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Digital Skills and Inter-Regional Income Disparity in Europe: An Empirical Analysis

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Abstract

While the economic effects of digitalization are a widely investigated topic, less attention has been paid to whether individuals' digital skills development can shorten regional income inequalities within nations. This study contributes to the literature by conducting a panel data empirical experiment, collecting records for 259 NUTS-2-level regions. Statistical regressions were applied using respectively the individual level of digital expertise and the percentage distance of regions' average disposable income relative to the national value as independent and dependent variables. The analyses included control variables, clustering of regions according to their level of productivity and distinct pre- and post-COVID periods evaluation. Results show that after the COVID-19 pandemic, digital skills significantly reduce the percentage gap between regional and national disposable income, both in the poorest and richest European regions. In contrast, regions with average development levels present the opposite trend, with digital skills negatively affecting the disposable income disparity, especially after the pandemic. Supplementary analyses using the GDP per capita gap as a dependent variable suggest that the relationship between digital skills and a region's average purchasing power might be more pronounced than with its overall productivity.

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Chapter 1

Introduction

1.1 The Digital Transformation and its Disruption

Digitalization has profoundly reshaped modern society, redefining how people work, communicate, and interact. The widespread adoption of digital services is driven by the clear advantages they offer, from optimizing operations to enabling new business opportunities. As a result, understanding the economic impact of Digitalization on business practices and daily routines has become a crucial area of recent researches.

The complexity of this mechanism is highlighted by Vial's (2019) [1] study, which analyzed 282 scientific works to offer a thorough conceptual overview of digital transformation. Vial's inductive framework posits that digitalization is a process where continuous technological innovations drive profound changes in an organization's structures, culture, and core operations. The paper describes how digital technologies create disruptions that consequently trigger strategic responses from organizations seeking to leverage this change to improve their value creation paths.

This dynamic begins with digital technologies acting as inherently disruptive forces that alter the operating environment for businesses. First, they allow customers to easily access communication and information (often via mobile devices), modifying their behavior and expectations. Consequently, markets observe that consumers become active participants in the dialogue rather than passive receivers of firms' decisions. In this context, companies need to anticipate rather than react to changes in customer expectations. Second, these technologies disrupt the competitive landscape by altering the demand for existing services and products to generate new digital offerings. This shift lowers barriers to entry and ultimately damages incumbent players' competitive advantage. Third, digital tools boost the availability of data, enabling firms to exploit digital traces generated by consumers to offer better services and generate a competitive advantage. In response to these pervasive disruptions, organizations develop strategic responses, which the literature divides into the Digital Business Strategy (DBS) and the Digital Transformation Strategy (DTS). DBS formulates and implements organizational strategy by leveraging digital resources, while DTS governs the transition to the integration of these technologies into products, processes, and organizational functions.

The need for strategic change in the face of this transformative shift has been a persistent concern for firms in recent years, as a study by Fitzgerald et al. (2014) [2] testifies. This research involved a global survey that gathered responses from 1,559 executives and managers. The research highlighted that 78% of respondents considered achieving digital transformation as a critical objective within the next two years. However, the report also revealed managers' frustration with the difficulty of obtaining significant results from the deployment of new technology, with 'lack of urgency' cited as the most frequent obstacle to this transformation. The inertia was primarily attributed to senior leadership's failure to propose a clear vision and roadmap, which, combined with their potential skepticism, resulted in organizational inertia.

1.2 The Shift to Skills-Based Economic Resilience

This historical strategic challenge became even more evident during the exogenous shock of the COVID-19 pandemic, when organizations were forced to adopt necessary strategic changes much faster than under normal circumstances. The exceptional government restrictions obliged companies to increase offers to work at home, accelerating the digital transformation of labor. A study by Nagel (2020) [3] investigates this acceleration through a survey conducted from March to April 2020 on the Amazon Mechanical Turk crowd-sourcing platform. The findings showed a significant increase in individuals working from home and revealed that those who believed the pandemic accelerated digital transformation (DT) are more likely to expect to work exclusively digitally in the future. Furthermore, digital work was perceived as a more secure source of income during the crisis compared to traditional employment.

The trends highlighted by the immediate response to the COVID-19 shock accelerated the need for all workers to acquire new digital competencies. A study by the OECD (*Skills for a Digital World* [4]) categorized these increasingly demanded capabilities as: ICT specialist skills (for developing applications and managing networks), ICT generic skills (for using technology for professional purposes), and

ICT complementary skills (such as information-processing, problem-solving, and communication). Since digital technologies tend to replace workers in performing routine tasks, demand for non-routine capabilities is simultaneously increasing. To adapt to this rapid technological change, the OECD stresses that workers should build a strong foundation of essential skills, including digital literacy, critical thinking, and social and emotional skills. In the digital economy, workers are required to deal with complex information, think systematically, and be flexible and creative.

The need for individuals to develop digital skills is confirmed in the study by the McKinsey Global Institute (MGI) [5], which focuses specifically on the American labor market and depicts how automation technologies are expected to affect it in the decade ahead. The study posits that automation will lead to a significant evolution of jobs and skills, shifting the day-to-day activities of a wide range of roles. MGI's analysis finds that the next wave of automation might replace many office support, food service, transportation, logistics, and customer service roles. At the same time, new jobs are expected to be created in high-growth areas, specifically in healthcare, STEM fields, and business services, as well as jobs demanding personal interaction. A key finding of the report reveals that workers with a high school diploma or less are approximately four times more likely to be employed in highly automatable roles compared to those with a bachelor's degree. This figure suggests that the replacement of middle-wage jobs will likely continue, with growth concentrating at the high and low ends of the wage interval.

1.3 Digitally Skilled Workforce and Economic Outcomes

The increasing demand for digital competencies is not only about workers' adaptability or job security. It is also fundamental for a country's productivity and collective economic well-being. At the regional level, the development of these skills is increasingly recognized as a key aspect to ensure economic prosperity and resilience. A skilled workforce in the digital field can foster innovation, increase productivity, and create a more dynamic local economy. This idea is confirmed by the report "OECD Skills Outlook 2023: Skills for a Resilient Green and Digital Transition" [6], which posits that a strong digital skills base positively affects a country's overall economic performance. Consequently, investments in this direction can prepare individuals to face the continuous technological innovations and secure economic and social well-being.

The study's conclusions are based on projections indicating that the demand for various skills will shift dramatically between 2019 and 2030. The shift to digital technology and a green economy revealed a gap between what labor in these fields requires and what education systems generally can provide. The research projects the largest growth in skills associated with for example interacting with computers, analyzing data and information, thinking creatively, and communicating with people outside an external stakeholder. In this context, achieving successful economic expansion and job growth is possible if countries are able to increase the adoption of digital technologies and take advantage of the productivity improvements they can produce. Thus, effective skills policies are essential to prevent these transformations from producing labor market and social vulnerability, and instead to promote an inclusive and positive transition.

1.4 Measuring the economic output of Digitalization

The positive economic outcomes of such policies can be evaluated through various indicators of economic well-being. Although Gross Domestic Product (GDP) is the traditional measure of a region's economic output, it does not always reflect the well-being of its citizens. GDP can be high due to factors such as foreign-owned corporate profits that do not stay in the region, or government spending that does not directly improve household living standards.

On the other hand, households' disposable income, which is the amount households have left after taxes and social contributions, can more effectively reflect the actual purchasing power of citizens. The report OECD Family Database [7] confirms this idea, explaining how disposable income serves as an insightful measure of the average purchasing power of people. Given that it is calculated the financial resources remained after taxes and social contributions have been paid, the indicator properly represents the income households have retained to either spend or save.

1.5 Problem Statement

Given the nature of digitalization, which relies on capital-intensive technologies that need to be developed and implemented, a gap has always existed between regions or nations capable of investing and benefitting from new developments, and those with fewer available resources. This phenomenon, commonly called the 'digital divide', initially entailed a distinction between those who had internet access and those who did not. However, this concept changed as digital tools became accessible to larger portions of the population.

The shift in recent research focus, which has moved to the so-called 'second-level digital divide', or 'digital inequality', confirms the increasing impact of disparities in user skills, the nature of usage, and the resulting socioeconomic outcomes. Supporting these arguments, the study by Hargitay and Hinnant (2008) [8] showed that inequalities are present even in highly connected societies, where specifically young adults with higher education levels are more likely to be involved in capital-enhancing online activities, differently from individuals with lower educational attainments. Similarly, Van Deursen and Van Dijk (2014) [9] revealed that while lower-educated individuals may spend more time online (often for leisure activities such as social interaction and gaming), those with higher social status tend to use the Internet more for professional development and information acquisition. These studies demonstrated that the traditional societal inequalities of the offline world persist and may even increase as digital access widens.

Despite the inequality issues it raises, digital technological development is central to macroeconomic policy, given its role in raising national competitiveness. Myovella et al. (2020) [10] described digitalization as an 'indispensable engine of prosperity' for both less developed, such as Sub-Saharan Africa, and more developed OECD economies. However, studies on how digitalization influences income distribution suggest that the benefits of these advances can be unevenly distributed among the population. For instance, Consoli et al. (2023) [11] demonstrated that the relationship between digital skills and income inequalities varies substantially across European regions' income groups, with higher inequalities registered among the lower groups and a mitigation of this discrepancy observed in higher ones.

As the aforementioned studies testify, the link between digital technology and income inequality is a significant area of interest for academic researchers. Several studies in the field have observed how factors such as the internet access rates or the presence of skilled human capital measures, such as the share of the population with tertiary education, can impact economic indicators such as GDP growth. However, the degree to which diffusion of ICT expertise can contribute to reducing inter-regional inequalities within a country has been less explored.

Contrary to the research by Consoli, which analyzed intra-regional income inequality, this study focuses on the impact of the regional stock of personal digital skills (covering competencies such as content creation and problem-solving) on inter-regional disposable income disparity relative to the national average. This study investigates whether, at the European level, digital proficiency translates into improvements in regional households' purchasing power relative to the national average.

1.6 Contribution of the Study

Unlike other studies, this thesis investigates whether the digital expertise of individuals is associated with an increase in the average wealth of a region and, consequently, can reduce the interregional wealth gaps. By using individuals' personal digital skills and average regional disposable income as central indicators, this research aims to provide a clear idea of how digital proficiency translates into positive economic outcomes and a region's economic growth. Therefore, the study's research question is:

To what extent is the evolution of digital skills associated with changes in regional disposable income?.

This research employs data from 259 NUTS-2-level European regions over the 2015–2023 period, and utilizes a panel data approach. The innovative contribution of this study lies in the variables choice: the share of individuals with basic or above basic digital skills serves as the independent variable, representing the human capital perspective, while the percentage difference of a region's disposable income compared to the national average is the dependent variable, providing a policy-relevant measure of regional economic disparity. This dependent variable is preferred over measures such as GDP per capita because disposable income offers a more insightful representation of households' wealth and purchasing power, with the use of relative disparities preventing from scale differences across countries.

The study's analytical strategy includes two main approaches to understand the relationship between digital skills and regional disposable income disparities: regional clustering and a pre- and post-COVID-19 analysis. The regional clustering approach divides NUTS-2 European regions into three groups based on their economic development and runs a separate analysis for each. This analysis is expected to reveal how the relevance of digital skills in economic prosperity varies across regions with different levels of economic productivity. The pre- and post-COVID-19 analysis divides the observational data into pre- and post-pandemic periods. This approach would highlight whether the exogenous shock of the pandemic actually accelerated digitalization's impact on economies and whether results changed after Eurostat reclassified its definition of digital skills (Digital Skills Indicator 2.0 4.2).

To isolate the specific effect of digital skills on regional income disparities, the study also employes the Control Variables: *Unemployment Rate*, *Regional Population*, and *Low Education Rate*. These variables account for other impactful socioeconomic factors, reducing the risk of omitted variable bias. Other than accounting for broader regional characteristics, it can be observed how adding control variables will significantly strengthens the statistical robustness of results

Initial findings indicate that including control variables significantly improved the statistical significance of the *Digital Skill Level* coefficient only in the post-COVID-19 analysis, confirming an acceleration of digital transformation as a key success factor across the majority of industries. Furthermore, the clustering analysis shows a more statistically significant positive effect of digital skills on wealth disparity in the post-pandemic period for both richer and poorer European regions.

1.7 Overview of the structure

To fully address the research question and achieve a deeper understanding of the dynamics of interest, this research first explores the relevant literature on the digital divide, the role of digital skills, and regional income disparities (2). Then, it provides a Theoretical Framework (3) that provides the foundation for the study and the hypotheses formulated.

Chapter 4 details the Methodology (4) employed, including data sources, variable construction, and the econometric model. Subsequently, the empirical Results (5) of the analysis are presented, including additional exploratory studies to observe the phenomenon using different indicators. Then, the Policy Implications (6) chapter analyzes the policy-relevant insights this study's results entail, focusing on workers' upskilling, education, and how interventions should differently target regions with heterogeneous levels of development to minimize income disparity.

Finally, the Conclusion (7) summarizes the main contributions, the policy implications generated, and suggests directions for future studies.

1.8 Empirical Insights

Results show that the economic significance of digital expertise became significantly more pronounced after the exogenous shock of the COVID-19 pandemic, both at the aggregate level and within each of the regional clusters analyzed. An interesting result was that of Less-Developed regions, where a non-significant connection between variables becomes significant and positive after the COVID-19 pandemic. Notably, Transition Regions show the opposite trend, raising the need for further research delving into the industry- and competency-specific reasons why these regions' disposable income appears to be negatively affected by digital expertise.

Exploratory analyses generally yielded less robust results than those in the original study, suggesting that the correlation between the chosen variables weakens when alternative but related indicators are considered. Replacing *Digital Skills Level* with *Internet Access* yielded results that were statistically weaker but generally consistent with those of the original study. Instead, using GDP per capita as the dependent variable instead of disposable income yielded a negative coefficient for digital skill level in the post-pandemic era. This highlights that while digital skill improvement generally helps minimize regional wealth disparities, the benefits might not immediately translate into aggregate regional productivity gains, potentially reflecting a temporary productivity lag.

Chapter 2

Literature review

Over the past few decades, the global economy has undergone a profound transformation driven by the rapid advancement of digital technologies. This is what the famous Solow model [12] would categorize as a 'neutral Technological change' capable of upward shifting the collective production function. The theory explains how these advances can overcome the natural tendency towards diminishing marginal productivity of capital by continually increasing the capital-labor ratio.

The impossibility of labor force growth in matching capital investment capacity can lead to potentially never-ending growth in output per-capita and, consequently, in continuous rising of real wages for workers.

The advent of digital services has fundamentally reshaped the labor market, creating an increasing demand for skilled workers capable of comprehending and implementing these technologies within existing operational frameworks. In this evolving landscape, the development of robust expertise in Information and Communication Technologies (ICT) has become crucial for individuals seeking access to the job market, enhancing their productivity, fostering innovation within their organizations, and consequently contributing to the overall economic growth (Maiti & Awasthi, 2020 [13]).

