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Digitalization of Entrepreneurial Ecosystems and Smart Specialization: The Importance of Place Specific Factors

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Contents

DECLARATION OF ORIGINALITY

I hereby declare that I am the sole author of this dissertation and that some parts of this dissertation have been published or submitted for publication. I affirm that all information sourced from the work of others has been appropriately acknowledged and that all text and ideas, unless specifically marked otherwise, are my own original work.

I understand that failing to comply with these requirements may mean that I will be subject to penalties under the academic dishonesty policies of the University of Pecs.

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ABSTRACT

This dissertation looks into the complex interactions between the digitalization of entrepreneurial ecosystems, the concept of smart specialization, and the role of place-specific factors in the context of Europe. It is conducted an extensive examination of the adoption of digital web technologies across European regions to understand how the local environment serves as a connecting link between entrepreneurial ecosystems and smart specialization initiatives. By employing a mixed research methodology that integrates quantitative data analysis with in-depth case studies on selected web technologies, this study examines how geographical location, path dependence, and the embrace of digital web technologies impact regional growth and labor productivity.

At the core of the study are three main questions aimed at discovering the connective role of local environment, the interconnections between geographical location and the adoption of digital technologies, and the association between digital complexity and regional economic performance within the European Union. The empirical approach includes spatial analysis, econometric models, and comparative case studies for specific web technologies, relying on a comprehensive self-developed dataset regarding the use of digital technologies in several European regions.

The research finds that place-specific factors play an important role in the adoption of digital web technologies, which, in turn, significantly affect regional innovation ecosystems and industry specialization. The result highlights the paradoxical negative link between digital complexity and regional productivity, as well as between the density of related technologies and their adoption rates in European Regions, emphasizing the need for integrated policy measures that foster digital innovation and the development of digital local infrastructure. In addition, the importance of Core-Periphery dichotomy is discussed.

By offering concrete empirical evidence on the influence of geographical factors on the digital technology adoption of regional economies, this dissertation enriches the discourse on regional development, innovation policy, entrepreneurship, and digital transformation. It advances the understanding of digitalization's impact on regional economic growth, how digital web technologies are adopted and provides valuable guidance for policymakers dedicated to strengthen-

ing regional innovation capabilities and competitiveness through tailored, place-based strategies.

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This dissertation stands not solely as a milestone of academic achievement, but as a cornerstone of the person who I am about to become.A different person, mind, and a new worldview.

LIST OF PUBLICATIONS

- Apostol, Stefan. 2022a. “THE EARLY-STAGE ENTREPRENEURIAL ACTIVITY OF WOMEN IN INDIVIDUALISTIC VERSUS COLLECTIVIST COUNTRY GROUPS: MOTIVES, DRIVERS AND INHIBITORS.” Economics and Sociology 15 (4): 146–167.

- Apostol, Stefan. 2022b. “Universities in Today’s World-between the Potential Regional Growth and Market Economy Absorption.” Management & Marketing. Challenges for the Knowledge Society 17 (s1): 449–470.

- Apostol, Stefan. 2023. “Digitalization and Platformization in Romania Based on the Digital Platform Economy Index 2020.” Central European Business Review 12 (4): 77–103.

- Apostol, Stefan, and Eduardo Hernández-Rodríguez. 2023. “Digitalisation in European Regions: Unravelling the Impact of Relatedness and Complexity on Digital Technology Adoption and Productivity Growth.” Utrecht University, Department of Human Geography and Spatial Planning.

- Apostol, Stefan, and Muthama Wencelaus Musyoka. 2024. "Complexity and FDI in market-dependent economies: The hidden effect of industrial offshoring." *Acta Oeconomica*, 74(2), 187-212. https://doi.org/10.1556/032.2024.00009

LIST OF TABLES

List of Tables

LIST OF FIGURES

List of Figures

LIST OF ABBREVIATIONS

API - Application Programming Interface

ARDECO - Annual Regional Database of the European Commission

BCG - Boston Consulting Group

CES - Central Eastern Europe

CMS - Content Management System

CSS - Cascading Style Sheets

DARPA - Defense Advanced Research Projects Agency

EEG - Evolutionary Economic Geography

EQI - European Quality of Government Index

ERDF - European Regional Development Funds

EU - European Union

EUROSTAT - Statistical Office of the European Union

FDI - Foreign Direct Investment

GDP - Gross Domestic Product

GEDI - Global Entrepreneurship and Development Index

GISCO - Geographical Information System of the Commission

GVA - Gross Value Added

HBR - Harvard Business Review

HTML - HyperText Markup Language

ICT - Information and Communication Technologies

IoT - Internet of Things

KCI - Knowledge Complexity Index

LISA - Local Indicators of Spatial Association

LL - Low-Low

LH - Low-High

NUTS 2 - Nomenclature of Territorial Units for Statistics 2

OLS - Ordinary Least Squares

OECD - Organisation for Economic Co-operation and Development

PFB - Penalty for Bottleneck

R&D - Research and Development

RCA - Revealed Comparative Advantage

RCI - Regional Competitiveness Index

RegPat - OECD Register of Patents

SMEs - Small and Medium-sized Enterprises

SS - Smart Specialisation

TA - Technology Adoption

TS - Technology Share

UK - United Kingdom

USA - United States of America

1 INTRODUCTION

1.1 Introduction

While starting a new chapter of digital transformation era, the role of digitalization, capacity to adopt new technologies and entrepreneurship for regional economies becomes more and more essential in steering economic futures. The dissertation, titled "Digitalization of Entrepreneurial Ecosystems and Smart Specialization: The Importance of Place-Specific Factors" looks into the complex interplay between digital technologies and the regional intricacies of entrepreneurial ecosystems. While the significance of digitalization has been recognized, the details of how companies are adopting new digital web technologies remain unclear, and a robust framework for that it is still not present. Besides, this shift towards a digital web environment and the factors affecting these digital systems has been to a certain extent overlooked by regional innovation policies, often treated as a black box area, despite its essential role in directing innovation. This dissertation selects the European Union's context to discover the effects of digitalization on smart specialization strategies (S3) and regional growth, but also how S3 influences the technology adoption, emphasizing the criticality of place-based factors.

The study's need has its roots from the recent digital economy's advance of both it's theory and application, where the undertaking and integration of internet-based technologies are increasingly more and more necessary for regional productivity and economic output. Despite acknowledging the important role of digital web technologies in driving innovation and economic advance, a considerable knowledge gap persists regarding their adoption and absorption within diverse regional and industry-specific settings. This dissertation aims to shrink this research gap through a comprehensive analysis that enlightens the complex and context-dependent interactions between digital complexity, productivity, and digital web technology adoption across European NUTS2 regions.

Positioning itself between the discussions on digital change, innovation policies, and regional growth, this research critically reviews theories on entrepreneurial ecosystems, smart specialization, and the impact of geographic, spatial and contextual factors. Including evidence from foundational theories but also recent studies, the dissertation advocates for a specific approach to understanding digitalization's interaction with regional innovation capabilities and regional economic strategies.

The reason for adopting this investigation is drawn from identified literature gaps, lack of digital technologies' adoption studies and pivotal observations about importance of digitization, presenting a compelling case for an in-depth examination of digital technologies' role in regional economic development, especially regarding place-specific elements. The study's justification is mainly driven by five main motives, collectively emphasizing the research's necessity.

First, it is the digitalization's dynamic nature and observed regional disparities that highlight the uneven digital transformation benefits distribution. Despite a consensus on digital technologies as key economic growth pilots, understanding their varied impacts across Europe's diverse regions remains lacking. This research seeks to demystify the complex relationships between digital complexity, web technology adoption, and regional productivity under the umbrella of the frameworks of smart specialization and entrepreneurial ecosystems, where digitalization is often viewed as a separate matter.

Second, existing literature highlights the important role of geographical proximity, cognitive proximity, related web technologies, and interconnected research and entrepreneurial networks in fostering innovation and technological diversification. This ecosystem-based view, characterized by relatedness and a mesh of existing and emerging technologies, suggests a departure from conventional views on digital complexity and technology adoption, offering the opportunity for a more profound empirical investigation.

The third motive is the role of contextual and spatial dynamics in the adoption of digital web technologies and digital complexity, while recognized for physical technologies, it demands further empirical exploration in the case of digital technologies. Although spatial factors and agglomeration effects are acknowledged for their innovation potential, the specific dynamics and spillover effects across different European regions are not completely understood. This study aims to fill this gap by closely examining how place-specific factors influence digital technology adoption and regional economic performance.

Fourth, integrating digitalization into smart specialization strategies offers a rich update for existing frameworks for research, but also novel empirical observations. Although the endowment of strategic regional factors and capabilities together with smart specialization strategies is believed to significantly boost innovation and economic growth, empirical evidence on the impact of digital technologies on smart specialization strategies, especially from a place-based perspective, is not present.But their effects are also underestimated. This research explores the interaction between digital complexity, adoption of related web technologies, and smart specialization strategies to address the existing gap, and promising valuable policy insights.

The fifth reason is that the fragmented literature on the adoption of digital technologies, entrepreneurial ecosystems, and regional economic growth requires a holistic integrative approach. The study responds to previous theoretical calls for an integrated framework that captures the effects of digitalization of firm functions in regional economies. In addition, its goal is to advance early scholarly discussions and provide practical advice to policymakers and industry pioneer stakeholders about digital technology adoption.

The research was started to bring empirical evidence regarding the challenges of firm digitization, but also about what the digital economy presents to regional development in a comprehensive way. By carefully analyzing the involved dynamics of regional economies, the study not only enriches academic debates but also guides the development of informed policies that focus on digital technologies' implementation for innovation and economic growth in various regional environments.

1.2 Problem Statement

The core problem this dissertation examines arises from the challenges regarding the process of digitalization of entrepreneurial ecosystems, the planning, and implementation of smart specialization strategies, and the crucial role of spatial and geographical considerations in these strategies. These challenges are layered, involving the difficulties of embedding digital technologies into regional development agendas, deciphering the patterns of technology adoption across diverse geographic settings, and unraveling the complex relationship between digital sophistication and regional economic performance.

There is a gap in research and policies when it comes to understanding how digital web technologies and their uptake are shaped by, and in turn shape, the local environment and geographical positions. We are missing detailed methods when examining digital relatedness and its impact on the regional economic output that connect digital growth, entrepreneurial ecosystems, and the spatial and geographical aspects of different places.

The dissertation also highlights that strategies for digital innovation do not make enough use of the unique aspects of place-specific factors. Although it is known of beneficial advantages of localized production and agglomeration economies, there is a lack of specific policies that use these factors to enhance the adoption of digital technologies and spur regional economic advancement.

The importance of this study is driven by the changing dynamics of digital economies, where the integration of web technologies, the degree of their complexity, and the density of relatedness are increasingly essential adoption of new technologies that later are transformed into regional competitiveness and economic health. Still, the way how these digital dimensions interact with spatial factors and contribute to the digital smart specialization of regions remains unexplored.

This dissertation tries to connect and solve these gaps in a holistic framework by conducting a comprehensive analysis of how the local environment is used as a connective link between digitalization and regional development strategies. Through a detailed examination of the linkages between physical location, digital technology adoption, digital complexity, and regional economic vitality, the research seeks to uncover the spatial dynamics essential for successful digital transformation strategies. By acknowledging the importance of geographic context in driving the digitalization trajectories of entrepreneurial ecosystems and smart specialization, this dissertation argues that a deep understanding of these dynamics can lead to more effective digitalization routes of entrepreneurial ecosystems and smart specialization.

Therefore, the study is positioned as a solution by examining empirical data and theoretical insights that can drive the formulation of place-specific digital innovation strategies. It states that policies should not only address the digital aspects of entrepreneurship and innovation, but also be customized to the unique spatial and geographic characteristics of each region. In this line Smart specialization efforts could be enhanced by adopting this strategy, and including digitalization resulting in a more dynamic, economically robust, and digitally progressive regional economy.

1.3 Research Aims and Objectives

The research aims to examine the relationships between the digitalization of entrepreneurial ecosystems, smart specialization, and the importance of place-specific factors within the European context. Moreover, the study aims to explore how local environment acts as a connecting element between digital technology adoption, entrepreneurial ecosystems, and smart specialization strategies, and investigates the extent to which physical location and web technology adoption influence regional productivity, innovation capacities and growth. Using mixed-methods approach such as spatial models, specific cases about web technologies, the research seeks to understand the impact of digital complexity, relatedness density, and technology adoption on regional economic development and provides insights for policymakers to enhance innovation capacity and competitiveness of regions through tailored, place-based strategies.

1.4 Research Questions

- Research Question 1: To what extent does the local context serve as a linking factor between entrepreneurial ecosystems and smart specialization frameworks?
- Research Question 2: What is the relationship between physical location and digital web technology adoption, does the place still matter?
- Research Question 3: What is the relationship between digital complexity, relatedness, technology adoption, and EU regional productivity?

1.5 Research Model

The dissertation framework enriched the understanding of digitalization and the possible regional framework, and shows a compelling story that demonstrates the transformative impact of digital technologies on the intricate relationship between smart specialization strategies and the entrepreneurial ecosystem. This unified view highlights the necessity of nurturing technological progress and web technology adoption within a context-rich setting, spotlighting the critical roles played by relatedness density and digital complexity in driving regional innovation and economic performance.

Digitalization is seen as a primary catalyst for growth, aided by relatedness density, which enhances the spread and uptake of novel technologies through cognitive and geographical proximity, technological interconnectivity, and digital complexity. Which later elevate organizational and regional competitiveness by advancing internet infrastructure and digital skills' proficiency. The exploration into digitalization augments the initial conceptual framework that makes the shift from physical to digital environment and the incorporation of advanced digital web technologies as essential for the fulfillment of smart specialization strategies and the success of entrepreneurial ecosystems.

This framework, in conjunction with the understanding gained from digitalization, emphasizes the importance of identifying and fostering competitive advantages and areas of technological expertise. The idea is to encourage regions to utilize their unique resources and abilities by investing in digital technologies that are relevant to their strengths, following the guidance of the European Union's Smart Specialization Strategy. This approach promotes the development of specialized domains of activity and technological proficiency to enhance economic cohesion and competitive advantage.

By incorporating the concept of the entrepreneurial ecosystem into this narrative, I highlight the beneficial relationship that can be exploited by and between various stakeholders, including enterprises, governments, educational institutions, and financiers, in creating an atmosphere that promotes innovation and entrepreneurship. The statement underscores the significance of context, encompassing spatial dynamics and cluster effects, in amplifying the economic advantages that arise from the adoption of technology.

This holistic model envisions a dynamic and iterative process of technical advancement and integration, emphasized by insights gained from digitalization. The framework model also demonstrates how digital technologies can accelerate innovation, improve competitive position, and boost economic growth by advocating for strategic approaches to digitalization initiatives such as related technologies. Moreover, the framework shows that place-specific factors and regional policy interventions are crucial in directing economic advancement toward increased productivity, growth, and innovation. Therefore, the digitalization process calls for a sophisticated policy design and execution approach, which is carefully tailored to the specific regional capabilities and infrastructure, but also takes into account the broader context of global innovation networks. In this framework, the complex economic environment is recognized, where technology, knowledge, and contextual factors are interconnected.

1.6 Research Hypotheses

The dissertation's hypothesis are elaborated to illuminate the complex interplay between relatedness density, digital complexity, technology adoption, and how they impact economic growth and regional development across European regions through an ecosystem-based digital smart specialization framework. These hypotheses are:

1. *Hypothesis H1:*

    (a) *Hypothesis H1a:* There is a positive relationship between relatedness density and related entry. In the case of web technologies, high relatedness density indicates a closer knowledge relationship between existing and new technologies. Relatedness density is expected to enhance the likelihood of related entry, where firms in regions enter new digital technological domains that are closely related to their previous capabilities.

    (b) *Hypothesis H1b:* There is a positive relationship between relatedness density and technology adoption. High relatedness density, indicating a closer relationship between previous and new technologies, is expected to facilitate technology adoption.

2. *Hypothesis H2:*

    (a) *Hypothesis H2a:* Digital complexity positively influences labor productivity. Regions with higher digital complexity are hypothesized to exhibit higher productivity levels. When firms are digitized and have complex web technologies, they are expected to be more productive, therefore influencing the overall regional productivity.

    (b) *Hypothesis H2b:* There is a positive relationship between digital complexity and technology adoption. Higher levels of digital complexity within a region are expected to lead to greater technology adoption rates. Here, a spillover effect is expected from firms with complex technologies to other firms in a region.

3. *Hypothesis H3:*

   (a) *Hypothesis H3a:* Contextual factors (human capital, quality of governance, infrastructure) positively influence web technology adoption. This suggests that developed place specific factors and concentration of related activities facilitate the adoption of new technologies.

   (b) *Hypothesis H3b:* Spatial spillovers have a positive relationship with web technology adoption. The hypothesis argues that if the neighboring region adopts a specific web technology, this will spill over and facilitate the adoption of new technologies in the current region.

   (c) *Hypothesis H3c:* Agglomeration effects have a positive relationship with web technology adoption. The hypothesis argues that being in an innovation-oriented context with spatial and agglomeration of human economic activities facilitates the adoption of new web technologies.

4. *Hypothesis H4:*

   (a) *Hypothesis H4a:* Contextual factors (human capital, quality of governance, infrastructure) positively influence digital complexity. This suggests that the rich local environment and knowledge externalities enhance a region's digital complexity.

   (b) *Hypothesis H4b:* Agglomeration effects have a positive relationship with digital complexity. This suggests that the broader environment and concentration of human economic activities enhance a region's or organization's digital complexity.

5. Hypothesis H5: There is a reciprocal positive relationship between digital technology adoption and GDP per capita. This implies that not only does technology adoption contribute to higher GDP per capita, but also that regions with higher GDP per capita are more capable of adopting new technologies.

1.7 Research Contribution and Novelty

The research contribution and novelty of this dissertation are very important. The focus was on the complex dynamics between digital relatedness density, digital complexity, and web technology adoption across European regions. Here are the key highlights:

The dissertation provides a comprehensive analysis that explains and describes the complex and context-dependent relationships between digital complexity, productivity, and digital technology adoption. Moreover, it advances the academic debate on effects of digital transformation by exploring the above-mentioned interconnected dynamics, contributing to a deeper understanding of the factors driving technology adoption and regional development from an ecosystem and economic geography perspective. The novel results, focused on digital technologies, highlight the importance of fostering connected ecosystems. By adopting a profound study approach to digital complexity, offering practical insights for policymakers and practitioners aiming to harness technological advancements for regional development. It looks at how the regional complexity influences, regional digital technology adoption, but also how following a path-dependent approach affects adoption of new digital technologies.

The novel dimension of this dissertation lies in its robust support for the hypothesis that a higher relatedness density significantly fosters the entry of related web technologies, emphasizing the role of cognitive proximity and interconnected ecosystems in regional innovation and digital technological adoption. Additionally, it is the first time when the economic complexity and relatedness frameworks are applied to digital web technologies. Another aspect is that the study challenges preconceived notions about digital complexity, suggesting a paradox in which regions with more advanced technologies might encounter diminishing returns in adopting new technologies as adoption requires higher capacity. Moreover, a spatial measurement of web technology adoption and used by firms was not performed. Such insights challenge the traditional understanding of digital adoption and highlight the need for a more detailed understanding of digital complexity's and relatedness density role in technology adoption and regional productivity.

1.8 Dissertation Structure

The dissertation undertakes a comprehensive examination of the entrepreneurial ecosystem and smart specialization strategies, especially in the context of digital transformation and its implications for regional economic development. It begins with an extensive literature review charting the evolution of the entrepreneurial ecosystem concept from its inception. This section meticulously dissects the framework and dynamics of these ecosystems, highlighting the critical roles of policy, finance, culture, and networks. It delves into the transformative impact of digital technologies, exploring how they reshape industries and foster the emergence of platform ecosystems.

In the Methodology chapter, the dissertation highlights its research design and analytical strategies, focusing on spatial panel fixed effects models to explore the interplay between digital complexity, productivity, and technology adoption across European regions. This methodological approach is critical for understanding spatial dependencies and the detailed relationships that underpin regional economic performance and the diffusion of digital technologies.

The narrative progresses to an analysis of Digital Complexity and Productivity, presenting empirical evidence to elucidate how digital technologies influence labor productivity. This chapter uncovers significant spatial spillovers, revealing the interconnected nature of regional economies and the paradoxical role of digital complexity in driving economic performance.

Later, the examination shifts towards Technology Adoption in the Digital Era, investigating the factors that support or impede the adoption of digital technologies. Through a detailed analysis, it identifies a paradox where regions of high digital complexity do not always lead in technology adoption, pointing towards the saturation effects and the importance of relatedness density.

The Role of Spatial Factors and Ecosystem Dynamics chapter further explores the geographical and economic factors shaping digital transformation. It provides insights into the core-periphery dynamics, highlighting how spatial factors and ecosystem dynamics are crucial in understanding the uneven distribution of digital technologies.

Concluding with the Policy Implications chapter, the dissertation synthesizes its findings, offering actionable insights for policymakers and regional planners. It advocates for comprehensive strategies that address both technological advancements and socioeconomic considerations, aiming to enhance regional competitiveness in the digital age. This chapter also sets the stage for future research, suggesting avenues for deeper exploration into the details of digital ecosystems and their broader economic implications.

2 LITERATURE REVIEW

2.1 Entrepreneurial Ecosystems

2.1.1 Evolution of Entrepreneurial Ecosystems Theory

The discussion about entrepreneurial ecosystems began around the beginning of the twenty-first century. However, prior to that, despite well-researched concepts such as entrepreneurship and innovation, these aspects of the economy were seen from a more individualistic perspective. An entrepreneur was seen as an innovator who, through individual initiative and a willingness to take risks, combined existing knowledge to solve a problem, innovate and then commercialize their idea. In his book, Schumpeter (1934) defines an entrepreneur as an individual who works in isolation, driven by his unique visions and ability to introduce new ideas.

When introducing a new idea, the 'lonely entrepreneur' challenges the existing market, as discussed by Schumpeter (1943), through the process of 'creative destruction.' Although communism and socialism do not specifically have entrepreneurs, they view entrepreneurship as the act of owning and controlling the means of production, extracting surplus value from the labor of workers, land, and machinery (Marx, 2018).Similarly, many other theorists failed to differentiate between the roles of entrepreneurs and capitalists. Until the late nineteenth century, countries were managed without realizing the impact of entrepreneurs' relationships and interactions with their environment, including resources, factors, and opportunities, which would ultimately lead to better economic output.

The term 'ecosystem' initially referred to a biotic community or ecological-physical environment, representing the complex interactions between the system's components (Tansley, 1935; Acs et al. 2017). In 2008, Daniel Isenberg sparked the scientific buzz about entrepreneurial ecosystems by highlighting the challenges firms face when trying to go global. These challenges include bridging cultural, language, education, political, religious, and economic development differences, which collectively create a psychic distance perspective. Moreover, from a regulatory perspective, they must navigate variations in political, regulatory, judicial, tax, environmental, and labor systems (Isenberg, 2008).

When considering building trust, respecting cultural differences, and navigating different institutional frameworks or complex supply chains, it becomes clear that the location of entrepreneurial activity is crucial. The author cites examples such as the Czech Republic, Israel, and Poland, where high-growth entrepreneurship has led to rapid job creation, GDP growth, and long-term productivity. According to Isenberg (2010), entrepreneurs in these countries were aided by government leaders who built environments that nurture and sustain entrepreneurship. Feld (2012) argues that entrepreneurs are responsible for the continued economic vitality of cities and regions. Entrepreneurial ecosystems have become a sought-after goal for governments worldwide seeking to promote entrepreneurship. To improve their entrepreneurial activity, countries should continuously measure and enhance their ecosystem components. Nevertheless, the same article cautions against governments attempting to replicate successful ecosystems, as each environment is unique and the ecosystem should be tailored to local conditions.

In 2011, Isenberg argued that entrepreneurial ecosystems are a necessary precondition for innovation systems, cluster strategies, knowledge-based economies, and national competitiveness policies (Isenberg, 2011). Therefore, he proposed an 'entrepreneurship ecosystem strategy' to address the lack of political attention given to entrepreneurship. This strategy is considered one of the most cost-effective and holistic approaches to economic development.

However, one may ask, isn't this approach too interventionist and centrally planned? This approach contradicts the free market's invisible hand, which, according to Adam Smith, miraculously solves coordination and resource allocation problems. The answer is yes, but the market and market context cannot solve all the glitches, and the government should intervene through purposeful planning of congregations of resources and agencies. The government also holds in check the big business from its monopolistic endeavors (Galbraith, 1956). Additionally, Mazzucato (2011) demonstrates that government intervention plays an essential role in the creation of innovative businesses. I will refrain from discussing the negative consequences that the market brings, such as inequalities, exploitation, and environmental destruction (DeVille and Burns, 2006). The entrepreneurial ecosystem approach serves as a tool to map the actors within the ecosystem and their interactions, ultimately aiding in addressing market failures (Stam, 2015). Regardless, both Smith (1887) and Hausmann (2008) warn that market interventionist processes are extremely difficult and require large amounts of information and numerous variables that interact in highly complex and specific ways. Consequently, Isenberg (2011) takes into account the recommendations regarding the complexity of an entrepreneurial ecosystem strategy and attempts to provide a solid framework for entrepreneurial ecosystems.

He views entrepreneurial ecosystems as a dynamic and interconnected environment that influences an entrepreneur's perceptions, decisions, and overall success. The ecosystem includes policy, finance, education, culture, markets, infrastructure, and networks. The complexity of the ecosystem makes it difficult to establish clear causal pathways, and effective policies require a multifaceted and holistic approach. Therefore, creating an environment conducive to entrepreneurship requires addressing a variety of factors. Additionally, this system is geographically concentrated and its successful development necessitates a focused, time-bound, and organized effort to enhance and cultivate the entire entrepreneurial landscape.

In 2014, Acs et al. provided the first holistic-systemic definition of an entrepreneurial ecosystem as a "dynamic, institutionally embedded interaction between entrepreneurial attitudes, ability, and aspirations, by individuals, which drives the allocation of resources through the creation and operation of new ventures" (p. 119). Their definition and research differ from previous measurements of ecosystems because they attempt to measure the resource allocation systems that combine individual-level opportunity pursuit and are structured by country-specific institutional characteristics. This research is similar to Lundvall's National Systems of Innovation, which takes an individual perspective that includes the entrepreneurial mindset, creativity, and risk-taking appetite of individuals. Yet, it also argues that these traits would not be possible without contextual factors such as institutions, culture, and interconnectedness (Shane and Venkataraman, 2000; Lundvall, 1992). It was then that I understood that innovation is an interactive process. And it is essential to understand both the micro-behavior and the wider setting in which it operates (Lundvall, 2007).

To measure the national systems of entrepreneurship, they created a Global Entrepreneurship and Development Index (GEDI), and it became a popular measurement of how well a country supports the entrepreneurship processes. The index measurement is composed of 14 pillars that are also composed of smaller indicators regarding people's attitudes, skills, and ambitions for entrepreneurship, but also indicators related to the local environment for entrepreneurship.

Acs et al. (2011) developed the Penalty for Bottleneck (PFB) methodology for calculating the GEDI index. Unlike other methodologies, this one assumes that a system's performance is determined by its weakest component. Therefore, they recommend addressing this bottleneck first due to its effects on other indicators of the system.

The analysis utilized the following pillars: Opportunity Perception, Startup Skills, Risk Acceptance, Networking, Cultural Support, Opportunity Startup, Technology Sector, Gender, Quality of Human Resources, Competition, Product Innovation, Process Innovation, High Growth, and Internationalization. However, Szerb et al. (2013) introduced a new measurement of regional ecosystems by noting the concentration and clustering of certain industries and economic actors at the regional and smaller levels, rather than at the country level.

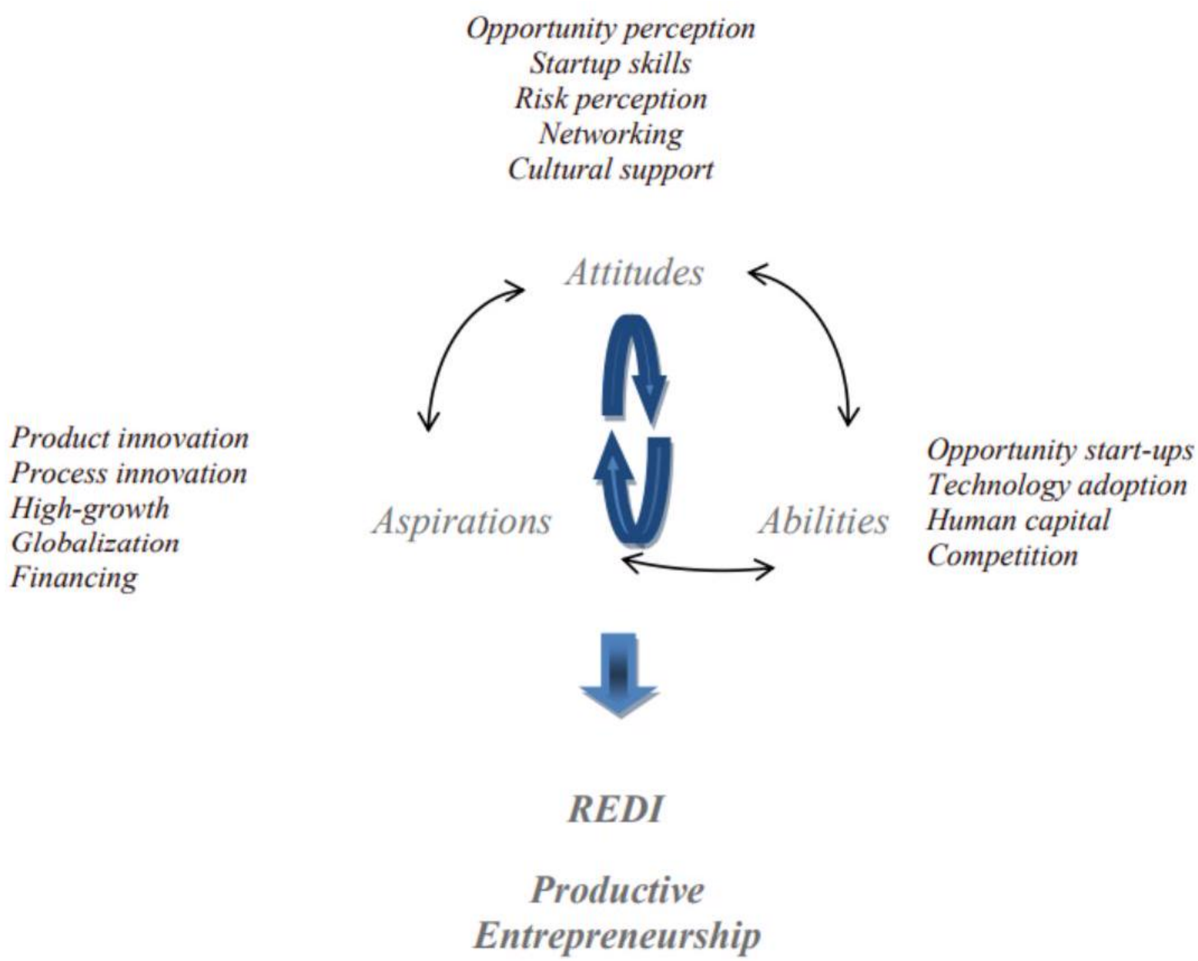

Figure 1: The structure of Regional Systems of Entrepreneurship. Source: Szerb et al. (2013)

This motivation was also strengthened by Feld (2012), who argued that technology startups cluster in specific cities such as Boulder, Colorado, due to their robust financial ecosystem, strong universities and research centers, quality of life, and engaged entrepreneurial community.

According to Szerb et al. (2013), the entrepreneurial context plays a fundamental role in determining the output of entrepreneurial action. This is because it determines the consequences of pursuing a particular opportunity. However, as mentioned by Stam (2015) and Acs et al. (2017), we should not only focus on the outputs of an entrepreneurship ecosystem. As entrepreneurs themselves are important actors in creating, developing, and maintaining a healthy system. In addition, it is noted that the quality of entrepreneurial activity is influenced by the surrounding context at various geographical levels. Stam (2015) critiques the previous approach of focusing solely on individual traits in the entrepreneurial ecosystem, arguing that the main drivers of entrepreneurship are specific types of enterprise rather than individuals.

Stam's argument regarding placing the enterprise at the center of the entrepreneurial ecosystem is mainly based on his work (Stam and Van Stel 2011; Stam et al. 2007; 2012). He mentions that macro-level growth is primarily the result of ambitious, high-growth entrepreneurship, as opposed to self-employment or large firm entrepreneurship. Still, it is believed that countries should strive to have different types of entrepreneurs at different stages of development, while cooperation between them is even more favorable (Baumol 2014; Rosenfeld 1996; Singh and Mitchell 2005). Firms at different stages of development will require different features for growth, and consequently, they will exhibit different location behaviors over time (Stam 2009). This research path towards regional or local entrepreneurial ecosystems has opened the way toward place-based entrepreneurial ecosystems.

Nonetheless, despite the fact that Stam and van de Ven (2021) emphasize the importance of interconnectedness, networking, and interaction between the elements of a system, they only provide a list of elements and benchmark ecosystem performance at the country level. Only in Leendertse, Schrijvers, and Stam's (2021) work do they attempt to quantify and qualify the regional entrepreneurial ecosystems and their effects on high-growth entrepreneurship. Although they claim to measure the interdependence between elements, they actually analyze the correlation between those elements. The interdependence web of entrepreneurial ecosystems is confirmed by the strong and positive correlations among the ecosystem elements in those regions. Yet, this does not necessarily demonstrate a complex system perspective. The researchers identify physical infrastructure, finance, formal institutions, and talent as central factors in the interdependence web of entrepreneurial ecosystems.

Returning to the initiation of entrepreneurial ecosystem theory (Mason and Brown, 2014), it is mentioned that creating favorable environments for new firms and start-ups may not necessarily lead to more high-growth entrepreneurship. Therefore, to address the gentle critics of the previous ecosystem measurements, which come as a conceptual umbrella, it is not just the elements of an ecosystem that matter, but rather how the interactions work symbiotically. Furthermore, disregarding the interdependencies between the elements and how they create and sustain the entire ecosystem renders most measurements of the entrepreneurial ecosystem as mere benchmarking tools. However, it is important to recognize the ability of these measurements to identify key inhibitors and obstacles to entrepreneurial activity (Szerb et al. 2020).

Recent fast technological advancement and industrial revolutions or financial crises in recent decades require entrepreneurial ecosystems to be resistant to shocks, evolve, and change in time, but also adapt and use failure as opportunities. Over time laws change, firms grow and become strong monopolists, markets crumble and ecosystems get trodden, therefore there's a need to study the dynamics of ecosystems and their capability of surviving disruptions (Barnett 2006). Until now, management research has focused on the internal dynamic capabilities of a specific firm rather than those between the firm and the external environment or an ecosystem's internal dynamics (Iansiti and Levien, 2004; Autio and Thomas, 2014).

Earlier in this chapter, I discussed entrepreneurial ecosystems and compared them to the complex and dynamic nature of ecological systems. One research path is attempting to assess the structures of multiple ecosystems, their interrelationships, and their historical development. The theory of entrepreneurial ecosystems derives from theories of life cycle dynamics in social and ecological systems (DeVille and Burns, 2006; Auerswald and Dani, 2017). Furthermore, Auerswald and Dani (2017) argue that the evolution of a particular industrial cluster may be influenced by the broader context of the regional entrepreneurial ecosystem, given that clusters are geographically dependent. This perspective aligns with the regional development literature lineage, as highlighted by Acs et al. (2017), which places a strong emphasis on the spatial and territorial aspects of economic activity, including the role of local resources, institutional frameworks, and community dynamics. Furthermore, Auerswald and Dani (2017) identified several evolutionary dimensions of ecosystems from the perspective of cluster dynamics. These dimensions include factors such as origin, diversity, selection, reorientation, connectivity, resilience, and adaptation, as discussed in their work from 2017, as well as in the study by Alvedalen and Boschma in the same year, which also relates to the second lineage outlined by Acs et al. (2017). Within the context of entrepreneurial ecosystems, this lineage emphasizes the importance of firms' strategic actions and their interactions with other actors in the ecosystem, including suppliers, customers, and competitors. Subsequently, Auerswald and Dani (2021) introduced the concepts of related diversification and related specialization as additional measures within the ecosystem framework.

However, I cannot discuss a dynamic and evolutionary geographical perspective on ecosystems without mentioning cluster theory. Michael Porter defines clusters as geographic concentrations of interrelated firms and institutions in a specific industry. They offer numerous benefits, including increased collaboration, knowledge spillover, and innovation (Porter, 1998). In the context of ecosystems, a cluster refers to a dynamic, geographic, and purposeful concentration of firms and features where participants interact and co-create value (Adner and Kapoor, 2010). The theory of clusters has emphasized the role of location in a country's competitive advantage. Location can enhance the productivity of companies, leading to increased productivity in the country.

In addition, clusters can enhance participants' capacity for innovation, stimulating new business formation indirectly (Porter, 2000). Even so, a cluster's capacity to perform depends heavily on the entrepreneurial environment. Although current economic theory focuses on globalization and macro-industrial policy, productivity is primarily micro in nature and strongly dependent on location. In fact, the more complex the economy becomes and the more knowledge it generates, the more it relies on local concentrations of skills, institutions, related businesses, infrastructure, or specific customers (Porter, 1998). Then, clusters emerge and co-evolve and managers will participate in the formation of new ecosystems as soon as it is advantageous for them to do so, provided that clusters assist them in maximizing value.

2.1.2 Entrepreneurial discovery process and importance of high growth firms

The previous chapter defined the ecosystem and discussed the emergence and evolution of entrepreneurial ecosystems, which are essential for fostering entrepreneurship and innovation. The historical perspective of entrepreneurship and innovation was traced from an individualistic point of view to the contemporary concept of ecosystems. The chapter highlights the role of geographic location and the interactions between various ecosystem components in the shaping of entrepreneurial success. It also touches on the importance of the adaptability and resilience of entrepreneurial ecosystems and the dynamic nature of entrepreneurial ecosystems in a world of continuous change.

Building on this foundation, the following chapter delves into the micro-part of the entrepreneurial ecosystem. It explores how individual components, mainly individuals and startups, create value. Michael Porter stated that if it is for a new firm to appear in a cluster, that cluster's location may already contain the required resources, skills, inputs, and qualified personnel. However, they are continuously waiting to be combined into a new enterprise (Porter, 1998). While ecosystem interventionist perspectives may improve certain factors in the local entrepreneurship system, it is important to note that without entrepreneurship creation policies, building entrepreneurial ecosystems without entrepreneurs may be complicated. It is crucial to understand who contributes the most to innovation, new business creation, and ecosystem strengthening.

According to Freeman and Soete (1997), inventing means discovering new methods or tools, in essence, discovering new knowledge. On the other hand, innovation refers to attempts to commercialize an invention, such as creating a new firm or spin-off, or even a new business branch. It is worth mentioning that not every new firm is innovative, as many are driven by profit rather than a focus on innovation (Baumol, 1990). Finally, it is the individual who is responsible for introducing 'innovation as new combinations'. As a result of these new combinations, a new product will be developed, a new method of production will be developed, a new market will develop, raw materials will be supplied from a new source, or half-manufactured goods will be produced (Schumpeter, 1939, pp. 84-85; Hagedoorn, 1996).If translated into a new business, this can destroy existing competencies in the industry and be unsafe for existing firms in an ecosystem. Therefore, established firms may avoid investing to gain these kinds of new capabilities able to produce drastic innovations, as it may lead to spin-offs that will cannibalize their current business activity (Christensen and Rosenbloom, 1995).

Teece et al. (1997) provided further justification for incumbent inertia in pioneering innovation due to the mismatch between organizational processes required to support conventional products or services and the demands of new ones. According to Hill (2003), incumbent firms often develop specific management procedures and highly structured routines that are incapable of supporting the new technology. This organizational inertia is a common reason for the failure of incumbents to commercialize radical technologies, even when they are the ones developing them. Similarly, new entrants frequently introduce architectural and revolutionary innovations into an industry due to their lack of organizational capabilities (J. Teece, 1986).

Regarding rapid technological change, incumbents may face immediate challenges from superior products that employ different standards (Teece et al. 1997). Hobijn and Jovanovic (2001) also note that in the age of technology, new products are created and adopted at a faster pace than ever before. One common example of incumbent lethargy is the resource allocation mechanism. In established firms, this mechanism is driven by the needs of existing customers and the demand for improvements of existing products (Walsh, Kirchhoff, and Newbert 2002). As a result, these firms tend to focus their research efforts away from, or initially undervalue, new technologies (Tripsas 1997). Established firms may avoid new technology due to the additional economic costs of investing in frontier methods when they already have old physical capital on hand (Hobijn and Jovanovic, 2001).

Agarwal and Audretsch (2001) argue that entrants are often drivers of innovation, but only in the initial phase of the industry life cycle, not in the mature or declining stages. Recent studies suggest that innovation is rarely autonomous, and that firms often require additional services such as advertising and post-sales product assistance. Complementary assets are essential for firms to remain competitive (Teece, 1986). They are part of a system or industry, and as technologies become more complex, both a firm's abilities and the interconnected capabilities of the system become increasingly important (Kapoor and Furr, 2015). Similarly, Kapoor and Furr (2015) note that these interdependencies provide insights into how firms innovate, compete, and maximize benefits in a new market.

