (0.116) | (0.0883) | (0.0650) | (0.0879) | (0.122) |
| $ICTAGG^2{}_{it}$v | -0.0334 | -0.0304* | -0.0252** | -0.0206 | -0.0169 |
| | (0.0226) | (0.0172) | (0.0127) | (0.0171) | (0.0238) |
| $R\&D_{it}$ | 0.0181 | 0.0163 | 0.0131 | 0.0102 | 0.00793 |
| | (0.0235) | (0.0179) | (0.0132) | (0.0178) | (0.0247) |
| $EDU_{it}$ | -0.00247 | -0.00278 | -0.00330** | -0.00377* | -0.00414 |
| | (0.00268) | (0.00204) | (0.00150) | (0.00203) | (0.00282) |
| $POP\_DENS_{it}$ | 0.00817 | -0.0149 | -0.0546 | -0.0904 | -0.118 |
| | (0.260) | (0.198) | (0.146) | (0.197) | (0.273) |
| $ECST_{it}$ | 1.034*** | 0.817*** | 0.443** | 0.105 | -0.159 |
| | (0.394) | (0.300) | (0.224) | (0.298) | (0.416) |
| $GDPC_{it}$ | 0.147 | 0.149 | 0.153** | 0.157 | 0.160 |
| | (0.131) | (0.0996) | (0.0733) | (0.0992) | (0.138) |
| Observations | 667 | 667 | 667 | 667 | 667 |

Notes: Clustered standard errors at the regional level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

***Section E.2 - Allowing for countries heterogeneity.***

The countries under consideration exhibit high heterogeneity in terms of their degree of innovativeness. To reduce this heterogeneity and establish a common basis for comparison, we have decided to utilize the Global Innovation Index[38] (2015) as a benchmark to merge our regions. By using this index, we can categorize, and group countries based on their innovation performance, thereby facilitating a more homogeneous analysis. The sample of countries can be divided into three categories based on the Global Innovation Index (GII), which ranks countries according to their level of innovation.[39] The results suggest that ICT agglomeration is particularly useful for less innovative countries that benefit most from the presence of ICT companies (Table E.3).

[38] The Global Innovation Index (GII) is an annual report that measures and ranks the innovation performance of countries worldwide. It provides a comprehensive assessment of various indicators related to innovation, including inputs (such as institutions, human capital, infrastructure, and market sophistication) and outputs (such as knowledge creation, technology transfer, and creative outputs). The GII is a collaborative effort of several organizations, including Cornell University, INSEAD, and the World Intellectual Property Organization (WIPO).

[39] Our list of countries categorized according to their Global Innovation Index (GII) scores (2015):
GII = 1 (Higher than 60 points): Sweden, Denmark.
GII = 2 (Between 50 and 60 points): Austria, Germany, Norway, France, Belgium.
GII = 3 (Between 40 and 50 points): Italy, Portugal, Spain.

**Table E.3 – The effect of ICT agglomeration on GTFP using the Global Innovation Index (2015)**

| VARIABLES | (1)<br>FE | (2)<br>FE | (3)<br>FE |
|---|---|---|---|
| $ICTAGG_{it}$ | -0.146 | 0.0123 | 0.0439*** |
| | (0.0887) | (0.00868) | (0.00777) |
| $R\&D_{it}$ | 0.00541 | -0.0311*** | 0.0146 |
| | (0.00488) | (0.00883) | (0.0105) |
| $EDU_{it}$ | 0.00426 | -0.000714 | -0.00218 |
| | (0.00444) | (0.00145) | (0.00154) |
| $POP\_DENS_{it}$ | -0.348 | 0.500*** | -0.0941 |
| | (0.428) | (0.102) | (0.112) |
| $ECST_{it}$ | 0.977 | -0.332 | -0.0696 |
| | (0.616) | (0.234) | (0.217) |
| $GDPC_{it}$ | 0.763* | 0.136 | 0.173*** |
| | (0.386) | (0.0938) | (0.0526) |
| Constant | -6.646 | -2.754* | -0.341 |
| | (3.510) | (1.404) | (0.603) |
| Observations | 32 | 215 | 375 |
| R-squared | 0.762 | 0.799 | 0.746 |
| Region FE | YES | YES | YES |
| Year FE | YES | YES | YES |
| N | 32 | 215 | 375 |
| N_clust | 8 | 39 | 39 |
| r2 | 0.762 | 0.799 | 0.746 |
| depvar | TFPCH | TFPCH | TFPCH |

Notes: Clustered standard errors at the regional level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

"It is impossible to progress without change, and those who do not change their minds cannot change anything."

George Bernard Shaw

# *Chapter 3*

## The impact of R&D on the information and communication technology (ICT) firms' growth. A firm level analysis on EU countries


## *Abstract*

The fundamental role of Information and Communication Technologies (ICT) as a tool for promoting the productivity growth of economies, revenue growth for businesses, and as a creator of high value-added jobs has, in recent years, prompted countries first, and then firms, to increase investment in research and development in order to reap the benefits of adopting advanced technologies in the ICT sector. The returns from R&D investments, nevertheless, also depend on specific characteristics of the firms that carry them out, an aspect on which the literature has not yet provided an explicit consensus. This paper, therefore, using a sample of ICT firms located in three EU economies, examines the contribution of R&D to the growth performance of ICT firms, mainly considering the moderating effects of size, age, and then investigating persistence in the firms' growth process. In the analysis, we first adopt a fixed-effects estimation, then mitigate potential problems of unobserved heterogeneity and endogeneity using IV, and, finally, we analyse growth persistence by adopting a dynamic model and a GMM strategy. The results - also consistent with robustness tests controlling for different size and age categories and heterogeneity across ICT sectors - document that firm-specific characteristics influence ICT sector growth with firm growth depending on R&D, firm size, and age. In the FE and IV models we obtain evidence of a moderating effect of size, where R&D returns to growth are stronger for SMEs than for large firms. Furthermore, the R&D premium as a function of age shows a positive and significant effect for the first three age categories, but not for larger firms. When we look at the persistence in the growth process of ICT companies, R&D returns in terms of growth are found to be important for SMEs and less relevant for large companies.



**Keywords:** ICT; R&D; Firm Growth; Firm age; Firm size.

**JEL classification:** O32; O12; O33.

## 1. Introduction

The decisive impact of Information and Communication Technologies (henceforth, ICT) on increasing economic productivity, boosting corporate revenues and creating high value-added jobs, has led countries to recognize the crucial role of ICT and, consequently, to intensify investment in research and development (R&D) and the development of new ICT infrastructures (Nair et al., 2020). In recent years, the centrality of the ICT has been widely recognised in the economic literature, highlighting the capabilities of these technologies in terms of efficiency and sustainability (Bresnahan and Trajtenberg, 1995; Corrocher and Ozman, 2020) and their being a natural vector of innovation for various industries (Koumpis and Pavitt, 1999) due to the inherent characteristic of general purpose technology (GPT) (Helpman, 1998). Indeed, ICTs are not only an important industry in their own right (with a significant contribution to GDP, international trade, and employment), but also provide "the crucial information and communications infrastructure without which economies and societies cannot function" (Fransman, 2010, p. 3).

In addition to this, as the economic literature has traditionally suggested, R&D plays a crucial role in the development of the economy. Over the past three decades, the role of research and development (R&D) as an engine of economic growth has been emphasized by various theoretical and empirical models. Aghion and Howitt (1996) developed a model showing how R&D drives long-term economic growth, while Acemoglu et al. (2006) show how productivity dynamics are influenced by innovation.

The ICT sector is one of the main innovators, with R&D accounting for around 25 per cent of all business expenditure (Veugelers et al., 2012). Indeed, R&D investments have led to innovations in the ICT sector which, in a virtuous circle, have in turn contributed to economic growth worldwide.

The interest in the economic literature in studying the effects of R&D investment on business performance has always been very intense and was further fueled by the emergence of the IT revolution in the 1990s in areas such as software, computerized information, big data and robotization.[40]

As a result of these transformations in the production environment, many countries have increased R&D investments in the digital economy and the intangibility of business capital has increased, playing a more important role in the productivity of the current knowledge economy (Bronzini and Piselli, 2009; Corrado et al., 2017). However, little is still known about ICT firm growth, its relationship with R&D and the role that firm-specific characteristics play in this relationship. In fact, studying the growth of ICT companies is one of the objectives listed in the European Framework

[40] In particular, the issues that most closely affect ICT companies and R&D are part of the so-called "Grand Challenges" of the 21st century. ICT-R&D priorities are focused on eight core topic areas: 1) physical computing foundations (for example, quantum computing); 2) computing systems and architectures; 3) converging technologies and scientific disciplines (for example, the intersection of ICT, biology, nanotechnology, and so on); 4) network infrastructures; 5) software engineering and data management; 6) digital content; 7) human-technology interfaces, and ICT and Internet security.

Programme for Research and Innovation - Horizon 2020 (European Commission, 2021). This is rather surprising when one considers that many ICT firms have experienced considerable growth and, more particularly, when one considers the crucial role of the ICT sector in the aggregate growth of world economies. A still rather limited literature finds that R&D investments by EU ICT firms are associated with increased innovation and business productivity (Kleis et al., 2012; Koutroumpis et al., 2020) and that intangibles positively influence total factor productivity in the ICT sector (Nakatani, 2021).

Given these premises, our aim is to contribute to the literature on the analysis of the determinants of ICT sector growth, as it is widely acknowledged that the ICT sector - which includes telecommunications, information technology, consumer electronics and Internet/media - is a fundamental part of the economy of all countries. Furthermore, firm characteristics such as age and size need to be explored in relation to ICT sector performance, as many contributions suggest that the limited presence of young and large ICT firms in the EU compared to the US leads to a growth gap between the two policy areas to the disadvantage of Europe (Veugelers, 2012; Veugelers & Cincera, 2010; Veugelers et al, 2012). In particular, as suggested again by European Framework Programme for Research and Innovation - Horizon 2020, it is important to study the impact of R&D on SMEs (European Commision, 2021).

