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TWIN TRANSITION AND CHANGING PATTERNS OF SPATIAL MOBILITY: A REGIONAL APPROACH

MOBI-TWIN D2.2 METHODOLOGICAL REPORT ON THE REGIONAL ATTRACTIVENSS INDEX FOR EU REGIONS

Work package	WP2: Redefining regional typologies based on spatial mobility and twin transition
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Abstract	This report examines drivers of spatial mobility and immobility using econometric analysis on diverse data sources. Key factors focus on green and digital transition indicators, together with individual demographics, regional conditions, and life stages, assessing their influence on mobility types (permanent, circular, short-term).
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List of terms and abbreviations

BOD	Benefit of the Doubt
CDD	Cooling Degrees Days
COVID-19	Coronavirus Disease 2019 caused by the SARS-CoV-2
DESI	Digital Economy and Society Index
EQI	European Quality of Government Index
EU	European Union
EU13	13 countries that joined the European Union (EU) after 2004, primarily from Central and Eastern Europe
EU15	Member states of the European Union (EU) before the major eastern expansion in 2004
EU27	27-member countries of the European Union (EU) after the United Kingdom officially left the EU on January 31, 2020 (Brexit).
EW	Equal Weighting
GDP	Gross Domestic Product
GHG	Greenhouse Gas Emissions
HDD	Heating Degrees Days
HEI	Higher Education Institution
ITC	Information and Communication Technology
KPI	Key Performance Indicator
NUTS0	Nomenclature of Units for Territorial Statistics. Level 0.
NUTS1	Nomenclature of Units for Territorial Statistics. Level 1.
NUTS2	Nomenclature of Units for Territorial Statistics. Level 2.
OECD	Organization for Economic Co-operation and Development
PCA	Principal Component Analysis
PPML	Poisson pseudo-maximum likelihood
RAI	Regional Attractiveness Index
RIS	Regional Innovation Scoreboard
RRI	Responsible Research and Innovation
TT	Twin Transition

List of Countries

AT	Austria
BE	Belgium
BG	Bulgaria
CY	Cyprus
CZ	Czechia (Czech Republic)
DE	Germany
DK	Denmark
EE	Estonia
EL	Greece
ES	Spain
FI	Finland
FR	France
HR	Croatia
HU	Hungary
IE	Ireland
IT	Italy
LT	Lithuania
LU	Luxembourg
LV	Latvia
MT	Malta
NL	Netherlands
PL	Poland
PT	Portugal
RO	Romania
SE	Sweden
SI	Slovenia
SK	Slovakia

Executive Summary

This report investigates regional attractiveness—the set of factors that draw and retain people in specific locations—by integrating traditional socio-economic indicators with the emerging pressures of the digital and green transitions. Its primary objective is to develop and apply a comprehensive composite index of attractiveness across European regions, revealing both persistent disparities and notable opportunities for development.

Context and Rationale

At the core of regional attractiveness lie economic strength, social well-being, and quality of life. Historically, indicators such as GDP per capita, employment rates, housing affordability, and institutional quality have proven useful for assessing a region's vitality. More recently, however, digital connectivity and environmental sustainability have gained prominence. The digital transition, characterized by broadband access, ICT-specialist employment, and rising digital skills, has created new forms of remote work and service delivery. Simultaneously, the green transition, with its emphasis on reducing emissions, promoting circular economy practices, and ensuring environmental quality, is reshaping economic structures and mobility preferences. Research shows these developments intensify existing imbalances. Urban and capital regions that can swiftly adopt green policies and digital infrastructure attract more talent and investment, widening the gap with rural or less-developed areas. Meanwhile, so-called "left-behind" regions—impacted by industrial decline or weaker governance—face the risk of further marginalization unless they adapt.

Methodological Overview

Building a composite index of regional attractiveness entails indicator selection, normalization, weighting, and aggregation. Traditional measures (e.g., GDP per capita, employment rate, sectoral composition) are combined with the TWIN dimensions: digital (e.g., broadband access, digital skills, ICT employment) and green (e.g., greenhouse gas emissions, circular economy jobs, reliance on extractive industries). This integrated approach accommodates both quantitative metrics (like per capita values) and qualitative signals (such as institutional quality). To account for varied data scales and units, techniques such as min-max normalization or z-scores ensure comparability. Weighting schemes also matter: the "baseline" index gives 50% weight to traditional measures and 25% each to digital and green factors, while alternative methods—including Principal

Component Analysis (PCA) and a “threshold fuzzy” approach—shed light on how methodological choices can alter outcomes.

Key Findings

Persistent Inequalities: The results confirm that northern and western Europe generally outperforms southern and eastern regions across traditional, digital, and green dimensions. Capital regions maintain a clear lead over non-capital areas, benefiting from greater infrastructure, policy attention, and agglomeration effects.

Urban-Rural Divide: Predominantly urban regions consistently rank higher than rural ones, both in traditional factors (employment opportunities, institutional quality) and emerging domains (digital connectivity, sustainability initiatives). This gap widened slightly in the study period (2010–2022), highlighting the continued concentration of resources in metropolitan centres.

Digital Growth: The digital domain has seen robust improvement across Europe, especially in broadband expansion and the rise of e-commerce, though southern and eastern regions still lag behind. Some of these lagging areas are nonetheless catching up through targeted investments in digital infrastructure and training.

Green Challenges and Opportunities: Progress in green attractiveness—lower emissions, sustainable jobs, circular economy practices—is more modest. Northern Europe leads, while many southern and eastern regions struggle with funding gaps or reliance on higher-carbon industries. Regions that do effectively adopt green policies benefit from new investment, a healthier environment, and greater public appeal.

Gender Dimensions: Men appear more influenced by digital opportunities (e.g., tech jobs), whereas women often prioritize environmental sustainability and quality-of-life factors. Slower progress in green policies may thus disadvantage regions seeking to attract or retain more environmentally oriented demographics.

Sensitivity and Robustness: Alternative indices highlight consistent broad patterns yet reveal differing outcomes at the margins. PCA closely mirrors the baseline index, while the threshold fuzzy approach—emphasizing relative benchmarks—can produce “unexpected” rankings, underscoring how methodological choices influence results. Sensitivity tests show that overweighting digital or green factors can enhance some regions’ standing while reducing others', further illustrating the context-dependent nature of regional attractiveness.

Conclusion
In sum, the report underscores how traditional, digital, and green factors jointly determine a region's attractiveness. While overall progress is visible, longstanding inequalities persist or are even exacerbated by the Twin transitions. A robust composite index approach helps diagnose these disparities, informing policymakers and stakeholders as they strive for sustainable, inclusive growth across the European landscape.

1. Introduction

This deliverable presents a methodological approach providing a synthetic index of regional attractiveness for EU regions and grounded on a list of indicators and insights derived from T1.3, T1.4 and T2.1, reported in previous deliverables.

As noted in the MOBITWIN Deliverable 2.2, the notion of regional attractiveness encompasses a wide range of factors and characteristics that make a specific location appealing to potential residents. It involves a thorough assessment of both concrete and intangible qualities that collectively enhance a region's overall allure. Economic prospects, educational options, job availability, quality of life, cultural offerings, and environmental factors are among the key elements considered. Furthermore, this concept is inherently dynamic and multidimensional, reflecting the diverse considerations that shape individuals' decisions when choosing to settle in a particular geographic area.

Silvanto and Ryan (2018) highlight five crucial drivers of regional attractiveness for highly skilled individuals: economic opportunities, cultural diversity, policy frameworks, networks of talent, and quality of life. Fostering employment prospects and welcoming cultural diversity are key to retaining and attracting human capital. Such regional characteristics underpin the capacity to keep current talent and lure new, specialized populations (Ruzzier and De Chernatony, 2013). However, uneven distribution of these drivers across European regions exacerbates disparities and perpetuates less favoured areas (European Commission 2014). Consequently, regional policies must explicitly incorporate strategies that strengthen attractiveness factors, particularly for disadvantaged regions, to establish robust human capital foundations essential for spurring alternative development pathways (Nadeau and Olafsen 2015). While economic conditions remain vital, technological innovation, sustainability considerations, and intangible elements are also important factors in shaping an area's pull for high-skilled migration and future development (Romão et al. 2018).

Left-behind places, emerging as a critical lens in the post-2008 crisis era, spotlight geographical disparities by contrasting dynamic "superstar" cities with regions experiencing decline and marginalization (Kemeny & Storper, 2020). They are characterized by limited capacity to benefit from dominant growth paradigms, often resulting in outward mobility and shrinking populations (Velthuis et al., 2023). However, these challenges vary across locations, with factors such as economic conditions, housing quality, and social capital producing distinct clusters—some dominated by working-class homeowners, others by immigrant communities, and yet others defined by higher education and income (Karp et al., 2022). Historically linked to deindustrialization, suburbanization, and demographic shifts, left-behind regions typically bear a disproportionate share of decline's consequences, struggling to maintain essential services (Franklin, 2021). Connecting this notion to the Twin Transition highlights how green and digital transformations influence individual spatial choices and underscores the need for nuanced, context-specific policy interventions aimed at reducing inequalities and promoting social justice.

The green transition's indirect effects, such as the concentration of green technologies and skilled workers in certain regions (Rodríguez-Pose & Bartalucci, 2023, 2024), risk amplifying inequalities and creating brain drain in left-behind areas lacking qualified labour, specialized infrastructures, and economic adaptability (Moreno & Ocampo-Corrales, 2022). Simultaneously, the digital transition reshapes regional attractiveness through increased access to virtual services, though insufficient digital skills or infrastructure may hinder rural communities (Salemink et al., 2017). Moreover, while migration can potentially spur development by infusing knowledge and innovation (Tietjen & Jørgensen, 2016), mismatches in local capacities and resistance to change can limit its benefits (Löfving et al., 2022). Together, these transitions underscore the importance of adequately integrating new technologies and embracing green transformations to avoid widening territorial divides, with skilled mobility functioning both as a force shaping—and an outcome of—left-behind regions' struggles to adapt and remain attractive.

Regional attractiveness serves as a critical prism through which to understand spatial mobility, the movement of people across geographic regions driven by a broad spectrum of economic, social, political, and environmental factors. As individuals weigh employment potential, living conditions, and personal networks, they are drawn to areas offering competitive wages, abundant services, and vibrant cultural scenes. This attraction is further reinforced by robust human capital, as higher educational attainment often correlates with a greater likelihood of relocating. The concurrent green and digital transitions amplify these dynamics, reshaping both the factors that make regions appealing and the ways in which people move. Regions adopting sustainable policies, clean-energy initiatives, and digitally enabled remote work opportunities can attract skilled workers seeking healthier lifestyles and flexible employment. Meanwhile, urban and rural areas alike face the challenge of maintaining or enhancing their attractiveness through the provision of amenities such as cultural venues, green spaces, and reliable digital connectivity. Thus, regional attractiveness and spatial mobility are intertwined, as the capacity of a place to draw newcomers and retain residents depends on its ability to meet evolving economic and social demands—demands increasingly shaped by ongoing green and digital transformations.

Developing a composite index of regional attractiveness is academically justified by its capacity to capture the multidimensional nature of regions' pull factors, facilitating more nuanced policy insights than single-indicator approaches (Nardo et al., 2008). Composite indices allow scholars and policymakers to systematically integrate economic, social, cultural, and environmental dimensions, enabling cross-regional comparisons that illuminate specific strengths and weaknesses (Annoni & Dijkstra, 2019). In the context of territorial cohesion and spatial disparities, such an instrument can reveal drivers of inequality while highlighting best practices for fostering inclusive and sustainable development (Rodríguez-Pose, 2018). By integrating diverse indicators—ranging from economic competitiveness and employment trends to social well-being and environmental quality—a composite index also provides clearer guidance for targeted policy interventions aimed at enhancing local attractiveness (Begg, 1999). Ultimately, this holistic approach uncovers underlying determinants of a region's ability to draw and retain talent, investment, and innovation, thereby serving as a strategic tool for both academic research and evidence-based policymaking.

2. Indicators of regional attractiveness

Building on the discussions in the previous section this new section broadens the scope by highlighting specific domains and indicators that capture a region's ability to draw and retain human capital. As part of an evolving global landscape increasingly defined by digital and green imperatives, understanding these indicators is critical for policymakers, businesses, and communities seeking sustainable development pathways. Traditional metrics (e.g., infrastructure quality, employment rates, GDP per capita) still offer valuable insights, but they now intersect with dimensions like digital readiness, cultural and research-driven innovation, and environmental consciousness. In the pages that follow, we outline a comprehensive set of indicators and frameworks—ranging from the well-established, such as the DESI (Digital Economy and Society Index) and the RIS (Regional Innovation Scoreboard), to novel indices targeting sustainability transitions—to illustrate how regions can remain competitive in this rapidly shifting environment. Ultimately, this integrated perspective underscores the need to balance economic growth with social inclusivity and ecological responsibility, recognizing that regional attractiveness hinges not only on conventional factors but also on how effectively a place navigates the twin challenges of digital and green transformation.

As reported in MOBI-TWIN Deliverable 2.1, several dimensions are identified in the literature affecting the attractiveness of a place focusing on the movements of people: (i) economically related factors; (ii) cultural diversity, referring to the ability of a region to efficiently welcome foreigners; (iii) policy-related factors; (iv) network-based aspects; and (v) quality of life features (Silvanto and Ryan, 2018). Given the focus of the MOBI-TWIN on the green and digital factors as drivers of attractiveness, we divide the domains into traditional, digital and green factors.

Finally, to account for a wide time span of the Regional Attractiveness Index, we have expanded our analysis from the initial years of the 2010 decade to the last available year for most indicators (2020-2022). This has implied an additional effort to homogenise the coding of regional NUTS2 classification, as there have been a wide list of changes (see Box 1 for a brief explanation of major changes).

Box 1. Key Updates in the NUTS2 Regional Classification Since 2010

Since 2010, the European NUTS2 regional classification has seen periodic updates—generally every three years—to reflect shifting administrative boundaries and reforms across Member States. These revisions include the splitting or merging of certain regions, new region names, and boundary adjustments prompted by national policy changes. In some cases, entirely new regions have been introduced, while others have been reorganised for greater statistical coherence. The goal of these adjustments is to maintain a consistent territorial framework for European statistics and regional policy, ensuring that the classification accurately represents current administrative realities. Below are some of the more significant changes introduced during this period:

Administrative Reorganisations in France (2016–2019). Several French regions were merged or redrawn, most notably in 2016 when the number of metropolitan regions was reduced from 22 to 13. This restructuring required the reallocation of NUTS2 codes and names to reflect newly created entities. Besides, there was the integration of Overseas Territories.

Reclassification of German Länder. Certain boundary modifications and internal reorganisations took place in Germany, leading to minor adjustments of NUTS2 regions (Länder). These changes aimed to align statistical definitions with evolving administrative layouts.

Refinements in Poland. Adjustments to Polish NUTS2 regions included changes in nomenclature and boundary fine-tuning for some voivodeships, ensuring that local administrative revisions were accurately mirrored in Eurostat's regional data.

Croatia's Inclusion Following EU Accession. When Croatia joined the European Union in 2013, its regional subdivisions were integrated into the NUTS system. Subsequent refinements to county boundaries and statistical regions have been incorporated into the classification updates.

Ongoing Minor Adjustments. Beyond these high-profile reforms, various Member States—such as Greece, Portugal, and Spain—have seen smaller, incremental changes to regional boundaries or naming conventions, reflecting local administrative reforms.

A wider explanation can be found at https://ec.europa.eu/eurostat/web/nuts/

2.1. Traditional factors of regional attractiveness

In the MOBITWIN deliverable 1.3 we described a list of variables that proxy traditional factors behind regional attractiveness. Next, we describe the domains covering traditional attractiveness and the indicators behind them. We use the definitions and sources described in MOBI-TWIN Deliverable 1.2 ("Complete MOBI-TWIN dataset").

Economy and Labour Market

Gross Domestic Product per capita. Scholars have explored more deeply into the economic fabric of regions by using GDP per capita as a key proxy for assessing economic opportunities. Although most migration flows are driven primarily by actual labour market outcomes—particularly wages—rather than by broad indicators of economic output, many studies employ GDP per capita as a stand-in for wages, chiefly because it offers a time-consistent and regionally disaggregated measure. According to Álvarez and Royuela (2023), whose meta-analysis examined the influence of labour-market factors on interregional migration, substituting GDP per capita for wages in statistical estimations does not significantly alter the estimated effects of these factors. We use total population and GDP in million euros at market prices, both collected from Eurostat.

Employment rate. Migration decisions are influenced by individuals' expectations, requiring consideration of both the likelihood of finding a job and the possibility of experiencing periods of unemployment, particularly during the initial stages of job searching in a new location (Todaro, 1969). Instead of focusing on unemployment indicators, we propose using a proxy for employment opportunities: the employment rate among the working-age adult population, defined as individuals aged 20 to 64 years. The data for this measure is sourced from Eurostat.

Sectoral composition. Sectoral composition and diversity strongly influence migration flows. Dissart (2003) shows that regions with a broader economic base exhibit greater resilience and attract more migrants. Likewise, Malizia and Ke (1993) highlight those diverse industries buffer labour markets from sector-specific shocks, enhancing employment stability and encouraging in-migration. Bartkowska and Riedl (2021) demonstrate that regions with balanced sectoral structures experience lower unemployment volatility, which in turn dampens out-migration. Thus, regions with thriving industries and diverse sectoral composition tend to attract a mobile workforce eager to capitalise economic opportunities. We use the share of activity in Industrial and Services Sectors in high value-added private sectors (financial, real estate, professional, scientific, technical, administrative, and support services). The source is Eurostat.

Visitor Appeal

Number of tourists arriving at accommodation establishments. The tourism sector significantly contributes to economic output and employment. Measuring overnight stays relative to population size reflects its local impact. Tourism arrivals serve as a useful proxy for regional attractiveness, reflecting both tangible factors (e.g., amenities and accessibility) and intangible aspects (e.g., reputation and cultural ambience). Crouch (2011) underscores tourism's role in capturing a region's broader appeal. From a regional attractiveness perspective, areas with high tourism intensity may appeal to new residents and investors but must address sustainability and resident well-being.

Residents Well-Being

Tertiary students. Higher education institutions play a pivotal role in shaping regional attractiveness and influencing student mobility. Universities contribute significantly to the perceived quality of life in regional towns, enhancing their appeal to prospective residents (Drummond et al., 2013). Student mobility, however, is driven by a combination of institutional and regional factors. Among these, institutional attributes—such as the quality and reputation of universities—tend to have a stronger impact on student mobility than regional characteristics (Sánchez Barrioluengo & Flisi, 2017).

Physicians per 100,000 inhabitants. Healthcare availability is a key factor in regional attractiveness (Bourecherouche & Forttas, 2021), especially for families seeking reliable, high-quality services (OECD, 2022). A higher number of doctors per capita suggests robust healthcare coverage, influencing relocation decisions by signalling accessible, well-funded services (European Commission, 2021). Ultimately, ensuring equitable access fosters social inclusion and strengthens competitiveness, making healthcare pivotal for attracting and retaining residents.

Housing affordability: it is a key factor shaping migration patterns and household location decisions. When housing costs are disproportionately high relative to income, workers may be incentivized to relocate to more affordable areas, thus affecting labour supply, local economic growth, and the long-term stability of local communities (Glaeser et al., 2001). By contrast, regions that manage to keep housing overburden rates low have the potentiality of having higher levels of in-migration and investment, as individuals and firms perceive them as more livable and conducive to business operations (Malpezzi, 1996). Housing affordability, as measured by the housing overburden rate, provides insight into the share of residents spending more than 40% of their disposable income on housing. This measure varies widely within countries, reflecting significant disparities between regions, which can highlight areas in need of policy intervention.

Regional Safety

Robbery rates. Crime victimization negatively affects quality of life, including parenting, work performance, and relationships (Hanson et al., 2010). Crime significantly reduces life satisfaction and increases worry among residents (Krekel & Poprawe, 2014), though its overall impact on happiness is smaller compared to factors like family life and health (Michalos & Zumbo, 2000). Overall, safer regions with lower crime rates are more attractive.

Institutional Quality

Quality of Government Index (EQI). Institutional quality is a key driver of regional attractiveness. Perception-based tools, such as surveys on public sector integrity and impartial service delivery, highlight the importance of institutional integrity for potential talent and investors. Institutional quality positively influences foreign direct investment inflows, economic growth, and productivity. High-quality institutions enhance a region's appeal to investors and talent (Moskalenko et al., 2022). Strong governance fosters greenfield investments by highly productive multinational enterprises, while weaker regions often attract acquisitions (Amendolagine et al., 2024). Additionally, efficient institutions amplify the impact of EU cohesion funds, driving growth in structurally weaker areas (Arbolino & Boffardi, 2017). At a local level, better institutional frameworks improve productivity in small and medium-sized enterprises, with the effects varying by firm characteristics such as size, age, and human capital (Agostino et al., 2020). These findings underscore the critical role of institutional quality in shaping regional competitiveness, attracting investment, and fostering economic resilience.

Environment

Cooling and Heating degree days. Heating Degree Days (HDD) and Cooling Degree Days (CDD) are weather-based technical indices that describe the energy requirements of buildings for heating and cooling across a year (Eurostat, 2024). While cooling currently accounts for a small share of household electricity use—about 3% across the EU—it has grown rapidly in recent decades and is expected to increase further due to climate change (Andreou et al., 2020). These indices can be both understood as vital tools for monitoring and interpreting energy demand in response to changing weather patterns, and as measures climate liveability and consequently as factors of regional attractiveness. Research suggests that climate-related factors, including heating and cooling needs, play a noteworthy role in location decisions (Cragg & Kahn, 1997; Rappaport, 2007). As global warming alters temperature patterns, regions offering more moderate climates could see increased in-migration, while those experiencing amplified extremes may encounter challenges in maintaining competitiveness and quality of life.

Air quality index. Air quality significantly shapes regional attractiveness, influencing both residential and business decisions as well as tourism flows. Poor air quality deters potential in-migrants and investors, while cleaner environments foster a healthier quality of life (Kahn, 2006). Empirical evidence from China shows that higher air quality raises property values and increases in-migration (Zheng & Kahn, 2013). In tourism, air quality is crucial, especially for nature-based destinations or when travelling with children (Eusébio et al., 2022; Łapko et al., 2020). Integrating air quality measures into regional development and destination management is thus vital for sustaining both resident and visitor appeal.

2.2. Digital transition

The digital transition refers to the widespread integration of digital technologies into all aspects of society and the economy, encompassing shifts in work practices, public services, and daily life. According to the European Commission (2022), this transformation revolves around upgrading digital skills, ensuring secure and interoperable infrastructures, promoting digital innovation within businesses, and modernising governmental services to foster inclusive, citizen-centric approaches. The OECD (2020) further emphasises that the digital transition involves restructuring economic processes, enhancing communication networks, and leveraging data in ways that drive productivity, improve service delivery, and stimulate new forms of social interaction. Collectively, these efforts aim to create a digitally empowered society capable of meeting contemporary challenges—ranging from economic competitiveness to environmental sustainability—while bolstering trust in the digital environment.

According to the decision establishing the Digital Decade Policy Programme 2030, key performance indicators must be employed to monitor the Union's progress against the digital targets outlined in that decision. These same KPIs should be used to track underlying national trends. Consequently, the Digital Economy and Society Index (DESI) should incorporate the KPIs set out in the decision. Moreover, the process used in DESI to define indicators and gather data must be constrained by the requirements of that decision. For our purposes, we use a concise set of indicators to represent the digital dimension of regional attractiveness, reflecting three main criteria: connectivity, ICT specialists, and digital skills.

Connectivity

Broadband access. Broadband connectivity is a key factor in regional attractiveness: High-speed internet supports business operations, remote work, e-learning, and telemedicine, making regions with reliable broadband more appealing to residents and investors (European Commission, 2022). Poor connectivity, in contrast, creates a digital divide, reducing regional competitiveness and opportunities for development (OECD, 2020). Studies show that robust broadband networks attract skilled workers and businesses, fostering balanced growth between urban and rural areas (Van Dijk et al., 2018). Thus, broadband access is essential for driving economic, social, and technological progress in regions.

ICT specialist

High-tech employment. The availability of ICT specialists and high-tech jobs is crucial for regional attractiveness, fostering innovation and economic growth. Skilled labour attracts businesses and drives digital transformation, enhancing competitiveness (European Commission, 2022). High-tech employment also offers career opportunities, boosting a region's appeal to talent while supporting economic resilience and diversification (OECD, 2020). Research indicates that the employment of ICT specialists and use of digital technologies can improve firm productivity by about 23% (Cette et al., 2020). ICT agglomeration promotes high-tech innovation, particularly in regions with ICT specialization, and inter-sectoral and inter-regional spillovers contribute to innovation development (Sergio et al., 2023).

Digital skills

Regions with a digitally skilled population attract businesses reliant on advanced technologies, driving competitiveness and economic development (European Commission, 2022; Tran et al., 2023). Enhanced digital skills also benefit less-developed areas, enabling them to diversify technologically (Castellacci et al., 2019). Digital skills and ICT specialists correlate strongly with economic growth, highlighting their importance in regional digital transformation strategies (Barinova et al. 2022). Additionally, regions investing in digital upskilling programs improve labour market prospects, quality of life, and institutional environments, which are key factors for attracting professionals and sustaining long-term advantage. We proxy the digital skills of the population by means of several indicators.

Internet used between individuals. Percentage of individuals who used the internet for private interaction in the last three months

Internet used with public authorities. Percentage of individuals who used the internet to interact with public authorities

Internet selling. Percentage of individuals who used the internet for selling goods or services.

Online banking. Percentage of individuals who use internet for online banking.

2.3. Green transition

The green transition is the shift towards sustainable, low-carbon economies to combat climate change while promoting economic growth. Anchored by the European Green Deal, it aims for net-zero emissions by 2050 and increased resource efficiency. However, its impacts are uneven, with disadvantaged regions facing higher costs, such as job losses in carbon-intensive sectors. Tailored policies are essential to address these disparities and ensure an equitable transition (Rodríguez-Pose & Bartalucci, 2024).

Measuring green transition is more complex, as there is no formal consensus on its metrics, although some attempts exist (Zhai et al., 2022). For green transition, we follow Rodríguez-Pose & Bartalucci (2024), examining how individuals make mobility choices based on variables likely to be impacted by the green transition.

Next, we describe the selection of indicators and how they constitute a key dimension of the green transition.

Greenhouse Gas (GHG) emissions. Greenhouse Gas emissions are a critical dimension of the green transition, serving as both a measure of environmental impact and a determinant of regional vulnerability. Regions with high GHG emissions, particularly those reliant on fossil fuels and carbon-intensive industries like mining, heavy industry, and road transportation, face significant challenges in adapting to the European Green Deal's low-carbon goals. These regions often experience economic disruptions, job losses, and increased costs associated with transitioning to greener energy and production methods.

The impact of GHG emissions on regional attractiveness is twofold. Regions capable of reducing emissions tend to attract greater investment, innovation, and skilled labour, enhancing their competitiveness. Conversely, regions with persistently high emissions may struggle to appeal to businesses and residents due to increased regulatory pressures and environmental degradation. Thus, addressing GHG emissions is essential for fostering sustainable development and improving regional attractiveness.

Circular economy employment. Circular economy employment is a key aspect of the green transition, driving sustainability through jobs in recycling, remanufacturing, and resource management. Regions adopting these practices attract investment and skilled labour, enhancing their competitiveness and economic resilience. Regions with strong governance and infrastructure benefit the most, boosting their appeal to businesses and residents. Peripheral regions, while offering potential in renewables, face challenges such as limited expertise and resistance to change. Addressing these gaps is essential to reduce regional inequalities and improve overall attractiveness.

Wages in the mining sector. Wages in the mining sector reflect the economic reliance of regions on extractive industries. High wage levels in mining indicate a significant contribution of this sector to regional GDP, making these areas economically vulnerable to decarbonisation policies under the European Green Deal. As mining-dependent regions transition away from fossil fuels, the reduction in mining activity and associated wages can lead to economic stagnation, unemployment, and outmigration, negatively impacting regional attractiveness.

Conversely, regions that manage to diversify their economies and invest in green technologies may offset these vulnerabilities. Supporting workforce retraining and leveraging green transition funding can mitigate the socioeconomic impacts of declining mining activities, improving long-term regional competitiveness and attractiveness.

Share of activity in Agriculture. As illustrated by Rodríguez-Pose & Bartalucci (2024) this sector will be the most affected by the green transition. Agriculture is a critical dimension of the green transition due to its significant carbon emissions and the sector's high dependency on traditional practices. Regions with a substantial share of economic activity in agriculture face challenges in adapting to climate policies, including shifts in consumer preferences towards sustainable and locally sourced food, reduced meat consumption, and the need for sustainable land use. These changes can conflict with established agricultural practices, potentially impacting regional economies reliant on agriculture.

The green transition may also introduce opportunities for agricultural regions to diversify into renewable energy or adopt innovative land use strategies. However, regions unable to adapt effectively may experience economic decline, deterring investment and outmigration, ultimately reducing their attractiveness. Balancing sustainability with economic resilience in agriculture is thus vital for maintaining regional competitiveness in the context of the green transition.

Tourism-to-GDP ratio. This is a significant indicator within the green transition, highlighting regions highly dependent on tourism as a key economic driver. This dependency can make regions particularly vulnerable to the impacts of climate policies and shifts towards sustainable practices. For example, regions with strong tourism sectors may face challenges in balancing environmental regulations, such as renewable energy development, with maintaining tourism appeal. The construction of wind turbines or other infrastructure linked to the green transition has been shown to negatively affect tourism demand in some regions. In terms of regional attractiveness, areas with a high tourism-to-GDP ratio must adapt their tourism strategies to align with sustainability goals, ensuring they remain appealing to environmentally conscious visitors. Successfully integrating sustainable practices can enhance their reputation and draw eco-tourism, which boosts both economic resilience and attractiveness in the long term.

3. Composite index of regional attractiveness in EU regions

3.1. Main considerations

Composite indices are valuable tools for condensing complex and multidimensional phenomena into a single, easily interpretable metric. They are especially useful for assessing areas such as sustainability, socio-economic development, or competitiveness. By summarising vast amounts of data, composite indices support comparisons across countries or regions, simplifying communication with policymakers and fostering public understanding. For example, the Human Development Index (HDI) provides a comprehensive snapshot by aggregating education, health, and income indicators.

Creating a composite index requires careful methodological decisions to ensure validity and reliability. The first step involves establishing a theoretical framework, which defines the concept being measured and its key dimensions. This framework guides the selection of indicators, ensuring they are relevant, measurable, and reflective of the underlying phenomenon. A comprehensive analysis of the selection of domains and indicators has been developed in the previous sections.

Once the indicators are chosen, normalisation is essential to standardise their scales and make them comparable. Techniques such as rescaling or z-scores are commonly applied, each with distinct implications for the results. Following this, weighting assigns relative importance to indicators, and aggregation combines them into a single value. These choices should align with the theoretical framework to avoid distortions in the final index.

Robustness and sensitivity analyses are critical to ensure the index's stability under different assumptions. These analyses help identify potential biases and assess the impact of methodological choices on rankings and outcomes. Transparency in these processes is vital to maintaining credibility and fostering informed decision-making.

Finally, clear documentation and visual presentation of results enhance the utility of composite indices. When constructed carefully, these indices become indispensable tools for guiding policy, benchmarking progress, and addressing global challenges, offering a simplified yet comprehensive lens on multifaceted issues.

This section is first devoted to describing the main methodological decisions in the standardization and aggregation of the indicators. Later we develop additional robustness and sensitivity analyses to keep a high credibility of the final outcomes. The next section will be describing the main results and display a visual representation of the Regional Attractiveness Index.

3.2. Normalization

Assessing regional attractiveness requires synthesising multiple indicators to capture its multidimensional nature. One common method is the aggregative-compensative approach, which combines indicators to construct a composite index (Boarini et al., 2006). In this study, the indicators were deemed substitutable, leading to the use of an additive method, specifically the arithmetic mean. This approach offers simplicity and clarity for decision-makers.

Principal Component Analysis (PCA) can be also considered as an alternative for its objectivity in determining weights and aggregation. However, its limitations include a reflexive nature, reliance on latent variables, and its inability to fully capture the variability of the data or allow for fully inter-spatial and inter-temporal comparisons (Mazziotta & Pareto, 2019). Additionally, its complexity may hinder understanding at the regional level. It has been also criticized for being based on a purely empiricist method, based on the variability of indicators and not on a theoretical conceptual framework. Here we will mainly focus on the compensatory approach, as it offers the benefit of beginning with a dashboard that provides a detailed view of territorial disparities, followed by an aggregated analysis at the levels of themes, domains, and ultimately an overall index. Its simplicity and clarity make it particularly accessible for decision-makers.

The OECD Handbook for building composite indicators suggests several ways to normalise the data, as normalisation is essential before data aggregation because indicators often have different units of measurement. Such handbook summaries the main methods:

Ranking: This simple method orders indicators based on their relative position. It is unaffected by outliers but sacrifices information on absolute levels. It is commonly used in indices like the ICT Index and healthcare performance studies.

Standardisation (z-scores): Converts indicators to a standard scale with a mean of zero and a standard deviation of one. This method emphasises outliers, which may skew the results unless adjusted during aggregation.

Min-Max Normalisation: Rescales indicators to a range of [0, 1]. While it can amplify the effect of indicators within narrow ranges, it is sensitive to outliers, which may distort the final index.

Distance to a Reference: Measures each indicator's relative position to a target or benchmark (e.g., Kyoto Protocol targets or leading countries). This method is useful for goal-oriented comparisons but is susceptible to distortion from extreme values.

Categorical Scale: Assigns scores based on percentiles, such as numerical stars or qualitative labels. Although simple, this method loses variance information and may force categorisation regardless of distribution.

Above/Below Mean Transformation: Transforms values around the mean to 0, with thresholds defining positive and negative deviations. It is straightforward but omits absolute information and is criticised for its arbitrary thresholds.

Cyclical Indicators: Used in business cycle analysis, this method reduces irregularities in composite indicators, giving less weight to erratic series unless smoothed beforehand.

These methods should be selected based on the nature of the data and the objectives of the composite index.

We consider several alternatives. The **min-max normalisation** enables absolute comparisons. The method standardises data from different ranges and units on to a common scale while maintaining the relationships between the original values. The minmax normalised variable considers the minimum and maximum observed values of the considered variable and rescales the outcome on a chosen scale (0-100 in our case):

$$X_i^N = \frac{X_i - X_{min}}{X_{max} - X_{min}} * 100$$

Where X_{max} represents the optimal value (the highest if the indicator is interpreted in a positive way). As a result, all variables are measured in a single scale.

Variables indicating a bad performance with high values follow an alternative expression indicating the maximum score for minimum values:

$$X_i^N = \frac{X_{max} - X_i}{X_{max} - X_{min}} * 100$$

The values corresponding to the minimum and maximum values of the variables is listed Table 3.1, and the correlation between groups of variables (traditional, digital and green drivers of attractiveness) are plotted next.

An alternative procedure for normalization is the **standardization**, which is another linear transformation in which the resulting outcomes have a zero mean and variance equal to one. As both the minmax normalization and the standardization are linear transformations the resulting information have a perfect correlation. Table 3.2 displays the statistics considered for the standardization.

$$X_i^Z = \frac{X_i - \overline{X}}{S_X}$$

Next, we display (Figure 3.1 the correlation between indicators within every group of indicators: traditional, digital and green drivers of attractiveness.