New firms are likely to seek environments with accessible complementary assets to facilitate innovation, meaning they encounter less resistance to commercialization (Kapoor and Furr, 2015). The context in which firms identify and respond to customers' needs, procure inputs, and react to competitors is known as a value network (Christensen and Rosenbloom, 1995, p. 234). According to Ansari and Krop (2012), disruptors can enhance their revolutionary innovations by connecting with their value networks, building new relationships, establishing advantageous governing structures, negotiating their roles, and connecting with new global value chains. It is important to work primarily with the incumbents, as they serve as the gatekeepers of the system. The same authors note that incumbents may be concerned about the distribution of value created by revolutionary innovation, such as revenues, networks, or future design, among system actors and their share of the innovation pie. However, transitioning from individual innovation to collective innovation is not a simple task.

In his 1998 work, Porter argued that a location's prosperity depends not on the industries it competes in, but rather on how they compete. The complexity of competition in a location is highly influenced by the existing business environment. For example, firms may struggle to compete without a strong supply chain, infrastructure, legal systems, university research, or successful collaboration with government or other companies.

Baumol (1990) argues that productivity is closely tied to the entrepreneurial spirit, the objectives of entrepreneurs, resource allocation, and competition within an ecosystem. Specific interventions can influence the types of entrepreneurs that dominate. Kirzner (1997) introduced the entrepreneurial discovery process as an alternative to the assumption of equilibrium economics and perfect competition in markets. This policy position is rooted in Mises' theory, which states that the driving force of the market is speculative and profit-seeking entrepreneurs. Hayek described competition in a system as a discovery process, with the market serving as the single instrument where entrepreneurial opportunities can co-exist in competition (Hayek, 1978). Therefore, weak involvement of entrepreneurs will lead to a weak entrepreneurial discovery process (Radosevic, 2017). This view of a market economy has a single condition: unrestricted entrepreneurial entry into markets where profit prospects are seen to ensure a dynamic competitive process.

As for Kirzner, entrepreneurial discovery approach considers market processes as dynamic systems driven by systematic equilibrating tendencies. Who's views are in contradiction to Schumpeter's (1943) creative destruction-based entrepreneurial discovery process. For the former, mutual discovery and learning episodes play a central role. Moreover, he emphasizes the entrepreneurial nature of markets and the importance of knowledge in facilitating effective market interactions. This approach highlights the concept of discovery, recognizing that new insights and knowledge can emerge through ongoing market interactions, ultimately resulting in shifts and adaptations within the market's equilibrium (Kirzner, 1997). The entrepreneurial discovery process is based on the idea that regions should incorporate local actors and utilize local knowledge to develop new fields of economic activity, promoting sustained growth and prosperity. This approach is similar to the quintuple helix introduced by Carayannis, Barth, and Campbell (2012), which aims to use ecology, knowledge, and innovation to achieve economy, society, and democracy. Collaboration and knowledge sharing among multiple players is believed to promote knowledge generation and absorption. Participating in discovery alone makes it nearly impossible to utilize external information (Aghion and Jaravel, 2015; Foray, 2015).

However, planning and implementing this process is not easy. Hausmann and Rodrik (2003) introduced the concept of self-discovery, which involves firms investigating profitable prospects and discovering highly productive sectors. The problem is that businesses rarely share exploratory expenditures, so collaboration with other actors is often avoided. One of the biggest challenges is determining who bears the costs and who receives the benefits. If these are not clearly defined or if the benefits are only partial for one party, sharing information becomes difficult. Similarly, if entrepreneurs only capture a small portion of economic rents, entrepreneurship of this kind will be scarce and will hinder economic growth.

Therefore, new small businesses are seen as agents of innovation, bringing scientifically based technologies to the market. However, current innovation systems do not fully embrace new firm innovation. Foray (2014) suggests that policies should aim to identify and support innovative pathways and fields that fall outside current practices and knowledge fields of innovation. Using previous discoveries can be profitable for new businesses in the short term. Moreover, relying solely on past innovations can lead to underinvestment in frontier innovation, ultimately weakening the economy. This phenomenon was observed by Hausmann and Rodrik (2003) and Lora, Eduardo, and Ugo Panizza (2002). In addition, larger companies may tend to internalize the process of entrepreneurial discovery. Governments have the difficult task of coordinating and transforming entrepreneurial discovery into productive entrepreneurship and new industries (Rodrik, 2004).

What is productive entrepreneurship, why is it important, and who is responsible for it? Productive entrepreneurship refers to entrepreneurial activities that contribute positively to economic growth and development. The concept was initiated by Baumol (1990). This type of entrepreneurship involves the development of new ideas and technologies, which increase net job creation, improve productivity and efficiency, and generate value for society. In contrast, unproductive entrepreneurship is considered to be more rent-seeking, referring to activities that generate profit for the entrepreneurs but little economic value for society. Therefore, governments must establish a specific set of rules that restrict the activity of these types of entrepreneurs. This should serve as a starting point to shift the focus towards supporting a group of enterprises with high potential for growth. Shane (2009) observed that the majority of startups do not reach maturity and lack the intention of growing. Reynolds et al. (2014) found that approximately 65% of businesses rely on a local production network, access to suppliers, and a skilled workforce.

Young companies may face challenges in raising capital for scaling up or large fixed-cost projects due to uncertainty (Lerner, 2012; Reynolds et al. 2014). As discussed earlier, large or incumbent firms may resist growth and change. The debate over whether new or established firms are the main drivers of innovation is not a new one. However, it has also been noted that radical innovation does not always result in growth and that high-tech firms do not necessarily lead to growth. High-growth firms tend to be early adopters of new technologies and pioneers of new products, which makes them more productive and efficient. These firms are defined as those "with at least 10 employees in the start year and annualized employment growth exceeding 20% during a 3-year period" (Coad et al. 2014, p. 95). Platform businesses are often viewed as exciting places to work and are able to attract top talent, particularly from the industries they disrupt. These businesses exhibit direct network effects, which allows them to rapidly gain market share while also creating value for all customers (Daunfeldt, Elert, and Johansson, 2016).

Lerner (2010) studied the importance of high-growth entrepreneurship and compared Jamaica with Singapore, which started from the same economic and temporal vantage point. But today they are at totally different levels of economic development. According to Bosma et al. (2018) and Bos and Stam (2014), the so-called 'gazelles' are responsible for most productivity growth and much of the employment. Drawing on the example of the Netherlands, where high-growth firms are a key component of the country's entrepreneurship policy, Stam et al. (2009) provided guidance for governments on policy measures to support high-growth entrepreneurs and their specific needs. To promote innovation and the development of high-growth firms

(HGFs), policymakers should focus on creating financial markets to finance growing firms, providing R&D and intellectual property protection, investing in creative and technically talented people, identifying new markets, and facilitating market entry for these firms (Stam et al. 2009; Minniti, 2008). New firms can contribute to economic growth if they are ambitious to grow, innovate, and employ more people (Bos and Stam, 2014). However, it is important to note that there are cases that contradict Gibrat's law, where new firms grow faster than already established high-growth firms. This depends on the number of young firms in an industry or the market concentration rate (Daunfeldt and Elert, 2013). Therefore, although high-growth firms may seem like the ideal type of entrepreneurship, young firms should also be considered (Coad et al. 2014). Still, it is possible that high-tech firms are not high-growth firms, or at least they may have higher output but fewer employees. Why are these young, growth-oriented entrepreneurs viewed more favorably? The ability to effectively mobilize the resources available in the ecosystem is crucial, and this often requires trial and error, a perspective explored in studies such as Ács, Autio, and Szerb (2014) and Cao and Shi (2021). But no type of entrepreneurial activity exists in a vacuum, whether it is low growth or high growth. Therefore, the entrepreneurial ecosystem is crucial for securing capital, fostering cooperation, and evaluating initiatives that create a competitive and supportive environment for firms.

2.1.3 Importance of place-based Entrepreneurial Ecosystems for regional economies

It is evident that high-growth, high-employment, and high-technology firms are ideal targets for policymakers seeking to enhance entrepreneurship policies. However, it is important to consider how these firms are created and how they can be supported. Do they emerge organically within a local ecosystem, or are they intentionally created through government intervention? It is worth noting that government intervention is typically motivated by market failures. Therefore, it is crucial to carefully evaluate what works and what does not work in order to determine the most effective ex-ante interventions (Coad et al. 2014). Marshall (1961) associates new growth-oriented firms with young trees in a forest. He describes their journey as an arduous ascent, where many falter along the way, only to be surpassed by the resilient few. These survivors gain a growing share of the market's resources year after year, much like the increasing light and air they receive as they reach greater heights. At times, they appear poised for perpetual growth and unwavering strength, overshadowing their competitors. Although, even the most enduring firms have their limits. Age inevitably exerts its influence, and even the tallest firms, despite their privileged access to resources, gradually lose their vitality. This makes way for a new generation of firms which, though perhaps less substantial in shear strength, carry the energy of youth and perpetuate the cycle of economic renewal. These firms are related to place as trees are related to the forest.

The literature on co-location is closely related to the cluster literature. The cluster creation policy was developed to increase local and national competitiveness by taking advantage of clusters. However, clusters are more like evolutionary organisms and their definition can vary. For instance, a nascent cluster in creation can be defined as a geographical agglomeration of emerging or potential firms in related, complementary, or overlapping activities. At this stage, firms are supported by local socio-institutional factors. As the cluster matures, it begins to share a common vision and become more integrated with other actors through horizontal or vertical intra- or intersectoral links. They start to compete and cooperate in other markets, both nationally and internationally (Pitelis 2012).

The co-location of firms and institutions can create efficiencies, facilitate knowledge sharing through network linkages, and promote innovation and competitiveness within a cluster. Nonetheless, it is important to note that clusters do not necessarily imply a specific geographic location, and drawing boundaries can often be difficult. Therefore, the term 'industrial district' may better define the place for an entrepreneurial ecosystem, as districts are more of a socio-territorial entity (Becattini 2017; R.A. Boschma and Kloosterman 2005). Furthermore, it should be noted that the difference between clusters and industrial districts lies mainly in the fact that while firms in industrial districts specialize in a single industry, clusters can encompass a wide range of industries.

Industrial districts prioritize flexible specialization, while clusters are defined by diversification (Amin and Thrift, 2007). Despite globalization, geography, and place remain strategically important for companies. Some industrial districts leverage local advantages to perform key functions and maintain their position in global networks. This highlights the continued relevance of geography and place-based agglomeration effects in the globalized industry (Amin and Thrift, 2007). The learning process is a crucial part of the entrepreneurial discovery process, but it is often dependent on the location. Entrepreneurship can be enhanced by localized capabilities and place-specific cognitive and institutional conditions (Visser and Boschma, 2004).

The theory progressed from the concept of local clusters and the recognition of institutional, cultural, and geographic factors to regional entrepreneurial ecosystems. Clusters and networks differ in their capacity to mobilize and organize resources around entrepreneurial discovery and exploitation, rather than flexible specialization in specific industries (Cao and Shi, 2021). The co-location and interrelatedness of firms and other institutions in a cluster create a supporting environment, making firm activity a crucial element (Nelson, 1993; Pitelis, 2012). Entrepreneurial activity varies by location, making it of interest to economic geographers. Research on geographically bounded factors can shed light on these differences. In a place-specific context, determinants of entrepreneurial activity come from different levels: individual, firm, and place-specific factors (Qian, Acs, and Stough 2013).

However, if the ecosystem is built at a specific geographical level, it will be directly affected by macro-level factors in a top-down manner. Additionally, entrepreneurial activity is not the only factor in knowledge production; knowledge spillovers also have a geographic dimension. Therefore, entrepreneurial discovery and development depend on this dissemination of knowledge. Whether knowledge will be created or absorbed by new firms or means of production depends on the absorption capacity of human capital and firms in a specific geographical zone (Qian, Acs, and Stough, 2013). In the case of human capital, information sharing occurs through face-to-face communication, which is later translated into knowledge spillover between firms and individuals. Furthermore, I refrain from emphasizing individual firm capabilities as regionally based resources such as training, collaborations between universities and industries, a robust network of suppliers, and technical research centers can supplement in-house capabilities (Berger, 2013).

Nevertheless, a healthy ecosystem is not solely determined by internal factors such as interactions and knowledge, but also by external factors such as culture and existing knowledge, physical aspects of the environment, and its perception by the agents. For example, crucial geographical dimensions include proximity to markets, accessibility by various modes of transportation, connectivity to other developed areas, and commute time (Stam and Welter, 2020). Physical infrastructure can facilitate connectivity between people, enable labor mobility, and promote the exchange of knowledge and information (Audretsch and Belitski, 2017). The relationship between socio-cultural factors, such as entrepreneurial culture, history, venture capitalists, knowledge, and universities, and place-specific factors, such as entrepreneurship infrastructure, co-working spaces, incubators, and research centers, are all embedded in the geographical setting (Fischer et al. 2022).

Entrepreneurial ecosystems are spatially bounded and have a specific spatial logic. As a result of close geographical proximity, networks are formed, learning processes are initiated, and knowledge exchange takes place, all of which are essential and emerging on a local scale. In addition, there may be nested geographies where ecosystems interact with factors from different geographical levels (Brown and Mason, 2017). Therefore, entrepreneurial ecosystems should not be considered primarily territorial phenomena, but rather a cross-regional phenomenon intersecting with different regions in different ways. They should be able to attract and integrate external assets into internal operations. Moreover, it can be argued that the measurement of entrepreneurial ecosystems is related to their location, which can vary in scale. In contrast, ecosystem governance is related to their boundaries, including administrative boundaries. Therefore, incorporating spatiality into theories and empirical studies of entrepreneurial ecosystems would weaken the existing link between ecosystems and governance or institutions, as these are spatially constrained (Schäfer 2021). On the other hand, place-based ecosystems can facilitate strategies for regional policy interventions (Szerb et al. 2020).

Based on this, it is understood that no ecosystem can be fully replicated due to the unique characteristics of each location. Regardless, policymakers can still aim to create similar environments in different cities or regions. Despite these efforts, differences will persist, as noted by Audretsch and Belitski (2017). According to Florida (2004), certain places are successful in attracting talented individuals, also known as the creative class, due to factors such as tolerance, diversity, and quality of life. Regardless of economic or agglomeration factors, these focal factors are crucial in creating environments that attract creative individuals. This, in turn, leads to the growth of high-technology industries and regional income (Florida, 2002). However, the importance of certain factors may vary depending on the industry. For example, industries that rely on natural resources may prioritize factors such as suppliers, distance to market, or connections to global value chains, as the geography of the location can significantly impact growth. In contrast, regions with economies that are primarily driven by knowledge-based and creative industries may prioritize areas with high concentrations of human capital (Mellander and Florida, 2021). In order for an ecosystem to thrive, it is essential to introduce new ideas and businesses through start-ups and spinoffs from the conversion of old competences. This is particularly true in the manufacturing industry, where the density and richness of available resources in countries like Germany and the USA have led to significant advancements. Asian supply geographies, for example, may become the future industrial hubs due to their current abundance, density, strong synergies, and capabilities.

Lafuente, Ács, and Szerb (2022) provide evidence of the importance of entrepreneurial ecosystems. They argue that understanding the complexity and diversity of these ecosystems is crucial for effective policy formulation. Tailored policies that target specific aspects of the ecosystem are more effective than one-size-fits-all approaches (Minniti 2008). The authors demonstrate that allocating resources based on priority pillars results in significant ecosystem enhancements, exceeding the impact of simply increasing ecosystem quantity. They also establish a positive correlation between changes in entrepreneurial ecosystems and increased venture capital activity, highlighting the potential of the model to inform policy. In the same line, Leendertse, Schrijvers, and Stam (2021) focus on the output of place-based ecosystems in EU regions. The authors state that there is a positive correlation between entrepreneurial ecosystems and measures of productive entrepreneurship, such as innovative startups and unicorns. Higher-quality ecosystems tend to produce more high-tech entrepreneurial outputs. The metrics provided by the authors offer a useful framework for policymakers to diagnose and monitor the health of regional entrepreneurial ecosystems, particularly in relation to high-tech entrepreneurship. The authors' index is advantageous due to its specificity to a particular location. Despite this, there are few studies that directly examine the impact of ecosystems on growth. Although some studies indirectly examine the effects, focusing on how ecosystems affect entrepreneurial activity, which in turn affects productivity growth, employment, or economic growth (Content et al. 2020; Z. Acs and Armington 2004; Urbano and Aparicio 2016; Bjørnskov and Foss 2016). It is often noted that these effects vary by region and are influenced by the quality of institutions.

It is now understood that a strong local industrial infrastructure and ecosystem are important because they compensate for the complementary capabilities that entrepreneurs cannot create themselves, such as human capabilities, capital, premarket R&D, suppliers, amenities, and knowledge (Berger 2013).Also, by exploring how ideas come in the air, Marshall (1920), identifies three sources of agglomeration that provide entrepreneurial opportunities, such as labor "market pooling, non-pecuniary economics, and knowledge externalities" (Audretsch et al. 2006, p.84). Still, it is argued that the most important factor cannot be easily acquired without significant investment and government efforts: invention and development laboratories that will spill over their ideas to the market, also known as the Factory of Ideas (Gertner 2012). Examples of such labs include Bell Labs, which had a great impact on fields such as telecommunications, information theory, and solid- state physics through their creative processes and significant contributions. The Dupont Experimental Station and institutions like MIT and Stanford have played a pivotal role in the development of scientific innovations and technological advancements. For example, Boston Dynamics' current research in robotics is a spin-off from MIT research. It is important to acknowledge the significant contributions of these institutions to research and technology, particularly as the main beneficiaries of defense and aerospace contracts. A strong ecosystem is essential for industrial policy, which has recently regained traction. The ecosystem should provide the necessary input to assemble prototypes, incrementally improve business operations, and make post-market modifications critical to the successful operationalization of innovation (Locke and Wellhausen, 2014).

Companies should not be assumed to conduct research independently, and should acknowledge the significant contribution of the USA Department of Defense and its agency DARPA (Defense Advanced Research Projects Agency) in fostering innovation. DARPA is known for its high-risk, high-reward research projects and has been a source of groundbreaking innovations. From government-funded research (Mazzucato, 2011), industrialization efforts, mostly resulting from military industries, could shift towards more advanced and skill-intensive industries over time. Place-based industrial policies can effectively promote local development, structural change, and agglomeration when well-targeted, but initial systemic conditions are crucial. Dedicated government efforts are necessary to ensure the effectiveness of policies. Without such efforts, policies may only have partial effects, such as GDP growth without employment (Neumark and Simpson 2015; Becker, Egger, and von Ehrlich 2010). However, interventions should be carefully considered. Policymakers should select regions with higher productivity elasticity with regard to agglomeration, as mentioned by Glaeser (2007). In other words, regions with low capacity and depravity will hardly achieve a critical mass of productivity for manufacturing or innovation.

2.1.4 Digitalization of entrepreneurial environment

2.1.5 The process of digitization

In recent times, there has been a fundamental change in the ways people interact, network, conduct business and generate economic value (as discussed by Kenney and Zysman, 2016). This shift is largely attributed to the advent of Internet of Things (IoT) technologies, which interconnect smart devices, self-driving cars, sensors, and automated production systems that continuously produce data. The Covid-19 pandemic has notably accelerated the growth of digital platforms and enterprises, particularly in service sectors such as delivery, lodging, and remote work (as noted by Bădoi, 2020). Yet, many businesses are still in the process of shifting from conventional to digital business models. Small and medium-sized enterprises (SMEs) have shown only modest innovation through technology, with limited advancement in the knowledge-based economy, despite being aware of the existing technologies to digitize their tools and procedures (Gheorghe, 2020). There are ongoing recommendations for the creation of supportive laws, the development of necessary infrastructure, and the provision of economic incentives to support businesses in this digital transformation (Pînzaru et al., 2017).

The spread of Internet technology has simplified and reduced the cost of connectivity (Evans and Schmalensee, 2016). Kenney and Zysman (2016) introduced the concept of "digitally enabled business, political, and social activities" to describe this phenomenon. The significant effects of the tech revolution on the downturn of tech companies and market values have been rightfully acknowledged (Hobijn and Jovanovic, 2001). Consequently, this has led firms to reevaluate traditional paradigms of value generation (Cairncross, 2002). Some businesses are diversifying their risks and exploring new markets through strategies like forging alliances, outsourcing production, and increasing engagements with more established companies (Cairncross, 2002). Prahalad and Krishnan (2008) argue that for companies to boost innovation and efficiency, they need the capability to tap into and restructure resources globally as well as from both large and small local companies in a timely manner. This interlinked resource network paves the way for a new competitive landscape filled with opportunities. Nonetheless, an overly extensive network could inhibit companies from investing in or joining the ecosystem due to the necessity of sharing both costs and profits (Gawer and Cusumano, 2014). Goldfarb and Tucker (2019) note that digitization of the economy impacts the expenses associated with discovering, duplicating, transporting, tracking, and authenticating goods.

The capacity for swift prototyping, duplication, and scaling of new products, along with providing customer service post-sale, is vital for the manufacturing sector. However, the potential for learning is often compromised by the lack of physical interaction in knowledge transfer within manufacturing firms, as digital technologies now link research and development, production, and consumers (Steinfeld, 2004). Nations can sustain innovation and development by retaining their manufacturing capabilities, incorporating servitization within manufacturing, and enhancing the quality of their business environments. Furthermore, digitalization is bringing about reductions in costs, increased global integration, and modularization of manufacturing processes. There is a transition in production process structures from being internally focused to more externally oriented, where firms of all sizes form part of a distinct ecosystem that is essential for their innovation and production capabilities (Locke and Wellhausen, 2014). In this interconnected and intricately linked world, it is crucial to broaden our understanding beyond the individual level to embrace the complexities at larger scales, acknowledging the dynamic interactions and transformations of individuals and entities in their digital contexts (Root, 2020).

Meyer and Williamson (2020) stress that in this ecosystem-centric approach, the roles of network flexibility, innovation, and learning are critical and should not be overlooked when striving for efficiency and growth.

2.1.6 The platform as a system

In the digital era of artificial intelligence and digital scaling technologies, platforms have become a cornerstone of understanding economic and technological advancements. A platform is a transaction intermediary that creates value through interaction between pairs of end users, according to Rochet and Tirole (2003).They transcend traditional market boundaries, creating a vast network of users, suppliers, and customers. This phenomenon has been highlighted in the works of Parker, Van Alstyne, and Choudary (2016), who explore the strategic and operational dynamics of platform ecosystems. As described by McAfee and Brynjolfsson (2017) in HBR, these systems are not only technological constructs but also deeply ingrained in the economic fabric, fueling innovation and growth. According to Baldwin and Woodard (2009), platforms serve as foundations for a wide range of services and products, promoting a culture of continuous development and collaboration. As Gawer (2014) notes, the interplay of these complex systems with global markets challenges traditional business models, pushing firms to adapt to the interconnected nature of modern economies. This introduction sets the stage for a detailed exploration of how platforms, as intricate networks of digital and economic activities, are reshaping industries and redefining the parameters of competition and cooperation in this century.

In the case of platform companies, geographic boundaries do not limit the ability of companies to connect with the best suppliers and customers while avoiding the pressures associated with connecting only with local actors. This model has the potential to bring together millions of users and agents with local knowledge (Sussan and Acs, 2017). It allows small businesses to access larger markets globally. Moreover, an ecosystem can be formed by aggregating platform participants. Both physical and digital production ecosystems provide companies with the ability to innovate.

Szerb et al. (2022) define platforms as a type of business that matches one group of users, such as people, buyers and contributors, with another group, such as suppliers, companies and stakeholders, by reducing the cost and time of connection. The main difference from traditional markets is the presence of network externalities, which enable interaction between both sides of the market through a shared platform (Rochet and Tirole, 2003). According to Adner (2017), the platform serves as the core of a complex system of interactions. Governance is carried out through a central position and different pricing models, access preferences, and incentives.

Platform business models primarily facilitate the matching of users with the help of advances in digitization and innovations in information and communication technologies (ICT) (Acs et al. 2021). As this is a two-sided market (Sussan and Acs, 2017), platform businesses might not have been invented without these advances in ICT and digital infrastructure. The platform combines software, hardware, operational, and networking (Kenney and Zysman, 2016, p7). This business model can be applied across a range of industry sectors, including software, games, portals, streaming media, payment schemes, advertising, and remote jobs (Rochet and Tirole, 2003). However, in these efficiency-driven economies, there is a tendency to focus on retail, service, or labor intermediation platforms with little innovation, even though multisided platforms offer significant opportunities for low- and middle-income countries. These "matchmaker" businesses primarily aim to connect customers and suppliers (Acs et al. 2021). In contrast, innovation-driven economies have shown a tendency to use platforms for both platform and digital tool development. However, it is only a matter of time before the IT skills and creativity of less developed countries are on the rise.

2.1.7 Digital technologies and their ecosystem

Digital transformation, encompassing artificial intelligence, online marketplaces, and extensive data analytics, is revolutionizing a wide array of sectors. This includes the shift in models for sharing vehicles and homes, as well as the redefinition of advertising, television, and the music business. No sector remains untouched by this wave of change (Meyer and Williamson, 2020; Prahalad and Krishnan, 2008). Yet, nurturing a robust entrepreneurial environment can ensure a balanced relationship between established companies and new market entrants. An 'entrepreneurial ecosystem' is defined as a synergistic network of interconnected organizations and individuals, collectively striving toward a common objective within a specific context (Sussan and Acs, 2017). This concept underlines the significance of geographical location and contextual variables in the promotion of entrepreneurial activities and overall national economic performance (Wurth et al. 2022; Acs et al. 2017). An ecosystem, as opposed to a mere system, incorporates interactive dynamics between living actors and inanimate components (Acs et al. 2017). Engaging with partners within these ecosystems can augment skills and knowledge, leading to streamlined transformation and innovation. However, traditional business education often lacks emphasis on instructing entrepreneurs on how to motivate intercompany collaboration and value exchange (Evans and Schmalensee, 2016). This kind of collaborative effort is crucial for tackling complex, integrated challenges that are more intricate than those faced in simple production tasks. Within an ecosystem where knowledge and skills are extensively distributed, no one firm can satisfy the evolving needs and tastes of consumers on its own. The structure of such ecosystems supports the interplay and mutual learning among entities, while still allowing for a degree of independence (Meyer and Williamson, 2020).

Ecosystem strategies have been shown to benefit traditional industries affected by advanced ICT, such as manufacturing and energy, as well as platform operators and e-Commerce companies. Ecosystems share characteristics such as collaborative innovation, shared products and services, and shared knowledge. Although digital ecosystems develop around two-sided platforms, the ecosystem leader plays a primary role in facilitating efficient information flows and assessing needs and capabilities. When participants join the platform, knowledge exchange between parties is highly structured, as are opportunities for joint learning and innovation, and the flexibility to cooperatively reconfigure value propositions. Self-coordinating platforms may struggle to combine all potential knowledge and capabilities in the absence of a leader (orchestrator) (Lang, 2019). The primary purpose of a leader is to foster trust between contributors and users, which is determined by perceptions of collective identity, legitimacy, and institutional work (Gawer and Cusumano, 2014).

Super-platforms in digital ecosystems combine knowledge from multiple industries, including both emerging and developed economies (Lang, 2019). These platforms often exhibit a distinct leadership structure, with business platforms operating under the guidance of central leaders and exercising remote control. This contrasts with ecosystems that lack a central control mechanism, instead operating through a decentralized network of actors. Nonetheless, the efficiency of these ecosystems, whether centrally managed or decentralized, depends on factors such as regional embeddedness, production capabilities, infrastructure, and geographical dimensions (Acs et al. 2009; Acs et al. 2021). One of the main differences between a two-sided platform and an ecosystem platform is that the former is primarily focused on matching, while the latter can also foster an environment that encourages complementary innovations, known as network-centric innovations (Gawer and Cusumano, 2014). In terms of governance, platforms are more concerned with interface governance, while ecosystems are more concerned with interconnection formation (Adner, 2017).

Ecosystems offer a multitude of advantages, yet they manifest in diverse formats that hinge on the industrial context and the digital prowess needed for their assimilation. The Boston Consulting Group has categorized them into three types: Digitizer networks, Platforms, and Super

Platforms (BCG, 2019). Of these, Digitizer networks are particularly advantageous for smaller-scale industries because they combine superior product features with minimal digital infrastructure. These networks enhance products with advanced hardware or software, thus improving customer engagement and loyalty to the product. Such ecosystems usually involve a limited number of contributors, in the tens or hundreds, which helps to prevent information overload and ensures that each participant's contribution is significant. The notion that smaller systems foster innovation could shed light on why these ecosystems are efficient. Yet, this innovation might be constrained to isolated, small teams, and may plateau beyond a certain threshold. As an ecosystem expands from a smaller to a medium scale, connectivity and intergroup cohesion enhance, potentially sparking greater creativity (Uzzi and Spiro, 2005). The Internet, currently a vast global network that facilitates the exchange of voice, video, and data, has the potential to morph into a distinct ecosystem itself. Network effects could unlock scaling opportunities that were previously unattainable, adding value to products and services for both suppliers and consumers. To capitalize on innovation and efficiency, businesses need the agility to tap into and reorganize resources on a global scale, as well as to collaborate with other entities, regardless of their size and whether they are local or international, and to do so instantaneously (Prahalad and Krishnan, 2008).

The global network of resources provides new opportunities for competition. However, an excessively large network may discourage firms from investing in or entering the ecosystem, since cost sharing also means profit sharing (Gawer and Cusumano, 2014). Because each ecosystem has its own unique structure and characteristics, standardized measures cannot be developed for all ecosystems. Different patterns show unique growth, shape, and self-organization at each scale of the system, and the norms of collaboration are different (Root, 2020). Nevertheless, benchmarking and comparing index scores across countries provides important insights into developing pillars (Szerb et al. 2019).

2.2 Evolutionary economic geography and Relatedness theory

2.2.1 Evolutionary economic geography

In the previous chapter, I highlighted the significance of place and its role in facilitating entrepreneurship within a community of interdependent actors. This concept is rooted in the biological interaction between living organisms and their physical environment (Stam 2015). While existing measurements often produce a list of factors for improvement, they are typically static and fail to capture the dynamic output of an ecosystem's evolutionary interaction.

Why use an evolutionary perspective? This approach focuses on the accumulation of knowledge and draws from Marshall's (1920) idea of agglomerations, which are locally based but can also create positive externalities. The evolutionary perspective of ecosystems explores how these agglomerations emerge, evolve, and impact local economies over time (Cantner et al. 2021). The lifecycle concept of agglomerations is derived from the theory of cluster evolution (Menzel and Fornahl, 2010).

Evolutionary economic geography (EEG) argues that the experiences, competencies, and knowledge acquired over time by individuals and entities in a particular place can represent current and future industrial and development paths, adding much to our understanding of ecosystems (Kogler 2015). Although the EEG literature was mostly developed in the first part of the 21st century, its roots can be traced back to Darwin's evolutionary explanations. Although he did not fully understand all the dimensions of evolution in a complex system, he was able to describe how evolution works in a more refined way through mapping and sequencing of genomes and through the inner evolution of the principles themselves. The use of EEG can expand our understanding of the dynamics, adaptation, and resilience of regional economies as complex systems (Feldman 2023). (Boschma and Martin, 2007, p. 539) define EEG theory as "the study of the processes that transform the economic landscape over time, including the spatial organization of economic production, circulation, exchange, distribution, and consumption".

To describe local economies, researchers use biological system terms such as 'diversity' (referring to the diversity of industries in a system), 'selection' (referring to the selection of specific industries or species), diversification (related or unrelated),'resilience' or 'adaptation' of a system to shocks (Boschma 2017; Auerswald and Dani 2017). It is assumed that entrepreneurs behave in adaptive ways and connect and interact in their specific environment. Mack and Mayer (2015) define four stages of entrepreneurial ecosystems from an evolutionary perspective: Birth phase, Growth phase, Sustainment phase, and Decline phase. Their framework enables the evaluation of gaps in an ecosystem and identifies next steps to help it transition between evolutionary stages. In this way, ecosystems in different regions can be compared, and it can be understood why some may be stagnating instead of evolving.

However, a deeper understanding of the interdependencies between ecosystem components and their evolutionary aspects requires further research. The measurements and dynamics of components such as networks, governments, rules, and customs can provide a starting point for guiding the evolution of an ecosystem from one stage to another (Mack and Mayer, 2015). Furthermore, the relationship between dynamic networks within a system and entrepreneurial output has not been thoroughly examined. Networks consist of actors and institutions, and links represent the connections between them (Alvedalen and Boschma, 2017). Notwithstanding, the life cycle perspective of complex systems has recently been heavily criticized for oversimplifying complexity, unpredictability, and the dynamic nature of reality (Brown, Mawson, and Rocha 2023). The authors also criticize the anthropomorphism of places and argue that places are not humans. David Birch also warned about the anthropomorphism of firms (Birch 1987).

Despite not being a new concept in evolutionary literature, the evolutionary perspective of ecosystems remains appealing to policymakers and researchers. They have attempted to comprehend the rise and fall of regional economies and the restructuring of industrial areas through studies of evolutionary models and concepts such as selection, path dependence, diversity, and resilience. Visser and Boschma (2004), Agarwal, Sarkar, and Echambadi (2002), Jürgen Essletzbichler and Rigby (2007), and R. A. Boschma and Lambooy (1999) have all explored these concepts.

At this point in the chapter, you may be wondering why I entered the discussion about evolutionary theory instead of continuing with the entrepreneurial ecosystem, or how the two are related. Evolutionary economic geography attempts to answer questions that ecosystems may not be able to address. The chapter discusses how regions choose new industrial paths and whether these paths are dependent on previous ones or are developed endogenously or brought into the regions by chance (Boschma and Lambooy, 1999). To clarify, in this study, regions refer to territorial units within countries that are used for socio-economic analyses. The European Union has prioritized observing the development of these regions due to observed divergence in economic growth. Researchers have been particularly interested in understanding why some regions maintain strong growth positions while others do not (Boschma 1997). The study also examines whether the creation of new industries is independent of regional spatial factors or strictly dependent on essential inputs. However, the evolutionary perspective differs from economic geography in terms of methodology, assumptions about firm behavior, conceptualization of time and space, and explanations of agglomeration. Economic geography concepts, such as institutions and real places, are viewed as conditions for evolution, but not as determinants of it (Boschma and Frenken, 2006). This means that while economic geography acknowledges the influence of physical locations and institutional frameworks, these elements are seen as the groundwork that allows evolutionary processes to unfold rather than the driving forces behind these processes.

Regions are undergoing cumulative and collective learning, which results in the development of an industrial path that is embedded in the regional context. As a result, firms rely on both the regional context and the regional path, which is defined by the accumulated skills, competences, knowledge, a specific techno-industrial structure, and institutions. This situation can lead to lock-in, where a region is stuck in its routines and cannot create new knowledge or enter new industries (Boschma and Lambooy 1999).Boschma's early research in 2004 highlighted the importance of taking an evolutionary perspective on regional change. He emphasized that regions evolve along historical paths, shaping their industrial composition, knowledge base, and institutional setup over time. Despite the diversity within regions in terms of firms, industries, and skills, this variety serves as the foundation for economic evolution through processes like selection, imitation, and innovation. Regions with greater diversity may have more potential for development. Evolutionary perspective recognizes that regions should be viewed as holistic systems, with interdependencies between the competencies of firms, the regional knowledge base, and formal/informal institutions that tend to co-evolve.

Expanding on this understanding, Boschma's (2005) work delved into the role of learning and knowledge creation in driving growth, particularly focusing on the concept of proximity in regions' ability to generate new knowledge. He argued that actors in proximity within a region find it easier to interact and collaborate due to the reduced physical distance between them. The author defines five types of proximity. The first is cognitive proximity, which refers to sharing the same knowledge base and expertise. The second is organizational proximity, which refers to the degree of organizational linkages and shared relationships. The third is social proximity, which refers to the extent of socially embedded trust-based relationships. The fourth is institutional proximity, which refers to sharing institutional rules, norms, and values. Finally, geographical proximity refers to physical or spatial distance between actors. Despite these useful dimensions for knowledge generation and learning, the authors warn about possible diverse types of lock-in, such as institutional inertia or innovation, and idea lock-in. Current economies are in a state of constant transformation, with new ideas replacing the old. Scholars have stressed dynamic change and internal self-transformation, alongside enterprise disruption and adaptation to innovation as primary change drivers from within (Metcalfe 1998; Boschma and Martin 2007; Schumpeter 2013). Yet, understanding dynamic change necessitates considering appearance, convergence, divergence, and other irregular patterns, also known as spatial transformation over time (Boschma and Martin 2007).

While Brian Arthur's (Arthur 1994) models explain how path dependence shapes the economic landscape. His work suggests that a series of small, early internal events can crucially influence the long-term development of an economic system, essentially determining its structure and future trajectory. Therefore, to the EEG definition it is added the part 'from within', therefore I will have the definition 'the processes by which the economic landscape: the spatial organization of economic production, circulation, exchange, distribution, and consumption is transformed over time from within'(Boschma and Martin 2010). Regardless, I have to mention that they do not necessarily conceptualize places as geographical entities. Early work of Boschma (2007), however, says that spatial outcome is unpredictable and questions how geography may feed back on that, making it both path dependent and path independent.

2.2.2 Innovations systems

While entrepreneurial ecosystem theory is related to the entrepreneurship theory, dynamic system theory, to cluster theory and more recently evolutionary economic geography, the same are the systems of innovation (Lundvall 2007). Still, in this case the target output of this system is innovation and not firm creation, commercialization of ideas or startups. In this case, the firm interaction is at the core of the innovation system. Same Lundvall sees systems of innovation similarly to entrepreneurial systems as a set of interconnected organizations and institutions that together promote the development but aimed at diffusion of new knowledge and innovations in the economy. If entrepreneurial ecosystem research plans to take over the systems of innovation, they must include the knowledge and learning aspects.

Perhaps by including in their frameworks the EEG aspects related to adaptive entrepreneurship, to a shared emphasis on knowledge creation, learning, plus the dynamic role of institutions in different stages of development. As national systems of innovation are more evolutionary in nature than entrepreneurial ecosystem and are aiming to explain how the system creates diversity, selects specific firms or industrial niches, imitate routines or products (Lundvall 2007).The evolutionary perspective sees firms as differentiated organizations capable of resource development and learning, rather than homogeneous profit-maximizing units (Cooke 2001). And we should not oversee the dynamics of the social dimension such as user routines and practices, regulations or industrial networks. While the relations and evolution of interaction between organizations and institutions are essential, I believe that the goal of innovation systems may be overreaching as they aim to promote all types of innovation, product, process, organizational (Edquist 2001). According to (Hekkert et al. 2007) innovation systems have several crucial functions to consider in design so that systems works properly:

1. Entrepreneurial activities
2. Knowledge development
3. Knowledge diffusion through networks
4. Guidance of the search
5. Market formation
6. Mobilization of resources
7. Counteracting resistance to change/Legitimation

Despite adopting a holistic view, innovation systems research has primarily concentrated on the knowledge aspects and the challenges faced by incumbent firms. Nonetheless, it fails to understand the roles of various types of entrepreneurs, predominantly new firms, in transforming potential new knowledge, networks, and markets into tangible actions. These actions are aimed at generating and capitalizing on new business opportunities, an area where entrepreneurship systems have a distinct advantage. Moreover, the spatial dimension of systems of innovation is not clearly defined, and it could exist at different levels, including national, regional, or sectoral, or it could even be inter-level. Often the evaluation of innovation systems was done through Data Envelopment Analysis which is a linear analysis often does not include any interaction, it only assumes that the output was because of the quality and interaction of a system' components, and the interaction is often not considered (Carayannis, Grigoroudis, and Goletsis 2016; Zabala-Iturriagagoitia et al. 2007).

The World Bank in 2009 advocated for a 'space-blind' approach in policy formulation, emphasizing national efficiency and factor mobility, alongside the development of agglomeration economies, instead of endorsing place-based aid for less developed areas. The belief was that although economic growth fueled by agglomeration might initially result in regional disparities, a natural progression towards regional balance would eventually occur. In spite of that, Piketty (2014) but also Krugman (1991) has argued that such theories lack empirical support, and the pattern across various regions. He argues that regions have shown persistent and increasing disparities. This trend seems likely to continue unless deliberately countered by strategic shifts in national policies.

2.2.3 Digital relatedness and knowledge diversity

The idea of Evolutionary economic geography is often related to cluster dynamics theory. And mostly in the fact that the capabilities of firms, networks of firms, and regional institutions all co-evolve and shape cluster/regional evolution. They both highlight that firms, industries, or regions are heterogeneous in their capabilities, knowledge, networks, and this variety drives change. The importance of path dependence and context specificity are not overlooked also for digital technologies. But most important is the related variety concept, and mostly arguing that diversification happens most easily into related activities is building on existing competences.

Therefore, regions transform through new combinations of related knowledge (Boschma and Fornahl 2011). In contrast, unrelated variety refers to the extent to which different industries or sectors in a region are unrelated to each other. This approach comes from the idea that the mix of residential, trade, entrepreneurial, and industrial activities in close proximity would support the interaction within a region. This is also known as Jacobs externalities, where the diversity and complexity of urban life can generate outcomes for the local economy (Jacobs 1969). Moreover, it is also expected to facilitate radical innovation and product innovation, as ideas from different sectors are recombined in new ways. Jacobs' externalities are hypothesized to be higher in regions with a related variety of sectors compared to regions with an unrelated variety of sectors. Related variety allows more knowledge spillovers to occur between firms in sectors that are technologically related (Frenken, Oort, and Verburg 2007).