This positive relationship between digitalization and economic growth has attracted significant attention from researchers worldwide. Their studies have explored how different regions have dealt with digital innovation and the resultant impact on wealth creation. This literature review aims to analyze the approaches and findings of existing research in this domain. While the central focus of this thesis is on the individual level of digital skills, it is pertinent to examine how scholars have investigated this phenomenon from diverse perspectives. For instance, studies have employed internet access as an independent variable (Gomes & Dias, 2024) [14] or

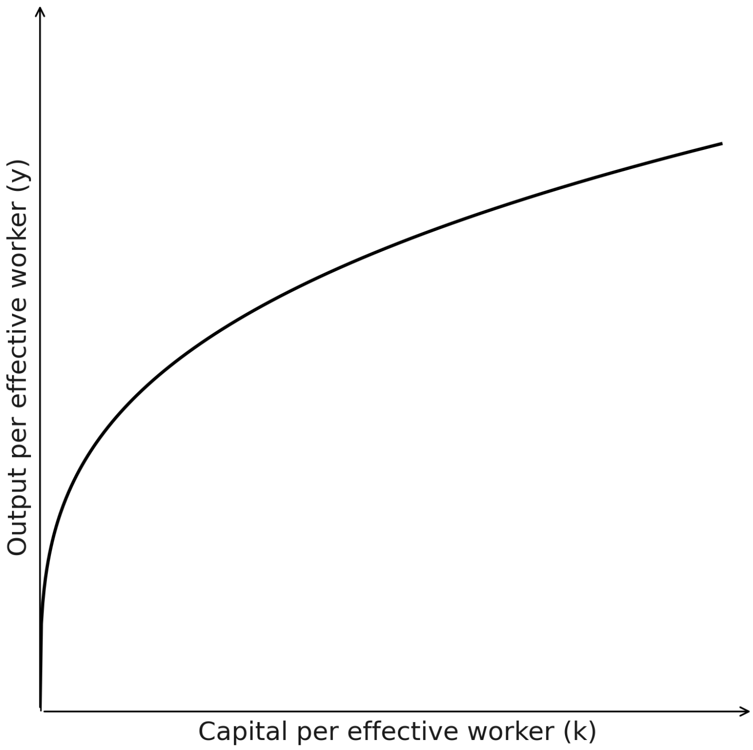

Figure 2.1: The Solow model's production function curve. The curve shows the relationship between output per effective worker and capital per effective worker, illustrating the concept of diminishing returns to capital accumulation.

utilized GDP growth as a measure of economic performance (Ibrahim, 2024) [15]. Furthermore, this review will consider whether novel research approaches, yet to be adopted, could offer valuable insights.

This section will first delve into the two sides of digital technologies: their contribution to economic growth and their potential to exacerbate economic disparities. Following this, the study describes the diverse research approaches, methodologies, and econometric techniques employed in key studies. The strengths and limitations of employed methodologies will be discussed, with a specific focus on identifying potential gaps in the current body of research.

2.1 Digitalization as Economic Growth's driver

The relationship between digitalization and economic growth has been widely studied in recent years, with basically all the results in the literature pointing to a positive link between the two. The development of Information and Communication Technologies (ICTs), such as internet and mobile phone technologies, can create new products, processes, market channels, and organizational complexities which represent the engine for countries' prosperity.

The endogenous growth theory, notably improved by the works of Romer (1990) [16] and Lucas (1988)[17], fundamentally reshaped our understanding of economic expansion by theorizing that internal economic processes — such as innovation, human capital, and knowledge acquisition—are the main drivers of nations' growth. This framework provided the foundation on which more recent empirical studies developed.

For instance, a key finding of the work by Myovella et al. (2020) [10] is that digitalization positively contributes to economic growth independently of a country's development level. The research illustrates that digital technologies contribute to economic improvement in both developing economies, such as Sub-Saharan Africa (SSA), and advanced economies, such as OECD members, with the magnitude of the effect differing between these groups. Complementing this, Bon (2021) [18] concludes that digitalization can help such developing countries to catch up with more advanced economies as it fosters workers' upskilling and productivity.

The regional grounded study by Ibrahim (2024) [15] lead to the same result, highlighting the role of digitalization in boosting economic expansion in terms of the GDP per capita. The analysis of both static and dynamic models shows how long-term benefits of digitalization are even higher than immediate ones, meaning that the benefits are cumulative and become even more substantial over time.

The importance of human capital in the adoption of digital technologies is confirmed by Ramos-Poyatos et al. (2024) [19]. In their study of European NUTS-2 regions, which demonstrates that regional-level general and digital human capital stocks increase work forces' ICT usage in daily work. This is conceptually linked to the enhancement of 'entrepreneurial absorptive capacity', meaning the ability of entrepreneurs to recognize and assimilate valuable outside knowledge. Furthermore, they find that knowledge spillovers from general and digital knowledge stocks are stronger in regions with lower GDP per capita, confirming the intuition by Bon (2021) [18] about ICT role in helping entrepreneurs catch up with their counterparts in richer regions and foster economic growth. Additionally, as Morris et al. (2024) [20] argue, the absence of necessary skills significantly hinders firm performance. The study shows the negative direct effect of skill shortages on firm productivity, particularly in industries characterized by a knowledge-intensive skill base. Their findings confirm the importance of having the requisite skills for maintaining and improving productivity, providing a complementary perspective on the value of human capital in the digital age.

2.2 Digitalization and Income Distribution

The development of expertise in digital fields follows different patterns across different countries and recognizes different technologies as the most adapt to support local economic activities. Myovella et al. (2020) [10] observed that, while digitalization produces economic growth both in less and more developed countries, the technological drivers differ among groups. Less developed countries benefit more from the introduction of mobile telecommunications, with the number of internet users having only a marginal impact on their economic growth. Conversely, more developed countries show the opposite pattern, where a larger internet user base has a greater impact than mobile telecommunications on economic growth. The diversity of growth paths derives from the possibility of developed countries both producing and using digital technologies, while less developed countries are primarily users. In addition, the availability of mature physical infrastructure, human capital, and appropriate policies help to reinforce and amplify the effects of digital technologies investments in high developed countries. In fact, the paper discusses the 'digital gap' between richer and poorer countries, with the latter lagging behind due to their position of competitive disadvantage.

The differences in adoption of digital technologies are vivid also within European countries, as discussed in the work by Gomes & Dias, (2024) [14] about different kinds of internet users in Eurozone. The results of the study clearly display how 'non-users' are concentrated in Balkan countries such as Romania, Greece and Bulgaria, while in northern European countries such as Sweden, the Netherlands and Denmark are located most of the 'advanced users'. Although some European initiatives succeeded in mobilizing some non-users and providing wider access to the internet, the study confirms how a gap in digital participation still exists and that it contributes to enhancing the disparity between more advanced and richer European economies from the less developed ones.

As Labudova & Fodranova (2024) [21] state, the observable division in ICT skills across Europe can be a consequence of the presence or absence of supporting policies and socioeconomic conditions. In-fact the presence of 'stimulative factors' such as investments in targeted education programs and research initiatives is shown to be effective in enhancing the average level of digital skills among the population. The study suggests a similar division to that observed by Gomes & Dias, (2024) [14], with northern countries leading in digital skills due to their robust education system and promoting inclusion and lifelong learning. Conversely, countries such as Bulgaria and Romania, due to their economic status, present the most consistent disincentive factors such as the absence of basic digital skills and lack in educational investments. Besides, disadvantaged regions often suffer negative demographic trends, such as depopulation. The paper by Garashchuk et al. (2024) [22] provides empirical evidence that digitalization may contribute to reversing negative demographic trends in these specific areas. It is demonstrated how, especially in poor regions, ICT development has a positive impact on natural changes in population and migration flows, preventing the region from depopulation. This underscores that targeted policies promoting digital inclusion, improving digital skills, and ensuring quality digital connectivity are crucial to enable digitalization to help attract or retain population and bridge the gap with more prosperous regions.

In conclusion, all the evidences point to a call for population digital skills' improvement, especially in poorer regions, where digital transformation, if not handled properly, is likely to exacerbate existing social inequalities and deprivation (Gonzalez-Relano et al, 2024 [23]). Relatedly, Consoli et al. (2023) [11] highlight a link between e-skills and within-region income disparity, finding that while higher e-skills are associated with lower inequality among high-income groups, they are correlated with greater inequality among lower-income groups. This suggests that increasing digital skills improvement within a region, without equitable access to its benefits, risks enlarging the gap between wealthier and poorer parts of the population.

2.3 Review of Prior Approaches

Literature in the field offers various examples of how to assess the social impact of digitalization, internet access and usage or the overall level of digital skills. Among these, the panel data is the most widely used due to its properties, which makes it particularly adept at assessing causality and changes over time, while considering some invariant regional-specific factors. Unlike cross-sectional studies, which provide a snapshot at a single point, panel data allows us to control time-invariant unobserved characteristics that could otherwise mislead in the results about dependent variables. Moreover, panel data captures dynamic effects, acknowledging that the social impacts of technology adoption are gradual.

However, the sources highlight other methods offering valuable insights about the social impact of digitalization. Gomes & Dias, (2024) [14] use Categorical Clustering, also known as Latent Class Analysis, which is a probabilistic method used to identify distinct groups or typologies of individuals based on their engagement with digital activities and indicators of the digital divide. This method allows researchers to 'catch' the heterogeneity within the population, revealing that the digital divide is not uniform but manifests in different patterns among various groups with characteristic socio-demographic profiles. Instead, Gonzalez-Relano et al, (2024) [23] use Factor Analysis, a multivariate technique, to analyze the underlying relationships and interdependencies between digital access or usage and deprivation. These methods provide powerful ways to classify populations and uncover hidden associations, complementing longitudinal analyses.

Regarding the understanding of how digital advancements can affect economic growth, it is interesting to observe how researchers followed different approaches in terms of choice of dependent variables and regression models. Among those who decided to employ panel data in their research, Consoli et al. (2023) [11] decided to point attention to individuals' skills, particularly those needed to operate digital technologies. The research aggregates indexes to assess the intra-regional income inequality due to e-skill changes, with the use of econometric methods and robustness analyses applied to address potential endogeneity issues.

The unavailability of disaggregate data for less developed countries makes it possible for studies such as the one by Myovella et al. (2020) [10] to focus only on national level indicators. In this case, the panel dataset is composed of 74 countries and 11 years in total. The research utilizes Generalized Methods of Moments (GMM) estimators, specifically the linear methods of moments (GMM), which is widely applied to assess dynamic impact of variables when dealing with panel data. This technique is suitable for panel data with a few time periods and many individuals (countries in this case).

Another regional-level study was conducted by Antonietti et al. (2025) [24], who first aimed to assess whether the level of digital technology (DT), measured as DT investments per employee, is correlated with income inequalities, then it poses the question whether institution should deal with the problem of an eventual positive relationship differently than what they currently do. The study compares data of 140 European NUTS2 regions over a 10-year period and conducts a panel fixed-effects estimator to assess whether the two variables are linked. The study also includes control variables such as investments in R&D, human capital (share of population with tertiary education), population, and population density, to create a more accurate description of the phenomena and avoid biased estimations.

2.4 The Research Problem and Methodology

As analyzed above, existing literature extensively investigates the link between digital technology and income inequality in Europe and elsewhere. These studies often rely on aggregate measures such as internet access rates (Gomes & Dias 2024) [14], broadband penetration (Garashchuk et al., 2024) [22], availability of digital infrastructure and ICT diffusion (Consoli et al.„ 2023) [11], or the distribution of digital services at regional or country levels (Antonietti et al., 2025) [24]. Research consistently finds that greater access to digital technology is associated with higher levels of income inequality, often due to the skill-biased nature of technological change that favors those with higher education and non-routine capabilities. However, the mechanism through which digital factors, such as ICT expertise, contribute to improved regional economic performance and consequently greater regional wealth, has received less attention in research.

While employing individual-level ICT usage frequency has yielded valuable insights into the role of human resources in digital transformation (Ramos-Poyatos et al.„ 2024) [19], this measure may not distinguish between productive and non-productive uses of technology. In contrast, choosing the level of digital skills as defined by Eurostat could offer a more nuanced assessment of individuals' capabilities, as it considers various facets of ICT usage, including information, communication, digital content creation, safety, and problem-solving skills.

Therefore, focusing specifically on the impact of an individual's personal level of digital skills on average regional disposable income represents a notable gap. This study can provide a more nuanced understanding of how personal digital proficiency translates into economic outcomes and contributes to reduce regional disparity of purchasing power.

Chapter 3

Theoretical framework and hypotheses

To what extent is the evolution of digital skills associated with changes in regional disposable income? To answer this question, the study develops a series of regressions using panel data collected from 259 NUTS-2 level European regions. This level of granularity enhances the number of observations in the statistical model, a crucial feature to ensure significance and reliability of the results. Moreover, this approach allows to account for intra-national disparities in digital development which are considerable even within Europe's largest economies, such as Italy and Germany.

This section first outlines the study's expected outcomes, describing the underlying mechanisms that are hypothesized to determine these. It then clarifies why these variables are considered appropriate for investigating the socioeconomic mechanism of interest.

3.1 Hypotheses

Based on extensive studies on the advantages of digitalization, this research hypothesizes that a skilled workforce is a key determinant of regional economic development and the general wealth growth. The principal manifestation of widespread digital expertise would be the productivity increase: as individuals acquire digital competencies, their efficiency in the labor market improves, leading to enhanced output capacity, higher wages and, consequently, an increase in household disposable income. At the regional level, this is expected to translate into an upgraded positioning relative to the national average. This mechanism suggests the formulation of the following hypotesis:

- **H1**: *An increase in individuals' digital skills is positively correlated with improvements in regional average disposable income relative to its national mean value.*

Regarding the econometric model, the Fixed Effects (FE) approach should be more effective in capturing the true relationship between variables. This is because the FE model controls unobserved, time-invariant region-specific characteristics (such as historical context and geographical advantage) that might be correlated with both regional digital skill levels and disposable income. In contrast, the Random Effects (RE) model assumes that these unobserved effects are uncorrelated with the model's regressors. This assumption is usually not applicable in socioeconomic panel data and could lead to biased estimates.