Table 3. 1. Values collected for min-max normalisation of indicators

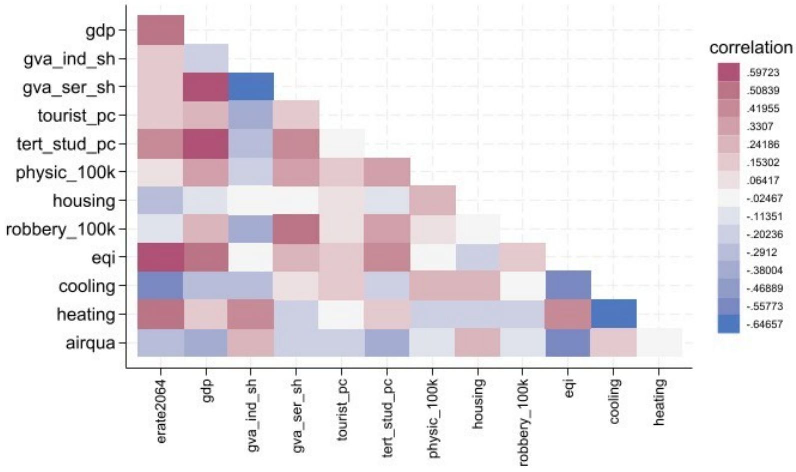
Variable	Max Value	Max Region	Max NUTS2	Max Year	Min Value	Min Region	Min NUTS2	Min Year
Employment rate	89.70	Åland	FI20	2022	42,10	Calabria	ITF6	2015
GDP pc	101200	Southern	IE05	2022	6800	Severozapaden	BG31	2010
Share of industry	69.03	Southern	IE05	2015	3.79	Ionia Nisia	EL62	2010
Share of services	49.06	Luxembourg	LU00	2017	7.75	Southern	IE05	2022
Tourists per 100k	22.40	Notio Aigaio	EL42	2019	0.15	Sud-Vest Oltenia	RO41	2010
Tertiary students	62.10	Sostinės regionas	LT01	2022	9.00	Severozápad	CZ04	2010
Physicians per 100k	911.04	Ciudad de Ceuta	ES63	2010	90.49	Åland	FI20	2019
Housing cost overburden rate	53.51	Kentriki Makedonia	EL52	2015	1.10	Malta	MT00	2015
Robberies per 100k	908.53	Région de Bruxelles-Capitale/ Brussels Hoofdstedelijk Gewest	BE10	2011	0.00	Dytiki Makedonia	EL53	2017
Institutional Quality	2.82	Åland	FI20	2013	-2.67	Bucureşti-Ilfov	RO32	2010
Cooling degree days	841.72	Malta	MT00	2022	0.00	Tirol	AT33	2014
Heating degree days	7011.09	Övre Norrland	SE33	2010	42.09	Canarias	ES70	2010
Air quality	39.51	Attiki	EL30	2017	2.80	Mellersta Norrland	SE32	2020
Broadband coverage	100.00	Flevoland	NL23	2016	15.46	Sud-Vest Oltenia	RO41	2010
High Tech employment	13.60	Budapest	HU11	2021	0.39	Thessalia	EL61	2016
Use of internet: private	99.44	Nordjylland	DK05	2021	29.09	Sud-Vest Oltenia	RO41	2010
Use of internet: public	94.35	Hovedstaden	DK01	2021	2.61	Vest	RO42	2013
Use of internet: banking	96.49	Helsinki-Uusimaa	FI1B	2021	0.55	Yuzhen tsentralen	BG42	2010
Use of internet: selling	54.09	Drenthe	NL13	2013	0.26	Centru	RO12	2010
GHG emissions	95896.13	Düsseldorf	DEA1	2012	86.32	Åland	FI20	2022
Circular employment	4311.81	Övre Norrland	SE33	2017	153.81	Région de Bruxelles-Capitale/ Brussels Hoofdstedelijk Gewest	BE10	2019
Wages in mining	64.48	Övre Norrland	SE33	2013	0.000	Bremen	DE50	2010
Agricultural Share	13.58	Thessalia	EL61	2021	0.005	Berlin	DE30	2022

Tourism over GDP ratio	1152.51	Andalucía	ES61	2019	1.29	Ciudad de Melilla	ES64	2020

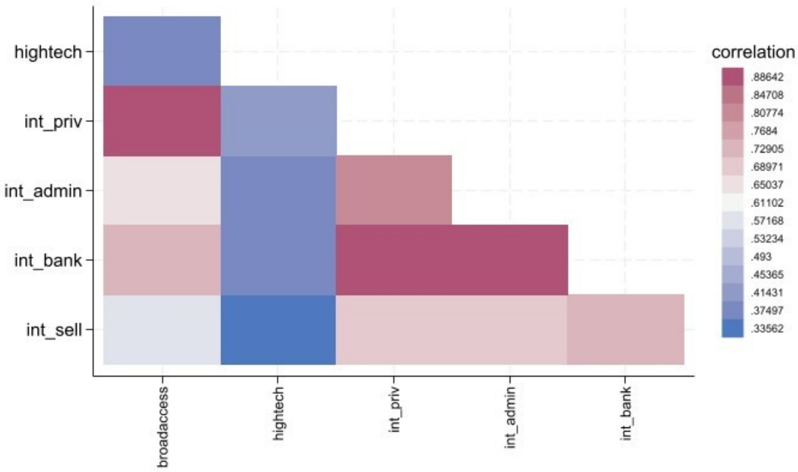
Table 3. 2. Descriptive statistics and values for standardization of indicators

Variable	Mean	SD	Min	Max	Q1	Q2	Q3
Employment rate	70.41981	8.69113	39.6	89.7	65.4	71.9	77.1
GDP pc	27278.26	11168.43	6300	101200	19500	25800	33000
Share of industry	21.30509	9.195405	3.79174	69.02902	14.66039	20.73596	26.85641
Share of services	22.75656	5.864361	7.752077	49.05927	18.79411	22.85782	26.02598
Tourists per 100k	2.074127	2.147728	0.091578	22.40328	0.879196	1.519718	2.438992
Tertiary students	28.65187	9.565942	9	62.1	21.5	27.55	34.5
Physicians per 100k	369.0112	112.7294	69.96941	911.04	287.04	367.22	431.09
Housing cost overburden rate	10.77872	7.3142	1.1	50.79087	5.835294	8.8	13.5
Robberies per 100k	58.3278	86.18054	0	908.53	15.54	33.75	63.46
Institutional Quality	0.112307	0.97703	-2.672	2.822	-0.69052	0.241735	0.961953
Cooling degree days	104.6543	140.2057	0	841.72	12.39	40.265	146.19
Heating degree days	2600.479	937.1019	42.09	7011.09	2097.24	2649.735	3111.02
Air quality	13.29675	4.982892	2.8	39.51429	9.775	12.53913	16.24
Broadband coverage	78.28712	14.05869	15.46	100	71.07	81.135	88.78406
High Tech employment	3.574085	2.0875	0.387978	13.6	2.1	3.1	4.5
Use of internet: private	79.42739	13.51601	29.09433	99.44	71.17657	82.53449	90.06976
Use of internet: public	49.9938	19.83369	2.61	94.35	35.58	50.7462	63.1
Use of internet: banking	47.86764	22.62996	0.553545	96.49	31.85548	48.94372	62.44
Use of internet: selling	16.90376	10.39781	0.26322	54.09	8.48	15.08852	25.12
GHG emissions	15871.5	13232.36	31.12145	95896.13	6859.613	12544.99	20759.01
Circular employment	850.8927	492.0662	153.8081	4311.806	524.87	746.9331	1045.706
Wages in mining	2.956337	5.461124	0	64.47822	0.661844	1.381447	3.205626
Agricultural Share	3.069262	2.682538	0.004663	13.57627	1.082857	2.282154	4.215054
Tourism over GDP ratio	119.0226	131.0213	1.29087	1152.514	45.20285	82.59899	133.1114
Population	1834623	1604336	27734	12354286	839751	1382167	2245470

a) Traditional factors



b) Digital Factors



c) Green Factors

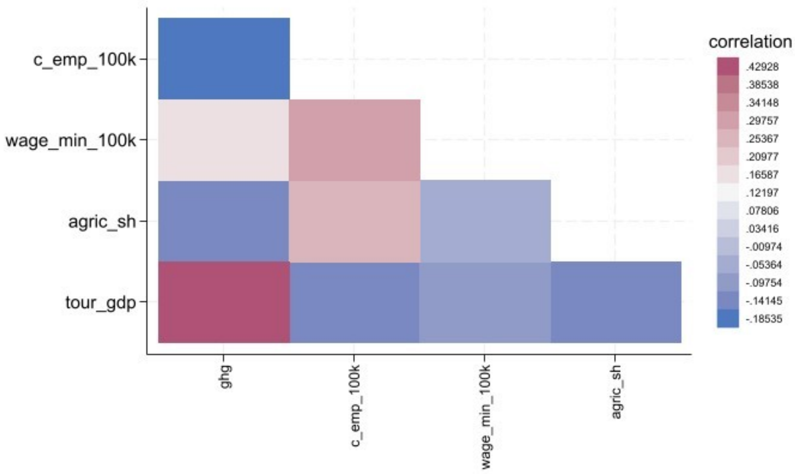


Figure 3. 1. Correlation heat-plot of indicators of attractiveness

Finally, a **threshold transformation** to derive belonging to a category is also considered. We interpret that a region is attractive if it is above a certain threshold. To define the thresholds, we follow the development trap literature in Diemer et al. (2022) and Rodríguez-Pose et al. (2024). The authors present alternative metrics for assessing the regional development trap. The more straightforward measure evaluates whether a region's growth in GDP per capita, productivity, and employment is: (1) slower than the EU average, (2) slower than the national average, and/or (3) slower than its own historical performance. This approach generates nine growth comparisons (3 indicators × 3 benchmarks). The trap risk quantifies the extent of vulnerability by counting the number of growth comparisons in which a region underperforms.

Here we follow a similar approach for every index, defining if a region is attractive in every indicator by means of the comparison of the relative performance against the national and EU average (levels) and the growth rate in national, and EU terms. This implies five comparisons for every indicator and consequently, four measures of attractiveness: the resulting score is a value of 1 for attractive regions if the value of a region is above the national or European mean (or the corresponding growth). On the contrary, if such region is below the relative thresholds, we assign a value of 0. Consequently, if a region is above the national and European average and it is growing more than the national or European growth rates, such region will have all four indicators with a value equal to 1.

We build an overall attractiveness measure for every indicator, rather than using the simple sum of all four measures, considering a **fuzzy approach**. Unlike classical set theory, where individuals are either fully identified with a group or not at all, the fuzzy set approach allows for partial membership. For example, one region can be partially identified as being attractive because it has a value over the EU mean, while not being attractive enough because it is below the country's average. The idea is that the shift from no attractive at all to fully attractive occurs gradually. As Lelli (2001, p. 6) notes, "Fuzzy reasoning aims at providing models that mirror people's intuitions and thinking processes when confronted with fuzzy categories in reality."

Here we follow Gómez Salcedo et al. (2017) and Royuela (2020) who use the fuzzy set technique to build composite measures of complex concepts, such as quality of work and European identity. This option is flexible enough to report an index of attractiveness for every indicator. The key advantage of this method lies in its avoidance of subjective weighting, as the weighting scheme adapts to the distribution of each attribute. Moreover, it considers the broader context by factoring in the cumulative distribution of all dimensions, with weights determined by the frequency of group membership. To our knowledge, this approach has not yet been applied to the study of regional attractiveness, making this analysis technically innovative.

This approach has also been widely utilised across various disciplines, including social sciences. Notable applications include studies on well-being and poverty (Lelli, 2001; Lemmi & Betti, 2006; Bérenger & Verdier-Chouchane, 2007) as well as the quality of work (Gómez et al., 2013; Agovino & Parodi, 2014; Gómez-Salcedo et al., 2017). Additionally, Nurmi and Kacprzyk (2007) provide an overview of its diverse applications in the field of political science.

The next Table 3.3 displays the descriptive statistics of the fuzzy measure of attractiveness for every indicator, including a last column with the correlation with the main indicator. As can be seen, even if for most indicators the association is positive, it is mild, and for some it is even genitive. The fact that we have defined such fuzzy indicators containing relative comparisons against national averages (both in level and in growths) imply that a capital region in a lagging country can be attractive in national terms while being unattractive when compared against overall measures, as the minmax or standardization approaches do. We believe that these new outcomes are enriching the analysis by providing a new perspective of attractiveness.

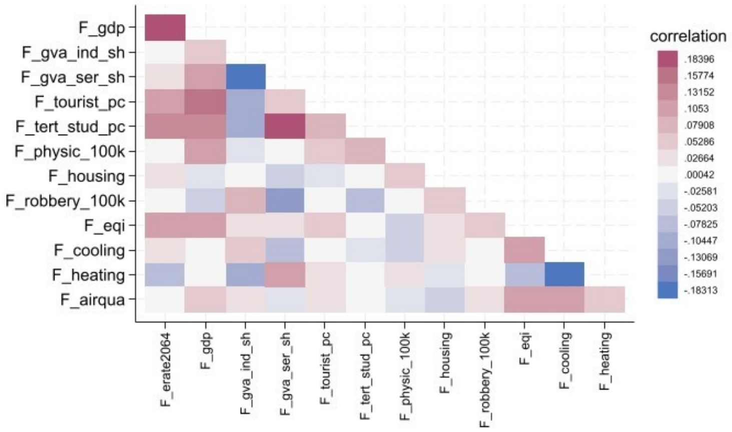
Table 3. 3. Descriptive statistics of the indicators based on fuzzy threshold approach

Variable	Mean	SD	Min	Max	Q1	Q2	Q3	Corr
Employment rate	23.01	34.10	0	100	0.83	5.57	29.02	0.331
GDP pc	15.87	28.76	0	100	0.58	3.71	19.74	0.471
Share of industry	21.26	33.21	0	100	0.66	5.42	25.60	0.494
Share of services	18.57	31.71	0	100	0.57	4.22	18.79	0.494
Tourists per 100k	13.43	26.91	0	100	0.34	2.93	9.28	0.425
Tertiary students	18.13	31.69	0	100	0.62	4.26	21.04	0.434
Physicians per 100k	13.56	26.98	0	100	0.45	3.33	5.50	0.389
Housing cost overburden rate	21.25	33.70	0	100	0.68	3.74	20.88	-0.280
Robberies per 100k	26.78	38.54	0	100	1.29	2.99	39.15	-0.199
Institutional Quality	18.01	30.44	0	100	0.53	4.12	18.50	0.364
Cooling degree days	31.94	40.18	0	100	2.12	7.37	39.52	-0.399
Heating degree days	19.90	32.05	0	100	0.64	4.88	26.91	-0.427
Air quality	22.88	34.28	0	100	0.61	4.49	28.67	-0.324
Broadband coverage	15.10	27.89	0	100	0.43	2.54	10.47	0.184
High Tech employment	17.42	31.84	0	100	0.00	3.83	21.78	0.519
Use of internet: private	15.96	27.23	0	100	0.84	2.96	18.81	0.191

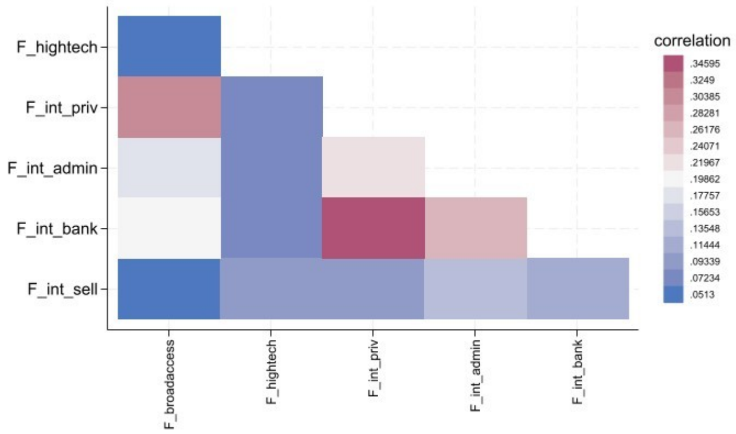
Use of internet: public	16.16	29.23	0	100	0.36	3.03	18.67	0.268
Use of internet: banking	13.21	24.17	0	100	0.46	2.64	15.76	0.198
Use of internet: selling	14.38	26.23	0	100	0.62	3.60	18.20	0.376
GHG emissions	24.75	36.19	0	100	2.52	5.98	20.51	-0.323
Circular employment	13.20	25.14	0	100	0.71	3.86	7.60	0.417
Wages in mining	29.57	40.66	0	100	1.32	3.57	48.90	-0.207
Agricultural Share	25.72	36.62	0	100	0.90	7.60	25.11	-0.390
Tourism over GDP ratio	30.03	39.71	0	100	2.96	9.22	41.80	-0.304

Finally, Figure 3.2 display the linear correlation between the fuzzy indicators of attractiveness, which are lower in magnitude than the initial indicators, very likely due to the stronger impact of the growth dimension of fuzzy attractiveness indexes.

a) Traditional factors



b) Digital Factors



c) Green Factors

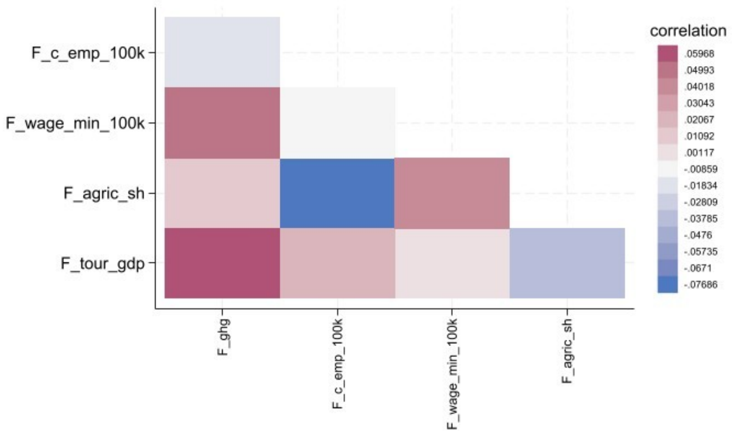


Figure 3. 2. Correlation heat-plot of indicators based on fuzzy threshold approach

3.3. Weighting

Weighting and aggregation play a crucial role in the construction of composite indicators, as they significantly influence rankings and overall results, as highlighted by the OECD Handbook on Constructing Composite Indicators. A variety of weighting techniques exist, each with advantages and limitations. For instance, equal weighting (EW) assumes all indicators have the same importance, yet this may introduce unintended imbalances if dimensions contain unequal numbers of variables. Statistical methods, such as principal components analysis (PCA) or factor analysis, allow weights to reflect correlations between indicators but are ineffective when no correlation exists. Alternatively, the benefit of the doubt (BOD) method allows data to determine weights, aligning with national priorities but introducing estimation challenges. Participatory approaches, such as budget allocation, enable stakeholders to assign weights based on perceived importance. While practical for limited indicators, this method can strain experts when too many variables are involved. Public opinion polls offer a simpler solution but may lack depth.

Aggregation methods vary based on compensability assumptions. Linear aggregation assumes constant trade-offs between indicators, allowing deficits in one dimension to offset gains in another. In contrast, geometric aggregation reduces compensability for low scores, incentivising improvement in weaker areas. Non-compensatory multi-criteria approaches ensure no trade-offs, crucial when aggregating diverse dimensions, such as social and environmental data.

While no "objective" method exists for determining weights or aggregation, transparency in methodology and alignment with the modeller's objectives remain essential. Proper documentation and sensitivity analysis are necessary to validate the robustness and relevance of the chosen approach.

Our proposal follows an aggregative-compensatory approach, the most common approach in the literature, which consists of aggregating all the indicators using appropriate mathematical methods to construct composite indicators.

Our approach assumes that the individual indicators are, to some extent, substitutable. To aggregate these indicators, we propose two methods. Our primary choice is a straightforward additive approach, employing a basic mathematical function such as the arithmetic mean. To ensure robustness, we complement this with Principal Components Analysis (PCA). While PCA offers valuable insights by identifying underlying latent variables, it has notable limitations. It can be challenging for non-expert decision-makers, particularly at the regional level, to fully grasp and endorse. Additionally, PCA is reflexive by nature, meaning it captures the effects of latent variables rather than directly representing the phenomenon being studied. Moreover, it overlooks the polarity of indicators, which could lead to misinterpretations of the data's relationship with the intended concept.

Based on the structure of our analysis, we define the overall index of regional attractiveness as the aggregation of three key domains: **traditional factors**, **digital factors**, and **green factors**. This approach aligns with the work of Fudge et al. (2021) and Boumahdi and Zaoujal (2023). The former work highlights that the most frequently referenced aspects of well-being include jobs and livelihoods (39%), health (38%), education and skills (34%), and the environment (30%).

In our work, we propose a basic initial approach, in which traditional factors contribute approximately 50% to the final composite index of attractiveness, while the digital and green dimensions each account for 25%.

The baseline approach

The first approach considers the aggregation of normalised indicators within every basic domain. If there are more than one indicator capturing a key concept, a further arithmetic mean is considered. Table 3.4 displays the structure of the Traditional factors' domain. Seven components are identified. When there is just one indicator, it accounts for the 100% of the domain, while if there is more than one, we average them. The final metrics of the composite index of traditional factors of regional attractiveness is the simple average of all domains. We use the minmax transformation of the indicators.

Table 3. 4. Traditional factors of regional attractiveness

Component	Indicator
Economy	Gross Domestic Product per capita
Labour market	Employment rate
Sectoral composition	Industry share
	High value-added private services share
Visitor Appeal	Number of tourists arriving at accommodation establishments per 100,000 inhabitants
Residents Well-Being	Tertiary students
	Physicians per 100,000 inhabitants
Housing affordability	Housing over burden rate
Regional Safety	Robbery rates
Institutional Quality	Quality of Government Index (EQI)

Environment	Cooling degree days index
	Heating degree days index
	Air quality index

$$RAI_{traditional} = \frac{1}{9} GDP\ pc + \frac{1}{9} Employment\ rate + \frac{1}{9}(0.5 * Industry\,\% + 0.5 * Services\,\%) + \frac{1}{9}$$

A similar approach is developed both for the digital and the green factors, which are summarized in Tables 3.5 and Table 3.6. The former is composed of three components and six indicators, and the latter by five components, one indicator each.

Table 3. 5. Digital factors of attractiveness

Component	**Indicator**
Connectivity	Broadband access
ICT employment	High-tech employment
Digital skills	Internet used between individuals
	Internet used with public authorities
	Internet selling
	Internet banking

$$RAI_{Digital} = \frac{1}{3} Boradband\ access + \frac{1}{3} High\ tech\ employment + \frac{1}{3}(0.25 * Internet\ private + 0$$

Table 3. 6. Green factors of regional attractiveness

Component	**Indicator**
Emissions	Greenhouse Gas (GHG) emissions
Circular economy	Circular economy employment
Mining	Wages in the mining sector
Agriculture	Share of activity in Agriculture
Tourism activity	Tourism-to-GDP ratio

$$RAI_{Green} = \frac{1}{5} GHG + \frac{1}{5} Circular\ employment + \frac{1}{5} Wages\ mining + \frac{1}{5} Agriculture\,\% + \frac{1}{5} Tour$$

The final Regional Attractiveness Index (RAI) is a weighted average of the three main components:

$$RAI = 0.50 * RAI_{Traditional} + 0.25 * RAI_{Digital} + 0.25 * RAI_{Green}$$

Principal Component Analysis

We propose an alternative way of building the main components indicators. We use the Principal Component Analysis approach to derive the RAI indicators of traditional, digital and green attractiveness.

The final Regional Attractiveness Index follows the same expression than above, but in this case the specific indices come from the PCA approach rather than the weightings simple. This composite index is labelled as RAI^{PCA}.

$$RAI_{\square}^{PCA} = 0.50 * RAI_{Traditional}^{PCA} + 0.25 * RAI_{Digital}^{PCA} + 0.25 * RAI_{Green}^{PCA}$$

Threshold-based fuzzy composite indicator

The final alternative index follows the same approach than the main index, although the indicators are the ones derived from the threshold-based fuzzy indicators. We label this alternative as RAI^{Fuzzy}.

$$RAI_{\square}^{Fuzzy} = 0.50 * RAI_{Traditional}^{Fuzzy} + 0.25 * RAI_{Digital}^{Fuzzy} + 0.25 * RAI_{Green}^{Fuzzy}$$

4. Main results

This section displays the main results of the Regional Attractiveness Index, considering the basic RAI as the defaults option. To follow a comprehensive discourse, we display the characteristics of the basic components as well as the composite indicator of attractiveness.

4.1. Traditional attractiveness

The next figures display the evolution of the composite index of traditional factors of attractiveness. The analysis of traditional factors from these graphs demonstrates clear trends and persistent disparities in regional attractiveness across different classifications. Predominantly urban regions consistently outperform intermediate and rural regions, maintaining the highest scores throughout the period from 2010 to 2022. Intermediate regions follow, showing steady growth but maintaining a significant gap compared to urban regions. Predominantly rural regions exhibit the lowest scores and grow at a lower rate than the other types of regions. The urban-rural divide increases over time, reaching the maximum in the last year.

Geographically, North-West regions lead in traditional factors, with scores consistently higher than other regions, reflecting their strong economic and social foundations. North-East regions follow closely, surpassing South-East regions in the last analysed years. South-West regions lag significantly, though they also show steady growth over time. The gap between northern and southern regions persists, underscoring the divide in traditional attractiveness.

When comparing EU15 and EU13 regions, EU15 regions consistently achieve higher scores, reflecting their more advanced economic and social structures. EU13 regions, improve substantially, narrowing the gap. Finally, capital regions perform better than non-capital regions, highlighting the concentration of resources, infrastructure, and opportunities in capitals. There is a growing gap between capital and non-capital regions.

Despite progress across all groups, regions with stronger socio-economic characteristics, such as urban areas, northern regions, EU15, and capitals, continue to lead in attractiveness, highlighting persistent inequalities. Nevertheless, the overall upward trajectory suggests general improvements in regional attractiveness across Europe, even though the disparities between different regional classifications remain significant and largely unchanged, if not increasing

(Figure 4.1). As can be seen in the dynamic scatterplot at Figure 4.2, there is no clear pattern of convergence between regions, with top regions growing substantially in the last subperiod.

The map (Figure 4.3) and the display of the top and bottom regions of every country in 2020 (Figure 4.4) stresses the pronounced disparities between European regions. The map reveals a clear concentration of high scores in northern and western Europe, particularly in Scandinavia, Luxembourg, Ireland, and the Netherlands and parts of central Europe. Conversely, eastern and southern European regions, including Bulgaria, Romania, and parts of Greece, exhibit much lower scores, reflecting persistent challenges in these areas related to economic development and social infrastructure. Large disparities are observed in Belgium, Spain and Italy.

The findings emphasize the stark divide between regions within and across countries, underscoring the continued dominance of traditionally strong regions in northern and western Europe while highlighting the challenges faced by southern and eastern regions in improving their traditional attractiveness factors.

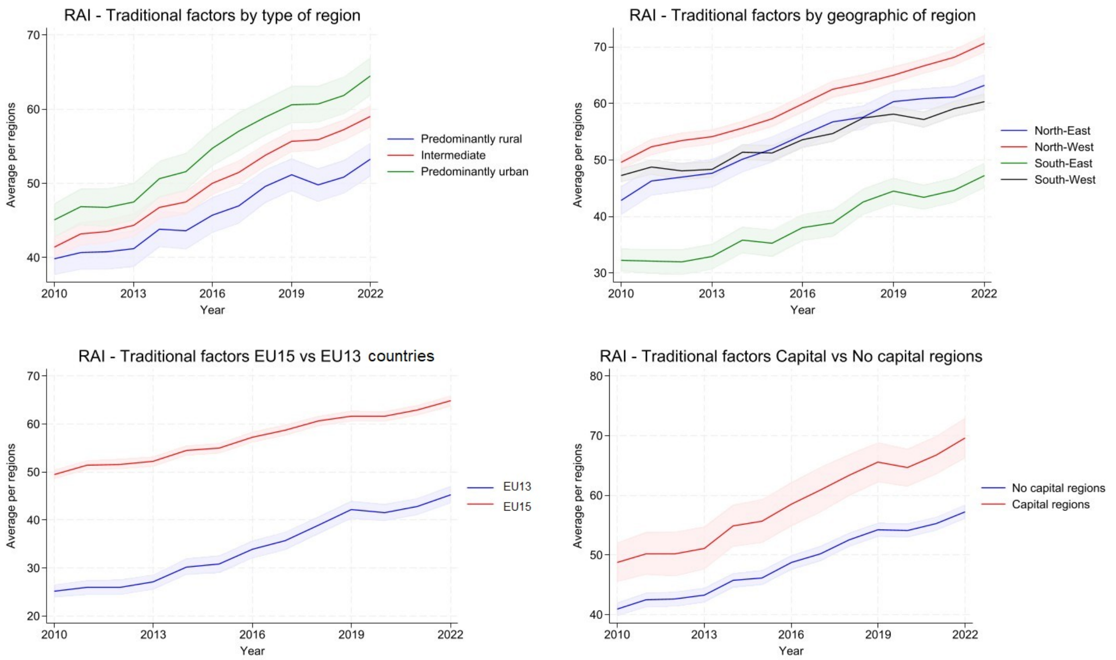


Figure 4. 1 Evolution of the RAI for traditional factors by typologies of regions

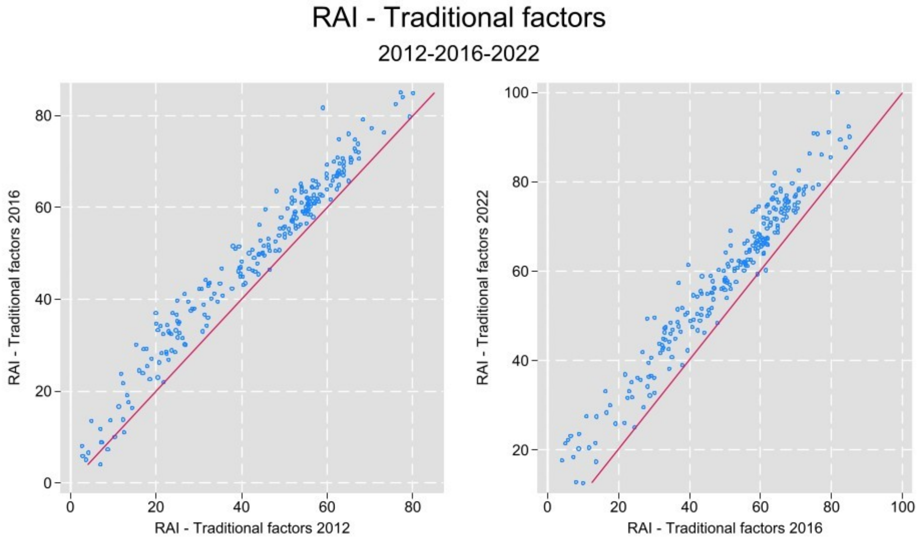


Figure 4. 2 Dynamic scatterplots of the RAI for traditional factors

Table 4. 1. Descriptive statistics of the RAI for traditional factors

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	69.4	8.9	53.3	90.7	63.3	68.7	74.3	24%
BE	52.7	14.2	16.9	82.0	42.2	53.9	64.0	63%
BG	25.1	9.5	7.3	49.6	18.1	25.1	31.8	104%
CY	53.2	4.9	46.2	62.4	49.6	51.9	56.9	23%
CZ	49.7	12.5	24.2	90.9	42.1	48.3	56.0	60%
DE	62.2	7.5	44.4	86.1	56.2	62.1	67.1	32%
DK	63.4	6.4	54.5	82.6	58.4	62.3	67.2	28%
EE	59.6	7.7	45.1	70.6	54.1	60.9	65.4	57%
EL	16.7	9.9	0.0	49.4	8.7	15.9	23.2	62%
ES	48.0	11.5	20.8	74.0	39.0	48.2	56.5	31%
FI	70.1	8.1	55.2	85.5	63.6	68.5	77.3	17%
FR	55.5	6.2	39.7	73.2	51.0	55.7	60.1	22%
HR	36.2	14.5	12.9	64.2	24.4	33.8	48.7	74%
HU	36.1	12.9	15.1	74.5	27.8	34.4	43.3	109%
IE	71.6	12.8	50.4	100.0	61.8	68.2	83.8	54%
IT	39.1	16.9	2.4	75.4	26.9	42.7	50.0	26%
LT	52.9	14.9	27.5	79.3	40.8	52.9	63.6	107%
LU	83.9	4.7	76.5	92.4	80.1	84.7	85.0	21%
LV	44.2	8.9	27.8	54.5	36.5	46.7	52.3	93%
MT	49.9	8.1	38.5	61.0	43.1	50.9	57.3	53%
NL	64.8	9.5	46.6	91.1	56.8	65.6	70.4	47%
PL	35.9	11.7	15.5	75.4	26.5	35.1	43.4	128%
PT	48.5	8.6	34.8	69.0	40.8	47.4	54.9	51%
RO	24.6	11.1	4.9	61.4	17.7	23.2	30.4	118%
SE	70.2	6.4	57.0	89.4	65.6	69.2	73.5	25%
SI	53.2	9.3	40.3	73.3	46.6	52.7	57.8	45%
SK	44.6	15.9	24.8	78.1	31.8	39.9	55.9	67%

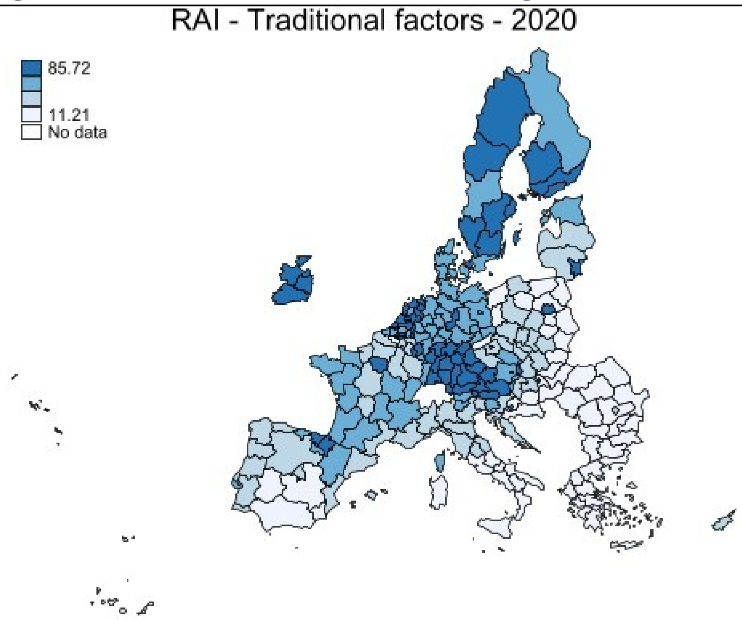


Figure 4. 3 Geographical distribution of the RAI for traditional factors - 2020

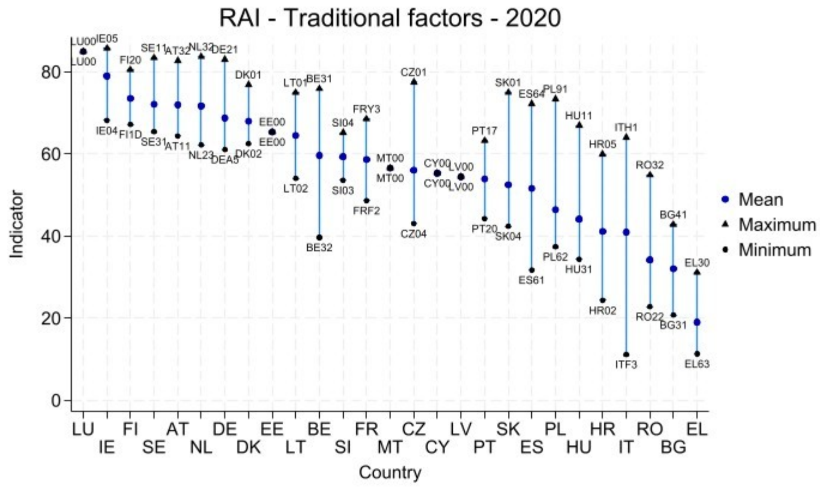


Figure 4. 4 Regional Disparities in RAI for traditional factors across EU countries - 2020

4.2. Digital attractiveness

As in the previous section, next we display graphical evolution and geographical distribution of the RAI for digital factors across different regional classifications and over time. The first four graphs highlight consistent growth in RAI values across all regions between 2010 and 2022, with significant disparities persisting between classifications. Predominantly urban regions outperform intermediate and rural regions, with urban regions showing a steady increase and achieving the highest values. Despite the sustained growth, the divide increased over the studied period (Figure 4.5)

Geographically, North-West regions lead in digital attractiveness, followed by North-East regions, with South-East and South-West regions lagging behind but improving steadily, and displaying a convergence path, with differences narrowing over time, although at a decreasing rate. Similarly, the comparison of EU15 and EU13 regions reveals a persistent but decreasing gap. In line with the urban-rural divide, capital regions also maintain a significant advantage over non-capital regions, highlighting the dominant role of capital cities in driving digital attractiveness. The scatterplots comparing RAI values across time periods (2012–2016 and 2016–2022) show a strong growth in the last years, with higher increases in lagging regions (Figure 4.6).