Providing evidence from several countries, the idea of relatedness was accepted between innovation and EEG scholars. This is mainly because technologically related sectors in a region have a higher cognitive proximity, and the more related sector, the more learning and combination opportunities leading to more regional growth (Frenken, Oort, and Verburg 2007; Boschma and Iammarino 2009; Boschma, Minondo, and Navarro 2011). The existence of previous related capabilities in a certain region could facilitate the future adoption of new technologies.[1] This is directly linked with the notion of absorptive capacity, thus, with the ease for a certain region to acknowledge, absorb, and adopt new methods, ideas, and technologies (Cohen and Levinthal, 1990). Likewise, we can make certain assumptions that in those regions who have more related variety of industries or related firms, for example, technological relatedness was observed to be positively related to urban industry portfolio membership and industry entry while negatively related to industry exit, which indicates for a resistance to different shocks within local economies (J. Essletzbichler 2013).A similar effect can be deduced from (Frenken, Oort, and Verburg 2007) who observe that related variety, measured as the diversity of sectors within broader industry categories, enhances job creation and employment growth at the regional level. Moreover, the related coevolution of institutions leads to organizational routines that can mediate conflicts between local actors.

The idea that evolutionary processes are interwoven with path dependence and the concept

[1]This finding was conducive to creation of the first hypothesis the conceptual model in Section 4.2

of relatedness is gaining traction (Hidalgo et al. 2018). This theory posits that regions are more likely to expand into areas that align with their existing strengths, meaning that they develop new products, industries, technologies, and occupations that are related rather than not related to their current capabilities (Hidalgo et al. 2007; Neffke et al. 2011; Xiao et al. 2018; Boschma et al. 2015; Balland et al. 2019; Farinha et al. 2019). In the same context, the uptake of digital and web technologies by a region is also thought to be influenced by this pattern of relatedness. It suggests that regions with proficiency in certain web technologies are more predisposed to adopt new digital technologies that are in some way connected to their existing technological know-how. This underscores the importance of regional capabilities in shaping the trajectory of regional industries' development. It raises the question of whether firms are learning from others within the same industry or branching out to acquire knowledge from different, yet related, sectors (Boschma, Minondo, and Navarro 2011).

Different studies look at this question, and while related variety can increase regional growth unconditionally, unrelated variety can increase productivity, however, only in regions with high level of absorptive capacity and business formation (Fritsch and Kublina 2018). Despite the fact that often this related variety may influence mostly knowledge intensive sectors, the role of related variety should not be overlooked in knowledge creation and business formation (Frenken 2016).The effects of related and unrelated knowledge were also examined at firm level where (Solheim, Boschma, and Herstad 2018) mention that unrelated experience variety within firms increases the probability of radical innovation, while related variety increases the probability of incremental innovation.

2.3 The concept of Specialization and Complexity

In the previous subchapters, we performed a comprehensive exploration of Evolutionary Economic Geography (EEG) and Relatedness Theory, how it relates to regional growth and how is that enhanced by strong regional ecosystem factors. In the following chapter it is argued why we don't need only related diversification of industries but also specialization in specific sectors and how to choose those sectors based on complexity theory. Moreover, it is discussed how presence of a complex system can also be associated with a strong entrepreneurial ecosystem.

This is the cornerstone is put for an entrepreneurial ecosystem based digital smart specialization framework.This is later discussed in the Conceptual Framework section (4.1).

Many industries can be related to the local knowledge, but we cannot invest in all of them. Division of labor may increase the productivity of labor, thereby increasing society's wealth (Smith, 1887). Division, subdivision, temporary and permanent division are just a few examples of how labor and industries can be divided. The specialization concept acquired prominence when profit began to be used as a measure of a country's success, and no one disputes the notion that specialization is the key to achieving such peaks of development and excellent performance. This split, however, crossed a perilous line when it separated intellectual activity from physical work.

The question appears, is it appropriate to specialize nations in particular industries, as we do with physical labor? Countries or regions may oppose specialization in favor of economic diversification because specialization would make them reliant on foreign nations for specific goods (Ali and Cantner, 2020). Besides, they would desire innovation abilities and resources from more other industries too. The desire for variety, both in terms of consumer preferences and business appetite for profitable industries, would lead to a trend of varied industries and professions within the same country, rather than their becoming specialized. A high number of diverse industries can result in a vast number of conceivable combinations of production assignments that can become entrenched industrial routes (Gomory and Baumol, 2000; Abernathy and Clark, 1985).

On the short term, specialization is the solution to extraordinary growth, but on the long term, it is intended to fade. As nations pursue diverse pursuits, they must be able to combine a variety of information and skills that also corresponds to the variety of abilities possessed by each individual. Current specialized industrial systems already contain the seeds of their demise. The cause for this is the disintegration of labor, namely the division of intellectual and physical labor. Integration of knowledge, entrepreneurial and technological, existing capabilities are the point of departure towards evolution and diversification of new industries (Foray, 2015). We may observe this at the country level as well, where certain countries are knowledge producers while others specialize in their labor or resources. The knowledge monopolies are another issue for discussion. Of course, we cannot doubt the importance of new machinery for growth.It has been suggested by Colquhoun (2005) that innovative machinery can encourage progress, and that investment and talent can revive it. This is corroborated by List (1841) that the ideal way for a country to grow is by combining science (knowledge production) and handicraft (application of knowledge), that is, by integrating education into processes of production, and not by specializing in either of them.

Following the post-industrial revolution, countries adopted various strategies to develop domestic industries and capabilities. Import substitution entails the replacement of foreign imports by protecting diversified domestic industries while promoting the adoption of cutting-edge technology was a preferred front-runner strategy (Kropotkin, 1909). Later, from the diversified industries with attendant capabilities and more complex products, new patterns emerged in the existing industries. In contrast, what I find today in developing nations is the exact opposite: first, multinational corporations aim to offshore their labor-intensive divisions to countries with low labor costs, compensating with transportation costs (Kovak et al. 2021). The desire to obtain low costs from cheap labor and protection from the governments leads to continuation of work from some employers with obsolete machinery and no technology improvement. However, low costs for accommodating localized labor to malleable technologies can impede the development or adoption of more effective production methods (Pagés, 2010). This form of capitalist model may be witnessed in the Visegrad group, where foreign investment was utilized to expand export sectors (Bohle and Greskovits, 2012). Nevertheless, a country's success is contingent on how well its domestic industries do in international trade, sometimes at the expense of other countries. Therefore, it is of interest for developed countries to keep emerging countries and industries at a certain level of growth (Gomory and Baumol, 2000). The export substitution idea was implemented by Taiwan that undertook a strategy of import restrictions, supply of technologies to new industries and subsidized entry of new firms, but also penalized unproductive firms. This led to an explosion of new local industries (Evans, 1995; Hausmann and Rodrik, 2003). While it was believed that technologies and innovation will be used for achieving the wellbeing of entire nations, these strategies are only benefiting few people or corporations (Kropotkin, 1909).

2.3.1 Economic complexity

It was Adam Smith's (1887) most significant discovery that the division of labor increased the productivity of labor, thereby increasing society's wealth and thus development is correlated with the quantum of activities and complexity of the products / economy. Furthermore, a country that specializes in only certain economic activities will have the skills to succeed in these endeavors, as well as in activities that require similar capabilities. The diversity and sophistication of a country exports and products highlight what a country can produce in the future. Economic complexity can explain differences in cross-country income differences as a result of the diversity of non-tradable "capabilities" available to a country (Hidalgo and Hausmann, 2009). Further, Hidalgo and Hausmann (2009) mention that the interaction between the growing number of individual activities that constitute an economy may be associated with wealth and development. Today in a developed country, knowledge is extensively diffused among numerous members, resulting in the accumulation of vast quantities of creative knowledge. Economic complexity was observed to have a negative relationship to income inequality, which indicates that an increase in diverse and complex products can lead to growth of incomes differences within the population (Hartmann et al. 2017; Ncanywa et al. 2021). Still, this relationship does not always hold as it can be influenced by other factors such as quality of governance institutions, and contextual factors (Bandeira et al. 2021). Moreover, economic complexity may lead to higher inequalities between labor groups.

Globalization has greatly impacted the way production activities are carried out, particularly in developing economies. Due to increasing interconnectivity and growth of Multinational Corporations (MNCs), many of the production activities and are now overseen by MNCs or their subsidiaries. In most cases, the production activities are conducted through the Foreign Direct Investment Model (FDI) (Wilhelms and Witter, 1998). It can be observed that the so-called "exploitative" countries or "assembler" countries as they are called export high-level manufacturing that is not accompanied by local technological capabilities. In comparison, developed countries possess the greatest share of technological capabilities (Schteingart, 2015). Recently it was observed that FDI positively influence the complexity of export basket that later will influence service export diversification and economic growth (Gnangnon 2022; Osinubi and Ajide, 2022). Regardless, some studies argue that FDI can also be a double edge sword, meaning that it can aid entering new markets but also can only use the resources of the existing ones, and only focuses on existing products, not advancing science (Tian and Song, 2015). Moreover, other studies claim that the effect of FDI on productivity is not necessarily significant which indicate that the spillover effects of FDI claimed in literature may not exist (Fan, He, and Kwan, 2022).

2.3.2 Technological complexity

The ability of a country to export a particular product is not a guarantee that it has the capabilities to manufacture it (Tesfachew, 2019). Another method of determining whether a country has the knowledge to produce specific products is by examining its invention activity in terms of patents. A common misconception is that research measures knowledge by inputs, rather than outputs, and what matters is the quality of the knowledge created.

Balland and Rigby (2017) propose a framework for measuring knowledge complexity based on the number of patents that a nation produces in different categories. As a complex system is composed of many interdependent elements interacting in complex ways (Frenken, 2006; Simon, 1969). Earlier studies indicate that information for innovation arises from the recombination of existing ideas and through localized discovery. Nonetheless, knowledge subsets created in one region tend to be difficult to duplicate elsewhere (Balland and Rigby, 2017; Schumpeter, 1934). In the emergence and evolution of technology, especially those which are more unique and complex, tacit knowledge plays a critical role, and this indicates toward the importance of the location of knowledge, as often this type of knowledge is sticky to space.[2]

Competitiveness is determined by the extent to which firms can extend their knowledge domains and to use more knowledge components, although this was not measured by existing frameworks (Balland et al. 2019). Similarly to economic complexity, excessive specialization in complex technologies may result in lock-in and monopolistic rents for existing firms, since this makes it more difficult for other enterprises to acquire the ability to dominate those technologies. A further disadvantage of complex knowledge is that spillover from such knowledge hardly occurs, and the type of knowledge that is often spread among local actors is the knowledge derived from moderately complex technologies (Sorenson et al. 2006). The production

[2]This finding was conducive to creation of the second hypothesis the conceptual model in Section 4.2

of complex products, vast amounts of knowledge that can only be accumulated through large networks of professionals sharing tacit knowledge.

2.4 Smart Specialization

This subsection describes how relatedness and complexity became a policy framework (Smart Specialization). And how this initiative has overseen the importance of regional entrepreneurial ecosystems during the ex-ante planning and implementation.

Innovation should result from the interaction and discovery of opportunities by actors. Even so, interaction in a complex system is difficult to quantify since it is a bottom-up, place-specific interaction and actions in which inventive activity types also vary (Ruhrmann, Fritsch and Leydesdorff, 2021). In 2011, the European commission initiated a massive experiment in innovation and industrial policy (Radošević et al. 2017). This new policy strategy, entitled Smart Specialization, aims to promote innovation and inclusive, sustainable growth in EU areas (SS). Aimed at decreasing the discrepancy between core and periphery regions of EU. It is a policy that through the learning process and activities of entrepreneurial actors aims to help regions to discover the research and innovation domains which a region can and is willing to develop (Foray, David, and Hall, 2009).Aiming to drive the localization and agglomeration of resources and competences within these areas (Foray 2014). Here, Foray (2014) strengthens the interventionist aspect of government in prioritization of these new activities. The SS concept is closely related to the concepts of evolutionary economic geography as discussed earlier such as relatedness, complex technologies, embeddedness in a system, interaction but also the contextual factors of the ecosystem theory (McCann 2015). This way identifying new but related explorative research paths while supported by existing structures and contextual factors. Smart Specialization was divided into the sides, mainly specialization or prioritization and concentration of resources and choice of priorities and the second size transformation and modernization of regions through diversification.

However, despite the fact that enterprises are viewed as the primary source of innovation and the key players in the entrepreneurial discovery process, they were somehow excluded from examination in innovation strategies (Szerb et al. 2020). Firms innovate in an embedded environment where contextual elements continuously interact and impact the discovery and commercialization of inventions (Audretsch and Belitski, 2017). In a complex economic system, the bottom-up method does not investigate the problem of local problem-solving and decision-making. Observing Darwin's theory of evolution, the bottom-up formation of intelligence also presented these sorts of challenges. How did a network of cells starts to cooperate and act as a society and collectively pursue goals? Scientists attribute the success to "modularity", or else the existence of competent problem-solver subunits (Levin and Yuste, 2022). According to the same authors, these modules perform their responsibilities until certain conditions are met and can complete a complex pattern. In any case, these modules are activated by a trigger and do not make judgments independently. They are capable of completing a pattern even without complete information. The completion of the pattern facilitates the emergence of intelligence and developmental complexity. Szerb et al. (2020) examine the entrepreneurial ecosystem as a holistic and comprehensive tool for measuring the bottlenecks in the environment in which the actors interact.

Ecosystem is not simply an addition of component scores, but also a synergy of other stakeholders, such as small and large businesses, colleges, financial institutions, and government agencies (Malecki, 2018). This complex, systemic interaction mainly drives entrepreneurial performance as needed by the SS policy (Audretsch, Keilbach and Lehmann, 2006). New technologies and industries will develop as a result of the collective ability of agents with diverse technological and industrial profiles (Balland et al. 2019). Despite criticism that pillar-index techniques of measuring the entrepreneurial environment are static and incapable of indicating the path to new industries, they remain one of the most effective approaches for benchmarking the entrepreneurial environment. Nevertheless, each region was pushed to have its own strategy in order to access European Regional Development Funds (ERDF) therefore policy practice was running ahead of theory.

Nevertheless, can Smart Specialization Strategy (S3) take the responsibility of developing the backward regions alone behaving as an all good, all knowing, all powerful for the cause of cohesion? A lack of connectivity, entrepreneurial spirit, market size, industrial diversity, quality of local governance, and a critical mass of capabilities, or, to put it succinctly, a good entrepreneurial climate, makes identifying local technology domains and entrepreneurial discovery challenging (Capello and Kroll, 2016). In addition, the new method requires a sound theoretical foundation and particular examples of good practices in underdeveloped places, which as discussed earlier unfortunately do not exist (Morgan, 2015). Moreover, what was meant to be one of the most straightforward paths for low developed regions to collaborate, prioritize, innovate and grow became one of the least understood policies. As it did not take into consideration certain features of the European regions. Knowledge bases and capacities that do not exist, different regional innovation systems, reliance on external technologies, and institutional and governance weaknesses are obstacles to smart specialization strategies (Isaksen, Martin and Trippl, 2018). Despite this, the success of smart specialization methodology is limited, and scattered approaches may be a contributing factor. A 'place-based' policy approach that seeks to utilize local territorial assets may not be possible in places that lack such advantages (Capello and Kroll, 2016).

2.4.1 The non-integrated methods for Smart Specialization prioritization

One of the reasons why SS still fails to deliver an integrated framework for technological domains choice for the growth of low developed regions may be separated methods between researchers. Some researchers propose smart specialization frameworks around the concepts of knowledge complexity and relatedness Balland et al. (2019), or diversification based on relatedness (Boschma, 2017). Relatedness comes both from patent citation but also labor shares and export basket in different industries. Yet, it is unclear if these approaches are optimal for smart specialization. First, this is based on product space and complexity approaches of (Hausmann, Hwang and Rodrik, 2007) and (Hidalgo et al. 2007) and is not clear if this is a measure of diversification or specialization. On the other hand, it may be simple for low developed regions to specialize in order to acquire human capital and technology skills, and then diversify in order to increase their sources of income and flourish.

While related specialization recognizes pre-existing sectors and technological paths, unrelated specialization or diversification focuses on leapfrogging, which is harder to forecast, and does not offer much information about the direction of specialization (Radošević et al. 2017). Despite the complexity frameworks' implicit dynamic of regional knowledge and skills to develop rare products, this is nevertheless prejudiced by export basket focus. This propelled eastern European nations to the top of the complexity ranking as a result of the exports of numerous multinational corporations (Hausmann, 2013). This framework is also limited by a lack of consideration of the contextual factors and existing regional capabilities, and not only to produce but also to collaborate and manage in policy implementation. Also, the existent framework disregards the role of institutions Grillitsch, (2016) and the entrepreneurial discovery (Kirzner, 1997).

2.4.2 The choice of the path in Smart Specialization

To grow, regions need to diversify by developing new complex technologies, and this can be done only by exploiting the existing capabilities and knowledge (Balland et al. 2019). Nevertheless, this argument is questionable, as both paths of specialization and diversification may have their own flaws. First, overspecialization in one technology may blind regions to other prospects, while also making it difficult for regions to adapt their specialism and their skills to new domains. Specialization may momentarily benefit regions, but this may not be the case in the long run. Protracted periods of specialization and path dependence might result in regional lock in (M. Valdaliso et al. 2014). As industrial disruptions occur more regularly, this becomes more challenging without particular dynamic capabilities (Karimi and Walter, 2015). That is why specialization and path following models are not optional. On the other hand, because new industries also imply experimentation, having a diverse pool of industries for diversification may make regions not better, but more paralyzed (Schwartz, 2007). The excess of diversity can also lead to loss of economies of scale and network externalities (Foray, 1997). Frequent diversification will also impact learning and hasten the process of learning (Lee, 2014).

Initial factor endowments, such as labor or natural resources, often cause regions to slip into path dependence, a situation requiring enormous capital and technological investments to make a transition. Therefore, the trade-based specialization stated previously is illogical, as it primarily follows the incumbent industries that capitalize on the region's comparative advantage.

Asking regions to upgrade to higher value-added activities based on incumbent industries or enter emerging industries based on related capabilities raises costs (wages, R&D, investments). These regions have already opted for factor-driven industries, asserting previously mentioned methodological claims as incredible. Nonetheless, the dilemma of technology choice was attempted to be solved by Lee (2014) through specialization in short-cycle technologies. This was also noticed at the business level, as the same author notes that countries seeking to catch up tend to specialize more and more in technologies with short cycle times. This may represent the window of opportunity for those regions that are attempting to catch up and enter the emerging industry (Archibugi and Pietrobelli, 2003).

Determining which technologies and disciplines a region may pursue can assist in the development of infrastructure, skills, and socioeconomic considerations. These windows of opportunities can be taken when a new generation of technologies appear or are brought on the market. Nevertheless, this should not replace the leapfrogging claim, as this happens based chiefly on related industries and happens in both intra- and inter-industrial sectors (Lee, 2014).

The short cycle of technology can represent also a solution to explain why some regions have a such diversified pool of technology, Christensen et al. (2007) show that innovation that is new to the market, however, based on existent technology can enable shorter product life, this means also shorter patent life which can lead to greater product diversity and associating this would mean a different set of competitive demands on the value chain. The increase in diversity is caused by the frequent changes in the knowledge and competences needed to produce a certain product, in this case long-term specialization on one product is not possible, as it is often disrupted. The destroying of competences in the existing industries by innovations also leads to short-cycle technologies (Tushman and Anderson, 1986; Malerba and Lee, 2021).

3 The importance of digitalization for regional innovation and economic growth

3.1 What is Digitalization, and Why is it Important?

The preceding chapters have already discussed digitalization and its contribution to the growth of local entrepreneurial ecosystems, as well as the implementation of more effective smart specialization strategies. The definition of digitalization and its quantification across disciplines remains unclear. Moreover, the digital economy has not been included much in the previous measurement of smart specialization and entrepreneurial ecosystems, while it occupies a massive share in the current economy.

First, let us define digitalization more clearly. Some academics define it as the process by which an organization converts data from analog or manual to digital format for use. Similarly, digitalization refers to an organization's implementation or expansion of computer and digital technologies to enhance operational processes or business models. The term 'complex transformation of socioeconomic systems driven by digital technologies' can be used to describe this process, although it originated from the development of physical technologies such as semiconductor technologies, network access technologies and software engineering (Katz et al., 2014).

Until recently, metrics of digitization have mainly been related to Internet and mobile phone penetration, Internet access, or broadband penetration. To study the geographic organization of the Internet, Wheeler and O'Kelly (1999) analyzed the hardware topology of the commercial Internet backbone. Haller and Lyons (2015) used broadband speed to investigate business performance. Internet infrastructure networks were used by Tranos et al. (2013). Blank et al. (2018) analyzed the distribution of internet users in the United Kingdom. By analyzing the number of business webpages, Tranos et al. (2021) investigated the long-term impact of early adoption of internet-related technologies on regional productivity in the United Kingdom.

In the past, during the first years of digital transformation (1995-2005), the main focus of digitalization was on internet access. Efforts were concentrated on building high-speed internet access networks and internet infrastructure in different geographic areas.Therefore, initial studies focused on who had access to physical internet infrastructure in the form of computers and internet connectivity. It became clear from the beginning that not all areas will benefit from the internet the same way, as inequality was visible in terms of who has and who has no internet infrastructure and access. This initial phase of the digital transformation, where access inequality was visible, was referred to as the digitalization with a "digital divide of the first order" (Blank et al. 2018). Subsequently, the focus shifted from accessing the Internet to addressing the growing digital divide, the usage divide and the participation gap (Hargittai, 2002; van Dijk, 2006) (Jenkins et al. 2006). Having gained access to the Internet, Europe and the entire world has faced the challenge of effectively using and benefiting from the outcomes of this connection. The effective usage challenge is commonly referred to as the usage gap or second-level digital divide (Blank et al. 2018), which still persists in some parts of the world. The inequality of outcomes and benefits is seen as the third-level digital divide. In case of business digitization, referring to the third-level divide, although the majority of companies have an online presence, only a minority of them take full advantage of the potential benefits. The heterogeneity observed in the website's presence and benefits may be attributed to the use of different digital web technologies during their development. Not all sites offer the same tools and capabilities to achieve similar goals. Although some technologies, such as digital advertising and online payment systems, are essential to enhance e-Commerce, others only provide contact information and business hours (Elia et al. 2021).

Geographic disparities in productivity gains from digitization may be due to differences in the use of digital web technologies to create web pages. In a future society where Internet access is universal in developed countries, it may be necessary to use the most advanced technologies to fully realize the benefits of digitization. This will require a shift in focus from access to use of digital web technologies, in line with previous research in this area.

The potential benefits of digitalization in various fields (Haefner and Sternberg, 2020; Tranos et al., 2021) have contributed to its increasing importance in policy agendas. For example, Moriset and Malecki (2009) pointed out that there is a tendency for firms to locate in regions with better digital connectivity, which can reduce unemployment in these areas. In addition, the debate on depopulation has highlighted the importance of Internet access for the maintenance of the population in rural areas (Pontones-Rosa et al., 2021). Although ICT diffusion can promote spatial decentralization, meaning that businesses and individuals can operate remotely, its effects are often offset by the benefits of agglomeration, Tranos and Ioannides (2020) argue.

While the rise of information and communication technologies (ICT's) has contributed to the geographical dispersion of economic activities, the effects on regional labor markets remain ambiguous.By creating incentives for offshoring, digitalization has been accused of creating unemployment. Van Slageren and colleagues (2022) contend that the purported ease of accessing new labor markets internationally tends to be overstated, with the gig economy's influence on EU labor markets being less impactful than anticipated due to geographic and linguistic hurdles. Moretti (2012) identified a dynamic interplay between high-tech roles and different employment levels, where each high-tech position established in a city typically generates several additional non-high-tech jobs locally, thus increasing overall employment. Yet, digitalization offers a variety of other advantages to regions. Some researchers posit that digital platforms might promote industrial symbiosis, encouraging resource reutilization in industrial activities and supporting the shift toward circular economies (Krom et al. 2022). Nham (2022) points out that the connection between digitalization and circular economic practices is complex and not strictly direct. Batabyal and Nijkamp (2016) present the idea that regions with a creative bent stand to gain from the interplay of digital technology and innovation policies, leading to the partial transfer of knowledge. On the digital front, Burgess et al. (2011) suggested that regional tourism organizations can leverage the Internet for marketing purposes and e-commerce, enhancing the visibility and economic activity of regions.

Nevertheless, perhaps the most significant advantage may lie in the potential productivity enhancements brought about by digitalization. Prior studies have established a robust positive correlation between digitalization and productivity, regardless of the chosen data source for empirical investigation. Najarzadeh et al. (2014) discovered a beneficial connection between internet usage and labor productivity. Blom et al. (2012) identified that information technology adoption positively affects the operational efficiency and productivity at the organizational level. Bertschek et al. (2013) examined the impact of broadband internet on organizational performance. Abbasiharofteh et al. (2023) found a strong link between the quality and density of an organization's online hyperlinks and its innovation capacity. Tranos et al. (2021), using web page analytics, observed that regional integration of internet technologies is associated with sustained productivity improvements. Mack and Faggian (2013) reported a positive association between broadband availability and productivity in U.S. counties, a finding echoed by Jung and Lopez-Bazo (2019) in the context of Brazil.

While the effects of digital technologies were discussed earlier, more attention needs to be paid to different types of technologies, such as digital web technologies. Web technologies, as Yoo et al. (2010) and Tsalgatidou and Pilioura (2002) have noted, represent the core infrastructure enabling communication, transactions, and innovation across the internet. They are a subset of broader internet technologies and part of the overall digital technology ecosystem that powers contemporary internet activity and online experiences.

3.2 Web technologies and their position in digital ecosystems

Web technologies encompass various software platforms, coding languages, and applications that enable the creation of websites, web services, and online tools on the internet (Morris, 2015). They are distinguishable from ordinary digital technologies due to their specific roles in structuring web content (HTML), styling (CSS), interactivity (JavaScript), content management (CMS), e-commerce, and web analytics. These technologies are fundamental in enabling daily activities online such as communication, social connections, shopping, banking, and education, impacting individuals, businesses, organizations, and societies worldwide (Varian, 2010). Nielsen and Loranger (2006) highlight how these advancements have significantly improved user experience, making the web more accessible and engaging. They enable websites to automatically adjust their layout and content to different screen sizes, enhancing accessibility and usability on mobile devices. Moreover, Mell and Grance (2011) explain how web technologies have facilitated the development of cloud-based services, providing scalable and flexible computing resources over the internet.

The impact of web technologies on innovation is known and researched by other scholars. As stated by Melville et al. (2004) new platforms, languages skills, and regional capabilities lead to the creation of digital products, services, and transformational technologies across different sectors. For example, the development of social networks, social marketing, the sharing economy, digital streaming, and telemedicine can all be traced back to improvements in web and mobile technologies.

In addition, these technologies significantly increase productivity, efficiency and economic performance for businesses and organizations by facilitating operations, reaching new customers, and enabling new business models (Crémer et al. 2019). Empirical research supports the economic and productivity benefits derived from investing in digital technologies. For instance, studies by Brynjolfsson and Hitt (2000) indicate that investments in digital technology, particularly web technologies, are strongly correlated with increases in firm productivity. Moreover, web technologies play a pivotal role in promoting entrepreneurship, and empowering new venture creation. They lower barriers to launching online businesses and accessing global markets, as highlighted by Acs et al. (2021). The digital economy, fueled by these technologies, has given rise to numerous innovative technology startups. Laudon and Traver (2020) emphasize how web technologies have enabled the creation of sophisticated online marketplaces, allowing businesses to reach a global audience and offering consumers a wider range of products and services.

The research conducted by Bresnahan and Trajtenberg (1995) on 'general purpose technologies' shows that web technologies, similar to electricity and the internal combustion engine in the past, are capable of transforming a wide variety of industries. Web technologies can also have a transformative impact on society, being the foundation for digital economies. As mentioned by Castells (2001) in his analysis of the 'network society,' which is characterized by the development of new social structures, business models and interaction dynamics through the use of the Internet.

3.3 Place and geography in the digitalization era

Digitalization influences and is influenced by spatial aspects. This is visible in terms of the distribution of digital technologies, industrial practices, and digital needs across different geographic locations, as well as their influence on spatial patterns and relationships, or workforce geography. Carayannis et al. (2023) have examined the impact of digitalization on small and medium-sized enterprises in rural areas and its effect on economic and entrepreneurial activities in a spatial sense. Initially, it was thought that the Internet would diminish the relevance of geographic and spatial distance. Still, recent studies have shown that spatial attributes and proximity play a crucial role in understanding web technology diffusion patterns (Kolko 2000; Keller and Yeaple 2013; Vicente and López 2011). Graham (2013) and Castells (2010) show that despite the global reach of the Internet, local geographic contexts significantly affect how digital technologies get adopted and used.

Digitalization can help reduce spatial inequalities in rural areas, mitigate disadvantages associated with rural areas, fight rural poverty, and reduce depopulation. It is important to note that the digital divide not only refers to access, but also to skills and technology utilization, which can reinforce existing regional disparities (Van Dijk 2020; Ragnedda and Muschert 2013).

Several studies have shown that geography plays a significant role in the spread of technology. Comin et al. (2012) concluded that technology diffuses more slowly to locations that are further from adoption leaders. Tranos et al. (2021) emphasized the spatial dimension and heterogeneity of the diffusion of digital technologies, which is influenced by agglomeration and existing economic strengths across regions. Researchers have noted that technology diffusion involves knowledge flows that degrade over time and space. Jaffe et al. (1993) found that knowledge spillovers are adversely affected by distance, as patents exhibit sharp distance decay effects. Henderson et al. (1995) report that diffusion is more rapid in regions near early adopters, even for new technologies, demonstrating the presence of spatial friction in the diffusion process.

Researchers recognize that clusters and proximity to innovative hubs have a significant impact on technology absorption. Tranos and Ioannides (2020) suggest that ICT adoption outweighs the benefits of agglomeration and contributes to spatial decentralization without the need for physical proximity. However, firms located closer to tech hubs are better positioned to take advantage of potential gains from new digital tools. The trajectory of digitalization is also influenced by regional characteristics and the dynamics of innovation ecosystems (Cooke 2001; Asheim and Isaksen 2002).

Furthermore, digitalization has the potential to diminish the cognitive gap between central and peripheral regions, even though the physical gap between urban and rural areas may persist. This duality presents a complex landscape where digital technologies bridge some divides while potentially exacerbating others. For instance, the emergence of remote work has opened opportunities for rural areas to integrate more closely with urban economies, yet the requirements for digital infrastructure and skills create new barriers (Florida 2020; Moriset 2013). Moreover, the spatial dynamics of ecommerce and online marketplaces reveal how digital platforms can both expand market access for rural producers and intensify competition, requiring new strategies for local economic development (Scott and Van Reenen 2014; Brynjolfsson and McAfee 2014).

Technology, geography, and socioeconomic factors interact in multifaceted ways in the spatial aspects of digitalization. For policymakers and businesses alike, understanding these spatial dimensions is increasingly important, particularly when strategizing for inclusive growth and regional development (OECD 2019; Rodriguez-Ardura and Meseguer-Artola 2020). Such studies, anyhow, must be conducted at the correct time in order to prevent the results from becoming too late. For example, some research indicates that early adoption of internet-related technologies and digitization practices results in higher returns compared to later adoption stages. (Tranos, Kitsos, and Ortega-Argilés, 2021). This implies that first-mover advantages are crucial to the digital economy. This perspective may actually produce unclear results if a study is conducted too late, since it will indicate that particular technologies are not beneficial to regions. Mack and Faggian (2013) as well as Jung and Lopez-Bazo (2019) have demonstrated that broadband provision has a positive, yet spatially heterogeneous effect on regional productivity. The question is, however, whether digital web technologies are capable of substituting or supplanting agglomeration forces, and whether they can make peripheral regions more competitive or whether they are entirely dependent on the absorption capacity or the industrial specialization of regions. The digital world does not yet know whether economies of scale will dictate how a region learns and grows, like they did in the past. In the past, agglomeration forces dictated how a region learned and grew through economies of scale. Grubesic and Mack, (2015) examined the impact of population density on the adoption of broadband. Where dense areas tend to have better internet infrastructure and a higher degree of technology adoption due to economies of scale. As part of their study of technology adoption dynamics, Rodriguez-Pose and Crescenzi (2008) examined how core-periphery dynamics affect technology adoption, with core regions typically having access to digital technologies more readily. This reinforces previous research regarding knowledge spillover and the importance of neighboring regions' socioeconomic and institutional conditions.

Recent research has investigated the relationship between technology adoption and knowledge spillover effects using sophisticated spatial econometric models. The study builds on the understanding of core-periphery dynamics in technology adoption. Qiang, Rossotto, and Kimura, (2009) and Barbero and Rodriguez-Crespo (2018) conducted studies that focused on the economic impact of broadband infrastructure. Spatial econometric models were utilized to analyze spillover effects, emphasizing the influence of broadband quality and presence in one region on adjacent areas. The study found that digital infrastructure benefits not only densely populated or technologically advanced areas, but also their neighboring regions economically. The study extends the concept of economies of scale in digital infrastructure to include the spatial dimension, demonstrating how investments in one area can have a wider economic impact. Arribas-Bel, Kourtit, and Nijkamp (2015) also utilized spatial models in their research on smart cities and digital technologies. The researchers are investigating the spatial distribution and effects of these technologies. This can provide insight into how the benefits of smart city innovations are not evenly distributed. They explore how the concentration of digital technologies in certain urban areas can lead to uneven development and a digital divide. The research highlights the importance of considering spatial factors when studying digital technologies. This ensures that the benefits of these technologies are more equitably measured and can be distributed across all regions of the country. It is important to note that broadband deployment is technologically challenging outside of population centers, which will also affect specific web technologies. The adoption of digital technologies may be affected by the unavailability of infrastructure in peripheral regions (Philip et al., 2015; Salemink, Strijker, and Bosworth, 2015).[3]

3.4 The effect of digital platforms on spatial organization and local embedding

Previously, it was argued that digital technologies may have contributed to the growing disparity in productivity performance across firms. Therefore, policies to promote digital adoption and enable laggard firms to catch up are could be useful. Additionally, the diffusion of digital technology has resulted in significant efficiency gains for firms in the telecommunications industry due to the digitalization of telephone lines. Early adoption of digital technology has been found to enhance regional productivity. It is well documented that digital technology adoption is associated with increased productivity at the firm level, especially in manufacturing and routine-intensive activities. These effects are stronger for more productive firms and weaker in the presence of skill shortages, indicating that digital technologies and other forms of capital can complement each other.

But digital technologies do not come alone, they have to be implemented as platforms. As also discussed earlier, platforms are defined as digital or online infrastructure that enables interactions and transactions between different user groups (Boudreau and Hagiu, 2009). This gives a chance for business to engage in entrepreneurial discovery not only through new business models and different forms of innovation, but also transforming the existent companies, through hori-

[3] This section contributed to the creation of the Hypothesis 3 and Hypothesis 4, related to how the contextual factors and space is contributing to technology adoption as seen in Section 4.2

zontal diversification (Nambisan, Wright, and Feldman, 2019; Boudreau and Hagiu, 2009).This is due to the fact that internet strongly supports home office jobs and income growth by reducing a range of geographic frictions, while (Nambisan, 2017) mention that digital involvement is also changing the spatial and societal boundaries of entrepreneurial discovery. While platforms may seem to work as a decentralization mechanism, that can be true if that is attributed to physical space, yet cognitively they are seen as to gather local players. Digital technologies are the backbone of platforms with which they can better coordinate activities and combine elements of markets with spatial hierarchies (Makadok and Coff, 2009). Digital platform firms set or modify their boundaries based on factors such as firm scope and platform design. The boundaries created are crucial for local economic landscapes because platform companies frequently act as intermediaries in spatial interactions and wield considerable influence over local economies (Graham 2020).

3.5 Main findings from the Literature Review

The literature provides foundational insights into the transformative potential of digital technologies in regional economies (Kenney and Zysman, 2016). Nonetheless, it falls short in dissecting the intricate mechanisms through which digital complexity directly contributes to regional productivity. The need for empirical evidence that delineates the relationship between digital complexity, technology adoption, and their combined impact on regional productivity is evident (Acs et al., 2017; Autio et al., 2018).

The intricate pathways through which digital technologies are adopted and adapted across diverse regional contexts remain underexplored. This gap extends to a comprehensive understanding of the symbiotic relationship between digital complexity, technology adoption, and regional productivity, particularly within the ambit of smart specialization.

Moreover, there is a lack of empirical evidence on the efficacy of digital innovation strategies tailored to place-specific characteristics. Although the importance of localized production and agglomeration economies is recognized (Porter, 1998; Florida, 2002), detailed case studies and quantitative analyses pinpointing the success factors of digital innovation strategies in enhancing regional economic outcomes are sparse.

Contradictions arise regarding the impact of digitalization on economic equality and sustainability within regions. Some scholars argue that digitalization propels regional economic development by fostering innovation and competitiveness (Autio et al., 2018; Cairncross, 2002), while others caution against its potential to exacerbate regional disparities and environmental concerns (Cohen and Kietzmann, 2014). These contradictions suggest that there's a need for empirically examining the complex relationship between digitalization and regional development outcomes, necessitating further investigation.

The study of Nambisan (2017) highlights how digital web technologies facilitate new forms of value creation and capture, enabling businesses to use vast datasets for enhanced decision-making and to foster global connectivity. Digital web technologies are slowly but increasingly recognized as essential enablers of innovation and economic growth, at least in the digital environment and for digital industries. Zahra and Nambisan (2012) further argue that these technologies are pivotal in supporting entrepreneurial activities by providing platforms for collaboration, reducing market entry barriers, and enabling rapid scaling of new ventures.

Moreover, Autio et al. (2018) suggest that these digital technologies can be leveraged to identify and exploit niche markets, enhance the efficiency of production processes, and foster innovation through data-driven insights. That's why digital web technologies offer invaluable opportunities for regional development, they require also specific capacities to be undertaken. Furthermore, it emphasizes the role of digital web technologies in enabling remote work and collaboration, which can contribute to the decentralization of economic activities and the revitalization of rural areas.

While the significance of digital web technologies is widely recognized, their regional adoption and integration into entrepreneurial ecosystems and smart specialization strategies present both challenges and opportunities. These will be empirically examined in the following chapters.

4 Conceptual Framework and Hypothesis Development

4.1 The Conceptual Framework

The following figure represents the conceptual framework of the entire study, focusing on the interplay between smart specialization and the entrepreneurial ecosystem, illuminates the strategic importance of fostering technological evolution and adoption within a contextually enriched environment. This framework underscores the essence of relatedness density and digital complexity as pivotal components in shaping regional innovation capabilities and economic outcomes. The conceptual framework and hypothesis development draw attention to the intricate mechanisms through which relatedness density, as a measure of cognitive proximity and technological connectedness, facilitates the diffusion and adoption of new technologies. It emphasizes the role of digital complexity in enhancing organizational and regional competitiveness through the advancement of technological infrastructure and capabilities.

From the perspective of smart specialization, the framework highlights the necessity of identifying and nurturing areas of competitive advantage, which are related to existing knowledge paths, and technological specialization. The framework suggests that regions can leverage their unique assets and capabilities through focused investment in related and complex digital technological domains, thereby fostering innovation and driving economic growth. This approach aligns with the European Union's smart specialization strategy, which advocates for regions to identify and develop their niches of technological expertise to enhance economic cohesion and competitiveness.

Moreover, the framework integrates the concept of the entrepreneurial ecosystem, emphasizing the synergistic relationship between various stakeholders, including firms, government, academia, and financial institutions, in cultivating an environment conducive to innovation, technology adoption and entrepreneurship. It points to the significance of contextual factors, such as spatial influence and agglomeration effects, in amplifying technological adoption capacity and its effects on economic outcomes. These factors are instrumental in creating a vigorous entrepreneurial ecosystem where knowledge spillovers, collaboration, and digital innovation thrive.