Why is it important to study the ICT sector? Firstly, the ICT sector has the highest proportion of firms that engage in collaborative innovation with others. However, certain types of collaborations are more common than others. Despite an increase in the number of ICT firms collaborating with others over time, the majority of innovative ICT firms still do not collaborate with national research institutes. On average, only 18% of innovative ICT firms in Europe collaborate with universities and 11% with research institutes. In contrast, 28% collaborate with clients and suppliers, while 42% collaborate with other firms. The highest levels of collaboration with external partners are found In Norway, the UK, Sweden, Hungary, Lithuania, and Cyprus, while the lowest levels of collaboration are reported in Germany and Spain. The least collaborative innovative ICT companies with research institutes are located in Southern European countries, such as Italy, Cyprus, and Portugal (European Commission, 2016). On the other hand, ICT firms can provide training and support for other companies to integrate new technologies into their operations in a number of ways. They can also provide training programs to teach employees of other companies how to use new technologies effectively, as well as offer ongoing support to help them troubleshoot any issues that may arise. Additionally, ICT firms can develop customized technology solutions that are tailored to the specific needs and objectives of other companies. Hence, by providing such services, ICT companies can help accelerate the adoption of new technologies by other companies, which in turn can improve productivity, efficiency, and competitiveness.

Furthermore, ICT firms often invest heavily in R&D to create new technologies and improve existing ones, which can have spill-over effects in other industries and contribute to overall economic growth.

Therefore, studying the ICT sector is essential for gaining insights into the latest technological advancements, as well as understanding the broader impact of the sector on the economy and society as a whole. In fact, investments in ICT have been shown to contribute significantly to productivity growth in Europe, accounting for 50% of the total growth (European Parliament, 2019). By supporting high-growth start-ups and expanding companies, we can promote innovation and create job opportunities. Therefore, studying the ICT sector, which is one of the most innovative sectors, can be key to improving the business environment, facilitating knowledge branching, and increasing productivity. On the other hand, ICT companies often generate new jobs as they expand, which can have a positive impact on the economy.

Hence, moving from a sample of ICT firms from three EU large countries (Germany, Sweden, Great Britain), for the period 2011-2019, this paper aims to disentangle the sensitiveness of firms' performance, measured as total assets growth to R&D investments, looking at how heterogeneity in size, age and sectors have a moderating impact on R&D investment, controlling for growth persistence, capital structure, profitability, and other financial variables. To strengthen our FE results, we adopt an instrumental variable approach to mitigate concerns linked to endogeneity or reverse causality issues running from firm growth to R&D investments. We further test for growth persistence adopting a dynamic model and a GMM system strategy.

The results of our analysis suggest that firm-specific characteristics influence the effect of R&D investment on ICT firm growth. Indeed, there is evidence that in the ICT sector, SME firms have greater growth benefits from R&D investment than larger firms. Moreover, we have evidence of a positive moderating effect of size on R&D returns to growth, with higher elasticities for SMEs than for large firms. Regarding age, investing in R&D helps younger firms that show higher returns than more mature firms (in our setting, over 40 years old).

In this context, when we also consider the dynamics of persistence in this growth phenomenon, again, SMEs benefit more from R&D investments than larger companies. Even within the ICT sector itself, however, there are heterogeneous dimensions with the benefits in terms of R&D investment growth being greater in ICT service companies than in manufacturing companies.

Our results are also useful to have several insights into policy issues by underlining the relevance of R&D in the growth of SMEs and suggesting that policy makers dealing with innovation-led growth should target R&D incentives to ICT firms. Our results not only underline the impressive contribution that research budgets can have in this technology sector (Bronzini and Piselli, 2016; OECD, 2015), but also suggest that current policy initiatives focused on younger firms need to be strongly supported. At the European and national level, much of the current policy interest and academic guidance is based on the observation that Europe has fewer innovative start-ups than the US, in relative terms.

The rest of the paper is organized as follows: In Section 2, there is a review of the key theoretical and empirical literature. In Section 3, we describe the estimation strategy. Section 4 outlines the data, the variable definitions, and provides some descriptive statistics. Sections 5 and 6 present our results. Finally, in Section 7, we conclude the work.

## 2. Literature Review & Hypotheses

The ICT industry experienced unprecedented progress over the last several decades, expanding from old telephone service to advanced fiber optics, cable, and wireless technologies. The ongoing development of 5G wireless technologies represents a further opportunity to radically expand the capacity and flexibility of wireless networks, which will profoundly influence broadband competition and productivity growth (OECD, 2020). Hence, the ICT industry is still facing significant challenges and opportunities of innovation and growth and as such can be defined as the largest, most dynamic, innovative, and productive industry (Canarella and Miller, 2018). In the Science, Technology, and Industry Scoreboard report (OECD, 2017), the ICT industry was defined as a key enabler of innovation.[41] According to OECD data (OECD, 2020) the ICT industry accounted for around one-third of patents owned in OECD countries, with even higher peaks in the US, Japan, Israel, and Korea. Drawing upon the OECD and the European Commission data and indicators, Daiko et a. (2017) sheds further light on the top R&D investors worldwide in the digital economy, their innovative and creative activities, and their branding strategies. The study pointed out that the top 2000 R&D investors are driving innovations in the ICT sector, where almost 75 per cent of them own ICT patents, another 60 per cent own ICT projects, and a third of all intellectual property deposited by these leading investors relate to the computer and electronic sectors.

The literature also claims that European ICT firms are less efficient than those in the US (Veugelers & Cincera, 2010; Veugelers et al, 2012,) and the ICT sector seems to be responsible for the productivity gap between the US and the EU (Veugelers et al, 2012).

Regarding the strengths and structure of the ICT firms in the European economic system, Fransman (2010) identified some of the points where the European economy lags the world's leading economies. According to the author, the European economy lags a) in the content industry and internet applications compared to the US; b) in the production of computers, semiconductors and electronic equipment compared to the US and Asia; c) in the area of infrastructure such as FTTP (optical fibre to the premises). The reasons behind the gap in terms of innovation and productivity between EU and US ICT companies thoroughly explained by Veugelers (2012) lies in several factors: 1) fewer young leading innovators (yollies) in new high-tech sectors.); 2) difficult access to financing capital; 3) intellectual property issues.

In this study, we will focus on the issue of size, age and financial constraints of ICT firms trying to address some of the core issues identified in Veugelers (2012) regarding the European ICT performance gap, adding a new perspective in terms of the role that R&D play across size, age, and subsectors.

[41] OECD 2013, Science, technology, and industry scoreboard, pp 152

Despite one of the main fields of study deserving further research concerning ICT is related to R&D the literature about these issues is still in an early stage.
Few studies have conducted a cross-country analysis at the ICT firm level. The only exception are two recent papers, which have shed light on how ICT companies do exploit R&D investment to enhance their productivity, providing mixed results. Nakatani (2021) adopts a sample including a mix of countries such as Spain, Italy, South Korea, Japan, and the UK for 2003-2015, showing that intangible assets are positively associated with TFP growth across countries for ICT firms. The positive effect of intangible assets on total factor productivity growth is larger for ICT manufacturing firms than for ICT service firms. Leverage has a positive relationship with total factor productivity development in the ICT sector. More relevant for our analysis, the author found that ICT firms tend to increase their TFP more if they are larger and/or younger. This result is far from the findings of Koutroumpis et al. (2020) which adopt a restricted sample related to Germany, Sweden and the United Kingdom and a span of time 2004-2013 and identify a particular sensitivity of productivity to R&D investment in small and/or old ICT firms. They also found that ICT firms have higher production elasticities with respect to R&D than non-ICT firms.
In conclusion, the literature emphasizes the role of ICT companies in terms of economic growth and innovative processes. It also underlines the high returns to R&D in ICT, but it ambiguously underlines the size and age dynamics of ICT companies and their moderating impact on the returns to R&D.
In this study, we want to fill the gap of knowledge which still exist on the ICT firms in EU concerning the role of R&D on ICT focusing on firm growth rather than on their productivity. We focus on a recent period (2011-2019), and on a sample focusing on three large EU countries: Germany, Sweden, and the United Kingdom.
This paper contributes to the literature in three ways. First, to the best of our knowledge, this is the first study of ICT firm growth in Europe examining the size-growth relationship in the ICT industry. Second, this paper hinges on two strands of the industrial organization literature: on the one hand on the newly developed microeconomics of R&D-based endogenous firm growth (Thompson, 2001), which emphasizes the importance of the stock of R&D as a mechanism of firm growth, on the other hand, on the large industrial business literature analysing age and size determinants of firm growth. The third contribution is that we use an instrumental variable approach to address the problems of endogeneity and unobserved heterogeneity in R&D investment (Roodman, 2009).
In the following, we review the relevant literature on the role of R&D, size, and age and we develop a series of statistical hypotheses that define the role of firm-specific characteristics in explaining firm growth in the ICT industry. The characteristics examined include the analysis of the impact on firm growth testing five hypotheses: (1) the impact of the stock of knowledge measured by the R&D stock; (2) the moderating role that size play on the R&D-growth nexus; (3) the moderating role that age play on the R&D- growth nexus; (4) how age and size together play a moderating role on the

R&D-growth nexus; (5) the growth persistence. In addition, we evaluate the effect of key controls, such as financial leverage, profitability, sectoral heterogeneity, on firm growth.

### *2.1. Research and development (R&D) and growth*

Different innovation capabilities lead to persistent differences in the performance and growth of competing firms, as emphasised by the evolutionary literature where innovation drives firm performance and the evolution of industrial structure (Nelson and Winter, 1982). In the ICT sector, where innovation is crucial to achieve growth and stay competitive in a dynamic market, we examine how ICT innovation capabilities (i.e., the stock of technological knowledge) allow firms to achieve better growth performances. Specifically, we measure R&D by building the stock of knowledge and the underlying learning processes through which the stock of knowledge accumulates.