The geographical distribution demonstrates a pronounced disparity across European regions. The map highlights the dominance of northern and western Europe, particularly Finland, Denmark, the Netherlands, and parts of Sweden and Germany, where regions achieve the highest scores, reflecting strong digital infrastructure and capacity. Several regions in Central European countries, such as Hungary, also perform exceptionally well, with values clustering towards the upper end of the index. In contrast, eastern and southern European regions, including Bulgaria, Romania, and Greece, generally exhibit the lowest RAI values, highlighting persistent challenges in digital attractiveness in these areas (Figure 4.7). The last graph (Figure 4.8) reveals significant intra-country disparities, particularly in nations such as Hungary, Slovakia, France and the Czech Republic, where the range between maximum and minimum values is substantial. This trend is less pronounced in highly developed nations like Finland and Denmark, and overall scores are consistently high.

Overall, the results indicate notable progress in digital factors across all classifications, while simultaneously emphasising the enduring inequalities between more and less developed regions in Europe, with northern and western regions far outpacing their southern and eastern counterparts.

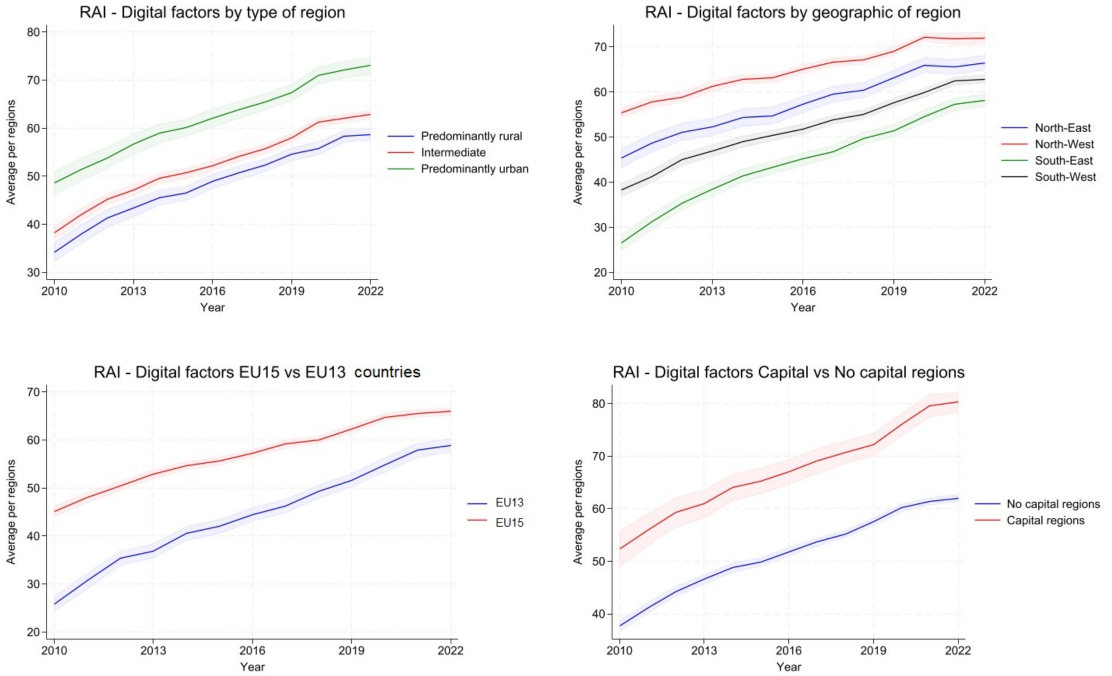


Figure 4. 5 Evolution of the RAI for digital factors by typologies of regions

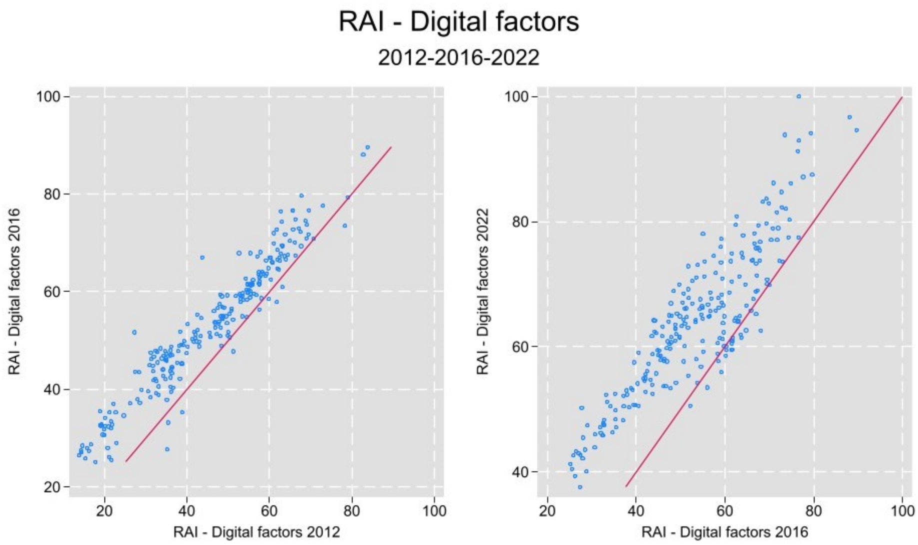


Figure 4. 6 Dynamic scatterplot of the RAI for digital factors

Table 4. 2. Descriptive statistics of the RAI for digital factors

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	56.8	8.8	38.1	83.2	50.8	56.9	62.2	65%
BE	62.4	10.1	41.7	93.9	54.4	61.9	69.6	44%
BG	31.8	13.8	5.5	70.0	22.5	31.4	39.4	409%
CY	45.0	12.3	25.4	64.2	35.4	44.0	53.9	152%
CZ	55.1	13.1	28.1	94.7	47.0	55.4	62.8	93%
DE	61.6	7.1	36.2	90.6	57.3	61.7	66.2	20%
DK	72.2	8.9	57.3	94.6	66.2	69.9	75.0	19%
EE	64.4	10.2	45.6	76.7	56.1	68.0	71.4	68%
EL	31.5	12.9	5.6	67.8	23.2	32.5	40.8	420%
ES	49.8	12.5	22.3	84.7	40.2	49.1	59.6	109%
FI	73.1	9.8	55.8	96.7	66.4	72.4	78.9	29%
FR	53.1	10.4	17.5	81.3	48.1	54.1	59.6	56%
HR	47.4	13.5	24.1	75.7	37.7	47.7	54.4	123%
HU	54.0	14.9	23.1	100.0	43.8	52.6	62.7	105%
IE	65.9	16.0	24.2	92.9	59.4	68.8	76.7	46%
IT	41.9	11.5	14.9	71.3	33.3	43.0	50.3	125%
LT	49.2	14.3	24.0	78.1	39.6	49.3	57.0	115%
LU	64.5	7.7	53.0	75.4	55.3	67.1	67.9	40%
LV	52.4	10.5	35.5	69.2	44.7	51.7	58.2	95%
MT	61.9	7.2	48.2	73.7	57.0	61.3	65.9	53%
NL	70.8	7.5	49.4	89.4	66.2	70.3	76.3	33%
PL	45.0	10.5	25.4	77.8	36.9	44.0	51.6	86%
PT	41.4	12.3	19.1	76.0	31.8	41.5	49.8	136%
RO	32.9	16.8	0.0	77.2	20.7	33.3	42.4	1340%
SE	67.9	8.6	53.2	94.1	62.0	66.2	72.7	20%
SI	60.1	10.5	39.3	79.9	50.7	61.3	65.8	54%
SK	56.3	13.8	30.7	95.2	48.3	53.3	64.1	75%

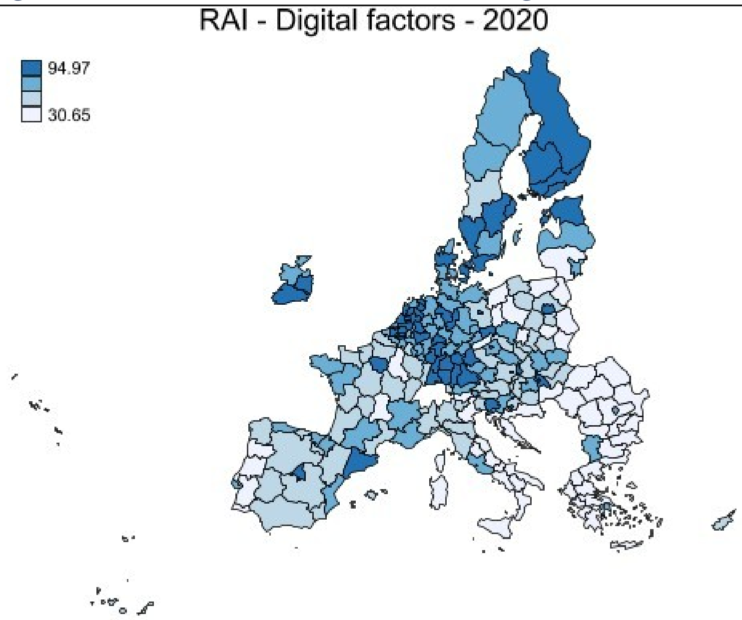


Figure 4. 7 Geographical distribution of the RAI for digital factors - 2020

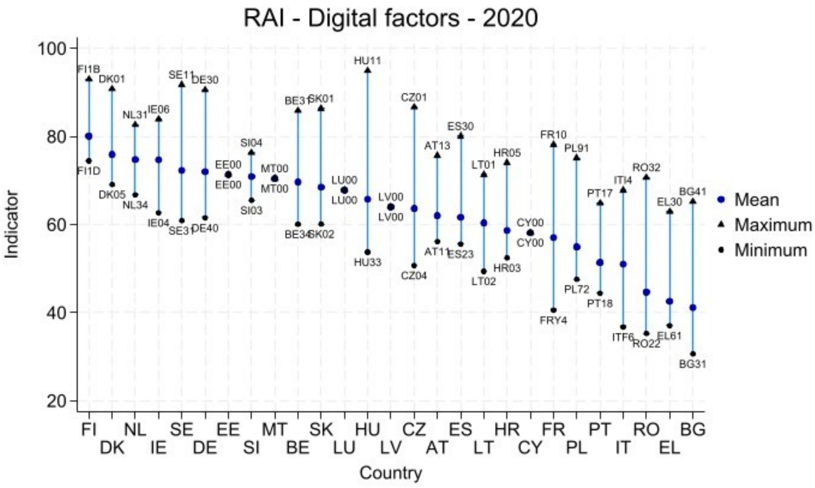


Figure 4. 8 Regional Disparities in RAI for digital factors across EU countries - 2020

4.3. Green attractiveness

The evolution of the RAI for green factors reveals a stagnation or slight increase in performance across most classifications from 2010 to 2022, with notable jump in 2020 because of the COVID-19 pandemic. Figure 4.9 shows small differences between urban and rural regions, with urban regions experiencing a sharp increase in green factor scores in 2929. Upward trend reflects growing emphasis on sustainability in all types of regions, with urban areas taking the lead in more recent times. Geographically, North-East regions lead in green factors, maintaining the highest scores throughout the period, followed closely by North-West regions. South-East and South-West regions, while improving slightly, remain significantly behind, indicating ongoing environmental and sustainability challenges. The gap between northern and southern regions remains pronounced, despite general progress across all areas.

When comparing EU15 and EU13 regions, EU15 regions consistently perform better, reflecting their more established sustainability frameworks. However, EU13 regions demonstrate significant progress, narrowing the gap by 2022. Capital regions maintain a clear advantage over non-capital regions, with the latter showing steady but slower progress.

The geographical distribution of RAI Green Factors in 2020 highlights significant variation across European regions. The map (Figure 4.11) illustrates a notable concentration of high-performing regions in northern Europe, particularly in Sweden, Finland, and the Baltic countries. Other central European regions also show good performance in green transition factors. Countries like Austria and Luxembourg show high average scores, reflecting consistent investments in environmental sustainability. In contrast, regions in southern and eastern Europe, particularly in Greece, Bulgaria, and parts of Romania, exhibit lower scores. This pattern suggests ongoing challenges in these areas, including limited resources, policy implementation gaps, and economic barriers to advancing green initiatives (Figure 4.12).

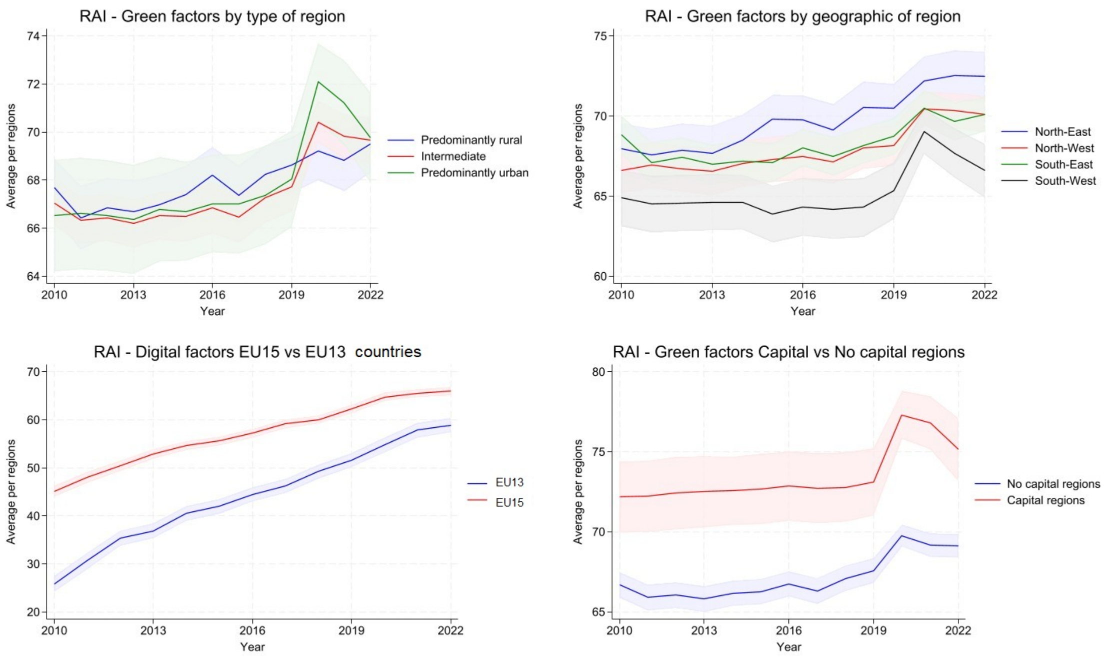


Figure 4. 9 Evolution of the RAI for green factors by typologies of regions

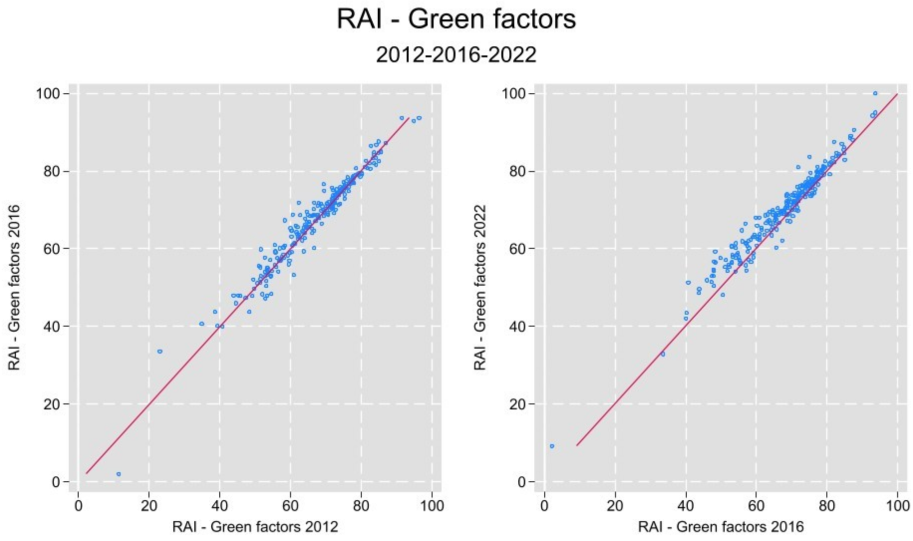


Figure 4. 10 Dynamic scatterplot of the RAI for green factors

Table 4. 3. Descriptive statistics of the RAI for green factors

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	79.7	4.1	69.8	85.8	77.0	79.6	83.7	0%
BE	74.7	3.3	67.1	80.4	71.9	75.7	77.0	1%
BG	60.9	9.0	48.3	80.7	54.3	58.4	63.3	3%
CY	72.3	1.2	70.6	74.6	71.6	71.9	72.5	2%
CZ	73.8	6.8	58.0	86.2	69.1	74.8	79.0	1%
DE	67.1	9.4	34.8	81.5	62.1	69.5	74.2	9%
DK	71.9	4.7	58.3	78.3	71.0	73.9	74.9	1%
EE	75.4	6.5	67.4	86.0	69.9	74.0	79.1	22%
EL	62.9	7.3	44.2	76.3	57.9	62.1	69.9	-2%
ES	62.0	18.7	0.0	98.6	53.0	62.5	72.0	2%
FI	73.3	6.2	65.0	88.7	69.0	71.7	75.4	1%
FR	65.7	10.3	38.6	82.4	57.8	66.5	74.1	4%
HR	66.8	13.8	48.1	91.8	55.6	62.2	80.3	13%
HU	66.2	11.6	48.3	88.0	54.8	67.0	74.3	0%
IE	67.2	3.7	60.3	75.0	65.4	66.4	69.6	8%
IT	65.3	11.4	38.4	88.1	56.2	66.2	74.7	3%
LT	75.4	11.5	60.0	89.1	64.4	75.7	86.7	6%
LU	77.0	0.7	75.8	78.1	76.7	77.1	77.4	2%
LV	84.3	2.8	78.7	88.6	82.7	84.5	86.5	13%
MT	84.5	0.8	83.3	85.7	83.6	84.5	85.2	2%
NL	64.8	7.4	46.5	78.3	60.9	64.8	70.0	4%
PL	63.5	12.3	23.0	83.6	57.7	65.7	71.6	11%
PT	67.0	9.2	46.7	81.1	61.0	68.7	72.1	-3%
RO	62.9	10.6	43.3	85.0	54.1	61.4	69.3	11%
SE	79.0	7.5	65.0	100.0	73.3	76.7	83.6	6%
SI	79.9	3.4	75.4	85.0	76.5	81.3	83.3	-1%
SK	78.2	5.0	68.7	86.6	74.0	79.9	82.4	-1%

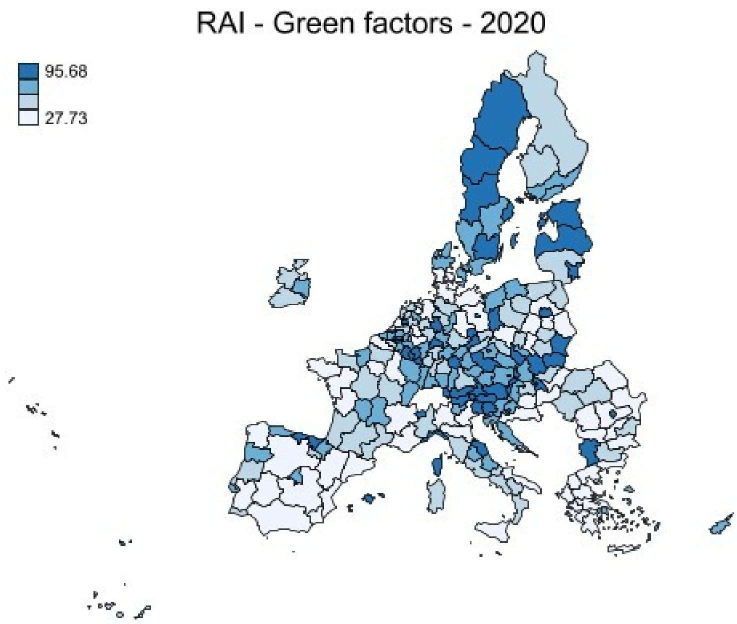


Figure 4. 11 Geographical distribution of the RAI for green factors - 2020

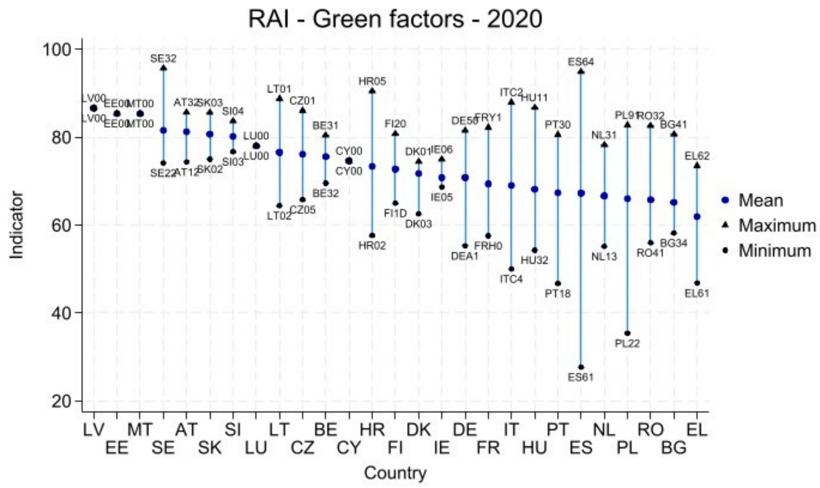


Figure 4. 12 Regional Disparities in RAI for green factors across EU countries - 2020

4.4. Regional attractiveness

The RAI overall index of attractiveness shows significant growth across all regional classifications from 2010 to 2022, highlighting improving regional development throughout Europe. The graphs illustrate the overall Regional Attractiveness Index (RAI) across different typologies, geographic areas, and country groupings within the EU. The first graph (Figure 4.13) highlights a consistent gap in the RAI between predominantly urban, intermediate, and rural regions. Urban areas consistently score the highest, followed by intermediate and rural regions. This gap has grown slightly over the years, indicating structural differences in regional attractiveness, with a lower growth path or rural regions. The second graph, by geographic location, shows the dominance of North-West regions, with North-East and South-West regions exhibiting lower but increasing scores. According to this regional classification, there is a convergence process between these groups of regions. The third graph highlights the persistent but decreasing gap between EU15 and EU13 countries. Similarly, capital regions outperform non-capital regions, as seen in the fourth graph. Differences increase over time.

The geographical distribution of the RAI overall index in 2020 reveals marked regional disparities across Europe. Northern regions, particularly in countries like Finland and Sweden, exhibit the highest scores, reflecting strong socioeconomic and infrastructural development. Western European countries, including Luxembourg, Ireland, and the Netherlands, also score prominently, indicating advanced regional policies and economic stability. Interestingly Estonia displays a strong performance in 2020. (Figure 4.15).

Conversely, regions in Southern and Eastern Europe, such as those in Bulgaria, Romania, and Greece, lag significantly, suggesting ongoing challenges in development and attractiveness. The high disparity between maximum and minimum scores within countries, evident in nations like Italy and Poland, highlights internal inequalities where certain regions excel while others remain underdeveloped. Interestingly, spatial inequalities are stronger in countries with lower averages (Figure 4.16).

Overall, the data underscores a clear divide between Europe's more developed northern and western regions and its lagging southern and eastern regions. Despite some convergence patterns, there is a clear divergence between more urbanised, and particularly capital regions, and intermediate and rural areas.

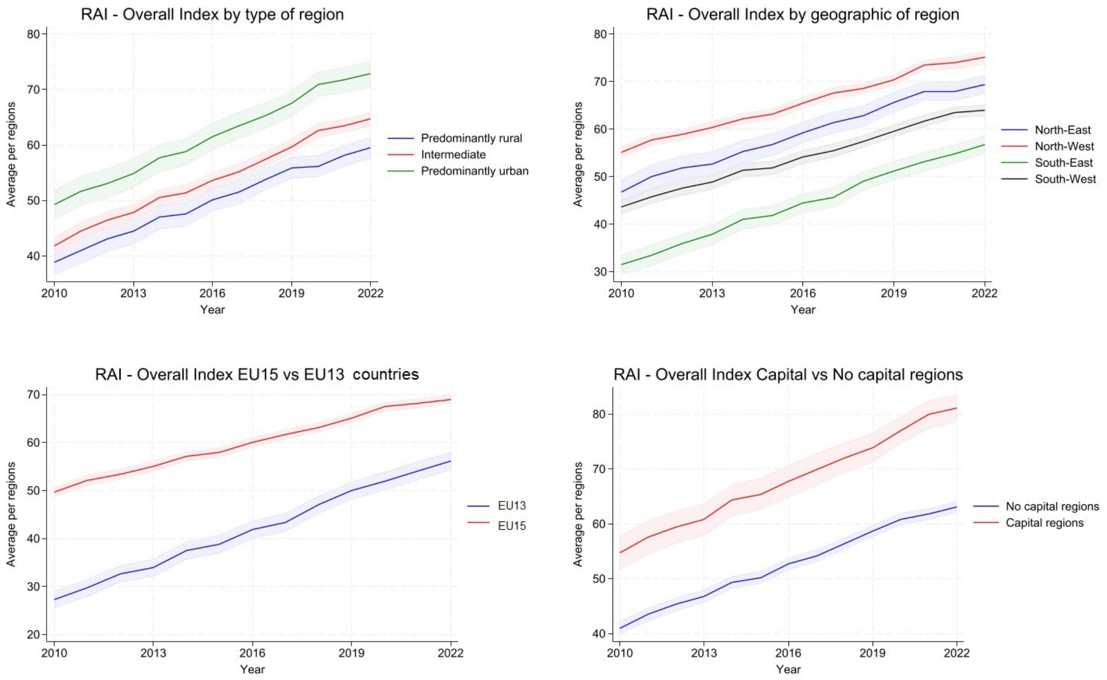


Figure 4. 13 Evolution of the RAI by typologies of regions

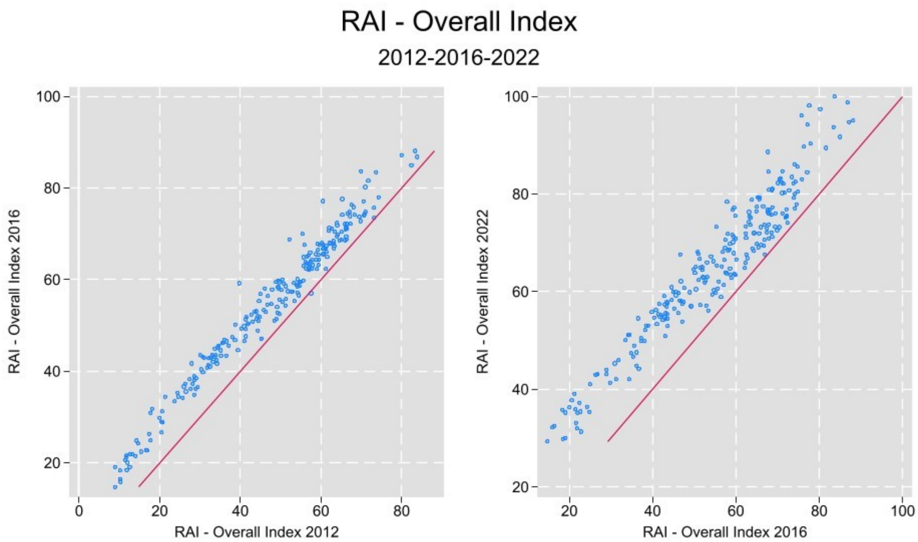


Figure 4. 14 Dynamic scatterplot of the RAI

Table 4. 4. Descriptive statistics of the RAI

Countries	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	69.0	7.9	51.4	85.6	63.3	69.1	74.4	39%
BE	63.1	11.4	36.7	96.1	55.6	63.1	70.6	46%
BG	28.6	13.9	5.8	67.6	18.0	26.7	35.9	266%
CY	52.6	9.4	40.1	68.2	44.4	50.8	60.2	70%
CZ	57.2	14.1	29.5	100.0	47.9	57.1	64.5	72%
DE	64.4	8.1	40.9	84.5	59.2	64.9	70.2	28%
DK	72.6	8.2	57.7	94.7	66.8	71.8	76.9	22%
EE	67.5	11.1	48.0	82.3	58.5	70.0	76.2	71%
EL	25.4	10.6	9.5	57.5	16.4	24.7	33.9	184%
ES	48.5	13.7	10.1	78.8	38.7	49.4	58.1	82%
FI	76.6	9.9	60.2	95.1	68.3	75.1	85.6	23%
FR	56.9	6.8	40.0	75.8	51.7	57.2	61.5	33%
HR	44.5	16.8	16.2	81.0	30.3	42.2	53.6	119%
HU	48.1	16.7	19.6	98.1	35.4	46.4	56.5	102%
IE	71.2	15.1	37.1	97.4	60.5	71.2	81.3	52%
IT	42.2	13.9	11.0	73.7	32.7	43.0	52.8	80%
LT	55.8	17.7	26.5	88.6	42.8	54.4	67.6	107%
LU	79.1	6.6	69.4	89.4	71.7	80.4	81.8	29%
LV	56.6	10.6	37.7	71.9	48.8	58.0	63.2	90%
MT	64.6	7.8	51.9	76.4	58.5	64.9	70.7	47%
NL	70.1	8.7	50.6	93.7	63.8	69.6	75.7	40%
PL	41.9	12.8	12.5	84.6	32.8	40.8	49.8	116%
PT	46.7	11.1	26.2	77.2	37.6	46.6	54.9	80%
RO	29.7	16.9	0.0	78.4	17.1	28.7	39.8	550%
SE	75.5	7.4	62.2	98.8	70.8	74.3	79.4	23%
SI	63.7	10.8	45.5	84.6	54.0	64.3	67.8	44%
SK	57.0	15.3	35.3	92.5	44.9	54.2	65.0	61%

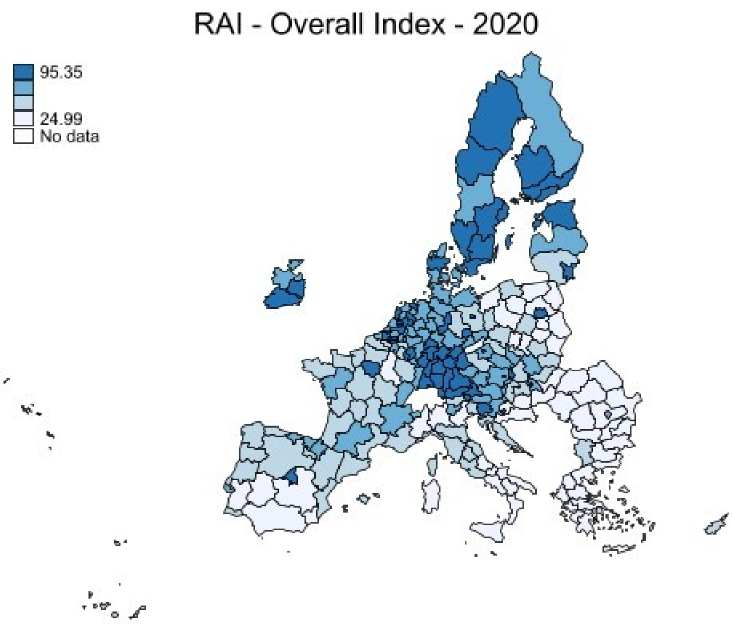


Figure 4. 15 Geographical distribution of the RAI - 2020

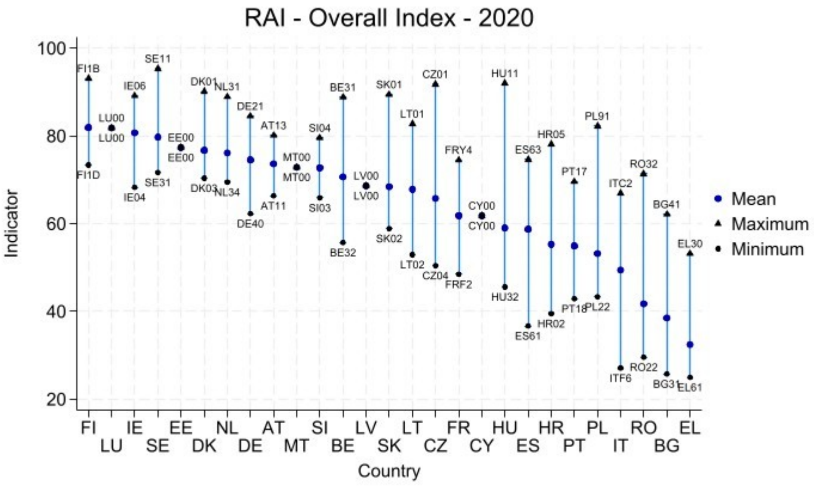


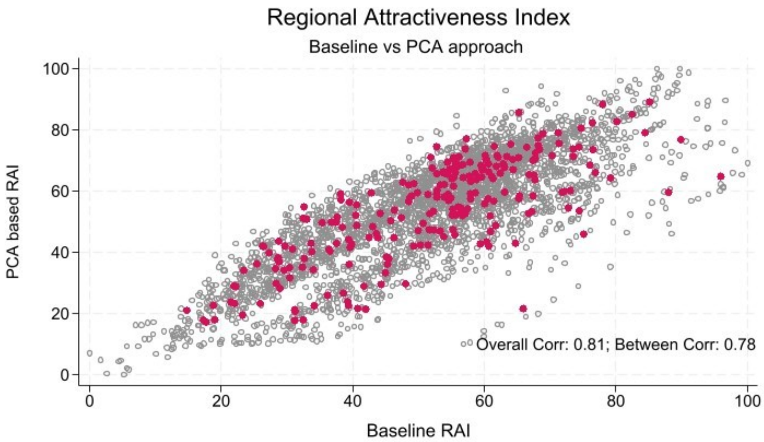
Figure 4. 16 Regional Disparities in RAI across EU countries - 2020

5. Robustness analysis

This section compares the basic results of the main Regional Attractiveness Index (RAI) and the alternative measures based on PCA and fuzzy indicators. While the results for these alternative indices are not reported for brevity, we display in this section the main similarities and differences between them.