Overall this framework and its associated hypotheses propose a comprehensive model where

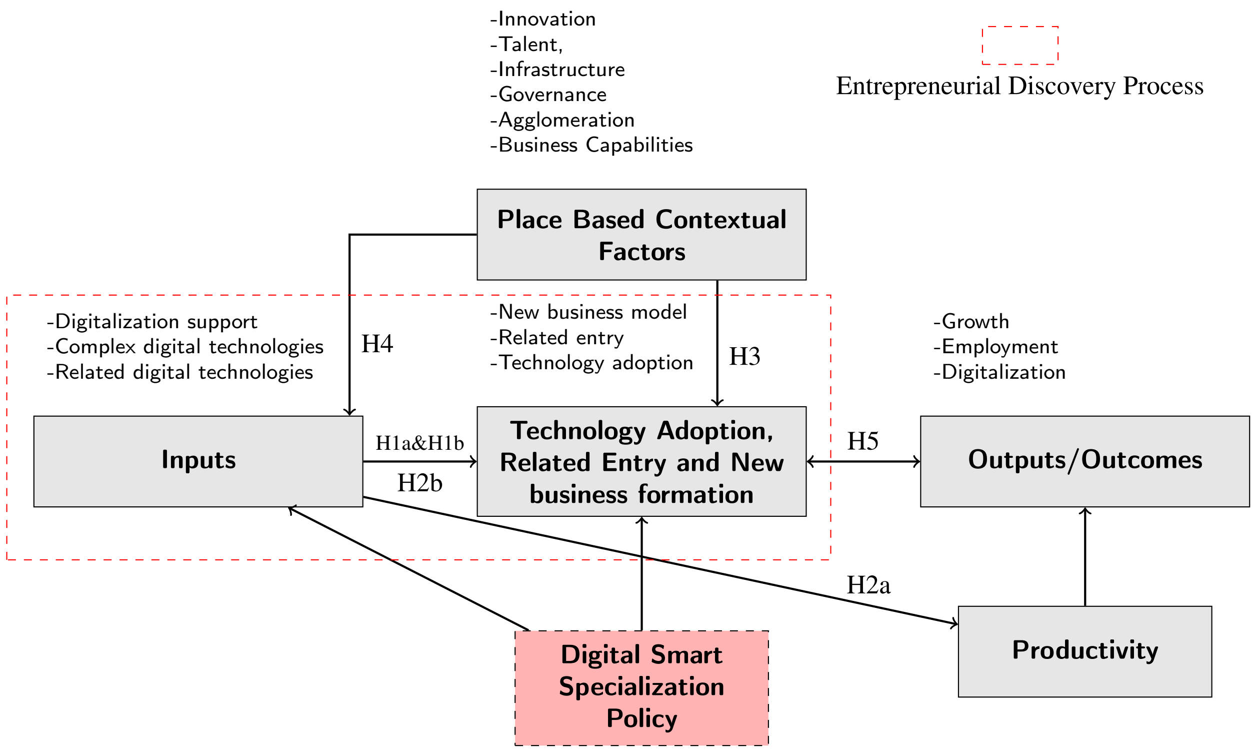

Figure 2: Conceptual framework of an Ecosystem-based Digital Smart Specialization Policy

digital technology, combined with a deep understanding of relatedness density and digital complexity, is deployed within a supportive entrepreneurial ecosystem, into an ecosystem-based smart specialization strategy. This model envisions a dynamic and iterative process of technological evolution and adoption, where contextual place-specific factors and policy interventions play a critical role in steering economic development towards higher digitalization, innovation, productivity, and growth.The idea of Entrepreneurial Discovery Process (EDP) was discussed in section 2.1.2 for knowledge and technologies in the physical realm. In the case of this digitalization framework, the EDP has a similar idea, it is the process in which local actors combine existent knowledge of complex and related digital technologies into new firms, new industries or simply improve their current way of doing business online by adopting new digital technologies.

The adoption of this framework signifies a strategic move towards embracing the complexities of the modern economic landscape, where technology, knowledge, and context interlink to shape the trajectories of regional and organizational growth. It calls for a detailed but straightforward approach to policy formulation and implementation, one that is attuned to the specificities of regional capabilities and the global innovation ecosystem.

4.2 Hypotheses Development

Relatedness Density and Technological Evolution:

The motivation for choosing the following hypotheses related to relatedness density and technological evolution is deeply rooted in the interplay between digital relatedness, knowledge diversity, and the evolutionary economic geography that frames the dynamic landscape of technological innovation and adoption. The concept of relatedness density, emphasizing the connectivity within a network of technologies, underscores the importance of cognitive proximity and the shared knowledge base which facilitates the recombination of ideas leading to innovation and growth (Frenken, Oort, and Verburg, 2007; Boschma and Iammarino, 2009). The evolutionary perspective, with its focus on how regions and organizations adapt and evolve over time, suggests that the presence of related capabilities within a region not only enhances the absorptive capacity but also significantly impacts the ease with which new methods, ideas, and technologies are acknowledged, absorbed, and adopted (Cohen and Levinthal, 1990).

Moreover, the discussion around smart specialization and the role of knowledge and learning in innovation systems further strengthens the argument that relatedness density is pivotal for regional growth. The interconnectedness of firms, industries, and regions, as highlighted by the evolutionary economic geography, indicates that diversification into related activities builds on existing competencies and facilitates transformation through new combinations of related knowledge (Boschma and Fornahl, 2011). This approach is aligned with the first hypothesis. This states that high relatedness density, indicating a closer relationship between existing and new technologies, is expected to enhance the likelihood of related entry and facilitate digital technology adoption.

Therefore, the adoption of new technologies and entry into new technological domains are seen as outcomes of complex interconnections between existing regional capabilities, the evolutionary dynamics of economic geography, and the strategic emphasis on smart specialization. The positive relationship between relatedness density and related entry (H1a), as well as between relatedness density and technology adoption (H1b), is supported by the underlying premise that regions with a rich tapestry of related capabilities and knowledge networks are better positioned to navigate the difficulties of digital technological evolution and adoption and leverage these connections for sustained economic growth and innovation. This motivation, rooted in the theoretical and empirical foundations of evolutionary economic geography and the relatedness theory, underscores the relevance and importance of exploring these hypotheses within the broader discourse on technological adoption.

1. Hypothesis H1:

1. *Hypothesis H1a:* There is a positive relationship between relatedness density and related entry. In the case of web technologies, high relatedness density, indicates a closer knowledge relationship between existing and new technologies. Relatedness density is expected to enhance the likelihood of related entry, where firms in regions enter new digital technological domains that are closely related to their previous capabilities

2. *Hypothesis H1b:* There is a positive relationship between relatedness density and technology adoption. High relatedness density, indicating a closer relationship between previous and new technologies, is expected to facilitate technology adoption.

Digital Complexity's Impact:

The intricate relationship between digital complexity and organizational outcomes illuminates the profound transformative power of digital technologies in the contemporary economic landscape. Digital complexity embodies the multifaceted dimensions of technological infrastructure and capabilities a region has, and plays a pivotal role in shaping organizational strategies and regional development policies. This complexity is not merely a reflection of technological advancement but also an indicator of a firm or region's capacity for innovation, adaptation, and competitiveness in an increasingly digitized world. The origin of the hypothesis lies in the understanding that digital technologies are not static tools but dynamic complex systems of factors that can significantly enhance operational efficiencies, foster innovation, and drive economic growth.

Empirical and theoretical investigations into economic complexity reveal that regions and organizations endowed with sophisticated and diverse economic activities tend to experience superior growth and highly technological and industrial paths. Complexity is closely linked to the ability to combine generate and capitalize on overlapping existent capabilities, suggesting a fertile ground for technological adoption and productivity enhancements (Hidalgo and Hausmann, 2009; Hartmann et al. 2017; Ncanywa et al. 2021; Bandeira et al. 2021). Furthermore, the concept of technological complexity underscores the necessity of vast knowledge networks and the cumulative nature of tacit knowledge in the production of complex products (Balland et al. 2019; Sorenson et al. 2006). Such environments are conducive to the adoption of new technologies and the innovation that fuels productivity and economic growth.

Digital complexity plays a critical role in achieving sustainable growth and innovation, as evidenced by the strategic focus on smart specialization and the integration of digitalization into policy agendas. The concept of smart specialization, which aims to leverage existing capabilities for economic development, is compatible with the hypothesis that digital complexity may play a significant role in influencing technology adoption and productivity (Foray, 2014; McCann, 2015). According to contemporary policy frameworks, the transition to the use of digital technologies further supports the argument that organizations and regions characterized by greater levels of digital complexity are better positioned to deal with the challenges and opportunities associated with the digital era (Katz et al. 2014 ; Elia et al. 2021).

2. Hypothesis H2:

1. *Hypothesis H2a:* Digital complexity positively influences labor productivity. Regions with higher digital complexity are hypothesized to exhibit higher productivity levels. When firms are digitized and have complex web technologies, they are expected to be more productive, therefore influencing the overall regional productivity.

2. *Hypothesis H2b:* There is a positive relationship between digital complexity and technology adoption. Higher levels of digital complexity within a region are expected to lead to greater technology adoption rates. Here it is expected a spillover effect from firms with complex technologies to other firms in a region.

The Role of Contextual Factors:

After the literature review, it is clear that the role of contextual factors, including spatial considerations and agglomeration effects, is central to understanding the dynamics of digital transformation and technological adoption. These elements significantly mold the digital landscape, delineating the boundaries of digital transformation across diverse ecosystems. The synthesis of cluster theory and the evolutionary dimensions of ecosystems emphasizes the geographic dependence of clusters and the various evolutionary dimensions such as origin diversity, selection, reorientation, and connectivity that influence the regional entrepreneurial ecosystem (Porter, 1998; Auerswald and Dani, 2017; Alvedalen and Boschma, 2017).

The interrelation of clusters, defined as geographic concentrations of interconnected firms, institutions, and industries, underpins the hypothesis that contextual factors bolster digital complexity and technology adoption. Clusters facilitate increased collaboration, knowledge spillover, and innovation, creating a dynamic geographic concentration where firms interact and co-create value (Porter, 1998; Adner and Kapoor, 2010). This collaborative environment not only boosts the region's or organization's digital complexity but also enhances its capacity for innovation and indirectly stimulates new business formation.

Moreover, the co-location of firms and institutions catalyzes efficiencies, facilitates knowledge sharing through network linkages, and promotes competitiveness within a cluster. This not only supports the hypothesis that spatial and agglomeration effects positively influence digital complexity but also asserts that such a conducive context facilitates the adoption of new technologies (Porter, 2000; Pitelis, 2012). The role of clusters in increasing the capacity of participants for innovation and their heavy dependence on the entrepreneurial environment highlight the importance of contextual factors in the digital and technological realm.

Therefore, hypotheses H3 and H4 are grounded in the understanding that the broader environment, characterized by spatial proximity, agglomeration economies, and the concentration of related activities, significantly enhances a region's or organization's digital complexity and facilitates technology adoption. These contextual factors, by fostering a conducive environment for collaboration, knowledge sharing, and innovation, play a crucial role in driving digital transformation and technological evolution across different ecosystems. In the following hypothesis, the contextual factors include innovation resources, talent availability, infrastructure, quality of governance, and firms are examined for their influence on digital complexity and digital technology adoption.

Initially I developed these hypotheses looking only at the contextual factors as a whole, however because contextual factors are too broad and include diverse factors. I divided the hypothesis into sub-hypothesis to separate spatial spillovers and agglomeration effects from the contextual factors. In the examination of contextual factors, we will consider only human capital, quality of governance and infrastructure.

5. Hypothesis H3:

1. *Hypothesis H3a:* Contextual factors (human capital, quality of governance, infrastructure) positively influence web technology adoption. This suggests that developed place specific factors and concentration of related activities facilitates the adoption of new technologies.

2. *Hypothesis H3b:* Spatial spillovers have a positive relationship with web technology adoption. The hypothesis argues that if the neighboring region adopts a specific web technology, this will spill over and facilitate the adoption of new technologies in the current region.

3. *Hypothesis H3c:* Agglomeration effects have a positive relationship with web technology adoption. The hypothesis argues that being in an innovation-oriented context with spatial and agglomeration of human economic activities facilitates the adoption of new web technologies.

6. Hypothesis H4:

1. *Hypothesis H4a:* Contextual factors (human capital, quality of governance, infrastructure) positively influence digital complexity. This suggests that the rich local environment and knowledge externalities enhance a region's digital complexity.

2. *Hypothesis H4b:* Agglomeration effects have a positive relationship with digital complexity. This suggests that the broader environment and concentration of human economic activities enhance a region's or organization's digital complexity.

Technology Adoption and Economic Outcomes:

Technology advancements play a pivotal role in catalyzing economic growth and development, according to the literature. In order to understand how technology adoption leads to improved economic indicators such as GDP per capita and overall economic growth, it is fundamental to study empirically this relationship. The dissertation provides a thorough exploration of the dynamics between technology adoption, particularly those driven by high-growth firms websites, and their substantial contribution to economic performance and structural transformation.

The emphasis on productive entrepreneurship, as highlighted by Baumol (1990), underscores the significant impact of entrepreneurial endeavors that not only drive job creation and enhance productivity but also contribute to societal value. This perspective aligns with the hypothesis that digital technology adoption, spearheaded by innovative firms and supported by conducive policy frameworks and digital ecosystems, serves as a catalyst for economic growth. The notion that high-growth firms, often early adopters of new technologies, play a crucial role in driving productivity and efficiency improvements further substantiates the link between technology adoption and positive economic outcomes (Coad et al. 2014; Lerner, 2010; Bosma et al. 2018).This led to the next hypothesis:

7. *Hypothesis H5:* There is a reciprocal positive relationship between digital technology adoption and GDP per capita. This implies that not only does technology adoption contribute to higher GDP per capita, but also that regions with higher GDP per capita are more capable of adopting new technologies.

Moreover, the discussion extends to the role of governmental and policy interventions in fostering an environment conducive to innovation and technology adoption. The strategic focus on identifying and assisting innovation pathways that diverge from current practices emphasizes the need for a supportive ecosystem that enables the flourishing of new businesses and the exploitation of emerging technologies (Foray, 2014; Hausmann and Rodrik, 2003). This ecosystem-centric approach to innovation and economic development suggests that technology adoption, supported by a robust entrepreneurial ecosystem, is instrumental in driving economic growth, thereby reinforcing hypothesis H5.

The dissertation's comprehensive analysis reveals the relationship between technology adoption, economic development, and the role of contextual factors in shaping this dynamic. The hypothesized reciprocal relationship between technology adoption and GDP per capita, along with the positive impact of technology adoption on economic growth, is rooted in the broader narrative of innovation-driven economic transformation. Through the lens of evolutionary economic geography and the entrepreneurial ecosystem framework, the study elucidates how regions and firms that embrace digital technological advancements and promote innovation are better positioned to achieve economic prosperity and resilience.

The motivation for the hypotheses concerning technology adoption and economic outcomes is deeply embedded in the understanding that technology adoption is not just an innovational activity, but a transformative force that reshapes economic landscapes and drives productivity. This hypothesis will highlight the critical role of technology adoption in achieving economic growth and underscores the importance of fostering a contextual environment that nurtures digital innovation and promotes growth through digitalization.

5 Research Design and Methodology

5.1 Data collection and variable description

5.1.1 Firms selection and geolocation

The objective of this research is to explore the hypothesis of a digital adoption divide across European regions and examine how evolutionary factors and regional characteristics influence web technology adoption and subsequent economic growth. To accomplish this, an understanding of the business landscape is crucial, particularly the geographical location, industry sector, and website ownership of companies. A meticulous selection process, facilitated by Crunchbase, identifies relevant companies for inclusion in the study. Crunchbase, known for its comprehensive database of start-ups and tech companies worldwide, employs a mix of automated algorithms and manual review to ensure the accuracy and reliability of its data. This approach is particularly aligned with the focus of my study on technology-driven enterprises and high-growth firms, which are recognized as key contributors to innovation (Kalafsky and Rice, 2017), innovation spillovers, the shaping of innovation policy (Goswami, Medvedev, and Olafsen, 2019), and regional economic development (Mazzucato and Parris, 2013). By focusing on high-growth technology firms and startups, my aim is to capture the forefront of digital innovation, which is crucial to understanding regional disparities in technological adoption and economic outcomes.

Given that most firms have basic online presences, including all Crunchbase firms, it is essential to distinguish between standard web pages and those belonging to entities at the forefront of innovation, such as high-growth potential startups and highly innovative companies. These entities often utilize cutting-edge digital web technologies, setting them apart in performance metrics. The diversity and competitive use of digital web technologies are critical to assessing the digital sophistication and interconnectedness of regions. Thus, the study focuses on 209,054 high-growth tech firms and startups, excluding other entities like investors. These selected companies are pivotal in introducing new knowledge into European regions, being at the innovation forefront and employing advanced digital web technologies.

Digital Web technologies span from basic utilities, like advertising and analytics tools, to more advanced functionalities, including e-commerce and online payment solutions. Whereas simple web pages may only incorporate essential technologies for basic operations and content display, sophisticated sites might integrate additional, complex technologies for enhanced services such as online transactions and fraud prevention. Despite the fact that all Crunchbase firms for Europe were included in the study, this chose criterion of using only high growth-high technological firms might exclude some small digitally active firms. This is one of the limitations of the dataset.

For a comprehensive analysis of the technology diffusion process, this study includes firms from a 21-year span between 2000 and 2020. Although the data was collected for 21 years, this time dimension was used mostly for the Digital Complexity and Relatedness study. For all other studies, the data used was only 2010–2020. The primary spatial units of analysis are the NUTS 2 (Nomenclature of Territorial Units for Statistics) European regions. To accurately locate companies within these regions, geocoding techniques were employed, assigning geo-coordinates to company locations based on city-level data and then mapping these to NUTS 2 regions using the "st_intersection" function from the "sf" package (Pebesma and Bivand, 2023), and integrating these data points with territorial polygons from the GISCO "Geographical Information System of the Commission" using shape files.

5.1.2 Relatedness Density Definition and Calculation

Relatedness Density is understood as the extent to which a particular digital technology is related to the existing set of technologies used within a region. Adapting the framework of Relatedness

Density from industries to the context of web technologies involves quantifying the extent to which a region's existing digital capabilities and web technology infrastructure are interconnected or complementary. It reflects the idea that regions are more adept or inclined to adopt new web technologies that align with or extend their existing digital capacities.

For web technologies, Relatedness Density could be determined by analyzing patterns of technology adoption across firms within a region, examining how certain technologies co-occur or complement each other. The computation of the relatedness density follows a two-step process (Hidalgo et al. 2007; Boschma et al. 2015; Balland et al. 2019). First, the relatedness between digital web technologies (ϕ) is obtained throughout a co-occurrence analysis. The data is divided into sum-matrices for the abovementioned non-overlapping 8-time windows (2000-2002, 2003-2005, 2006-2008, 2009-2011, 20122014, 2015-2017, 2018-2020, and 2021-2022), with regions (r) in the rows and digital web technologies (i) in columns. Then, the times of co-occurrence $(\wedge)$ of two digital web technologies $\left(i_j, i_g\right)$ in the same region (r) in each time period (t) is divided by the times this co-occurrence happens in all regions (R) in that time period, as shown in Equation 5:

$$\phi_{i_j,i_g,t} = \frac{\left(i_j \wedge i_g\right)_{r,t}}{\left(i_j \wedge i_g\right)_{R,t}} \tag{1}$$

This measurement of relatedness between digital web technologies can be utilized to construct a map of the digital web technologies' space. As has been previously accomplished in the literature for products (Hidalgo et al. 2007), industries (Neffke et al. 2011; Xiao et al. 2018), technologies (Boschma et al. 2015; Balland et al. 2019), and occupations (Farinha et al. 2019), the subsequent network of the analysis demonstrates the relationships among digital web technologies based on the co-occurrence analysis outlined above.

Then, the Relatedness Density for each region r and digital web technology i at time t is determined by summing all the relatedness values of the digital web technologies that are connected to digital web technology i_j, and in which region r possesses an RCA greater than or equal to one. This can be mathematically represented as follows:

$$\text{Relatedness Density}_{r,i,t} = \frac{\sum_i x_{r,i,t}\,\phi_{i_j,i_g,t}}{\sum_i \phi_{i_j,i_g,t}} \tag{2}$$

Where the parameter $x_{r,i,t}$ is a dummy variable taking value 1 when the RCA of a digital web technology i in region r at time t is higher or equal to 1, and 0 otherwise. The relatedness density is calculated for each region and digital web technology for the 8 considered time windows, however for the on Technology adoption an annual measurement of Relatedness density was performed using the EconGeo R package (Balland, 2017). For the plot on geographical representation of Relatedness density, the average relatedness density for the European regions between the period 2000-2022 was calculated.

Third, it is needed to calculate Related entry, which refers to the specialization or adoption of new digital web technologies by regions, based on their previous digital capabilities. It is used as a dummy variable to indicate this specialization (entry), which is set to 1 when a region r acquires a Revealed Comparative Advantage (RCA) greater than or equal to 1 in a new digital technology i, in which it was not specialized in the previous period $t-1$. Otherwise, the variable is set to 0.

The RCA is calculated based on the relative use of a digital web technology in a region compared to its use at a broader level, such as Europe as a whole. If the share of firms using a particular technology in the region is higher than the average share across Europe, then the region is said to have an RCA in that technology.

5.1.3 Digital Complexity Definition and Calculation

In order to derive the Digital complexity, the starting point is the above-defined $r \times i$ matrix. Combining information on both, which regions use specific digital web technologies (diversity), and how common specific digital web technologies are across regions (ubiquity), the digital complexity of regions can be measured. Empirically, this metric is obtained following the method of reflections, pioneered by Hidalgo and Hausmann (2009), and using the Knowledge Complexity Index (KCI) function from the EconGeo R package (Balland, 2017). The KCI is computed through the application of the eigenvector reformulation of the above-mentioned method of reflections (Balland and Rigby, 2017).

This method considers the regions that are significant users of digital web technologies. Thus, the previous $r \times i$ matrix is operationalized into an $r \times i$ two-mode matrix $(M = M_{r,i})$, where $M_{r,i}$ states whether or not a region r has a revealed comparative advantage (RCA) in the use of the digital web technology i. This RCA takes the form of a location quotient or Balassa index, in which a region r has an RCA in the use of the digital web technology i at time t if the share of web-domains using digital web technology i in the region is higher than the share of web-domains using the digital web technology i in Europe as a whole. This can be mathematically formulated as follows:

$$
\begin{aligned}
RCA_{r,i}^{t} = 1 \text{ if } \frac{\text{Web} - \text{domains}\,_{r,i}^{t} / \sum_i \text{Web} - \text{domains}\,_{r,i}^{t}}{\sum_r \text{Web} - \text{domains}\,_{r,i}^{t} / \sum_r \sum_i \text{Web} - \text{domains}\,_{r,i}^{t}} \geq 1 \\
RCA_{r,i}^{t} = 0 \text{ if } \frac{\text{Web} - \text{domains}\,_{r,i}^{t} / \sum_i \text{Web} - \text{domains}\,_{r,i}^{t}}{\sum_r \text{Web} - \text{domains}\,_{r,i}^{t} / \sum_r \sum_i \text{Web} - \text{domains}\,_{r,i}^{t}} < 1
\end{aligned}
\tag{3}
$$

As articulated previously, the method of reflections merges the diversity of regions with the ubiquity of digital web technologies (Hidalgo and Hausmann, 2009). This approach captures these dimensions as the two-mode degree centrality of both regions $(K_{r,0})$ and digital web technologies $(K_{i,0})$ in the network linking regions to digital web technologies. The expressions for these measures are delineated as follows:

$$
\begin{aligned}
\text{Diversity } = K_{r,0} = \sum_i M_{r,i} \\
\text{Ubiquity } = K_{i,0} = \sum_r M_{r,i}
\end{aligned}
\tag{4}
$$

The diversity of regions and the ubiquity of digital web technologies are quantified by the count of digital web technologies for which a region demonstrates a Revealed Comparative Advantage (RCA), and the tally of regions holding an RCA in a specific digital web technology, respectively. These metrics, diversity and ubiquity, are iteratively merged through a series of n iterations, applying the methodology established by Hidalgo and Hausmann (2009):

$$
\begin{aligned}
KCI_r = K_{r,n} = \frac{1}{K_{r,0}} \sum_i M_{r,i} K_{i,n-1} \\
KCI_i = K_{i,n} = \frac{1}{K_{i,0}} \sum_i M_{r,i} K_{r,n-1}
\end{aligned}
\tag{5}
$$

Consequently, for empirical purposes, the binary two-mode matrix, M along with its transpose M^T, are both row standardized. Therefore, by computing the product of the two $\left(B = M^* M^T\right)$, resulting in a square matrix, the Knowledge Complexity Index (KCI) for each region (KCI_r) is determined by the second eigenvector of this matrix B. Conversely, by altering the multiplication order $\left(D = M^T * M\right)$, the second eigenvector calculates the KCI for each digital web technology (KCI_i) (Balland and Rigby, 2017). For the analysis conducted, only the KCI_r is utilized, which is standardized on a scale from 0 to 100 to enable comparison across various time intervals.

5.1.4 Identification and Monitoring of Web Technologies

Following the selection and geographical positioning of the companies, the next step involves pinpointing the web technologies they employ. Websites serve as crucial repositories of information, revealing insights into a company's research directions, capabilities, technological assets, and operational ecosystems (Kinne and Axenbeck, 2020; Barnewold and Lottermoser, 2020; Abbasiharofteh et al. 2023). Notably, previous analyses have typically not accounted for temporal variations, rendering a single-year observation inadequate for our investigation into regional technological evolution. To address this gap and monitor the adoption of technologies across companies and regions, I utilize the BuiltWith API. BuiltWith functions as a comprehensive tool for website analysis, lead generation, and market intelligence, offering detailed records of technology deployment and withdrawal from web domains since the year 2000 (BuiltWith, 2022). This capability enables us to trace the initial introduction of a technology within a region and observe its propagation both locally and beyond, thus facilitating a longitudinal study of technology diffusion across NUTS 2 regions.

The spectrum of digital web technologies identified spans from elementary tools like web frameworks and ad analytics to more sophisticated functionalities, including financial instruments, online payment systems, and e-commerce platforms. In this landscape, the basic digital technologies found on websites of less innovative, non-technological firms primarily support basic operations and content display. For the purpose of examining Digital Complexity and Relatedness density, a total of 218 web technologies have been cataloged (a comprehensive list will be provided in the Annex). However, for analyzing web technology adoption within this study, only a select ten technologies were deemed relevant (Affiliate-programs, Ad-analytics, Livechat, CMS, Currency, Application performance, Javascript-library, Audience-measurement, Framework, Marketing-automation).Here is presented brief description of these technologies as extracted from different websites.[4]

Table 1: Description of the selected web technologies

Web Technology	**Description**
Ad-analytics	Ad analytics tools helps gather data from many marketing channels to report collectively, allowing marketers to create reports, perform competitive analysis, track campaign success, and optimize the marketing mix without relying on data scientists.
JavaScript Library	A collection of pre-written JavaScript code that helps developers create applications, especially those using web-centric technologies like AJAX. Simplifies integration of JavaScript with other web development technologies.
Framework	A framework is a software created to facilitate the creation of web applications, encompassing web services, web resources, and APIs. It streamlines routine tasks in web development and encourages the recycling of code.
Live-chat	A technology enhancing customer experience in e-Commerce by allowing real-time interaction between visitors and operators, enabling businesses to offer personalized experiences and initiate proactive chats.
Marketing Automation	Utilizes technology to streamline marketing efforts across channels, making them more effective by automating repetitive tasks and allowing for personalized customer outreach.

[4] Links related to technologies:
1.Ad-analytics: https://hbr.org/2013/03/advertising-analytics-20 2.JavaScript Library: https://en.wikipedia.org/wiki/JavaScript_library 3.Framework: https://en.wikipedia.org/wiki/Web_framework 4.Live-chat: https://www.proprofschat.com/blog/live-chat-technology-for-retail/ 5.Marketing Automation: https://www.salesforce.com/eu/learning-centre/marketing/what-is-marketing-automation/ 6.CMS: https://kinsta.com/knowledgebase/content-management-system/ 7.Audience Measurement: https://en.wikipedia.org/wiki/Web_audience_measurement 8.Application Performance: https://www.techtarget.com/searchapparchitecture/tip/Top-application-performance-monitoring-tools 9.Affiliate Programs: https://www.bigcommerce.com/articles/ecommerce/affiliate-marketing/

Table 1: Description of the selected web technologies

Web Technology	Description
CMS (Content Management System)	CMS, or Content Management System, is software that allows individuals to create, manage, and adjust website content without the need for in-depth technical skills, making it easier to build and maintain different kinds of websites.
Audience Measurement	Tracks metrics like site exposure, reach, and usage frequency to better understand target demographics and measure audience across digital channels.
Application Performance (Monitoring)	Application performance encompasses tracking an application's functioning to guarantee its efficiency and provide a smooth experience for users.
Currency	Refers to the use of the Euro (€) symbol for example as a currency on a website, indicating that it may accept payments in Euros.
Affiliate Programs	A software that can help individuals earn commission by promoting and selling another's products, relying on affiliate technology to track sales and manage commissions.

These technologies were chosen based on their prevalence as of the year 2000, their varied functionalities, and their differing adoption dynamics. For instance, JavaScript libraries, which offer pre-coded solutions to enhance web development, contrast with Live-chat technologies that necessitate deeper integration with a website's underlying systems for real-time user interaction. Live-chat technology, requiring coordination with CRM systems, databases, and application interfaces, may thus present a more intricate adoption process. The final selection criteria for these technologies revolved around their ubiquity in the early 2000s, the unique functions they fulfill, and their complexity levels. The period for data collection extended from September 2022 through December 2022.

For a more detailed visualization of the evolution of web technologies, but also a detailed graph of top and bottom web technology innovators (NUTS 2), please see the Figures 13, 14,15, 16 in the Annexes.

5.1.5 Technology adoption and contextual factors collection

The primary objective is to examine how regional characteristics influence the uptake of certain technologies. To facilitate this analysis, I merged data from companies with information on technological usage, using the web domain name as a unique identifier common to both datasets. For each European NUTS 2 region and specified year, I determined the adoption rate of ten selected web technologies by dividing the number of firms employing each technology by the total number of firms with an online presence. This method enabled us to quantify both the absolute and relative frequency of firms adopting each technology annually across all European NUTS 2 regions:

$$W_{r,t,i} = \sum_{t'=1}^{t} N_{r,t',i} \tag{6}$$

$$TA_{r,t,i} = \left(\frac{W_{r,t,i}}{\sum_{t'=1}^{t} W_{r,t'}} \right) \times 100 \tag{7}$$

Where $TA_{r,t,i}$ represents technology adoption or the proportion of enterprises (websites) applying the i-th web technology in a specific region r and up to and including year t. To calculate $TA_{r,t,i}$, I first find $W_{r,t,i}$, the number of firms (N) employing the i-th web technology in region r for all years up to and including year t, as explained in Equation 1. Then, I use Equation 2 to calculate $TA_{r,t,i}$ by dividing $W_{r,t,i}$ by the sum of $W_{r,t'}$ for all years up to and including year t in that region, and then multiplying by 100 to express it as a percentage.In order to account for all firms that have adopted the technology, including both established and newly formed companies, it is essential to sum the data over all years. Nevertheless, the percentage change in adoption may remain small if the total number of firms adopting the technology yearly is minimal.

We have calculated the variable Technology Adoption (TA) as both a dependent variable and an indicator to observe the geographical spread of technologies across Europe. Nevertheless, in this context, I also require several variables to assess the factors influencing or impeding this process. A comprehensive list and description of these variables is given in Table 1. However, the calculation process for some of them is given in the following sections of the methodology.

For variables such as quality of government, corruption, infrastructure, and business sophistication, data were only accessible from 2010 onward and collected every 2 or 3 years.Therefore, there is a need for a weighted average in calculating these variables and building a balanced panel dataset for the empirical models. As these indicators exhibit gradual changes over time, a Min-Max normalization technique was applied to the available data for each year. To estimate their values for the missing years, I employed a weighted average calculation, represented by the following equations:

$$WA_t = \frac{2 \cdot X_{\text{norm },t-1} + X_{\text{norm },t+2}}{2+1} \tag{8}$$

$$WA_t = \frac{X_{\text{norm },t-2} + 2 \cdot X_{\text{norm },t+1}}{1+2} \tag{9}$$

The formulas calculate the weighted average (WA_t) for a specific year t. For that purpose, two data points are considered: $X_{\text{norm },t-1}$ (the normalized data for the year before t) and $X_{\text{norm },t+2}$ (the normalized data for the year two years after t). I give a weight of 2 to $X_{\text{norm },t-1}$ and a weight of 1 to $X_{\text{norm },t+2}$. The denominator $2+1$ represents the sum of the weights. The first formula essentially gives more weight to the data from the year before t compared to the data from two years after t. In the second year, I give a weight of 1 to $X_{\text{norm}, t-2}$ and a weight of 2 to $X_{\text{norm },t+1}$. The second formula effectively grants more weight to the data from the year after t compared to the data from two years before year t. The time dimension of the modeling data (2010-2020) is solely limited by the contextual variables' availability. The final step is to merge the data on the regional absorption of the web technologies with the impact (contextual) factors into a spatial file.

The following table delineates the variables utilized in our analysis, providing a comprehensive overview of each variable's role and source:

Table 2: Variable description.

Variable name	**Description**	**Type**	**Source**
Technology Adoption (TA)	In a specific region and year, the count of firms utilizing each of the ten web technologies was divided by the count of all firms with a website. This calculation aimed to determine the prevalence of each technology among the website-owning firms.	Proportion	Own calculation
GDP/cap.	GDP per capita representing the economic performance of a region in a year, is obtained by dividing the gross domestic product of that region and year by the population of that region and year.	Continuous	ARDECO
Population	Total Population (Regional Accounts)	Discrete	ARDECO
Employment	Total Employment	Discrete	ARDECO
Quality of Institutions	European Quality of Government Index (EQI)	Continuous	Quality of Government Institute
Corruption	Pillar of the EQI: aggregate of survey questions assessing corruption in the provision of public services.	Continuous	Quality of Government Institute
Quality of Infrastructure	A pillar of the RCI that consists of three components: road transport performance, rail transport performance, and accessibility to passenger flights.	Continuous	EU Regional Competitiveness Index (RCI)
Business Sophistication	A pillar of the RCI that evaluates the sophistication of businesses based on their employment distribution, contribution to GVA, innovation collaboration, and the adoption of marketing or organizational innovations.	Continuous	EU Regional Competitiveness Index
Talent	The indicator measures the percentage of individuals aged 25 to 64 who have achieved tertiary education (ISCED levels 5-8). This indicator provides insights into the educational attainment and the proportion of the population with advanced knowledge and skills.	Proportion	EUROSTAT

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Table 2 – continued from previous page

Variable name	Description	Type	Source
Related Entry	Indicates whether a region has specialized in a new digital web technology, based on achieving an RCA greater than or equal to 1 compared to the previous period. It takes a value of 1 when specialization is achieved and 0 otherwise.	Dummy	Own calculation based on BuiltWith and Crunchbase data
Relatedness density	A measure of how similar the digital web technologies used by firms in a region are, in terms of their co-occurrence within that region.	Continuous	Own calculation based on BuiltWith and Crunchbase data
Digital complexity	A metric reflecting the digital complexity of EU NUTS 2 regions based on the digital web technologies adopted by firms within a region.	Continuous	Own calculation based on BuiltWith and Crunchbase data
Patent application	The number of patent applications made by firms in a region, indicating innovation levels.	Discrete	Own calculation based on OECD RegPat
GVA	Gross Value Added, a measure of economic productivity which assesses the contribution of each individual producer, industry or sector in the economy.	Continuous	ARDECO
Productivity	A measure of the efficiency of production, calculated as the ratio of GVA outputs to labor inputs used in the production process.	Continuous	Own calculation on the data from ARDECO
Age of firms	The average age of firms within a region at the moment of adoption of the web technology, indicating the maturity of businesses.	Continuous	Own calculation based on BuiltWith and Crunchbase data
Number of Firms	The total number of firms within a region in the year of web technology adoption.	Discrete	Crunchbase

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Table 2 – continued from previous page

Variable name	Description	Type	Source
Existent Technologies	The average number of different web technologies identified in web domains at the time of adoption of a specific web technology within a region and in a specific year.	Continuous	Own calculation based on BuiltWith data
Core-Periphery	A binary measure where '0' represents core regions with high levels of economic activity but also central position in the EU and '1' represents EU geographical peripheral regions and also with less economic activity.	Binary	Own classification based on the article of Rodríguez-Pose and Di Cataldo (2015), including Bulgaria, Greece, Finland, while excluding Estonia as a periphery
Diversity (Entropy)[5]	A measure of the diversity of industries within NUTS regions. Based on Crunchbase industries, I created annual (incidence) regions—industries matrices. Using the 'EconGeo' package, I calculated the entropy indicator and then applied the annual normalization procedure. A value closer to '1' implies a higher diversity of industries in the region.	Continuous	Own calculation based on Crunchbase firm-industries
Herfindahl Hirschman Index (HHI)	A measure of the concentration or specialization of industries within NUTS regions. Based on Crunchbase industries, I created annual (incidence) regions - industries matrices. Using 'EconGeo' package I calculated the Herfindal index and then I applied the annual normalization procedure.A value closer to '1' implies higher concentration of industries in the region.	Continuous	Own calculation based on Crunchbase firm-industries

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[5]The calculation methodology for Diversity is described by the "entropy" function of the 'EconGeo' package while for the HHI index is the "herfindal" function.https://cran.r-project.org/web/packages/EconGeo/EconGeo.pdf

Table 2 – continued from previous page

Variable name	Description	Type	Source
Share of ICT	A share of NACE Section J - Information and Communication employment population in the total employment in the region	Proportion	Own calculation based on Eurostat regional statistics

Note: In order to fill in gaps in the data at either the start or the end of the series, interpolation techniques were applied. These techniques estimate missing values using the available data points from the beginning and end of the data series for each region.

5.2 Local Indicators of Spatial Association (LISA) analysis

This LISA methodology effectively combines spatial and statistical analysis to explore spatial patterns in the 'Digital Complexity' variable across different regions (Anselin, 1995; Bivand, Pebesma, and Gómez-Rubio, 2013). The LISA analysis is particularly useful for identifying local clusters and outliers, contributing to a deeper understanding of spatial dependencies in the data (Anselin, 1995).

The LISA analysis is conducted using the sfweight package in the R environment (Pebesma, 2018). This involves creating spatial weights and calculating spatial lags. Spatial contiguity is determined (st_contiguity), which identifies neighboring regions (Bivand, Pebesma, and Gómez-Rubio, 2013). Then, spatial weights are computed (st_weights), reflecting the spatial relationship between each region and its neighbors. The spatial lag of the 'Digital Complexity' variable from the Complexity data is calculated (st_lag). This represents the average value of 'Digital Complexity' for the neighboring regions of each area (Bivand and Piras, 2015). LISA categories are then determined using categorize_lisa, which categorizes each region based on the local correlation between its 'Digital Complexity' value and the average 'Digital Complexity' of its neighbors. As a result, the regions are classified in 4 clusters, mainly: HH (High-High), LL (Low-Low), HL (High-Low), and LH (LowHigh), each indicating different types of spatial clustering or outliers (Anselin, 1995). HH (HighHigh) regions are areas with high values of the variable of interest, surrounded by neighboring regions with similarly high values, indicating a cluster of high values or a hotspot. LL (Low-Low) regions have low values and are surrounded by neighbors with low values as well, indicating a cluster of low values or a cold spot. HL

(High-Low) regions are characterized by high values but are surrounded by neighbors with low values, suggesting these regions are positive outliers in their spatial context.

Conversely, LH (Low-High) regions have low values but are surrounded by neighbors with high values, indicating that these regions are negative outliers compared to their surroundings.

5.3 Summary statistics and empirical models

5.3.1 Summary statistics

Table 3: Summary of Variables

Variables	**N**	**Mean**	**SD**	**Min**	**Max**
Year	2090	2015	3.16	2010	2020
Related Entry	367,484	0.105	0.306	0	1
Relatedness density	384,751	26.424	15.457	0.00	100
Digital complexity	2,273	44.68	22.46	0.00	100
Population density	2090	342.90	844.11	3.30	10817.80
Patent application	2090	219.17	589.65	0.00	6817.19
GDP/cap.	2090	27607.25	14148.09	3123.79	101762.25
Total Population	2090	1951113.79	1676164.36	27734.00	12291557.00
GVA	2090	49588.18	62069.15	1010.72	674282.76
Total Employment	2090	882.34	787.79	17.46	6530.39
Productivity	2090	53.04	21.63	6.82	123.90
Quality of Governance	2090	0.55	0.21	0.00	1.00
Corruption	2090	0.57	0.21	0.00	1.00
Quality of Infrastructure	2090	0.37	0.24	0.00	1.00
Tech. Readiness	2090	0.63	0.23	0.00	1.00
Business Sophistication	2090	0.29	0.19	0.00	1.00
Talent	2090	28.07	9.04	9.00	59.70
Age of firms	2090	15.76	10.07	0.00	124.00

Continued on next page

Table 3 – continued from previous page

Variables	N	Mean	SD	Min	Max
Number of Firms	2090	68.73	135.18	0.00	1885.00
Existent Technologies	2090	14.36	5.69	0.00	38.00
Core-Periphery	2090	0.39	0.49	0	1

5.3.2 Empirical modeling and explanation

In this section, the empirical models implemented in this thesis are presented. First, I look into the effects of digital complexity, (which was defined and described in the previous 5.1.3 section) on regional labor productivity. To do that, it is first performed a simple OLS regression without controlling for any time or region-fixed effects. Because according to spillover theory, the productivity of neighboring regions might affect the productivity of the regions under analysis, I first calculated the weights and the spatial lag and introduced them into the model, doing the same for the spatial lag of GDP/cap and digital complexity. The spatial lag was chosen to control how geographical spillover factors still influence the performance of regions in terms of labor productivity. Here is the empirical model of this first analysis:

$$\begin{aligned}\ln\left(\text{Productivity}_i\right) = \beta_0 + \beta_1 \times \text{Digital Complexity}_i + \beta_2 \times \text{Spatial Lag of Productivity}_i \\ + \beta_3 \times \text{Spatial Lag of GDP/cap}_i + \beta_4 \times \ln(\text{Population Density}_i) \\ + \beta_5 \times \ln(\text{Patent Applications}_i) + \varepsilon_i\end{aligned} \tag{10}$$

Where:

- $\ln(\text{Productivity}_i)$ is the natural logarithm of the productivity for unit i.
- β_0 is the constant term in the model.
- $\beta_1 \times \text{Digital Complexity}_i$ is the effect of the "Digital Complexity" variable on the log of productivity.
- $\beta_2 \times \text{Spatial Lag of Digital Complexity}_i$ is the effect of the spatial lag of digital complexity on productivity.
- $\beta_3 \times \text{Spatial Lag of GDP/cap}_i$ accounts for the effect of the spatial lag of GDP per capita on productivity.
- $\beta_4 \times \ln(\text{Population Density}_i)$ is the natural logarithm of population density.