Empirical studies have shown a positive relationship between R&D intensity and firm growth (e.g., Hall, 1987; Yang and Huang, 2005; Del Monte and Papagni, 2003), although some have found a non-significant effect (Heshmati and Loof, 2006; Almus and Nerlinger, 2000). However, given the importance of investigating the growth dynamics of ICT companies, as emphasised in the European Framework Programme for Research and Innovation - Horizon 2020 (European Commission, 2021), we suggest the following first hypothesis:

***Hypothesis 1:*** *R&D intensity in the ICT industry produces a positive effect on firms' growth.*

### *2.2. Research and development (R&D) and size*

Corrocher et al. (2007) underline that large companies are often the best innovators of both new applications and new inventions. In fact, big established firms are major players in promoting new applications and inventions (Pavitt, 1994; Patel and Pavitt, 1997). This depends on: a) prior knowledge accumulated over the years; b) better financial capabilities; c) larger and more competitive research teams (Nelson and Winter, 1982; Malerba and Montobbio, 2003). Firm size has been found to have a positive effect on the level of R&D investment (Acs & Audretsch, 1988), however, evidence for scale economies in R&D is mixed (Cohen & Klepper, 1996). Certainly, larger companies can benefit from economies of scale, but above all they can more easily turn to external sources of finance (Magri, 2009). Other studies have found that larger, older, and more productive firms have higher returns to R&D expenditure (Peters et al., 2017). On the other hand, Criscuolo et al. (2012) find that R&D incentive programmers have a higher positive effect on employment, investment, and net income (but not on total factor productivity) for smaller firms. Similarly, Bronzini and Piselli (2016) find that the smaller the firm, the greater the impact of an R&D policy on the intensity and likelihood of patenting. The evolutionary literature suggests that different innovation capabilities can lead to persistent differences in the performance and growth of competing firms. This mechanism is particularly relevant in the ICT sector, one of the most R&D-intensive

sectors, where technological innovations are crucial for achieving growth and remaining competitive in a dynamic and ever-changing market. Large, established firms in this sector often have accumulated prior knowledge, better financial capabilities, and larger and more competitive research teams, enabling them to be major players in promoting new applications and inventions. However, smaller firms may benefit more from R&D incentive programs and have a greater impact on patenting. Therefore, it is important to study the impact of R&D in small to medium-sized ICT companies as well. The European Framework Programme for Research and Innovation - Horizon 2020 (European Commission, 2021) has also emphasized the importance of investigating the growth dynamics of ICT companies.

Given the controversial evidence we suggest the following neutral hypothesis:

***Hypothesis 2:*** *Size plays a moderating role on the R&D-growth nexus in the ICT industry.*

### 2.3. Research and development (R&D) and age

In terms of the effect of firm age, the empirical findings are also mixed. On the one hand, there are learning effects, as firms gain experience and build on previous routines and capabilities, innovate more effectively, and subsequently achieve better firm performance (Sorensen and Stuart, 2000). Mature firms can accumulate resources, managerial knowledge, and the ability to handle uncertainty, such that previous R&D experience for older firms results in more persistent and less erratic innovation (García-Quevedo et al., 2014). With age firms can accumulate reputations and beneficial market positions, which facilitate relationships with suppliers, customers, and potential collaborators, leading to improved performance. Furthermore, recent research has also found that successful entrepreneurs themselves are middle-aged, not young, and that prior experience in a specific industry predicts greater entrepreneurial success (Azoulay et al., 2018). On the other hand, another strand of literature suggests that young firms are characterized by a disruptive innovation drive (Veugelers, 2012). Older firms may also experience organizational inertia that can hinder learning (Majumdar, 1997). In line with these ideas, firm age has been found to be negatively correlated with the quality of technical innovations, and this effect is greater in rapidly advancing areas of technology (Balasubramanian and Lee, 2008). Others have provided evidence that older firms tend to show lower probabilities of successful innovation (Huergo & Jaumandreu, 2004), although R&D investments by younger firms appear to be significantly riskier than those of more mature firms (Coad et al., 2016). Understanding the effect of firm age on the R&D-growth nexus in the ICT sector is important because it can inform policy decisions and resource allocation strategies. For example, if it is found that younger firms are more likely to generate disruptive innovations, then policymakers may want to focus on supporting and incentivizing the creation of new firms in the ICT sector. On the other hand, if it is found that older firms have accumulated more resources and experience and are more

successful at translating R&D investment into growth, then policymakers may want to consider policies that support the growth and expansion of existing firms.
In this case, again, given the controversial evidence, we suggest the following neutral hypothesis:

***Hypothesis 3:*** *Age plays a moderating role on the R&D-growth nexus in the ICT industry.*

### 2.4. The combined effect of size and age in the growth returns of Research and development (R&D)

According to Veugelers (2015) the lack of private R&D spending in Europe compared to the United States can be explained by the fact that the EU has fewer young companies in the mold of Google or Amazon among its leading innovators, as another previous Bruegel research has shown (Veugelers and Cincera, 2010). "Yollies" firms, i.e., young leading enterprises, such as Google, Fb, Microsoft, are characterized by being young but dynamic and quite big. The yollies (young leading innovators) that Europe has are less R&D intensive. The question investigated by Veugelers (2015) is why European yollies invest less in R&D than their US counterparts. The explanation based on the small size does not tell the entire story. A better explanation is the presence of barriers - often discussed in the European innovation literature - such as the difficulty in accessing external funding.[42] However, less investigated is the opposite question: how R&D can be a better booster for firm growth for young and small ICT companies? To fill this void of knowledge we try to investigate this hypothesis:

***Hypothesis 4:*** *Age and size together play a moderating role on the R&D-growth nexus in the ICT industry.*

### 2.5. Growth persistence

Does firm growth persist over time? The Penrose effect predicts that growth rates in successive periods do not correlate or correlate negatively and do not persist over time due to strategic management problem. Thus, a positive estimate on lagged growth contradicts the Penrose effect, implying the absence of "managerial diseconomies of growth" (Geroski, 2005).[43] Additionally, it also contradicts the Gibrat's law which assumes the absence of autocorrelation in the error terms or no persistence of growth. A few studies such as Wagner (1992), Bottazzi and Secchi (2003), Canarella and Miller (2018) find growth persistence. On the contrary, others like Oliveira and Fortunato (2006) and Goddard et al. (2002) find no evidence of persistence, describing a pattern of oscillating growth, where positive and negative growth alternate with each other. While the literature

[42] Young innovative firms, which often have weaker financial strength and established reputations, are more susceptible to external financial barriers because they are more likely to lack sufficient internal funds for their investment projects (Hall, 2009).
[43] Penrose (1959) argued that managerial constraints limit firm growth through dynamic adjustment costs (Lucas, 1967) that result from adjustments of new productive resources (Marris, 1963).

on growth persistence offers mixed results, recent evidence suggests that high-growth firms, in general, do not tend to maintain their exceptional performance over the long term. However, given the unique characteristics of the ICT sector, it is possible that growth persistence may be more prevalent in this industry. For example, ICT firms may benefit from network effects, where growth in one firm can lead to growth in other firms in the same network, creating a self-reinforcing cycle of growth. Additionally, the rapid pace of technological change in the ICT sector may favor firms that can quickly adapt and innovate, potentially leading to sustained growth. Further research is needed to investigate whether these factors contribute to growth persistence in the ICT sector.

We measure growth persistence using the first lag of firm growth. We propose the following hypothesis regarding persistence and firm growth in the ICT industry:

***Hypothesis 5:*** *Firm growth in the ICT industry exhibits persistence.*

## 3. Estimation strategy

To test the hypothesis described in the previous sections, and to measure the effects of R&D investments on firms' growth, we move from the following baseline equation:

$$Y_{i,t} = \beta X_{it-1} + b_5(R\&DStock_{it-1} \times D_{it-1}) + \lambda_f + \chi_{ct} + \phi_s + \varepsilon_{it} \quad (1)$$

Where the subscripts $i$ and $t$ denote firms and year respectively. Furthermore, $Y_{i,t}$ is firm growth, measured as the log difference in the value of total assets. Then, we include a vector of (log) controls that could affect firms' growth: $solv_{it-1}$ representing the solvency ratio of firm;[44] the $ROE_{it-1}$ as a measure of profitability; then, to control for firms' size, we include both the number of employees ($emp_{i,t-1}$) and the level of assets at t-1 to control for firm capitalization ($assets_{i,t-1}$). Total assets are defined as the sum of current assets, net property, plant and equipment, and other noncurrent assets, including intangible assets, such as patents and other forms of intellectual property, which have become one the most valuable corporate assets in the ICT industry. Using assets measure for proxying firms' size, compared to sales, can be useful for two reasons: first, for new firms or start-up activities in established firms, assets can grow before sales grow (Barbosa and Eiriz, 2011); second, Coad and Hozl (2012) argue that sales may overstate firm size as sales not only reflect the value-added of a company but also the prices of inputs.

In order to test the effect of R&D on firm growth in ICT sector, we include the interaction between R&D stock and a dummy ($R\&DStock_{it-1} \times D_{it-1}$) changing accordingly to the category we consider. In our analysis, we use the variable measured in stocks since different innovation capacity endowments can lead to differences in the growth of competing companies (Canarella and Miller,

[44] The solvency ratio is available in ORBIS and it is computed as the ratio between the shareholders' funds and total assets.

2018). To have a measure of the stock of knowledge available to firms, which would allow us to take into account not only the net amount of knowledge generated, but also the cumulated knowledge generated by past R&D activity, we use the recursive formula following a standard Perpetual Inventory Method (PIM) with declining balance depreciation (Griliches, 1981; Peri, 2005; Quatraro and Scandura, 2019), by initiating the R&D activity in the first year we observe a firm in our dataset.

$$R\&D_{it} = (1 - \delta) stock\_r\&d_t + r\&d_t \quad (2)$$

where $stock\_r\&d_t$ is the end-of-period stock of R&D capital and $r\&d_t$ is the (real) expenditures during the year. The obsolescence rate (δ) applied to depreciate the stock of past R&D is set to 15%, as suggested by the literature (Keller, 2002; Hall et al., 2005). The stock of innovation (R&D) is taken at the beginning of the period (2011). The variable measured in stocks allows taking into account not only the net amount of patents generated, but also the cumulated knowledge generated by past R&D activity. There are multiple reasons for using stock variables in our case. Firstly, accounting for cumulated knowledge may provide a more comprehensive picture of the phenomenon at stake, being the R&D characterised by large fluctuations in time. For this reason, we use the R&D stocks accounting also for the net amount of R&D generated in each ear. The stock variable instead capitalises past and current generated knowledge, thereby providing an unbiased measure of the amount of technical knowledge. Additionally, with respect to R&D flows, R&D stocks allow to account for the fact that the benefits accruing from R&D are likely to persist into future years. Therefore, it is advisable to include opportunely discounted R&D to account for its potential future value.

Finally, in Eq. 1, we control for unobserved heterogeneity by also including firm ($\lambda_f$), country-by-year ($\chi_{ct}$), and industry ($\boldsymbol{\phi_s}$) fixed effects.