We start by showing the correlation between the baseline RAI and the alternatives based on PCA and on threshold fuzzy approach (Figure 5.1). In both cases the correlations are positive, although it is higher for the PCA approach. In both cases the correlation is strongly grounded on the permanent characteristics of the regions, as displayed by the between information, which captures the average of the regions over the considered period. This is particularly true for the case of the fuzzy based index

a) PCA based attractiveness index



b) Threshold-based fuzzy attractiveness index

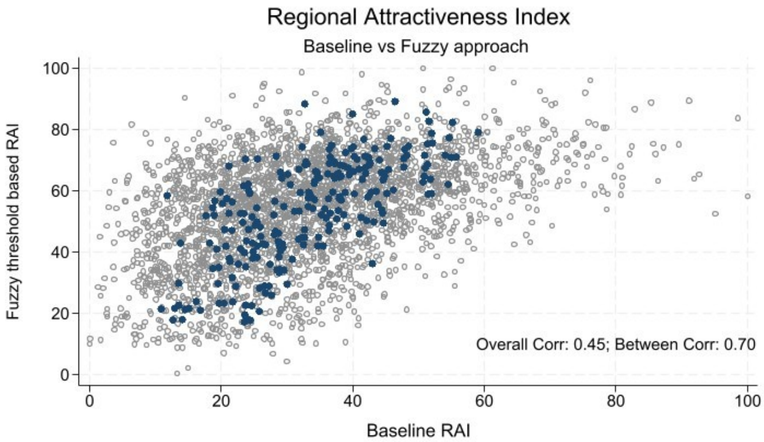
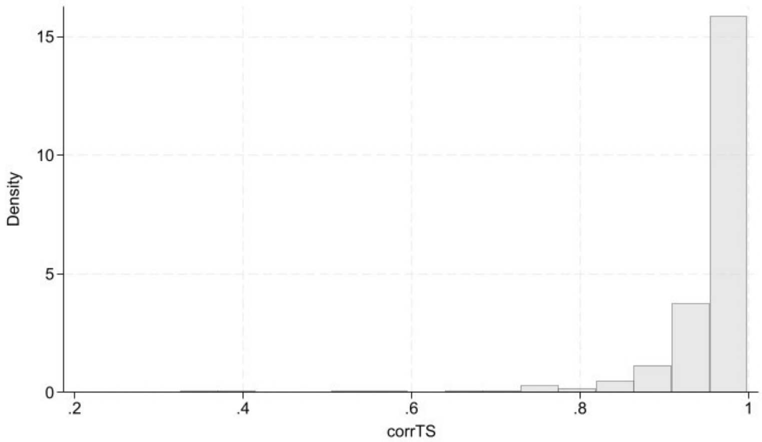


Figure 5. 1 Correlation between baseline and alternative RAI definitions: overall and between region analysis

To inspect the association between the indices over time rather, we have computed the correlation of the evolution of the alternative attractiveness indices for each region. It implies that we have over 200 correlations, one for each region, showing how the indices evolve over time. Figure 5.2 displays the histogram of the time series correlations between the baseline RAI and the alternative indices. As can be seen, the evolution of PCA and the baseline RAI are strongly correlated for most regions, with only a very minor number of regions with a correlation below 0.8. On the contrary, the evolution of the baseline RAI and the fuzzy based RAI are strongly heterogeneous, with almost half regions displaying negative outcomes and in general most of the showing negligible correlations.

a) PCA based attractiveness index



b) Threshold-based fuzzy attractiveness index

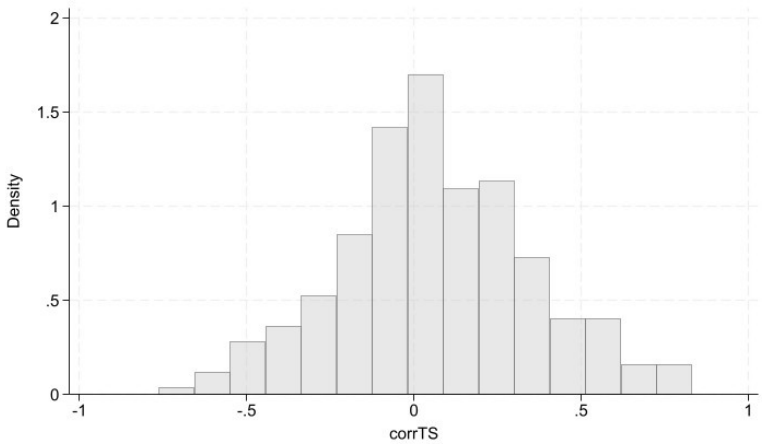
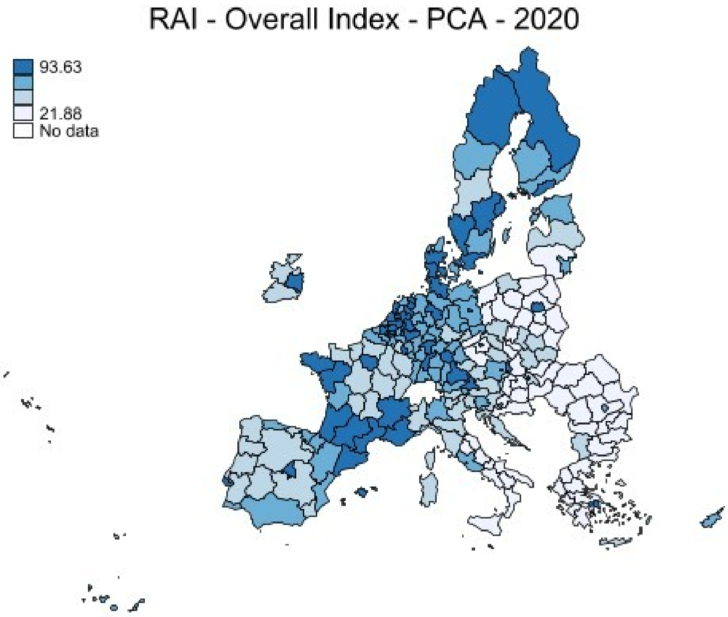


Figure 5. 2 Distribution of time series correlation between indices for all regions

We finally display the map (Figure 5.3) for every alternative index and the sorting of countries and regional disparities in figures XXX and XXX for every index. Overall, the threshold fuzzy based approach displays a strongly heterogeneous behaviour compared to the baseline scenario, and with some results that are unexpected for several countries and regions. On the contrary, the PCA approach, basically mimics the evolution of the baseline index while not contributing particularly to the understanding of the impact of every indicator in the final index.

a) PCA based RAI



b) Fuzzy threshold-based RAI

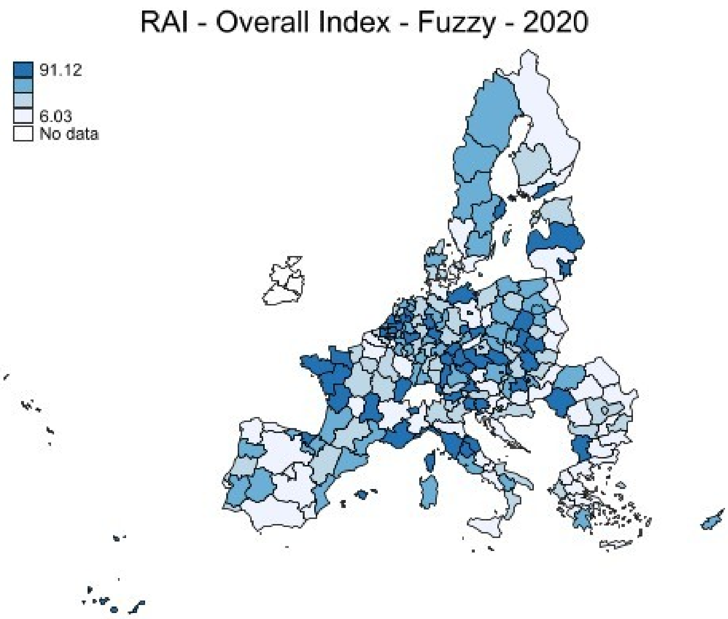
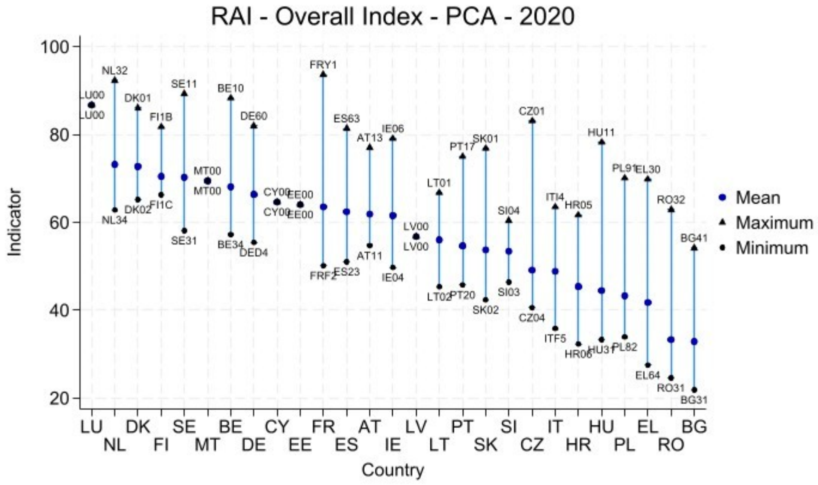


Figure 5. 3 Regional disparities of the alternative RAI indices across EU countries - 2020

a) PCA based RAI



b) Fuzzy threshold-based RAI

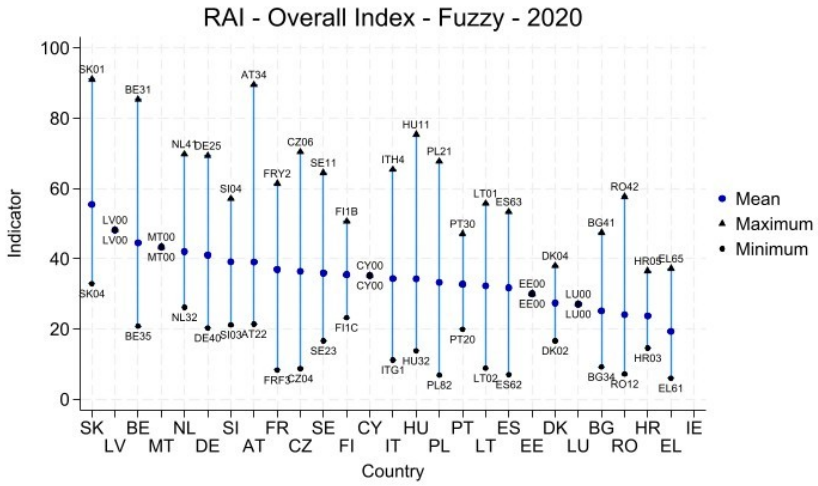


Figure 5. 4 Regional disparities of the alternative RAI indices across EU countries - 2020

6. Sensitivity analysis

This section inspects the key role of the Twin Transition in the definition of regional attractiveness. As found in MOBITWIN deliverable 1.3, green and digital factors play distinct roles in shaping migration intentions and flows. Green factors strongly influence migration intentions, particularly among environmentally conscious individuals. These factors also drive long-term mobility, with regions featuring lower greenhouse gas (GHG) emissions and sustainable job opportunities (e.g., circular economy) attracting migrants. Green concerns act as deterrents in high-emission areas, especially for minority groups, highlighting the pivotal role of environmental quality in migration decisions.

In contrast, digital factors, including broadband access, e-commerce, and high-tech employment, have a more nuanced impact. While these factors show limited influence on recent migration flows, they significantly shape future migration intentions as digitalisation grows. Digital preferences encourage short-term and circular mobility, with internet usage acting as both a push factor in origin regions and a pull factor in destination regions. High-tech employment attracts certain demographics, particularly men and mid-career professionals, but its overall influence on mobility is less consistent compared to green factors.

Green and digital factors influence different types of mobility flows in distinct ways. Long-term mobility, which involves permanent relocation for employment or education, is more significantly shaped by green factors. Environmentally conscious individuals are drawn to regions with low greenhouse gas (GHG) emissions, sustainable job opportunities, and good air quality. High GHG levels in origin regions act as barriers to migration, particularly for minority groups, while sustainable practices in the circular economy enhance the appeal of destination regions.

Short-term mobility, such as seasonal work or education, is influenced by both green and digital factors. Green concerns, including GHG emissions and tourism activity, play a key role in short-term flows. Regions with high tourism activity often see higher outflows, while agricultural areas with environmental concerns tend to attract fewer short-term movers. Digital factors like broadband access and e-commerce play a moderating role, with better connectivity at the origin reducing the need for physical movement.

Circular mobility, including commuting and multilocal living, is more influenced by digital factors. Internet usage and public e-services can reduce commuting needs by providing alternatives through remote work. However, regions with robust digital infrastructure may also attract individuals seeking a balanced work-life dynamic.

Overall, green factors predominantly shape long-term mobility flows, aligning with sustainability priorities, while digital factors have a stronger influence on short-term and circular mobility, reflecting their role in enabling flexible and digitally integrated lifestyles.

The role of twin transition factors—green and digital—on regional mobility varies significantly between men and women. According to the findings in MOBITWIN Deliverable 1.3, men are more influenced by digital factors, such as internet accessibility and high-tech employment opportunities, which act as strong drivers of migration decisions. For men, access to robust digital infrastructure and specialised job markets often increases the attractiveness of destination regions, particularly in the context of career advancement and technological opportunities. Women, on the other hand, show a stronger preference for green factors, such as tourism-related environmental amenities, low greenhouse gas emissions, and sustainable practices. These elements align more closely with their migration intentions, as women are more likely to prioritise destinations that offer enhanced environmental quality and better living standards.

In this section we use the wide list of considered indicators of every dimension, and we look at the result of stressing the role of green and/or digital drivers in regional attractiveness. The approach is based on the construction of additional indices of attractiveness in which the weights differ from the baseline approach. We propose the use of three alternative indices, the Digital RAI, the Green RAI and the Twin RAI. Every additional index is overweighting each dimension at the expense of the other dimensions of attractiveness. The indices are built according to the following expressions, highlighting the overweight of the digital, green and twin dimensions at the expense of the other ones:

$$RAI_{Digital} = 0.45 * RAI_{Traditional} + 0.35 * RAI_{Digital} + 0.20 * RAI_{Green}$$

$$RAI_{Green} = 0.45 * RAI_{Traditional} + 0.20 * RAI_{Digital} + 0.35 * RAI_{Green}$$

$$RAI_{Twin} = 0.40 * RAI_{Traditional} + 0.30 * RAI_{Digital} + 0.30 * RAI_{Green}$$

Once computed, we inspect the impact in overall attractiveness by comparing the new indices with baseline RAI:

$$diff - RAI_i = RAI - RAI_i$$

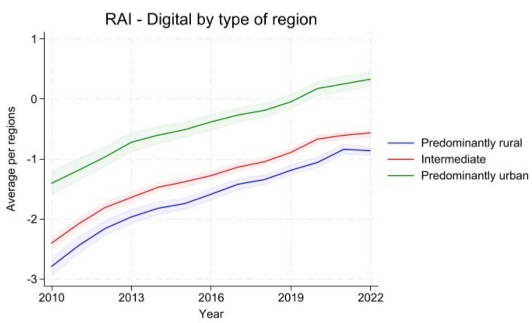
Next, we look at difference in overall attractiveness derived from the different weights.

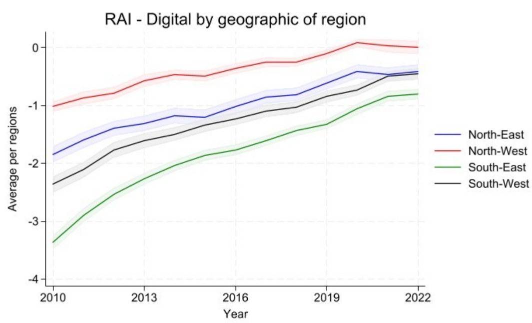
6.1. Digital attractiveness

Figure 6.1 displays the impact by regional typologies derived from the overweight of digital factors in the overall attractiveness. The first aspect is the differential growth of the digital component compared with traditional and green factors. The digital transition has been taking place over the last two decades, what results in an important increase in this dimension. As a result, there is an increasing attractiveness which departs from lower positions, given the lower rates of development of digital factors at the beginning of the analysed period.

As in previous analysis, we see a convergence path driven by the stronger role of digital drivers between geographical areas and between EU15 and EU13. On the contrary, capital and more urban regions become more attractive in general because of the overweight in digital factors.

Interestingly, as can be seen in the geographical distribution in Figure 6.2, there are several regions which in 2020 are worse off if the digital drivers are over weighted. In some countries, such as Bulgaria, Romania, Greece or Portugal, most regions are in fact worse off in terms of attractiveness if digital factors are counting more.





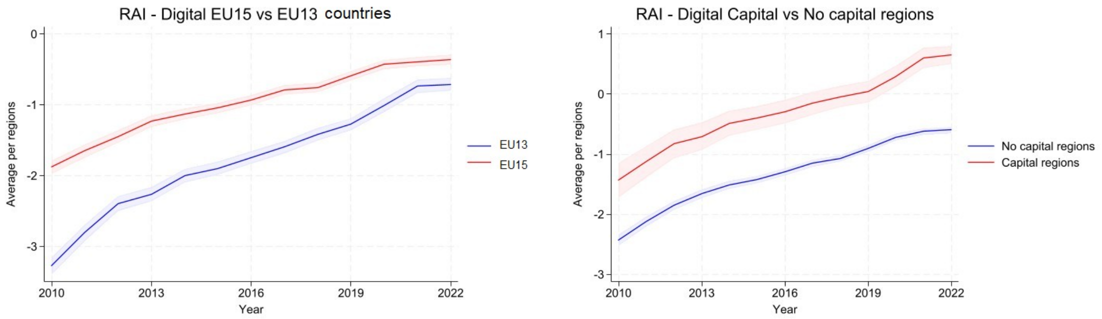


Figure 6. 1 Digital RAI differential: Trends by rural-urban type, geography, EU Membership, and Capital Status

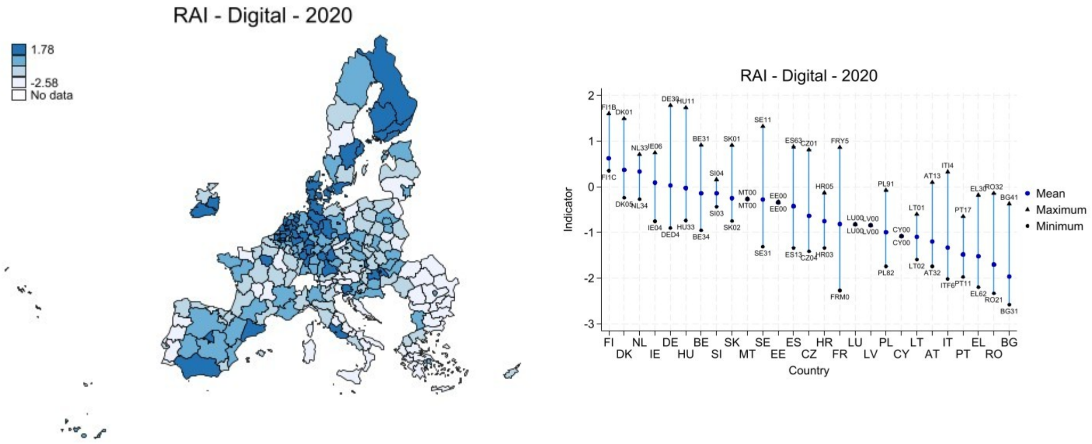


Figure 6. 2 Digital RAI differential: Map and regional dispersion - 2020

6.2. Green attractiveness

Figure 6.3 illustrates the impact of green factors on regional attractiveness based on typologies. Unlike digital factors, the green dimension shows a negative differential in its relative importance over time. This reflects the sluggish growth path of the green RAI index described in section 4.3. This affects regions that traditionally relied on green components like environmental sustainability, agricultural activity, or tourism to those prioritising other dimensions of regional development. Despite the stronger role of green factors, we can still see the divergence between rural and urban (particular capital) regions, and the convergence between geographical areas, particularly between EU15 and EU13 countries.

The geographical distribution in Figure 6.4 highlights regions in countries like Greece, Bulgaria and Romania, where green factors contribute significantly to attractiveness. These regions risk being less attractive if the green transition is not effectively managed. Large disparities can be observed in Italy, Poland, France and Spain.

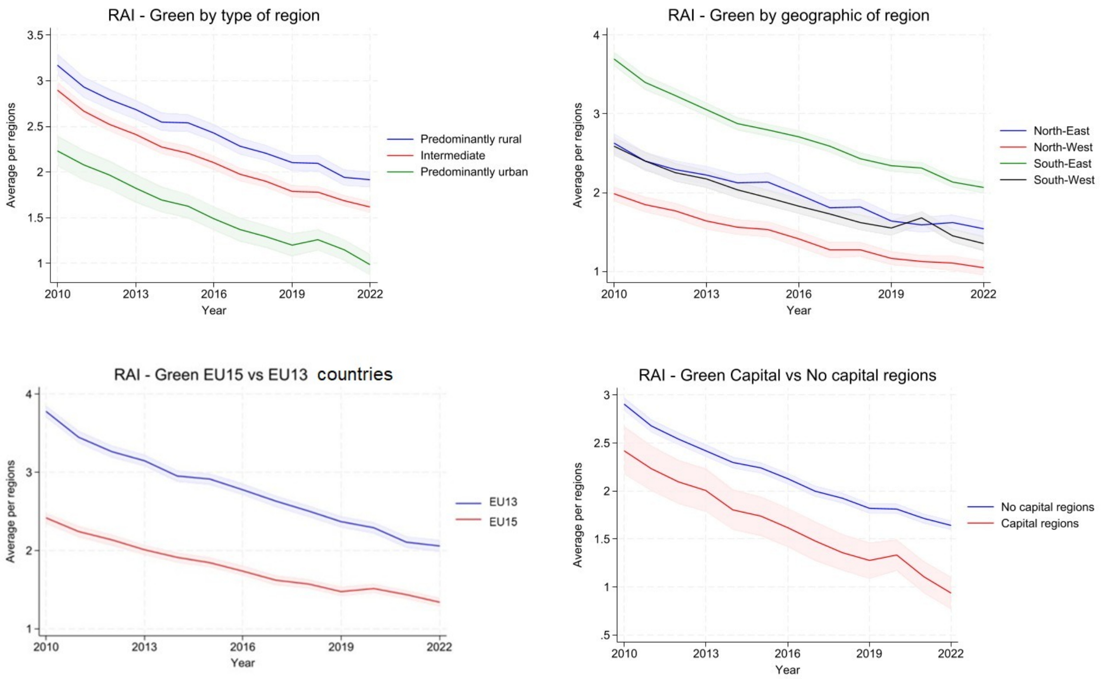


Figure 6. 3 Green RAI differential: Trends by rural-urban type, geography, EU Membership, and Capital Status

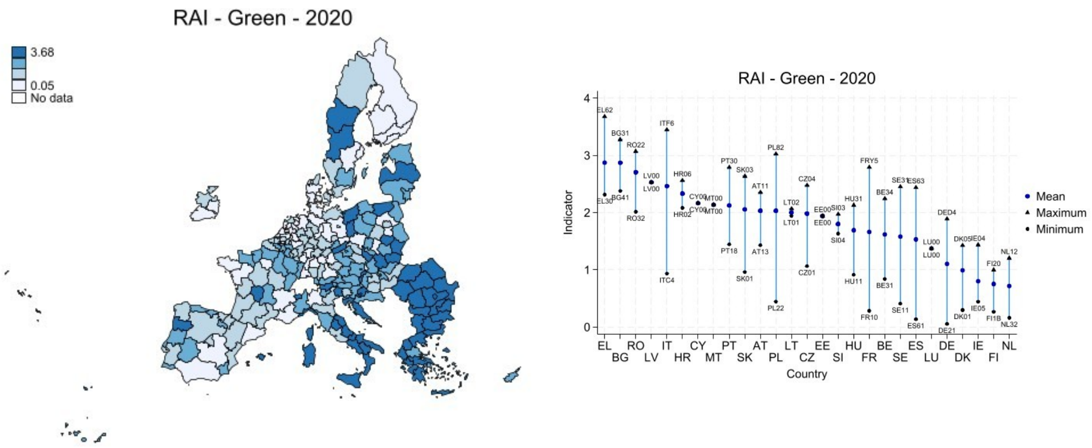


Figure 6. 4 Green RAI differential: Map and regional dispersion - 2020

6.3. Twin attractiveness

We finally look at the joint role of the Twin Transition drivers, which now account jointly 60% of the weight, compared to the 40% assigned to traditional factors.

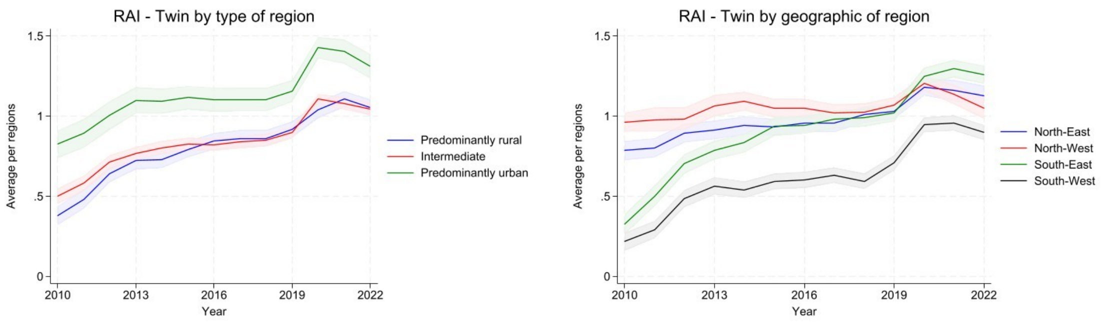
These factors underscore the growing interplay between sustainability and digitalisation in shaping regional dynamics over the past decade.

The analysis shows a steady rise in the overall influence of Twin Transition factors, particularly in predominantly urban and capital regions. These areas benefit from synergistic advancements in both green policies and digital infrastructure, making them increasingly attractive. Intermediate and rural regions, while showing improvements, continue to lag-behind urban centres, reflecting persistent disparities in the adoption and integration of twin transitions.

Geographically, compared to EU15, regions in the EU13 are the ones outperforming the differential attractiveness derived from the Twin Transition. South regions, particularly those in the Southeast, are the ones enjoying a differential joint benefit of the Twin Transition (Figure 6.5).

As seen in the geographical distribution (Figure 6.6), the differential distribution of the Twin Transition can be found in almost all countries, with regions in countries such as Bulgaria or Romania outperforming the national average of many countries. This indicates the strong role that the green and digital factors can have in a balanced territorial development between countries. Nevertheless, there are also many other regions exhibiting lower differential attractiveness, what represents a challenge for within country cohesion.

This dual analysis of green and digital factors reveals that regions with robust integration of both transitions enjoy higher levels of attractiveness, reinforcing the need for coordinated policies that address sustainability and digitalisation in tandem. Such policies should prioritise rural and less developed regions to ensure balanced growth across the EU.



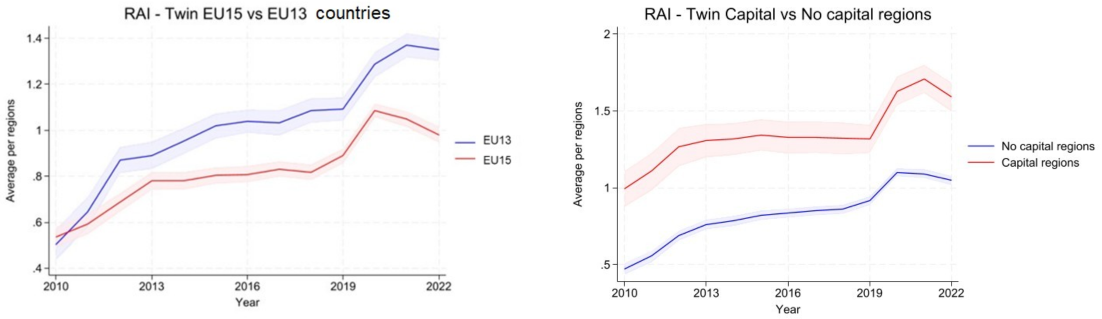


Figure 6. 5 Twin RAI differential: Trends by rural-urban type, geography, EU Membership, and Capital Status

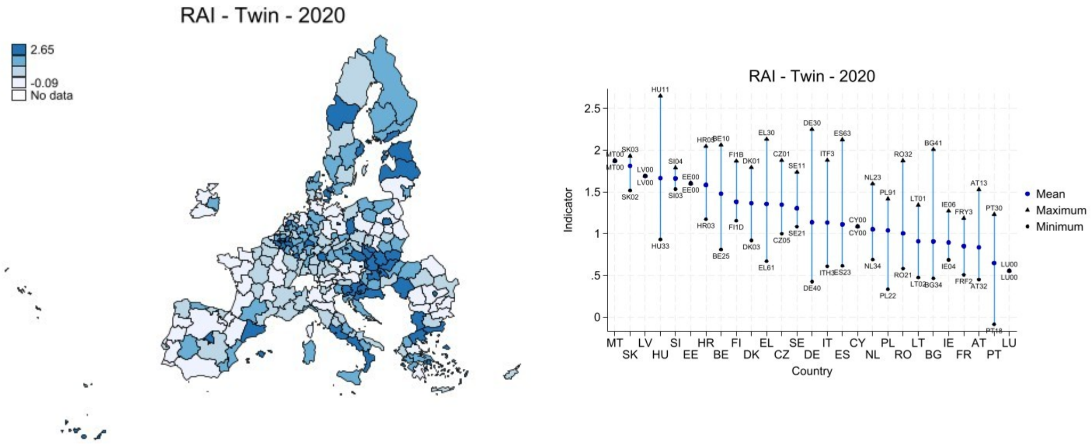


Figure 6. 6 Twin RAI differential: Map and regional dispersion - 2020

6.4. Gender implications

The differential effects of digital and green factors on regional attractiveness reveal distinct patterns for men and women, reflecting their varying preferences and priorities in migration decisions. The increasing importance of digital factors has significantly enhanced the attractiveness of urban and capital regions, what would be orienting migration flows of men towards such regions compared to women. The sluggish path over time of the green factors would impact women, who exhibit stronger preferences for regions prioritising environmental sustainability, tourism-related amenities, and quality of life. Rural and intermediate regions, where green factors traditionally play a central role, would be becoming less attractive due to the slower growth of green transitions.

7. Integration of relevant RRI pillars

MOBI-TWIN places the societal dimension of spatial mobility at the core of its research activities. It aligns the project's activities with the pillars of Responsible Research and Innovation (RRI) — science education, gender equality, governance, open science, public engagement and ethics — to ensure that outcomes, outputs and impacts meet as much as possible the needs of society (MOBI-TWIN D4.1).

The RRI pillars mainstreamed into the activities described in this report are gender equality, open science and ethics.

The integration of the gender dimension

The analysis in this deliverable has not performed a specific gender analysis in the definition and implementation of the regional attractiveness index. Nevertheless, we have integrated the findings in previous deliverables to infer a differential effect of the twin transition in types of regions more favoured by green or digital factors.

The integration of open science

The outcomes of D2.2 will be made available in an open access repository after approval by the EC. Both the indicators and baseline RAI indices will be made available in open access repositories along with the related forthcoming scientific publication.

The integration of ethics

The work carried out in D2.2 followed the ethical standards set by the GA, Articles 13 (Confidentiality and Security), 14 (Ethics and Values; specific ethics rules are set out in Annex 5) and 15 (Data Protection).

Data management was elaborated in line with the EC Guidelines on FAIR Data Management, which provide details on; (i) the type of data collected; (ii) why these data were collected; (iii) how they were collected; (iv) how these data were treated and who has access to these data, as well as the kind of metadata standards that were applied and where these data are stored in order to ensure their safe and FAIR management.

All personal data collected within the survey was processed in accordance with the principles of the General Data Protection Regulation (GDPR), ensuring that it is stored securely, used only for its intended purpose, and retained for no longer than necessary.

8. Summary and main conclusions

Over the course of this report, we have examined *regional attractiveness* through multiple lenses—traditional economic and social factors, the Twin Transition, the interplay of digital and green transitions, and the methodological considerations that underpin any composite index of attractiveness. The notion of regional attractiveness, as established from the outset, is inherently *multidimensional*. It includes economic opportunities, cultural diversity, policy frameworks, talent networks, and quality of life elements such as health care, safety, and environmental quality. These dimensions collectively influence the capacity of a region to attract or retain skilled workers and to remain resilient amid rapid societal and technological changes. The twin transitions—*green* and *digital*—further reshape this landscape by introducing new criteria for evaluating where people choose to live, work, and invest.

A key insight arising from our exploration is the *persistent inequality* in how these attractiveness factors are distributed across Europe. Many regions experience a structural disadvantage, either because they lack robust infrastructures or have economic histories that do not align readily with contemporary policy priorities. These so-called "left-behind places" have lower adaptive capacity, often resulting in deindustrialization, demographic aging, and outward migration. Even with the advent of remote work and emerging green technologies, the risk remains that only those regions with strong financial, technological, or human capital will capitalize on new opportunities. Consequently, understanding the comparative advantage or structural deficits of each region becomes paramount, and this is precisely where a *composite index* approach can add value.

Within the *traditional dimension* of regional attractiveness—covering metrics such as GDP per capita, employment rates, sectoral composition, housing affordability, governance quality, and visitor appeal—our findings demonstrate both the robustness of these longstanding indicators and the complexity of interpreting them within changing contexts. While GDP per capita and employment rates remain critical for signalling economic well-being, quality-of-life factors like healthcare availability, housing costs, and personal safety profoundly affect a region's liveability. Equally noteworthy is institutional quality: places characterized by transparent governance, efficient public services, and trust in local institutions gain a reputational edge that fosters investment and encourages both domestic and international mobility. Environmental parameters, such as Heating and Cooling Degree Days and air quality, also gain urgency as climate change impacts where—and how comfortably—people can live. Traditional factors thus form the *foundation* of a region's attractiveness but must increasingly be interpreted through the lens of *transitions* reshaping labour markets and lifestyles.

Shifting our focus to the *digital transition*, the report identifies three core drivers of attractiveness: *connectivity* (broadband and high-speed internet), the presence of

ICT specialists, and the overall *digital skills* of the population. These dimensions are becoming indispensable for both individual well-being and business productivity. Regions that excel in digital infrastructure and skill-building have a significant advantage in retaining and attracting talent, because they can support remote work, foster tech entrepreneurship, and create network effects that benefit multiple sectors. Conversely, regions with poor connectivity or limited digital skill sets risk being relegated to the periphery of economic growth, thereby intensifying the divergence between “digital haves” and “digital have-nots.” Our empirical results underscore that some parts of northern and western Europe have made major strides in digital readiness, while eastern and southern regions are improving but still lag behind. Notably, *capital cities* consistently outpace non-capital areas, reflecting a concentration of resources, policy attention, and labour market dynamism.

On the *green transition* side, indicators such as greenhouse gas (GHG) emissions, circular economy employment, sectoral reliance (e.g., on extractive industries or agriculture), and tourism intensity collectively reveal how effectively a region is adapting to sustainability imperatives. Our analysis shows that high-performing regions—many of them in northern Europe—demonstrate well-established policies or infrastructures that mitigate GHG emissions and encourage environmental stewardship. However, the process remains *uneven*: many southern and eastern locales, including parts of Greece, Bulgaria, and Romania, are still grappling with limited resources or policy frameworks that slow their green transformation. The growing importance of sustainability in personal relocation decisions amplifies these disparities. Younger, environmentally conscious workers may be less inclined to reside in high-emission regions, particularly if green job opportunities and public commitments to climate action are scarce. Paradoxically, regions that have historically relied on mining or intensive agriculture confront greater obstacles; to stay competitive, they must find ways to diversify, retrain workforces, and manage transitions in ways that do not leave entire communities behind.