To account for the complexity of these mechanisms, researchers in this field usually add other variables to their empirical analyses. This practice aims to isolate the independent variable's effect from other factors influencing the dependent variable. Including control variables is expected to help accounting for factors that are correlated with the variables of interest, thereby improving the model's explanatory effectiveness and mitigating potential omitted variable bias. Following this:

- **H2**: *The observed positive correlation becomes more robust once control variables — specifically the regional unemployment rate, regional population size, and the rate of low-educated individuals — are included.*

Furthermore, the strength of this relationship is expected to vary significantly across different levels of regional economic development, as categorized by EU Cohesion Policy [25]. For instance, less developed regions, which traditionally rely more on sectors like agriculture or low-value added manufacturing, digital skills would show a weaker correlation with regional income. In such contexts, the demand for advanced digital skills may be lower and developing digital skills may not yield remarkable economic improvements to individuals. Conversely, more economically advanced regions are expected to exhibit a stronger positive correlation between variables. Their economies are generally more technologically advanced, relying more on service-oriented and high value-added sectors. In these environments, digital skills are likely to be more required and better exploited, leading to gains in productivity and, consequently, contributing to regional wealth increases. Therefore, we can hypotyze that:

- **H3**: *The positive correlation between individual digital skill levels and a region's relative disposable income will be stronger and more statistically significant in more advanced regions compared to less developed ones, where the correlation is expected to be weaker or even insignificant.*

Moreover, we can anticipate that this relationship between digital skills and regional income significantly strengthens after the COVID-19 period. The pandemic accelerated digital transformation significantly, permanently changing various work dynamics and the accessibility to knowledge and skills. Beyond the widespread adoption of remote work and video conferencing, the crisis incentivized firms to accelerate business processes digitalization (e.g., e-commerce, cloud computing), increased population reliance on digital public services (e-government, telehealth), and emphasized the critical role of digital tools in education and training. In this context, digital skills are essential to individuals' economic participation across all sectors, leading to a positive impact on regional average income.

- **H4**: *The positive correlation between individual digital skill levels and a region's relative disposable income is expected to significantly strengthen in the post-COVID-19 period across all analyses, reflecting the increased economic importance of digitalization following the pandemic shock*

3.2 Independent variable

The *Individuals' level of Digital Skills* is selected as independent variable, among other indicators, because of the increasingly critical role these competencies play in today's labor market, enhancing workers' productivity and consequently their wages and wealth.

Other digital development proxies mentioned in the literature may be less effective in explaining the changes in regional income disparities. For example, Eurostat's statistics report that for only 13, among the more than 300 European regions[1] observed, the share of households with internet connection is less than 85 percent. This suggests that basic connectivity alone is no longer a robust measure for assessing regional digital disparities. Moreover, measures such as the frequency of internet use by individuals fail to distinguish between professional and unproductive activities. Studies by Hargittai & Hinnant (2008) [8] and Van Deursen & Van Dijk (2014) [9] have explored the 'second-level digital divide', demonstrating how inequalities in Internet use persist even among connected populations. Indeed, while highly educated individuals tend to use digital applications more for capital-enhancing tasks, such as online banking or information research, less educated people are more likely to pursue leisure activities, such as gaming and social interaction. Despite the latter group spending more time online in their spare time — a key finding from Van Deursen & Van Dijk's study in the Netherlands — this

[1] Considering also country which are geographically but not formally part of European Union (UK, Serbia, Albania etc.)

usually does not translate into improved digital capabilities, leading to a ’usage gap’ that can reinforce existing social inequalities.

On the other hand, Eurostat assesses the individual level of digital skills of respondents based on their competence across different areas and applications, such as information and communications and problem solving. Based on respondents’ self-reported proficiency in performing tasks in each area, their digital skill level is classified as ’null’, ’basic’, ’above basic’. Despite its limited ability to capture individuals’ depth of digital knowledge, this indicator captures the share of regional population which possesses the fundamental skills which are strictly necessary to participate in the digital economy.

In this study, the indicator displays the percentage of people with ’basic’ or ’above basic’ digital skills. The choice of considering also ’basic’ proficiency is based on the idea that broad digital literacy—including skills such as communication, safety, and problem-solving—is a prerequisite for nearly all modern job roles (National Skills Coalition, 2023 [26]). As confirmed by the World Economic Forum (2023) [27], today’s labor market requires, at the very least, basic digital literacy, as job resilience depends on the capacity of the entire workforce to adapt to technological shifts. Consequently, this indicator can effectively capture the population’s ability to work utilizing digital technologies and contribute to regional wealth.

3.3 Dependent variable

The dependent variable in this study is the percentage difference between regional and national disposable income. This measure is calculated to reflect how far each NUTS-2 region’s average disposable income positions relative to the correspondent national average. This specific formulation is preferred over an absolute difference measure because it effectively controls scale differences across countries. By focusing on relative disparities, results are not biased by the magnitude of discrepancy in income level between a richer and poorer nation, supporting more meaningful comparisons across the European’s diverse economic contexts.

The figure of average disposable income was chosen over other measures of regional economic prosperity, such as Gross Domestic Product (GDP) per capita, as it provides a clearer representation of households’ wealth and purchasing power. Since GDP per capita measures the total economic output of a region, this indicator might not adequately reflect cases of income inequality, particularly when wealth is concentrated among a small segment of the population. In contrast, disposable income represents the income available to households for spending and saving after taxes and transfers. This makes it a more effective indicator of the resources available to households for accessing goods, services, and opportunities, including those related to digital inclusion.

Furthermore, this relative measure of regional disposable income offers advantages over other inequality indices such as the Gini coefficient for assessing regional disparities. While the Gini coefficient, used for example by Consoli et. al [11] in their study, focuses on income inequality within a specific region or country, it does not directly capture the between-region income gap in relation to the national context. Instead, the above-mentioned variable measures the extent to which households in a region are richer or poorer relative to their country's average, which is crucial to understand how digital skill development might contribute to regions either getting closer or further falling behind the national average disposable income.

3.4 Control variables

Initially, regressions aim to estimate the relationship between individuals' level of digital skills and regional average disposable income. Subsequently, a set of control variables are incorporated into the model. This inclusion allows to account for factors that are correlated with the variables of interest, thereby improving the model's explanatory effectiveness and mitigating potential omitted variable bias. An analysis of this study's specific needs, combined with a review of similar research in the literature, led to the selection of the following control variables:

- *Unemployment rate*: this parameter, calculated as a percentage of the workforce involuntary unemployed, is a key determinant of regional income level and disparities. Higher regional unemployment rates are typically associated with lower average disposable income as this segment of the population relies on social assistance rather than collecting earnings. Including unemployment rates allows to isolate the effect of digital skills on regional income from the existing labor market conditions.

- *Regional population*: the number of individuals in a region can affect our variables in several ways. For example, larger regions may benefit from agglomeration effects, which consist of geographic concentration of economic activities and firms in a specific area [28]. They may also count on more diverse economies, which can buffer against economic shocks. Including population size as a control variable ensures the observed effect of skill level on average income is not only a function of a region's size.

- *Low education rate*: the regional educational attainment level is seemingly a strong determinant of income and skill acquisition. Regions with large proportion of uneducated people are usually poorer and less inclined to acquire digital skills. The choice of using the level of low educated people is aimed at avoiding multicollinearity between digital skills and the share of highly educated individuals.

Taken together, these control variables help isolate the effect of individual level of digital skills on regional income disparities from other impactful features, such as labor market conditions, workforce availability and overall educational attainment.

Chapter 4

Methodology

This research employs an empirical, quantitative method to test the hypotheses derived from the theoretical framework. Data regarding the variables of interest are collected from Eurostat and utilized in a panel data format to assess the effect of changes of digital skills on regional average disposable income. The approach is particularly suitable for this research as it offers two key advantages. Firstly, panel data allows to observe the evolution of digital skills and regional income disparities and their dynamic connections within the same regions. Secondly, it allows to isolate time-invariant regional characteristics, such as geography or specific institutional frameworks, which might otherwise distort the observed correlation between variables.

The analysis focuses on European NUTS-2 regions as units of observation. To achieve a comprehensive coverage of European territory, small European nations without NUTS-2 subdivisions (e.g., Estonia, Malta) were treated as individual regions, resulting in a total of 259 entities. Each region provides only six annual observations over the period 2015-2023, as data on the individual level of digital skills were unavailable for 2018, 2020 and 2022. Thus, the analysis relies on six observations per region for a total of 1,554 records: a solid base to support significant statistical analysis.

Given the relatively short time series (six observations per region) and the resulting panel structure, econometric analyses are performed with a significance threshold (α) of 10% (i.e., a 90% confidence interval). This approach is useful in based on limitedtime-series data, where the 5% threshold might be excessively stringent and lead to rejection meaningful relationships. The value of 10% is therefore chosen as the maximum accepted threshold for result robustness.

All econometric analyses are performed using the software Stata (version 2017).

4.1 Data Description and Distribution

The distribution of digital skills across the analyzed countries shows an evident geographical pattern.

Table 4.1: Share of individuals with at least basic digital skills across 27 European countries. Data are expressed as percentages and refer to the year 2023. Countries are ordered from the highest to the lowest value

Country	Digital Skills
Netherlands	82,70
Finland	81,99
Ireland	72,91
Denmark	69,62
Czechia	69,11
Sweden	66,44
Spain	66,18
Austria	64,68
Malta	63,02
Estonia	62,61
Luxembourg	60,14
France	59,67
Belgium	59,39
Croatia	58,95
Hungary	58,89
Portugal	55,97
Lithuania	52,91
Greece	52,40
Germany	52,22
Slovakia	51,31
Cyprus	49,46
Slovenia	46,70
Italy	45,75
Latvia	45,34
Poland	44,30
Bulgaria	35,52
Romania	27,73

Based on table 4.1, which presents 2023 figures, expertise tends to concentrate in Northern and Central European states. Countries like the Netherlands, Finland, and Denmark occupy the top ranks, while lower proficiency levels are observed in

Southern and Eastern European nations, with Romania and Bulgaria recording the lowest shares.

It is important to note the case of Germany, which ranked on average as 6^{th} country in this rank before 2020, but dropped to the 19^{th} place in 2023 due to a data anomaly which will be discussed later in this section (4.6).

4.2 Analytical strategy

The statistical study aims to capture how the evolution of digital skills can affect the wealth of a region, which is measured as percentage difference in its average disposable income relative to the national figure.

Initially, regressions will involve only dependent and independent variables, utilizing Fixed and Random Effect models to determine which estimator best accounts for their interaction. Subsequently, control variables will be introduced in the model to account for other regional-specific characteristics which affect observations, mitigating the omitted variable bias. Finally, the analysis will be repeated after dividing regions into clusters based on the classification the EU uses for the allocation of Cohesion Policy funds. According to this approach, regions are categorized into three types based on their GDP per capita relative to the European average[1]:

- Less Developed Regions: If GDP per capita is lower than 75% of the European average;
- Transition Regions: If GDP per capita is between 75% and 100% of the European average;
- More Developed Regions: If GDP per capita is higher than 100% of the European average.

Regressions will always be performed separately for pre- and post-COVID19 periods. This distinction is crucial as Eurostat reclassified the definition and measurement of digital skills during this period, implementing the Digital Skills Indicator 2.0 (DSI 2.0) which aligns with the European Commission's Digital Competence Framework for Citizens (DigComp 2.0). The updated indicator was developed between 2019 and 2022 and began to be used in official statistics from 2021 onwards. In order to provide a more comprehensive definition of digital skills, Eurostat expanded the

[1] Regional classifications (Less Developed, Transition, More Developed) are based on their GDP per capita relative to the European average, using 2023 data. This approach ensures consistent regional categorization throughout the analysis period.

array of competency to five dimensions, including areas such as content creation and safety skills, and added new types of digital activities individuals could be evaluated on [29]. In this way, policymakers could more realistically track advances towards the objectives in the European Commission's policy priorities and the Digital Action Plan, which emphasizes the necessity for at least 80% of the adult population to acquire a minimum set of digital skills by 2030 [30].

4.3 Proxy Construction for Regional Digital Skills

An operational challenge of this study derives from the nature of the independent variable's observations: Eurostat currently provides individual digital skills data only at the national level. Given the impossibility of collecting the underlying microdata, and considering the interest in analyzing regional level phenomena, a fundamental assumption is introduced: *the regional distribution of digital skills resembles the regional share of human resources working in science and technology-related fields (HRST).*

The HRST dataset, available on Eurostat with the regional level detail, defines this category as individuals who either possess a tertiary level education or are employed in a 'science and technology' occupation according to the International Standard Classification of Occupations (ISCO). To estimate regional digital skill levels, a proportional adjustment method is employed. First, the percentage deviation of HRST for each region from its corresponding national average is calculated. Then, this percentage deviation is applied to the observed national digital skill level, yielding an estimated regional digital skill level. Specifically, if $DS_{national}$ denotes the national digital skill level and $Discrepancy_{HRST}$ represents the regional HRST percentage deviation from the national average, the estimated regional digital skill level ($DS_{estimated,regional}$) is calculated as:

$$DS_{estimated,regional} = DS_{national} \times (1 + Discrepancy_{HRST}) \tag{4.1}$$

Table 4.2 illustrates examples of this calculation using 2023 data. The *Individuals' level of Digital Skills* represents the percentage of population with basic or above basic digital abilities, while the HRST indicator represents the percentage of human resources in science and technology-related fields (whether in studies or in the labor market).

This methodological approach inherently introduces some limitations regarding the precision of regional digital skill estimates. However, this simplification is assumed to be reasonable as human resources tend to concentrate in geographical areas where their expertise is required and appropriately remunerated. Therefore,

Table 4.2: Example of regional digital skills' calculation using 2023 data. All data are expressed as percentage values

Nation	Region	HRST	HRST % Diff. (vs. National)	National DS	Estimated DS
Belgium		23,90		59,39	
	Prov. Vlaams-Brabant	25,60	7,1		63,61
	Prov. Hainaut	18,70	-21,8		46,4
Germany		28,70		52,22	
	Oberbayern	35,20	22,6		64,05
	Arnsberg	26,40	-8,0		48,04
Italy		17,70		45,75	
	Lombardia	21,70	22,6		56,09
	Puglia	12,50	-29,4		32,31

the distribution of HRST is expected to represent a robust proxy for the relative distribution of digital skills at the regional level.

4.4 Data Pre-processing

Proper data preprocessing is crucial for ensuring coherence and reliability of econometric results. This study adopted different solutions to account for potential dataset issues, including missing data, outliers or out-of-scale data.

The 2023 regional disposable income statistics were particularly affected by missing data, probably due to reporting delays by national statistical offices. Attempts were made to derive these missing values by substituting them with estimates based on trends from preceding years. However, this approach consistently led to statistically insignificant results in initial model runs. This outcome suggests that the simulated values might have introduced artificial noise within the observed data and thus weakened the reliability of the findings. Consequently, actual observations were prioritized over estimated ones, and regressions were conducted on the resulting reduced dataset, which is still sufficiently numerous to sustain statistically robust analysis.

The methodology employed to estimate the regional level of digital skills led to the creation of outliers that represent logically unfeasible observations. Especially within countries characterized by marked territorial digital inequalities, it was observed that highly skilled human resources tend to concentrate in few regions, which consequently outperform the national average HRST. Translating this substantial discrepancy into the digital skill area might result in more than 100 percent of the population possessing an above-basic level of digital skills. Table 4.3 illustrates the examples of Praha and Budapest regions for 2023:

Table 4.3: Examples of regions with an estimated digital skills' population share exceeding 100%. All data are expressed as percentage values.

Nation	Region	HRST	HRST % Diff. (vs. National)	National DS	Estimated DS
Czechia		23,3		69,11	
	Praha	41,5	78,1		123,09
Hungary		22,3		58,89	
	Budapest	40,4	81,2		106,69

To manage these unrealistic values, any recording of digital skills exceeding 100 percent was adjusted to 100 percent. While hypothesizing that the entire population in these regions possesses an above-basic level of digital skills likely misrepresents reality, such limit cases are accepted for operational necessity when utilizing this approximation. Capping this variable permit to capture the deviation of regions with respect to their national average while maintaining respective the variables' logic limits.