Then, to test our hypothesis, we interact the stock of R&D with dummies identifying different firm characteristics and how the latter influence firm growth. First, we exploit the age dimension by dividing ICT firms in four different age classes: from 0 to 10 years, 11-20 years, 21-40 years, and more than 40 years ($R\&DStock_{it} \times AGE_{it}$). Then, we look at different size classes by interacting the stock of R&D with two dimensions: we, indeed, compare the role of the stock of knowledge for small and medium enterprises (SMEs), i.e. those firms with less than 250 employees, and big firms, with more than 250 employees ($R\&DStock_{it} \times SIZE_{it}$). Finally, we consider the effect of both dimensions, age and size, by splitting the sample in eight categories ($R\&DStock_{it} \times AGE_{it} \times SIZE_{it}$). This way, we can investigate heterogeneity in the impact of knowledge stock on growth according to firm's age and size, with unobserved heterogeneity absorbed by our structure of fixed effects.

However, the fixed-effects specification of Eq.1 might be subject to estimation bias due to endogenous input choice. For example, a firm may anticipate demand growth in its market and decide to invest in R&D projects to capitalize on the expansion, or a firm may have unobserved competencies that improve their returns to R&D. To evaluate the possibility of reverse causality running from revenue to R&D capital, we implement IV strategy by predicting in a zero-stage regression the level of R&D expenditure including a set of fixed effects: industry FE capturing time-invariant industry-specific characteristics ($\phi_s$), and country-by-year FE ($\chi_{ct}$). Furthermore, we include firm FE ($\lambda_f$) interacted with a dummy proxying the Sovereign debt crisis which is covered by our sample and hit the ICT firms.

$$R\&D_{it} = \alpha + \phi_s + \lambda_f * Crisis_{2011-2013} + \chi_{ct} + \epsilon_{it} \tag{3}$$

We predict firms-specific expenditure in R&D ($\widehat{R\&D_{it}}$) by using the estimated coefficients from Eq. 3. Then, we compute the "predicted" stocks in R&D ( $R\&\widehat{DStock_{it}}$) by using the PIM as for actual values and use them as instrument for actual knowledge stocks.[45]

We exploit the effect of the sovereign debt crisis as, after a moderate and short-lived recovery in 2009 and 2010, market speculation about the sustainability of sovereign debt and the challenges of negotiating fiscal consolidation dampened expectations of a rapid and complete recovery of the global economy. The impact of these speculations on the output of many of the major economies, their financial institutions and public finances led to a downturn in the business cycle with negative influences on innovation performance. The pressures experienced in the years 2011 to 2013 by financial institutions that play a pivotal role in intermediating with companies for their investments in innovation and the public finances that support these investments, led to a downturn in R&D investments especially for younger companies. As a result of the post-2008 recession, innovative companies in many developed economies suffered a reduction in demand for their products, also linked to substantial uncertainties about future consumption trends. Innovative firms suffered with those belonging to high-technology sectors, which saw their revenues decline significantly with the drop in demand for higher quality innovative products that tends to occur during recessions (Lien, 2010; Piva and Rossi-Lamastra, 2011). This led to a reduction in public support for innovation, which faced challenges more related to fiscal consolidation and market speculation on possible sovereign defaults during this period (OECD, 2012). Although the global financial crisis affected both developed and developing economies, the sovereign debt crisis had an even more pronounced effect on developed economies than on developing ones, with corresponding differences in the impact on innovation.

According to the OECD (2012), three are the potential effects of global financial and public debt crises on R&D and innovation: first, there is a reduction in the demand for innovative goods and

[45] The predicted value of R&D stocks correlates with actual stocks values very significantly. We provide first stage results in Appendix C.1.

services, as they could become more expensive, reducing cash flows to firms. Second, policy makers could reallocate public expenditure towards more short-term policies. Finally, there could be less liquidity available in the financial sector for firms to access, and to make investments in R&D. This happened during the sovereign debt crises of 2011-2013 as documented by the recent literature. Garicano and Steinwender (2016), for example, look at Spanish firms and find that after the 2008 crisis there is a shift from long to short-term investments. Similarly, Peia and Romelli (2022) document, on a sample of European firms, how two contractions in credit supply in Europe following the 2008–09 financial crisis and the 2012 Euro area debt crisis have impacted the composition of corporate investment, leading to a drop in R&D spending. In the next Sections, we describe the data and present the results from our estimations.

## 4. Data and descriptive statistics

We examine a sample of 367 ICT firms in Germany, Sweden, and United Kingdom in a nine-year period (2011-2019). Our data sample was taken from the Orbis database, managed by Bureau van Dijk, including balance sheets and profit and loss accounts of listed and unlisted companies.

Our dataset consists of all the ICT companies that have made or are making investments in R&D in the reference years. The resulting dataset contains 1141 observations. Table 1 shows the distribution of the sample in the ICT sector according to NACE Code 2.0.[46,47]

In order to analyse in depth, the dynamics related to the size and age of ICT companies, we classify companies a) by distinguishing between SMEs and large companies using the variable size and b) by following an experience scale ranging from 0-10 for young companies, 11-20 for relatively young companies, 21-40 for medium-age companies, and finally >40 for mature companies.[48]

The SMEs in our dataset represent about 75 per cent of the entire sample. Thus, large enterprises account for only 25% (see Table A.2 in Appendix). Young enterprises (0-10) account for 9.66 per cent, medium-young enterprises (11-20) for about 34 per cent, medium-senior enterprises (21-40) for about 40 per cent and more mature enterprises (>40) for only 15.88 per cent (see Table A.3 in the Appendix). Using the OECD classification (2013) by size, however, the sample is more evenly divided: 51.71% large enterprises and 48.29% small enterprises. (see Table A.4 in Appendix).

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[46] To compare the resulting sample extracted from Orbis, we used the distribution taken by Eurostat (see Table B.1 and B.2 in Appendix B).

[47] As robustness check we decided to apply the definition of SMEs provided by the Commission Recommendation of 6 May 2003 of the European Union to enhance the robustness of our results (Table D.1). Another potential weakness of our results is the absence of deflated data. To address this limitation, we have deflated our values using the price index as a reference value, with 2015 as the base year (Table D.2).

[48] In addition, to strengthen our results, in the robustness check section 6.1, we also use the classification of big companies (+100 employees) provided by OECD (2013).

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**Table 1 - ICT distribution by NACE Code 2.0 sector (2018)**

| | Freq. | Percent | Cum. |
|---|---|---|---|
| Manufacture of electronic components and boards | 148 | 12.97 | 12.97 |
| Manufacture of computers and peripheral equipment | 53 | 4.65 | 17.62 |
| Manufacture of communication equipment | 47 | 4.12 | 21.74 |
| Manufacture of consumer electronics | 14 | 1.23 | 22.96 |
| Manufacture of magnetic and optical media | 3 | 0.26 | 23.23 |
| Wholesale of information and communication equipment | 70 | 6.13 | 29.36 |
| Software publishing | 87 | 7.62 | 36.99 |
| Telecommunications | 94 | 8.24 | 45.22 |
| Computer programming, consultancy, and related activities | 581 | 50.92 | 96.14 |
| Information service activities | 41 | 3.59 | 99.74 |
| Repair of computers and personal and household goods | 3 | 0.26 | 100.00 |
| Total | 1141 | 100.00 | |

We compute firm growth as the first logarithmic difference of total assets using the FOD transformation. Unlike the first difference (FD) transformation, which subtracts the previous value from the current value, the forward-orthogonal deviation transformation (FOD), suggested by Arellano and Bover (1995), subtracts the average of all available future observations from the current value.

**Table 2 - Descriptive Statistics**

| Variable | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|
| $Y_{it}$ | 1141 | .234 | 1.903 | -9.255 | 7.222 |
| $Y\_cpi_{it}$ | | .715 | 4.666 | 0 | 1076 |
| $solv_{it}$ | 1139 | 47.247 | 24.486 | -82.84 | 100 |
| $assets_{it}$ | 1141 | 315251.63 | 1924476.4 | 1.899 | 32385178 |
| $assets\_cpi_{it}$ | | 223052 | 962625.4 | 2.046854 | 10843240 |
| $emp_{it}$ | 1141 | 510.77 | 1841.996 | 2 | 20492 |
| $ROE_{it}$ | 1124 | 13.851 | 104.643 | -971 | 821.09 |
| $R\&DStock_{it}$ | 1141 | 190139.04 | 1846649.8 | .435 | 22872992 |
| $R\&DStock\_cpi_{it}$ | 1076 | 190790.1 | 1879000 | .415 | 23153132 |
| $Size_{it}^{100}$ | 1141 | .517 | .5 | 0 | 1 |
| $Size_{it}^{sme}$ | 1141 | .252 | .434 | 0 | 1 |
| $SME_{it}$ | 1141 | .161 | .367 | 0 | 1 |
| $AGE\_N_{it}$ | 1139 | 25.234 | 15.37 | 1 | 101 |
| $AGE_{it}$ | 1108 | 2.619 | .864 | 1 | 4 |
| $Size^{sme}$[49] | 1141 | 0.161 | 0.347 | 0 | 1 |

From Table 2, we can see that the average R&DStock in our sample is €19015 million, which confirms that, on average, ICT companies invest heavily in research and development.

In the table we also show the results of the other variables we use in our model. The average number of employees per company is 510 and age is on average 25 years. Thus, on average, our data sample is mostly represented by large and experienced companies. The oldest company in the dataset is 101 years old, while the youngest was founded in 2018. The average total assets of the companies in the dataset are €315 million.

## 5. Results from FE and IV estimations

In this section, we present the results of our baseline estimations. Table 3 summaries the results from the FE estimation (columns 1-4). We first add to a set of control variables our focal variable: R&D stock (column 1); then we interact R&D with size (columns 2), age (columns 3) and with both size and age (column 4). We then present our IV estimation (columns 5). All the regressions are estimated using a set of year dummies, country-time dummies to control for macroeconomic shocks and, thus, capture any unobserved heterogeneity across time and common to all firms. We also include industry, and firm fixed effects.

[49] We decided to apply the definition of SMEs provided by the Commission Recommendation of 6 May 2003 of the European Union to enhance the robustness of our results (Section D.)

All the regressions use firm growth as the dependent variable, computed as the first difference of firm size proxied by assets and computed with the forward orthogonal deviations transformation (FOAD).