Methodologically, constructing a *composite index* to capture these diverse aspects of regional attractiveness brings its own complexities. As our report details, *normalization* of indicators is essential, given their varied scales and units. Techniques like min-max rescaling or z-score standardization ensure comparability but come with trade-offs related to how extremes or outliers are treated. Similarly, the *weighting* and *aggregation* choices can dramatically influence the final rankings. While we experimented with additive approaches—50% weight on traditional factors and 25% each on digital and green—alternative methods like *Principal Component Analysis (PCA)* or a *fuzzy logic threshold* approach yield different nuances in both cross-sectional and temporal analyses. PCA, for instance, correlates strongly with our baseline measures but is often less transparent in illustrating the direct influence of each variable. The fuzzy approach, on the other hand, introduces relative thresholds (e.g., comparing a region’s performance to EU and national averages), thus capturing a more *context-dependent* notion of attractiveness.

However, it also yields results that can diverge significantly from the baseline, underlining how methodological choices must be both transparent and carefully justified.

The core results from applying these approaches across European regions (2010–2022) highlight *incremental gains* in regional attractiveness but also *entrenched divides*. *Urban regions* consistently post better outcomes than rural ones, a pattern reflecting the agglomeration effects of job opportunities, infrastructure, and capital investment. At the same time, *northern and western Europe* generally outperforms the *southern and eastern* corridors, although there are signs of *convergence* for EU13 countries that have received targeted EU structural funds and are steadily catching up. Capital regions stand out for attracting resources, companies, and institutions, thereby widening the gap relative to non-capital counterparts. Notably, *digital attractiveness* has grown more uniformly than many might expect, with certain lagging regions starting to close the gap by improving broadband access and digital literacy. Nonetheless, pockets of inequality remain, with some countries exhibiting stark internal disparities (e.g., the gap between their capital city and peripheral areas).

Focusing more closely on the *green dimension*, we observe that while northern regions excel, overall progress has been comparatively slower than in the digital domain. The COVID-19 pandemic appears to have temporarily boosted the "green scores" of some urban areas—potentially reflecting changes in lifestyle, reductions in industrial output, or local policy shifts during the crisis. Yet, environmental pressures and the need for resilience persist, especially for regions heavily reliant on tourism or agriculture. Balancing the allure of scenic or cultural heritage with the need for renewable energy infrastructure can be delicate. For instance, wind turbine installations may spark local resistance if they threaten to alter landscapes that draw visitors in the first place. Hence, although "green" strategies promise a path toward both sustainability and higher attractiveness, they require nuanced, place-based policies.

Robustness analyses confirm that different methodological routes converge on a broadly similar hierarchy of winners and losers, with a generally strong correlation between the baseline index and the PCA-based variant. The threshold fuzzy method diverges more significantly, particularly in its time-series evolution for certain regions. These discrepancies highlight how critical it is for policymakers and researchers to understand *why* certain methodological choices produce different rankings and to avoid overreliance on any single composite measure. The "right" method ultimately depends on whether the goal is to *diagnose universal strengths and weaknesses* or to *identify region-specific relative performance*—both of which can be valuable in designing targeted interventions.

The *sensitivity analysis* on the weighting of digital and green factors further underscores how each domain brings distinct benefits and challenges to regional development. Overweighting digital drivers (e.g., broadband, e-commerce, high-tech employment) tends to advantage urban and capital regions, reinforcing their lead and exacerbating gaps in places that have historically struggled with internet penetration or ICT skill-building. Conversely, overweighting green indicators (e.g., low GHG emissions, sustainable agriculture, circular economy jobs) benefits some rural and intermediate regions that possess greater natural capital or have already pivoted toward greener pathways. Yet the slow pace of green transition in many areas means that real-world impacts are not as pronounced as one might hope. Combining digital and green into a "Twin Transition" framework (with heavier weight on both) reveals that certain EU13 and southern regions can secure a comparative advantage if they capitalize on synergies—demonstrating that forward-looking policy can indeed elevate the prospects of less-favoured areas.

Gendered dimensions of regional attractiveness emerge as another critical layer. Our underlying research suggests that men are more likely to respond to digital-oriented incentives, such as tech employment or robust online services, whereas women more often prioritize environmental sustainability, housing conditions, and community well-being. This gender divergence in preferences points to an important policy consideration: the distribution of green and digital investments can shape migration flows in ways that reinforce or reduce existing gender imbalances. By acknowledging these nuances, local authorities and regional planners can design more inclusive and effective strategies—for instance, by focusing on family-friendly, environmentally conscious, and digitally equipped environments that cater to a broader spectrum of the workforce.

Putting all these insights together, the overarching message is that *regional attractiveness* remains an evolving concept, shaped by a wide array of *traditional, digital, and green* drivers. If addressed holistically, these dimensions can guide policymakers toward *evidence-based interventions* that strengthen weaker areas and sustain well-performing ones. The composite index approach has proven its merit in synthesizing large volumes of data, revealing patterns of both convergence and divergence across Europe. Nevertheless, the data also reveal that bridging entrenched disparities—be they urban-rural, north-south, east-west, or men-women—requires *tailored, context-sensitive* policy measures. Investments in digital infrastructure, green technologies, reskilling programs, and robust governance mechanisms must go hand in hand, ensuring that less-advantaged regions are not left further behind. Achieving this balance is paramount if Europe is to fulfil its aspirations for *inclusive, sustainable growth* in the face of looming challenges such as climate change, demographic shifts, and the rapid evolution of the digital economy.

In conclusion, the composite indices—whether additive, PCA-based, or fuzzy threshold—consistently highlight that the *twin transitions* are already reshaping the geography of attractiveness. Regions best positioned to harness the transformations of the digital and green revolutions are set to reap the greatest benefits, both in economic prosperity and in quality-of-life measures that entice people to stay or move in. Those that lag risk facing a downward spiral of outmigration and underinvestment. The critical next step is for *policymakers, businesses, and communities* to interpret these indices not as definitive rankings set in stone but as dynamic, diagnostic tools. Next steps within the MOBITWIN project will use the outcomes of this deliverable to improve knowledge and policy recommendations.

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Appendix 1. Attractiveness indicators: Relevance, Data, Treatment and Coverage

During the analysis period of the MOBITWIN project, significant changes have been observed in the coding of NUTS2 regions. These changes can be grouped into four main categories. The first category consists of purely nominative changes, with regions in countries such as Greece and France serving as clear examples. The second type of change involves slight modifications to the surface area and affected population, leading to the disappearance of certain NUTS2 regions and the creation of new ones under different codes. Examples of this can be found in Bulgaria and Denmark.

The third type of change pertains to the merging of NUTS2 regions to create new ones, as seen in countries like Germany and France. Finally, some regions have been divided into two or more regions, a process that has occurred in countries such as Croatia and Ireland.

In total, during the analysis period (2005–2022) of the MOBITWIN project, five major changes in the regional classification of NUTS2 in Europe have been identified. These occurred during the following periods: 2003–2006, 2006–2010, 2010–2013, 2013–2016, and 2016–2021. Across the 2005–2022 period, approximately 150 changes of various types have been observed.

To address these changes, the Joint Research Center (JRC), in collaboration with the Commission's Directorate-General for Regional and Urban Policy (DG REGIO), developed a NUTS converter tool. However, due to certain limitations of this tool—particularly in relation to the indicators used in this project—and the need to apply specific econometric techniques to address missing information at both NUTS2 and NUTS1 levels, each indicator has been analyzed and treated individually.

To ensure a consistent time series with minimal disruptions from NUTS2 reclassification over time, the geographical scope of the analysis has been limited to the European Union's 27-member states excluding France's outermost regions (NUTS1 coded as "FRY"), and the period has been restricted to 2010–2022. For the analysis, different classifications of regions have been considered. If the region belongs to ue15/ue13 groups or not.

- if the region hosts the capital of the country or not
- if the region is predominantly urban or rural or not
- If the region is in the North-West, the North-East, the South-West or the South-East of the European Union.

Dealing with the geographical position of the regions, the classification has been carried out according with the centre of the UE27, that is established at: Veitshöchheim, 97209, Germany:49.84297 and 9.901914[1]. The shape of the EU27 can be observed in the following map.

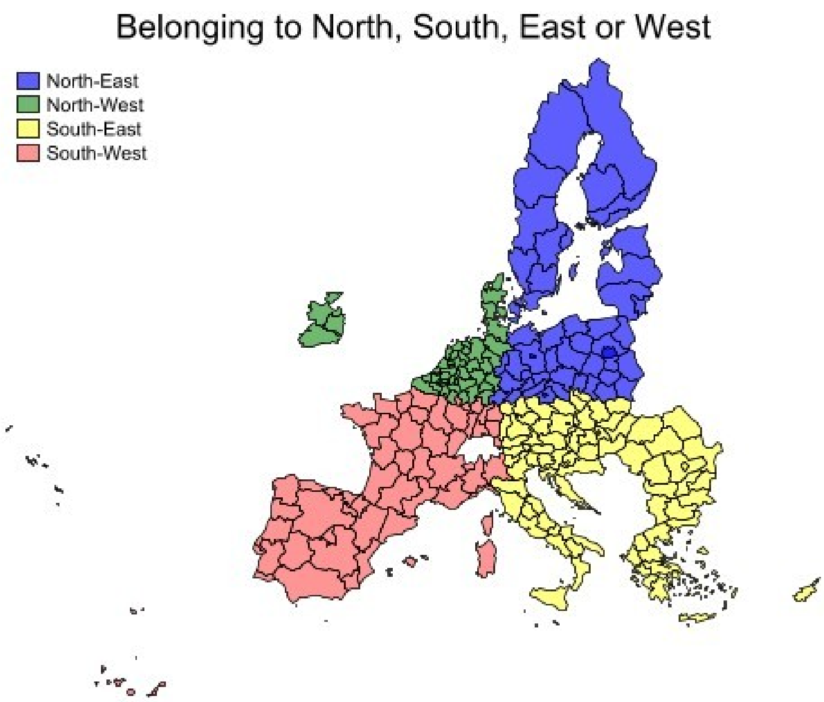

Figure A1.1. Geographical distribution of the European Union Regions.

The following pages provide a detailed explanation of how each indicator has been treated. For each indicator, the relevance of the data, its source, the applied treatment, coverage, and a brief descriptive analysis are presented.

As previously mentioned, there is a lag in the availability of information for some NUTS2 regions, necessitating the application of specific methodologies to fill in

[1] https://www.atlasobscura.com/places/the-geographical-center-of-the-european-union
https://www.theguardian.com/world/2017/apr/06/gadheim-the-bavarian-hamlet-at-the-centre-of-post-brexit-eu
https://en.wikipedia.org/wiki/Geographical_midpoint_of_Europe#Geographic_centre_of_the_European_Union

missing data. While these methodologies are explained in detail for each indicator considered, the general approaches are outlined below:

- **Method 1: Simple Linear Regression.** This method combines various simple linear regression models between the indicator at the NUTS2 level and the indicator at the NUTS1 or NUTS0 levels, or between the NUTS1 and NUTS0 levels. One or more regression models have been applied depending on the specific needs of each indicator.
- **Method 2: Relative Change in the Last Observation.** When insufficient information is available for regression techniques, the relative change from the most recent observation at the aggregated level is calculated and applied to the subsequent disaggregated level as needed. This approach aims to reconstruct time series while preserving the overall trends observed at the aggregated level.
- **Method 3: Mean of Adjacent Observations.** For missing values observed in isolated years, the mean of the preceding and subsequent observations has been used to fill the gaps.
- **Method 4: Aggregated NUTS-Level Value.** When no data is available for any NUTS level, but information exists at the national level (NUTS0), and the indicator is a percentage (not influenced by the size of the territorial unit), the aggregated value has been applied to the corresponding disaggregated levels.
- **Method 5: Completing Time Series.** For indicators that do not cover the entire period from 2001 to 2022, missing observations at the beginning and end of the series have been filled using the nearest available observations to ensure a balanced panel dataset.

A1.1. Regional profile: Urban vs Rural, UE15/13 and Capital

A) Relevance of the Indicator.

Urban and rural typology. This indicator is very relevant in the analysis because the factors of attractiveness can be very different depending on the nature of the region analysed (urban vs. rural).

The variable was calculated from GHSL population data containing the total population, urban centre population, urban cluster population and rural population per GID_2 code:

1. Joining the population data to NUTS level 2 area codes
2. Calculating the sum of populations living in urban centres and urban clusters per NUTS level 2 area
3. Calculating the percentual share of both urban areas (URBAN_SHARE) and rural areas (RURAL_SHARE) per NUTS level 2 area
4. Defining a classification function:
    a. if RURAL_SHARE is 50 % or more → area is predominantly rural
        i. but if the urban centre population is 200 000 or more and it is at least 25 % of the total population → area is intermediate
    b. if RURAL_SHARE is more than 20 % but less than 50 % → area is intermediate
        i. but if the urban centre population is 500 000 or more and it is at least 25 % of the total population → area is predominantly urban
    c. if RURAL_SHARE is 20 % or less ® predominantly urban.

Being membership of ue15/ue13 groups significantly influences regional attractiveness through economic development, infrastructure, and perception. UE15 regions often benefit from stable economies, advanced infrastructure, higher income levels, and established reputations, making them attractive to high-tech industries, skilled workers, and investors. Meanwhile, UE13 regions offer cost advantages, younger workforces, and growth opportunities, particularly in industries seeking lower production costs. EU cohesion funds have helped UE13 regions modernize and improve competitiveness, yet disparities in governance, institutional efficiency, and global perception remain. Migration also plays a role, with UE15 attracting skilled workers and UE13 experiencing emigration. Overall, these dynamics shape investment, mobility, and growth potential across both groups.

Capital. Hosting a country's capital significantly enhances a region's attractiveness due to its political, economic, and social prominence. Capitals typically serve as administrative, cultural, and economic hubs, attracting government institutions, foreign embassies, and major corporations, which stimulate investment and employment opportunities. These regions often benefit from better infrastructure, such as transportation networks, education systems, and healthcare facilities, making them appeal to businesses and skilled workers. Capitals also attract tourism, international events, and cultural activities, which can boost their global visibility. However, this concentration of resources may create regional imbalances, with other areas receiving less attention and investment. Consequently, hosting the capital amplifies a region's influence and development potential, often making it the most attractive part of the country.

B) Data, source, treatment and coverage.

Description:	The regional profile data (a CSV file) is based on data downloaded from the Eurostat database and the Global Human Settlement Layer (GHSL) database describing the regional characteristics related to geographical analyses. The datasets used are from years 2005, 2010, 2015, 2016, 2020 and 2021 (urb_rur_tipology). According to EU15/ EU13 membership, a dummy variable has been created (ue15/ue13). Similarly, it has been considered relevant to control whether the region contains the country's capital or not (capital).
Indicator(s):	urb_rur_tipology, ue15, ue13 and capital
Unit of Measurement:	urb_rur_tipology (categories): Predominantly rural, Intermediate and Predominantly urban ue15 (categories): Yes / No. ue13 (categories): Yes / No. capital (categories): Yes / No
Frequency	Annual
Source:	University of Helsinki. MOBITIWN DATASET.
DOI	https://doi.org/10.5281/zenodo.14228376

Methods applied for filling NUTS2 time-series (urb_rur_typology).

- **Method 1. Simple linear regression.** Not applied
- **Method 2. Relative change in last observation.** Not applied
- **Method 3. Mean Adjacent observations.** Not applied
- **Method 4. Aggregated nuts level value.** Not applied

- **Method 5**. **Completing time-series.** As data is available for years 2010, 2015 and 2021, to balance the panel data, missing observations have been filled, respectively, with following and previously non-missing observations.

C) Profile maps.

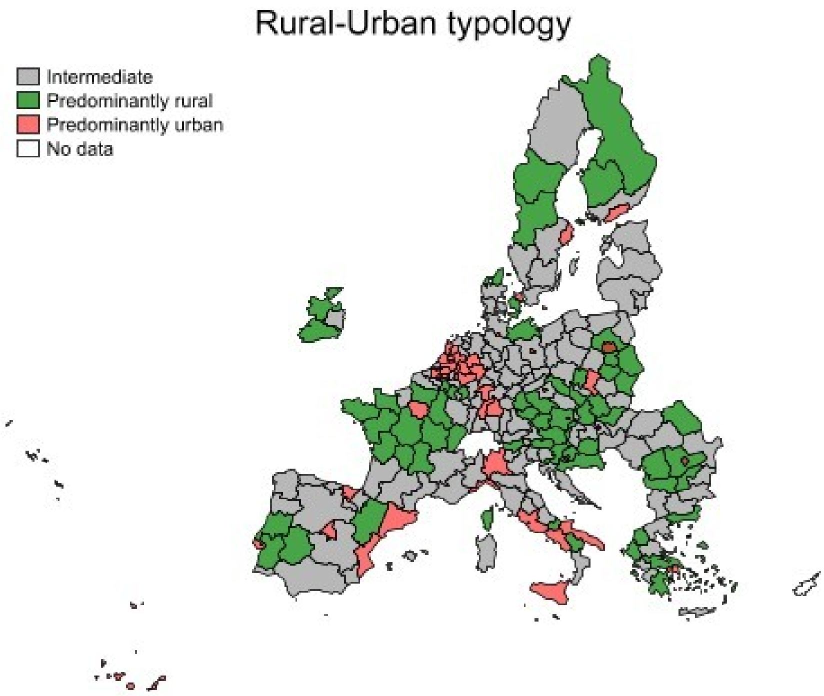

Figure A1.2. Rural-Urban typology of European Union Regions. Year 2020.

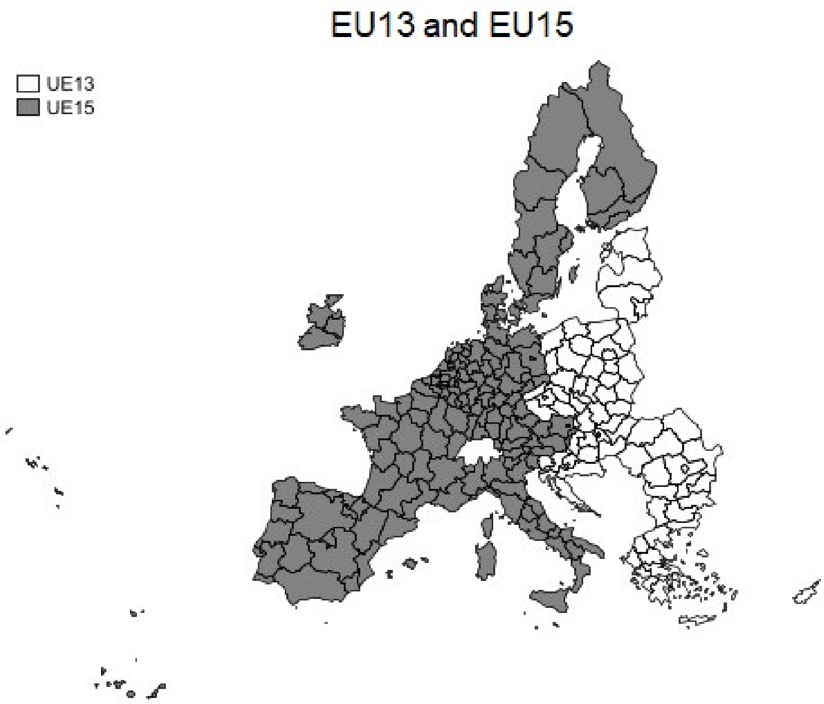

Figure A1.3. European Union Regions belonging to UE15 or UE13.

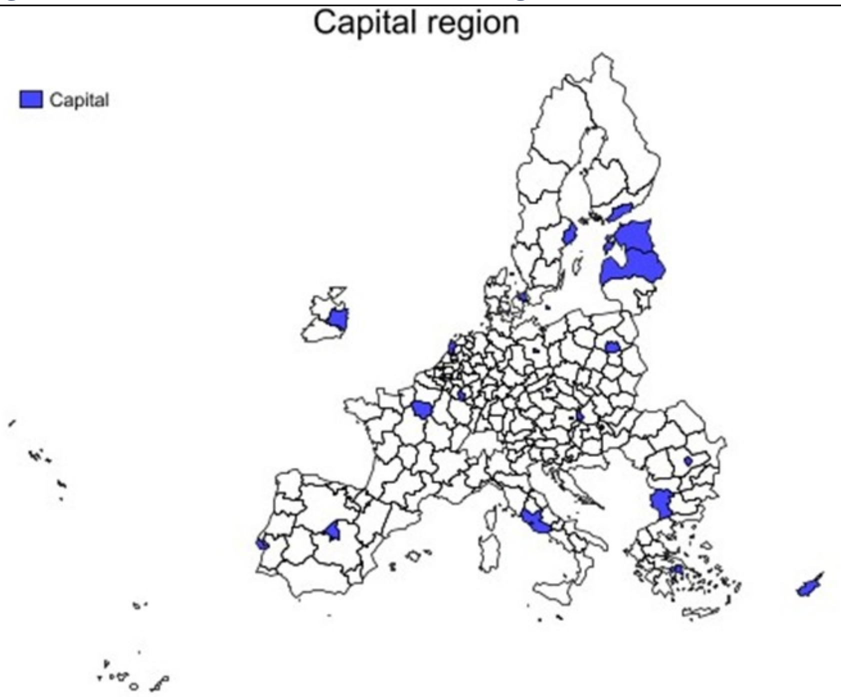

Figure A1.4. European Union Regions hosting the capital of the country.

A1.2. Population

A) Relevance of the Indicator.

Population. Population plays a crucial role in weighting data when comparing different regions, as it ensures that metrics are adjusted to reflect the size of each region's population, allowing for fair and meaningful comparisons. In this context, it is particularly important to rescale certain indicators to address missing observations at the NUTS2 level by utilizing information from the NUTS1 or country level.

B) Data, source, treatment and coverage.

Description:	Total persons on 1 January
Indicator:	pop
Unit of Measurement:	Number of Persons
Frequency	Annual
Source:	Eurostat. Population on 1 January by age, sex and NUTS2 region
DOI	https://doi.org/10.2908/DEMO_R_D2JAN

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.

  1st. Regression: Regressing NUTS1 indicator over NUTS2. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1

  2nd. Regression: Regressing NUTS0 indicator over ip1. If ip1 exists, ip1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2=pop.

- Method 2. Relative change in last observation. Not applied
- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. Not applied
- Method 5. Completing time-series. Not applied.

Table A1.1. Population -pop-. Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2010	2022	2010	2022
BE	2010	2022	2010	2022	2010	2022
BG	2010	2022	2010	2022	2010	2022
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2022	2010	2022	2010	2022
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2022	2010	2022	2010	2022
ES	2010	2022	2010	2022	2010	2022
FI	2010	2022	2010	2022	2010	2022
FR	2010	2022	2010	2022	2010	2022
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2022	2010	2022	2012	2022
IT	2010	2022	2010	2022	2010	2022
LT	2010	2022	2010	2022	2010	2022
LU	2010	2022	2010	2022	2010	2022
LV	2010	2022	2010	2022	2010	2022
MT	2010	2022	2010	2022	2010	2022
NL	2010	2022	2010	2022	2010	2022
PL	2010	2022	2010	2022	2010	2022
PT	2010	2022	2010	2022	2010	2022
RO	2010	2022	2010	2022	2010	2022
SE	2010	2022	2010	2022	2010	2022
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

C) Basic Descriptive Analysis.

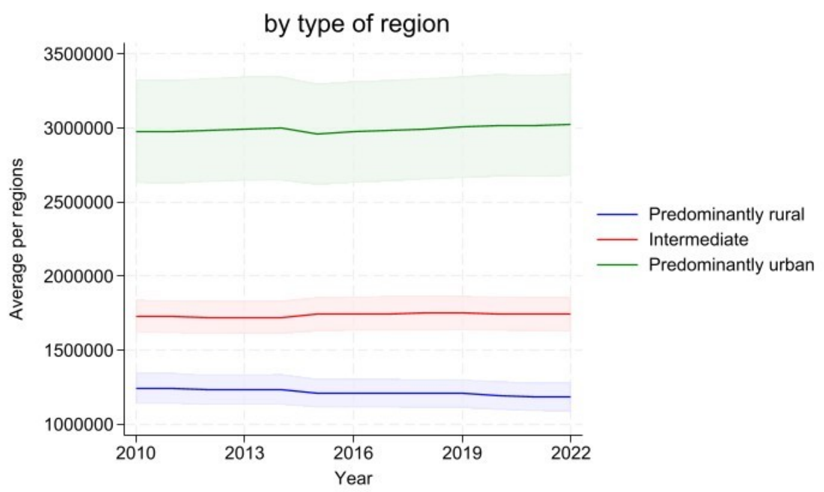

Figure A1.5. Population by type of region.

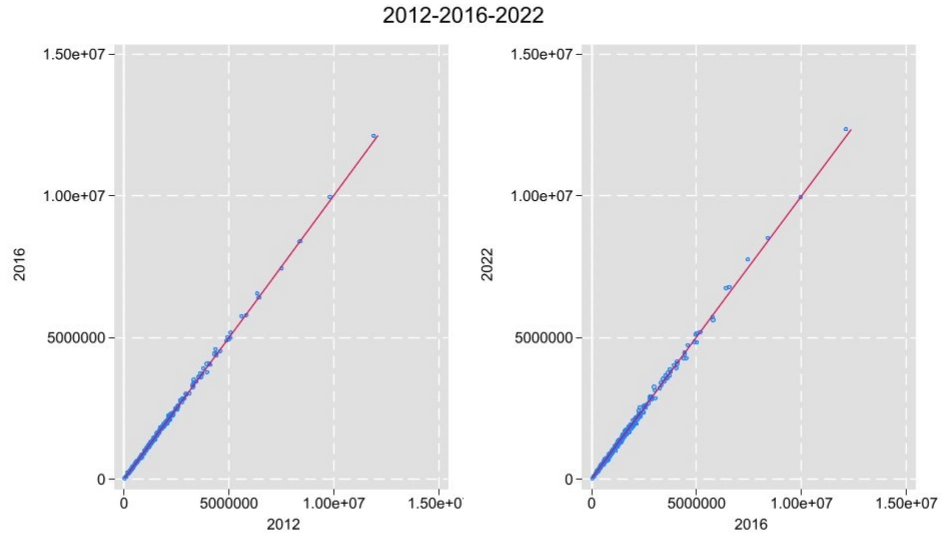

Figure A1.6. Dynamic scatterplot of Population.

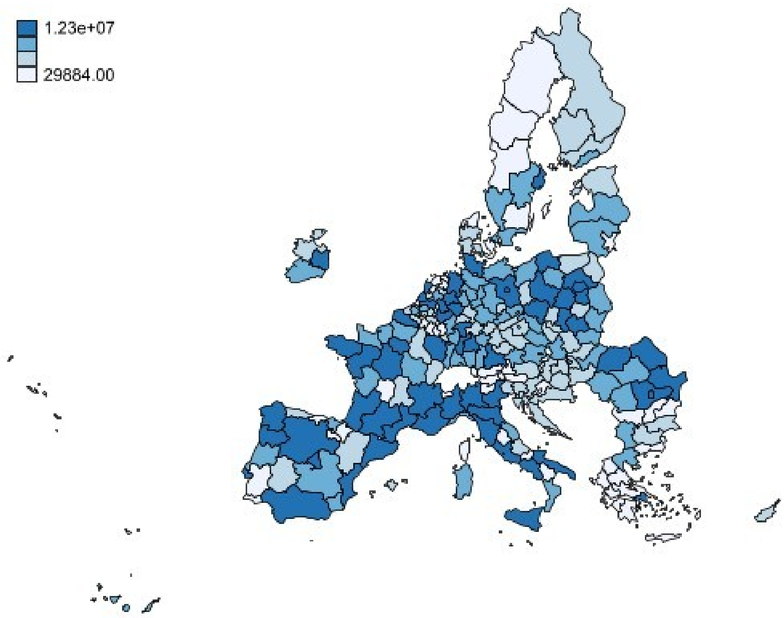

Figure A1.7. Geographical distribution of population. Year 2020.

Table A1.2. Descriptive statistics. Population.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	962791	550748	283697	1931593	531898	739139	1482095	6.8%
BE	1025764	457642	269023	1890627	496891	1116087	1331455	7.3%
BG	1157203	468840	682036	2133731	827640	962810	1393542	-14.4%
CY	863366	23553	819140	904705	848319	862011	875899	10.4%
CZ	1318453	177193	1082108	1701802	1211300	1234371	1440748	0.5%
DE	2155690	1123076	513794	5207457	1309209	1846767	2614229	1.3%
DK	1140692	415941	579628	1867948	819763	1211770	1320678	5.1%
EE	1323493	6849	1314870	1333290	1315944	1324820	1329660	-0.1%
EL	834273	964250	195229	4002871	332652	579182	682583	-6.0%
ES	2462721	2465540	76049	8511185	652797	1468367	2702605	1.9%
FI	1093948	558436	27734	1714741	1152719	1297144	1379749	4.4%
FR	2463752	2422198	156410	12354286	861210	1854407	3237097	7.0%
HR	1026972	243765	766824	1415971	793305	936547	1265047	-9.6%
HU	1224788	251959	863057	1741601	1026920	1207760	1365377	-4.1%
IE	1594618	617291	821369	2548091	872406	1575504	2219296	12.4%
IT	2851852	2460039	123360	10027602	873744	1642492	4439768	-2.1%
LT	1456428	668358	795088	2317783	803673	1406121	2099118	-7.5%
LU	575191	48023	502066	645397	537039	576249	613894	28.5%
LV	1977030	73894	1875757	2120504	1919968	1968957	2023825	-11.5%
MT	458689	40889	414027	520174	421464	449635	492968	25.6%
NL	1419668	1036275	380621	3753944	537206	1126710	2277315	5.1%
PL	2226188	953374	902444	4590630	1404441	2117781	2875180	-3.8%
PT	1490345	1302893	237113	3705980	264650	725914	2820766	-1.9%
RO	2487841	479986	1669479	3712396	2253866	2369363	2833014	-11.1%
SE	1235991	651523	368182	2415139	667161	1131117	1809287	9.3%
SI	1035590	63886	947302	1105046	971995	1046824	1097198	3.1%
SK	1356593	453570	597999	1842763	1017113	1469116	1720831	3.9%

A1.3. Gross domestic product

A) Relevance of the Indicator.

Gross Domestic Product per capita. Scholars have explored more deeply into the economic fabric of regions by using GDP per capita as a key proxy for assessing economic opportunities. Although most migration flows are driven primarily by actual labour market outcomes—particularly wages—rather than by broad indicators of economic output, many studies employ GDP per capita as a stand-in for wages, chiefly because it offers a time-consistent and regionally disaggregated measure. According to Álvarez and Royuela (2023), whose meta-analysis examined the influence of labour-market factors on interregional migration, substituting GDP per capita for wages in statistical estimations does not significantly alter the estimated effects of these factors.

B) Data, source, treatment and coverage.

Description:	Gross domestic product at current market prices per inhabitant
Indicator:	GDP_pc
Unit of Measurement:	Purchasing power standard (PPS, EU27 from 2020), per inhabitant
Frequency	Annual
Source:	Eurostat. Gross domestic product (GDP) at current market prices by NUTS2 region
DOI	https://doi.org/10.2908/NAMA_10R_2GDP

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression. Not applied
- Method 2. Relative change in last observation. Not applied
- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. Not applied
- Method 5. Completing time-series. Not applied.

Table A1.3. Gross Domestic Product -gdp_pc-. Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2010	2022	2010	2022
BE	2010	2022	2010	2022	2010	2022
BG	2010	2022	2010	2022	2010	2022
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2022	2010	2022	2010	2022
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2022	2010	2022	2010	2022
ES	2010	2022	2010	2022	2010	2022
FI	2010	2022	2010	2022	2010	2022
FR	2010	2022	2010	2022	2010	2022
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2022	2010	2022	2010	2022
IT	2010	2022	2010	2022	2010	2022
LT	2010	2022	2010	2022	2010	2022
LU	2010	2022	2010	2022	2010	2022
LV	2010	2022	2010	2022	2010	2022
MT	2010	2022	2010	2022	2010	2022
NL	2010	2022	2010	2022	2010	2022
PL	2010	2022	2010	2022	2010	2022
PT	2010	2022	2010	2022	2010	2022
RO	2010	2022	2010	2022	2010	2022
SE	2010	2022	2010	2022	2010	2022
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

C) Basic Descriptive Analysis.

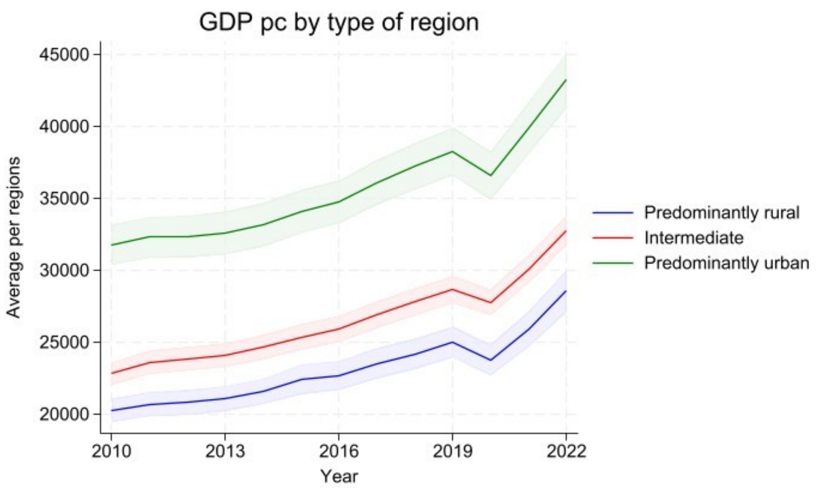

Figure A1.8. GDP_pc by type of region.

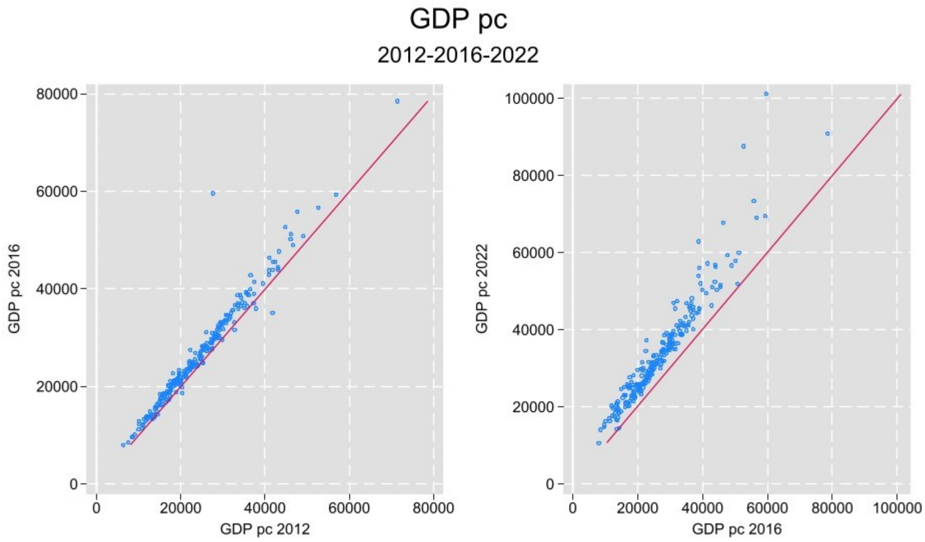

Figure A1.9. Dynamic scatterplot of GDP_pc.