Moreover, the control variable population number was normalized to facilitate interpretation and evaluation of results. In particular, the raw data about inhabitants per region was divided by 10,000. This transformation ensures the coefficient for population reflects the effect that 10,000 inhabitants change has on the average disposable income of a region. This change eases the interpretation of results and provides more policy-relevant figures compared to interpreting the effect of a single-unit (i.e., one inhabitant) change.

For the purpose of this study, data are organized longitudinally to apply Stata's panel data regression techniques. The software requires the definition of panel identification variable and time variable, which in this case are, respectively, European regions and years between 2015-2023. The textual variable region is first encoded so the model assigns a specific index to each of the 259 NUTS-2 regions involved in the research. Finally, the 'xtset' command ensures Stata recognizes the panel structure of data and uses appropriate estimation techniques.

4.5 Econometric technique

This section explains the econometric approach employed in this empirical study.

To examine the relationship between regional digital skill levels and regional income disparities, the following empirical model was employed:

$$Y_{it} = \beta_0 + \beta_1 \mathrm{DS}_{it} + \beta_2 \mathrm{Controls}_{it} + \epsilon_{it} \tag{4.2}$$

Where:

- Y_{it} represents the percentage difference in disposable income of region i at time t, with respect to the national average.
- DS_{it} denotes the estimated digital skill level for region i at time t.
- $Controls_{it}$ is a vector of control variables for region i at time t, including regional unemployment rate, population number, and low education rate.
- β_0, β_1,β_2 are the coefficients to be estimated.
- ϵ_{it} is the error term.

Regarding the estimation technique, the Fixed Effects Model (FEM) and Random Effects Model (REM) were preferred over other approaches, such as Pooled Ordinary Least Squared (OLS). Despite its simplicity, OLS considers all observations as independent, thus failing to account for time-invariant differences among regions and possibly leading to inconsistent estimates.

On the other hand, FEM and REM account for these heterogeneities, though using different approaches. The FEM addresses time-invariant regional factors by introducing a single intercept for each region ($\beta_{0,i}$). This is achieved by subtracting from each observation the entity-specific mean value. This feature makes fixed effects models particularly adept at separating effects of variable of interest from unobserved, time-invariant characteristics and mitigates the underlying risk of omitted variable bias. Instead, REM assumes that unobserved effects are part of the error term and are uncorrelated with the independent variables of interest. If this assumption holds, the model yields more efficient estimates than the FEM. The choice between FEM and REM will be based on the results of the Hausman test, which formally tests the core REM assumption as null hypothesis. In case the null hypothesis is rejected, a correlation between unobserved effects and the variables of interest is detected and the Fixed Effects Model is chosen to avoid the omitted variable bias. Conversely, if the null hypothesis cannot be rejected, the Random Effect Model is preferable for conducting the analyses.

4.6 Addressing Potential Issues

Addressing potential econometric challenges, such as heteroskedasticity and endogeneity, is a crucial step to ensure the robustness of results and acknowledge the limits of research findings.

The problem of heteroskedasticity arises when the variance of the error term varies across observations. If not properly managed in regressions, heteroskedasticity could lead to incorrect estimations of standard error, with a consequent weakening of statistical inferences and hypothesis test significance. To account for potential heteroskedasticity and autocorrelation within regions, cluster-robust standard errors are employed in all regressions. This method improves the reliability of results by allowing for intra-regional correlation patterns so that hypothesis tests are valid even when the error term varies among observations.

Another critical point to address is endogeneity, which can arise from various sources including simultaneity and omitted variable bias. In the context of this study, where the impact of digital skills on regional income disparities is analyzed, a reverse causality, or simultaneity, could exist it is reasonable to think that the income level, indicating the level of wealth of a region, is a main driver of digital skills development. In fact, education standards and labor market demand are crucial in incentivizing the development of expertise in this field. The existence of this bidirectional relationship entails that estimated coefficients should be interpreted as robust associations rather than strict causal effects.

Additionally, while the fixed effects model accurately accounts for time-invariant regional characteristics, there are still various factors that might dynamically affect both the independent and the dependent variables, leading to the presence of omitted variable bias. These might include, but are not limited to, region-specific industrial investments, dynamic changes in local educational practices, or major exogenous shocks such as the COVID-19 pandemic.

Despite acknowledging the potential influence of endogeneity, this study can still contribute to a better understanding of this societal dynamics. Indeed, demonstrating the existence of a robust and statistically significant association between digital skills and income disparities among regions can provide crucial insights to policymakers, highlighting the potential economic benefits that initiatives in this direction could yield.

Finally, the accuracy of data might be negatively affected by measurement errors. While this study generally assumes that Eurostat's rigorous data collecting standards ensure negligible data errors, a detailed analysis of data consistency was necessary to avoid potential incoherences. In this analysis, a notable inconsistency was detected for Germany's observations of the variable *Individuals level of digital skills*. As illustrated by table 4.4, the country seems to have experienced an approximate 20 percent-point drop in the share of population possessing basic or above-basic levels of digital skills between 2019 and 2021.

Table 4.4: Observed Inconsistency in Germany's Digital Skills Data (2015-2023)

Nation	2015	2016	2017	2019	2021	2023
Germany	66,71	67,54	68,18	70,16	48,92	52,22

Despite Eurostat's change in digital skills measurement methodology after 2020 (Section 4.2), such a massive reduction in the data would drastically change Germany's position relative to pre-covid figures and represents an isolated case that is difficult to rationally explain. The problem was reported to Eurostat, which recognized the inconsistency and is investigating the possible reasons behind this anomaly.

4.7 Exploratory and Supplementary Analyses

In order to gain a more comprehensive understanding of the link between digitalization and regional economic outcomes, this section tests alternative model specifications. Specifically, separate regressions are performed where:

- the percentage difference of regional GDP per capita relative to the national average is used as dependent variable.
- the share of people who can access the internet in each region is used as independent variable.

Such analyses are expected to provide valuable insights into the consistency of results when the initial variables are replaced by related but conceptually distinct indicators. Following this logic, GDP was selected to replace disposable income as it captures the regional overall productivity rather than the purchasing power of individuals. In order to ensure methodological continuity with the original study, the updated dependent variable is the percetage difference of regional GDP per capita relative to the national average. Likewise, the share of people who can access the internet offers a different indication from the individual's level of digital expertise, as it reflects the availability of infrastructure rather than individual human capital.

A final robustness check involves the introduction of the lagged dependent variable to account for potential autocorrelation of disposable income levels. Results indicate that precedent regional disposable income observations significantly influence subsequent recordings, confirming the importance of path-dependence in regional economic phenomena. However, the introduction of this dynamic term leads to the statistical insignificance of the digital skills coefficient, as the strong explanatory power of the lagged dependent variable appears to absorb much of the remaining variance. This result highlights the presence of complex, long-term economic dynamics—such as the dominance of income path-dependence—which require dedicated dynamic modeling techniques (e.g., GMM). As the focus of this study is on the contemporaneous cross-sectional and temporal variation captured by the Fixed Effects model, a deeper analysis of these long-run dynamic effects is considered beyond the current scope and is reserved for future research. This specific analysis is presented in the Appendix 7.6 (table .2).

Chapter 5

Empirical Findings

This chapter illustrates the results of the regressions performed on observational data. The following Sections will discuss whether empirical findings align with the hypotheses previously developed in the Theoretical Framework 3.

Specifically, the first Section presents the outcomes of the Fixed Effects (FE) and Random Effects (RE) analysis, determining which model is more appropriate for this research based on the Hausman test. These results are be crucial to assess the validity of Hypothesis $H1$ (3.1), regarding the positive correlation between individual digital skill levels and the positioning of a region's average disposable income relative to its national average. The subsequent Section examines how the inclusion of control variables impacts the robustness of the results, as proposed by Hypothesis $H2$ (3.1). Following this, findings regarding the impact of digital skills on regional economic disparities will be discussed, specifically when regions are clustered according to their GDP per capita ($H3$, 3.1). Finally, all analyses makes it possible to assess whether results' statistical significance effectively improves after the exogenous shock of COVID-19 pandemic, addressing Hypothesis $H4$ (3.1).

The final Section presents the results of the supplementary analyses discussed in Section 4.7, which will test the consistency of observed trends when replacing independent or dependent variables. The numerical results of each regression are reported in the Appendix (7.6).

5.1 Fixed vs. Random Effects (Hausman Test)

To determine the appropriate panel data estimator between Fixed Effects (FE) and Random Effects (RE) models, a Hausman-type test was conducted. Given the likely presence of heteroskedasticity and within-group correlation across regions, standard errors were clustered at regional level for both models. This approach demanded the use of a generalized version of the Hausman test, which in its traditional format would assume homoskedasticity in standard errors. Specifically, the *xtoverid* command in Stata provides valid results for model choice even in the presence of clustered standard errors.

Since this test aims at determining the most suitable model for this study, regressions are performed on the aggregate dataset, without being divided between pre- and post-COVID periods. Additionally, due to the described data reliability concerns for Germany throughout the overall period 4.6, the country was excluded from this analysis.

Table 5.1: Results of Fixed Effects (FE) and Random Effects (RE) models.

	Fixed Effects (FE)	**Random Effects (RE)**
Digital Skills Level	0.0217	0.0713
Std. Error	0.0216	0.0239
t/z-value	1.00	2.98
P-value	0.317	0.003
90% CI	[-0.014, 0.057]	[0.0319, 0.11]
Constant	-3.13 (p = 0.006)	-5.79 (p = 0.000)
R^2 Within	0.0017	0.0017
Groups	214	214
Observations	1,106	1,106
Hausman (XToverid)	$\chi^2(1) = 63.49, p = 0.000$ ($\rightarrow$ FE preferred)	

The results in table 5.1 indicate that both Fixed Effects and Random Effects analyses yield a positive coefficient for the independent variable (*Digital Skills Level*), although with notable differences in the magnitude of its estimated impact and its statistical significance. Specifically, the coefficient from the Fixed Effects analysis presents a p-value that exceeds 0.1, which is commonly recognized as the threshold for statistical significance. This implies that we cannot reject the null hypothesis that the individuals' digital skill level is insignificant in explaining the variation of the dependent variable. Despite the Random Effects analysis yielding a very low p-value, the Hausman test confirms that the Fixed Effects model should be preferred for this study. In fact, the test strongly rejects the null hypothesis (p-value < 0.05) that the Random Effects model is consistent and efficient, thus suggesting the use of the Fixed Effects model. This outcome confirms the existence of unobserved intra-regional factors (which can be attributable to cultural, economic, and other territory-specific features) that affect observations throughout our period of interest. The Fixed Effects model addresses this potential issue by subtracting the region-specific mean over the whole period from each observation.

Using the most reliable Fixed Effects model, initial findings indicate that a positive impact of individuals' digital skill level on the regional difference in disposable income relative to the national average cannot be confirmed. In fact, the low statistical significance (p-value = 0.317) of the results suggests that we cannot draw definitive conclusions about the direction or magnitude of this impact. The following Sections add granularity to the analysis by introducing control variables, distinguishing between pre- and post-covid periods, and clustering regions with similar economic positioning. This approach aims to isolate the effect of digital skills from other context-specific factors, with the goal of providing a more detailed and statistically significant understanding of its impact.

5.2 Control variables integration

The econometric analysis is further extended by adding control variables. These are particularly helpful in mitigating the risk of omitted variable bias, which occurs when the independent variable's effect is distorted by other unobserved factors. As previously mentioned in Section 3.4, this study includes *Unemployment rate*, *Regional population*, and *Low education rate* as control variables. Those allow to isolate the effect of individuals' level of digital skills respectively from the labor market conditions, the region's size in terms of population and the level of educational attainment.

Regressions will be now divided into pre- and post-COVID19 periods, to account for the change in digital skills measurement discussed in Section 4.2. Furthermore, observations from Germany, previously excluded due to data inconsistencies, will be incorporated as their data exhibits consistency when analyzed within these distinct periods.

Results show that including control variables significantly improves the statistical significance of the *Digital Skill Level* coefficient only within the post-COVID-19 analysis. As Figure 5.1 clearly displays, the coefficient not only becomes statistically significant but also shifts to a positive value when comparing pre- and post-COVID-19 periods. This finding supports the idea that the COVID-19 exogenous shock likely fostered digital technologies adoption by many companies, making digital expertise a key success factor for regional economies.

Furthermore, it is worth pointing out the resulting coefficient for the 'Low education rate' variable, which signals a potential positive impact of the percentage of individuals with less than tertiary education on the difference in regional average

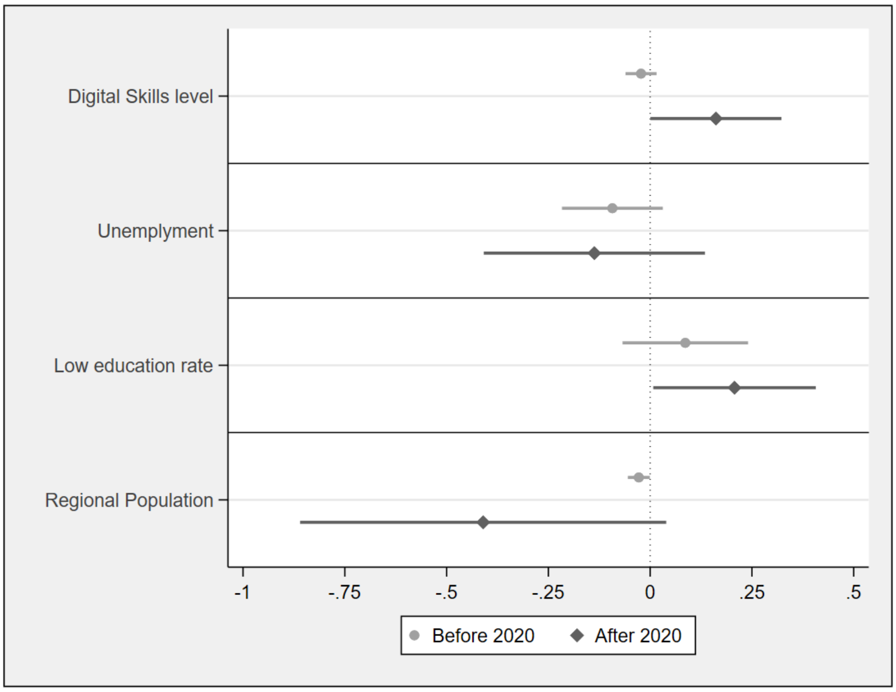

Figure 5.1: Pre- and post-COVID regression with control variables

disposable income relative to the national average. This could be attributable to the strong presence of traditional industries (e.g., manufacturing) within regions with low levels of education, or to the fact that those regions' cost of living is likely lower than the national average, thereby influencing households' purchasing power. While statistically significant, the interpretation of this coefficient is complex and moves beyond the scope of this study. The behavior of control variables was found to be unstable across the different analyses so, not being them the core interest of this study, it will not be further discussed in the following regressions.