The explanatory variables in the baseline model include lagged size; lagged assets; lagged ROE; lagged solvability; lagged R&D stock. Using lagged explanatory variables does not eliminate unobserved heterogeneity. However, it reduces the effect of simultaneity.

Let us first comment on the results of these control variables to then turn the focus on the key variables under analysis and on the different hypothesis sketched out in section 2. First, let us describe the expected outcomes related to our control variables and the results we got.

We use lagged size as the natural logarithm of total assets in line with a large literature (e.g., Dunne and Hughes, 1994; Fama and French, 2002; Rahaman, 2011; Coluzzi et al., 2015). Firm size is the backbone of many models of firm growth and most empirical results find a relationship between firm growth and size.

The inclusion of size in our model also provides the focus of empirical tests of Gibrat's law. As discussed in section 2, the expected sign is mixed: Hall (1987), Dunne and Hughes, (1994), Becchetti and Trovato (2002) show that firm growth inversely relates to firm size suggesting that smaller firms grow faster than larger firms. Conversely, there are also opposite findings showing that firm growth positively relates to firm size and that large firms grow proportionately faster than small firms (Canarella and Miller, 2018; Bentzen et al., 2012), or studies which find that firm growth does not relate to firm size, consistent with Gibrat's law (Acs and Audretsch, 1990; Wagner, 1992).

**Table 3 - The effect of R&D and firms' characteristics on growth**

| VARIABLES | (1) FE | (2) FE | (3) FE | (4) FE | (5) IV |
|---|---|---|---|---|---|
| $\log assets_{it-1}$ | 0.400*** | 0.399*** | 0.401*** | 0.395*** | 0.405*** |
| | (0.0916) | (0.0915) | (0.0949) | (0.0947) | (0.093) |
| $\log emp_{it-1}$ | 0.136** | 0.145** | 0.111* | 0.119* | 0.098 |
| | (0.0660) | (0.0659) | (0.0658) | (0.0653) | (0.069) |
| $solv_{it-1}$ | 0.000681 | 0.000631 | 0.000883 | 0.000830 | 0.001 |
| | (0.00163) | (0.00163) | (0.00168) | (0.00166) | (0.002) |
| $ROE_{it-1}$ | -2.49e-05 | -2.54e-05 | -1.41e-05 | -1.93e-05 | 0.0001 |
| | (0.00020) | (0.00020) | (0.00021) | (0.00021) | (0.0001) |
| $R\&DStock_{it-1}$ | 0.0412** | | | | |
| | (0.0200) | | | | |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme}$ | | 0.0432** | | | |
| | | (0.0200) | | | |
| $R\&DStock_{it-1} \times Size_{it-1}^{large}$ | | 0.0351* | | | |
| | | (0.0200) | | | |
| $R\&DStock_{it-1} \times Age_{it-1}^{0-10}$ | | | 0.0472** | | |
| | | | (0.0225) | | |
| $R\&DStock_{it-1} \times Age_{it-1}^{11-20}$ | | | 0.0466** | | |
| | | | (0.0203) | | |
| $R\&DStock_{it-1} \times Age_{it-1}^{21-40}$ | | | 0.0401** | | |
| | | | (0.0201) | | |
| $R\&DStock_{it-1} \times Age_{it-1}^{>40}$ | | | 0.0298 | | |
| | | | (0.0216) | | |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme} \times Age_{it-1}^{0-10}$ | | | | 0.0559** | 0.0859* |
| | | | | (0.0230) | (0.0505) |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme} \times Age_{it-1}^{11-20}$ | | | | 0.0561*** | 0.0931* |
| | | | | (0.0196) | (0.0476) |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme} \times Age_{it-1}^{21-40}$ | | | | 0.0422** | 0.0830* |
| | | | | (0.0197) | (0.0483) |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme} \times Age_{it-1}^{>40}$ | | | | 0.0259 | 0.0750 |
| | | | | (0.0224) | (0.0519) |
| $R\&DStock_{it-1} \times Size_{it-1}^{large} \times Age_{it-1}^{0-10}$ | | | | 0.0410** | 0.0798* |
| | | | | (0.0204) | (0.0477) |
| $R\&DStock_{it-1} \times Size_{it-1}^{large} \times Age_{it-1}^{11-20}$ | | | | 0.0324 | 0.0746 |
| | | | | (0.0203) | (0.0479) |
| $R\&DStock_{it-1} \times Size_{it-1}^{large} \times Age_{it-1}^{21-40}$ | | | | 0.0350* | 0.0794 |
| | | | | (0.0206) | (0.0487) |
| $R\&DStock_{it-1} \times Size_{it-1}^{large} \times Age_{it-1}^{>40}$ | | | | 0.0287 | 0.0779 |
| | | | | (0.0211) | (0.0510) |
| Constant | -4.835*** | -4.867*** | -4.724*** | -4.716*** | |
| | (0.867) | (0.866) | (0.915) | (0.911) | |
| Observations | 1,141 | 1,141 | 1,093 | 1,093 | 1,054 |
| R-squared | 0.979 | 0.979 | 0.979 | 0.979 | 0.980 |
| Firm FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Sector FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Country#Year FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| K-Paap F-stat | | | | | 9.073 |

Notes: Clustered standard errors at the firm level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

Our findings provide strong evidence that firm size affects firm growth albeit not with a strong significance ($p < 0.05$ in columns 1 and $p < 0.10$ in the other cases). These results provide evidence against Gibrat's law and in line with the large empirical literature opposing this law.

Total assets - for which we check consistent with the statement that the firm involves a set of assets under common ownership and control (Grossman and Hart, 1986) - have the expected positive correlation with firm growth suggesting that the most capitalized firms tend to show better performance in terms of growth.

As regards the financial side of firms, in our Eq. 1 we include two indicators: ROE and the firm solvency ratio. The first, which equals the ratio of net income to common equity, does not appear to correlate with growth in our results. This is a puzzling finding since generally profitable firms have greater internal financing resources, which should allow them to attract external sources of financing and grow more than firms experiencing internal financing constraints. However, the literature provides rather conflicting results in this respect. Some studies show a negative effect of profit on growth (Markman and Gartner, 2002; Lee, 2014) and others show a rather limited influence of profit on growth (Coad, 2007; Bottazzi et al., 2010; Delmar et al., 2013). The solvency ratio, on the other hand, is positively correlated to growth but this relationship is not statistically significant.

As for the results for R&D investment stock on firms' growth in column 1 (Table 3), the effect is positive and highly significant. This result, which confirms our hypothesis H1, is consistent with the industrial organization literature (Hall, 1987; Klette and Griliches, 2000) and the innovation-based endogenous growth models (e.g., Thompson, 2001), which underline the importance of R&D as a mechanism of firm growth. In columns 2-4 we exploit different sources of heterogeneity in firms' performance by splitting the sample by firms' size and age and the combination of the two. The results in column 2 suggest that ICT firms, both big and small ones, have a good elasticity with respect to R&D but the SME have a higher R&D elasticity (H2). Assuming a doubling of R&D expenditure for large ICT firms, the increase in output is 3.5% in large firms compared to 4.3% for SME ICT firms. The difference between the coefficients of SMEs and large companies is significant.[50]

In column 3 we analyze the effect of different age categories on firms' performance (H3). The results show significantly higher advantages from R&D for the first category (less mature enterprises, below 10 years old): assuming a doubling of R&D expenditure for large ICT firms, the increase in growth is 4.7% in this type of firms, compared to 4.6% for firms between 20 and 30 years of age, and 4 per cent for firms between 30 and 40 years of age. Hence, the impact of R&D is positive on the growth of the higher age categories but with a decreasing elasticity and turns into non-significant when we consider firms above 40 years old. Probably, more experienced ICT firms show better resilience and adaptability to the market but are less dynamics in terms of growth.

Column 4 suggests for our H4 that SME and the two lowest age categories companies have the greatest elasticity with respect to R&D: a doubling of R&D spending produces a growth increase of

[50] $F(2,366) = 2.79 \mid Prob > F = 0.0624$

almost 6%. It also supports, but with lower elasticity (4%), the growth of SMEs between 20 and 40 years old, whereas it is not significant for the top age category including firm more than 40 years old. As for large firms, the coefficient of the interacted term is only significant for the lower age category. We may compare the results from the full specification of column 4 of the FE, where both age and size are interacted with R&D, with those from the IV estimation in column 5. In the IV model our results hold. The R&D premium to age and size in the SME exhibit a positive and significant effect across the first three age categories but not for older firms (above 40 years old). Different results are shown by large firms which confirm that the R&D premium on growth is much lower for them but also in this case it is only significant for the lower age category.

In conclusion, age and size seem to play a decisive role in this analysis. In general, although large ICT companies benefit from more favorable conditions for R&D, the SMEs get the higher returns to R&D. Besides, the young ICT companies show a more important growth premium from R&D both in the SME and in the large firms.

### *5.1 Persistence in growth*

Until this point, we have considered our FE and IV models following equation 1. Now, to study the growth persistence keeping unchanged the set of controls and the FE structure, we estimate a modified version of Eq. 1 in which we include the lagged dependent variables by using a GMM (Generalized Method of Moments) model. The equation is as follows:

$$Y_{it} = Y_{it-1} + \beta X_{it-1} + b_5(R\&DStock_{it-1} \times D_{it-1}) + \lambda_f + \chi_{ct} + \phi_s + \varepsilon_{it} \qquad (4)$$

in which we include the lagged dependent variable ($y_{i,t-1}$) on the right-hand side of the equation to capture persistence effects in the growth of ICT firms. This type of setting introduces an element of dynamics, which requires an econometric strategy capable of minimizing any bias in the estimates. The most widely used alternatives to the FE estimation in presence of a dynamic panel model are the dynamic panel GMM estimators (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998) which provide an adequate tool for obtaining asymptotically efficient results and, in addition to avoiding the dynamic panel bias, also address unobserved heterogeneity and endogeneity of regressors. We adopt the system GMM estimator, developed by Blundell and Bond (1998).

In Table 4, we show the results from the GMM estimation. The estimated coefficient on the lagged dependent variable is positive and significant at the 1 percent level. This result suggests that growth is persistent over time and confirms our H5. This finding is consistent with Coad (2007) and with Bottazzi and Secchi (2003). According to these studies, the Penrose effect does not dominate firm dynamics since growing firms do not stagnate in the subsequent time period due to managerial constraints. Growth encourages growth, or, in the evolutionary perspective, “success breeds success” through a positive “self-reinforcing” effect (Nelson and Winter 1982).