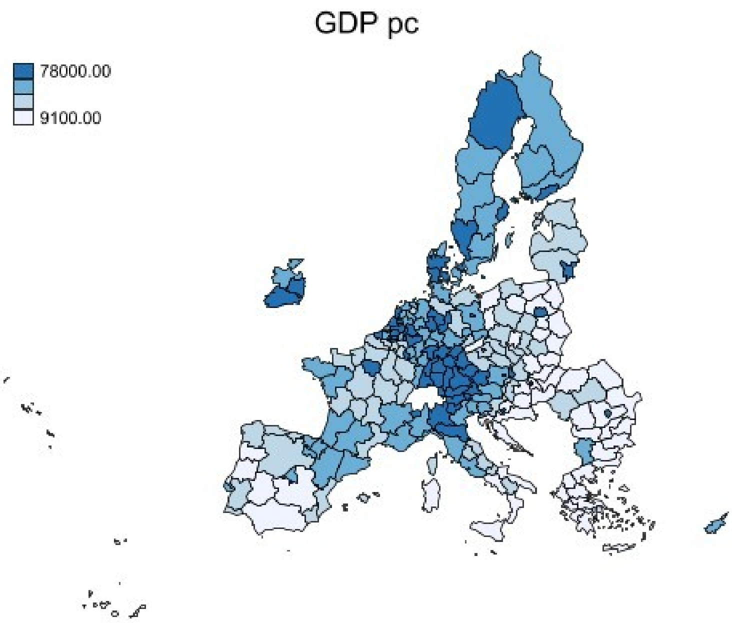

Figure A1.10. Geographical distribution of GDP_pc. Year 2020.

Table A1.4. Descriptive statistics. Gross domestic product.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	36050	6898	21200	52500	30800	36000	41000	42%
BE	32947	11633	19400	69500	23600	30300	37600	40%
BG	12892	5813	6800	34500	9200	10950	13900	99%
CY	26131	3455	21600	33400	23600	25400	27600	31%
CZ	25617	12673	15800	73400	18800	21600	24850	50%
DE	33978	8077	20100	69100	28200	32750	38200	38%
DK	34394	8962	22200	67800	29000	32200	38400	44%
EE	22677	4051	16300	30100	19800	21700	25600	85%
EL	17205	3799	11800	32000	14500	16300	18600	12%
ES	24842	5308	16500	41400	20700	23400	28700	25%
FI	32674	6479	23700	49500	27200	30400	37600	29%
FR	24566	7112	6300	57900	21900	24300	26700	32%
HR	19592	9472	10300	47400	12300	15850	26750	72%
HU	19066	9683	9800	56100	13050	15900	20150	67%
IE	45336	22506	17700	101200	25200	42400	62800	156%
IT	28132	8096	15800	56900	20800	28300	34400	31%
LT	25673	9268	12700	47000	17700	23850	31100	105%
LU	77492	6285	68400	90900	72800	78000	79000	33%
LV	18900	3612	13400	25700	16300	18500	21500	92%
MT	27785	4963	21500	36800	23300	27500	31000	70%
NL	34762	7860	24100	59400	28600	33500	39450	35%
PL	18996	7569	10800	57200	14500	17100	20700	78%
PT	21944	4286	16000	36100	18800	20600	23900	39%
RO	18513	10408	7600	62900	12450	15200	20400	110%
SE	33825	6873	26100	56700	29600	31400	35100	33%
SI	25008	5865	17200	38600	19500	25650	28200	51%
SK	25581	14730	12900	53200	15800	18600	35150	31%

A1.4. Employment rate

A) Relevance of the Indicator.

Employment rate. Migration decisions are influenced by individuals' expectations, requiring consideration of both the likelihood of finding a job and the possibility of experiencing periods of unemployment, particularly during the initial stages of job searching in a new location (Todaro, 1969). Instead of focusing on unemployment indicators, we propose using a proxy for employment opportunities: the employment rate among the working-age adult population, defined as individuals aged 20 to 64 years. The data for this measure is sourced from Eurostat.

B) Data, source, treatment and coverage.

Description:	Employment rate for aged 20-64 years old
Indicator:	Erate2064
Unit of Measurement:	Percentage (%)
Frequency	Annual
Source:	Eurostat. Employment rates by sex, age and NUTS2 region (%)
DOI	https://doi.org/10.2908/LFST_R_LFE2EMPRT

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression. Not applied
- Method 2. Relative change in last observation. Not applied
- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. Not applied
- Method 5. Completing time-series. Not applied.

Table A1.5 Employment Rate -erate2064-. Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2010	2022	2010	2022
BE	2010	2022	2010	2022	2010	2022
BG	2010	2022	2010	2022	2010	2022
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2022	2010	2022	2010	2022
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2022	2010	2022	2010	2022
ES	2010	2022	2010	2022	2010	2022
FI	2010	2022	2010	2022	2010	2022
FR	2010	2022	2010	2022	2010	2022
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2022	2010	2022	2012	2022
IT	2010	2022	2010	2022	2010	2022
LT	2010	2022	2010	2022	2013	2022
LU	2010	2022	2010	2022	2010	2022
LV	2010	2022	2010	2022	2010	2022
MT	2010	2022	2010	2022	2010	2022
NL	2010	2022	2010	2022	2010	2022
PL	2010	2022	2010	2022	2010	2022
PT	2010	2022	2010	2022	2010	2022
RO	2010	2022	2010	2022	2010	2022
SE	2010	2022	2010	2022	2010	2022
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

C) Basic Descriptive Analysis.

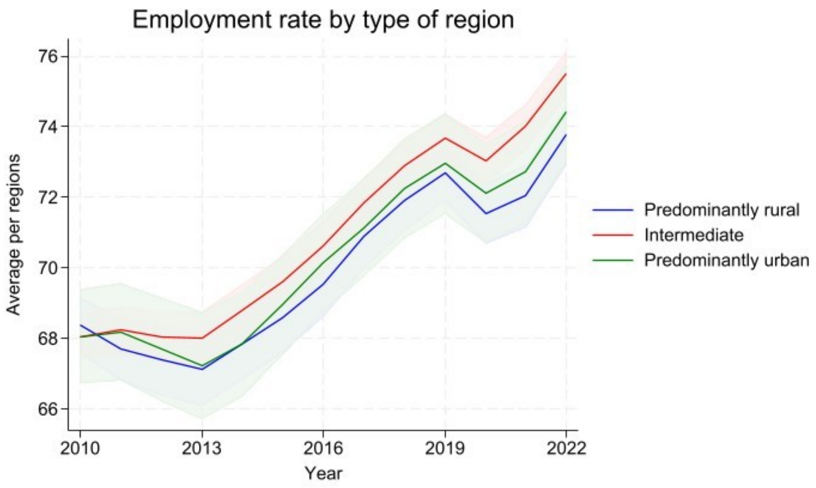

Figure A1.11. Employment rate by type of region.

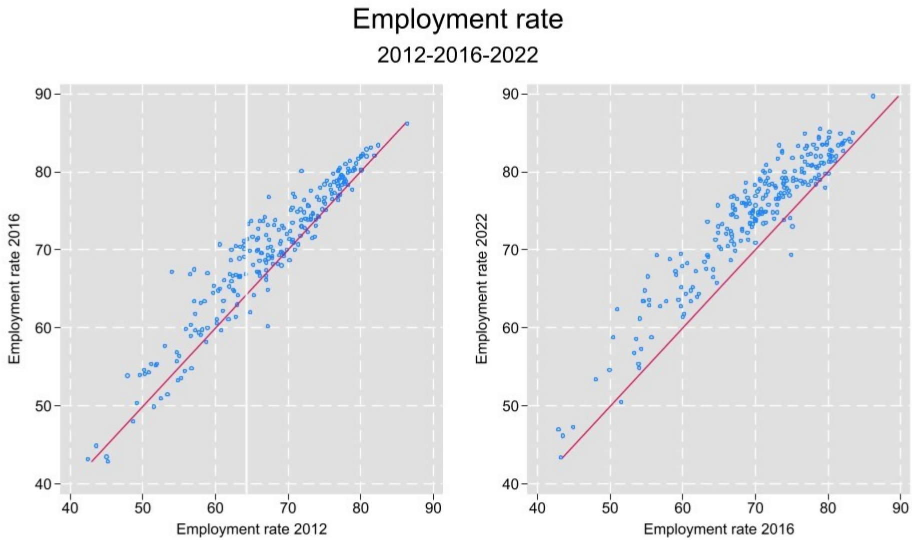

Figure A1.12. Dynamic scatterplot of Employment rate.

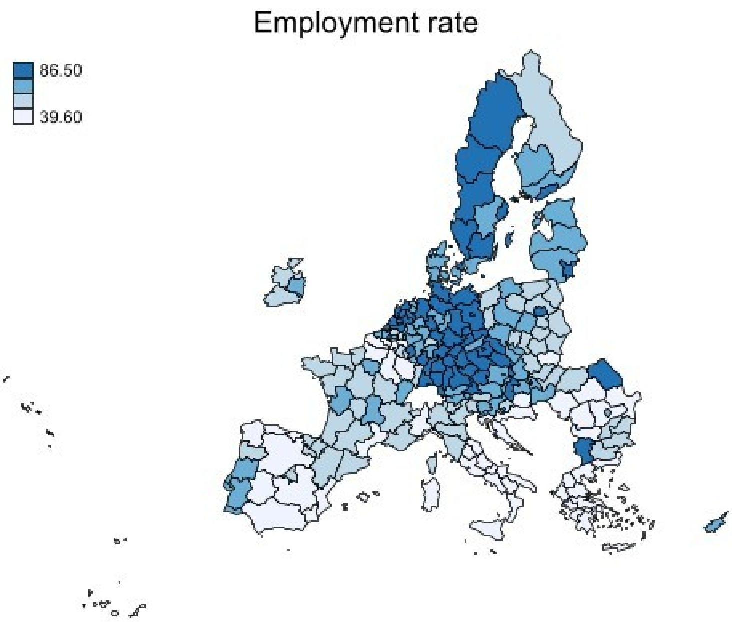

Figure A1.13. Geographical distribution of Employment rate. Year 2020.

Table A1.6. Descriptive statistics. Employment rate.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	75.8	3.3	67.7	80.9	73.7	76.3	78.1	5%
BE	68.6	5.8	56.8	80.0	63.3	69.4	73.3	6%
BG	67.4	6.2	58.0	81.7	62.0	66.9	72.1	18%
CY	72.4	3.8	67.2	78.6	68.7	73.4	75.2	5%
CZ	76.1	4.6	66.7	84.4	72.9	76.9	79.9	16%
DE	78.6	3.0	69.3	84.9	76.6	78.8	80.8	8%
DK	76.0	2.3	72.2	82.0	74.3	75.7	77.7	7%
EE	75.9	4.3	66.8	81.9	73.3	76.4	79.1	23%
EL	59.0	4.9	47.9	69.3	55.3	59.0	62.7	2%
ES	63.3	6.9	47.9	74.8	57.7	64.1	68.9	10%
FI	76.8	5.8	68.2	89.7	72.3	76.3	79.2	8%
FR	67.0	8.1	39.6	77.3	65.0	69.7	72.4	7%
HR	63.9	7.0	50.2	77.6	58.9	64.2	68.6	12%
HU	69.7	7.8	53.2	84.9	64.4	70.7	75.8	34%
IE	70.5	4.5	62.8	79.2	66.3	71.4	73.3	19%
IT	62.7	10.4	42.1	79.2	54.3	67.0	70.8	6%
LT	74.8	6.0	63.5	84.4	70.1	74.5	80.1	24%
LU	71.9	1.4	70.1	74.8	70.9	71.5	72.1	6%
LV	72.5	4.4	64.3	77.4	69.7	73.2	76.8	20%
MT	70.6	6.4	60.1	80.1	66.2	71.1	75.6	33%
NL	77.9	3.1	70.6	85.1	75.5	77.6	80.3	9%
PL	69.2	5.4	58.5	85.5	64.9	68.7	73.5	19%
PT	70.9	4.5	61.0	79.2	67.8	70.6	74.6	8%
RO	66.7	5.2	57.2	79.9	63.0	65.7	69.6	6%
SE	80.3	2.3	75.7	85.6	78.4	80.3	81.9	6%
SI	72.1	4.2	65.2	80.1	69.1	71.8	74.8	11%
SK	70.7	6.5	59.6	84.5	66.4	70.7	75.1	18%

A1.5. Sectoral composition

A) Relevance of the Indicator.

Share Industry and Services. Sectoral composition and diversity strongly influence migration flows. Dissart (2003) shows that regions with a broader economic base exhibit greater resilience and attract more migrants. Likewise, Malizia and Ke (1993) highlight those diverse industries buffer labour markets from sector-specific shocks, enhancing employment stability and encouraging in-migration. Bartkowska and Riedl (2021) demonstrate that regions with balanced sectoral structures experience lower unemployment volatility, which in turn dampens out-migration. Thus, regions with thriving industries and diverse sectoral composition tend to attract a mobile workforce eager to capitalise economic opportunities. We use the share of activity in Industrial and Services Sectors in terms of gross value added. The source is Eurostat.

Share of activity in Agriculture. As illustrated by Rodríguez-Pose & Bartalucci (2024) this sector will be the most affected by the green transition. Agriculture is a critical dimension of the green transition due to its significant carbon emissions and the sector's high dependency on traditional practices. Regions with a substantial share of economic activity in agriculture face challenges in adapting to climate policies, including shifts in consumer preferences towards sustainable and locally sourced food, reduced meat consumption, and the need for sustainable land use. These changes can conflict with established agricultural practices, potentially impacting regional economies reliant on agriculture.

The green transition may also introduce opportunities for agricultural regions to diversify into renewable energy or adopt innovative land use strategies. However, regions unable to adapt effectively may experience economic decline, deterring investment and outmigration, ultimately reducing their attractiveness. Balancing sustainability with economic resilience in agriculture is thus vital for maintaining regional competitiveness in the context of the green transition.

B) Data, source, treatment and coverage.

Description:	Sectoral gross value added at basic prices
Indicator(s):	**gva** -gvatotal, gvaa, gvabe, gvac, gvaf, gvagj, gvakn and gvaou
Unit of Measurement:	Million Euro
Frequency	Annual
Source:	Eurostat. Gross value added at basic prices by NUTS 3 region
DOI	https://doi.org/10.2908/NAMA_10R_3GVA

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression. Not applied
- Method 2. Relative change in last observation. Not applied
- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. Not applied
- Method 5. Completing time-series. As different indicators do not cover the complete period 2001-2022, to balance the panel data, last observations have been filled with previous one.

Table A1.7. Gross Value-Added Total -gvatotal- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2010	2022	2010	2022
BE	2010	2022	2010	2022	2010	2022
BG	2010	2022	2010	2022	2010	2022
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2022	2010	2022	2010	2022
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2022	2010	2022	2010	2022
ES	2010	2022	2010	2022	2010	2022
FI	2010	2022	2010	2022	2010	2022
FR	2010	2022	2010	2022	2010	2022
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2022	2010	2022	2010	2022
IT	2010	2022	2010	2022	2010	2022
LT	2010	2022	2010	2022	2010	2022
LU	2010	2022	2010	2022	2010	2022
LV	2010	2022	2010	2022	2010	2022
MT	2010	2022	2010	2022	2010	2022
NL	2010	2022	2010	2022	2010	2022
PL	2010	2022	2010	2022	2010	2022
PT	2010	2022	2010	2022	2010	2022
RO	2010	2022	2010	2022	2010	2022
SE	2010	2022	2010	2022	2010	2022
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

Table A1.8. Gross Value-Added Agriculture, forestry and fishing -gvaa- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2021	2010	2021	2010	2021
BE	2010	2022	2010	2022	2010	2022
BG	2010	2021	2010	2021	2010	2021
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2021	2010	2021	2010	2021
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2021	2010	2021	2010	2021
ES	2010	2022	2010	2022	2010	2022
FI	2010	2021	2010	2021	2010	2021
FR	2010	2021	2010	2021	2010	2021
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2021	2010	2021	2010	2021
IT	2010	2021	2010	2021	2010	2021
LT	2010	2021	2010	2021	2010	2021
LU	2010	2022	2010	2022	2010	2022
LV	2010	2021	2010	2021	2010	2021
MT	2010	2022	2010	2022	2010	2022
NL	2010	2021	2010	2021	2010	2021
PL	2010	2021	2010	2021	2010	2021
PT	2010	2021	2010	2021	2010	2021
RO	2010	2021	2010	2021	2010	2021
SE	2010	2021	2010	2021	2010	2021
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

Table A1.9. Gross Value-Added Industry (except construction) -gvabe- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2021	2010	2021	2010	2021
BE	2010	2022	2010	2022	2010	2022
BG	2010	2021	2010	2021	2010	2021
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2021	2010	2021	2010	2021
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2021	2010	2021	2010	2021
ES	2010	2022	2010	2022	2010	2022
FI	2010	2021	2010	2021	2010	2021
FR	2010	2021	2010	2021	2010	2021
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2021	2010	2021	2010	2021
IT	2010	2021	2010	2021	2010	2021
LT	2010	2021	2010	2021	2010	2021
LU	2010	2022	2010	2022	2010	2022
LV	2010	2021	2010	2021	2010	2021
MT	2010	2022	2010	2022	2010	2022
NL	2010	2021	2010	2021	2010	2021
PL	2010	2021	2010	2021	2010	2021
PT	2010	2021	2010	2021	2010	2021
RO	2010	2021	2010	2021	2010	2021
SE	2010	2021	2010	2021	2010	2021
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

Table A1.10. Gross Value-Added Manufacturing -gvac- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2021	2010	2021	2010	2021
BE	2010	2022	2010	2022	2010	2022
BG	2010	2021	2010	2021	2010	2021
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2021	2010	2021	2010	2021
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2021	2010	2021	2010	2021
ES	2010	2022	2010	2022	2010	2022
FI	2010	2021	2010	2021	2010	2021
FR	2010	2021	2010	2021	2010	2021
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2021	2010	2021	2010	2021
IT	2010	2021	2010	2021	2010	2021
LT	2010	2021	2010	2021	2010	2021
LU	2010	2022	2010	2022	2010	2022
LV	2010	2021	2010	2021	2010	2021
MT	2010	2022	2010	2022	2010	2022
NL	2010	2021	2010	2021	2010	2021
PL	2010	2021	2010	2021	2010	2021
PT	2010	2021	2010	2021	2010	2021
RO	2010	2021	2010	2021	2010	2021
SE	2010	2021	2010	2021	2010	2021
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

Table A1.11. Gross Value-Added Construction-gvaf- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2021	2010	2021	2010	2021
BE	2010	2022	2010	2022	2010	2022
BG	2010	2021	2010	2021	2010	2021
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2021	2010	2021	2010	2021
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2021	2010	2021	2010	2021
ES	2010	2022	2010	2022	2010	2022
FI	2010	2021	2010	2021	2010	2021
FR	2010	2021	2010	2021	2010	2021
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2021	2010	2021	2010	2021
IT	2010	2021	2010	2021	2010	2021
LT	2010	2021	2010	2021	2010	2021
LU	2010	2022	2010	2022	2010	2022
LV	2010	2021	2010	2021	2010	2021
MT	2010	2022	2010	2022	2010	2022
NL	2010	2021	2010	2021	2010	2021
PL	2010	2021	2010	2021	2010	2021
PT	2010	2021	2010	2021	2010	2021
RO	2010	2021	2010	2021	2010	2021
SE	2010	2021	2010	2021	2010	2021
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

Table A1.12. Gross Value-Added Wholesale and retail trade; transport; accommodation and food service activities; information and communication-gvagj- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2021	2010	2021	2010	2021
BE	2010	2022	2010	2022	2010	2022
BG	2010	2021	2010	2021	2010	2021
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2021	2010	2021	2010	2021
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2021	2010	2021	2010	2021
ES	2010	2022	2010	2022	2010	2022
FI	2010	2021	2010	2021	2010	2021
FR	2010	2021	2010	2021	2010	2021
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2021	2010	2021	2010	2021
IT	2010	2021	2010	2021	2010	2021
LT	2010	2021	2010	2021	2010	2021
LU	2010	2022	2010	2022	2010	2022
LV	2010	2021	2010	2021	2010	2021
MT	2010	2022	2010	2022	2010	2022
NL	2010	2021	2010	2021	2010	2021
PL	2010	2021	2010	2021	2010	2021
PT	2010	2021	2010	2021	2010	2021
RO	2010	2021	2010	2021	2010	2021
SE	2010	2021	2010	2021	2010	2021
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

Table A1.13. Gross Value-Added Financial and insurance activities; real estate activities; professional, scientific and technical activities; administrative and support service activities-gvakn- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2021	2010	2021	2010	2021
BE	2010	2022	2010	2022	2010	2022
BG	2010	2021	2010	2021	2010	2021
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2021	2010	2021	2010	2021
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2021	2010	2021	2010	2021
ES	2010	2022	2010	2022	2010	2022
FI	2010	2021	2010	2021	2010	2021
FR	2010	2021	2010	2021	2010	2021
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2021	2010	2021	2010	2021
IT	2010	2021	2010	2021	2010	2021
LT	2010	2021	2010	2021	2010	2021
LU	2010	2022	2010	2022	2010	2022
LV	2010	2021	2010	2021	2010	2021
MT	2010	2022	2010	2022	2010	2022
NL	2010	2021	2010	2021	2010	2021
PL	2010	2021	2010	2021	2010	2021
PT	2010	2021	2010	2021	2010	2021
RO	2010	2021	2010	2021	2010	2021
SE	2010	2021	2010	2021	2010	2021
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

Table A1.14. Gross Value-Added Public administration and defence; compulsory social security; education; human health and social work activities; arts, entertainment and recreation, repair of household goods and other services-gvaou- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2021	2010	2021	2010	2021
BE	2010	2022	2010	2022	2010	2022
BG	2010	2021	2010	2021	2010	2021
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2021	2010	2021	2010	2021
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2021	2010	2021	2010	2021
ES	2010	2022	2010	2022	2010	2022
FI	2010	2021	2010	2021	2010	2021
FR	2010	2021	2010	2021	2010	2021
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2021	2010	2021	2010	2021
IT	2010	2021	2010	2021	2010	2021
LT	2010	2021	2010	2021	2010	2021
LU	2010	2022	2010	2022	2010	2022
LV	2010	2021	2010	2021	2010	2021
MT	2010	2022	2010	2022	2010	2022
NL	2010	2021	2010	2021	2010	2021
PL	2010	2021	2010	2021	2010	2021
PT	2010	2021	2010	2021	2010	2021
RO	2010	2021	2010	2021	2010	2021
SE	2010	2021	2010	2021	2010	2021
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

C) Basic Descriptive Analysis.

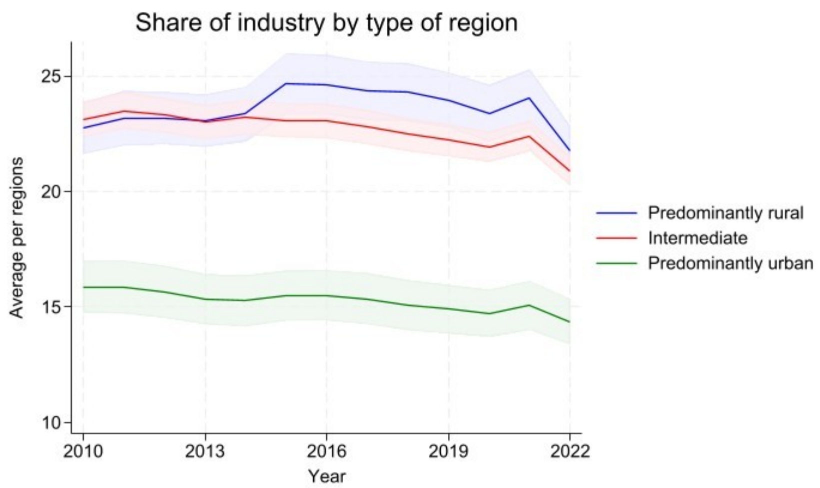

Figure A1.14. Share of industry by type of region.

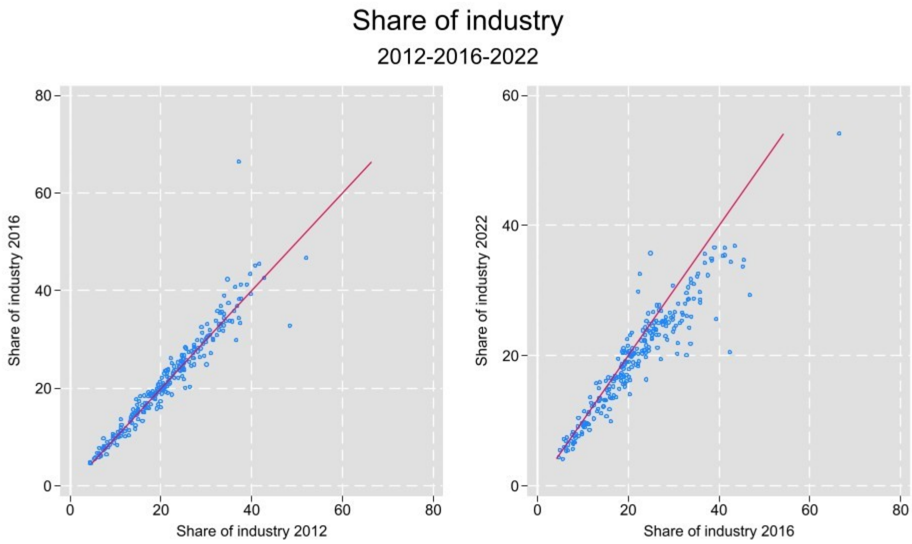

Figure A1.15. Dynamic scatterplot of Share of industry.

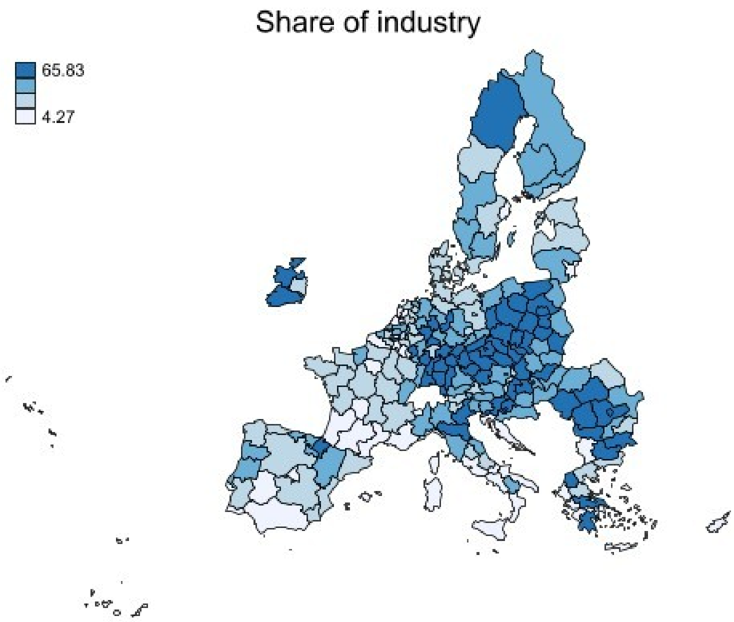

Figure A1.16. Geographical distribution of Share of industry. Year 2020.

Table A1.15. Descriptive statistics. Share of industry.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	23.1	6.6	8.7	33.3	18.9	23.6	27.5	-11%
BE	17.1	6.2	4.4	32.7	11.6	18.7	20.8	-8%
BG	26.1	7.4	10.7	42.3	20.6	28.9	31.2	-15%
CY	7.8	0.5	7.1	8.4	7.4	7.8	8.2	2%
CZ	34.0	9.4	10.0	43.4	33.3	37.0	39.7	-7%
DE	25.8	6.4	8.6	41.4	21.0	25.8	30.1	-8%
DK	17.5	2.2	12.9	21.4	16.3	17.9	19.0	4%
EE	21.0	1.1	18.9	22.4	20.5	21.3	21.9	-7%
EL	16.5	11.5	3.8	53.3	9.4	13.1	18.2	13%
ES	16.8	7.2	4.2	30.9	10.7	18.9	21.1	10%
FI	19.4	6.1	8.1	29.8	15.3	20.8	24.6	-9%
FR	14.4	5.1	5.4	25.4	9.4	15.5	18.3	-9%
HR	22.0	7.9	13.0	35.4	14.7	20.6	28.4	-8%
HU	29.1	9.6	10.6	45.5	23.3	26.5	38.9	-8%
IE	32.9	18.3	14.1	69.0	18.9	24.1	42.0	28%
IT	17.6	6.1	7.4	29.3	12.9	17.4	22.9	0%
LT	21.1	5.5	11.8	28.5	16.0	20.1	26.4	-27%
LU	6.7	0.5	5.7	7.8	6.4	6.7	6.9	-18%
LV	16.3	1.1	15.2	18.1	15.3	16.0	17.3	-16%
MT	10.9	2.1	9.0	15.2	9.4	10.2	12.2	-41%
NL	18.4	8.0	6.9	48.6	12.2	18.9	22.2	-17%
PL	27.2	5.7	11.1	37.2	23.1	28.0	31.3	-7%
PT	14.2	8.4	4.2	26.7	6.6	9.5	23.5	-14%
RO	29.1	8.1	9.9	49.6	23.7	29.9	34.1	-44%
SE	22.0	6.1	9.2	37.8	18.2	22.7	26.0	-12%
SI	27.2	7.2	17.9	35.2	20.5	26.6	34.7	6%
SK	25.1	6.6	14.5	35.7	20.5	24.8	29.8	5%

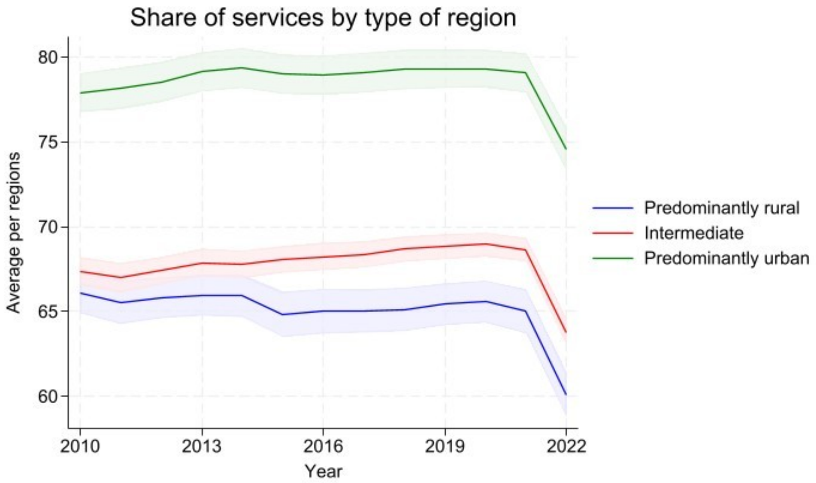

Figure A1.17. Share of services by type of region.

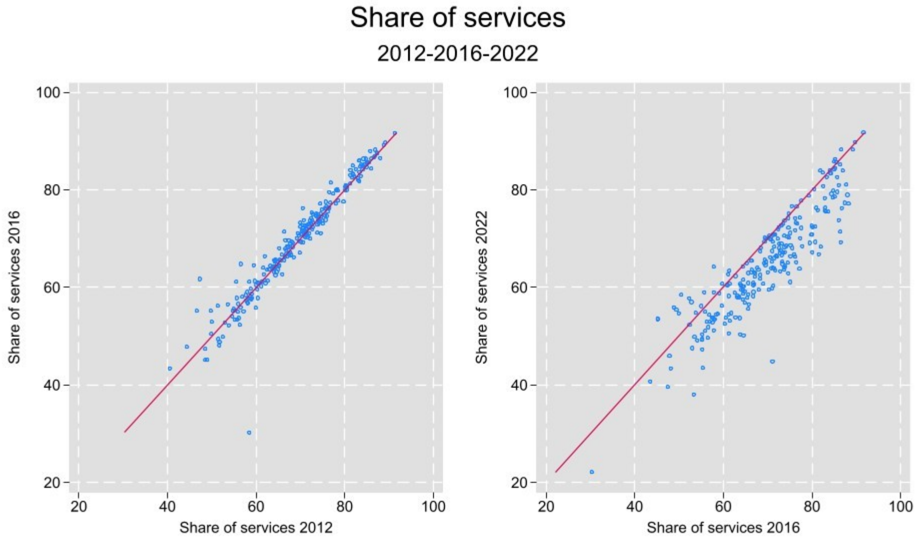

Figure A1.18. Dynamic scatterplot of Share of services.

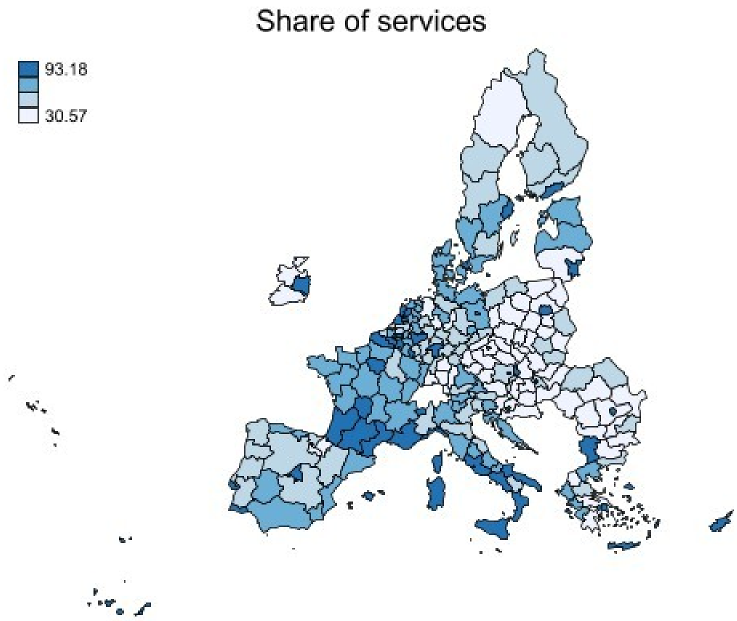

Figure A1.19. Geographical distribution of Share of services. Year 2020.

Table A1.16. Descriptive statistics. Share of services.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	67.5	7.8	53.8	86.6	61.9	66.1	71.0	-11%
BE	76.2	7.3	64.0	93.2	70.5	74.2	82.6	2%
BG	60.8	9.4	43.4	82.6	54.7	57.5	64.3	-18%
CY	84.4	1.4	81.2	86.5	83.3	84.5	85.2	4%
CZ	57.4	10.5	48.8	85.1	51.7	53.4	57.4	7%
DE	67.3	6.8	51.2	86.7	63.7	66.4	71.7	-7%
DK	74.6	4.4	69.7	84.4	71.6	72.8	75.7	-3%
EE	69.2	1.6	66.5	71.9	68.0	69.6	70.0	2%
EL	72.7	13.1	38.0	89.3	67.2	74.7	84.0	-16%
ES	73.3	8.9	58.5	90.4	67.2	70.7	83.2	3%
FI	69.8	7.5	58.6	83.1	64.1	65.8	77.3	-7%
FR	76.3	6.0	59.5	87.6	72.0	74.7	81.7	-5%
HR	67.9	11.5	53.7	84.2	57.1	66.3	79.5	3%
HU	59.5	10.9	44.9	85.4	51.9	58.0	62.5	0%
IE	61.6	19.3	22.1	84.2	51.7	67.6	78.4	-38%
IT	73.7	6.2	53.9	85.5	69.4	72.8	79.4	-9%
LT	67.6	8.8	50.6	78.5	60.6	62.8	76.6	-17%
LU	87.6	0.5	86.5	88.3	87.4	87.7	88.0	1%
LV	72.5	3.6	61.1	75.0	72.4	73.5	74.3	-16%
MT	83.8	2.4	78.6	86.0	82.2	85.0	85.6	9%
NL	73.4	8.7	47.2	88.1	69.6	72.1	79.7	-7%
PL	59.9	6.5	39.6	80.4	56.9	59.3	62.7	-12%
PT	75.7	9.5	58.2	87.1	66.7	78.4	85.9	-11%
RO	56.3	9.4	34.5	80.0	49.8	55.5	61.6	8%
SE	68.5	7.5	50.2	85.1	63.9	68.0	71.1	-4%
SI	64.5	9.3	54.2	75.0	55.1	65.1	73.3	-3%
SK	64.7	8.6	53.4	79.8	59.7	61.8	71.6	2%

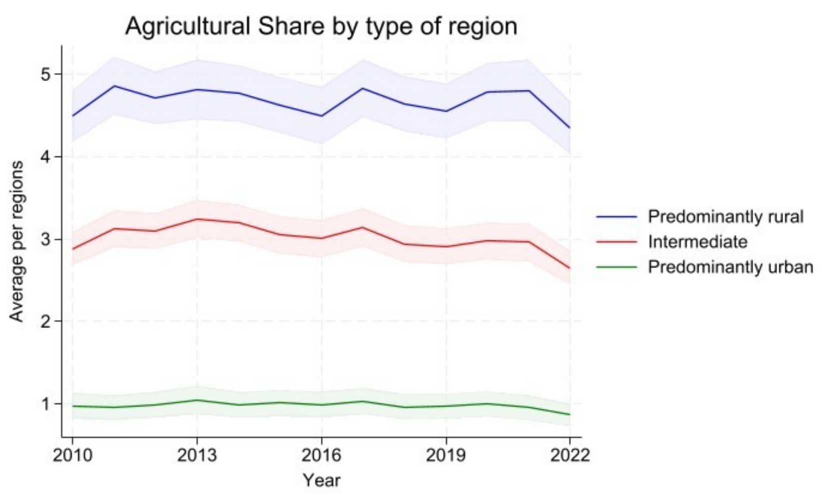

Figure A1.20. Agricultural share by type of region.