Overall, the expected increase in robustness upon adding the control variables theorized in hypotesis *H2* (3.1), is only partially realized, specifically in the post-COVID-19 timeframe. This result suggests that digital expertise might have shifted from being a marginal determinant of economic wealth to a crucial one in the post-pandemic era.

5.3 Clustering of regions

In this Section regions are divided according to their GDP per capita level and separate regressions are performed for each group. This study employs the categorization criterion used by the European Union for the allocation of Cohesion funds

[25], a measure aimed at mitigating regional economic disparities. As discussed in Section 4.2, the methodology divides NUTS2 European regions into *Less Developed*, *Transition* and *More Developed* regions. Specifically, the number of regions within each category is detailed in table 5.2:

Table 5.2: Number of regions by development category

Category	Quantity
Less Developed	105
Transition	56
More developed	120

This analysis is expected to yield valuable insights into the role played by Digital Skills for regions with different levels of economic productivity, which should then enable an assessment of whether more developed regions are indeed more reliant on digital skills compared to less developed ones to enhance wealth (hypotesis $H3$, 3.1).

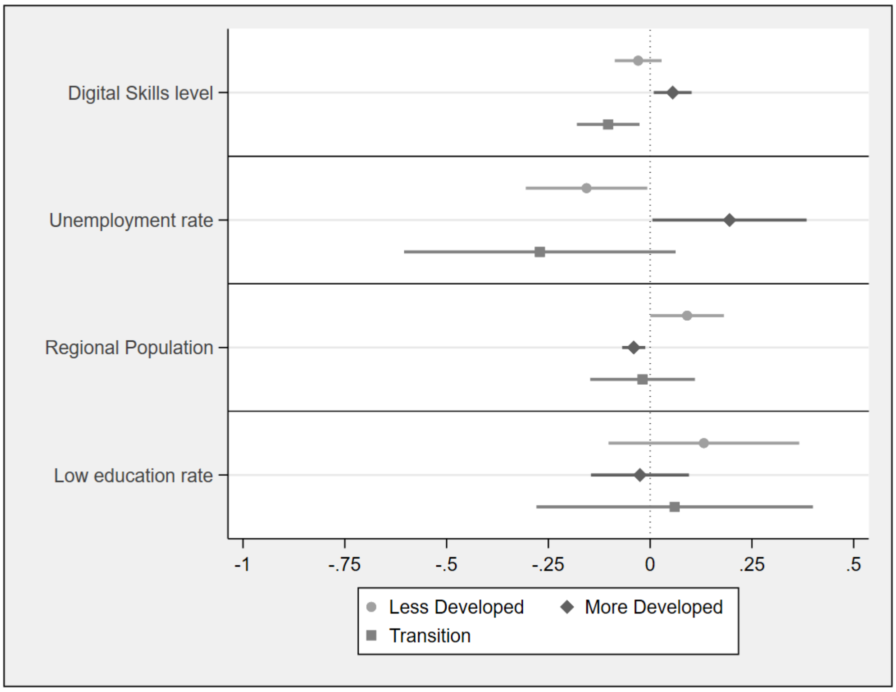

Figure 5.2: Estimated coefficients for the three regional clusters before the COVID-19 pandemic

Before going in detail of the specific findings for each regional category, the aggregated regression results for all the regional categories are presented. This provides a high-level overview of how the relationships between the variables have changed from the pre- to the post-2020 period.

As figure 5.2 shows, the results for the pre-pandemic timeframe differ among the three categories: the effect of the *Digital Skill Level* is not statistically significant for Less Developed regions, while it is significant but with coefficients of opposite signs for the More Developed and Transition regions. Likewise, control variables' coefficients vary both in sign and magnitude for the three categories, highlighting the heterogeneous impact that the same factor has on regions with diverse economic prosperity.

On the other hand, the post-pandemic analysis of the *Digital Skill Level* displays more homogeneous results, with all coefficients being statistically significant. Both More Developed and Less Developed regions exhibit a positive coefficient for the independent variable. For Transition regions, however, the regional difference in disposable income relative to the national average remains negatively impacted by the level of digital expertise. This result deviates from the trend observed in the other categories and it will be examined in detail in Section 5.3.2.

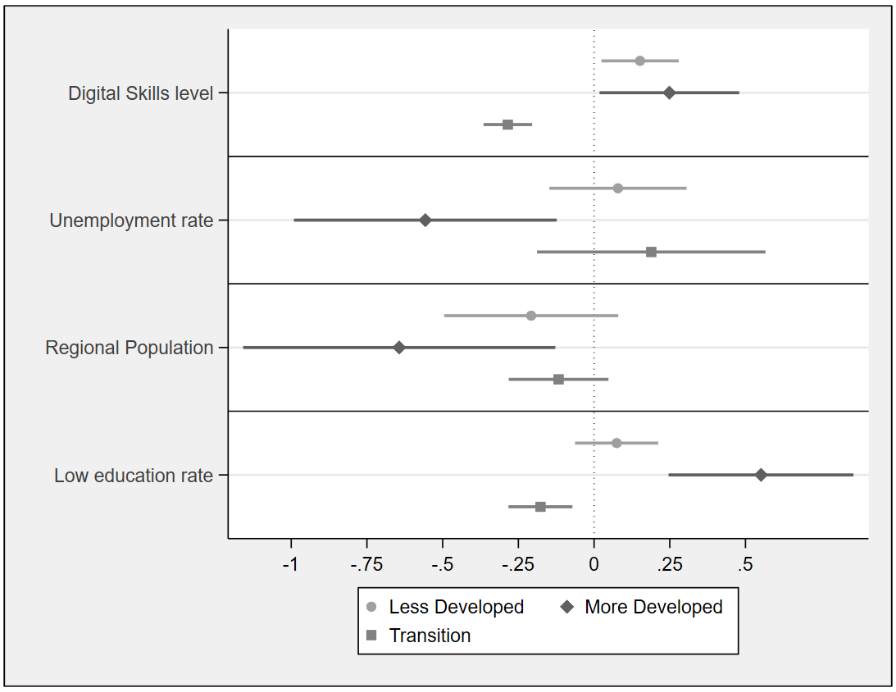

Figure 5.3: Estimated coefficients for the three regional clusters after the COVID-19 pandemic

5.3.1 Less Developed regions

These regions are defined as those with a GDP per capita that is lower than 75% of the European average. Most of these regions are in the south or east of Europe, with Poland, Greece, and Hungary having the highest number of regions within this classification (17, 14, and 11 regions respectively).

Table 5.3: Highest Quantity of Less Developed Regions by Country

Country	Quantity
Poland	17
Greece	14
Hungary	11
Spain	9
Czechia	8

Results for this group display how the digital skill level becomes a significant driver of wealth enhancement in the post-COVID-19 period.

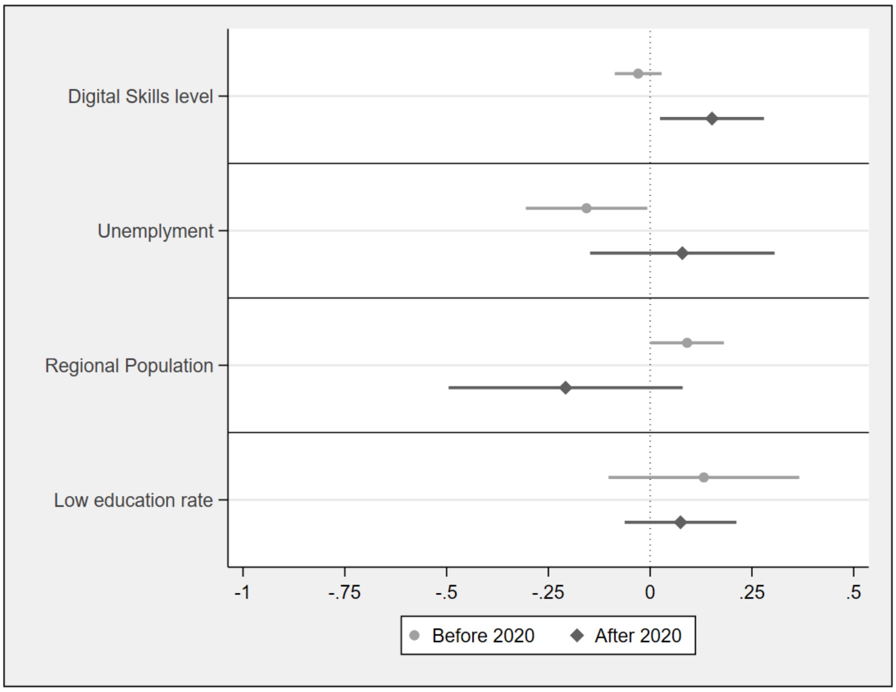

Figure 5.4: Estimated coefficients for Less Developed Regions, comparing the pre- and post-pandemic periods

The significant improvement in statistical significance after the pandemic suggests that digital expertise started generating positive effects even on economies traditionally reliant on less knowledge-intensive industries. Specifically, since these regions generally possess a negative percentage distance of disposable income relative to the national average, the positive coefficient observed implies that higher digital skill levels augment this percentage difference by making it less negative. Consequently, this effect acts as a powerful force for convergence and helps mitigating the income gap between these poorer regions and the national average. This offers valuable insights to policymakers involved in developing measures to support the less developed regions of their countries.

5.3.2 Transition regions

Transition regions are characterized by a GDP per capita located between 75% and 100% of the European average. Most French regions belong to this category (23), while Spain and Germany respectively count 8 and 7 regions in this category. It is important to note that the limited sample size (only 56 regions) may be a determinant of weak statistical significance. This is particularly relevant for the post-COVID-19 period, for which only data from 2021 and a portion of 2023 records were available.

Table 5.4: Highest Quantity of Transition Regions by Country

Country	**Quantity**
France	23
Spain	8
Germany	7
Italy	4
Belgium	4

Findings in this group evidently deviate from those of other regressions as after the pandemic the coefficient of *Digital Skill Level* seems to worsen the gap between regional and national average disposable income.

This result is in contrast to those observed for More Developed and Less Developed regions and highlights the complexity of economic dynamics across European regions. A possible explanation for this observation comes from the theory of labor market polarization by Autor [31]. This study demonstrated how automation in the U.S. labor market was mainly affecting middle-skilled workers, for example, in the manufacturing, service, and administration sectors. The research posits that the reason for job automation lies on job routines rather than workers' education, leaving highly skilled workers, such as managers in companies, and low skilled employees, such as cleaners, with non-routine jobs less exposed to automation.

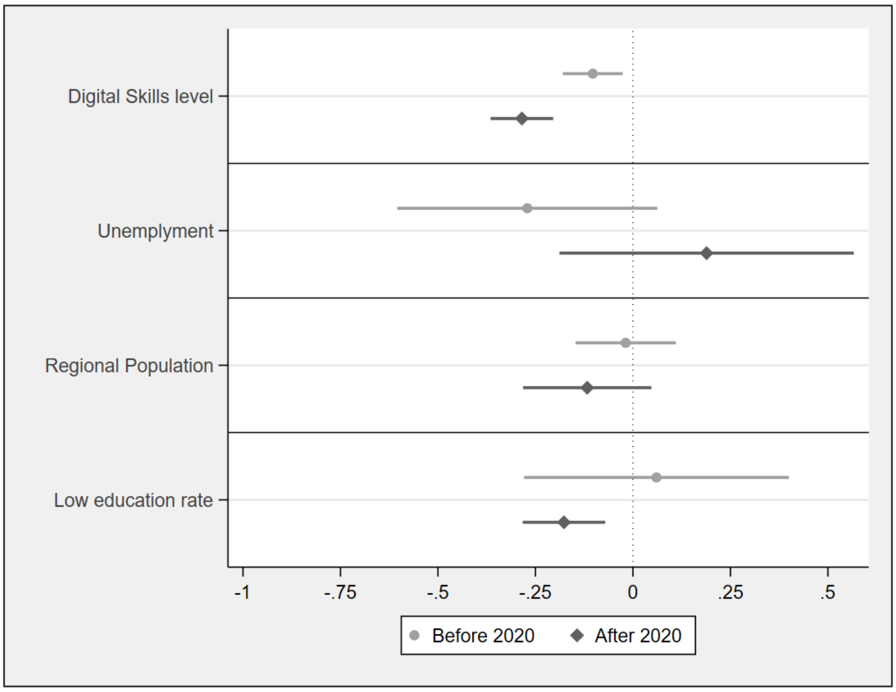

Figure 5.5: Estimated coefficients for Transition Regions, comparing the pre- and post-pandemic periods

Likewise, Transition Regions, with their 'middle' level of GDP per capita, are likely characterized by middle-skilled jobs which, after the 2020 pandemic, may have been more susceptible to automation or wage stagnation. Therefore, the creation of high-value jobs is crucial for the economic growth of regions that suffer these labor market changes.

It is worth pointing out that the study by Autor et al. focused on the U.S. labor market, and European economies may be characterized by different dynamics. Nevertheless, this theoretical framework helps in formulating hypotheses that could be tested in dedicated further studies.

5.3.3 More developed regions

The European Parliament refers to More Developed regions as those whose GDP per capita exceeds the European average (31.383€ per inhabitant in 2023). Most German regions (39) belong to this category, as well as central-north Italian regions (11). Also, countries such as Sweden, Denmark, and the Netherlands have no regions whose GDP per capita falls below the European threshold.

As Figure 5.6 illustrates, the individuals' level of digital skills becomes an even

Table 5.5: Highest Quantity of More Developed Regions by Country

Country	Quantity
Germany	39
Sweden	12
Netherlands	11
Italy	11
Austria	9

more impactful determinant of inter-regional disposable income disparity after the COVID-19 pandemic.