Evidence on our variables of interest confirms that the R&D – growth transmission is amplified for younger firms. The returns to R&D in terms of growth persistence are both for SME firms and for large ones a negative function of age: positive and significant if firms are in a range of 10 and 40 years and less significant in the higher age categories. Hence, we find evidence partially consistent with the IV model. When we only consider the interaction between $\mathrm{age}_{\mathrm{it}-1}$and $R\&DStock_{it-1}$ , it appears that younger firms are more elastic to R&D compared to older ones.

The specification test results of the AR(2) reveal that the models do not suffer from second-order serial correlation, and both the Hansen and Sargan test results show that the instruments used are not over-identified. Thus, well conjectured inferences can be made from our results.

**Table 4 - GMM system estimations**

| VARIABLES | (1)<br>GMM | (2)<br>GMM | (3)<br>GMM | (4)<br>GMM |
|---|---|---|---|---|
| $Y_{it-1}$ | 1.205*** | 1.335*** | 1.216*** | 1.420*** |
| | (0.235) | (0.473) | (0.264) | (0.468) |
| $\log assets_{it-1}$ | -0.316 | -0.453 | -0.328 | -0.546 |
| | (0.235) | (0.512) | (0.267) | (0.480) |
| $\log emp_{it-1}$ | 0.115** | 0.117 | 0.113* | 0.121* |
| | (0.0584) | (0.0789) | (0.0618) | (0.0711) |
| $solv_{it-1}$ | 0.00120 | 0.000186 | 0.00161* | 0.000852 |
| | (0.000963) | (0.00153) | (0.000916) | (0.00139) |
| $ROE_{it-1}$ | -0.000133 | -0.000144 | -0.000122 | -0.000177 |
| | (0.000115) | (0.000284) | (0.000117) | (0.000275) |
| $R\&DStock_{it-1}$ | 0.0142 | | | |
| | (0.0108) | | | |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme}$ | | 0.0198* | | |
| | | (0.0120) | | |
| $R\&DStock_{it-1} \times Size_{it-1}^{large}$ | | 0.0173 | | |
| | | (0.0152) | | |
| $R\&DStock_{it-1} \times Age_{it-1}^{0-10}$ | | | 0.0134* | |
| | | | (0.00801) | |
| $R\&DStock_{it-1} \times Age_{it-1}^{11-20}$ | | | 0.0193* | |
| | | | (0.0101) | |
| $R\&DStock_{it-1} \times Age_{it-1}^{21-40}$ | | | 0.0144 | |
| | | | (0.00950) | |
| $R\&DStock_{it-1} \times Age_{it-1}^{>40}$ | | | 0.0143 | |
| | | | (0.0115) | |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme} \times Age_{it-1}^{0-10}$ | | | | 0.0149 |
| | | | | (0.0103) |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme} \times Age_{it-1}^{11-20}$ | | | | 0.0233** |
| | | | | (0.0110) |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme} \times Age_{it-1}^{21-40}$ | | | | 0.0180* |
| | | | | (0.0105) |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme} \times Age_{it-1}^{>40}$ | | | | 0.0180 |
| | | | | (0.0121) |
| $R\&DStock_{it-1} \times Size_{it-1}^{large} \times Age_{it-1}^{0-10}$ | | | | 0.0195 |
| | | | | (0.0125) |
| $R\&DStock_{it-1} \times Size_{it-1}^{large} \times Age_{it-1}^{11-20}$ | | | | 0.0241 |
| | | | | (0.0151) |
| $R\&DStock_{it-1} \times Size_{it-1}^{large} \times Age_{it-1}^{21-40}$ | | | | 0.0146 |
| | | | | (0.0119) |
| $R\&DStock_{it-1} \times Size_{it-1}^{large} \times Age_{it-1}^{>40}$ | | | | 0.0201 |
| | | | | (0.0155) |
| Constant | 2.498 | 3.851 | 2.586 | 4.722 |
| | (2.337) | (4.923) | (2.628) | (4.743) |
| Observations | 1,141 | 1,141 | 1,103 | 1,103 |
| Number of id | 367 | 367 | 367 | 367 |
| j | 92 | 63 | 95 | 69 |
| ar1p | 0.00353 | 0.00403 | 0.00575 | 0.00574 |
| ar2p | 0.943 | 0.899 | 0.933 | 0.870 |
| sarganp | 0.792 | 0.576 | 0.848 | 0.637 |
| hansenp | 0.424 | 0.589 | 0.315 | 0.546 |

Notes: Clustered standard errors at the firm level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

## 6. Robustness checks

### *6.1. Sensitivity to size*

In this section, we aim to strengthen the results shown so far by considering large (≥100) and small (<100) firms size categories as defined by the OECD (2013). As with the baseline, we decided to perform our estimation for both FE and IV. As already seen in previous estimates, this first robustness test also confirms the importance of age in business innovation dynamics. Indeed, whether firms are large or small, age plays a key role: in particular, the youngest age groups for ICT firms are the most elastic to the stock of R&D. In the first column of Table 5, the first three age groups are significant regardless of size.

The second column (model IV) confirms the results of the FE in column 1. Being young plays a key role in the ability of small enterprises (<100 employees) to transform R&D investments into size growth, with the only exception of young firms, for which the interaction is not significant. Comparable results are obtained for large firms (≥ 100 employees).

In conclusion, relatively young (<40 years old and more than 10 years old) enterprises, regardless of their size, have the greatest capacity to transform R&D investments into dimensional growth.

**Table 5 - The determinants of ICT firms' growth: OECD size categories**

| VARIABLES | (1) FE | (2) IV |
|---|---|---|
| $\log assets_{it-1}$ | 0.391*** | 0.400*** |
| | (0.0887) | (0.0873) |
| $\log emp_{it-1}$ | 0.116* | 0.0902 |
| | (0.0636) | (0.0676) |
| $solv_{it-1}$ | 0.000710 | 0.000801 |
| | (0.00163) | (0.00161) |
| $ROE_{it-1}$ | 1.38e-05 | 0.000142 |
| | (0.000210) | (0.000188) |
| $R\&DStock_{it-1} \times Size_{it-1}^{<100} \times Age_{it-1}^{0-10}$ | 0.0475** | 0.0801 |
| | (0.0235) | (0.0510) |
| $R\&DStock_{it-1} \times Size_{it-1}^{<100} \times Age_{it-1}^{11-20}$ | 0.0624*** | 0.101** |
| | (0.0211) | (0.0477) |
| $R\&DStock_{it-1} \times Size_{it-1}^{<100} \times Age_{it-1}^{21-40}$ | 0.0401** | 0.0809* |
| | (0.0201) | (0.0472) |
| $R\&DStock_{it-1} \times Size_{it-1}^{<100} \times Age_{it-1}^{>40}$ | 0.0102 | 0.0701 |
| | (0.0211) | (0.0521) |
| $R\&DStock_{it-1} \times Size_{it-1}^{\geq 100} \times Age_{it-1}^{0-10}$ | 0.0547** | 0.0916** |
| | (0.0217) | (0.0462) |
| $R\&DStock_{it-1} \times Size_{it-1}^{\geq 100} \times Age_{it-1}^{11-20}$ | 0.0370** | 0.0781* |
| | (0.0178) | (0.0467) |
| $R\&DStock_{it-1} \times Size_{it-1}^{\geq 100} \times Age_{it-1}^{21-40}$ | 0.0392** | 0.0834* |
| | (0.0185) | (0.0477) |
| $R\&DStock_{it-1} \times Size_{it-1}^{\geq 100} \times Age_{it-1}^{>40}$ | 0.0297 | 0.0795 |
| | (0.0199) | (0.0501) |
| Constant | -4.641*** | |
| | (0.882) | |
| | | |
| Observations | 1,093 | 1,054 |
| R-squared | 0.980 | 0.130 |
| Firm FE | ✓ | ✓ |
| Sector FE | ✓ | ✓ |
| Country×Year FE | ✓ | ✓ |
| N | 1093 | 1054 |
| Firms | 357 | 340 |
| K-Paap F-stat | | 9.008 |

Notes: Clustered standard errors at the firm level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

### *6.2 Focus on ICT sectors and sub-sectors*

A further control we decided to develop relates to the various sectors that make up ICT in accordance with NACE Code 2.0. The aim is to identify which ICT sectors are more elastic with respect to the R&D stock. In this case we develop two fixed-effects estimates; in the first column of Table 6, we focus on the two macro-sectors, services, and manufacturing; in the second column we go into the details of the ICT sub-sectors.

The first column of Table 6 suggests that services in general is the most dynamic sector for ICT, probably due to the general characteristics of the sector, which is of course mainly related to the world of services.

In the second column, we focus on ICT sub-sectors. For manufacturing, we highlight the result for Manufacture of magnetic and optical media, while for services, the enterprises related to Information service activities seem to be particularly dynamic. Repair of computers and personal and household goods activities, on the other hand, tend to have a bad relationship with R&D stock: in fact, it seems that the stock of R&D even reduces the growth potential of the company belonging to this sector.