- $\beta_5 \times \ln(\text{Patent Applications}_i)$ is the natural logarithm of patent applications.
- ε_i is the error term.

$*$ However, because all the regional data is to some extent geographical in nature, often the dependent variables display spatial autocorrelation.To test that assumption, I performed several robust LM tests[6] for spatial dependence.They measure wherever there is a spatial auto correlation of the dependent variable or the error term.The following, the empirical model regarding the effect of digital complexity on labor productivity is presented, this time as a spatial lag model:

$$\ln(\text{Productivity}_i) = \rho \cdot W \ln(\text{Productivity}_i) + \beta_0 + \beta_1 \times \text{Digital Complexity}_i + \mathbf{X}_i \beta_{2:6} + \mu_i + \gamma_t + \varepsilon_i \tag{11}$$

Where:

- $\ln(\text{Productivity}_i)$ is the natural logarithm of the productivity for unit i.
- $\rho \cdot W \ln(\text{Productivity}_i)$ represents the spatially lagged dependent variable.
- β_0 is the constant term in the model.
- $\beta_1 \times \text{Digital Complexity}_i$ is the effect of the "Digital Complexity" variable on the log of productivity.
- $\mathbf{X}_i$ is a vector of the other independent variables, such as GDP per capita, Population density, Productivity spatial lag, Complexity spatial lag, and GDP per capita spatial lag.
- $\beta_{2:6}$ is the vector of coefficients corresponding to the variables in $\mathbf{X}_i$.
- μ_i and γ_t are the fixed effects for unit i and time t, respectively.
- ε_i is the error term.

$*$ The definition and calculation of the Relatedness density and Related entry were earlier presented in Section 5.1.2. Later, it is investigated how related digital technologies influence the adoption of new related technologies. The probability of the entry of related web technologies in a given region, represented in log-odds, is determined by the following model equation:

$$\begin{aligned}
&\log\left(\frac{P(\text{Related Entry} = 1)}{1 - P(\text{Related Entry} = 1)}\right) \\
&\quad = \beta_0 + \beta_1 \times \text{Relatedness Density} + \beta_2 \times \text{GDP per capita}(\log) \\
&\quad + \beta_3 \times \text{GVA}(\log) + \beta_4 \times \text{Total Employment}(\log) \\
&\quad + \beta_5 \times \text{Population Density}(\log) + \beta_6 \times \text{Patent Applications}(\log) + \mu_i + \tau_t
\end{aligned} \tag{12}$$

[6] There are two types of spatial dependence tests, for spatial lag and spatial error. These are presented in the 'spdep' R package. https://rdrr.io/rforge/spdep/man/lm.LMtests.html

Where:

- $P(\text{Related Entry} = 1)$ is the probability of the entry of related web technologies.
- β_0 is the constant term (not provided for the full model with FEs).
- $\beta_1, \beta_2, \ldots, \beta_7$ are the coefficients for the respective variables.
- μ_i represents the region-specific fixed effects.
- τ_t represents the year-specific fixed effects.

Each β coefficient corresponds to the impact of one unit change in the respective independent variable on the log-odds of the entry of related web technologies.

$*$ The empirical model of technology adoption was developed to quantitatively assess the impact of digital complexity and relatedness density on the rate at which technologies are adopted across regions. This model is crucial in understanding how the intricate interplay between a region's digital infrastructure and its technological interconnectedness influences the propensity to embrace new technologies. Given the study's focus on the spatial dynamics of technology adoption and digital transformation, this model facilitates a careful exploration of the variables that significantly drive technological change within regions, highlighting the importance of both digital complexity and relatedness density in fostering a conducive environment for technology adoption. First, to differentiate between the use of either the fixed effects model or random effects model the Hausman Test is applied.[7]

$$\mathrm{TA}_{it} = \alpha_i + \beta_1 \times \text{ Digital Complexity }_{it} + \beta_2 \times \log(\text{ Relatedness Density }_{it}) + \mathbf{X}_{it}\beta_{3:8} + \varepsilon_{it}$$

Where:

- TA_{it} is the share of adopted technology for region i at time t.
- α_i represents the region-specific fixed effects, capturing unique characteristics and influences of each region that do not change over time.
- β_1 and β_2 are the coefficients for 'Digital Complexity' and the logged 'Relatedness Density', respectively.
- Digital Complexity $_{it}$ and log (Relatedness Density $_{it}$) are the corresponding independent variables.

[7] The Hausmann Test is part of the R 'plm' package: https://search.r-project.org/CRAN/refmans/plm/html/phtest.html

- $\mathbf{X}_{it}$ is a vector of other independent variables (such as 'Patent Application', Business Sophistication, 'Talent', 'Quality of Institutions', 'Quality of Infrastructure').
- $\beta_{3:8}$ is the vector of coefficients corresponding to the variables in $\mathbf{X}_{it}$.
- ε_{it} is the error term.

$*$ The next section of the empirical strategy deals with the examination of the spatial effects in Technology Adoption (TA), and the following equation describes this analysis. The spatial autocorrelation coefficient ρ indicates the level of dependence between regions, also known as the spillover effects. It measures the influence of neighboring regions. Moreover, it is calculated based on W which is the spatial weights' matrix, reflecting the geographic proximity between regions.

$$\mathrm{TA}_{i,t} = \alpha_i + \rho + \mathrm{TA}_{i,t} + \beta_1 \times \text{GDP per capita}_{i,t} + \beta_2 \times \text{Total Population}_{i,t} + \mathbf{x}_{i,t}\beta_{3:n} + \varepsilon_{i,t} \quad (13)$$

where:

- $\mathrm{TA}_{i,t}$ is the level of adoption of affiliate programs for region i at time t.
- α_i represents the region-specific fixed effects, capturing unique characteristics and influences of each region that do not change over time.
- ρ_{t-1} is the spatial autocorrelation coefficient for the previous period.
- ρ is the spatial autocorrelation coefficient, this represents the influence of neighboring regions' technology adoption on region i's adoption level, also known as spillovers
- GDP per capita$_{i,t}$ and Total Population$_{i,t}$ are examples of the independent variables affecting technology adoption, with their respective coefficients β_1 and β_2.
- $\mathbf{x}_{i,t}$ is a vector of other independent variables included in the model (e.g., Total Employment, Quality of Governance, etc.).
- $\beta_{3:n}$ is the vector of coefficients corresponding to the variables in $\mathbf{x}_{i,t}$.
- $\varepsilon_{i,t}$ is the error term.

$*$ The model analyzing the impact of technology adoption on gross domestic product change is designed to explore the economic ramifications of technological integration within regions. By examining how shifts in technology adoption rates influence GDP per capita changes, this model underscores the critical role of technology in driving economic growth and reshaping regional economic landscapes. It reflects the dissertation's broader aim to link technology adoption with economic outcomes, providing empirical evidence to support the argument that technological advancement is a key determinant of economic prosperity.

$$
\begin{aligned}
\Delta \log(\text{GdpCap}_{it}) = \beta_0 + \beta_1 \times \Delta\text{TA}_{it} + \beta_2 \times \Delta \log(\text{PopDens}_{it}) \\
+ \beta_3 \times \Delta\text{Core\_Periphery}_{it} + \beta_4 \times \Delta\text{Number\_of\_Firms}_{it} \\
+ \beta_5 \times \Delta\text{Bus\_Sophi\_average}_{it} + \beta_6 \times \Delta\text{Avg\_Ex\_Techs}_{it} \\
+ \beta_7 \times \Delta\text{Tech\_readiness\_average}_{it} + \beta_8 \times \Delta\text{PatApp}_{it} \\
+ \beta_9 \times \Delta\text{Infrastructure\_average}_{it} + \beta_{10} \times \Delta\text{EQI\_average}_{it} \\
+ \beta_{11} \times \Delta \log(\text{Employment}_{it}) + \beta_{12} \times \Delta\text{Talent}_{it} + \varepsilon_{it}
\end{aligned}
$$

In this equation:

- $\Delta \log(\text{GdpCap}_{it})$ represents the change in the logarithm of GDP per capita for each region i at time t. This is the dependent variable and reflects the year-to-year variation in GDP per capita.
- β_0 is the intercept of the model.
- $\beta_1, \beta_2, \ldots, \beta_{12}$ are the coefficients for the respective independent variables, each representing how a unit change in the independent variable (in its first-difference form) is expected to affect the dependent variable.
- The differences of the independent variables are: ΔTA_{it}, $\Delta \log(\text{Population Density}_{it})$, $\Delta\text{Core\_Periphery}_{it}$, $\Delta\text{Number of Firms}_{it}$, $\Delta\text{Business Sophistication}_{it}$, $\Delta\text{Existent technologies}_{it}$, $\Delta\text{Tech Readiness}_{it}$, $\Delta\text{Patent Applications}_{it}$, $\Delta\text{Quality of Infrastructure}_{it}$.
- ε_{it} is the error term, capturing the variation in $\Delta \log(\text{GdpCap}_{it})$ not explained by the model.

The use of first differences (Δ) helps to eliminate the influence of any time-invariant unobserved individual heterogeneity that could bias the estimates. Moreover, this eliminates the omitted variable bias. In this case the "Core Periphery" dichotomy does not change over time therefore such a model is useful to measure how the Core-Periphery position influences the adoption of one or another technology.

5.4 Summary of Research Design and Methodology chapter

The previous section presents a detailed and comprehensive approach towards analyzing the digital adoption divide across European regions, emphasizing the interplay between evolutionary factors and regional characteristics on technology adoption and subsequent economic growth.

This section is meticulously created, employing a multisided methodology that includes the selection and geolocation of firms, identification, and monitoring of web technologies, and the collection of technology adoption and contextual factors.

The research utilizes Crunchbase to identify high-growth technology firms and startups, focusing on those at the forefront of digital innovation. This selection process is crucial for understanding regional disparities in technological adoption and its economic outcomes, with firms chosen based on their geographical location, industry sector, and website ownership.

In the case of identification and Monitoring of Web Technologies, the BuiltWith API tracks the adoption of digital web technologies by these companies, enabling a longitudinal study of technology diffusion across NUTS 2 European regions. This analysis is pivotal for examining Digital Complexity and Relatedness density across regions (the so-called smart specialization framework), identifying a spectrum of digital web technologies from basic utilities to advanced functionalities.

The study quantifies the adoption rate of selected web technologies, merging company data with technological usage information. It also integrates various contextual factors like the quality of government, infrastructure, and business sophistication to assess their influence on technology adoption.

The dissertation uses data from diverse and comprehensive sources, ensuring a rich and novel empirical foundation:

Crunchbase provides data on high-growth tech firms and startups, crucial for identifying firms at the innovation forefront. BuiltWith offers detailed records of technology deployment on web domains, enabling the study of technology diffusion. ARDECO supplies economic performance indicators such as GDP per capita and employment, vital for understanding the economic context. EUROSTAT and Quality of Government Institute contribute data on educational attainment and governance quality, contextualizing the technological adoption within broader socio-economic frameworks. EU Regional Competitiveness Index (RCI) provides insights into the quality of infrastructure and business sophistication, influencing the adoption and effectiveness of digital technologies. Analytical Models The methodology incorporates sophisticated analytical techniques, including spatial econometric models and the method of reflections, to explore the interconnectedness of digital web technologies within regions with the latter and their impact on economic outcomes like labor productivity with the former methodology. These models evaluate the probability of the entry of related web technologies in a given region and assess the impact of digital complexity on labor productivity, incorporating various independent variables and utilizing fixed effects to account for unobserved heterogeneity.

This comprehensive examination, combining novel and rich data sources (millions of technologies entry events) with advanced spatial empirical models, underlines the dissertation's exploration of digital adoption divides and the significant role of regional characteristics and evolutionary factors in shaping digital technology adoption and economic growth. Through this approach and new questions asked, the research aims to contribute valuable insights to the discourse on digitalization and regional development, offering a detailed understanding of the factors influencing digital technological advancement and economic dynamics across European regions.

6 Results of the research:

6.1 The role of relatedness in digital technology adoption-regional level

The plot in Figure 3 represents a network visualization of digital web technologies, where each node corresponds to a different technology. The size of each node is indicative of the eigenvector centrality of the respective digital web technology. Eigenvector centrality is a measure of the influence of a node within a network; larger nodes in this context imply that a technology has a greater influence within the web of digital technologies, likely due to its widespread use or integration with other technologies.

The relatedness between web technologies is depicted through the lines connecting the nodes. A greater number of lines between technologies indicates a higher degree of relatedness, suggesting that these technologies are often used together or have complementary functionalities. For instance, technologies related to analytics, content management systems (CMS), hosting, and shopping could be more interconnected due to their joint role in the ecosystem of an e-commerce platform.Technology space analysis can help to identify key enabling technologies that drive digital industry coalescence and new digital industry emergence (Trincado-Munoz et

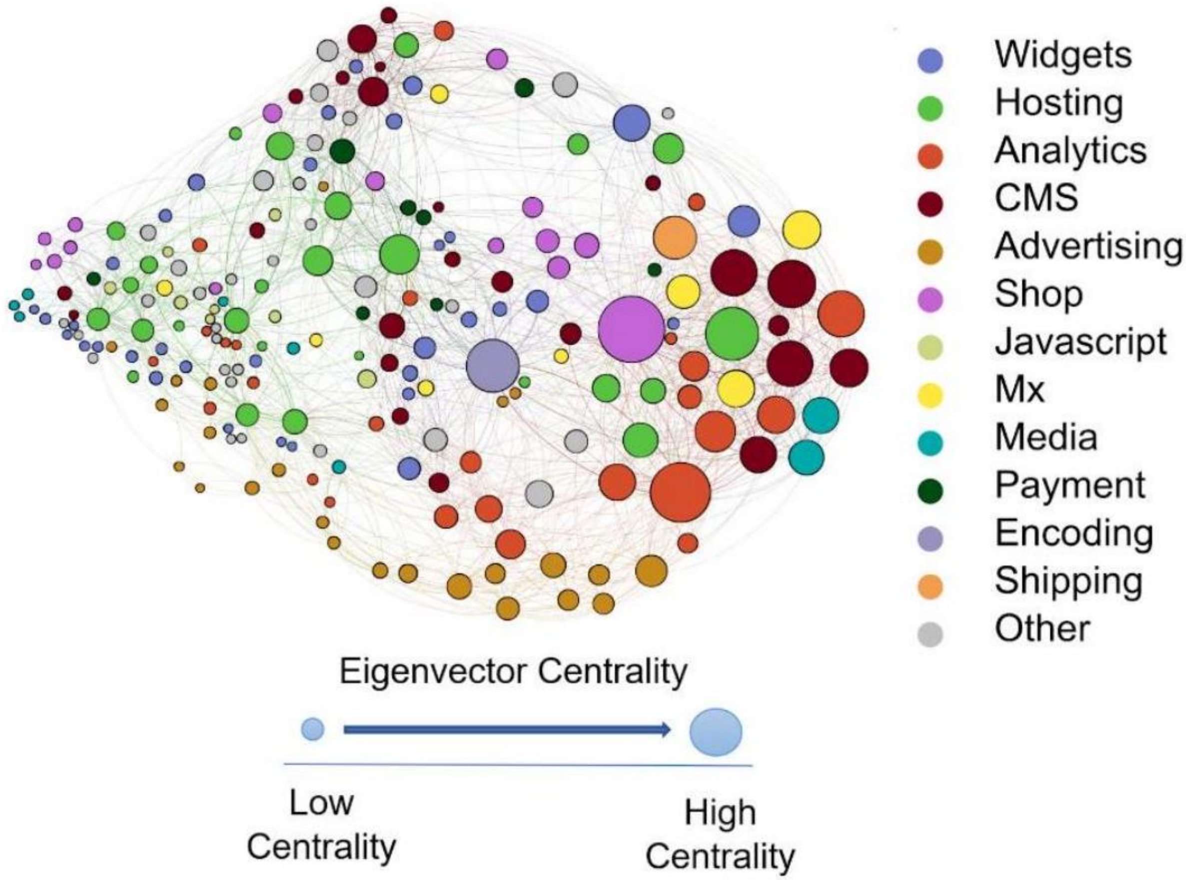

Figure 3: The digital space of the web technologies. Source: Authors' own elaboration.

al. 2023). This analysis also elucidates which technologies singularly influence industry digitalization and which technologies operate synergistically as a system.

The colors of the nodes differentiate the technology groups, providing a visual segmentation of the various categories like CMS, advertising, media, payment, etc. This color-coding helps in quickly identifying clusters of related technologies within the network, showing how certain categories of technologies are central to the digital ecosystem.

In discussing this plot, it can be deduced that technologies with high eigenvector centrality, such as those related to Hosting, Analytics, Shop or CMS, are likely crucial for the functionality and efficiency of a broad range of web applications. These central technologies could be seen as the backbone of the digital infrastructure, enabling a multitude of other web-based services and functions to operate effectively. The strategic integration of digital technologies and the shift towards digital organizational models via the adoption of web technologies might serve as key catalysts for the growth of digital economies (Polyakov and Kovshun 2021). And in this case the relatedness based framework of technology adoption could be a solution, as it makes digital tech's adoption easier and emergence of new industries higher (Boschma, Minondo, and Navarro 2013).

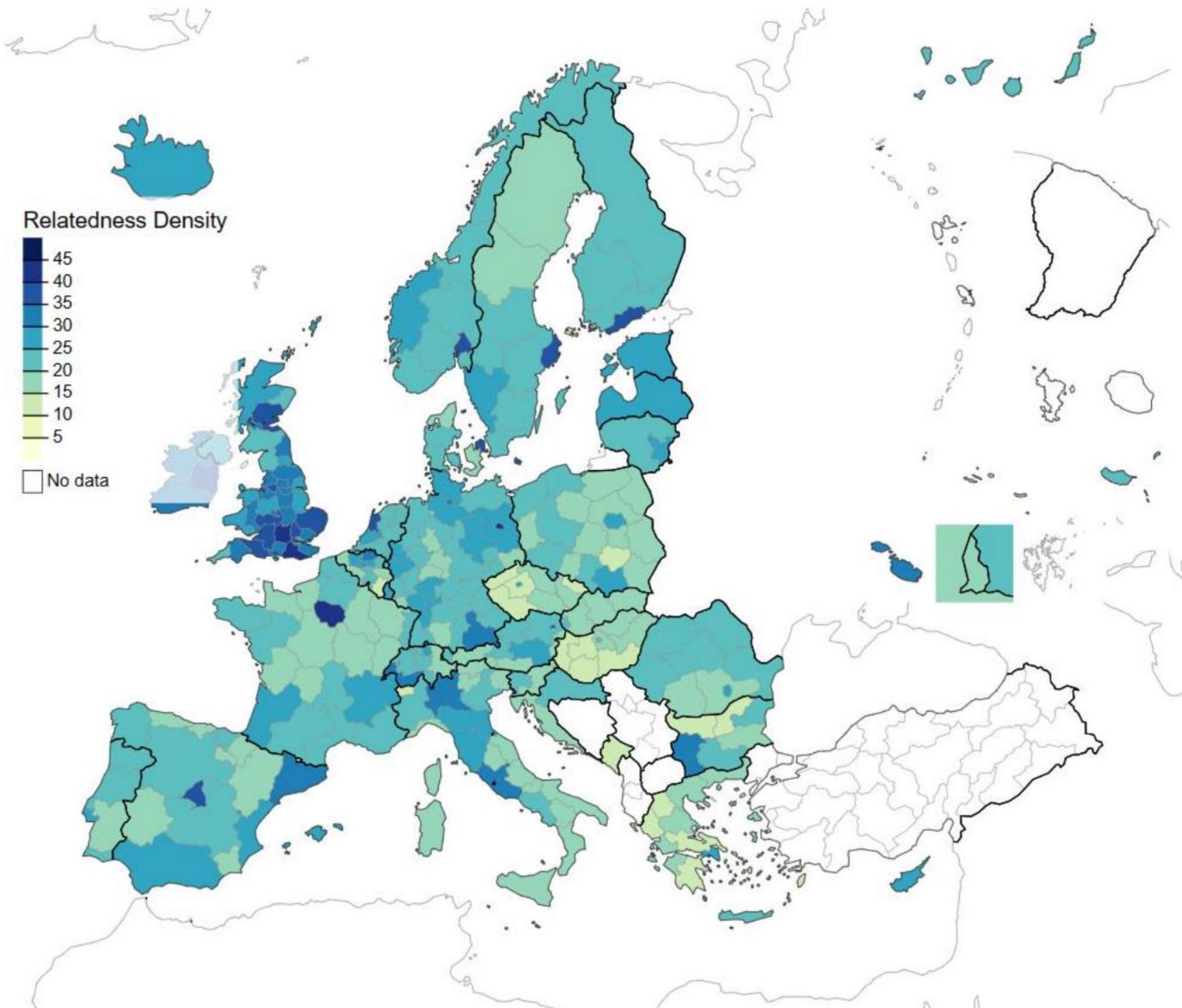

Figure 4: Average Relatedness Density Across European Regions from 2000 to 2022. Source: Authors' own elaboration.

The map in Figure 4 depicts the average relatedness density of web technologies across European NUTS 2 regions. Regions with darker shades represent higher relatedness density scores, indicating that these areas have a more interconnected web technology sector. Web technologies in these regions are likely to complement and enhance each other, suggesting a cohesive and potentially more innovative web technology environment. Those regions with lighter shades correspond to lower relatedness density scores. In these regions, web technologies may be less developed or less integrated. This could mean there is a less cohesive network of web technologies, which might result from a focus on a narrower range of technologies or from a less mature web technology sector. In assessing the regional average relatedness density (RD) of web technologies between Central Eastern Europe (CEE) and Central and Western Europe, notable contrasts emerge. CEE displays generally lower RD scores, indicative of a less interconnected web technology sector. This can be attributed to historical economic constraints, resulting in lower investments in technology and innovation.The web technology environment here is likely in its developmental stages, focusing on a limited range of technologies due to factors like economic history, education, and resource allocation. This suggests a budding market with growth potential, but currently characterized by less complexity and integration. Conversely, Central and Western Europe show higher Relatedness density scores, reflecting a mature, diverse, and well-integrated web technology sector. This is supported by stronger economic and educational infrastructures, substantial investments in R&D, and a longstanding commitment to technological advancement.

The higher integration and complexity of web technologies in these regions can be linked to a more established innovation culture, supported by robust government policies and access to expansive markets. This maturity is a product of historical advantages, richer educational systems in technology, and more favorable economic conditions. The disparity in Relatedness density scores between these regions stems from varied historical paths, economic development levels, educational systems, government policies, and market access. While CEE presents a landscape ripe for growth and development in web technology, Central and Western Europe's tech sector is already well-established, benefiting from a confluence of favorable factors that have nurtured its growth and sophistication.This situation could potentially cause a split in the adoption of web technologies, as Central and Eastern European (CEE) regions lack a clear strategy for embracing complex and interconnected technologies. If the European Union aims to promote the use of more advanced technologies, it must prioritize bridging the capability gap over simply expanding the existing pool of technologies through an ecosystem of digital technologies (Di Girolamo et al. 2023).

Table 4: Related entry model: logit models.

	Dependent variable: Related Entry $(=1)$			
	(1) Baseline	(2) Controls	(3) Full model	(4) Full model Fixed Effects
Constant	-1.752^{***} (0.00913)	-1.822^{***} (0.0154)	-1.752^{***} (0.0102)	
Relatedness density	0.0281^{***} (0.000869)		0.0300^{***} (0.000936)	0.0270^{***} (0.00112)
(log) GDP/cap		1.929^{**} (0.858)	-1.163^{*} (0.676)	0.457 (1.183)
(log) Total population		1.713^{**} (0.846)	-0.996 (0.679)	-9.238^{***} (1.312)
(log) GVA		-1.798^{**} (0.844)	0.920 (0.665)	0.293 (1.152)
(log) Total employment		0.129 (0.124)	-0.0749 (0.0800)	-1.155^{***} (0.289)
(log) Population density		0.0474^{***} (0.0161)	0.0159 (0.0113)	7.055^{***} (1.279)
(log) Patent applications		0.00486 (0.0146)	0.0957^{***} (0.0113)	0.0810^{***} (0.0302)
Observations	218,268	218,268	218,268	87,732
R-squared (Pseudo)	0.02	0.003	0.02	-
Region-Tech Fixed Effects	NO	NO	NO	YES
Year FEs	NO	NO	NO	YES

Notes: All predictor variables have been standardized around the mean and are delayed by one time period. Standard errors that are robust to heteroscedasticity (and clustered by region) are presented in brackets for all models except the two-way fixed effects (4). Coefficient values reach statistical significance at the $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$ levels.

Table 4 represents the results of logistic regression models that predict the likelihood of entry of related web technologies in a given region, with ' 1 ' indicating the entry. The positive coefficients Relatedness density across all models indicate that a higher relatedness density significantly increases the likelihood of entering related web technologies. This effect remains robust even after controlling for other variables and fixed effects in models (3) and (4). The coefficient of GDP per capita is positive and significant in model (2), suggesting that regions with higher GDP per capita are more likely to see the entry of related web technologies. However, in the full model (3), this turns negative, indicating that when other factors are controlled, higher GDP per capita might not necessarily lead to the entry of related web technologies. In the case of Total employment, this variable is not significant in models (2) and (3), and it has a negative coefficient in the full model(4), suggesting that higher employment might be associated with a lower likelihood of entry of related web technologies when controlling for other factors. This factor may indicate a lock in effect which takes place at regional level, or so-called entrenchment of personnel. As the majority of individuals in a region are employed by a couple of industries, they do not have the capacity to diversify and introduce new related projects and web technologies. It is conceivable that the interaction between digitalization and job markets is bidirectional, where not only does digitalization transform job markets, but the dynamics of job markets also affect the uptake of corresponding digital technologies.To avoid any biases by introducing “Population” and log(Population density) in the model, it was performed a robustness check (Table 18 in the Annex) which is consistent with the positive effect of relatedness density to related entry.

The positive and significant Population density coefficient in model (2) suggests that more densely populated regions are more likely to see the entry of related web technologies. The significance disappears in the full model without fixed effects but reappears positively in the full model with fixed effects.This corresponds with Jacobs’ (1969) concept of externalities and the subsequent cluster theory, which suggest that the variety of skills and ideas present in densely populated urban areas act as catalysts for innovation. This concept is equally valid for the entry of web technologies. As expected, the positive coefficients of patent applications in models (3) and (4) indicate that regions with more patent applications are more likely to see the entry of related web technologies, suggesting a relationship between innovation and the entry of related digital web technologies. This finding aligns with the research from Acs, Anselin, and Varga (2002), which suggests that regions with higher patenting activity are likely to be more innovative. However, this current finding contributes to the discussion on the relationship between the digital and physical worlds, challenging the idea of the "death of space." It shows that, contrary to expectations, spatial relevance has not diminished in the digital era.

Based on the comprehensive analysis of research findings, which illustrates a positive correlation between relatedness density and the propensity for related entry in web technologies across European regions, I confidently accept Hypothesis H1a. This acceptance underscores the pivotal role of relatedness density in facilitating technological evolution and innovation at the regional level.

Accepting Hypothesis H1a posits a significant advancement in our understanding of the dynamics at play in digital technology adoption at the regional level. The empirical evidence, as demonstrated by the logistic regression models and the visualization of relatedness density across European regions, underpins the assertion that a higher relatedness density substantially increases the likelihood of related entry in the web technology sector. This outcome aligns with the initial premise that regions characterized by a closely connected network of existing and new technologies manifested through higher relatedness density exhibit a greater propensity for entering new technological domains that are closely related to their existing capabilities.

The acceptance of Hypothesis H1a not only reinforces the theoretical groundwork of evolutionary economic geography and relatedness theory, but also offers practical implications for regional development strategies. It suggests that fostering an environment where knowledge and technologies can easily intersect and recombine can significantly enhance the innovative capacity of regions. This is particularly relevant for policymakers and stakeholders who want to cultivate a vibrant ecosystem that supports technological evolution, diversification, and economic growth. By acknowledging the critical role of relatedness density, regions can strategically invest in building and strengthening their technological networks, thereby elevating their potential for technological adoption and innovation. This approach, rooted in the use of the symbiotic relationship between existing and emerging technologies, provides a roadmap for enhancing regional competitiveness in the digital era. Later, this measurement will be used as an important part of the digital smart specialization framework, guiding regions on how to digitalize their economies.

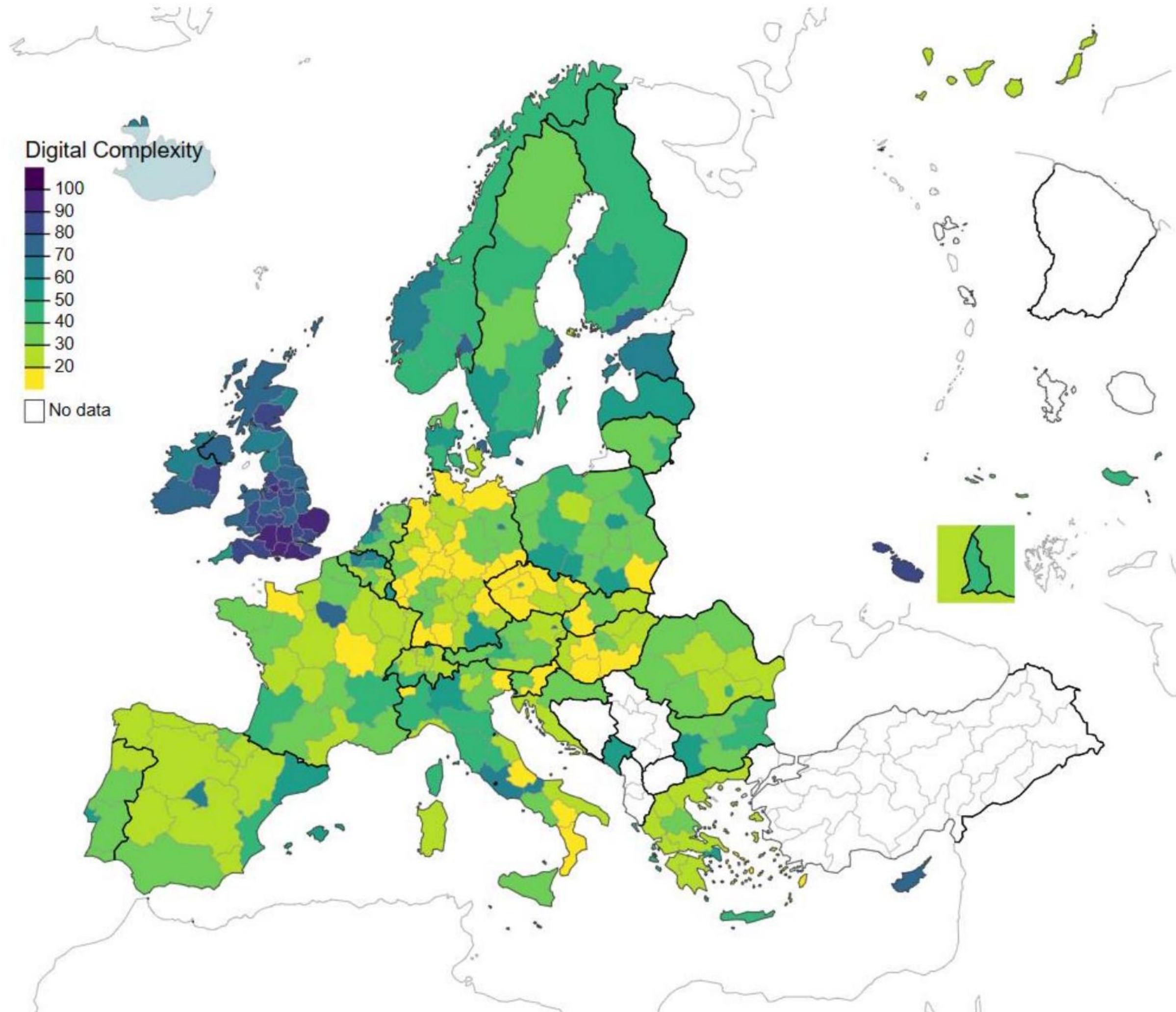

Figure 5: Digital complexity in European regions classified at the NUTS 2 level. Source: Authors' own elaboration.

6.2 Digital Complexity

The following figure, Figure 5 shows the degree of digital web complexity in European regions classified as NUTS 2 level. The map uses a color gradient to indicate the varying degrees of digital complexity, with different shades representing different levels. The data reveal that areas denoted by dark green have the most intricate digital infrastructure, with scores ranging from 90 to 100. It is probable that these areas possess sophisticated digital infrastructures, considerable levels of digital literacy, and resilient digital economies. Digital complexity is moderate to high in regions denoted by lighter green hues, where scores range from 50 to 89. This indicates that the digital environment is highly developed, but not to the same extent as the darkest green regions. The yellow regions, in contrast, indicate a moderate level of digital complexity, as indicated by scores ranging from 30 to 49. These regions may be in the middle of digital infrastructure development or face gaps in digital literacy and access. Lastly, areas colored pale yellow to white, which receive scores ranging from 0 to 29, represent reduced digital complexity. This implies that these areas can face difficulties in improving their digital infrastructure, accessibility, or digital literacy.

It is a common observation that regions with central capitals appear to undermine the digital complexity of nearby regions. Certain locations may find the availability and accessibility of a competent labor force, which is nurtured by institutions of higher education, to be of the utmost importance. However, as a result of population density-induced surges in demand for digital services and the subsequent supply response, human capital is often absorbed by urbanized locations, which also exhibit a greater degree of digital complexity. A comparative analysis between German NUTS 2 regions and their Western European counterparts yields insightful disparities. The normalized digital complexity scores reveal that while regions such as Berlin (DE30) exhibit considerable digital infrastructure with scores around 61.96, they do not quite reach the sophistication levels of Western European leaders like Île de France (FR10) at approximately 75.02 and Copenhagen (DK01) at about 78.62. Delving deeper into the German spectrum, Upper Bavaria (DE21) stands at a moderate digital complexity score of approximately 52.41, which, when juxtaposed with Brussels (BE10) at around 67.27, indicates potential for growth in digital complexity despite its economic stature in Germany. Contrasts are observed in regions such as Saxony (DED2), where the digital complexity score plummets to approximately 13.41, starkly underperforming when placed alongside Lisbon (PT17) in Portugal at around 53.51 and significantly lagging behind the front-runner, Inner London - West (UKI3) in the UK, which reaches the highest score of 100. It can be argued here that the inherent economic makeup of regions plays a pivotal role, with industrial regions focusing on manufacturing historically exhibiting slower digital integration compared to regions with service-oriented economies. Correlating with digital complexity, regions like Île de France and Inner London, specialized more into service industries and have likely benefited from more substantial investments in digital infrastructure compared to some German counterparts or CEE countries.

In Figure 6 I have the visual representation of the LISA analysis of digital complexity in

NUTS 2 regions throughout Europe. The concept of spatial autocorrelation in LISA analysis refers to the degree of similarity between a location and its neighboring locations. The plot provides insight into the spatial distribution and regional disparities in digital development. The map clearly shows the different areas classified into categories like HH (High-High), LL (Low-Low), LH (Low-High), and HL (High-Low), and areas classified as "Island" for which no neighbors could be calculated.

HH Regions represent areas with high digital complexity surrounded by regions with similarly high complexity. These could be tech hubs or regions with advanced digital infrastructure. HL Regions are regions with high digital complexity surrounded by low-complexity areas. These might be isolated pockets of digital advancement.

On the other hand, LL Regions characterize areas with low digital complexity surrounded by similarly low-complexity regions. These might be less developed or rural areas.And finally, LH Regions are areas with low digital complexity but surrounded by high-complexity regions. These could be regions that are lagging in digital development despite being near more advanced areas.

There are significant disparities in digital complexity across Europe. Western and Northern European regions, especially in countries like the UK, Sweden, Finland, and Norway, generally exhibit higher levels of digital complexity, as indicated by the prevalence of HH (High-High) regions. This suggests a well-developed digital infrastructure and a strong presence of tech industries and services. Eastern and Southern European regions on the other hand show more variability, with a mix of LL (Low-Low), HL (High-Low), and LH (Low-High) regions. This indicates that while there are clusters of advanced digital development, there are also areas that lag behind, highlighting a digital divide within these parts of Europe. The presence of HL regions in some Eastern European countries and parts of Italy suggests isolated hubs of advanced digital development. These could be specific cities or areas that have significantly higher digital complexity compared to their surrounding regions. On the other hand, the existence of these LL clusters highlights a pronounced digital divide within Europe. LL regions may be indicative of rural or less urbanized areas. Spatial distribution of LL regions suggests that policy interventions and investments in digital infrastructure need to be geographically targeted. Regions with low digital complexity are likely to face various economic and social disadvantages. This includes limited access to digital services, fewer opportunities for digital innovation and business development, and potential challenges or lack of interest in integrating into the broader digital economy.

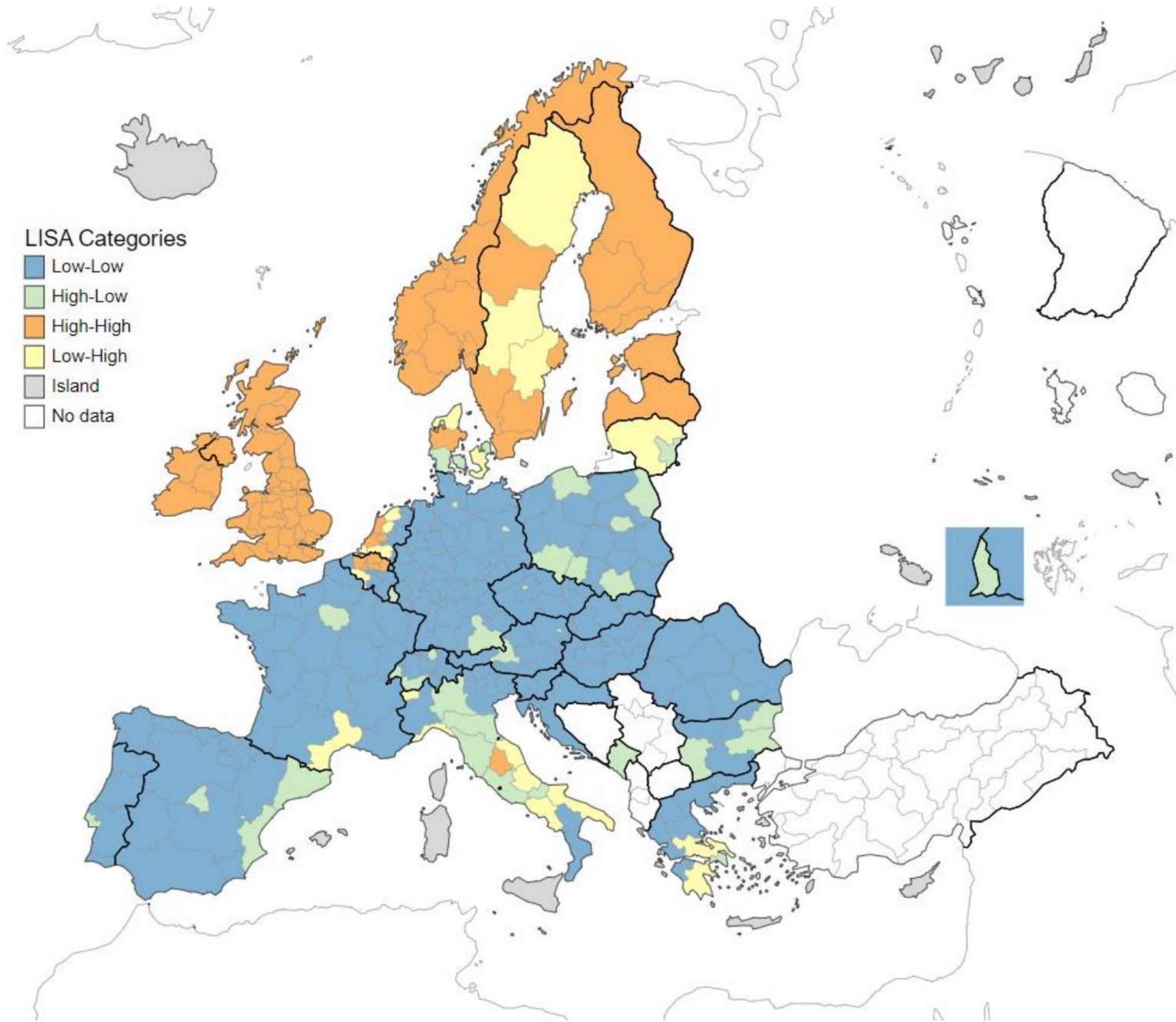

Figure 6: LISA analysis of digital complexity in NUTS 2 regions across Europe. Source: Author's own elaboration.