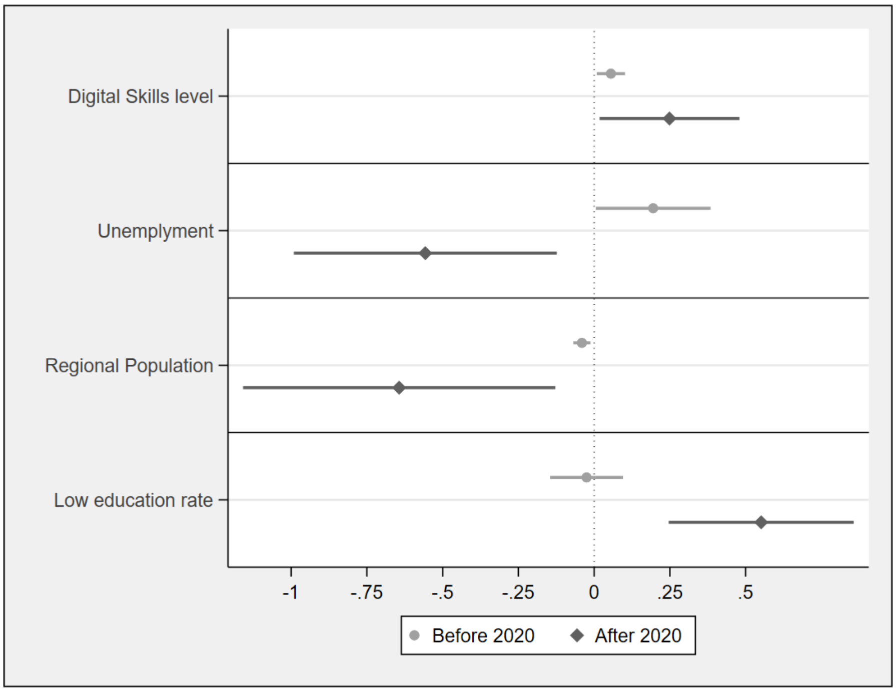

Figure 5.6: Estimated coefficients for More Developed Regions, comparing the pre- and post-pandemic periods

This result confirms the thesis of $H4$ 3.1, which posits that the impact of the independent variable would be stronger in More Developed regions since their economies are increasingly reliant on digital-intensive industries, such as fintech, software development, and e-commerce. As Ibrahim notes [15], more developed areas are typically better positioned in terms of physical infrastructure, human capital, and policies, which magnify the advantages of investments in digital technologies. When combined with digital expertise and organization, ICT investments can lead to significant increases in productivity and, consequently, to economic growth in these areas.

5.4 Exploratory and Supplementary Analyses

As explained in Section 4.7, two supplementary analyses were performed substituting the primary independent and dependent variables with related but conceptually distinct indicators. This approach should expand the understanding of the link between digitalization and regional economic outcomes within European regions.

5.4.1 Substituting Digital Skills with a Proxy for Internet Access

The following analysis employs the same control and dependent variables as the original study, while considering the share of regional population who can access the internet as independent variable. Instead of focusing on individuals' level of expertise, this approach highlights the role of technological infrastructures in improving regional purchasing power relative to the national average.

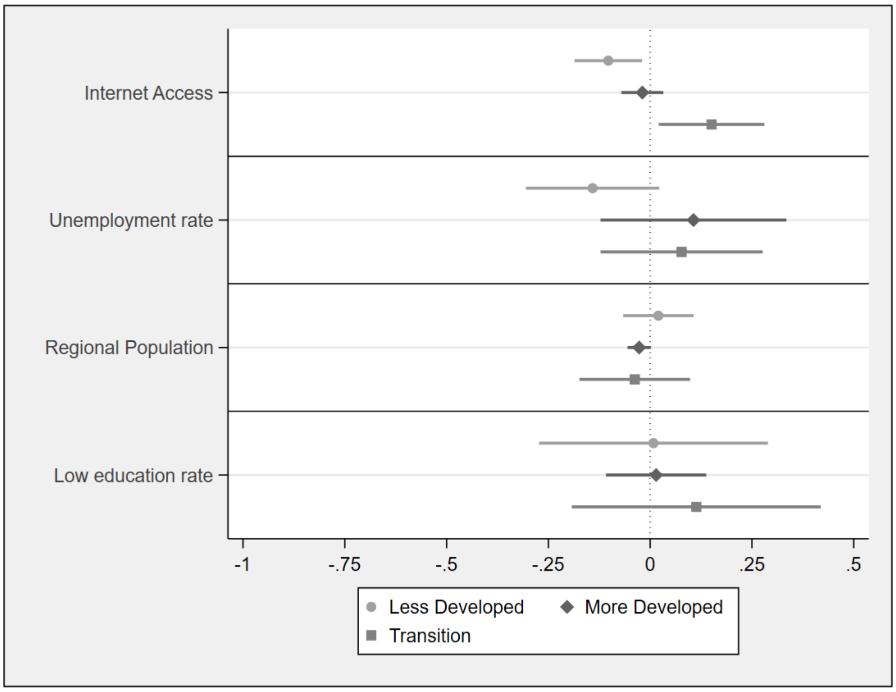

Figure 5.7: Estimated coefficients for the impact of internet access on disposable income, by regional cluster, during the pre-pandemic period

As Figures 5.7 and 5.8 display, internet access is a determinant of purchasing power improvement relative to the national average in Less Developed regions in the post-2020 period, while it was a hindering factor before 2020. Transition regions display a similar trend to that of Section 5.3, with a positive sign before 2020 and a negative value afterward. Interestingly, the coefficients for More Developed regions are not statistically significant in either the pre- or post-2020 periods.

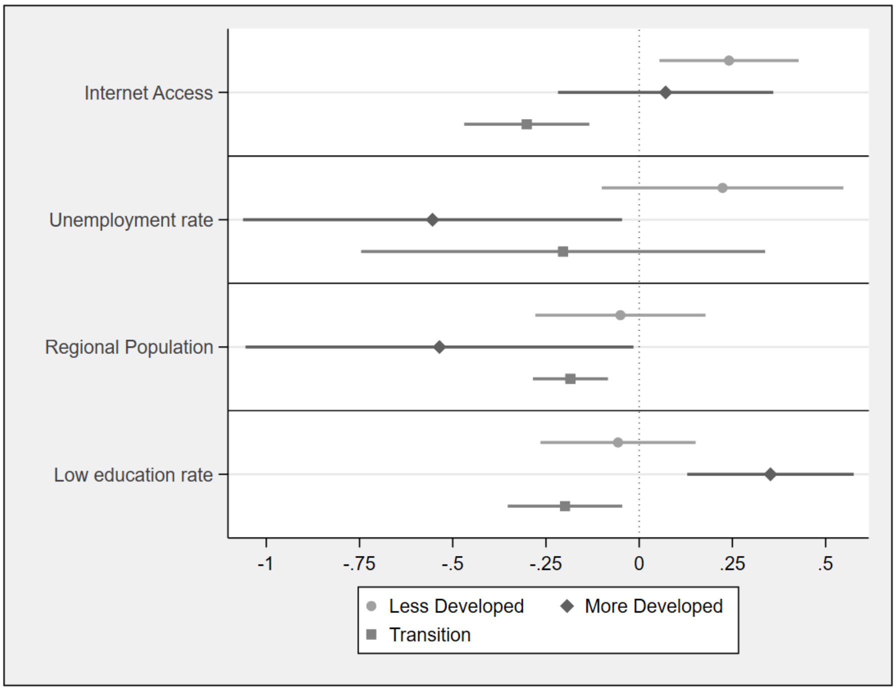

Figure 5.8: Estimated coefficients for the impact of internet access on disposable income, by regional cluster, during the post-pandemic period

These results are overall aligned with those of the original study, signaling that internet access and digital skills' development are correlated factors and have a similar effect on average regional disposable income trends. However, regressions that do not include regional categorization and control variables are not statistically significant (tables 10, 11, 12). The greater statistical significance of the digital expertise coefficient, compared to that of internet coverage, suggests that the level of digital expertise is a more reliable predictor of changes in regional purchasing power relative to the national average.

5.4.2 The Impact of Digital Skills on Regional GDP per Capita

This additional regression employs the GDP per capita instead of the average disposable income as dependent variable. To ensure methodological continuity, the indicator measures the percentage difference between the GDP of regions per capita and the national average. This approach highlights the impact that regional level of digital skills has on regional productivity rather than the average purchasing power.

As reported in the Appendix (tables 21 - 26), tests with regional categorization led to statistically insignificant results, while the regression on the overall sample led to a statistically significant coefficient in the post-2020 period.

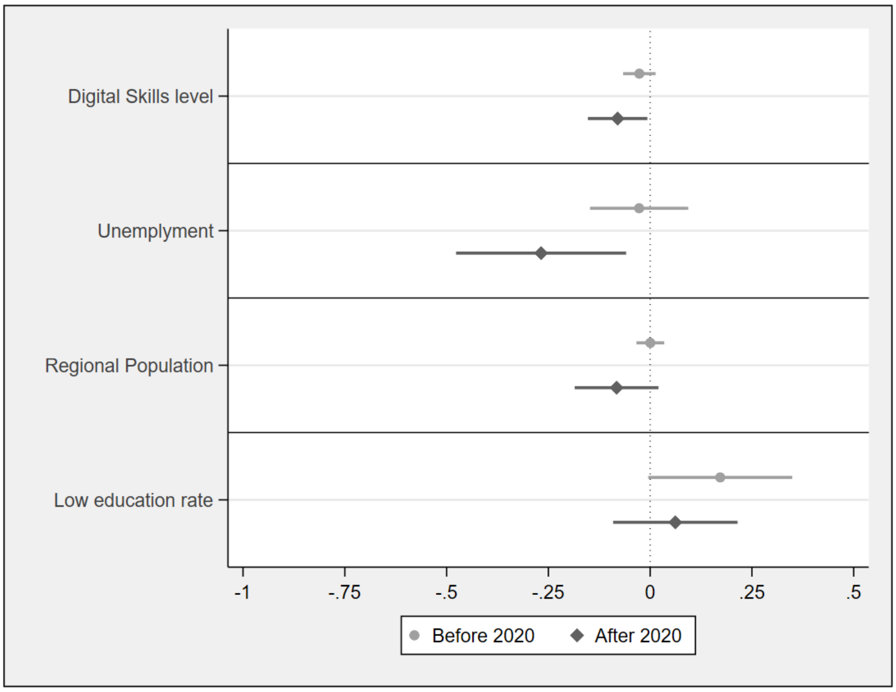

Figure 5.9: Estimated coefficients for the impact of digital skills on GDP per capita during pre- and post-pandemic periods

The surprising finding of this result is the negative coefficient of *Digital Skill level* in the post-pandemic period, meaning that in that period a higher level of regional digital expertise is associated with a lower GDP per capita relative to the national figure. Instead, results in Section 5.2 showed how the level of digital expertise positively impacted the average disposable income of a region relative to the national figure.

These opposite results highlight the complexity of these economic dynamics, which can lead to counter-intuitive findings. The negative relationship between the *Digital Skill level* and a region's GDP per capita may be an evolution of IT productivity paradox, a phenomenon described by Brynjolfsson and Hitt [32]. Their study highlights how large-scale investment in information technology often does not immediately translate into higher productivity, leading to a temporary lag. This is primarily attributed to the need for firms to make significant complementary investments in organizational changes and business process redesign to effectively utilize the new technology. Even though the Brynjolfsson and Hitt study focused on firm-level IT investments and their impact on productivity, the acceleration of post-pandemic regional digital investments may have produced a similar lag.

According to the results analyzed, the level of digital skills in a region positively affects local purchasing power, while slightly limiting regional overall productivity. This provides an interesting perspective for policy makers involved in designing plans aimed at minimizing regional wealth disparity. Specifically, prioritizing digital skills development may be a more effective strategy for minimizing socioeconomic inequality than for increasing aggregate regional productivity.

Chapter 6

Policy implications

The core finding of this research is that, following the exogenous shock of the COVID-19 pandemic, the average level of digital expertise positively affects a region's positioning in terms of disposable income relative to the national average. The robustness of results registered even in Europe's Less Developed Regions designates digital skills acquisition as a powerful cohesion policy tool for supporting more homogeneous wealth growth across Europe. The increased economic impact of digital skills after the pandemic confirms the importance of digital expertise in today's labor market and demands urgent policy interventions.

6.1 The Policy Imperative: Digital Skills as a Cohesion Tool

The potential of digital skills in reducing income disparity, even for the poorest regions, confirms that targeted investments in the development of digital competencies are crucial for less developed areas to bridge the gap with wealthier ones.

This finding aligns with the work by Myovella et al. (2020) [10], which demonstrates how digitalization positively contributes to economic growth regardless of a country's development level, although the magnitude of this effect may vary for richer and poorer countries. Similarly, Bon (2021) [18] concludes that, leveraging digitalization, developing countries can foster workers' upskilling and productivity increases, thereby lowering the distance with more advanced economies. This thesis provides an additional layer to these studies by focusing on the inter-regional wealth disparity (in terms of disposable income) rather than country-level growth rates.

Moreover, this research offers an additional perspective to the study by Consoli et al. (2023) [11], whose research focused on the link between e-skills and within-region (intra-regional) income disparity. The research concluded that while higher e-skills are associated with lower inequality among high-income groups, they are correlated with greater inequality among lower-income groups. Consequently, policies aiming in this direction must be carefully designed to ensure equal accessibility to the population to avoid wealth gaps increases across individuals within regions.

6.2 Nuance in Policy Design: The Case of Transition Regions

While digital skills generally reduce wealth disparity, the analysis reveals a more complex dynamic within Transition Regions. For this cluster, results show that the relationship between digital skills and the disposable income gap is negative, even after the 2020 pandemic and the consequent acceleration in digital technologies' adoption. This counter-intuitive result suggests that digitalization's impact is not uniform and may depend on specific regional characteristics, such as industrial composition and the capabilities of the existing workforce.

A possible explanation of this outcome could lie on transition economies employing significant shares of mid-skilled workers who perform repetitive and predictable tasks and are, consequently, highly susceptible to automation. This mechanism might lead to job displacement or wage stagnation, which negatively impacts disposable income, even if the general level of digital skills increases. This finding demands that policy interventions be carefully designed and tailored to the unique industrial structure and specific labor market needs of different regions.

6.3 Addressing the Supply Side: Lifelong Learning and Reskilling

Given the impact digital skills can have on reducing regional economic gaps, any effective policy in this direction must incentivize the broad upskilling of the regional workforce. This requirement is particularly pertinent in Europe, where the long-lasting trends of aging populations and demographic decline require the existing workforce to increase its productivity. This is why digital upskilling and reskilling initiatives should actively involve older individuals who do not possess this skill set. Studies confirm that senior workers often face increased barriers to acquiring digital skills, including a lack of formal training and the challenge of adapting to rapidly evolving tools (LIUC (2025) [33]).

To prevent job displacement and maintain economic competitiveness, policymakers must prioritize accessible and tailored learning opportunities. Initiatives such as the Reskilling 4 Employment (R4E) [34], a company-driven program launched by the European Round Table for Industry (ERT), provide a positive example of what policymakers should incentivize. The R4E built corporate and educational partnerships, aligning training with high-demand digital occupations and successfully transitioned at-risk workers into modern roles that are more reliant on digital technologies.

6.4 Investing in the Future: Digital Education

In order to provide a sustained digital skills-based economic transformation, a decisive push must come from new generations, who are inherently well positioned for the adaptability and open-minded view required for facing advanced technological challenges. For younger generations to be prepared to steer such change, the educational system must involve studying digital literacy from an early age. This would empower students to become not just consumers of technology, but active participants in identifying avant-garde solutions to drive growth in emerging sectors. To prevent digital skill deficits and prepare new generations to lead this evolution, policies must foster training in these fields throughout the entire pre-tertiary educational path.