**Table 6 - Focus on ICT sectors and sub-sectors.**

| SECTOR | VARIABLES | (1) FE | (2) FE |
|---|---|---|---|
| | $R\&DStock_{it-1} \times Manufacturing$ | 0.0544** | |
| | | (0.0222) | |
| | $R\&DStock_{it-1} \times Services$ | -0.0267 | |
| Manufacturing | | (0.0209) | |
| | Manufacture of electronic components and boards × $R\&DStock_{it-1}$ | | -0.0329 |
| | | | (0.0227) |
| | Manufacture of computers and peripheral equipment × $R\&DStock_{it-1}$ | | 0.0105 |
| | | | (0.102) |
| | Manufacture of communication equipmen t× $R\&DStock_{it-1}$ | | -0.0448 |
| | | | (0.0379) |
| | Manufacture of consumer electronics × $R\&DStock_{it-1}$ | | 0.187 |
| | | | (0.209) |
| | Manufacture of magnetic and optical media × $R\&DStock_{it-1}$ | | 2.479*** |
| Services | | | (0.251) |
| | Wholesale of information and communication equipment × $R\&DStock_{it-1}$ | | 0.130 |
| | | | (0.128) |
| | Software publishing × $R\&DStock_{it-1}$ | | 0.119 |
| | | | (0.104) |
| | Telecommunications × $R\&DStock_{it-1}$ | | 0.0218 |
| | | | (0.0229) |
| | Computer programming, consultancy, and related activities × $R\&DStock_{it-1}$ | | 0.0387 |
| | | | (0.0261) |
| | Information service activities × $R\&DStock_{it-1}$ | | 0.157*** |
| | | | (0.0556) |
| | Repair of computers and personal and household goods × $R\&DStock_{it-1}$ | | -1.746*** |
| | | | (0.315) |
| | Observations | 1,141 | 1,141 |
| | Controls | ✓ | ✓ |
| | Firm FE | ✓ | ✓ |
| | Sector FE | ✓ | ✓ |
| | Country×Year FE | ✓ | ✓ |
| | Firms | 367 | 367 |
| | $R^2$ | 0.979 | 0.980 |

Notes: Control variables: $log\ assets_{it-1}$ , $log\ emp_{it-1}$, $solv_{it-1}$ , $ROE_{it-1}$. Clustered standard errors at the firm level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

## 7. Concluding remarks

The objective of the paper is to study ICT firms and R&D for three European countries between 2011 and 2019 using the ORBIS database and the firms whose R&D data were reported. For this reason, we have developed an analysis considering age and company size. The main finding is that the growth elasticity of ICT firms to R&D is high. In addition to this, the sensitivity of small ICT firms to R&D is higher than the R&D-growth nexus for larger firms. Furthermore, age is also a favorable factor for the growth of ICT companies, but especially young ICT companies are more responsive to R&D spending. IV estimates confirm that ICT firms defined as small and young are able to achieve better R&D results than larger and older firms. Therefore, larger companies, while benefiting from the greater potential deriving from economies of scale, have easier access to capital and have less important returns on R&D in terms of growth.

In terms of policy, our results suggest that policy makers should target R&D incentives to ICT firms to stimulate the business environment and have a huge impact on growth. Furthermore, as pointed out by Veugelers et al. (2012), young ICT companies in Europe are losing ground in terms of growth. It would be necessary to relaunch an industrial policy capable of promoting the growth of this type of enterprise, including policies of tax incentives for innovation (Dechezleprêtre, et al., 2016). This would help both small and young companies to grow and innovate.

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## Appendix

## Section A – Classifications and description of ICT sector

In this section we present the ICT sector classification (A.1), the variables and the descriptive statistics of our sample (A.2).

### *Section A.1 – Classifications and description of ICT sectors*

The sectoral coverage of ICT follows the assignment of the NACE code economic activity sectors according to the official OECD definition: “The output (goods and services) of a candidate industry must be primarily intended to perform or enable the function of processing and communicating information by electronic means, including transmission and display”.

**Table A.1 - NACE v.2 ICT Industry classification**

| | | | |
|---|---|---|---|
| ICT Sector | ICT Manufacturing | 26.1 | Manufacture of electronic components and boards |
| | | 26.2 | Manufacture of computers and peripheral equipment |
| | | 26.3 | Manufacture of communication equipment |
| | | 26.4 | Manufacture of consumer electronics |
| | | 26.8 | Manufacture of magnetic and optical media |
| | ICT Services | 46.5 | Wholesale of information and communication equipment |
| | | 58.2 | Software publishing |
| | | 61 | Telecommunication |
| | | 62 | Computer programming, consultancy, and related activities |
| | | 63.1 | Data processing, hosting, and related activities; web portals |
| | | 95.1 | Repair of computers and communication equipment |

The codes of the relevant economic activities that meet the official definition of the ICT sector are detailed in Table A.1 below. They can be grouped into three aggregates: “ICT Sector – Total,” “ICT Manufacturing” and “ICT Services”.

“More than a third of the 165.000 applications received by the EPO in 2017 concerned ICT directly or indirectly. The EPO recognizes the growing importance of ICT to industry, society and the economy while believing that high-quality patents are critical to encouraging, promoting, and protecting innovation in ICT. As such, the Office has created an ICT technical sector within the office, bringing together the EPO's examination competence and specialization in telecommunications, computers, and related areas” (European Patent Office, 2019).

### *Section A.2 – Insights on our sample*

Our sample consists of approximately 75% small and medium-sized enterprises (those with fewer than 250 employees) (Table A.2). The most prevalent sector in our sample is Computer programming, consultancy, and related activities. Approximately 39% of companies in our sample are between 21 and 40 years old (Table A.3). Following OECD (2013), we have divided the companies into big and small, with big being defined as companies with at least 100 employees (Table A.4).

**Table A.2 - Distribution of the sample by size**

| | Large | | SMEs | |
|---|---|---|---|---|
| | Freq. | Percent | Freq. | Percent |
| Manufacture of electronic components and boards | 57 | 19.86 | 91 | 10.66 |
| Manufacture of computers and peripheral equipment | 11 | 3.83 | 42 | 4.92 |
| Manufacture of communication equipment | 19 | 6.62 | 28 | 3.28 |
| Manufacture of consumer electronics | 3 | 1.05 | 11 | 1.29 |
| Manufacture of magnetic and optical media | 0 | 0 | 3 | 0.35 |
| Wholesale of information and communication equipment | 9 | 3.14 | 61 | 7.14 |
| Software publishing | 21 | 7.32 | 66 | 7.73 |
| Telecommunications | 44 | 15.33 | 50 | 5.85 |
| Computer programming, consultancy, and related activities | 112 | 39.02 | 469 | 54.92 |
| Information service activities | 0 | 0 | 30 | 3.51 |
| Repair of computers and personal and household goods | 11 | 3.83 | 3 | 0.35 |
| Total | 287 | 100.00 | 854 | 100.00 |

**Table A.3 - Distribution of the sample by age**

| | 0-10 | | 11-20 | | 21-40 | | >40 | |
|---|---|---|---|---|---|---|---|---|
| | Freq. | Percent | Freq. | Percent | Freq. | Percent | Freq. | Percent |
| Manufacture of electronic components and boards | 9 | 8.41 | 25 | 6.51 | 56 | 12.70 | 55 | 31.25 |
| Manufacture of computers and peripheral equipment | 0 | 0 | 11 | 2.86 | 34 | 7.71 | 8 | 4.55 |
| Manufacture of communication equipment | 4 | 3.74 | 2 | 0.52 | 25 | 5.67 | 14 | 7.95 |
| Manufacture of consumer electronics | 2 | 1.87 | 4 | 1.04 | 7 | 1.59 | 0 | 0 |
| Manufacture of magnetic and optical media | 0 | 0 | 2 | 0.52 | 0 | 0 | 0 | 0 |
| Wholesale of information and communication equipment | 7 | 6.54 | 21 | 5.47 | 35 | 7.94 | 6 | 3.41 |
| Software publishing | 2 | 1.87 | 31 | 8.07 | 31 | 7.03 | 20 | 11.36 |
| Telecommunications | 11 | 10.28 | 37 | 9.64 | 38 | 8.62 | 7 | 3.98 |
| Computer programming, consultancy, and related activities | 66 | 61.68 | 227 | 59.11 | 204 | 46.26 | 66 | 37.50 |
| Information service activities | 6 | 5.61 | 21 | 5.47 | 11 | 2.49 | 0 | 0 |
| Repair of computers and personal and household goods | 0 | 0 | 3 | 0.78 | 0 | 0 | 0 | 0 |
| Total | 107 | 100.00 | 384 | 100.00 | 441 | 100.00 | 176 | 100.00 |

**Table A.4 - Distribution of the sample by OECD size classes.**

| | <100 | | ≥100 | |
|---|---|---|---|---|
| | Freq. | Percent | Freq. | Percent |
| Manufacture of electronic components and boards | 52 | 9.44 | 96 | 16.27 |
| Manufacture of computers and peripheral equipment | 21 | 3.81 | 32 | 5.42 |
| Manufacture of communication equipment | 11 | 2.00 | 36 | 6.10 |
| Manufacture of consumer electronics | 7 | 1.27 | 7 | 1.19 |
| Manufacture of magnetic and optical media | 3 | 0.54 | 15 | 2.54 |
| Wholesale of information and communication equipment | 55 | 9.98 | 38 | 6.44 |
| Software publishing | 49 | 8.89 | 61 | 10.34 |
| Telecommunications | 33 | 5.99 | 284 | 48.14 |
| Computer programming, consultancy, and related activities | 297 | 53.90 | 18 | 3.05 |
| Information service activities | 23 | 4.17 | 3 | 0.51 |
| Total | 551 | 100.00 | 590 | 100.00 |

***Section A.3 – Correlation***

Table A.5 shows the correlation matrix between the variables.

**Table A.5 - Correlation among variables**

| Variables | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| (1) $Y_{it}$ | 1.000 | | | | | | | | | |
| (2) $solv_{it}$ | -0.030 | 1.000 | | | | | | | | |
| (3) $assets_{it}$ | 0.436*** | -0.095*** | 1.000 | | | | | | | |
| (4) $empl_{it}$ | 0.548*** | -0.080*** | 0.677*** | 1.000 | | | | | | |
| (5) $ROE_{it}$ | 0.070** | 0.070** | -0.074** | -0.027 | 1.000 | | | | | |
| (6) $R\&DStock_{it}$ | 0.292*** | 0.007 | 0.421*** | 0.782*** | -0.013 | 1.000 | | | | |
| (7) $Size_{it}^{100}$ | 0.651*** | -0.043 | 0.151*** | 0.243*** | 0.122*** | 0.097*** | 1.000 | | | |
| (8) $Size_{it}^{sme}$ | 0.665*** | -0.023 | 0.256*** | 0.397*** | 0.074** | 0.169*** | 0.560*** | 1.000 | | |
| (9) $AGE\_N_{it}$ | 0.267*** | 0.046 | 0.089*** | 0.249*** | 0.091*** | 0.207*** | 0.255*** | 0.261*** | 1.000 | |
| (10) $AGE_{it}$ | 0.274*** | 0.056* | 0.061** | 0.218*** | 0.081*** | 0.136*** | 0.215*** | 0.277*** | 0.860*** | 1.000 |

Notes: In the Table, correlations among variables are displayed. *** p<0.01, ** p<0.05, * p<0.1

## Section B – Data cleaning

To have our final sample, in the first instance, we focused on eliminating errors in reporting values: for example, negative values for revenue, R&D, added value and so on. Companies whose NACE codes were missing, and therefore impossible to classify, were also excluded. We have also excluded observations where the ratio of intangible fixed assets to total fixed assets exceeded unity. Then we have the errors related to companies with negative age, that are also excluded. We also selected only those companies whose R&D value was known via a Boolean variable. We then decided not to eliminate extreme values, as is proposed in many works (Nakatani, 2021), since the boolean variable R&D has already eliminated most of those extreme values and/or gross errors.