The following Figure 7 shows the distribution of labor productivity and digital complexity across Europe, using a core-periphery model within economic geography to highlight the disparities in development and innovation. In such a model, the core regions are identified by their high levels of development, innovation, and economic activity, which often manifest in both high labor productivity (indicated by darker blue-purple shades) and advanced digital infrastructure (represented by stronger green patterns). These core areas are typically urbanized, have diversified economies and are technologically advanced, likely to include major cities or capitals with robust digital economies. In contrast, peripheral regions, which are shaded lighter in blue-purple and have weak or no green patterns, display lower labor productivity and digital complexity, pointing to a more rural character or lesser development, with economies that might still rely on traditional industries and where digital infrastructure is less developed. There are also regions that might show a discrepancy between the two measures, such as high digital complexity against a backdrop of lower labor productivity, possibly indicating transitional areas that have seen significant digital investment but where this has not yet translated into overall labor productivity gains. Or, in contrast, where high productivity has not been accompanied by digital development, perhaps reflecting regions with strong traditional industrial sectors that are economically productive but have not fully integrated advanced digital technologies. This core-periphery pattern reflects a group of influencing factors, including historical development trajectories, levels of investment and policy-driven initiatives, access to education and skilled labor, and the quality of infrastructure. Core areas typically benefit from a cycle of compounding growth and innovation due to concentrated investment and talent, whereas peripheral areas may lag, often hampered by a lack of similar resources or conditions conducive to rapid development, illustrating the economic and digital landscape of Europe through a lens of regional inequality.

The map presents a particularly interesting case for Germany, where I observe a digital complexity paradox. Despite being shaded darkly, indicating high labor productivity, Germany exhibits a less dense green pattern, suggesting that its digital complexity is not as advanced as its economic output might predict. This could imply that while Germany's economy is highly efficient and its workforce produces a significant amount of economic value per capita, its integration of advanced digital technologies is not as prevalent or sophisticated as its general economic productivity level might suggest.

This paradox could arise from several factors. Firstly, Germany has a strong industrial base with sectors such as automotive, mechanical engineering and chemical manufacturing, which have traditionally been less dependent on cutting-edge digital technologies than sectors like information technology or digital services. Secondly, there may be a lag in digital transformation in which the existing economic strength has been built on traditional manufacturing and industrial prowess, and the shift to digitalization, while underway, is not yet reflected in a measure of

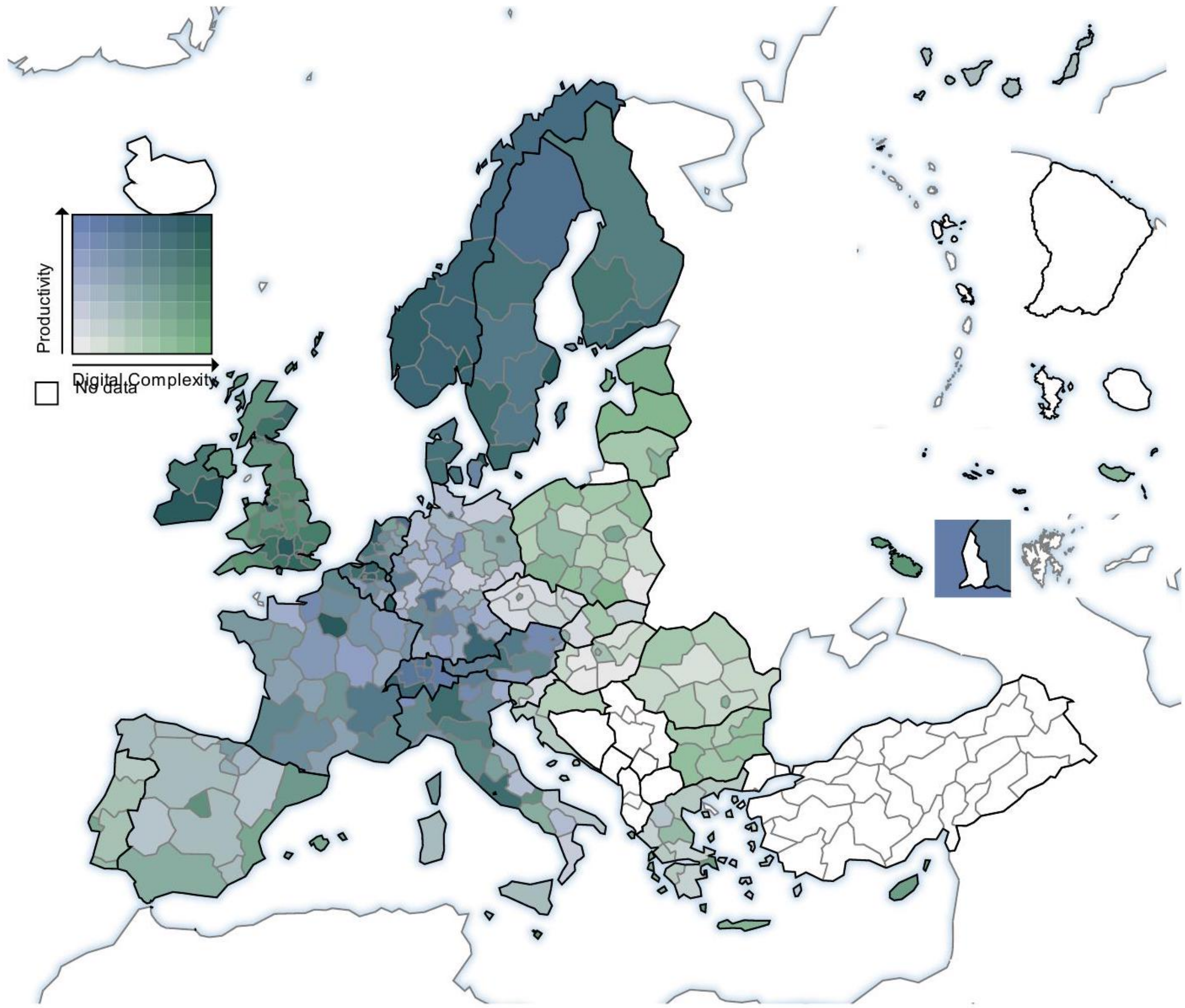

Figure 7: Distribution of labor productivity and digital complexity across Europe. Source: Authors' own elaboration.

digital complexity.

In addition, this situation could be influenced by regulatory environments, investment priorities, or workforce skill sets that are more aligned with traditional sectors rather than digital sectors. It is also possible that the digital complexity measure used in the map is capturing a specific aspect of digital technology use that does not fully encapsulate the breadth of digital activities in Germany's economy. For example, German industries may be utilizing digital technologies in a way that enhances productivity without necessarily increasing the complexity of their digital footprint (web platforms or websites), such as through automation and efficiency-improving digital technologies rather than consumer-facing digital services.

Ultimately, this paradox points to the comprehensive nature of economic and technological development, where high productivity does not always go hand-in-hand with advanced digital complexity.

The analysis of the impact of digital complexity on productivity, as reflected in the following provided Table 5, underscores a multisided relationship that is highly dependent on the modeling approach and the specificities of the data considered. In a pooled ordinary least squares (OLS) framework, digital complexity demonstrates a uniformly positive effect on productivity. This general positive association may be attributed to the overarching benefits of digital technology adoption, which, even at basic levels, can significantly enhance productivity across various sectors. However, this simplified aggregation inherent in pooling OLS models may not reveal the complex relationship between digital complexity and productivity that is evident when spatial and temporal dynamics are taken into account.

Although the pooled OLS model provides an initial indication of the positive impact of digital complexity on productivity, a deeper investigation using spatially and temporally sensitive models unveils a more complex picture. This complexity is characterized by varying impacts in different regions and times, underscoring the critical role of contextual factors in shaping the economic benefits of digital advancement. Therefore, I need a much deeper look into the time and space effects.

The following Table 6 provides a more comprehensive analysis of how digital complexity influences labor productivity across Europe, using a spatial panel fixed effects model to account for both time and regional variations. The parameter of interest, rho (ρ), indicates the spatial lag of productivity, reflecting the degree to which productivity in one region is influenced by productivity in neighboring regions. Across the five models presented, is consistently significant ($p<0.01$), with values ranging from 0.1945 to 0.5473, suggesting a strong spatial dependency in productivity levels between regions. This indicates that closely situated regions tend to exhibit similar productivity levels, underscoring the importance of spatial factors in economic performance.

Model 1 shows a significant positive impact of digital complexity on productivity (coefficient = 0.0022, $p<0.01$), highlighting that increases in digital complexity tend to enhance labor productivity. Nonetheless, in models 3 and 4, where additional variables are included, and fixed

Table 5: The effect of Digital Complexity on productivity

	Dependent variable:			
	log(Productivity)			
	(1)	(2)	(3)	(4)
Digital Complexity	0.001***	0.002***		0.001**
	(0.0002)	(0.001)		(0.0003)
Spatial lag of productivity	0.996***		0.898***	0.893***
	(0.011)		(0.054)	(0.050)
Spatial Lag of GDP/cap			0.093*	-0.001
			(0.049)	(0.045)
Spatial Lag of Digital Complexity		-0.0001	-0.0002	-0.0004
		(0.001)	(0.0003)	(0.0004)
ln(Population Density)				0.010**
				(0.004)
ln(Patent Applications)				0.049***
				(0.004)
Constant	0.004	10.646***	0.178	0.896***
	(0.116)	(0.034)	(0.145)	(0.147)
Region FE	NO	NO	NO	NO
Time FE	No	No	No	No
Observations	1,505	1,505	1,505	1,505
R^2	0.852	0.011	0.851	0.875
Adjusted R^2	0.852	0.010	0.851	0.874
F Statistic	4,316.912*** (df=2;1502)	8.328*** (df=2 ; 1502)	2,854.938*** (df=3; 1501)	1,739.960*** (df = 6; 1498)

Notes: The model in use is a Pooling OLS model without controlling for time and space. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

effects are accounted for, the coefficient for digital complexity turns negative (though still significant), suggesting that the relationship between digital complexity and productivity may not be entirely direct and potentially influenced by other regional characteristics or by the inclusion of spatial lags of productivity.

The inclusion of GDP per capita and population density as control variables in models 2 and 4 provides additional information. GDP per capita is strongly positively associated with productivity, as expected. Population density, nonetheless, shows a mixed relationship with productivity, being negative in Model 2 and positive in Model 4, reflecting differing urbanization impacts on productivity in different contexts.

The apparent positive relationship in the pooling OLS model suggests that the initial or

Table 6: Spatial study of the effect of Digital Complexity on productivity

	Dependent variable: log (Productivity)				
	SAR (1)	SAR (2)	SAR (3)	SAR (4)	SEM (5)
rho	0.5473***	0.4310***	0.1945***	0.3021***	0.3021***
	(0.0237)	(0.0279)	(0.0322)	(0.0302)	(0.0302)
(Intercept)	10.6589***	2.3326***	–	–	–
	(0.0345)	(0.0798)	–	–	–
log (Digital complexity)	0.0022***	–	−0.0004**	−0.0003***	−0.0002***
	(0.0006)	–	(0.0001)	(0.0001)	(0.00007)
log (GDP/cap)	–	0.8509***	–	0.7752***	0.77521***
	–	(0.0085)	–	(0.0118)	(0.0117)
log (Population density)	–	−0.0278***	-0.0673	0.1953***	0.1952***
	–	(0.0028)	(0.0506)	(0.0259)	(0.0258)
log (Patent applications)	–	-0.0012	0.0438***	0.0040	0.0040
	–	(0.0028)	(0.0055)	(0.0028)	(0.0028)
log (Productivity spatial lag)	–	–	0.8221***	0.1478***	0.1478***
	–	–	(0.0194)	(0.0142)	(0.0142)
Region FE	No	No	Yes	Yes	Yes
Time FE	No	No	Yes	Yes	Yes
RLMerr	265.7961***	82.4813***	55.3480***	6.8785**	6.8785**
RLMlag	2.2397	2.5857	38.445***	4.2590*	4.2590*
SARMA	280.8054***	83.8916***	55.3480***	6.8785*	6.8785*
Observations	1575	1575	1505	1505	1505

Notes: The model in use is a spatial panel fixed effects model, controlling for time and space. Model (5) differs from Model (4) by using an error model instead of a lag model. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

widespread adoption of web technologies can lead to broad productivity gains. However, this analysis might not capture the differentiated impacts that emerge over longer periods or with more substantial changes in digital complexity. The transition from a pooling OLS to more sophisticated spatial panel fixed-effects models reveals varying effects, indicating that the influence of digital complexity on productivity is not uniform across regions or time periods. This variability could arise from disparities in digital infrastructure quality, the digital maturity of economies, and the digital intensity of specific sectors.

Initially, the positive coefficients for digital complexity in the pooling Ordinary Least Squares (OLS) models indicate a general positive influence of digital complexity on productivity, supporting the acceptance of Hypothesis H2a. This finding aligns with the hypothesis that regions or organizations with higher digital complexity are hypothesized to exhibit higher productivity levels.

However, the transition to spatial panel fixed effects models, which account for regional and temporal variations, reveals a more complex relationship. The mixed results, where digital complexity initially shows a positive impact on productivity but then demonstrates negative coefficients in models adjusted for spatial and temporal dynamics, suggest that the relationship between digital complexity and productivity is contingent upon specific regional characteristics, or time. This result is further investigated in the next model.

Moreover, the significant spatial dependencies highlighted in the models emphasize the importance of geographical proximity in determining how digital complexity influences other regions' productivity. Such findings point to the necessity of adopting a meticulous analytical lens, incorporating both spatial and temporal variations to fully understand the complex dynamics at play. This complexity, particularly the negative coefficients observed in more refined models, may imply that, while digital complexity contributes to productivity, its effects are not universally positive across all regions and circumstances. Factors such as the maturity of the digital infrastructure, the adaptability of the workforce, and the existing economic structure of a region may play critical roles in determining the extent to which digital complexity can translate into productivity gains.

To further examine in a more profound way these regional characteristics and the confusing spatial relationships, I performed the spatial dependence diagnostic tests:

Table 7: Spatial dependence diagnostic tests:

Test Name	**Test Value**	**P-Value**
LM_err	79.5420	< 0.001
LM_lag	1.7200	0.1897
RLM_err	80.8070	< 0.001
RLM_lag	2.9847	0.08405
SARMA	82.5270	< 0.001

Notes: LM_err = Lagrange Multiplier Test for Spatial Error Dependence; LM_lag = Lagrange Multiplier Test for Spatial Lag Dependence; RLM_err = Robust Lagrange Multiplier Test for Spatial Error Dependence; RLM_lag = Robust Lagrange Multiplier Test for Spatial Lag Dependence; SARMA = Lagrange Multiplier Test for Spatial Autoregressive Moving Average. All coefficients are statistically significant at the following levels: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

As observed in the upper table, the spatial dependence tests (LMerr) indicate that spatial error dependence is present. In such cases, a model accounting for spatial error dependence, such as the SEM (Spatial Error Model) or SARAR (Spatial Autoregressive model with Autoregressive

Errors), is appropriate.This suggests that there's a high correlation between the error term of spatial units (regions) The SARAR Equation with Region and Time Fixed Effects is presented here:

$$y_{it} = \rho W y_{it} + X_{it}\beta + \alpha_i + \gamma_t + u_{it}$$

Where:

- y_{it} is the dependent variable for region i at time t (y_{it} represents $\Delta \log(Productivity)$).
- ρ is the spatial autoregressive parameter for the dependent variable.
- W is the spatial weights' matrix.
- X_{it} is the matrix of explanatory variables for region i at time t (Digital complexity, GDP per capita, population density).
- β is the vector of coefficients for the explanatory variables.
- α_i represents the region fixed effects, accounting for region-specific unobserved heterogeneity.
- γ_t represents the time fixed effects.
- u_{it} is the spatially autocorrelated error term, modeled as:

$$u_{it} = \lambda W u_{it} + \varepsilon_{it}$$

Where:

- λ is the spatial autoregressive parameter for the error term.
- ε_{it} is the independent and identically distributed error term.
- σ^2 is the variance of the error term.

In this empirical part (Table 8), when controlled for fixed effects of the region in models 1 and 2, Digital complexity has a significant positive relationship with changes in labour productivity. Later when time fixed effects are introduced (Model 3), although positive, this relationship is not significant. These effects suggest that while digital complexity has a stronger association with productivity in earlier years, this effect tends to decrease in later years when these web technologies mature, become ubiquitous, and their effects are homogenous in all regions. However,

Table 8: Spatial Error Productivity Models

Dependent variable: $\Delta\log$(Productivity)			
Variable	SEM (Model 1)	SARAR (Model 2)	SARAR (Model 3)
(Intercept)	-	-	-
Digital complexity (log)	0.0101* (0.0042)	0.0090* (0.0040)	0.0029 (0.0041)
GDP pc (log)	-0.0092 (0.0160)	0.0003 (0.0163)	0.0573*** (0.0164)
Population density (log)	0.0789 (0.0510)	0.0965** (0.0486)	0.182*** (0.0533)
Patent applications (log)	-0.0116* (0.0049)	-0.0119** (0.0048)	-0.0218*** (0.0053)
rho	-	-0.2548*** (0.0555)	0.5380*** (0.0660)
delta	0.6917*** (0.0188)	0.7898*** (0.0200)	0.0300 (0.0998)
Observations	1290	1290	1290
Region Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	NO	NO	Yes
Sigma	0.0698	0.0700	0.0577
AIC	-6296.22	-6307.15	-6408.21
BIC	-6270.41	-6276.17	-6377.23

Notes: All coefficients are statistically significant at the following levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Standard errors are shown in parentheses. Observations are mean-centered. The dependent variable is the change in labor productivity. The models include region and year fixed effects, where indicated. Where SEM = Spatial error model, and SARAR = Spatial autoregressive combined model.

adding too much FEs (region and time) on top of the already hard assumptions coming from the spatial model, reduces largely the variation of my explanatory variable (Digital complexity).

Given the previous considerations and the additional tests performed, it would be more accurate to state that I partially accept Hypothesis H2a. This partial acceptance acknowledges the positive impact of digital complexity on productivity under certain conditions, while also recognizing the limitations and variability of this impact across different spatial and temporal contexts. The evidence suggests that the influence of digital complexity on productivity is significant but complex, influenced by a multitude of factors and policies at the regional level that can enhance or mitigate its effectiveness, but also the right timing could also have an effect.

In Figure 8 it is provided a scatter plot that looks at NUTS 2 level regions in two dimensions, the relatedness density of web technologies and their digital complexity.This is often seen as a smart specialization strategy for EU regions, by specializing in related and complex technologies, regions can develop new industries and catch up economically with other developed regions. The horizontal axis (Digital Complexity) measures the complexity of web technologies within each region, likely considering the diversity and sophistication of web-related capabilities and digital infrastructure. Regions to the right, with higher values on this axis, are considered to have more complex web technologies, possibly indicating a more advanced and diverse web technology ecosystem. On the other hand, the vertical axis (Relatedness Density) represents the relatedness of web technologies within the regions, indicating how interconnected and complementary the web technologies are. Higher values suggest that the web technologies within a region are more closely related, allowing for more synergistic and cohesive development.

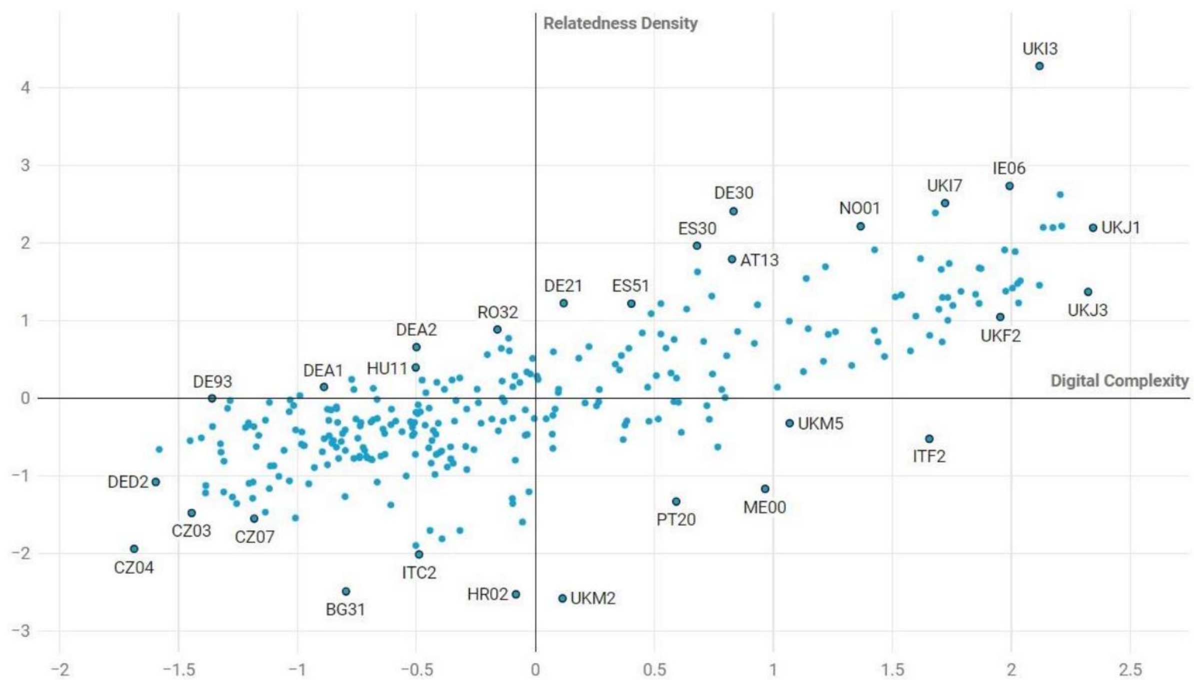

Figure 8: Regions specializing in both complex and related web technologies - the Digital Smart Specialization framework. Source: Authors' own elaboration.

Interpretation of quadrants from Figure 8 is done through the perspective of best policy choice for regions at different levels of development.

Regions in the Top Right Quadrant (I) area (like UKI3, IE06, UKJ1) have both high digital complexity and high relatedness density. They are likely to be leaders in web technology, with a rich ecosystem of related technologies that reinforce each other. This suggests a high level of innovation, a strong talent pool, and significant investment in digitalization of different sectors. In this quadrant, all regions should aspire to be. However, regions in the Bottom Right Quadrant (II) (like ITF2, ME00) have high digital complexity but lower relatedness density. This could mean that these regions have a diverse array of advanced web technologies, but they may not be as interconnected. There might be opportunities to improve by enhancing collaboration and integration between different web technologies.

Regions falling into the Bottom Left Quadrant (III) (like CZ04, CZ03) have both low digital complexity and low relatedness density. They might be at an early stage of developing their web technology sector or may not place a priority on it. These regions could benefit from strategies to both diversify and integrate their web technologies.

Finally, Regions in the Top Left Quadrant (IV) (like DEA2 and HU11) have lower digital complexity but high relatedness density. This indicates a more focused but less diverse technological environment. These regions might have specialized in a few web technologies that are well-integrated.

The positioning of regions in this plot can provide valuable insights for policymakers and businesses, mainly who need to invest more and in what directions or where. Regions in the top right quadrant are likely to have competitive advantages in the digital economy, while those in the bottom left might need to invest in both diversification and integration of web technologies to improve their standing.Regions that want to enter into new, more favorable quadrants need to focus on specific complex or related technologies and leverage on their comparative advantage.

In the following two plots the first map (Figure 9 (1)), indicates the adoption of live chat technology, uses varying shades of pink to represent the degree of technology share, indicating technology adoption (TS). The lighter shades suggest lower adoption rates, while darker shades indicate higher adoption rates. From the map, it seems that live chat technology is less uniformly adopted across Europe, with some countries showing moderate to low adoption rates.

The map illustrating the adoption of live chat technology shows a varied landscape, with generally lighter shades of pink, indicating lower technology share. The distribution suggests that the adoption of live chat technology is relatively lower across the board, with no country reaching the highest category on the provided scale. This could imply that while live chat technology is present, it hasn't reached a high level of market penetration in Europe, possibly due to the nature of the businesses operating there or the preferences of consumers who may use alternative communication channels.

In contrast, the map of JavaScript library adoption in Figure 10 (2) is shaded with deeper blues, denoting a higher technology share. JavaScript libraries are fundamental to modern web development, offering a range of functionalities that can enhance the user experience and website performance. The darker shades, especially in Western and Central Europe, suggest that these regions have a high adoption rate of JavaScript libraries, indicating a robust web development landscape with a possible focus on advanced and interactive web functionalities.

When comparing the two maps, it is evident that JavaScript library technology has a higher adoption rate compared to live chat technology across most of Europe.However because of saturation effect and higher number or higher numbers of firms in the western regions, it seems that some periphery regions are higher adopters of Javascript technologies. This could reflect the essential role of JavaScript libraries in web development, as opposed to the more specialized function of live chat services. In terms of core-periphery patterns, Western and Central Europe, often considered the economic "core" of the continent, show higher adoption rates for JavaScript libraries. This is consistent with the idea that core regions are more technologically advanced and economically developed. The "periphery", which often includes Eastern European countries, shows a lower adoption rate of both technologies. This might be due to a variety of economic, infrastructural, and market-related factors that influence the uptake of new technologies. The higher adoption rates in the core can be attributed to several factors, including a greater concentration of tech companies, higher investment in IT infrastructure, and a workforce with advanced technical skills. Moreover, core regions are often the first to adopt new technologies, which gradually diffuse to the periphery.

In conclusion, the adoption patterns of live chat and JavaScript library technologies in Europe seem to reflect broader economic and technological trends associated with the core-periphery model, with the core regions of Western and Central Europe leading in the integration of these web technologies. However, this is much dependent on the types of industries and activities that the core and periphery perform. Where the periphery seems to dominate some technologies such as the Live-chat web technology.

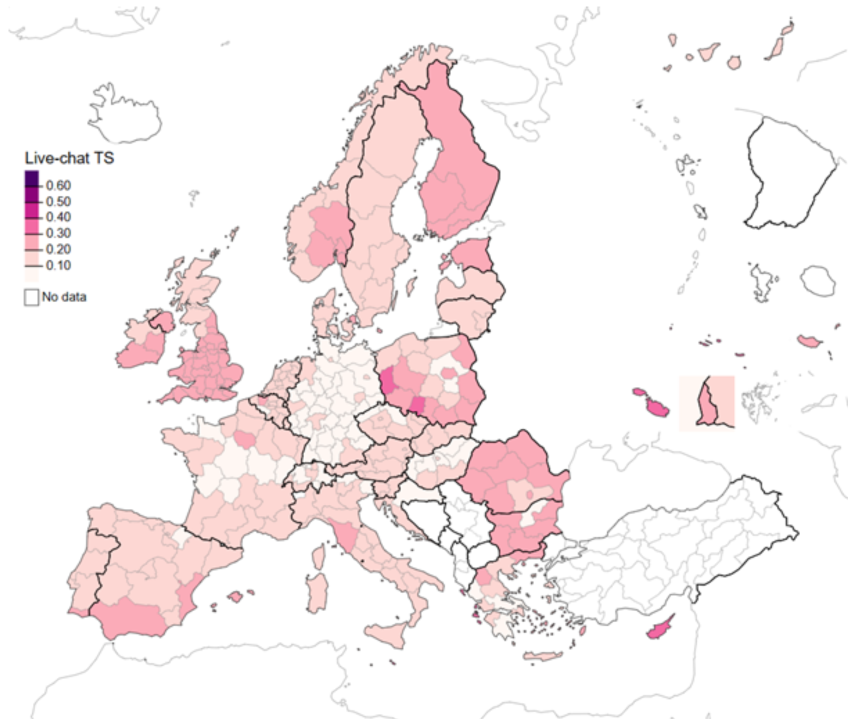

Figure 9: Picture 1. Technology adoption patterns in Europe: Live Chat Adoption. Source: Authors' own elaboration.

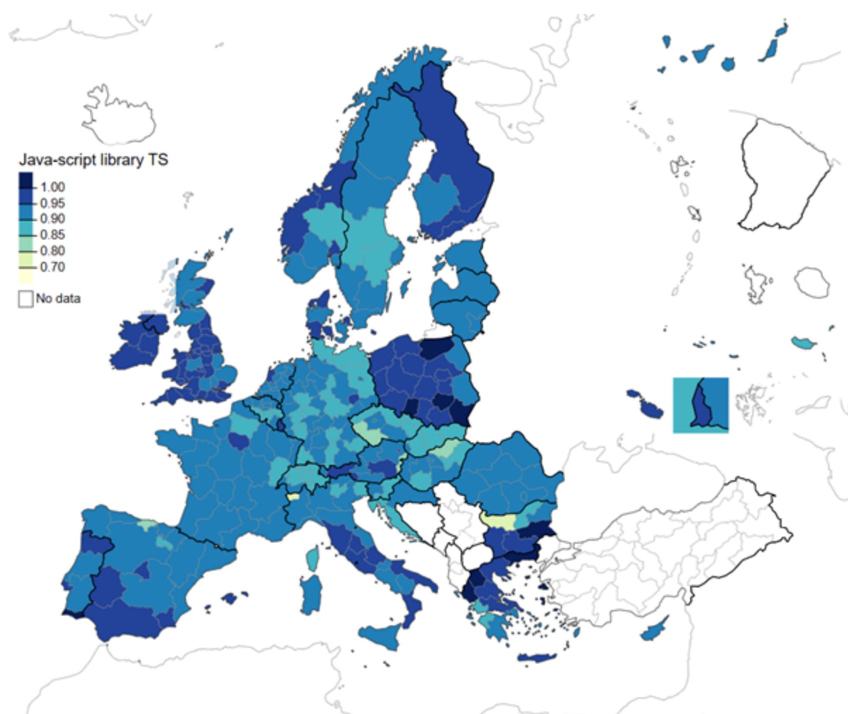

Figure 10: Picture 2. Technology adoption patterns in Europe: JavaScript Library Adoption. Source: Authors' own elaboration.

To prove the idea that the geography and local factors shape technology adoption and is not the technology that shrinks the space, you can see the following figure, Figure 11. Let us focus specifically on the spatial distribution of live chat technology adoption in Eastern Europe and the Central-West/South regions.In Eastern Europe, including countries like Poland, the Czech Republic, Slovakia, Romania, Bulgaria, and the Baltic States, the LISA map indicates High-High (HH) associations, which are shown in dark purple. This suggests that these regions have high levels of live chat technology adoption and are also surrounded by regions with similar levels of adoption.

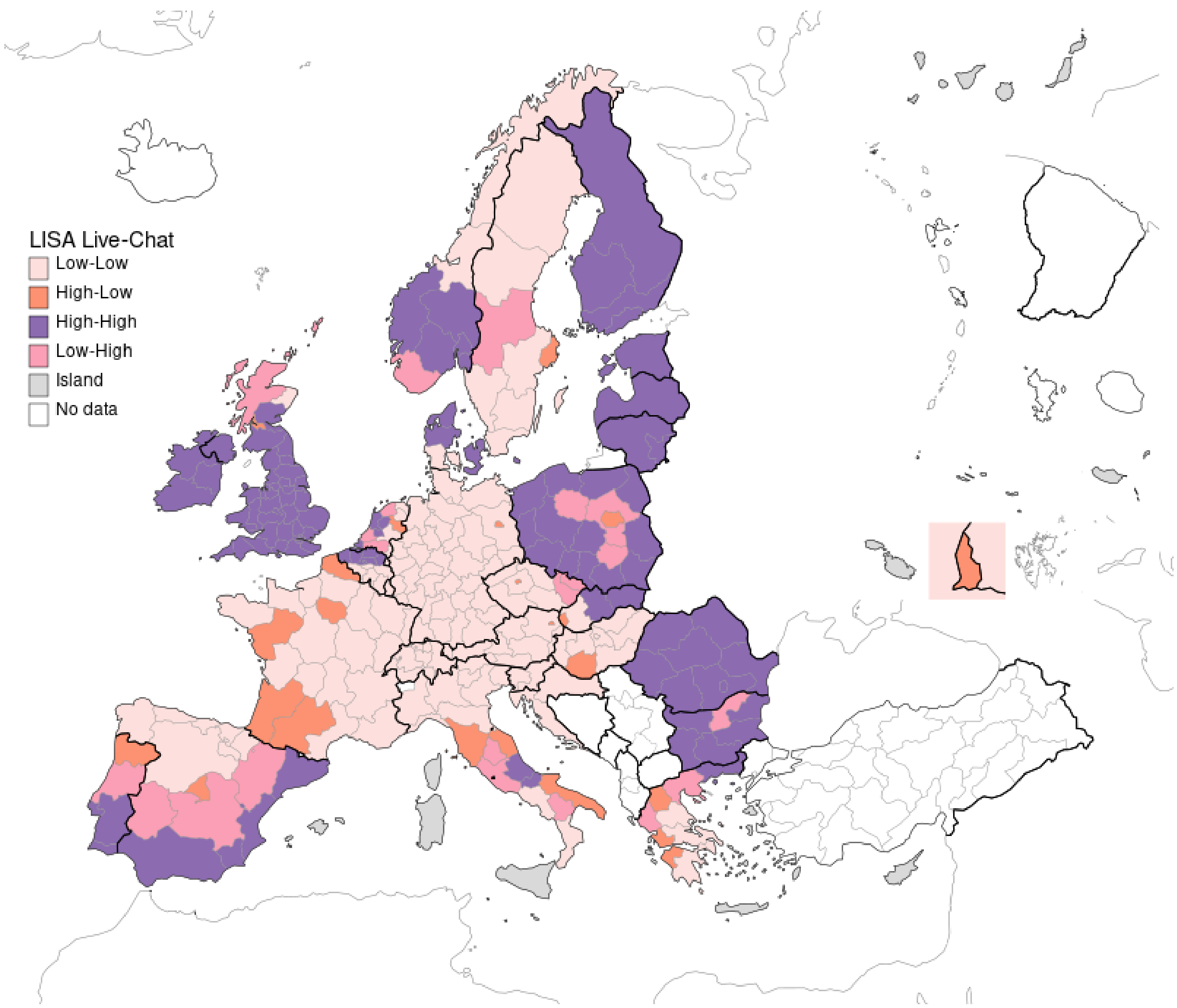

Figure 11: Local Indicators of Spatial Association (LISA) for the live-chat web technology adoption. Source: Authors' own elaboration.

Comparatively, Central-West or Central-South Europe may show different patterns, potentially mixing High-High and Low-High (LH) associations. The LH associations could indicate that while some central areas have a high adoption rate, they are adjacent to areas with lower adoption levels, which may reflect varying economic conditions, the presence of rural areas, or differing priorities in technological investments. When comparing live chat technology with JavaScript libraries, I can surmise that the former's adoption goes beyond the mere presence of technological solutions. This indicates a strategic choice to enhance customer interaction and improve service delivery. Live chat systems involve a complex blend of technology and human interaction, requiring a more sophisticated infrastructure, greater digital literacy, and potentially more investment in customer service. The high levels of adoption in Eastern European countries suggest that these regions have not only caught up with central-western regions, but might be leading in implementing complex web technologies for business communications solutions. However, this could also be associated with the region's growing role as a hub for offshoring activities, including client service centers and call centers.The presence of offshoring activities, particularly those focused on customer service and live chat, may explain the high adoption rates of live chat technologies in the region.This is later tested in the empirical model through the industrial structure variable.

Companies that offshore these operations must integrate live chat systems that are capable of handling complex customer interactions, often involving coordination with CRM systems, databases, and various application interfaces. The adoption of live chat technology in these areas suggests not only the presence of the necessary technological infrastructure, but also a business environment that values and invests in advanced communication tools for customer service excellence. Geographically speaking, Eastern Europe is well-positioned to serve as a bridge between Western Europe and Asia. The time zone overlap with Western European countries allows for real-time communication, which is a critical aspect of live chat services. But also often Eastern Europe and Baltic countries offer a more cost-effective environment for businesses due to lower wage levels compared to Western Europe. We should also consider the skilled workforce that speaks many foreign languages and recent developments in internet infrastructure. in these regions.

6.3 The impact of the digitalization, Ecosystem and Spatial factors on Technology Adoption

In the analysis of the factors influencing the adoption of technology across different digital technologies, Table 9 provides important insights that deserve a detailed discussion in the context of this dissertation. The findings from this table guide a straightforward interpretation of Hypotheses 1b and 2b, which concern the roles of relatedness density and digital complexity in technology adoption, respectively.

Firstly, Hypothesis 1b shows a positive relationship between relatedness density and technology adoption. This hypothesis is robustly supported by the data, which exhibits significant positive coefficients for the log of relatedness density across all analyzed technology categories. This consistent pattern underscores the premise that regions with a higher density of related technological capabilities and knowledge networks are more adept at adopting new digital technologies. Such a finding aligns with the theoretical frameworks suggesting that cognitive proximity and shared knowledge bases facilitate the diffusion and assimilation of innovative technologies. There are no deviations from this positive relationship across the different models. This reinforces the importance of fostering interconnected and innovative ecosystems to improve the adoption rates of new digital technologies.

In contrast, Hypothesis 2b, which anticipates a positive relationship between digital complexity and technology adoption, encounters a contradictory narrative in the empirical evidence. Despite initial expectations, digital complexity is associated with significant negative coefficients in nearly all technologies examined. This counterintuitive result suggests that regions with higher levels of digital complexity might face diminishing returns in the adoption of additional new technologies. Potential explanations for this phenomenon could include saturation effects, where highly digitized regions prioritize the optimization of existing technologies over the adoption of new ones, or encounter barriers related to compatibility issues and the incremental costs of adopting further technologies. Such findings necessitate a reevaluation of the assumed linear benefits of digital complexity on technology adoption and point towards the complexity of navigating digital ecosystems that are already highly developed.

Moreover, acceptance of Hypothesis 1b based on the data underscores the strategic value of relatedness density in promoting technology adoption. It highlights the necessity for regions to cultivate and leverage their technological networks and capabilities to facilitate the seamless integration of new technologies. On the other hand, the rejection of Hypothesis 2b challenges preconceived notions about digital complexity's role in fostering technological adoption, suggesting a paradox where increased digital sophistication does not straightforwardly translate to higher adoption rates of new technologies.I tested the exponential relationship and the results are similar, showing a negative relationship between digital complexity and technology adoption.

Finally, this analysis not only reaffirms the critical role of relatedness density in enhancing digital technology adoption but also highlight the complex and sometimes inverse relationship between digital complexity and the propensity to adopt new digital technologies.

In the case of the place specific factors, we can see that often patent application have a negative relationship with technology adoption, which might suggest that those regions that more productive in terms of physical technologies are less productive in adoption of web technologies.However, the human capital or talent almost always has a positive relationship with web technology adoption, suggesting that only those regions that have more education population might benefit from the digital transformation, also discussed as a digital divide.

Infrastructure also plays a significant role in the adoption of web technologies. This leads to the acceptance of the Hypothesis 3a which tests the impact of place-specific factors on web technology adoption.

Table 9: The Influence of Digital Complexity and Relatedness on Technology Adoption

	Dependent variable: TA (Technology Adoption)									
	Ad analytics	Javascript library	Affiliate programs	Marketing automation	Audience measurement	Application performance	Live chat	CMS	Currency	Framework
Digital complexity	-0.001^{***}	-0.003^{***}	-0.001^{***}	-0.001	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.002^{***}	-0.002^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
log(RelatednessDensity)	0.019^{***}	0.265^{***}	0.006^{***}	0.034^{***}	0.135^{***}	0.136^{***}	0.089^{***}	0.017^{***}	0.045^{***}	0.109^{***}
	(0.002)	(0.008)	(0.002)	(0.004)	(0.006)	(0.007)	(0.004)	(0.001)	(0.010)	(0.010)
log(Population density)	0.001	-0.005	0.001	-0.002	-0.002	-0.002	-0.001	-0.001	-0.005	0.001
	(0.001)	(0.004)	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)	(0.005)	(0.005)
Patent Applications	-0.001	-0.001^{*}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.001^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Business Sophistication	0.037^{***}	0.496^{***}	-0.017^{***}	-0.001	0.090^{***}	0.117^{***}	-0.058^{***}	0.004	-0.166^{***}	0.066^{***}
	(0.005)	(0.019)	(0.005)	(0.010)	(0.015)	(0.016)	(0.010)	(0.003)	(0.026)	(0.023)
Talent	0.003^{***}	0.010^{***}	0.002^{***}	0.011^{***}	0.003^{***}	0.005^{***}	0.010^{***}	0.001^{***}	0.011^{***}	0.024^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Quality of Governance	-0.007	-0.161^{***}	0.010	0.122^{***}	-0.010	0.015	0.045^{**}	0.047^{***}	0.421^{***}	0.316^{***}
	(0.012)	(0.042)	(0.011)	(0.023)	(0.034)	(0.035)	(0.022)	(0.006)	(0.056)	(0.051)
Quality of Infrastructure	0.033^{***}	0.063^{**}	0.023^{***}	0.155^{***}	0.047^{**}	0.055^{**}	0.138^{***}	0.007^{*}	0.157^{***}	0.349^{***}
	(0.007)	(0.026)	(0.007)	(0.014)	(0.021)	(0.022)	(0.013)	(0.004)	(0.035)	(0.032)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No	No	No	No	No
Observations	2,013	2,088	2,024	2,066	2,088	2,088	2,077	1,980	2,088	2,088
R^2	0.480	0.848	0.161	0.585	0.507	0.537	0.675	0.325	0.221	0.653
Adjusted R^2	0.426	0.832	0.073	0.542	0.455	0.488	0.641	0.255	0.140	0.617
F Statistic	210.184^{***} (df = 8; 1822)	$1,320.852^{***}$ (df = 8; 1890)	43.798^{***} (df = 8; 1832)	329.933^{***} (df = 8; 1870)	242.500^{***} (df = 8; 1890)	273.658^{***} (df = 8; 1890)	488.413^{***} (df = 8; 1880)	108.014^{***} (df = 8; 1792)	66.962^{***} (df = 8; 1890)	445.377^{***} (df = 8; 1890)

Notes: $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.All models are panel linear models estimated using the 'plm' package in R with a 'within'(fixed effects) model specification and individual effects. Dataset corresponding to specific technology: Ad Analytics,Javascript, Affiliate Programs, Marketing Automation, Audience Measurement, Application Performance, Live Chat, CMS, Currency, and Framework. Regional fixed effects are included in all models, while time fixed effects are not considered.