Current data highlights a critical failure in this area: over 40% of 13-14-year-olds in the EU lack basic digital skills (ICILS, 2023 [35]). This result should alarm EU legislators, whose objective is to reduce this figure to below 15% by 2030. This gap is often attributed to the lack of digital infrastructure in schools and a lack of preparedness among teachers to integrate technology into their lessons. To mitigate these concerning results, greater focus and resources should be dedicated to initiatives such as the EU Digital Education Action Plan (2021-2027) [36]. This plan was adopted to foster online learning and to address the problems of teachers being unprepared to integrate digital technologies in their lessons, and that overall digital skills levels remain low across the EU. This initiative is thought for prioritizing the development of a high-performing digital education ecosystem and the enhancement of digital skills in face of the digital transition. Specifically, the Plan involves measures to increase connectivity and digital equipment in schools, provide free specializing training and support for educators. This would improve teachers' digital confidence while updating their curricula to integrate emerging technologies. The final goal is to pose the educational focus on mastering digital skills and ensure the EU workforce is prepared to face the challenges of future labor market.

Effective policy must, therefore, prioritize professional development for educators and ensure equitable access to high-quality digital tools and infrastructure for every student. By posing an increased focus on digital competencies in compulsory education, regions can provide the future workforce with useful skill sets to deploy in the labor market. As demonstrated, investments in this direction can significantly contribute to shortening income disparity between poorer and richer regions in European countries.

6.5 Targeted Regional Strategies for Wealth Creation

The findings of this research emphasize that interventions tailored to the specific industrial composition and development level of each region should be preferred over unique country-level policies.

Transition Regions offer an example of heterogeneity among the clusters, with the negative relationship between digital skills and the disposable income gap registered even after the COVID-19 pandemic. While general policies toward upskilling workers are crucial to maintain competitiveness, these regions might require them to be coupled with a rethinking of the industrial mix toward more digital-related and knowledge-intensive sectors. Upskilling workers without intervening on the regional economic structure might induce gaps in the demand for work, with the workforce being overqualified and able to be involved in jobs that do not yet exist in their region.

On the other hand, for More Developed Regions, the post-COVID-19 acceleration in digitalization has significantly increased the impact of digital skills on income levels. Given richer regions can usually count on important levels of capital, infrastructure, and a skilled workforce, the market demand and companies' direct investments may be sufficient to incentivize citizens to develop digital skills autonomously. Policy focus here might lie on ensuring equal access to digital training and education rather than direct funding.

Finally, the primary target for cohesive policy intervention should be Less Developed Regions. Results consistently show that these regions can effectively shorten income gaps through digital skills development. Here, public investments in digital infrastructure and skills training might play a key role in reducing intra-national income disparity. Such investments can foster the emergence of successful initiatives like the Divina Wine Hub Šmarje case, which involved the implementation of Digital Innovation Hubs (DIHs) in rural areas. These hubs positively impacted local businesses by supporting them with technology and skilled personnel. The DIH model is an example of how digital services in less-developed areas can contribute to improving local welfare, one that policymakers should encourage for maximizing the economic returns on digital skills investment in poorer European regions.

Chapter 7

Conclusion

7.1 Summary of Research and Methodology

This study aimed to investigate the extent to which the evolution of individuals' digital skills is associated with changes in regional disposable income relative to the national average. The research employed a panel data empirical design involving records from 259 NUTS-2-level European regions over the 2015–2023 period.

The principal variables of interest were: the share of individuals with basic or above basic level digital skills (independent variable), which includes abilities such as problem-solving and safety skills; the percentage difference of a region's average disposable income compared to the national average (dependent variable). The individuals' digital skill level was chosen over other indicators (such as Internet access or usage frequency) because this measure better captures the population's average expertise in using digital technologies productively. Conversely, regional disposable income disparity provides a policy-relevant measure of intra-national differences in households' purchasing power, while avoiding scale-related distortions among countries with different levels of economic development.

The econometric analysis was conducted with the Fixed Effects (FE) model, which was confirmed as the preferred estimator by the Hausman test. This method effectively controls for unobserved, time-invariant regional characteristics (e.g., historical context or geographical advantages) that could lead to omitted variables bias.

To account for other important factors, the analytical strategy involved: introducing the control variables *Unemployment rate*, *Regional population*, and *Low education* rate to account for labor market, demographic, and educational dynamics; dividing between pre- and post-COVID-19 periods; dividing regions into clusters based on their level of GDP per capita. The cluster division was particularly useful to observe the impact of digital skills on regions with different levels of economic development. Likewise, the pre- and post-pandemic distinction was crucial given the acceleration of digital transformation this exogenous shock provoked, which also coincided with Eurostat's reclassification of the digital skills indicator (DSI 2.0, 4.2).

7.2 Core Findings and Contribution

The core results established a generally statistically significant and positive association between digital skills and percentage regional-national difference in disposable income, especially after the COVID-19 pandemic. However, a divergent trend was observed for Transition Regions, which, unlike More and Less Developed regions, registered a negative impact of digital skills that even worsened after COVID-19.

The initial analysis using the Fixed Effects model revealed a positive but statistically insignificant relationship between digital skills and changes in disposable income disparity, suggesting that the relationship was not statistically robust without controlling for other influential factors. The inclusion of control variables only achieved statistical significance for the *Digital Skill Level* coefficient in the post-COVID-19 analysis, confirming that after the pandemic digital expertise became a determinant of economic growth for various industries.

The subsequent clustering analysis revealed three key findings:

- Less Developed Regions shifted from a non-significant connection between variables before 2020 to a positive and statistically significant relation after the pandemic, suggesting that digital skills have recently become a determinant of improvements in disposable income levels for the poorest European regions.
- In More Developed Regions, the individual level of digital skills already positively impacted disposable income before 2020 and became even more impactful afterward, confirming that advanced economies increasingly rely on digital-intensive industries for growth.
- Transition Regions presented a divergent finding: digital skills appear to negatively affect the regional disposable income positioning after the pandemic. This result is potentially explained by the theory of labor market polarization, where repetitive jobs performed by mid-skilled workers are susceptible to automation, leading to wage stagnation or job displacement, even as general digital skill levels rise.

A supplementary analysis using GDP per capita instead of disposable income yielded a contrasting result: the coefficient for digital skill level was negative in the post-pandemic era. This finding suggests that while digital skill improvement generally helps minimize intra-national purchasing-power disparities, these benefits might not immediately translate into regional increases of productivity. This could be a consequence of the productivity paradox or lag, which manifests when significant complementary investments are needed to fully leverage new technologies. This suggests that focusing on digital skills might be a more immediate strategy for bridging wealth gaps than for immediately increasing aggregate regional productivity.

7.3 Positioning in Existing Literature

This study contributes to the literature by addressing the unexplored relationship between digital expertise and inter-regional inequality. Contrary to other work, which focused on aggregate measures (such as Internet access [14]) or on the impact on intra-regional inequality [11], this thesis focuses on the impact that human capital can produce on regional wealth. Moreover, the percentage difference in disposable income relative to the national average offers a clear metric of changes in households' purchasing power within a region, while being robust against scale differences across countries.

7.4 Policy Implications

The results across regional clusters generate insights for policy interventions, specifically in the perspective of using digital skills as a societal cohesion tool. The fact that digital skills reduce income disparity, especially in Less Developed Regions, indicates digital expertise as a powerful factor for contrasting inter-regional wealth inequalities and for supporting more homogeneous wealth growth across Europe. Given the increased economic impact of digital skills post-2020, policymakers are demanded to promptly intervene, prioritizing public investments in digital infrastructure and skills training, especially in these less developed areas.

However, the heterogeneous results underscore that interventions must be tailored to the specific industrial composition and development level of each region. In particular:

- Transition Regions require specialized attention due to the hypothesized labor market polarization. Here, policy interventions towards digital skill enhancement may need to be coupled with a rethinking of the industrial mix toward more digital-related and knowledge-intensive sectors.

- More Developed Regions should focus on sustaining their high-value expertise by ensuring continuous investment in advanced digital education and maintaining quality infrastructure to amplify the benefits of digital technology investments. The focus of policies here might lie on ensuring equal access to advanced training rather than direct funding.
- Less Developed Regions should remain the primary target for cohesion policy intervention, incentivizing the development of digital skills as a key factor to reduce the wealth gap with More Developed regions.

Effective policies must also incentivize the broad upskilling and reskilling of the regional workforce, particularly involving elder individuals, who are often the most vulnerable class of workers in the face of job displacement. Additionally, to provide a sustained and digital-driven transformation of the regional industrial composition, the educational system must encourage digital training throughout the educational path. Given the concerning fact that over 40% of 13–14-year-olds in the EU lack basic digital skills [35], greater resources should be dedicated to training teachers and offering free advanced digital services to students.

7.5 Limitations and Caveats

To ensure accuracy, the existing limitations of this study must be acknowledged, especially concerning the methodology employed and the resulting data interpretation.

A primary limitation stems from the creation of the independent variable: since Eurostat only provided digital skills data at the national level, the regional digital skill level was proxied by assuming it was exactly concentrated as Human Resources in Science and Technology (HRST) in the same area. Despite the plausibility of this assumption, relying on HRST as a proxy introduces limitations regarding the precision of regional estimates.

Furthermore, these types of studies inherently suffer from endogeneity, arising from the possibility of reverse causality among variables. As regional income level is likely a main driver of digital skills development, the estimated coefficients should be interpreted as robust associations rather than strict causal effects.

Moreover, a robustness check using a lagged dependent variable revealed that the prior year's disposable income significantly influences subsequent observations. This confirms the importance of path-dependence in regional economic phenomena.

Finally, a visible data inconsistency was detected in the German digital skills variable between 2019 and 2021, where a drastic reduction was observed in the share of the population possessing basic or above-basic digital skills. Although Germany was excluded from the overall initial analysis and this represented an isolated anomaly, it introduces some uncertainty regarding the data collection methodology employed by Eurostat.

7.6 Directions for Future Research

The findings of this study provide insights for future research that could improve the understanding of these complex dynamics.

Future research should specifically investigate the divergent findings in Transition Regions. Dedicated studies could analyze the industrial composition of such regions to verify whether the negative impact of digital skills is fully attributable to labor market polarization, or if other region-specific factors are at play.

Further work might as well track the temporary productivity lag suggested by the negative GDP per capita coefficient in the supplementary analysis. Future research could examine whether this lag persists, how long it lasts beyond the pandemic period, and whether the positive effects of digital skills eventually translate into regional productivity gains.

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Appendix

.1 Numerical results

This Annex contains the full numerical output for the statistical models presented in the 'Results' chapters 5. These tables are provided to support the summarized findings and to aid in replication and detailed review.

Table 1: Numerical results of the overall analysis (no Contro Variables) before and after 2020 (5.1)

	Before 2020	**After 2020**
Skill Level	-0.0121	0.0325
Std. Error	0.0263	0.0456
t-value	-0.46	0.71
P-value	0.646	0.476
90% CI	[-0.0555, 0.0313]	[-0.0427, 0.1077]
Constant	-1.290 ($p = 0.365$)	-3.225 ($p = 0.179$)
R^2 Within	0.0005	0.0049
Groups	259	258
Observations	1,012	319

Table 2: Numerical results of the analysis with Control Variable integration Before 2020 (5.2)

Statistic	**Skill Level**	**Unemplyment**	**Population**	**Education**
Coefficient	-0.0224	-0.0927	-0.0278*	0.0864
Std. Error	0.0231	0.0750	0.0164	0.0934
t-value	-0.97	-1.24	-1.70	0.92
P-value	0.334	0.218	0.091	0.356
90% CI Low	-0.0605	-0.2166	-0.0548	-0.0678
90% CI High	0.0158	0.0311	-0.0007	0.2406
Constant	4.413 ($p = 0.286$)			
R^2 **Within**	0.0112			
Groups	257			
Observations	1,003			
* Denotes significance at the $p < 0.10$ level.				

Table 3: Numerical results of the analysis with Control Variable integration After 2020 (5.2)

Statistic	**Skill Level**	**Unemplyment**	**Population**	**Education**
Coefficient	0.1615*	-0.1370	-0.4101	0.2072*
Std. Error	0.0975	0.1645	0.2723	0.1209
t-value	1.66	-0.83	-1.51	1.71
P-value	0.099	0.406	0.133	0.088
90% CI Low	0.0006	-0.4086	-0.8598	0.0076
90% CI High	0.3225	0.1346	0.0395	0.4069
Constant	73.178 ($p = 0.157$)			
R^2 **Within**	0.2007			
Groups	254			
Observations	315			
* Denotes significance at the $p < 0.10$ level.				

Table 4: Numerical results for Less Developed Regions analysis Before 2020 (5.3.1)

Statistic	Skill Level	Unemplyment	Population	Education
Coefficient	-0.0294	-0.1562*	0.0908*	0.1320
Std. Error	0.0346	0.0898	0.0543	0.1409
t-value	-0.85	-1.74	1.67	0.94
P-value	0.399	0.085	0.098	0.351
90% CI Low	-0.0870	-0.3054	0.0006	-0.1022
90% CI High	0.0282	-0.0070	0.1811	0.3661
Constant	-24.4237 ($p = 0.006$)			
R^2 Within	0.0194			
Groups	93			
Observations	363			
* Denotes significance at the $p < 0.10$ level.				

Table 5: Numerical results for Less Developed Regions analysis After 2020 (5.3.1)

Statistic	Skill Level	Unemplyment	Population	Education
Coefficient	0.1519*	0.0790	-0.2076	0.0747
Std. Error	0.0769	0.1364	0.1730	0.0826
t-value	1.98	0.58	-1.20	0.90
P-value	0.051	0.564	0.233	0.368
90% CI Low	0.0242	-0.1476	-0.4951	-0.0626
90% CI High	0.2796	0.3057	0.0799	0.2120
Constant	18.2688 ($p = 0.491$)			
R^2 Within	0.2154			
Groups	92			
Observations	109			
* Denotes significance at the $p < 0.10$ level.				

Table 6: Numerical results for More Developed Regions analysis Before 2020 (5.3.3)

Statistic	Skill Level	Unemplyment	Population	Education
Coefficient	0.0554*	0.1949*	-0.0403**	-0.0249
Std. Error	0.0280	0.1141	0.0171	0.0726
t-value	1.97	1.71	-2.35	-0.34
P-value	0.051	0.091	0.020	0.732
90% CI Low	0.0088	0.0056	-0.0687	-0.1453
90% CI High	0.1019	0.3843	-0.0119	0.0955
Constant	8.9684 ($p = 0.079$)*			
R^2 **Within**	0.0732			
Groups	110			
Observations	429			
* Denotes significance at the $p < 0.10$ level; ** Denotes significance at the $p < 0.05$ level.				