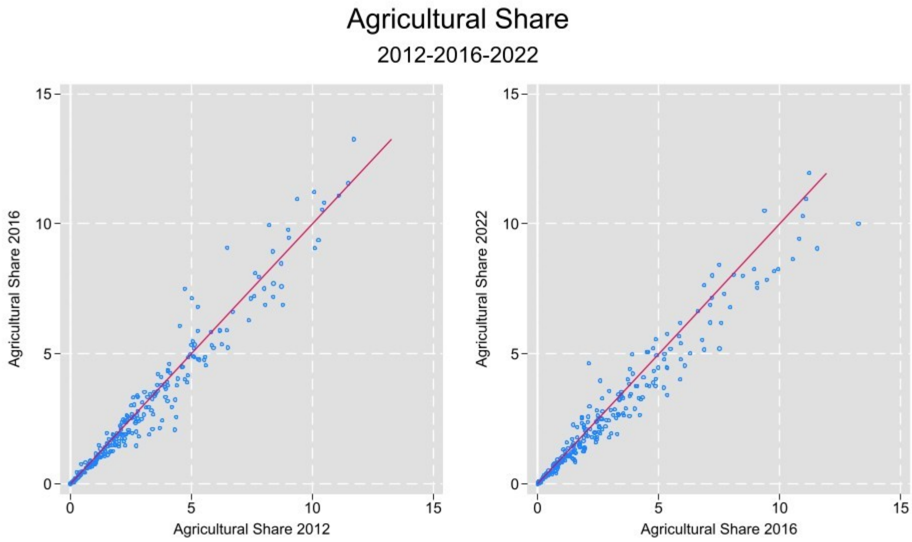

Figure A1.21. Dynamic scatterplot of Agricultural share.

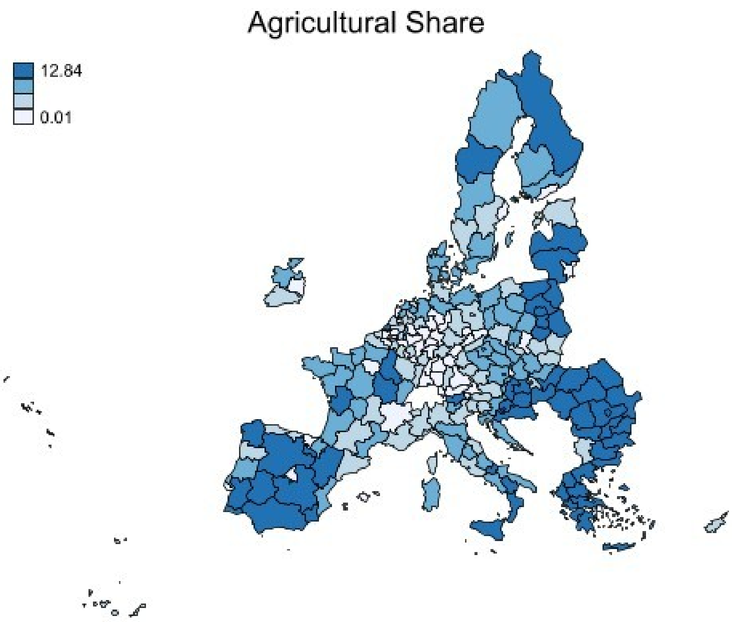

Figure A1.22. Geographical distribution of Agricultural share. Year 2020.

Table A1.17. Descriptive statistics. Agricultural share.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	1.6	1.1	0.0	4.2	0.7	1.5	2.3	-9%
BE	0.9	0.6	0.0	2.4	0.5	0.8	1.3	-17%
BG	7.1	3.3	1.0	13.3	5.5	7.2	9.6	-8%
CY	2.1	0.2	1.8	2.4	2.0	2.1	2.3	-22%
CZ	2.6	1.1	0.2	4.8	1.8	2.7	3.4	27%
DE	1.1	0.8	0.0	4.2	0.5	1.0	1.5	-19%
DK	2.0	1.1	0.1	4.3	1.6	2.2	2.5	-3%
EE	3.1	0.7	2.2	4.2	2.5	2.8	3.6	-22%
EL	6.7	3.1	0.3	13.6	4.7	7.2	8.9	5%
ES	3.4	2.8	0.1	10.4	0.8	2.3	5.7	-9%
FI	3.1	1.9	0.3	6.3	2.2	2.9	4.1	-5%
FR	2.8	1.7	0.1	10.6	1.7	2.4	3.5	-3%
HR	4.9	4.2	0.2	12.3	1.1	3.9	9.0	-14%
HU	6.1	3.6	0.1	12.0	3.9	5.2	9.7	10%
IE	1.7	1.0	0.4	3.4	0.4	1.6	2.6	-12%
IT	2.9	1.5	1.0	6.3	1.8	2.6	4.1	3%
LT	3.3	2.4	0.7	6.5	0.9	3.0	5.7	-10%
LU	0.3	0.0	0.2	0.3	0.2	0.3	0.3	-11%
LV	4.1	0.3	3.6	4.7	4.0	4.1	4.3	-12%
MT	1.0	0.2	0.5	1.4	0.8	1.0	1.1	-39%
NL	2.4	1.2	0.4	5.6	1.8	2.3	3.1	-23%
PL	3.9	2.5	0.5	11.7	1.8	3.7	5.0	-34%
PT	4.4	3.6	0.3	12.0	1.6	3.5	8.5	-4%
RO	6.3	2.7	0.3	11.2	5.0	7.0	8.1	-11%
SE	2.5	1.4	0.1	5.8	1.5	2.5	3.4	-27%
SI	2.4	1.2	1.1	4.1	1.3	2.2	3.6	-3%
SK	2.3	1.0	0.5	4.1	1.5	2.6	3.1	52%

A1.6. Arrivals at tourism accommodation

A) Relevance of the Indicator.

Number of tourists arriving at accommodation establishments. The tourism sector significantly contributes to economic output and employment. Measuring overnight stays relative to population size reflects its local impact. Tourism arrivals serve as a useful proxy for regional attractiveness, reflecting both tangible factors (e.g., amenities and accessibility) and intangible aspects (e.g., reputation and cultural ambience). Crouch (2011) underscores tourism's role in capturing a region's broader appeal. From a regional attractiveness perspective, areas with high tourism intensity may appeal to new residents and investors but must address sustainability and resident well-being.

Tourism-to-GDP ratio. This is a significant indicator within the green transition, highlighting regions highly dependent on tourism as a key economic driver. This dependency can make regions particularly vulnerable to the impacts of climate policies and shifts towards sustainable practices. For example, regions with strong tourism sectors may face challenges in balancing environmental regulations, such as renewable energy development, with maintaining tourism appeal. The construction of wind turbines or other infrastructure linked to the green transition has been shown to negatively affect tourism demand in some regions. In terms of regional attractiveness, areas with a high tourism-to-GDP ratio must adapt their tourism strategies to align with sustainability goals, ensuring they remain appealing to environmentally conscious visitors. Successfully integrating sustainable practices can enhance their reputation and draw eco-tourism, which boosts both economic resilience and attractiveness in the long term.

B) Data, source, treatment and coverage.

Description:	Total (Domestic and Foreigner) number of persons arriving at hotels; holiday and other short-stay accommodation; camping grounds, recreational vehicle parks and trailer parks
Indicator:	tour_acc
Unit of Measurement:	Number of persons
Frequency	Annual
Source:	Eurostat. Arrivals at tourist accommodation establishments by NUTS2 region
DOI	https://doi.org/10.2908/TOUR_OCC_ARN2

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.

- 1st. Regression: Regressing NUTS1 indicator over NUTS2. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
- 2nd. Regression: Regressing NUTS0 indicator over ip1. If ip1 exists, ip1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2=tour_acc.

- Method 2. Relative change in last observation. Not applied
- Method 3. Mean Adjacent observations. When missing values have been observed for isolated years, the mean of previous and following observations have been applied.
- Method 4. Aggregated nuts level value. Not applied
- Method 5. Completing time-series. Not applied.

Table A1.18. Arrivals at Tourism Accommodation -tour_acc- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2010	2022	2010	2022
BE	2010	2022	2010	2022	2010	2022
BG	2010	2022	2010	2022	2010	2022
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2022	2010	2022	2010	2022
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2011	2022	2011	2022	2011	2022
ES	2010	2022	2010	2022	2010	2022
FI	2010	2022	2010	2022	2010	2022
FR	2010	2022	2010	2022	2010	2022
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2022	2010	2022	2018	2022
IT	2010	2022	2010	2022	2010	2022
LT	2010	2022	2010	2022	2015	2022
LU	2010	2022	2010	2022	2010	2022
LV	2010	2022	2010	2022	2010	2022
MT	2010	2022	2010	2022	2010	2022
NL	2010	2022	2010	2022	2010	2022
PL	2010	2022	2010	2022	2010	2022
PT	2010	2022	2010	2022	2010	2022
RO	2010	2022	2010	2022	2010	2022
SE	2010	2022	2010	2022	2010	2022
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

C) Basic Descriptive Analysis.

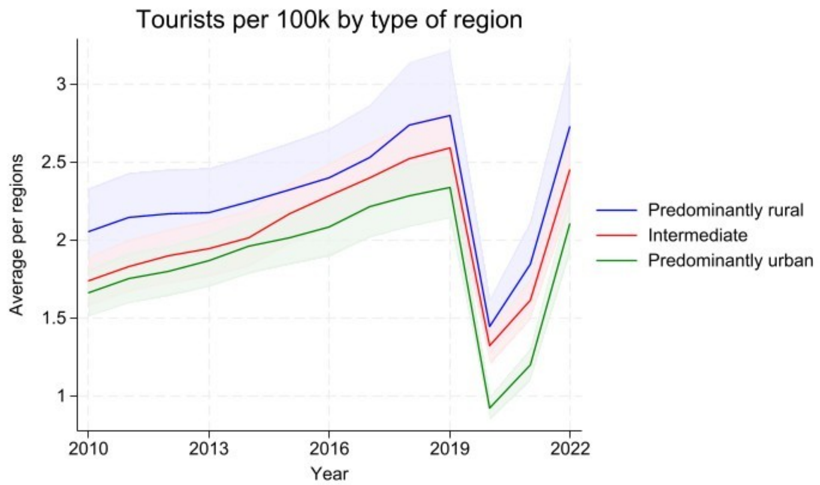

Figure A1.23. Tourists per 100k by type of region.

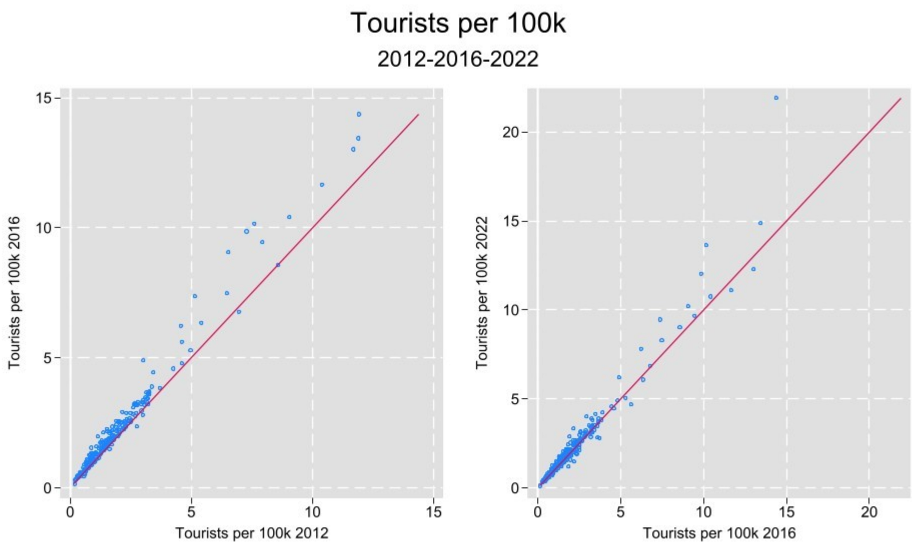

Figure A1.24. Dynamic scatterplot of Tourists per 100k.

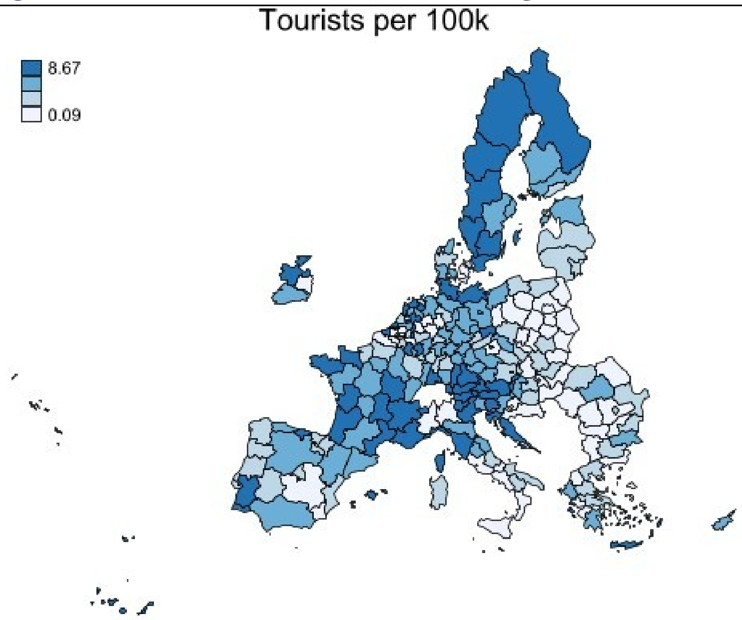

Figure A1.25. Geographical distribution of Tourists per 100k. Year 2020.

Table A1.19. Descriptive statistics. Arrivals at tourism accommodation.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	4.80	3.69	0.87	13.92	2.04	3.35	5.29	12%
BE	1.39	0.98	0.21	3.91	0.69	0.98	2.15	32%
BG	0.91	0.53	0.23	2.18	0.47	0.75	1.30	102%
CY	2.92	0.63	1.24	3.70	2.76	2.97	3.22	5%
CZ	1.55	1.31	0.43	6.15	0.83	1.17	1.61	74%
DE	1.85	0.88	0.42	5.09	1.23	1.70	2.27	15%
DK	1.18	0.43	0.55	2.20	0.72	1.29	1.48	40%
EE	2.25	0.43	1.48	2.86	2.05	2.35	2.53	36%
EL	3.48	4.38	0.25	22.40	1.08	1.67	2.91	49%
ES	2.31	1.98	0.27	10.76	1.25	1.87	2.56	32%
FI	2.84	1.97	0.93	7.54	1.63	2.03	2.75	6%
FR	2.06	1.50	0.09	9.04	1.15	1.91	2.68	26%
HR	2.66	3.80	0.20	12.76	0.42	0.62	3.29	171%
HU	1.00	0.58	0.24	2.69	0.54	0.82	1.33	73%
IE	2.15	0.78	0.44	3.63	1.72	2.23	2.52	12%
IT	2.68	2.97	0.30	14.89	0.97	1.57	2.78	24%
LT	1.02	0.44	0.31	2.02	0.76	0.88	1.28	287%
LU	1.89	0.36	1.00	2.25	1.83	1.96	2.12	20%
LV	1.02	0.29	0.62	1.49	0.77	1.05	1.17	87%
MT	3.30	0.81	1.37	4.18	3.23	3.49	3.63	13%
NL	2.41	1.50	0.84	7.81	1.31	1.83	3.20	50%
PL	0.67	0.39	0.17	2.04	0.39	0.55	0.85	70%
PT	2.90	2.44	0.72	10.87	1.33	1.91	3.29	101%
RO	0.52	0.28	0.15	1.35	0.33	0.44	0.67	131%
SE	2.87	0.69	1.40	4.26	2.33	3.02	3.36	23%
SI	2.04	1.01	0.99	4.42	1.20	1.78	2.64	91%
SK	0.93	0.55	0.29	2.38	0.55	0.75	1.23	34%

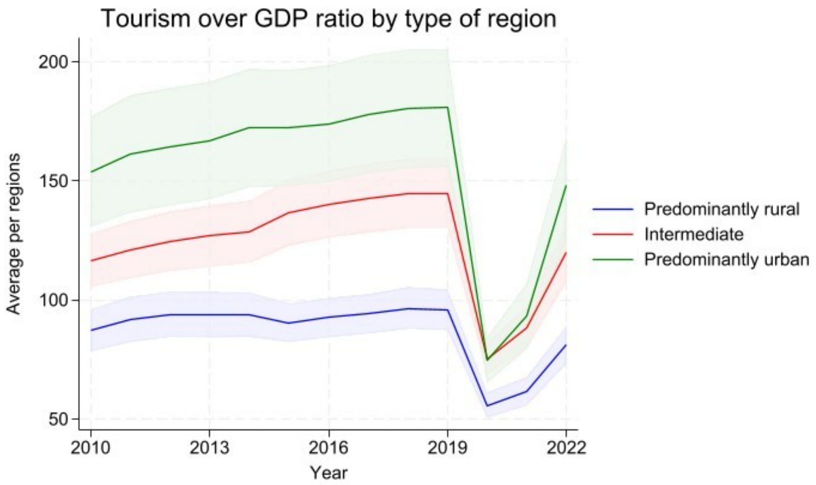

Figure A1.26. Tourism over GDP ratio by type of region.

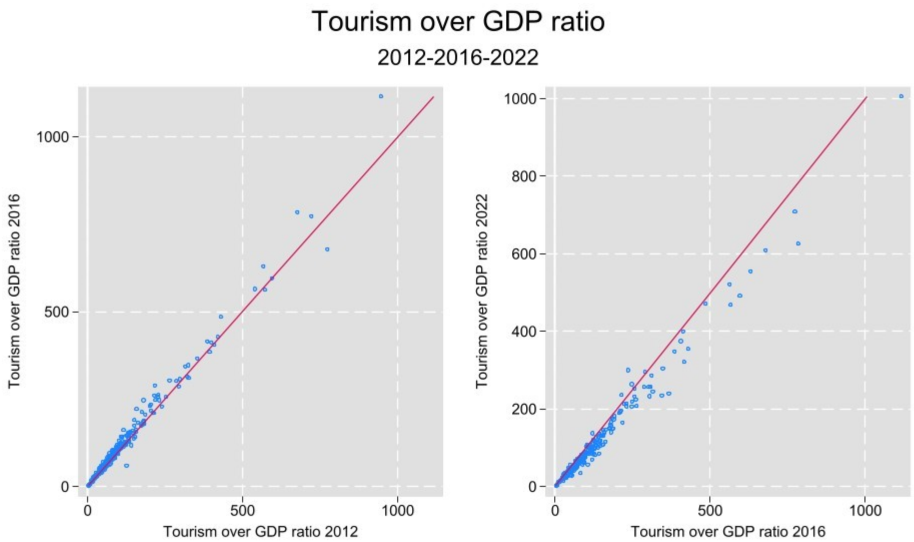

Figure A1.27. Dynamic scatterplot of Tourism over GDP ratio.

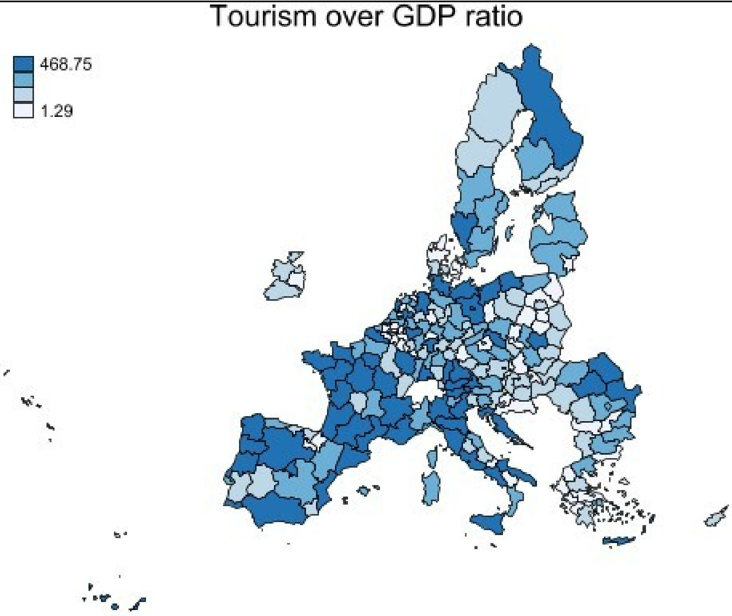

Figure A1.28. Geographical distribution of Tourism over GDP ratio. Year 2020.

Table A1.20. Descriptive statistics. Tourism over gdp ratio.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	97.9	58.3	24.2	253.2	51.5	84.8	129.9	-16%
BE	39.1	25.8	2.5	123.9	22.8	35.3	46.5	1%
BG	80.9	41.3	17.3	165.8	42.9	82.1	114.2	-13%
CY	97.3	21.3	40.5	115.1	95.6	107.2	109.7	-12%
CZ	75.0	30.6	27.6	130.4	43.4	75.1	100.5	17%
DE	115.7	75.0	16.6	374.4	64.4	93.9	143.7	-15%
DK	38.0	16.0	16.7	74.4	26.0	30.6	52.7	2%
EE	134.6	28.3	75.8	153.2	145.4	147.9	149.1	-27%
EL	100.1	84.0	4.3	363.6	39.5	68.4	149.7	27%
ES	230.1	263.9	1.3	1152.5	62.7	104.2	347.3	7%
FI	69.2	40.2	2.7	135.1	47.2	73.5	86.2	-14%
FR	192.1	175.7	2.8	777.6	70.5	151.7	240.8	1%
HR	187.7	287.2	9.3	840.3	24.6	31.5	202.2	44%
HU	62.8	21.1	17.0	105.1	45.1	62.6	80.4	-2%
IE	82.8	36.1	14.7	140.7	58.1	82.5	116.9	-50%
IT	173.3	139.3	4.3	590.5	75.0	129.6	262.6	-7%
LT	62.5	36.6	11.5	113.3	28.8	58.3	100.9	77%
LU	14.0	2.6	8.0	16.8	13.3	14.5	16.2	16%
LV	107.7	24.8	56.3	134.4	97.9	112.8	124.5	-14%
MT	55.0	13.2	23.8	64.0	58.8	60.6	62.4	-16%
NL	82.9	57.6	12.6	292.7	44.0	70.5	109.6	17%
PL	79.9	52.3	11.8	269.1	39.7	68.8	103.4	-8%
PT	122.2	77.3	11.2	290.7	51.2	129.3	180.0	43%
RO	74.0	33.1	20.1	161.8	47.4	67.2	94.5	-3%
SE	96.0	40.0	34.6	187.3	62.2	93.8	114.7	1%
SI	79.8	19.9	48.9	131.9	67.1	74.2	85.1	31%
SK	52.5	26.0	9.4	110.9	28.8	53.8	71.4	7%

A1.7. Tertiary students

A) Relevance of the Indicator.

Tertiary students. Higher education institutions play a pivotal role in shaping regional attractiveness and influencing student mobility. Universities contribute significantly to the perceived quality of life in regional towns, enhancing their appeal to prospective residents (Drummond et al., 2013). Student mobility, however, is driven by a combination of institutional and regional factors. Among these, institutional attributes—such as the quality and reputation of universities—tend to have a stronger impact on student mobility than regional characteristics (Sánchez Barrioluengo & Flisi, 2017).

B) Data, source, treatment and coverage.

Description:	Percentage of population aged between 25 and 64 with tertiary education (levels 5-8)
Indicator:	ter_stu
Unit of Measurement:	Percentage (%)
Frequency	Annual
Source:	Eurostat. Population by educational attainment level, sex and NUTS2 region (%)
DOI	https://doi.org/10.2908/EDAT_LFSE_04

Methods applied for filling NUTS2 time-series.

- **Method 1. Simple Linear Regression.**
    - **1st. Regression:** Regressing NUTS1 indicator over NUTS2. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
    - **2nd. Regression:** Regressing NUTS0 indicator over ip1. If ip1 exists, ip1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2=ter_stu.
    - **3rd. Regression:** Regressing NUTS0 indicator over NUTS1. It NUTS1 exists, NUTS1 value assigned, otherwise, adjusted regression value is assigned. New indicator ip3. value is assigned to ter_stu.
- **Method 2. Relative change in last observation.** Not applied
- **Method 3. Mean Adjacent observations.** Not applied

- **Method 4**. **Aggregated nuts level value.** Not applied
- **Method 5. Completing time-series.** Not applied.

Table A1.21. Tertiary Students -ter_stu- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2010	2022	2010	2022
BE	2010	2022	2010	2022	2010	2022
BG	2010	2022	2010	2022	2010	2022
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2022	2010	2022	2010	2022
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2022	2010	2022	2010	2022
ES	2010	2022	2010	2022	2010	2022
FI	2010	2022	2010	2022	2010	2022
FR	2010	2022	2010	2022	2010	2022
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2022	2010	2022	2012	2022
IT	2010	2022	2010	2022	2010	2022
LT	2010	2022	2010	2022	2013	2022
LU	2010	2022	2010	2022	2010	2022
LV	2010	2022	2010	2022	2010	2022
MT	2010	2022	2010	2022	2010	2022
NL	2010	2022	2010	2022	2010	2022
PL	2010	2022	2010	2022	2010	2022
PT	2010	2022	2010	2022	2010	2022
RO	2010	2022	2010	2022	2010	2022
SE	2010	2022	2010	2022	2010	2022
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

C) Basic Descriptive Analysis.

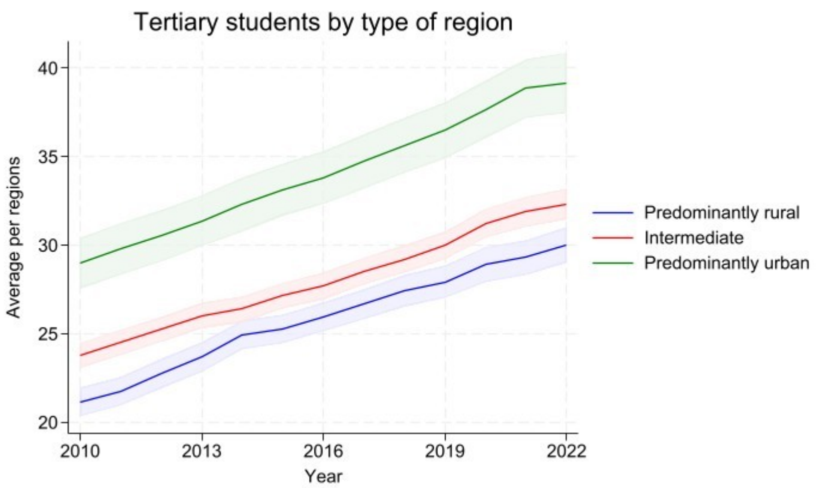

Figure A1.29. Tertiary students by type of region.

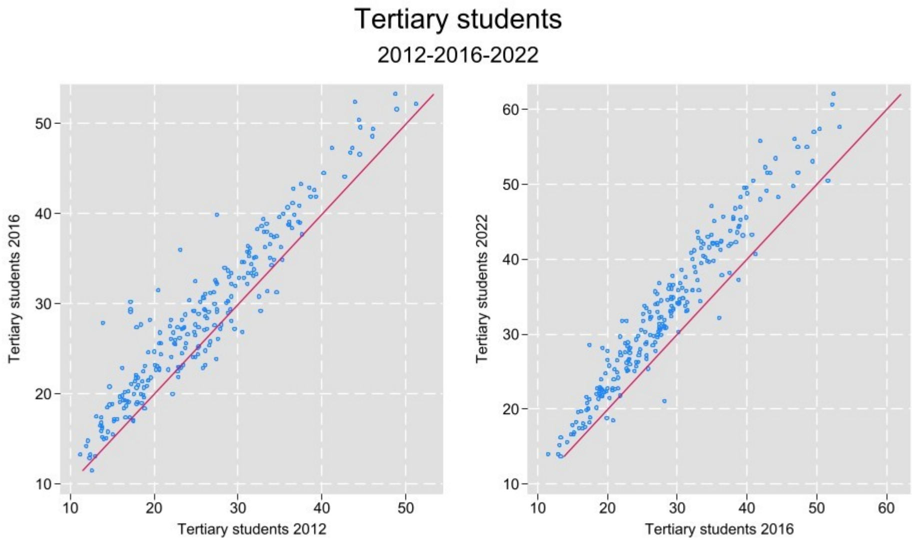

Figure A1.30. Dynamic scatterplot of Tertiary students.

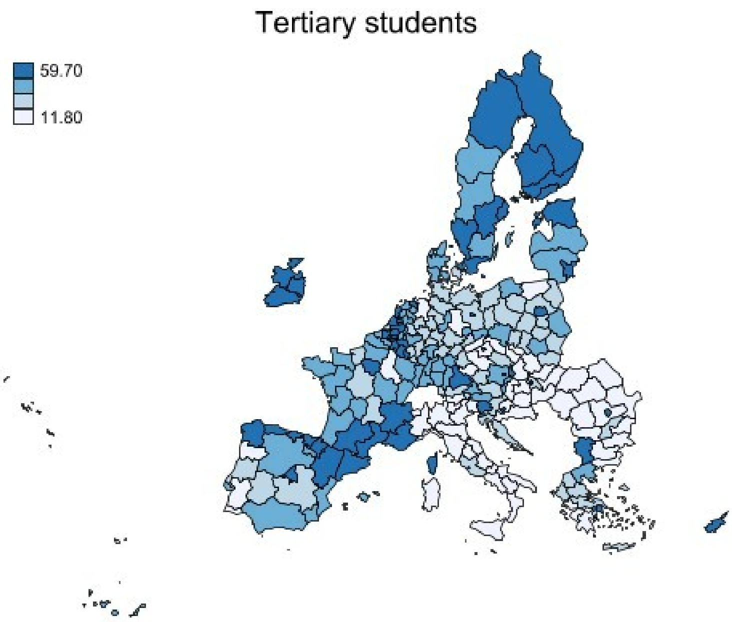

Figure A1.31. Geographical distribution of Tertiary students. Year 2020.

Table A1.22. Descriptive statistics. Tertiary students.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	27.4	7.2	13.9	45.6	19.8	28.8	31.5	91%
BE	39.7	7.9	26.1	60.7	33.5	37.7	44.1	31%
BG	24.8	6.7	17.4	43.2	20.6	22.4	26.3	24%
CY	42.0	3.6	35.7	48.0	39.3	41.9	44.6	34%
CZ	22.1	8.9	9.0	51.5	16.5	20.1	23.8	61%
DE	28.2	4.7	19.7	48.3	24.8	27.4	30.9	19%
DK	35.2	7.9	26.5	54.1	29.3	32.1	38.9	25%
EE	38.4	1.9	35.5	42.1	37.4	37.7	39.5	19%
EL	24.7	6.0	12.3	45.6	20.6	24.1	27.6	52%
ES	34.8	7.6	18.9	55.0	28.3	34.5	40.0	31%
FI	39.9	6.6	26.4	54.9	36.0	38.8	42.6	15%
FR	30.2	7.1	17.6	55.0	24.8	29.7	34.5	45%
HR	23.8	9.9	13.2	44.5	16.3	20.0	29.2	30%
HU	23.0	9.1	14.2	55.8	17.8	19.5	23.0	43%
IE	44.0	6.2	33.7	57.0	39.1	43.2	49.4	42%
IT	17.7	3.2	11.0	26.7	15.3	17.4	20.0	39%
LT	42.9	10.2	29.2	62.1	34.6	40.6	52.4	43%
LU	43.3	5.1	35.5	52.3	39.9	42.6	47.0	47%
LV	33.1	4.1	26.9	39.5	30.2	33.4	35.7	47%
MT	23.7	6.0	14.9	32.1	19.6	22.1	29.7	113%
NL	34.8	7.1	22.0	56.1	29.3	33.7	38.7	37%
PL	27.9	7.8	16.6	58.1	23.1	26.5	30.0	53%
PT	20.6	6.4	9.9	39.0	15.7	20.1	23.9	83%
RO	17.0	7.6	9.9	42.2	12.7	14.2	17.5	41%
SE	38.3	6.9	26.3	57.4	33.2	37.4	42.8	44%
SI	31.7	7.0	19.5	46.0	26.8	31.0	35.7	70%
SK	25.5	9.9	13.9	47.0	17.8	21.9	30.9	67%

A1.8. Physicians per 100k inhabitants

A) Relevance of the Indicator.

Physicians per 100,000 inhabitants. Healthcare availability is a key factor in regional attractiveness (Bourecherouche & Forttas, 2021), especially for families seeking reliable, high-quality services (OECD, 2022). A higher number of doctors per capita suggests robust healthcare coverage, influencing relocation decisions by signalling accessible, well-funded services (European Commission, 2021). Ultimately, ensuring equitable access fosters social inclusion and strengthens competitiveness, making healthcare pivotal for attracting and retaining residents.

B) Data, source, treatment and coverage.

Description:	Physicians per 100,000 inhabitants
Indicator:	phyisic_100k
Unit of Measurement:	Per hundred thousand of inhabitants
Frequency	Annual
Source:	Eurostat. Physicians by NUTS2 region World Bank Group. World Health Organization's Global Health Workforce Statistics, OECD, supplemented by country data for Malta
DOI	Eurostat. https://doi.org/10.2908/HLTH_RS_PHYSREG
Data	World Bank Group: https://data.worldbank.org/indicator/SH.MED.PHYS.ZS

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.
  - 1st. Regression: As information for NUTS1 is not available for any region NUTS0 indicator is regressed directly over NUTS2. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1=physicians_100k
- Method 2. Relative change in last observation. Not applied
- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. For Germany and Ireland NUTS2 regions all values are missing, and the country value has been assigned. Regions from Malta (MT) remain as missing. For Malta Eurostat does not provide data and World Bank Group data have been considered. For completing some missing observations an interpolation with a time trend has been applied.

- Method 5. Completing time-series. For Cyprus (CY), Denmark (DK), Estonia (EE), Finland (FI), Iceland (IS), Luxembourg (LU), Latvia (LV) and Sweden (SE), series have been completed forward with previous non missing observation. For Belgium (BE) and Greece (EL) series have been completed backwards with following non missing observations.