Moreover, analyzing Table 10 and 11 reveals interesting findings. First, Table 10 examines the influence of agglomeration factors and geography on web technology adoption, it also looks at the effects of the core-periphery perspective on the adoption of digital technology. The analysis demonstrates that being in a core or periphery region significantly affects technology adoption rates, with core regions not always leading in the adoption of new technologies like Javascript library and Live Chat. This finding challenges traditional notions of innovation diffusion, suggesting that peripheral regions may also be active participants in the adoption of certain technologies, possibly due to specific needs, niche markets, or the presence of unique ecosystems that support such adoptions. In the second case about Spatial Spillovers. The significant positive values of ρ across many models in Table 11 indicate that technology adoption in one region is likely influenced by the adoption rates in neighboring regions, highlighting the importance of spatial spillovers. This phenomenon is particularly pronounced in the adoption of the Javascript library and Live Chat technologies, where spatial dependencies suggest that regions do not operate in isolation but are part of a broader, interconnected regional-technological landscape. This suggests that regions are interdependent in their web technology adoption, contrary to the idea of knowledge decentralization due to digitalization. This leads to acceptance of Hypothesis 3b, which questions the positive relationship between spatial spillovers in web technology adoption. In the case of Hypothesis 3c, the relationship between human-specific agglomeration and web technology adoption is not clear and direct and maybe a little paradoxical. In the case of the simple linear model, this relation is positive; however, this effect changes when fixed effects are included, see Table 17 in the annexes. This suggests that there are other better factors describing web technology adoption. I partially accept Hypothesis 3c.

In general, Hypothesis 3 is accepted. The analysis brings to the forefront the critical role of geographical factors and spatial spillovers in the adoption of technology. The analysis underscores the significance of geographical factors and spatial spillovers in technology adoption, with core-periphery dynamics and the presence of spatial autocorrelation (ρ) playing crucial roles. This acceptance highlights the enduring importance of geography in shaping technological landscapes, even in the digital age. The acceptance of Hypothesis 3 underscores the enduring relevance of geographical considerations in understanding and fostering web technology adoption, even in the increasingly digital and interconnected world.

It can be concluded that the landscape of technology adoption is shaped by a multitude of factors, where the presence of conducive elements such as skilled labor, business sophistication, infrastructure, and relatedness density coexists with challenges posed by digital complexity, governance quality, and infrastructural needs. This complex interplay suggests that the promotion of a supportive environment for technology adoption requires a holistic approach that not only leverages existing strengths but also addresses the inherent challenges within the regional ecosystem. Moreover, when looking at the role of industrial structure and specific fixed effects in the model, the results are interesting, but not always straightforward. First, Table 16 proves in the short term the negative effect of digital complexity on Technology Adoption. Moreover, in 5 out of 10 web technologies, industrial diversity (entropy) is positively associated with web technology adoption, while industrial specialization is positively associated only in 3 technologies. In the same table, it is shown how important it is to have business activities in a region with high ICT employment, which is again positively associated with web technology adoption. However, this image changes in the following Table 17, where when controlling for time fixed effects the relationship between digital complexity and technology adoption becomes negative. Similarly, the effect of industrial diversity in certain cases (3 models) becomes negative, still it is a weak level of significance $p<0.1$.

Nevertheless, such insights and unique evaluations are crucial for policymakers, business leaders, and regional planners aiming to stimulate technological innovation and adoption, underscoring the need for targeted strategies that address both the technological and socio-economic dimensions of the digital technology adoption process.

Table 10: The influence of agglomeration factors and geography on Web Technology Adoption

	Dependent variable:									
	Technology Adoption									
	Ad analytics	Javascript library	Affiliate programs	Marketing automation	Audience measurement	Application performance	Live chat	CMS	Currency	Framework
Core-Periphery	-0.007***	0.045***	−0.011***	0.002	0.006	0.005	0.008***	−0.002**	−0.022***	0.023***
	(0.002)	(0.007)	(0.002)	(0.004)	(0.006)	(0.007)	(0.003)	(0.001)	(0.008)	(0.006)
log(Population Density)	0.002**	−0.015***	0.001*	-0.001	0.005**	0.002	0.001	−0.001***	0.006*	-0.004
	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.003)	(0.002)
Number of Firms	0.001***	0.001	0.001***	0.001***	0.001	0.001***	0.001***	0.001***	0.001***	0.001***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Business Sophistication	0.042***	0.354***	-0.007	−0.024**	0.063***	0.062***	−0.053***	0.002	-0.001	0.020
	(0.007)	(0.020)	(0.005)	(0.012)	(0.017)	(0.019)	(0.009)	(0.003)	(0.023)	(0.018)
Existent Technologies	0.001***	0.020***	0.001***	0.002***	0.006***	0.006***	0.003***	0.001***	0.003***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Tech. Readiness	−0.026***	0.143***	-0.009	−0.062***	0.028	-0.005	−0.048***	0.014***	−0.075***	0.095***
	(0.008)	(0.024)	(0.007)	(0.015)	(0.020)	(0.022)	(0.011)	(0.003)	(0.028)	(0.022)
log(Patent Applications)	0.001*	-0.001	0.001	-0.001	-0.001	−0.001***	−0.001***	−0.001**	−0.001***	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Quality of Infrastructure	−0.017***	−0.084***	-0.003	0.022**	−0.080***	−0.103***	0.001	0.012***	-0.020	0.074***
	(0.005)	(0.016)	(0.004)	(0.009)	(0.014)	(0.015)	(0.007)	(0.002)	(0.019)	(0.015)
Quality of Governance	−0.037***	−0.199***	−0.026***	-0.022	−0.061***	−0.102***	−0.049***	−0.010***	0.114***	−0.070***
	(0.009)	(0.026)	(0.008)	(0.016)	(0.022)	(0.024)	(0.012)	(0.004)	(0.031)	(0.024)
log(Total Employment)	−0.014***	−0.011***	−0.006***	−0.014***	-0.001	−0.011***	−0.015***	−0.006***	−0.018***	−0.043***
	(0.001)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)	(0.001)	(0.004)	(0.003)
Talent	0.001***	0.001	−0.001***	0.002***	0.003***	0.004***	0.001***	−0.001***	0.001	−0.003***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Constant	0.124***	0.547***	0.085***	0.107***	0.576***	0.635***	0.123***	0.060***	0.381***	0.522***
	(0.009)	(0.025)	(0.007)	(0.016)	(0.022)	(0.024)	(0.012)	(0.004)	(0.030)	(0.023)
Observations	2,013	2,090	2,024	2,068	2,090	2,090	2,079	1,980	2,090	2,090
R^2	0.257	0.687	0.113	0.341	0.331	0.368	0.570	0.312	0.153	0.636
Adjusted R^2	0.253	0.685	0.108	0.337	0.327	0.365	0.568	0.308	0.148	0.634
F Statistic	62.883*** (df = 11; 2001)	414.056*** (df = 11; 2078)	23.245*** (df = 11; 2012)	96.644*** (df = 11; 2056)	93.308*** (df = 11; 2078)	110.015*** (df = 11; 2078)	249.172*** (df = 11; 2067)	81.158*** (df = 11; 1968)	34.094*** (df = 11; 2078)	330.471*** (df = 11; 2078)

Notes: All models are panel linear models estimated using the 'plm' package in R with a 'pooling' model specification. The dependent variable is Technology Adoption. The model uses a unique dataset corresponding to specific sectors: Ad Analytics, Javascript, Affiliate Programs, Marketing Automation, Audience Measurement, Application Performance, Live Chat, CMS, Currency, and Framework. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 11: The effect of spatial spillovers on Technology adoption.Does the place still matter?

	Dependent variable: Technology adoption									
	Ad analytics	Javascript library	Affiliate programs	Marketing automation	Audience measurement	Application performance	Live chat	CMS	Currency	Framework
ρ	0.125	0.107^{***}		0.102	0.213^{***}	0.210^{***}	0.146	0.310^{***}	0.501^{***}	0.504^{***}
	(0.088)	(0.029)		(0.311)	(0.029)	(0.029)	(0.161)	(0.041)	(0.023)	(0.023)
ρ_{t-1}	0.195^{**}	0.331^{***}		0.514	0.090^{**}	0.094^{*}	0.500^{***}	0.289^{***}	0.312^{***}	0.157^{***}
	(0.081)	(0.027)		(0.492)	(0.043)	(0.048)	(0.219)	(0.033)	(0.024)	(0.032)
ln (GDP/cap)	0.061^{***}	0.248^{**}	0.050^{***}	0.075	0.141	0.166	0.141^{***}	0.009	0.038	0.215^{***}
	(0.019)	(0.122)	(0.011)	(0.046)	(0.098)	(0.110)	(0.031)	(0.016)	(0.024)	(0.024)
ln (Total Population)	0.144	-0.303	0.084	0.257	-0.073	0.054	0.051	-0.042	0.296^{***}	0.067
	(0.088)	(0.965)	(0.071)	(0.332)	(0.784)	(0.872)	(0.233)	(0.040)	(0.112)	(0.099)
ln (Total Employment)	-0.064	-0.042	0.022^{**}	0.099	-0.007	-0.003	0.008	0.004	0.248^{***}	0.063
	(0.078)	(0.390)	(0.025)	(0.153)	(0.322)	(0.358)	(0.107)	(0.030)	(0.067)	(0.059)
Quality of Governance	-0.033	-0.043	-0.024	0.063	-0.092	-0.078	-0.078	0.013	0.257^{***}	-0.113^{**}
	(0.063)	(0.121)	(0.034)	(0.281)	(0.105)	(0.115)	(0.198)	(0.032)	(0.061)	(0.053)
Corruption	-0.025	-0.128^{***}	0.032	-0.054	0.002	-0.007	0.003	0.006	-0.200^{***}	0.240^{***}
	(0.048)	(0.043)	(0.028)	(0.211)	(0.040)	(0.043)	(0.147)	(0.036)	(0.049)	(0.043)
Quality of Infrastructure	0.024^{**}	0.055^{**}	0.024^{***}	0.077^{***}	0.057^{**}	0.050^{*}	0.094^{***}	0.006	0.023	0.225^{***}
	(0.011)	(0.027)	(0.008)	(0.024)	(0.024)	(0.026)	(0.016)	(0.036)	(0.026)	(0.024)
Business Sophistication	0.052^{***}	0.299^{***}	-0.016	-0.011	0.039	0.071^{*}	-0.008	0.020	-0.065^{***}	0.073^{***}
	(0.013)	(0.046)	(0.011)	(0.044)	(0.040)	(0.042)	(0.031)	(0.026)	(0.023)	(0.021)
Talent	0.001^{***}	0.007^{***}	0.001^{**}	0.005^{***}	0.004^{***}	0.005^{***}	0.004^{***}	0.001^{***}	0.005^{***}	0.008^{***}
	(0.0004)	(0.001)	(0.0005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.0003)	(0.001)	(0.001)
Constant			-1.873^{*}							
			(1.084)							
Adj. (Pseudo) R^2	0.569	0.803	0.642	0.680	0.327	0.391	0.780	0.372	0.549	0.775
Region fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	2013	2090	2024	2068	2090	2090	2079	1980	2090	2090
LM test for spatial lag	62.69^{***}	424.54^{***}	0.106	276.57^{***}	101.01^{***}	87.54^{***}	553.83^{***}	172.81^{***}	1076.6^{***}	802.32^{***}
LM test for spatial error	37.93^{***}	120.79^{**}	2.15	123.99^{***}	66.88^{***}	47.96^{***}	275.38^{***}	132.17^{***}	937^{***}	561.94^{***}

Notes: Rho represents the spatial lag of the dependent variable.All models are panel linear models estimated using the 'splm' package in R with a 'Spatial model with individual (Regions) effects' model specification. The dependent variable is Technology Adoption.Each model uses a unique dataset corresponding to a specific web technology. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

The following models in Table 12, looks into the combination of technology adoption with digital complexity and relatedness density, especially when examining Javascript library and Live Chat technologies, and unveils that a complex interplay between these factors significantly affects the spread of new digital tools within regions and regional economies. This intricate relationship, as outlined in the provided data, gives us a deeper understanding of how the adoption of emerging technologies is shaped by the pre-existing digital landscape and the network of technological capabilities that pervade a given area.

The analysis of the interaction between technology adoption and digital complexity, as well as relatedness density, particularly with respect to Javascript library and Live Chat technologies, demonstrates the detailed mechanisms through which the adoption of new digital web technologies is influenced by and, in turn, impacts regional economies. This exploration, grounded in the provided models, delineates the complex interactions between the existing digital infrastructure, the network of technological capabilities, and the economic outputs of regions.

In regions with advanced digital complexity, the adoption of Javascript library technologies not only integrates seamlessly into the existing digital ecosystem but also signifies a positive correlation with economic indicators such as GDP per capita. The implication is that in areas where the digital infrastructure is robust, the introduction of new technologies like Javascript libraries not only finds a conducive environment for adoption but also contributes to economic growth. This relationship underscores the importance of a well-established digital foundation in fostering technological innovation and diffusion, thereby enhancing the region's economic performance.

Similarly, for Live Chat technologies, a positive interaction with digital complexity suggests that regions with sophisticated digital infrastructures are better positioned to leverage these technologies effectively. The adoption of Live Chat technologies in such regions does not merely benefit from the pre-existing digital environment but also plays a role in further economic development, highlighting the reciprocal relationship between technological adoption and economic advancement.

The interaction between technology adoption and relatedness density offers insights into how the interconnectedness within a region's technological ecosystem facilitates the adoption of new technologies and influences economic outcomes. For the Javascript library, a positive coefficient indicates that regions with a dense network of related technologies and knowledge domains are more adept at incorporating new technologies, which in turn can drive economic growth. The presence of related technologies and knowledge bases not only eases the adoption process but also contributes to the region's economic dynamism by fostering an environment conducive to innovation and collaboration.

For Live Chat technologies, the combination with relatedness density similarly reflects a region's capacity to assimilate and exploit these technologies based on its network of related capabilities. A positive interaction suggests that regions rich in interconnected technologies and competencies not only facilitate the adoption of Live Chat technologies, but also leverage these technologies to boost economic performance. The collective knowledge and cognitive proximity inherent in such regions provide a fertile ground for innovation diffusion, which is instrumental in driving economic development.

This combined analysis reveals that the adoption of digital web technologies like Javascript libraries and Live Chat is significantly shaped by the digital complexity and relatedness density of regions. Moreover, it highlights the critical role these factors play in influencing regional economic outputs. High digital complexity and relatedness density not only provide the necessary infrastructure and collaborative framework for technology adoption but also have a profound impact on economic growth, underscoring the intertwined nature of digital technological innovation, diffusion, and economic development. Thus, understanding and harnessing the interaction between technology adoption, digital complexity, and relatedness density is pivotal for fostering regional economic advancement in the digital age. It emphasizes the need to consider both the structural and relational dimensions of a region's technological ecosystem to fully grasp and encourage the widespread adoption of novel digital technologies.

Table 12: The impact of contextual variables and technology adoption on Digital Complexity, Relatedness and the Economic Output

	Dependent variable:						
	Digital Complexity	Relatedness Density	log(GDP/cap)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Technology Adoption				-0.158^{***}	-0.156^{***}	0.222^{***}	-0.400^{***}
Digital Complexity				-0.003^{***}		-0.001^{***}	
Relatedness Density					-0.002^{**}		0.001
log (Population Density)	-0.726	0.239	-0.004	-0.003	-0.004	0.001	0.002
Number of Firms	-0.010^{**}	0.001	0.001^{***}	0.001^{***}	0.001^{**}	-0.001	-0.001^{**}
Business Sophistication	-26.325^{***}	-5.777^{***}	-0.311^{***}	-0.352^{***}	-0.313^{***}	-0.283^{***}	-0.256^{***}
Existent Technologies	0.202^{***}	0.025	0.001	0.001	0.001	-0.001	-0.001
Technological Readiness	-17.893^{***}	-9.063^{***}	-0.032	-0.012	0.008	-0.019	0.004
Patent Application	0.001	0.002^{***}	0.001	0.001^{***}	0.001^{*}	0.001^{***}	0.001^{***}
Quality of Infrastructure	-21.844^{***}	-4.524^{***}	-0.114^{***}	-0.131^{***}	-0.114^{***}	-0.156^{***}	-0.154^{***}
Quality of Governance	-20.402^{***}	-15.693^{***}	0.055	0.027	0.064^{*}	0.053	0.087^{**}
log(Total Employment)	11.822	-0.743	0.554^{***}	0.503^{***}	0.517^{***}	0.522^{***}	0.479^{***}
Talent	1.222^{***}	0.088^{**}	-0.006^{***}	-0.007^{***}	-0.007^{***}	-0.006^{***}	-0.008^{***}
Technology Adoption*Digital Complexity				0.003^{***}		0.002^{*}	
Technology Adoption*Relatedness Density					0.006^{***}		0.023^{***}
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Effect	Two-Ways	Two-Ways	Two-Ways	Two-Ways	Two-Ways	Two-Ways	Two-Ways
Observations	2,088	2,088	2,090	2,088	2,088	2,077	2,077
R^2	0.119	0.104	0.212	0.237	0.240	0.228	0.254
Adjusted R^2	0.021	0.004	0.124	0.150	0.154	0.140	0.170
F Statistic	25.315^{***}(df = 10; 1878)	21.713^{***}(df = 10; 1878)	50.468^{***}(df = 10; 1880)	44.701^{***}(df = 13; 1875)	45.625^{***}(df = 13; 1875)	42.282^{***}(df = 13; 1865)	48.906^{***}(df = 13; 1865)

Notes: The dependent variables are Digital Complexity, Relatedness Density' log(GDP/cap) '. Dataset corresponding to specific technology: Javascript library (Models 4 and 5) and Live Chat (Models 6 and 7). $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

For Hypothesis 4, the findings suggest a partial acceptance. The influence of contextual factors on digital complexity and relatedness density is evident but manifests in complex and sometimes counterintuitive ways. While certain factors like quality of infrastructure and business sophistication positively influence digital complexity, suggesting that a well-developed infrastructure and a sophisticated business environment are conducive to enhancing digital complexity, other factors do not uniformly lead to increased digital complexity. This partial acceptance indicates that while some contextual factors are pivotal in fostering a complex digital landscape, not all factors contribute equally, and the overall influence is not entirely clear.

6.4 Does Technology adoption affect economic growth, or economic growth affect Technology adoption?

Finally, the simultaneous relationship between technology adoption and economic growth is examined in Table 11 and Table 13. The examination of this relationship is aimed to test the literature which suggest a simultaneous relationship. First, Table 13 which is titled "The relationship between Technology Adoption and Economic Growth" presents a comprehensive analysis of how the adoption of various digital web technologies influences GDP per capita, as a proxy for economic growth. The dependent variable across all models is the logarithm of GDP per capita, which allows for a detailed understanding of growth rates across different technological adoptions. I examine a range of web technologies, including Ad Analytics, Javascript Library, Affiliate Programs, Marketing Automation, Audience Measurement, Application Performance, Live Chat, CMS (Content Management System), Currency, and Frameworks.

The results indicate a mixed impact, with the adoption of certain web technologies like the Javascript Library significantly positively affecting economic growth, as evidenced by a positive and statistically significant coefficient. This suggests that the adoption of Javascript Library technologies, a technology essential to the development of interactive and functional web applications, contributes to economic productivity and growth. Moreover, this type of technology drives innovation and operational efficiency. This allows companies to interact and create value in various sectors such as in e-commerce, online services, and digital marketing by enhancing their offerings and customer engagement possibilities. This ease of adoption of this technology ensures that businesses can quickly leverage these technologies to stay competitive and innovative, which is translated into growth.

On the other hand, the adoption of other technologies, such as Live Chat and CMS, is associated with negative coefficients. This implies a potential short-term drag on economic growth, or this effect is not seen in all the regions, therefore the result is negative. This could reflect also the costs and adjustments required to integrate these technologies into existing systems and workflows, but also that this technology is used only in specific regions that need this technology.

Live-chat technologies, which enable real-time communication between businesses and their customers, exhibit a more complex (negative) relationship with GDP per capita. While intuitively one might expect a positive impact due to improvements in customer service and engagement, the negative association observed could be explained by the immediate costs and organizational changes required to effectively implement live chat solutions. These technologies may not yield immediate economic benefits for certain regions, particularly those where digital infrastructure is still developing, or the regions are not specialized in sectors that use the technology and traditionally contribute to GDP.

Additionally, the utility of live chat is highly sector-specific. Regions that are predominantly driven by sectors such as manufacturing or agriculture might not see an immediate uplift in GDP from the adoption of live chat technologies. This is contrasted with service-oriented economies, where digital customer engagement plays a crucial role in economic activities.

The control variables included in the analysis, such as Population Density, Number of Firms, Business Sophistication, Existent Technologies, Technological Readiness, Patent Application, Quality of Infrastructure, Quality of Governance, and Total Employment, provide a broader context for understanding the conditions under which technology adoption impacts economic growth. For instance, the negative coefficients for Business Sophistication and Quality of Infrastructure across most models may suggest that while these factors are important for supporting technology adoption and usage, they alone do not guarantee positive economic outcomes without effective integration and utilization of new digital web technologies.

The positive impact of Patent Applications across all models highlights the importance of innovation in driving economic growth. This is in line with the idea that economies that promote innovation through patents tend to experience higher growth rates due to the commercialization of new ideas and inventions, but also they are the ones digitalizing the most.

The analysis of the relationship between GDP per capita and the adoption of web technologies, specifically Javascript libraries and Live-chat, based on Table 11 , reveals a more broad picture of how economic development influences technological adoption. This connection highlights the multifaced nature of GDP per capita and its impact on the integration of advanced digital tools.

In regions with higher GDP per capita, there is a noticeable trend towards the greater adoption of Javascript libraries. This trend can be attributed to several key factors that are inherently tied to economic prosperity. Firstly, richer regions possess the financial resources necessary for investing in new technologies. The availability of funds makes it easier for businesses and individuals to afford the costs associated with adopting and integrating complex web technologies. Secondly, these areas often boast a skilled workforce, a direct result of better access to education and professional training. Such a workforce is adept at utilizing and implementing advanced technologies, making Javascript libraries more accessible and useful. Lastly, a strong economic base supports the development of robust digital infrastructure, essential for the effective deployment and use of these technologies. High-speed internet access and modern IT infrastructure, more prevalent in economically prosperous areas, facilitate the adoption of sophisticated web technologies.

Conversely, the adoption of Live-chat technology, while influenced by GDP per capita, may not show a uniformly positive relationship across all regions. The specific utility and application of Live-chat systems play a significant role in this variance. Live-chat technology is especially beneficial in service-oriented sectors, such as retail, finance, and customer support. Therefore, regions with a strong emphasis on these industries might see a more pronounced impact of GDP growth on the adoption of Live-chat technologies. Additionally, the demand for direct customer interaction, which varies by industry and market, correlates with the economic environment. Economies with a significant digital services sector, which are often more prosperous, are likely to have a higher demand for live-chat solutions. This is further supported by the level of digital penetration within a region; economies with higher GDP per capita generally enjoy wider access to digital technologies, increasing the potential user base for Live-chat services.

Looking through the prism of the hypothesis, Hypothesis H5 posits a reciprocal relationship between technology adoption and GDP per capita, suggesting a bidirectional influence where technology adoption boosts GDP per capita, and simultaneously, regions with higher GDP per capita are more inclined to adopt new digital technologies. The evidence from the analysis supports this hypothesis, demonstrating that digital technology adoption varies with economic prosperity. For instance, technologies like Javascript libraries show a positive relationship with GDP per capita, indicating that wealthier regions tend to adopt these technologies more readily, possibly due to better resources and infrastructure. Conversely, the adoption of these technologies contributes to economic growth, as seen in the positive impacts on GDP per capita for specific technologies. Therefore, Hypothesis H5 is accepted, reflecting the intertwined relationship between economic prosperity and the embracement of new web technologies.

Despite the need for a more robust reverse causality analysis and posible application of a simultaneous equation model such as Three Stage Least Squares Methodology (3SLS) this was not possible due to the data limitations and and the scale of this study. I consider this a limitation of the study and a posibility for further research.

Table 13: The relationship between Technology Adoption and Economic Growth

	Dependent variable:									
	log(GDP/cap)									
	Ad analytics	Javascript library	Affiliate programs	Marketing automation	Audience measurement	Application performance	Live chat	CMS	Currency	Framework
Technology Adoption	-0.029	0.061***	0.099	-0.067*	0.025*	0.018	-0.119***	-0.226**	-0.037***	-0.159***
log(Population density)	-0.001	-0.002	0.001	-0.002	-0.002	-0.001	-0.002	0.002	0.004**	-0.001
Number of Firms	0.001	0.001	0.001	0.001	0.001	0.001	-0.001***	-0.001	-0.001	-0.001***
Business Sophistication	-0.079***	-0.099***	-0.073***	-0.074***	-0.076***	-0.074***	-0.074***	-0.070***	-0.078***	-0.078***
Existent Technologies	0.001	-0.001	0.001	-0.001	-0.001	-0.001*	-0.001	-0.001**	0.001	0.001
Tech. Readiness	0.005	0.020	0.005	0.015	0.015	0.014	0.005	0.013	0.016	0.002
Patent Application	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***	0.001
Quality of Infrastructure	-0.083***	-0.088***	-0.086***	-0.091***	-0.096***	-0.096***	-0.095***	-0.078***	-0.094***	-0.065***
Quality of Governance	-0.123***	-0.055	-0.128***	-0.092**	-0.080**	-0.082**	-0.076**	-0.111***	-0.079**	-0.054
log(Total Employment)	0.823***	0.797***	0.820***	0.804***	0.791***	0.789***	0.784***	0.817***	0.802***	0.683***
Talent	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.004***	-0.003***	-0.004***	-0.003***
Constant	0.021***	0.020***	0.021***	0.022***	0.022***	0.022***	0.025***	0.022***	0.023***	0.029***
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No	No	No	No	No
Observations	1,830	1,900	1,840	1,880	1,900	1,900	1,890	1,800	1,900	1,900
R^2	0.233	0.222	0.231	0.220	0.214	0.213	0.221	0.237	0.218	0.274
Adjusted R²	0.228	0.218	0.227	0.216	0.209	0.208	0.217	0.232	0.213	0.270
F Statistic	50.204*** (df = 11 1818)	49.104*** (df = 11; 1888)	49.972*** (df = 11 1828)	47.925** (df = 11 1868)	46.613*** (df = 11; 1888)	46.458*** (df = 11 1888)	48.566*** (df = 11 1878)	50.479*** (df = 11 1788)	47.823*** (df = 11; 1888)	64.690*** (df = 11; 1888)

Notes: The dependent variable is ' log(GDP/cap) '. Dataset corresponding to specific technology: Ad Analytics, Javascript, Affiliate Programs, Marketing Automation, Audience Measurement, Application Performance, Live Chat, CMS, Currency, and Framework. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

7 Discussion and Conclusion

7.1 Discussion

This dissertation delves into understanding the complex interactions between relatedness density, digital complexity, and technology adoption across European regions, elucidating the dynamics of digital web technology evolution and adoption and its spatial distribution in EU NUTS regions. Moreover, it looks at how place-specific factors interact with digital web technology adoption. I aimed at building the literature and empirically studying several hypotheses. First, it was expected that the relatedness density would enhance the likelihood of related entry, where firms in regions enter new digital technological domains that are closely related to their previous capabilities. My investigation provides robust support for Hypothesis H1a, showing that higher relatedness density significantly increases the odds of the entry of related web technologies. This finding emphasizes the importance of cognitive proximity and interconnected entrepreneurial ecosystems in regional innovation and technological advancement, aligning with the theoretical frameworks of evolutionary economic geography and relatedness theory. It suggests that regions characterized by a dense network of existing and new technologies characterized by higher relatedness density are more keen on navigating the intricacies of technological evolution and adopting new business models or adopting new web technologies, leveraging these connections for sustained economic growth and innovation. Besides, this should warn us regarding the weak capabilities of other regions, as they may be trapped in the incapacity to adopt new technologies without existing capabilities.

Second, Hypothesis H1b, expected a positive relationship between relatedness density and technology adoption. High relatedness density, indicating a closer relationship between existing and new technologies, is expected to facilitate technology adoption. In this case, the acceptance of Hypothesis H1b reinforces the importance of relatedness density in facilitating digital technology adoption. Regions with higher relatedness density exhibit a greater propensity for adopting new technological domains that are closely related to their existing capabilities. This highlights the need for strategic regional smart specialization policies that promote environments where knowledge and technologies can easily be interconnected and recombined. In a similar line to the Schumpeterian "New combinations". Similar to the framework proposed in this dissertation. Therefore, enhancing the firm digitalization, innovative capacity, and competitiveness of EU regions in the digital age.

For Hypothesis H2a, it was expected that Digital complexity positively influences labor productivity. In another way said, regions with higher digital complexity were hypothesized to exhibit higher productivity levels. When firms are digitized and have complex web technologies, they are expected to be more productive, therefore influencing the overall regional productivity. While, for Hypothesis H2b, it was expected a positive relationship between digital complexity and technology adoption. Higher levels of digital complexity within a region are expected to lead to greater technology adoption rates. Here it is expected a spillover effect from firms with complex technologies to other firms in a region.

However, my analysis presents a distinct picture when examining the role of digital complexity. Contrary to the expected positive relationship hypothesized in H2a by digital complexity on productivity, and in H2b by digital complexity on technology adoption, the empirical evidence reveals a more complex and sometimes inverse relationship. Higher levels of digital complexity, rather than straightforwardly translating to higher rates of technology adoption, show a paradox where regions with advanced digital ecosystems and complex technologies encounter lower rates of adoption of new digital technologies. This paradox highlights the complexities of navigating a highly developed digital environment and calls for a careful study of digital complexity's role in technology adoption. While I can suggest that when a region has more complex technologies this makes it harder for other firms to adopt them and requires higher capacities, this needs to be further investigated. This challenges the preconceived notions and underscores the potential for saturation effects and compatibility barriers, suggesting that increased digital complexity does not uniformly lead to higher digital technology adoption rates or enhanced productivity.Here I can conclude after further analysis that Hypothesis H2a is accepted, meaning that Digital complexity has a positive on productivity while H2b is not accepted,or partially accepted, as the expected positive effect of Digital complexity on web technology adoption is actually negative, leading to so the called complexity paradox.

In general, this analysis not only reaffirms the essential role of relatedness density in enhancing web technology adoption and facilitating the entry of related web technologies but also sheds light on the negative relationship between digital complexity and digital technology adoption.

The findings contribute to a deeper understanding of the factors influencing digital web technology adoption and regional development through the digitalization of smart specialization frameworks. It suggests a complex and context-dependent relationship between digital complexity, productivity, and technology adoption. This enlarges the academic discourse on path dependency and what factors inhibit digital technology adoption, and provides actionable insights for policymakers and practitioners. The dissertation one more time underscores the importance of fostering an ecosystem that nurtures innovation and leverages technological advancements for all types of firms and economic benefits, and not solely for competitive advantage.

In the next case for Hypothesis H3a, H3b, H3c where contextual factors, spatial proximity and agglomeration, have a positive effect on technology adoption. The hypothesis argues that being in an innovation-oriented context with spatial and agglomeration advantages facilitates the adoption of new web technologies.

Hypothesis 3 explores the impact of spatial proximity and agglomeration economies on web technology adoption. Technology adoption is the share of firms that adopt a specific web technology in a specific region. It states that being in a region with a developed environment and gaining from spatial and agglomeration advantages facilitates the adoption of new technologies. This enhances the understanding that clusters of interconnected firms, institutions, and industries create a dynamic entrepreneurial environment where knowledge spillover, collaboration, and innovation thrive. And when these environmental aspects are working, this accelerates the diffusion and adoption of new web technologies. Aside from that, the visible spatial autocorrelation effects as well indicate an interdependence between neighboring regions. This means that adopting a specific technology in one region will influence also the adoption in the neighboring regions. Furthermore, it was often observed in several cases a positive effect of industrial diversity (entropy) on the web technology adoption. The support for Hypothesis 3 highlights the crucial role of contextual factors in creating an ecosystem conducive to technological advancement and web technology adoption.

Moreover, the study shows how important geographical positioning is for the type of technologies to be adopted. The more integrative technologies such as the Javascript library will have smoother diffusion and will be adopted faster by firms. However, the specialized, isolated technologies (Live Chat technologies) will diffuse more slowly as they require higher adoption capacity, and it depends on the industrial specialization of the regions. So industrial specialization will eventually drive digital technologies that are adopted. Concluding that the place still matters for digital web technology adoption.

While for Hypothesis Hypothesis H4a, H4b, contextual factors and agglomeration effects respectively positively influence digital complexity. This suggests that the well developed entrepreneurial environment and concentration of related activities enhance a region's digital complexity.I expected a positive relationship because the regional digital complexity in itself represents an ecosystem with different actors and different fields of application.However, I reject Hypothesis 4 entirely as there was no evidence to show that local factors and human agglomeration does not influence the digital complexity of regions, or how complex a regions' web technologies are.This requires further investigation.

These hypotheses explain the complicated interplay between the place-based factors, the business environment and the dynamics of web technology adoption in EU regions. The findings suggest that the spatial factors and agglomeration characteristics of a region do not just support the development of digital complexity but also play a pivotal role in enabling web technology adoption. Therefore, refuting the idea of the death of space. This reinforces the idea that beyond the intrinsic characteristics of web technologies and the cognitive proximity between them, the spatial context and the density or geographical positioning of economic and industrial activities within a region are critical determinants of both digital complexity and the capacity for digital technological innovation and adoption.

Lastly, Hypothesis H5 expected a reciprocal positive relationship between digital technology adoption and GDP per capita. This implies that not only does technology adoption contribute to higher GDP per capita, but also that regions with higher GDP per capita are more capable of adopting new technologies.

As seen in the results, the effects of digital technology adoption on economic indicators, Hypothesis 5 investigates the complex interplay between digital technology adoption and economic growth. As seen in the results while testing Hypothesis 5 there is a reciprocal relation between technology adoption and GDP per capita, however not for all technologies. This indicates a symbiotic ecosystem dynamic where digital technological advancements contribute to economic prosperity, the relationship is significant and positive only for certain technologies

(Javascript library and Audience measurement) and negative for others. Therefore, I only partially accept the 5 hypothesis. In turn, economic prosperity creates a conducive environment for further web technology adoption for the majority of web technologies. This hypothesis is supported by empirical evidence demonstrating that regions with higher levels of economic prosperity in terms of GDP show a greater probability of adopting new technologies, such as Javascript libraries, likely due to better resources, skilled labor and the infrastructure available. This mutual influence highlights the critical role of economic conditions in shaping technology adoption patterns, highlighting that economic prosperity and technological advancements are mutually reinforcing.

Overall, Hypothesis 5 elucidates the mutual relationship between digital technology adoption and economic outcomes. It highlights the transformative power of technology in reshaping economic landscapes, driving productivity, and propelling regions towards higher levels of economic development. This discussion highlights the importance of fostering an ecosystem that encourages innovation and leverages technological adoption for economic benefit, moreover it emphasizes the bidirectional influence between technology and economic prosperity.

Finally, it is needed to integrate the insights from Hypotheses 3, 4 and 5 with the broader conceptual frameworks of entrepreneurial ecosystems and smart specialization. Here, I can extend the discussion to encapsulate how the study's findings can be integrated with the above-mentioned theoretical constructs. The dynamics of web technological innovation, adoption, and regional economic development observed in this dissertation are instrumental in understanding the entrepreneurial ecosystem and smart specialization strategy (S3).

Smart specialization recognizes the role of entrepreneurial discovery and the prioritization of innovation domains by specializing on the existent capabilities, advocating for a place-based, bottom-up approach to regional development. The findings of this study align with the S3 strategy relating to the positive impact of contextual factors on digital complexity and technology adoption (Hypotheses 2, 3 and 4). By fostering synergistic environments where entrepreneurs can leverage existing competencies and resources, regions can effectively absorb and capitalize through digital technology adoption on the opportunities presented by digital transformation. Smart specialization aims to reduce discrepancies between core and periphery regions by underlining the importance of place-specific innovation strategies that are ex-ante informed by existing local conditions and entrepreneurial activities. This can be achieved by undertaking a place-based view also on digital technology adoption.

Furthermore, the interaction between entrepreneurial ecosystems and smart specialization strategies highlights the necessity of a supportive framework for innovation and economic growth aided by digital technologies (Hypotheses 3, 4 and 5). The entrepreneurial ecosystem, with its focus on the interconnectedness of actors, resources, and institutions, provides a fertile ground for the implementation of smart specialization strategies aided by the adoption of digitally complex and related technologies. This ecosystem fosters the development of competencies and the aggregation of resources necessary for the exploration of new and related digital technological paths, as evidenced by the positive relationship between technology adoption and economic growth for specific technologies.

The study's findings highlight the importance of contextual place-based factors and the reciprocal relationship between technology adoption and GDP per capita. Moreover, the significant impact of technology adoption and density of related technologies on economic growth resonates with the core principles of smart specialization. By identifying and supporting areas of potential growth that are closely related to existing strengths, regions can achieve transformative and sustainable economic development as their new capabilities are related to their old ones. This approach not only leverages the inherent advantages of related technologies and digital complexity but also by digital technology adoption aligns with the entrepreneurial discovery processes where digital technology adoption is transformed into new business models and spin-offs, that are central to the entrepreneurial ecosystem and smart specialization framework.

In summary, this dissertation attempts to integrate entrepreneurial ecosystems and smart specialization strategies with Economic Geography aspects and digitalization. Within the study, I highlight the complex inter-dependencies between related and complex digital technologies, digital technology adoption, economic growth, and regional innovation policies. All these previously enumerated findings ask for a detailed understanding of regional development, where the synergies between digital technological advancements, economic and business conditions, and policy frameworks with a place-based focus are recognized and improved to foster sustainable growth and digital innovation across European regions.

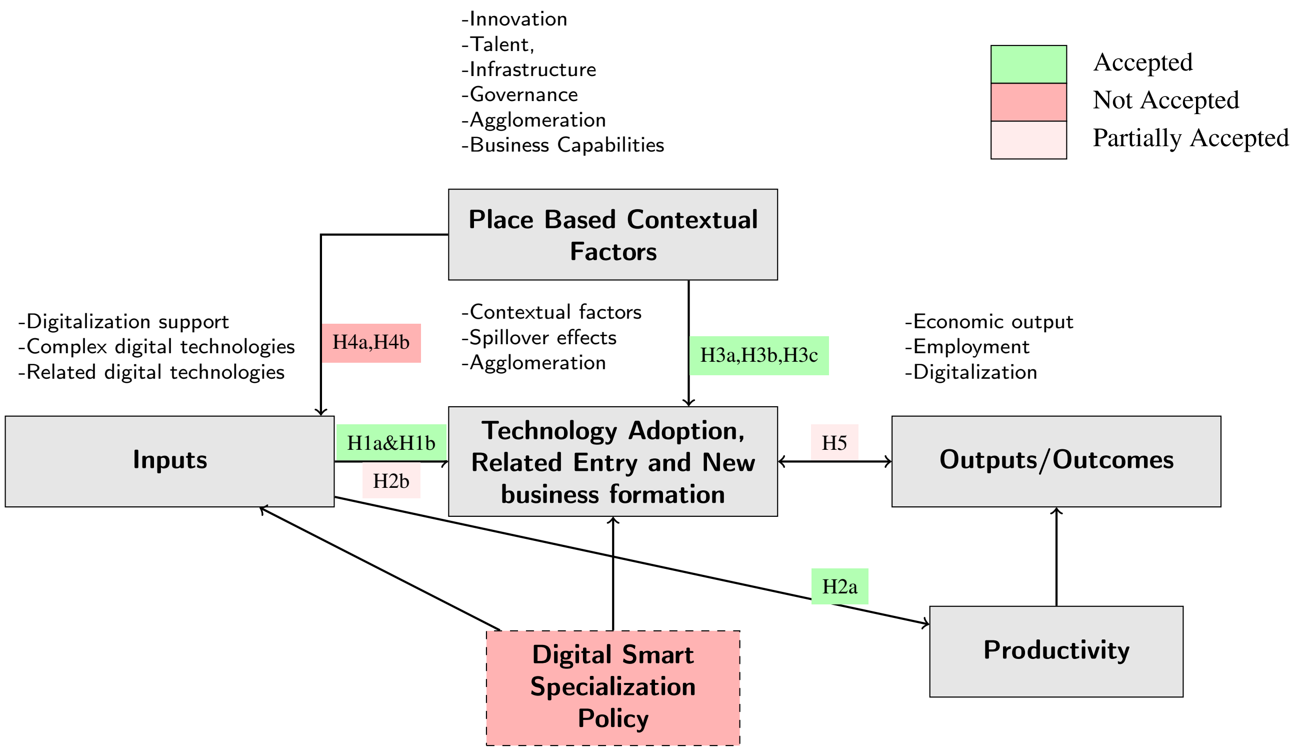

Figure 12: Results of the hypothesis testing

7.2 Implications for Policy and Practice

The strategic implications of this dissertation for policymakers and stakeholders are significant, particularly when digitalization is viewed through the lenses of space, geography, smart specialization (S3), and entrepreneurial ecosystems. The significance of relatedness density in enhancing digital technology adoption and digital complexity presents a compelling case for the development of interconnected technological ecosystems. These findings highlight the importance of using spatial and geographic advantages in regional development policies to foster environments that support the integration of new technologies. Policymakers are encouraged to recognize the spatial dimensions of digitalization and innovation, ensuring that regional policies capitalize on each region's unique geographic characteristics and existing digital technological capabilities or industrial orientation.