Table 7: Numerical results for More Developed Regions analysis After 2020 (5.3.3)

Statistic	Skill Level	Unemplyment	Population	Education
Coefficient	0.2488*	-0.5572**	-0.6435**	0.5514**
Std. Error	0.1390	0.2616	0.3107	0.1840
t-value	1.79	-2.13	-2.07	3.00
P-value	0.076	0.035	0.041	0.003
90% CI Low	0.0181	-0.9911	-1.1589	0.2460
90% CI High	0.4794	-0.1232	-0.1281	0.8567
Constant	140.9199 ($p = 0.047$)**			
R^2 **Within**	0.3894			
Groups	109			
Observations	142			
* Denotes significance at the $p < 0.10$ level; ** Denotes significance at the $p < 0.05$ level				

Table 8: Numerical results for Transition Regions analysis Before 2020 (5.3.2)

Statistic	Skill Level	Unemplyment	Population	Education
Coefficient	-0.1030**	-0.2709	-0.0186	0.0603
Std. Error	0.0459	0.1992	0.0768	0.2028
t-value	-2.24	-1.36	-0.24	0.30
P-value	0.029	0.180	0.810	0.767
90% CI Low	-0.1799	-0.6043	-0.1472	-0.2792
90% CI High	-0.0262	0.0625	0.1100	0.3999
Constant	11.4522 ($p = 0.525$)			
R^2 **Within**	0.0628			
Groups	54			
Observations	211			
* Denotes significance at the $p < 0.10$ level; ** Denotes significance at the $p < 0.05$ level.				

Table 9: Numerical results for Transition Regions analysis After 2020 (5.3.2)

Statistic	Skill Level	Unemplyment	Population	Education
Coefficient	-0.2848**	0.1889	-0.1172	-0.1769**
Std. Error	0.0479	0.2253	0.0983	0.0631
t-value	-5.94	0.84	-1.19	-2.80
P-value	0.000	0.406	0.239	0.007
90% CI Low	-0.3651	-0.1884	-0.2817	-0.2826
90% CI High	-0.2045	0.5662	0.0474	-0.0712
Constant	40.5410 ($p = 0.054$)*			
R^2 **Within**	0.6184			
Groups	53			
Observations	64			
* Denotes significance at the $p < 0.10$ level				

Table 10: Numerical results using Internet Access and no Control Variables for pre- and post-2020 periods (5.4.1)

Statistic	**Before 2020**	**After 2020**
Internet Acc	-0.0156	0.0047
Std. Error	0.0282	0.0923
t-value	-0.55	0.05
P-value	0.581	0.960
90% CI Low	-0.0622	-0.1478
90% CI High	0.0310	0.1572
Constant	-0.7074 ($p = 0.767$)	-1.8914 ($p = 0.824$)
R^2 **Within**	0.0020	0.0000
Groups	196	196
Observations	754	257

Table 11: Numerical results using Internet Access and Control Variables, period before 2020 (5.4.1)

Statistic	**Internet Acc**	**Unemplyment**	**Population**	**Education**
Coefficient	-0.0132	-0.0392	-0.0141	0.0652
Std. Error	0.0443	0.0626	0.0171	0.1208
t-value	-0.30	-0.63	-0.82	0.54
P-value	0.766	0.531	0.411	0.590
90% CI Low	-0.0864	-0.1426	-0.0424	-0.1344
90% CI High	0.0600	0.0641	0.0142	0.2649
Constant	1.1469 ($p = 0.879$)			
R^2 **Within**	0.0058			
Groups	196			
Observations	754			

No coefficients are significant at the $p < 0.10$ level.

Table 12: Numerical results using Internet Access and Control Variables, period after 2020 (5.4.1)

Statistic	**Internet Acc**	**Unemplyment**	**Population**	**Education**
Coefficient	0.0811	-0.1293	-0.2916	0.1297
Std. Error	0.0946	0.1707	0.2367	0.0863
t-value	0.86	-0.76	-1.23	1.50
P-value	0.392	0.450	0.220	0.135
90% CI Low	-0.0752	-0.4115	-0.6828	-0.0130
90% CI High	0.2374	0.1529	0.0997	0.2723
Constant	52.2215 ($p = 0.289$)			
R^2 **Within**	0.1258			
Groups	196			
Observations	257			
No coefficients are significant at the $p < 0.10$ level.				

Table 13: Numerical results using Internet Access and Control Variables for Less Developed Regions, period before 2020 (5.4.1)

Statistic	Internet Acc	Unemplyment	Population	Education
Coefficient	-0.1028**	-0.1413	0.0202	0.0083
Std. Error	0.0497	0.0981	0.0517	0.1683
t-value	-2.07	-1.44	0.39	0.05
P-value	0.043	0.155	0.697	0.961
90% CI Low	-0.1858	-0.3051	-0.0661	-0.2728
90% CI High	-0.0198	0.0226	0.1065	0.2894
Constant	-4.6716 ($p = 0.655$)			
R^2 **Within**	0.0481			
Groups	63			
Observations	246			
** Denotes significance at the $p < 0.05$ level.				

Table 14: Numerical results using Internet Access and Control Variables for Less Developed Regions, period after 2020 (5.4.1)

Statistic	Internet Acc	Unemplyment	Population	Education
Coefficient	0.2410**	0.2237	-0.0503	-0.0566
Std. Error	0.1118	0.1940	0.1367	0.1246
t-value	2.16	1.15	-0.37	-0.45
P-value	0.035	0.253	0.714	0.651
90% CI Low	0.0543	-0.1003	-0.2785	-0.2647
90% CI High	0.4276	0.5477	0.1779	0.1515
Constant	-22.7909 ($p = 0.236$)			
R^2 **Within**	0.2996			
Groups	63			
Observations	80			
** Denotes significance at the $p < 0.05$ level.				

Table 15: Numerical results using Internet Access and Control Variables for More Developed Regions, period before 2020 (5.4.1)

Statistic	**Internet Acc**	**Unemplyment**	**Population**	**Education**
Coefficient	-0.0192	0.1064	-0.0270	0.0146
Std. Error	0.0310	0.1372	0.0172	0.0741
t-value	-0.62	0.78	-1.57	0.20
P-value	0.537	0.440	0.120	0.844
90% CI Low	-0.0708	-0.1219	-0.0555	-0.1086
90% CI High	0.0323	0.3347	0.0016	0.1378
Constant	12.1404 ($p = 0.020$)**			
R^2 **Within**	0.0545			
Groups	84			
Observations	319			
** Denotes significance at the $p < 0.05$ level.				

Table 16: Numerical results using Internet Access and Control Variables for More Developed Regions, period after 2020 (5.4.1)

Statistic	**Internet Acc**	**Unemplyment**	**Population**	**Education**
Coefficient	0.0710	-0.5542*	-0.5355*	0.3521**
Std. Error	0.1735	0.3056	0.3128	0.1342
t-value	0.41	-1.81	-1.71	2.62
P-value	0.684	0.073	0.091	0.010
90% CI Low	-0.2177	-1.0625	-1.0558	0.1288
90% CI High	0.3596	-0.0459	-0.0153	0.5753
Constant	127.5723 ($p = 0.139$)			
R^2 **Within**	0.3032			
Groups	84			
Observations	117			
* Denotes significance at the $p < 0.10$ level; ** Denotes significance at the $p < 0.05$ level.				

Table 17: Numerical results using Internet Access and Control Variables for Transition Regions, period before 2020 (5.4.1)

Statistic	**Internet Acc**	**Unemplyment**	**Population**	**Education**
Coefficient	0.1510*	0.0772	-0.0378	0.1133
Std. Error	0.0773	0.1187	0.0811	0.1823
t-value	1.95	0.65	-0.47	0.62
P-value	0.057	0.518	0.644	0.537
90% CI Low	0.0212	-0.1218	-0.1737	-0.1925
90% CI High	0.2807	0.2763	0.0982	0.4192
Constant	-9.2821 ($p = 0.640$)			
R^2 **Within**	0.1267			
Groups	49			
Observations	189			
* Denotes significance at the $p < 0.10$ level.				

Table 18: Numerical results using Internet Access and Control Variables for Transition Regions, period after 2020 (5.4.1)

Statistic	**Internet Acc**	**Unemplyment**	**Population**	**Education**
Coefficient	-0.3016***	-0.2040	-0.1844***	-0.1990**
Std. Error	0.1000	0.3230	0.0600	0.0915
t-value	-3.02	-0.63	-3.07	-2.17
P-value	0.004	0.531	0.004	0.035
90% CI Low	-0.4693	-0.7458	-0.2851	-0.3525
90% CI High	-0.1338	0.3377	-0.0837	-0.0455
Constant	68.6607 ($p = 0.002$)***			
R^2 **Within**	0.5955			
Groups	49			
Observations	60			
** Denotes significance at the $p < 0.05$ level; *** Denotes significance at the $p < 0.01$ level.				

Table 19: Numerical results using percentage GDP difference, period before 2020 (5.4.2)

Statistic	**Skill Level**	**Unemplyment**	**Population**	**Education**
Coefficient	-0.0265	-0.0270	0.0004	0.1721
Std. Error	0.0242	0.0731	0.0207	0.1071
t-value	-1.10	-0.37	0.02	1.61
P-value	0.273	0.712	0.984	0.109
90% CI Low	-0.0664	-0.1476	-0.0337	-0.0047
90% CI High	0.0134	0.0936	0.0346	0.3489
Constant	-7.7211 ($p = 0.137$)			
R^2 **Within**	0.0279			
Groups	257			
Observations	1,003			
No coefficients are significant at the $p < 0.10$ level.				

Table 20: Numerical results using percentage GDP difference, period after 2020 (5.4.2)

Statistic	**Skill Level**	**Unemplyment**	**Population**	**Education**
Coefficient	-0.0799*	-0.2678**	-0.0824	0.0619
Std. Error	0.0443	0.1265	0.0623	0.0925
t-value	-1.80	-2.12	-1.32	0.67
P-value	0.073	0.035	0.188	0.504
90% CI Low	-0.1530	-0.4767	-0.1853	-0.0909
90% CI High	-0.0068	-0.0590	0.0206	0.2147
Constant	17.1157 ($p = 0.209$)			
R^2 **Within**	0.0436			
Groups	254			
Observations	506			
* Denotes significance at the $p < 0.10$ level; ** Denotes significance at the $p < 0.05$ level.				

Table 21: Numerical results using percentage GDP difference for Less Developed Regions, period before 2020 (5.4.2)

Statistic	Skill Level	Unemplyment	Population	Education
Coefficient	0.0067	-0.0795	0.0228	0.3016
Std. Error	0.0347	0.1024	0.0577	0.2041
t-value	0.19	-0.78	0.39	1.48
P-value	0.848	0.440	0.694	0.143
90% CI Low	-0.0510	-0.2497	-0.0732	-0.0375
90% CI High	0.0644	0.0907	0.1187	0.6408
Constant	-27.8682 ($p = 0.003$)***			
R^2 **Within**	0.0756			
Groups	93			
Observations	363			
*** Denotes significance at the $p < 0.01$ level.				

Table 22: Numerical results using percentage GDP difference for Less Developed Regions, period after 2020 (5.4.2)

Statistic	Skill Level	Unemplyment	Population	Education
Coefficient	-0.0473	-0.2639*	0.0451	0.0922
Std. Error	0.0493	0.1361	0.0841	0.1182
t-value	-0.96	-1.94	0.54	0.78
P-value	0.340	0.056	0.593	0.437
90% CI Low	-0.1293	-0.4901	-0.0947	-0.1043
90% CI High	0.0346	-0.0376	0.1849	0.2887
Constant	-23.4667 ($p = 0.081$)*			
R^2 **Within**	0.0625			
Groups	92			
Observations	184			
* Denotes significance at the $p < 0.10$ level.				

Table 23: Numerical results using percentage GDP difference for More Developed Regions, period before 2020 (5.4.2)

Statistic	Skill Level	Unemplyment	Population	Education
Coefficient	-0.0079	0.1204	-0.0026	-0.0258
Std. Error	0.0429	0.2756	0.0263	0.1276
t-value	-0.18	0.44	-0.10	-0.20
P-value	0.854	0.663	0.921	0.840
90% CI Low	-0.0790	-0.3367	-0.0462	-0.2375
90% CI High	0.0632	0.5776	0.0410	0.1859
Constant	5.3696 ($p = 0.537$)			
R^2 **Within**	0.0040			
Groups	110			
Observations	429			
No coefficients are significant at the $p < 0.10$ level.				

Table 24: Numerical results using percentage GDP difference for More Developed Regions, period after 2020 (5.4.2)

Statistic	Skill Level	Unemplyment	Population	Education
Coefficient	-0.1067	-0.2619	-0.1807	-0.0753
Std. Error	0.0944	0.3119	0.1250	0.2021
t-value	-1.13	-0.84	-1.45	-0.37
P-value	0.261	0.403	0.151	0.710
90% CI Low	-0.2633	-0.7793	-0.3880	-0.4106
90% CI High	0.0498	0.2555	0.0266	0.2600
Constant	61.9152 ($p = 0.065$)*			
R^2 **Within**	0.0400			
Groups	109			
Observations	216			
* Denotes significance at the $p < 0.10$ level.				

Table 25: Numerical results using percentage GDP difference for Transition Regions, period before 2020 (5.4.2)

Statistic	Skill Level	Unemplyment	Population	Education
Coefficient	-0.0710	-0.0817	-0.0231	0.1272
Std. Error	0.0495	0.1094	0.0380	0.0867
t-value	-1.43	-0.75	-0.61	1.47
P-value	0.158	0.459	0.545	0.148
90% CI Low	-0.1539	-0.2649	-0.0867	-0.0179
90% CI High	0.0119	0.1016	0.0405	0.2723
Constant	0.5220 ($p = 0.956$)			
R^2 **Within**	0.0898			
Groups	54			
Observations	211			
No coefficients are significant at the $p < 0.10$ level.				

Table 26: Numerical results using percentage GDP difference for Transition Regions, period after 2020 (5.4.2)

Statistic	Skill Level	Unemplyment	Population	Education
Coefficient	-0.1537*	-0.7232	-0.1762	0.1622
Std. Error	0.0787	0.5904	0.1426	0.2712
t-value	-1.95	-1.23	-1.24	0.60
P-value	0.056	0.226	0.222	0.552
90% CI Low	-0.2854	-1.7119	-0.4149	-0.2920
90% CI High	-0.0219	0.2655	0.0626	0.6164
Constant	42.6798 ($p = 0.220$)			
R^2 **Within**	0.1369			
Groups	53			
Observations	106			
* Denotes significance at the $p < 0.10$ level.				

.2 Lagged dependent variable analysis

The following table presents the numerical results of dynamic panel analysis performed using the 1-year lagged dependent variable *Lad Disp*. This dynamic specification allows evaluating a possible 'path dependence', in this case meaning that a region's current income level is significantly influenced by its income level in the preceding period.

Table 27: Numerical results of the dynamic Fixed-Effects Regression with Lagged Dependent Variable (4.7)

Statistic	**Lag Disp**	**Skill Level**	**Unemply**	**Population**	**Education**
Coefficient	-0.2116	0.0094	-0.0032	-0.0535	0.0406
Std. Error	0.0503	0.0256	0.0791	0.0397	0.0928
t-value	-4.21	0.37	-0.04	-1.35	0.44
P-value	0.000	0.714	0.968	0.179	0.662
90% CI Low	-0.2946	-0.0328	-0.1338	-0.1189	-0.1125
90% CI High	-0.1286	0.0516	0.1274	0.0120	0.1937
Constant	7.9578 ($p = 0.364$)				
R^2 **Within**	0.0894				
Groups	257				
Observations	493				