Another issue in using the Orbis database is the elimination of duplicate data. When we found duplicate accounts, we eliminated the accounts that were not used for annual reporting.

## Section C – Zero Stage result

In Table C.1, we show the results of the first stage in which we regress the actual R&D stocks on the predicted ones estimated as in Eq. 3., as well as on the control variables and fixed effects we use in the second stage, as in Eq. 1. The results show nice correlation of the predicted stocks - which do not take into account country-time variation that we control for in the second stage - with the observed ones, with coefficient being very strongly correlated with the actual ones.

**Table C.1 – Zero stage result**

| | $R\&DStock_{it}$ |
|---|---|
| $\widehat{R\&DStock}_{it}$ | 0.773*** |
| | (0.0918) |
| $\log assets_{it-1}$ | 0.0995** |
| | (0.0470) |
| $\log emp_{it-1}$ | 0.243*** |
| | (0.0877) |
| $solv_{it-1}$ | 0.000279 |
| | (0.000884) |
| $ROE_{it-1}$ | -5.95e-05 |
| | (0.000115) |
| Observations | 1,085 |
| Firm×Crisis FE | ✓ |
| Sector FE | ✓ |
| Country×Year FE | ✓ |
| Firms | 339 |
| $R^2$ | 0.990 |

Notes: Clustered standard errors at the firm level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

## Section D – Additional results

We decided to apply the definition of SMEs provided by the Commission Recommendation of 6 May 2003 of the European Union to enhance the robustness of our results. According to this recommendation, SMEs are classified as enterprises that employ fewer than 250 persons and have an annual turnover not exceeding EUR 50 million and/or an annual balance sheet total not exceeding EUR 43 million (European Commission, 2003, pp. 36-41).

The results largely confirm the results obtained in previous estimates, in particular we point out that small and young enterprises often have a higher elasticity (Table D.1).

Another potential weakness of our results is the absence of deflated data. To address this limitation, we have deflated our values using the price index as a reference value, with 2015 as the base year. In Table D.2, we present the recalculated values of the dependent variable, total assets, and R&D stock after applying the deflation procedure.[51] The estimation further strengthens our results, indicating that SMEs exhibit greater elasticity to changes in the R&D stock compared to larger companies. Additionally, our findings suggest that young companies tend to benefit more from increases in the R&D stock.

[51] On average, the dependent variable is now 5% higher, the R&D stock is 10% higher, and the total asset is 25% lower.

**Table D.1 – The effect of R&D and firms' characteristics on growth - SMEs definition provided by the Commission Recommendation**

| VARIABLES | (1) FE | (2) IV | (3) FE | (4) IV |
|---|---|---|---|---|
| $\log assets_{it-1}$ | 0.396*** | 0.406*** | 0.385*** | 0.396*** |
| | (0.0902) | (0.0881) | (0.0950) | (0.0939) |
| $\log emp_{it-1}$ | 0.137** | 0.113 | 0.105 | 0.0896 |
| | (0.0656) | (0.0700) | (0.0645) | (0.0684) |
| $solv_{it-1}$ | 0.000655 | 0.000686 | 0.000630 | 0.000789 |
| | (0.00162) | (0.00161) | (0.00168) | (0.00167) |
| $ROE_{it-1}$ | -2.24e-05 | 9.05e-05 | -1.00e-05 | 0.000115 |
| | (0.000201) | (0.000180) | (0.000220) | (0.000201) |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme}$ | 0.0635** | 0.102** | | |
| | (0.0264) | (0.0485) | | |
| $R\&DStock_{it-1} \times Size_{it-1}^{large}$ | 0.0397** | 0.0858* | | |
| | (0.0195) | (0.0478) | | |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme} \times Age_{it-1}^{0-10}$ | | | 0.0650* | 0.0922* |
| | | | (0.0365) | (0.0559) |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme} \times Age_{it-1}^{11-20}$ | | | 0.0773*** | 0.108** |
| | | | (0.0289) | (0.0498) |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme} \times Age_{it-1}^{21-40}$ | | | 0.0543** | 0.0897* |
| | | | (0.0265) | (0.0484) |
| $R\&DStock_{it-1} \times Size_{it-1}^{sme} \times Age_{it-1}^{>40}$ | | | 0.0217 | 0.0592 |
| | | | (0.0306) | (0.0509) |
| $R\&DStock_{it-1} \times Size_{it-1}^{large} \times Age_{it-1}^{0-10}$ | | | 0.0504** | 0.0840* |
| | | | (0.0223) | (0.0481) |
| $R\&DStock_{it-1} \times Size_{it-1}^{large} \times Age_{it-1}^{11-20}$ | | | 0.0391* | 0.0811* |
| | | | (0.0200) | (0.0466) |
| $R\&DStock_{it-1} \times Size_{it-1}^{large} \times Age_{it-1}^{21-40}$ | | | 0.0366* | 0.0811* |
| | | | (0.0199) | (0.0472) |
| $R\&DStock_{it-1} \times Size_{it-1}^{large} \times Age_{it-1}^{>40}$ | | | 0.0366* | 0.0908* |
| | | | (0.0204) | (0.0492) |
| Constant | -4.818*** | | -4.538*** | |
| | (0.855) | | (0.914) | |
| Observations | 1,141 | 1,100 | 1,093 | 1,054 |
| R-squared | 0.979 | 0.122 | 0.979 | 0.126 |
| Firm FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Sector FE | YES | YES | YES | YES |
| Country#Year FE | YES | YES | YES | YES |
| N_clust | 367 | 349 | 357 | 340 |
| Rkf | | 45.34 | | 9.307 |

Notes: Clustered standard errors at the firm level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.

**Table D.2 – The effect of R&D and firms' characteristics on growth - Estimates with deflated values (CPI)**

| VARIABLES | (1) FE | (2) FE | (3) FE | (4) IV |
|---|---|---|---|---|
| $\log assets\_cpi_{it-1}$ | 0.402*** | 0.401*** | 0.401*** | 0.394*** |
| | (0.0940) | (0.0938) | (0.0966) | (0.0962) |
| $\log emp_{it-1}$ | 0.131* | 0.141** | 0.101 | 0.113* |
| | (0.0695) | (0.0693) | (0.0685) | (0.0679) |
| $solv_{it-1}$ | 0.000772 | 0.000721 | 0.000898 | 0.000877 |
| | (0.00171) | (0.00172) | (0.00177) | (0.00174) |
| $ROE_{it-1}$ | -6.72e-05 | -6.72e-05 | -4.08e-05 | -4.55e-05 |
| | (0.000231) | (0.000231) | (0.000245) | (0.000245) |
| $R\&DStock\_cpi_{it-1}$ | 0.0437** | | | |
| | (0.0204) | | | |
| $R\&DStock\_cpi_{it-1} \times Size^{sme}_{it-1}$ | | 0.0458** | | |
| | | (0.0204) | | |
| $R\&DStock\_cpi_{it-1} \times Size^{large}_{it-1}$ | | 0.0372* | | |
| | | (0.0205) | | |
| $R\&DStock\_cpi\_{it-1} \times Age^{0-10}_{it-1}$ | | | 0.0560** | |
| | | | (0.0237) | |
| $R\&DStock\_cpi_{it-1} \times Age^{11-20}_{it-1}$ | | | 0.0481** | |
| | | | (0.0204) | |
| $R\&DStock\_cpi_{it-1} \times Age^{21-40}_{it-1}$ | | | 0.0392* | |
| | | | (0.0200) | |
| $R\&DStock\_cpi_{it-1} \times Age^{>40}_{it-1}$ | | | 0.0286 | |
| | | | (0.0214) | |
| $R\&DStock\_cpi_{it-1} \times Size^{sme}_{it-1} \times Age^{0-10}_{it-1}$ | | | | 0.0648*** |
| | | | | (0.0235) |
| $R\&DStock\_cpi_{it-1} \times Size^{sme}_{it-1} \times Age^{11-20}_{it-1}$ | | | | 0.0597*** |
| | | | | (0.0195) |
| $R\&DStock\_cpi_{it-1} \times Size^{sme}_{it-1} \times Age^{21-40}_{it-1}$ | | | | 0.0412** |
| | | | | (0.0194) |
| $R\&DStock\_cpi_{it-1} \times Size^{sme}_{it-1} \times Age^{>40}_{it-1}$ | | | | 0.0246 |
| | | | | (0.0221) |
| $R\&DStock\_cpi_{it-1} \times Size^{large}_{it-1} \times Age^{0-10}_{it-1}$ | | | | 0.0485** |
| | | | | (0.0212) |
| $R\&DStock\_cpi_{it-1} \times Size^{large}_{it-1} \times Age^{11-20}_{it-1}$ | | | | 0.0316 |
| | | | | (0.0204) |
| $R\&DStock\_cpi_{it-1} \times Size^{large}_{it-1} \times Age^{21-40}_{it-1}$ | | | | 0.0340* |
| | | | | (0.0203) |
| $R\&DStock\_cpi_{it-1} \times Size^{large}_{it-1} \times Age^{>40}_{it-1}$ | | | | 0.0275 |
| | | | | (0.0208) |
| Constant | -4.807*** | -4.844*** | -4.637*** | -4.650*** |
| | (0.886) | (0.885) | (0.928) | (0.921) |
| Observations | 1,076 | 1,076 | 1,032 | 1,032 |
| R-squared | 0.978 | 0.978 | 0.978 | 0.978 |
| Firm FE | YES | YES | YES | YES |
| Year FE | YES | YES | YES | YES |
| Sector FE | YES | YES | YES | YES |
| Country#Year FE | YES | YES | YES | YES |
| N_clust | 353 | 353 | 343 | 343 |

Notes: Clustered standard errors at the firm level in parentheses. ***, **, and * indicate significance at the 1, 5, and 10 percent levels, respectively.