The concept of smart specialization can serve as a key framework for achieving the upper objectives. It advocates for policies that promote innovation and inclusive sustainable growth by focusing on the existent unique regional strengths, capabilities and competitive advantages. Smart Specialization can take a similar view on digitalization. As its approach aligns with the need to foster environments that leverage existing digital technological capabilities, diversity of industries and knowledge networks, enabling regions to effectively integrate new digital technologies and maintain their competitiveness in the digital era. Policymakers should embrace the principles of smart specialization to guide the strategic prioritization and development of regional entrepreneurial ecosystems, emphasizing the importance of entrepreneurial discovery and innovation-driven economic development in digitalization.

Moreover, the digital complexity paradox identified in this study highlights the challenges of digital technology saturation, the complexity of adoption and compatibility issues, necessitating a balanced approach to digital advancement. By following the smart specialization strategy, policymakers should focus on optimizing existing technological infrastructures while carefully integrating new digital innovations. This requires considering attention to understanding digital complexity's role in technology adoption, emphasizing the need for policies that support sustainable technological advancement and economic growth within the context of each region's unique spatial and geographic characteristics.

By integrating the concepts of smart specialization, entrepreneurial ecosystems and digital technology adoption into regional development strategies, policymakers can create a supportive environment for innovation and further technology adoption or new business models. This environment will encourage collaboration among stakeholders, leverage the region's unique spatial and geographic advantages, and focus on building and strengthening the interconnected digital-physical technological ecosystems that are crucial for the digital era. Thus, crafting policies that reflect an understanding of the spatial dynamics of innovation, the principles of smart specialization, and the importance of entrepreneurial ecosystems becomes essential for fostering technology adoption, digitalization and overall regional economic growth.

7.3 Limitations and Directions for future research

This dissertation can serve as the cornerstone for numerous directions of future research. A limitation of this thesis is in the sample of firms used for analysis. While Crunchbase is an exciting database, its focus on highly technological-high growth firms might exclude a relevant number of firms that were overlooked by the Crunchbase algorithms. Another aspect that requires attention is that this work used Digital Complexity as a proxy for digitalization of regions. While complexity is a good measurement of the novel knowledge and capability, it might exclude those regions that do not have high-growth businesses or those that lack complex technologies. Applying fixed effects in the panel model often changed the sign of the result parameter, this indicated data limitations or limitations of the empirical strategy. One critical area that requires attention involves understanding the mechanisms through which regional digital complexity might negatively impact technology adoption but also productivity. Moreover, future studies should explore the effects of market saturation of digital technology, compatibility issues, and the incremental costs associated with the adoption of new digital web technologies, especially in regions with advanced digital ecosystems. In this study I focused more on the impact of related technologies and, therefore on incremental innovations, a deeper focus on unrelated web technologies is required. Additionally, there is a need for comparative studies across different geographic contexts to unravel the spatial dynamics of technology adoption and digital complexity. While this empirical study attempted to examine the place-specific factors, more attention should be paid to digital infrastructure and digital adoption capacities, as few digitalization controls were considered. Such research could elucidate our understanding of how different regions navigate the challenges and opportunities of digital transformation. To diminish the gap between developed and underdeveloped regions in their capacity to digitalize, policy interventions are necessary, and this dissertation offers valuable insights for both policymakers and practitioners, but more specific case studies are needed. Finally, there's a need for a more robust framework for testing the relationship between web technology adoption and economic growth. A reverse causality analysis and possible application of a simultaneous equation model such as Three Stage Least Squares Methodology (3SLS) was not possible due to the data limitations and the scale of this study.

7.4 Conclusion

This dissertation has shed light on the relationships between relatedness density, digital complexity, and web technology adoption across European regions. By exploring these dynamic interactions, the study contributes to a deeper understanding of the factors that drive digital technological evolution and regional development. The findings underscore the importance of fostering interconnected innovation and entrepreneurial ecosystems and adopting a direct and clear approach to digital complexity. As we move forward with the digitalization, it is imperative that policymakers and stakeholders heed these insights, leveraging them to foster environments that support innovation, economic growth, and technological advancement. This study designed a framework and identified specific factors influencing digital technology adoption. Future research in this domain holds the potential to further refine our understanding of these complex dynamics, offering guidance for navigating the challenges of the digital era.

This comprehensive exploration not only advances the academic discourse on digital transformation but also provides actionable recommendations for policymakers and practitioners aiming to harness the benefits of digital technological advancements for regional development.

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Appendix A The comprehensive list of Digital Web Technologies used under analysis

Table 14: The comprehensive list of Digital Web Technologies under analysis

No.	Tech Group	Tech Category	No.	Tech Group	Tech Category
1	Ads	AD Analytics	51	CDN	CDN
2	Ads	AD Blocking	52	CDNS	CDN
3	Ads	AD Exchange	53	CDNS	CDNS
4	Ads	AD Network	54	CDNS	Edge Delivery Network
5	Ads	AD Server	55	CMS	Agency
6	Ads	ADS TXT	56	CMS	Automotive
7	Ads	ADS	57	CMS	Blog
8	Ads	Adult	58	CMS	CMS
9	Ads	Affiliate Programs	59	CMS	Community CMS
10	Ads	Audience Targeting	60	CMS	Ecommerce Enabled
11	Ads	Bitcoin	61	CMS	Enterprise
12	Ads	Content Curation	62	CMS	Financial

Continued on next page

Table 14 – continued from previous page

No.	Tech Group	Tech Category	No.	Tech Group	Tech Category
13	Ads	Contextual Advertising	63	CMS	Forum Software
14	Ads	Data Management Platform	64	CMS	Headless
15	Ads	Demand Side Platform	65	CMS	Healthcare
16	Ads	Digital Video ADS	66	CMS	Hosted Solution
17	Ads	Dynamic Creative Optimization	67	CMS	Job Board
18	Ads	Fraud Prevention	68	CMS	Landing Page
19	Ads	Header Bidding	69	CMS	Learning Management System
20	Ads	Local ADS	70	CMS	Mobile
21	Ads	Mobile	71	CMS	Non-Profit
22	Ads	Multi-Channel	72	CMS	Open Source
23	Ads	Retargeting Remarketing	73	CMS	Real State
24	Ads	Search	74	CMS	Simple Website Builder
25	Analytics	AB Testing	75	CMS	Social Management
26	Analytics	Advertiser Tracking	76	CMS	Ticketing System
27	Analytics	Analytics	77	CMS	WIKI
28	Analytics	Application Performance	78	CMS	WIX App
29	Analytics	Audience Measurement	79	Copyright	Copyright
30	Analytics	Call Tracking	80	Encoding	Encoding
31	Analytics	Cart Abandonment	81	Feeds	Feeds
32	Analytics	Conversion Optimization	82	Framework	Framework
33	Analytics	Conversion Tracking	83	Framework	Magento Theme Framework
34	Analytics	CRM	84	Framework	Mobile
35	Analytics	Customer Data Platform	85	Framework	Schema
36	Analytics	Data Management Platform	86	Framework	WordPress Theme

Continued on next page

Table 14 – continued from previous page

No.	Tech Group	Tech Category	No.	Tech Group	Tech Category
37	Analytics	Error Tracking	87	Hosting	Australian Hosting
38	Analytics	Feedback Forms and Surveys	88	Hosting	Canadian Hosting
39	Analytics	Fraud Prevention	89	Hosting	Chinese Hosting
40	Analytics	Lead Generation	90	Hosting	Cloud Hosting
41	Analytics	Marketing Automation	91	Hosting	Cloud PaaS
42	Analytics	Mobile	92	Hosting	Czech Hosting
43	Analytics	Personalization	93	Hosting	Dedicated Hosting
44	Analytics	Product Recommendations	94	Hosting	Dutch Hosting
45	Analytics	Real State	95	Hosting	Ecommerce Hosting
46	Analytics	Retargeting Remarketing	96	Hosting	French Hosting
47	Analytics	Site Optimization	97	Hosting	German Hosting
48	Analytics	Social Management	98	Hosting	Hong-Kong Hosting
49	Analytics	Tag Management	99	Hosting	Hosting
50	Analytics	Visitor Count Tracking	100	Hosting	Italian Hosting
101	Hosting	Japan Hosting	155	Payment	Payments Processor
102	Hosting	Polish Hosting	156	Payment	Payment
103	Hosting	Romanian Hosting	157	Registrar	Registrar
104	Hosting	Russian Hosting	158	Robots	Robots
105	Hosting	Shared Hosting	159	Server	Server
106	Hosting	Spanish Hosting	160	Shipping	Shipping
107	Hosting	Swedish Hosting	161	Shop	Agency
108	Hosting	Swiss Hosting	162	Shop	Automotive
109	Hosting	Turkish Hosting	163	Shop	Enterprise
110	Hosting	UK Hosting	164	Shop	Hosted Solution
111	Hosting	US Hosting	165	Shop	Multi-Channel
112	Hosting	VPS Hosting	166	Shop	Non Platform
113	Hosting	WordPress Hosting	167	Shop	Open Source

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Table 14 – continued from previous page

No.	Tech Group	Tech Category	No.	Tech Group	Tech Category
114	JavaScript	Animation	168	Shop	Plugin Module
115	JavaScript	Charting	169	Shop	Shipping Provider
116	JavaScript	Compatibility	170	Shop	Shop
117	JavaScript	Framework	171	Shop	Shopify App
118	JavaScript	JavaScript Library	172	Shop	Shopify Theme
119	JavaScript	JavaScript	173	Shop	SMB Solution
120	JavaScript	jQuery Plugin	174	Shop	WooCommerce Extension
121	JavaScript	Slider	175	Shop	WordPress Plugins
122	JavaScript	UI	176	SSL	Extended Validation
123	Language	Language	177	SSL	Root Authority
124	Link	Adult	178	SSL	SSL
125	Link	Link	179	SSL	Wildcard
126	Mapping	Mapping	180	Web Master	Web Master
127	Mapping	Maps	181	Web Server	Web Server
128	Media	Digital Video ADS	182	Web Server	Varnish Server
129	Media	Enterprise	183	Widgets	Bookings
130	Media	Live Stream Webcast	184	Widgets	Bookmarking
131	Media	Media	185	Widgets	Call Tracking
132	Media	Online Video Platform	186	Widgets	Captcha
133	Media	Social Video Platform	187	Widgets	Charting
134	Media	Video Analytics	188	Widgets	Cobrowsing
135	Media	Video Players	189	Widgets	Comment System
136	Mobile	Mobile	190	Widgets	Content Modification
137	MX	Business Email Hosting	191	Widgets	Customer Data Platform
138	MX	Campaign Management	192	Widgets	Ecommerce
139	MX	DMARC	193	Widgets	Error Tracking
140	MX	Marketing Platform	194	Widgets	Feedback Forms and Surveys

Continued on next page

Table 14 – continued from previous page

No.	Tech Group	Tech Category	No.	Tech Group	Tech Category
141	MX	MX	195	Widgets	Financial
142	MX	Secure Email	196	Widgets	Fonts
143	MX	Transactional Email	197	Widgets	Image Provider
144	MX	Web Hosting Provider Email	198	Widgets	Joomla Module
145	NS	Enterprise DNS	199	Widgets	Live Chat
146	NS	NS	200	Widgets	Login
147	NS	TLD Redirects	201	Widgets	Marketing Automation
148	Parked	Parked	202	Widgets	Mobile
149	Payment	Bitcoin	203	Widgets	Privacy Compliance
150	Payment	Checkout Buttons	204	Widgets	Push Notifications
151	Payment	Currency	205	Widgets	Schedule Management
152	Payment	Donation	206	Widgets	Site Search
153	Payment	Pay Later	207	Widgets	Social Sharing
154	Payment	Payment Acceptance	208	Widgets	SSL Seals
209	Widgets	Tag Management	214	Widgets	Web Badge
210	Widgets	Ticketing System	215	Widgets	Widgets
211	Widgets	Tour Site Demo	216	Widgets	WIX App
212	Widgets	Translation	217	Widgets	WordPress Hosting
213	Widgets	VAT Registration	218	Widgets	WordPress Plugins

Appendix B Supplementary figures

Appendix C Additional factors influencing technology adoption, tables, and robustness checks

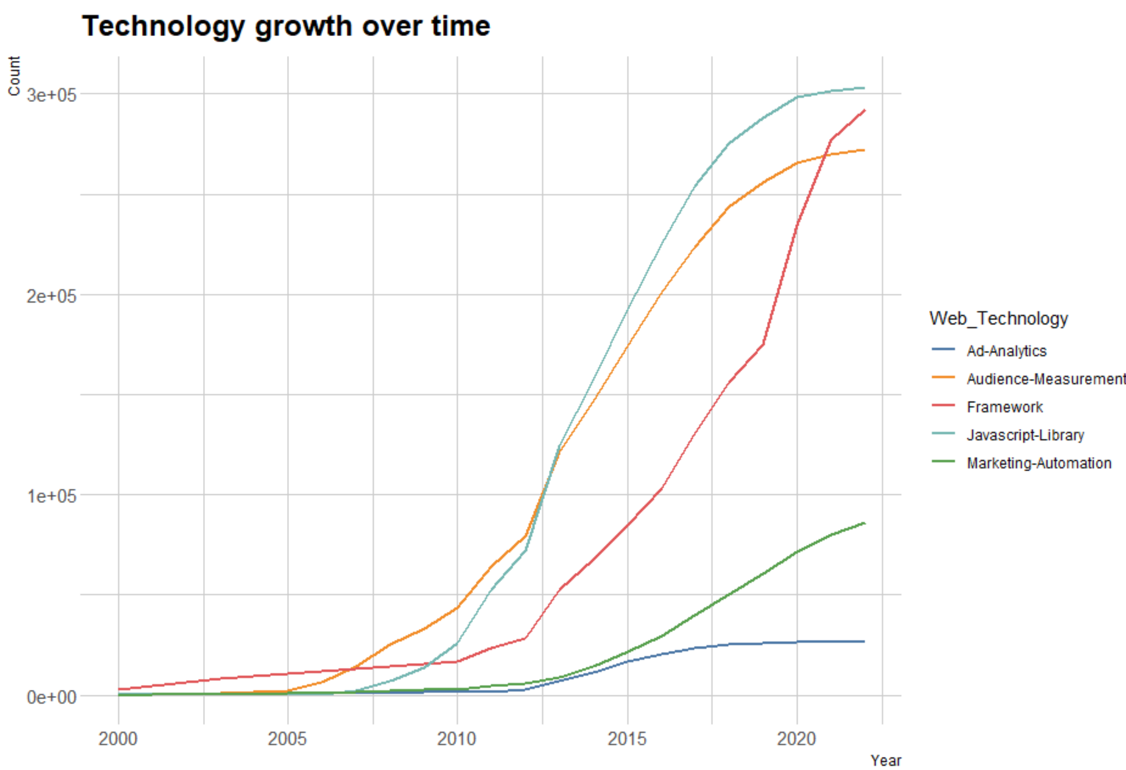

Figure 13: Evolution of web based technologies. Source: Authors' own elaboration.

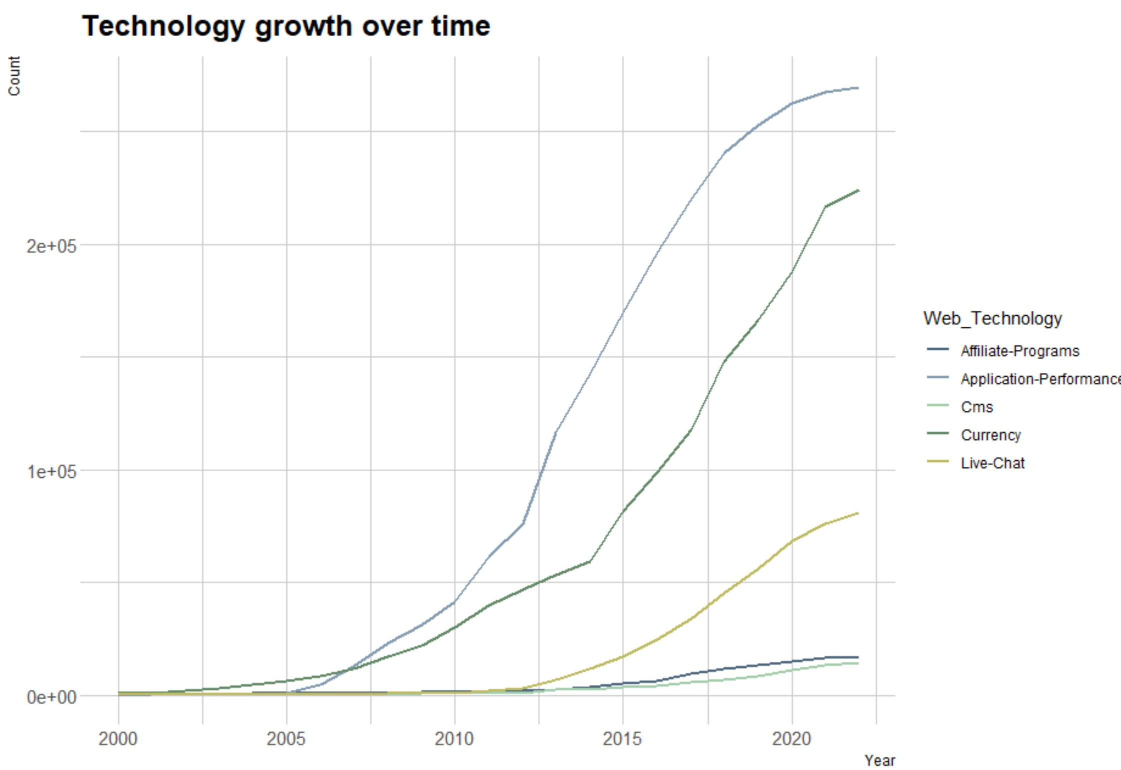

Figure 14: Evolution of other 5 web based technologies. Source: Authors' own elaboration.

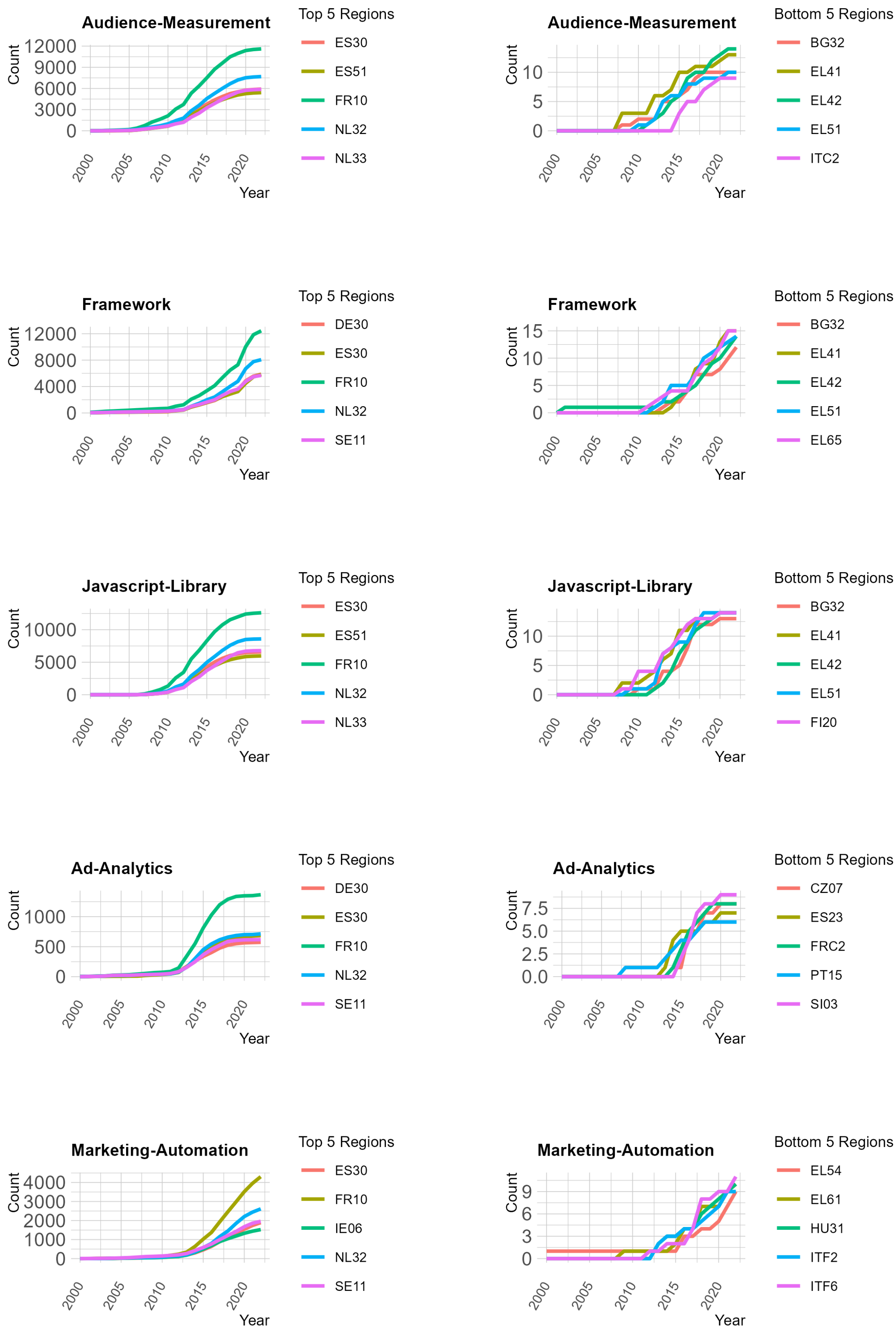

Figure 15: Top and bottom regions owning a specific technology in Europe(Excluding UK). Source: Authors' own elaboration.

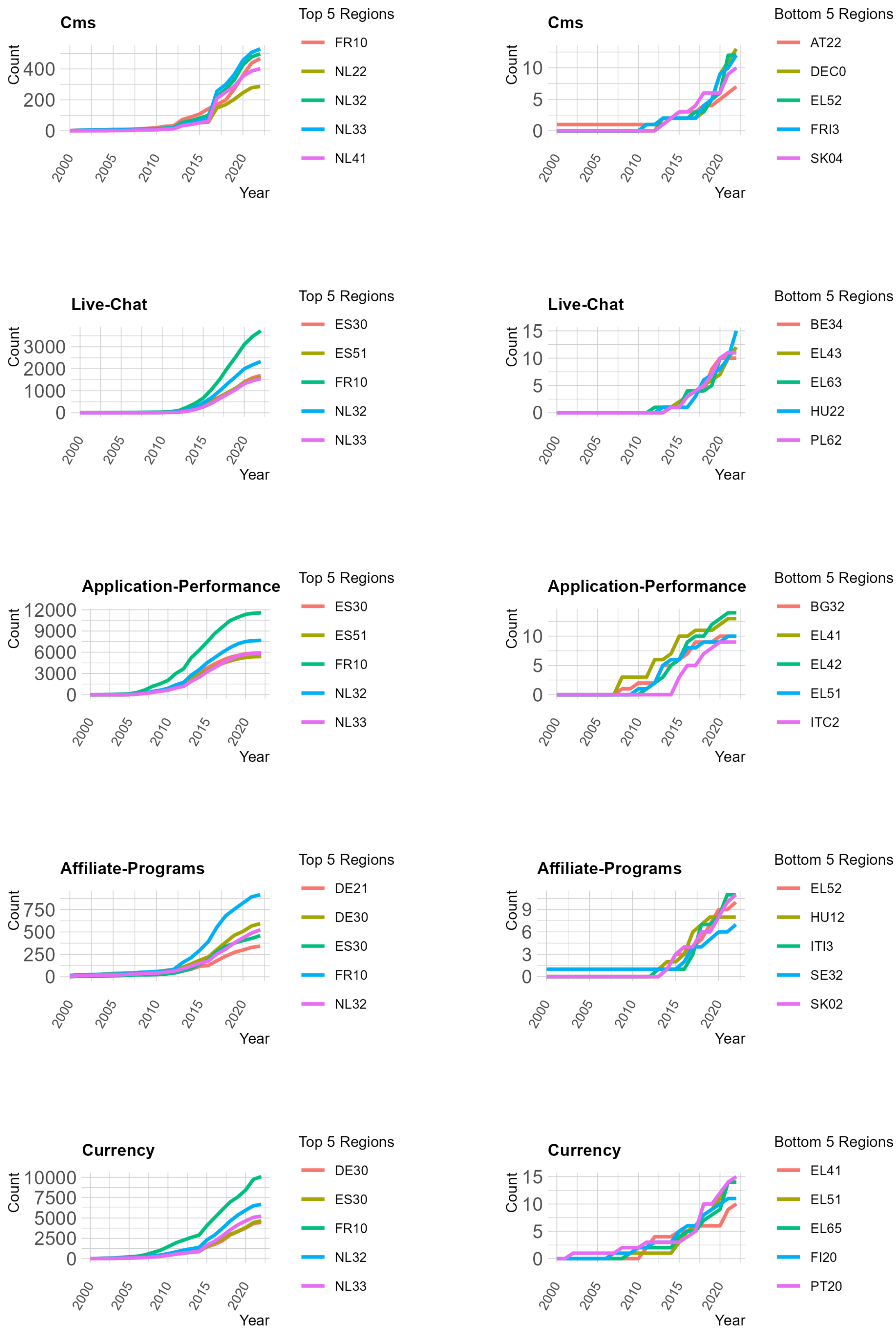

Figure 16: Top and bottom regions owning a specific technology in Europe (Excluding UK). Source: Authors' own elaboration.

Table 15: Technology Adoption effects on Gross Domestic Product (Two-way Fixed effects model

	Dependent variable:									
	Δlog(GDP/cap)									
	Ad analytics	Javascript library	Affiliate programs	Marketing automation	Audience measurement	Application performance	Live chat	CMS	Currency	Framework
Technology Adoption	0.173**	−0.073***	0.264***	-0.019	-0.036	−0.054**	0.285***	-0.005	−0.112***	0.061**
	(0.071)	(0.024)	(0.073)	(0.035)	(0.022)	(0.022)	(0.047)	(0.130)	(0.018)	(0.024)
log((Population Density)	-0.004	-0.004	0.0004	-0.003	0.001	0.003	0.0001	0.002	0.003	0.003
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Number of firms	0.0004***	0.0001***	0.0001	0.0001	0.0001***	0.0001***	-0.00004	0.0001	0.00002	0.00003
	(0.0001)	(0.00003)	(0.0002)	(0.0001)	(0.00003)	(0.00003)	(0.0001)	(0.0002)	(0.00003)	(0.00002)
Business Sophistication	−0.317***	−0.304***	−0.309***	−0.298***	−0.305***	−0.302***	−0.265***	−0.290***	−0.267***	−0.293***
	(0.019)	(0.020)	(0.019)	(0.019)	(0.020)	(0.020)	(0.020)	(0.019)	(0.020)	(0.019)
Existent Technologies	-0.0001	0.0004	0.0001	0.0003*	0.00004	0.0003	-0.0003	-0.0001	0.001**	−0.001*
	(0.0001)	(0.0004)	(0.0001)	(0.0001)	(0.0004)	(0.0004)	(0.0002)	(0.0002)	(0.0002)	(0.0003)
Tech. Readiness	0.002	-0.033	0.003	0.002	-0.031	-0.029	-0.024	-0.006	-0.031	−0.042*
	(0.026)	(0.025)	(0.027)	(0.027)	(0.025)	(0.025)	(0.025)	(0.027)	(0.025)	(0.025)
log(Patent Applications)	0.00002***	0.00001	0.00002***	0.00002***	0.00001**	0.00001**	0.00002***	0.00002***	0.00002***	0.00002***
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Quality of Infrastructure	−0.101***	−0.114***	−0.119***	−0.124***	−0.120***	−0.122***	−0.143***	−0.111***	−0.135***	−0.134***
	(0.020)	(0.021)	(0.020)	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	(0.021)	(0.021)
Quality of Governance	-0.013	0.043	0.025	0.045	0.045	0.044	0.063*	0.037	0.048	0.049
	(0.032)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.035)	(0.034)	(0.034)	(0.034)
log(Total Employment)	0.637***	0.545***	0.636***	0.564***	0.555***	0.552***	0.526***	0.594***	0.549***	0.537***
	(0.042)	(0.045)	(0.044)	(0.045)	(0.045)	(0.045)	(0.045)	(0.044)	(0.044)	(0.045)
Talent	−0.006***	−0.006***	−0.007***	−0.006***	−0.006***	−0.006***	−0.007***	−0.006***	−0.006***	−0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	2,013	2,090	2,024	2,068	2,090	2,090	2,079	1,980	2,090	2,090
R^2	0.249	0.215	0.243	0.211	0.211	0.212	0.222	0.223	0.224	0.210
Adjusted R^2	0.165	0.128	0.158	0.123	0.122	0.124	0.134	0.136	0.137	0.122
	54.523***	46.899***	52.967***	45.188***	45.566***	45.967***	48.353***	46.393***	49.241***	45.454***
F Statistic	(df = 11; 1809)	(df = 11 1879)	(df = 11 1819)	(df = 11 1859)	(df = 11 1879)	(df = 11 1879)	(df = 11 1869)	(df = 11 1779)	($df = 11$ 1879)	(df = 11 1879)

Notes: All models are panel linear models estimated using the 'plm' package in R with a 'first-difference' (fd) model specification and individual effects. The dependent variable is 'log(GdpCap)'. Each model uses a unique dataset corresponding to a specific a specific web technology. Standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 16: Factors influencing Technology Adoption and Industrial Structure(Individual effects)

	Dependent variable:Technology Adoption(TA)									
	Ad Analytics	Java script	Affiliate Programs	Marketing Automation	Audience Measurement	Application Performance	Live Chat	CMS	Currency	Framework
Digital Complexity	-0.0001^{***}	-0.003^{***}	-0.0002^{***}	0.00001	-0.001^{***}	-0.001^{***}	-0.001^{***}	-0.0002^{***}	-0.002^{***}	-0.002^{***}
	(0.00005)	(0.0002)	(0.00004)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.00002)	(0.0002)	(0.0002)
log(RD)	0.020^{***}	0.284^{***}	-0.002	0.027^{***}	0.086^{***}	0.085^{***}	0.051^{***}	0.007^{***}	-0.045^{***}	0.107^{***}
	(0.003)	(0.009)	(0.003)	(0.005)	(0.007)	(0.008)	(0.005)	(0.001)	(0.013)	(0.011)
log(Population Density)	0.001	-0.004	0.001	-0.002	-0.004	-0.003	-0.004^{**}	-0.001	-0.011^{**}	-0.003
	(0.001)	(0.003)	(0.001)	(0.002)	(0.003)	(0.003)	(0.002)	(0.0005)	(0.005)	(0.004)
Patent Applications	-0.00001	-0.00001^{*}	-0.00001^{***}	-0.00002^{***}	-0.00001^{***}	-0.00002^{***}	-0.00002^{***}	-0.00001^{***}	-0.0001^{***}	-0.0001^{***}
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Industrial Diversity(entropy)	0.049	0.156	0.056	0.537^{***}	0.573^{***}	0.678^{***}	0.824^{***}	0.020	1.879^{***}	1.159^{***}
	(0.044)	(0.152)	(0.042)	(0.086)	(0.120)	(0.125)	(0.076)	(0.024)	(0.208)	(0.182)
Industrial specialization(HHI)	0.050	0.196	-0.008	0.459^{***}	0.093	0.174	0.266^{***}	-0.016	0.732^{***}	0.261
	(0.045)	(0.154)	(0.042)	(0.087)	(0.122)	(0.127)	(0.077)	(0.023)	(0.211)	(0.184)
Share ICT employment	-0.254^{*}	1.088^{**}	0.209^{*}	1.314^{***}	1.231^{***}	1.355^{***}	1.458^{***}	0.023	0.727	4.211^{***}
	(0.132)	(0.463)	(0.123)	(0.262)	(0.368)	(0.383)	(0.232)	(0.066)	(0.635)	(0.553)
Business Sophistication	0.040^{***}	0.536^{***}	-0.009^{*}	0.017	0.141^{***}	0.172^{***}	0.006	0.012^{***}	-0.105^{***}	0.124^{***}
	(0.006)	(0.020)	(0.005)	(0.011)	(0.016)	(0.016)	(0.010)	(0.003)	(0.027)	(0.023)
Talent	0.003^{***}	0.008^{***}	0.002^{***}	0.010^{***}	0.002^{***}	0.004^{***}	0.008^{***}	0.001^{***}	0.010^{***}	0.019^{***}
	(0.0002)	(0.001)	(0.0002)	(0.0005)	(0.001)	(0.001)	(0.0004)	(0.0001)	(0.001)	(0.001)
Quality of Governance	-0.007	-0.139^{***}	0.018	0.140^{***}	0.014	0.049	0.119^{***}	0.052^{***}	0.540^{***}	0.418^{***}
	(0.012)	(0.040)	(0.011)	(0.023)	(0.032)	(0.033)	(0.020)	(0.006)	(0.055)	(0.048)
Quality of Infrastructure	0.035^{***}	0.054^{**}	0.027^{***}	0.142^{***}	0.051^{***}	0.053^{***}	0.119^{***}	0.011^{***}	0.132^{***}	0.253^{***}
	(0.007)	(0.025)	(0.007)	(0.014)	(0.020)	(0.020)	(0.012)	(0.003)	(0.034)	(0.029)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	No	No	No	No	No	No	No	No	No
Observations	1,923	1,976	1,923	1,965	1,976	1,976	1,976	1,890	1,976	1,976
R^2	0.509	0.868	0.177	0.610	0.524	0.563	0.723	0.349	0.295	0.713
Adjusted R^2	0.456	0.854	0.088	0.568	0.472	0.516	0.693	0.279	0.219	0.683
F Statistic	163.324^{***} (df = 11; 1735)	$1,070.446^{***}$ (df = 11; 1783)	33.860^{***} (df = 11; 1735)	252.537^{***} (df = 11; 1773)	178.188^{***} (df = 11; 1783)	209.207^{***} (df = 11; 1783)	423.040^{***} (df = 11; 1783)	83.109^{***} (df = 11; 1705)	67.853^{***} (df = 11; 1783)	403.602^{***} (df = 11; 1783)

Notes: All models are panel linear models estimated using the 'plm' package in R with a 'within' (fixed effects) model specification and individual effects. The dependent variable is 'Dependent_Share'. Each model uses a unique dataset corresponding to specific technology: Ad Analytics, Javascript, Affiliate Programs, Marketing Automation, Audience Measurement, Application Performance, Live Chat, CMS, Currency, and Framework. Regional fixed effects are included in all models, while time fixed effects are not considered. Standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 17: Factors influencing Technology Adoption and Industrial Structure (Fixed effects)

	Dependent variable: Technology Adoption (TA)									
	Ad Analytics	Java script	Affiliate Programs	Marketing Automation	Audience Measurement	Application Performance	Live Chat	CMS	Currency	Framework
Digital Complexity	0.0003^{***}	-0.0003^{**}	0.0001^{*}	0.001^{***}	0.0001	0.0004^{***}	0.001^{***}	-0.0001^{***}	-0.0003	0.001^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.00003)	(0.0002)	(0.0001)
log(Relatedness Density)	-0.015^{***}	0.066^{***}	-0.019^{***}	-0.039^{***}	0.042^{***}	0.023^{**}	-0.014^{***}	0.003	-0.006	-0.059^{***}
	(0.004)	(0.009)	(0.004)	(0.006)	(0.009)	(0.009)	(0.005)	(0.002)	(0.012)	(0.008)
log(Population Density)	0.001	-0.002	0.001	-0.002	-0.003	-0.003	-0.004^{***}	-0.001^{*}	-0.007^{**}	-0.004
	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)	(0.001)	(0.0004)	(0.003)	(0.002)
Patent Applications	-0.00001	-0.00001	-0.00001	0.00001	-0.00001	-0.00001^{*}	-0.00001	0.00001	-0.00002^{***}	-0.00001
	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Industrial diversity(entropy)	0.058	0.298^{**}	-0.081^{*}	0.026	0.463^{***}	0.528^{***}	0.372^{***}	-0.101^{***}	0.133	-0.208^{*}
	(0.044)	(0.118)	(0.044)	(0.078)	(0.121)	(0.126)	(0.063)	(0.023)	(0.167)	(0.114)
Industrial specialization(HHI)	0.041	0.178	-0.033	0.332^{***}	0.039	0.095	0.134^{**}	-0.036^{*}	0.343^{**}	-0.058
	(0.041)	(0.109)	(0.041)	(0.072)	(0.111)	(0.116)	(0.058)	(0.021)	(0.154)	(0.105)
Share ICT employment	-0.309^{**}	-0.294	-0.007	0.142	0.322	0.317	0.293	-0.170^{***}	-1.916^{***}	0.623^{*}
	(0.122)	(0.335)	(0.121)	(0.220)	(0.343)	(0.356)	(0.179)	(0.061)	(0.473)	(0.323)
Business Sophistication	0.008	0.086^{***}	-0.006	-0.018	0.109^{***}	0.131^{***}	-0.027^{**}	0.010^{***}	0.284^{***}	-0.038^{**}
	(0.007)	(0.020)	(0.007)	(0.013)	(0.020)	(0.021)	(0.011)	(0.004)	(0.028)	(0.019)
Talent	0.001^{***}	-0.001	0.0004	0.003^{***}	-0.001	-0.001	0.002^{***}	0.0002	0.001	0.002^{***}
	(0.0002)	(0.001)	(0.0002)	(0.0004)	(0.001)	(0.001)	(0.0004)	(0.0001)	(0.001)	(0.001)
Quality of governance	-0.021^{*}	0.002	-0.035^{***}	-0.034	-0.038	-0.029	-0.048^{***}	0.016^{***}	-0.143^{***}	-0.013
	(0.012)	(0.032)	(0.012)	(0.021)	(0.033)	(0.034)	(0.017)	(0.006)	(0.045)	(0.031)
Quality of infrastructure	0.026^{***}	0.021	0.008	0.070^{***}	0.023	0.014	0.045^{***}	-0.003	-0.051^{**}	0.033^{*}
	(0.006)	(0.018)	(0.006)	(0.012)	(0.018)	(0.019)	(0.010)	(0.003)	(0.025)	(0.017)
Region FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,923	1,976	1,923	1,965	1,976	1,976	1,976	1,890	1,976	1,976
R^2	0.052	0.062	0.033	0.198	0.065	0.061	0.162	0.062	0.097	0.067
Adjusted R^2	-0.057	-0.045	-0.077	0.106	-0.042	-0.046	0.067	-0.046	-0.005	-0.040
F Statistic	8.521^{***} (df = 11; 1725)	10.593^{***} (df = 11; 1773)	5.397^{***} (df = 11; 1725)	39.541^{***} (df = 11; 1763)	11.173^{***} (df = 11; 1773)	10.537^{***} (df = 11; 1773)	31.173^{***} (df = 11; 1773)	10.152^{***} (df = 11; 1695)	17.398^{***} (df = 11; 1773)	11.534^{***} (df = 11; 1773)

Notes: All models are panel linear models estimated using the 'plm' package in R with a 'within' (fixed effects) model specification. The dependent variable is 'Technology Adoption Share'. Each model uses a unique dataset corresponding to a specific technology: Ad Analytics, JavaScript, Affiliate Programs, Marketing Automation, Audience Measurement, Application Performance, Live Chat, CMS, Currency, and Framework. Regional fixed effects are included in all models, while time-fixed effects are also considered. Standard errors are shown in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

Table 18: Logistic Regression Models Summary

	Dependent Variable: Entry $(=1)$			
	(1) Baseline	(2) Controls	(3) Full Model	(4) Full Model Fixed Effects
Constant	-6.692^{***} (0.0497)	-8.535^{***} (0.1624)	-5.898^{***} (0.1633)	-27.761 (28.517)
log(RD)	1.344^{***} (0.0150)		1.434^{***} (0.0167)	1.431^{***} (0.0410)
log (GDP/cap)		0.602^{***} (0.0170)	-0.061^{***} (0.0181)	0.176^{*} (0.0951)
log (Population density)		0.057^{***} (0.0054)	-0.075^{***} (0.0057)	1.069^{***} (0.2965)
lnpatents		-0.083^{***} (0.0054)	-0.018^{**} (0.0056)	-0.060^{*} (0.0289)
Observations	343,350	343,350	343,350	343,116
Pseudo R-squared	0.0595	0.0088	0.0613	0.0938
AIC	174,709	184,138	174,387	168,796

Notes: Standard errors in parentheses. Coefficient values are statistically significant at the $^{*}p < 0.10$, $^{**}p < 0.05$, and $^{***}p < 0.01$ levels. The pseudo R-squared values represent the McFadden's pseudo R-squared metric for each model.