Table A1.23. Physicians -phyisic_100k- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		NUTS1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022			2010	2022
BE	2010	2022			2011	2022
BG	2010	2022			2010	2022
CY	2010	2019			2010	2019
CZ	2010	2022			2010	2022
DE	2010	2022				
DK	2010	2021			2010	2021
EE	2010	2019			2010	2019
EL	2010	2022			2013	2022
ES	2010	2022			2010	2022
FI	2010	2021			2010	2021
FR	2010	2022			2010	2022
HR	2010	2022			2010	2022
HU	2010	2022			2010	2022
IE	2011	2022				
IT	2010	2022			2010	2022
LT	2010	2022			2010	2022
LU	2010	2017			2010	2017
LV	2010	2019			2010	2019
MT					2010	2021
NL	2010	2022			2010	2022
PL	2010	2022			2010	2022
PT	2010	2022			2010	2022
RO	2010	2022			2010	2022
SE	2010	2021			2010	2021
SI	2010	2022			2010	2022
SK	2010	2022			2010	2022

C) Basic Descriptive Analysis.

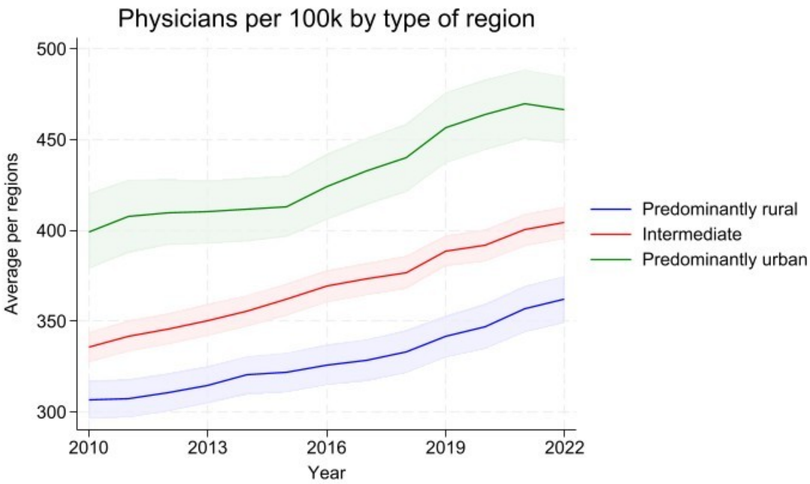

Figure A1.32. Physicians per 100k by type of region.

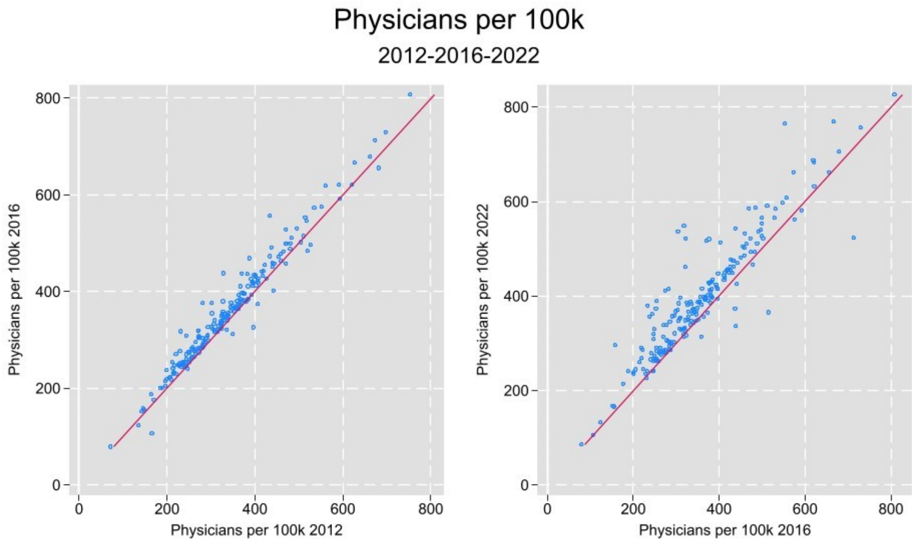

Figure A1.33. Dynamic scatterplot of Physicians per 100k.

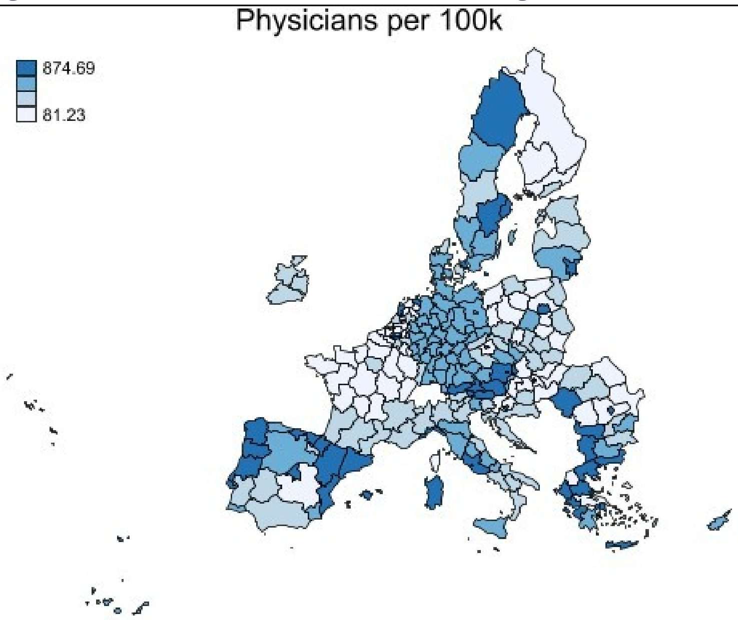

Figure A1.34. Geographical distribution of Physicians per 100k. Year 2020.

Table A1.24. Descriptive statistics. Physicians per 100k.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	488.7	89.0	351.6	705.6	424.0	469.9	527.6	18%
BE	318.2	83.3	219.7	553.7	250.5	281.0	373.1	12%
BG	383.1	45.9	307.3	477.5	341.9	385.1	414.9	16%
CY	368.1	54.0	289.2	427.2	319.5	376.8	427.2	48%
CZ	393.8	135.4	248.9	795.2	326.0	356.0	396.6	20%
DE	419.6	24.3	374.8	455.0	403.5	418.6	439.7	21%
DK	390.3	54.9	298.4	522.5	353.8	376.4	428.5	22%
EE	340.1	8.6	324.4	348.3	333.5	345.6	346.9	7%
EL	491.3	145.5	283.2	827.0	360.5	482.9	612.3	15%
ES	431.4	114.6	254.7	911.0	350.7	419.3	495.3	21%
FI	245.3	60.9	90.5	321.0	228.7	255.4	283.2	3%
FR	284.3	57.1	70.0	408.4	262.0	285.0	320.4	2%
HR	343.9	149.1	153.1	662.5	243.9	301.8	444.6	40%
HU	304.6	96.6	180.1	587.1	239.3	274.0	329.4	27%
IE	313.1	38.2	266.7	402.5	270.7	319.2	331.7	25%
IT	392.9	46.9	292.2	501.8	357.8	385.2	428.3	11%
LT	475.1	90.3	359.2	594.1	395.0	460.3	562.4	10%
LU	290.5	8.6	277.0	298.5	283.0	290.7	298.5	8%
LV	321.4	6.0	310.7	330.4	319.1	321.3	326.7	5%
MT	352.3	127.4	213.0	548.5	239.5	317.8	456.2	158%
NL	304.8	112.2	121.5	567.5	229.6	297.0	372.6	26%
PL	268.9	98.6	145.0	593.1	212.1	241.4	283.6	52%
PT	408.7	123.0	206.7	687.9	318.9	387.3	501.3	63%
RO	304.3	133.1	137.0	765.4	208.9	284.0	350.7	51%
SE	404.4	43.4	316.8	479.1	367.8	404.1	441.3	18%
SI	297.2	61.3	192.8	388.0	252.2	295.8	355.0	40%
SK	398.1	159.2	251.2	686.7	286.9	331.8	499.3	9%

A1.9. Housing cost overburden rate

A) Relevance of the Indicator.

Housing affordability: it is a key factor shaping migration patterns and household location decisions. When housing costs are disproportionately high relative to income, workers may be incentivized to relocate to more affordable areas, thus affecting labour supply, local economic growth, and the long-term stability of local communities (Glaeser et al., 2001). By contrast, regions that manage to keep housing overburden rates low have the potentiality of having higher levels of in-migration and investment, as individuals and firms perceive them as more liveable and conducive to business operations (Malpezzi, 1996). Housing affordability, as measured by the housing overburden rate, provides insight into the share of residents spending more than 40% of their disposable income on housing. This measure varies widely within countries, reflecting significant disparities between regions, which can highlight areas in need of policy intervention.

B) Data, source, treatment and coverage.

Description:	Percentage of population living in a household where the total housing costs (net of housing allowances) represent more than 40% of the total disposable household income (net of housing allowances)
Indicator:	housing
Unit of Measurement:	Percentage (%)
Frequency	Annual
Source:	Eurostat. Housing cost overburden rate by sex - EU-SILC survey
DOI	https://doi.org/10.2908/TESSI160

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression. There are not enough regional observations for applying regression techniques.
- Method 2. Relative change in last observation. As there are some NUTS2 regions with some data but enough for applying regression techniques the change of each observation with the last available observation has been obtained for the aggregated level and then, apply this change to the following level if it has been needed. This is the main correction method for this indicator.
- Method 3. Mean Adjacent observations. Not applied.

- Method 4. Aggregated nuts level value. As there is no regional data for some countries, country level data has been assigned to all NUTS2 regions. See details in Table A1.25.

- Method 5. Completing time-series. For missing values for 2010 and 2011, 2012 data have been assigned.

Table A1.25. Housing cost overburden rate -housing- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2012	2022				
BE	2012	2022	2021	2022	2021	2022
BG	2012	2022	2021	2022	2021	2022
CY	2012	2022				
CZ	2012	2022			2021	2022
DE	2012	2022	2021	2022	2021	2022
DK	2012	2022			2021	2022
EE	2012	2022				
EL	2012	2022	2021	2022	2021	2022
ES	2012	2022	2021	2022	2021	2022
FI	2012	2022	2021	2022	2021	2022
FR	2012	2022				
HR	2012	2022			2021	2022
HU	2012	2022	2021	2022	2021	2022
IE	2012	2022			2021	2022
IT	2012	2022	2021	2022	2021	2022
LT	2012	2022			2021	2022
LU	2012	2022				
LV	2012	2022				
MT	2012	2022				
NL	2012	2022	2021	2022		
PL	2012	2022	2021	2022	2021	2022
PT	2012	2022			2021	2022
RO	2012	2022	2021	2022	2021	2022
SE	2012	2022	2021	2022	2021	2022
SI	2012	2022			2021	2022
SK	2012	2022			2021	2022

C) Basic Descriptive Analysis.

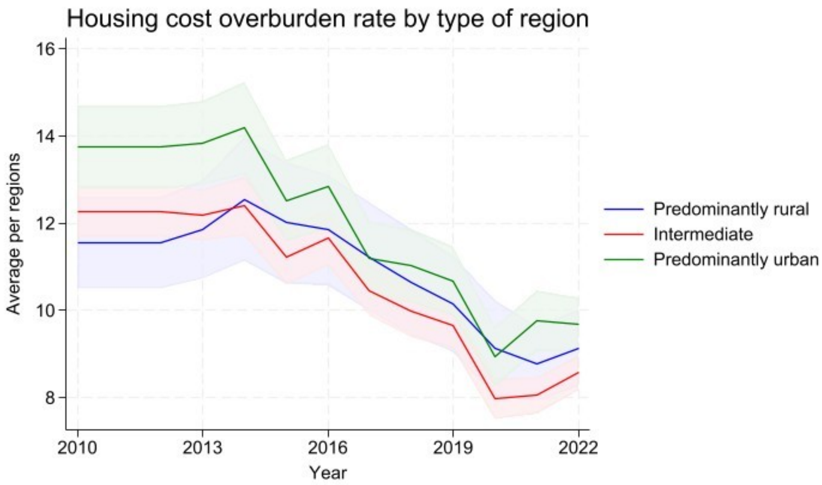

Figure A1.35. Housing cost overburden rate by type of region.

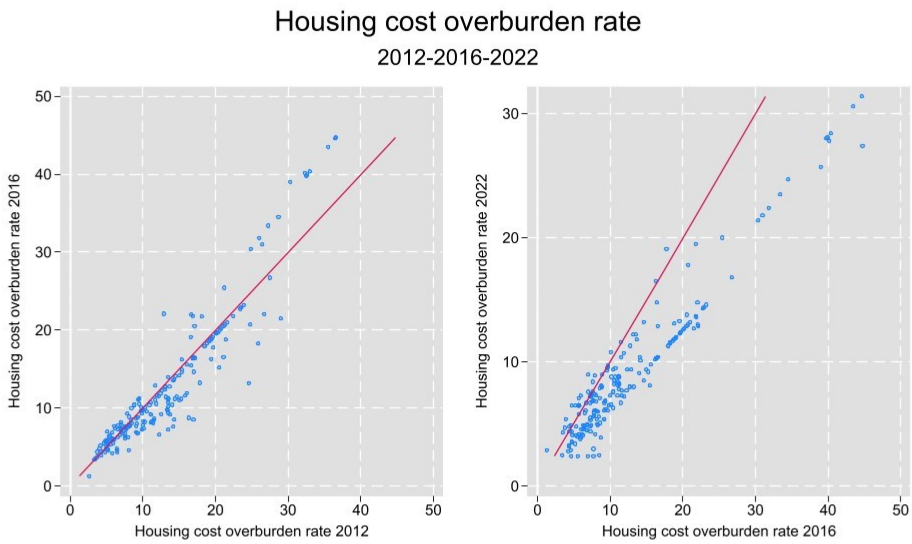

Figure A1.36. Dynamic scatterplot of Housing cost overburden rate.

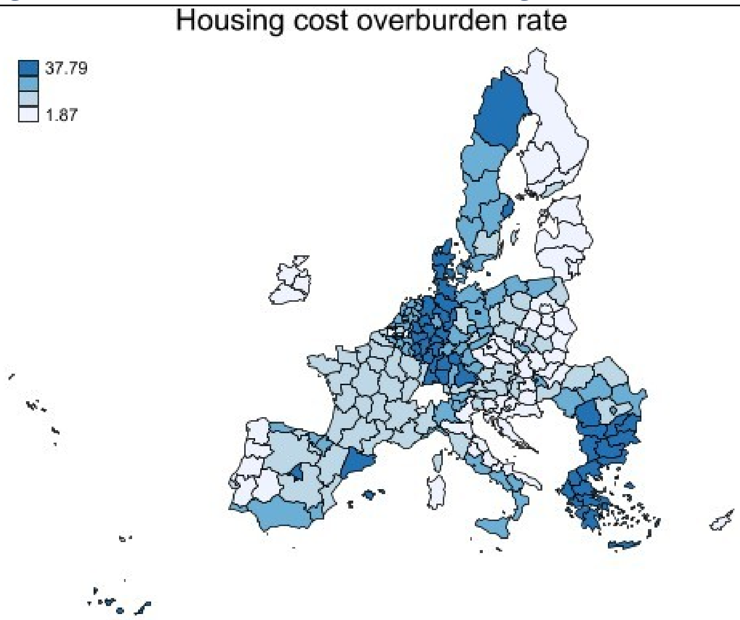

Figure A1.37. Geographical distribution of Housing cost overburden rate. Year 2020.

Table A1.26. Descriptive statistics. Housing cost overburden rate.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	6.82	0.48	5.90	7.70	6.30	7.00	7.20	4%
BE	9.38	4.55	3.46	24.78	6.06	8.22	11.06	-29%
BG	17.38	3.64	8.00	26.89	14.57	17.05	20.29	-8%
CY	2.98	0.80	2.00	4.40	2.20	3.30	3.30	-24%
CZ	10.73	5.43	3.90	30.41	6.83	9.64	12.12	-44%
DE	15.37	4.33	5.32	27.49	11.95	15.38	18.82	-38%
DK	14.42	3.65	8.48	22.90	11.60	13.18	17.75	-12%
EE	6.03	1.68	4.30	8.30	4.60	4.90	8.10	-40%
EL	33.84	6.58	21.40	49.61	28.69	32.98	38.12	-15%
ES	9.36	3.21	3.92	17.80	6.90	8.47	11.64	-14%
FI	4.43	1.00	2.95	7.30	3.74	4.25	4.80	22%
FR	5.33	0.61	4.30	7.10	5.00	5.10	5.60	29%
HR	5.56	1.70	2.40	10.16	4.30	5.24	6.96	-41%
HU	10.24	5.16	1.20	24.90	6.75	9.79	13.41	-48%
IE	4.87	1.28	2.30	6.60	4.10	4.60	6.40	-41%
IT	7.04	2.32	3.00	12.89	5.09	6.80	9.23	-14%
LT	5.92	2.90	1.50	11.59	3.90	5.66	8.02	-63%
LU	6.95	1.89	4.90	10.10	5.10	6.50	8.20	76%
LV	7.63	2.21	4.20	11.40	6.10	7.10	10.00	-39%
MT	2.10	0.64	1.10	2.90	1.60	2.40	2.60	12%
NL	11.79	2.71	7.80	16.10	9.10	11.20	14.45	-37%
PL	8.63	3.09	2.69	16.76	6.10	8.28	10.91	-51%
PT	7.18	2.85	2.96	16.35	5.08	6.64	8.22	-36%
RO	13.69	5.75	4.10	28.99	9.33	12.87	17.00	-55%
SE	8.72	1.33	6.15	11.99	7.60	8.50	9.82	1%
SI	5.07	0.76	4.10	6.50	4.30	5.10	5.70	-18%
SK	7.06	2.42	2.40	12.70	5.40	7.85	8.90	-70%

A1.10. Robberies per 100k inhabitants

A) Relevance of the Indicator.

Robbery rates. Crime victimization negatively affects quality of life, including parenting, work performance, and relationships (Hanson et al., 2010). Violent crime significantly reduces life satisfaction and increases worry among residents (Krekel & Poprawe, 2014), though its overall impact on happiness is smaller compared to factors like family life and health (Michalos & Zumbo, 2000). Overall, safer regions with lower crime rates are more attractive.

B) Data, source, treatment and coverage.

Description:	Robberies per 100,000 inhabitants
Indicator:	robberies_100k
Unit of Measurement:	Per hundred thousand of inhabitants
Frequency	Annual
Source:	Eurostat. Police-recorded offences by NUTS 3 region.
DOI	https://doi.org/10.2908/CRIM_GEN_REG

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.
    - 1st. Regression: Regressing NUTS1 indicator over NUTS2. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
    - 2nd. Regression: Regressing NUTS0 indicator over ip1. If ip1 exists, ip1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2=robberies_100k
- Method 2. Relative change in last observation. Not applied
- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. Not applied
- Method 5. Completing time-series. There is no data for some countries even at country level so NUTS2 time-series have been completed forwards (backwards) with previous (next) non-missing observation.

Table A1.27. Robberies-robberies_100k- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2010	2022	2010	2022
BE	2010	2022	2010	2022	2010	2022
BG	2010	2022	2010	2022	2010	2022
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2012	2019	2012	2019	2012	2019
DK	2010	2022	2010	2022	2010	2022
EE	2018	2022	2018	2022	2018	2022
EL	2010	2022	2010	2022	2010	2022
ES	2010	2022	2010	2022	2010	2022
FI	2010	2022	2010	2022	2010	2022
FR	2016	2022	2016	2022	2016	2022
HR	2018	2022	2018	2022	2018	2022
HU	2017	2022	2017	2022	2017	2022
IE	2015	2022	2015	2022	2015	2022
IT	2014	2022	2014	2022	2014	2022
LT	2010	2022	2010	2022	2010	2022
LU	2010	2022	2010	2022	2010	2022
LV	2010	2022	2010	2022	2010	2022
MT	2010	2022	2010	2022	2010	2022
NL	2010	2022	2010	2022	2010	2022
PL	2013	2022	2013	2022	2013	2022
PT	2010	2022	2010	2022	2010	2022
RO	2015	2022	2015	2022	2015	2022
SE	2010	2022	2010	2022	2010	2022
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

C) Basic Descriptive Analysis.

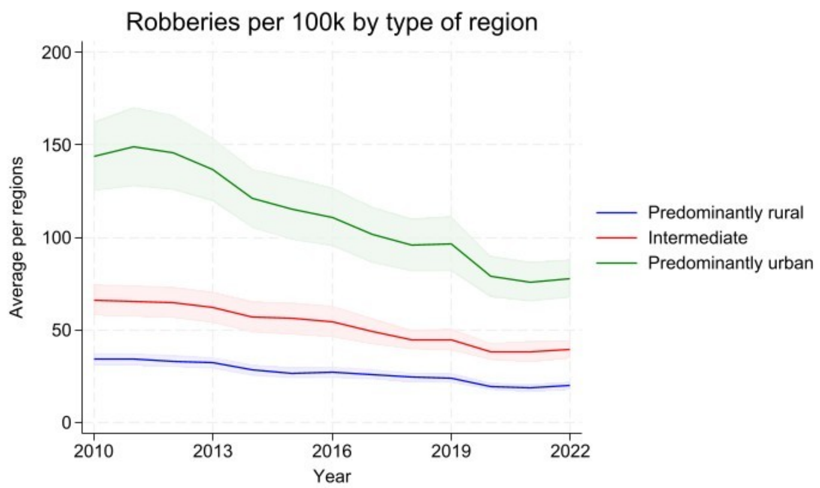

Figure A1.38. Robberies per 100k by type of region.

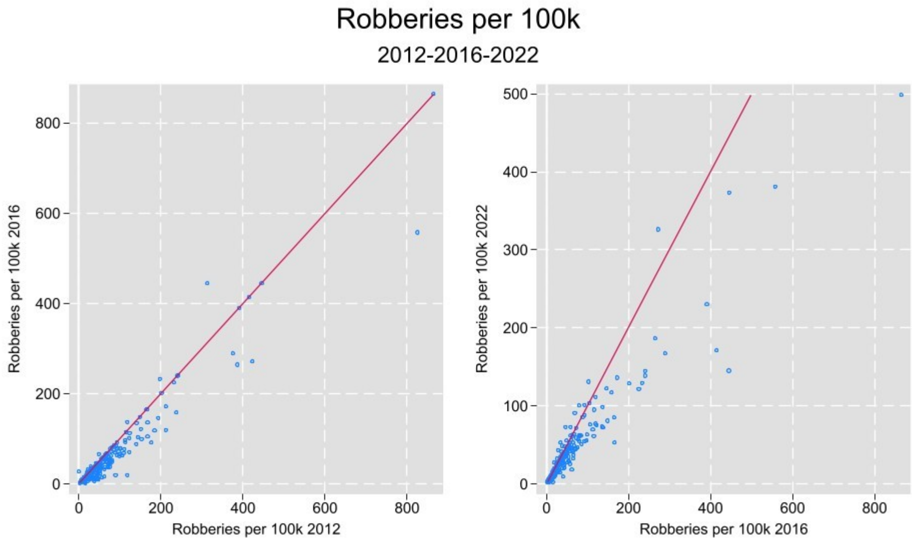

Figure A1.39. Dynamic scatterplot of Robberies per 100k.

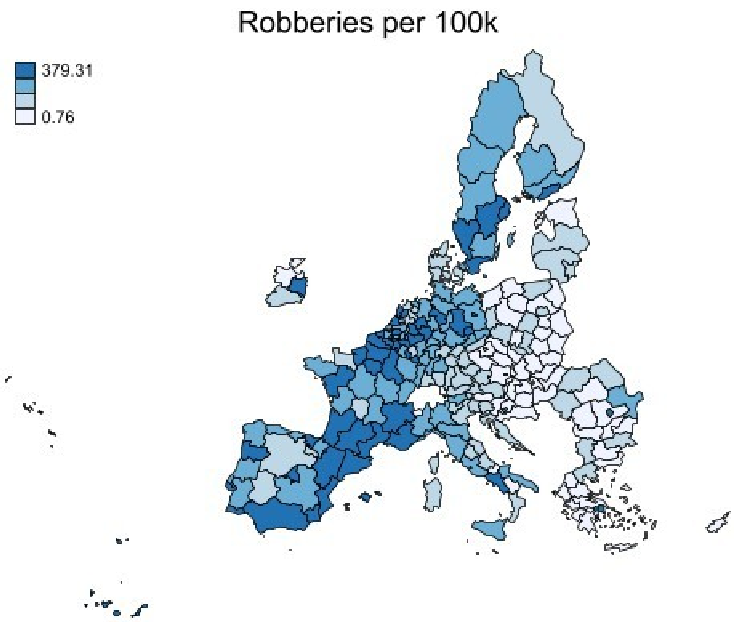

Figure A1.40. Geographical distribution of Robberies per 100k. Year 2020.

Table A1.28. Descriptive statistics. Robberies per 100k.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	26.4	34.7	3.0	184.9	12.5	16.3	20.4	-22%
BE	148.4	158.4	27.6	908.5	60.1	90.5	184.3	-48%
BG	24.2	15.4	6.9	78.8	13.1	19.8	32.2	-74%
CY	12.2	4.5	6.3	20.1	8.8	11.0	16.3	-44%
CZ	21.7	12.8	7.0	67.6	11.6	19.4	27.3	-65%
DE	48.3	36.7	11.7	212.1	27.0	39.8	55.0	-22%
DK	34.3	22.3	13.7	111.9	20.4	27.1	37.3	-57%
EE	11.6	1.8	7.4	12.6	11.5	12.6	12.6	-41%
EL	16.3	23.1	0.0	128.6	4.1	9.7	15.4	-50%
ES	114.6	99.4	19.9	444.8	45.3	75.0	139.3	-24%
FI	26.3	13.9	0.0	73.0	20.1	24.5	27.8	138%
FR	134.1	157.7	17.4	864.7	43.1	69.1	148.5	-32%
HR	21.9	21.2	4.3	67.1	7.3	10.4	31.2	-11%
HU	7.2	3.3	2.6	15.1	4.9	6.7	8.0	-39%
IE	33.3	30.3	4.4	87.8	12.4	18.0	68.9	-45%
IT	37.2	26.5	5.5	140.4	18.6	28.1	49.8	-20%
LT	50.8	33.6	9.2	140.3	23.8	49.3	67.8	-86%
LU	88.3	14.3	74.4	111.9	75.4	79.7	100.4	35%
LV	33.0	11.6	13.9	50.2	25.7	33.0	43.8	-70%
MT	43.1	13.2	19.6	61.5	35.3	44.3	52.8	-46%
NL	49.4	32.7	9.5	160.3	26.4	39.4	63.8	-67%
PL	23.1	20.9	5.2	117.7	10.3	14.1	34.6	-76%
PT	107.6	94.8	22.8	445.3	48.0	68.8	139.2	-41%
RO	17.3	11.5	6.3	65.3	9.3	13.7	19.4	-9%
SE	63.5	37.4	20.9	157.6	31.3	50.6	88.6	-27%
SI	14.7	7.6	4.5	35.3	8.7	13.6	18.7	-52%
SK	12.4	8.5	3.9	43.5	7.7	10.0	14.1	-74%

A1.11. European quality of government index

A) Relevance of the Indicator.

Quality of Government Index (EQI). Institutional quality is a key driver of regional attractiveness. Perception-based tools, such as surveys on public sector integrity and impartial service delivery, highlight the importance of institutional integrity for potential talent and investors. Institutional quality positively influences foreign direct investment inflows, economic growth, and productivity. High-quality institutions enhance a region's appeal to investors and talent (Moskalenko et al., 2022). Strong governance fosters greenfield investments by highly productive multinational enterprises, while weaker regions often attract acquisitions (Amendolagine et al., 2024). Additionally, efficient institutions amplify the impact of EU cohesion funds, driving growth in structurally weaker areas (Arbolino & Boffardi, 2017). At a local level, better institutional frameworks improve productivity in small and medium-sized enterprises, with the effects varying by firm characteristics such as size, age, and human capital (Agostino et al., 2020). These findings underscore the critical role of institutional quality in shaping regional competitiveness, attracting investment, and fostering economic resilience.

B) Data, source, treatment and coverage.

Description:	The index focuses on both perceptions and experiences with public sector corruption, along with the extent to which citizens believe various public sector services are impartially allocated and of good quality in the EU.
Indicator:	eqi
Unit of Measurement:	Index
Frequency	Annual
Source:	The QoG Institute. https://www.gu.se/en/quality-government/qog-data/data-downloads/european-quality-of-government-index
Data	https://www.qogdata.pol.gu.se/data/qog_eqi_long_24.dta

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.
    - 1st. Regression: Regressing year over NUTS2 indicator. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
    - 2nd. Regression: Regressing year over NUTS1 indicator. If NUTS1 value exists, NUTS1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2.

- 3rd. Regression: Regressing year over NUTS0 indicator. If NUTS0 value exists, NUTS0 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip3.
- If ip1 exists, ip1 is assigned, otherwise ip2 or ip3 is assigned.
- Finally, for the cases of Spanish NUTS2 regions of Ciudad de Ceuta (ES63) and Ciudad de Melilla (ES64) values or the region of Andalucia (ES61) have been borrowed, the nearest region with a high degree of similarity in cultural and political aspects.

* Method 2. Relative change in last observation. Not applied
* Method 3. Mean Adjacent observations. Not applied
* Method 4. Aggregated nuts level value. Not applied
* Method 5. Completing time-series. Not applied.

Table A1.29. European Quality of Government Index -eqi- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT					2010	2021
BE			2010	2021		
BG					2010	2021
CY	2010	2021				
CZ					2010	2021
DE			2010	2021		
DK					2010	2021
EE	2010	2021				
EL					2010	2021
ES					2010	2021
FI					2010	2021
FR					2010	2021
HR					2010	2021
HU					2010	2021
IE					2010	2021
IT					2010	2021
LT					2010	2021
LU	2010	2021				
LV	2010	2021				
MT	2010	2021				
NL					2010	2021
PL					2010	2021
PT					2010	2021
RO					2010	2021
SE					2010	2021
SI					2010	2021
SK					2010	2021

C) Basic Descriptive Analysis.

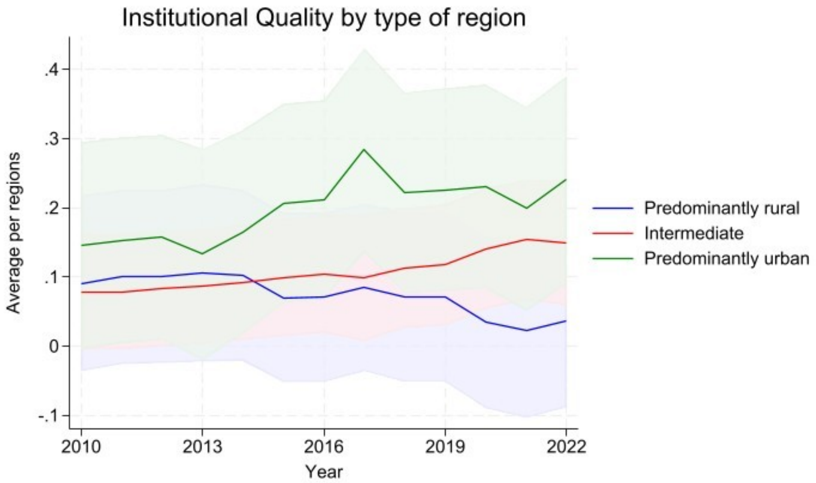

Figure A1.41. Quality of government index by type of region.

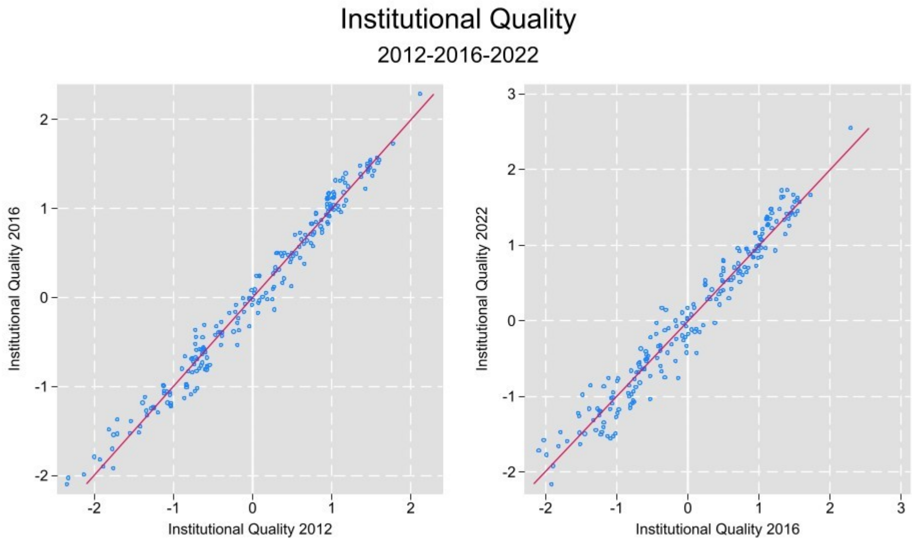

Figure A1.42. Dynamic scatterplot of Quality of government index.

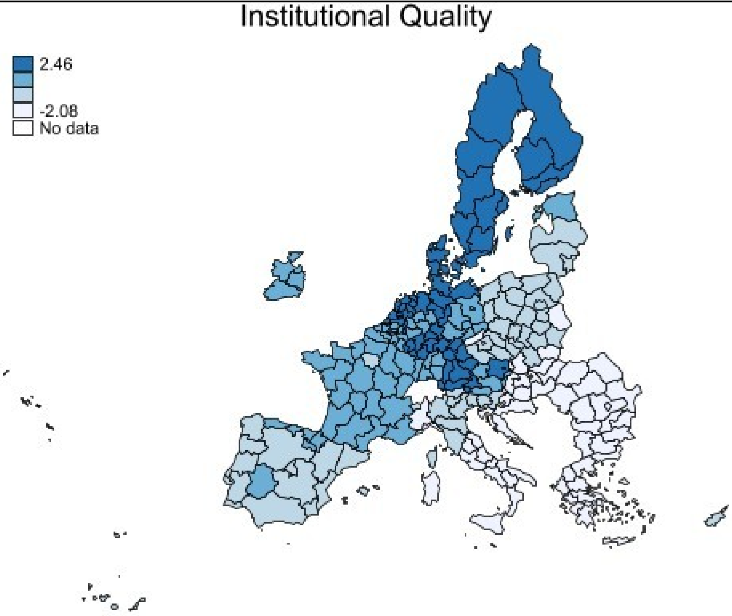

Figure A1.43. Geographical distribution of Quality of government index. Year 2020.

Table A1.30. Descriptive statistics. European quality government index.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	1.0	0.2	0.6	1.5	0.9	1.0	1.1	-25%
BE	0.5	0.4	-0.3	1.1	0.2	0.4	0.9	429%
BG	-1.6	0.4	-2.6	-0.4	-1.9	-1.6	-1.2	-16%
CY	0.0	0.2	-0.3	0.3	-0.2	0.0	0.1	-204%
CZ	-0.3	0.2	-0.9	0.1	-0.4	-0.3	-0.2	-23%
DE	1.0	0.2	0.3	1.4	0.9	1.0	1.1	25%
DK	1.5	0.2	1.1	1.9	1.4	1.6	1.6	-16%
EE	0.2	0.2	0.0	0.5	0.1	0.2	0.4	3690%
EL	-1.1	0.2	-1.6	-0.2	-1.2	-1.1	-1.0	63%
ES	0.1	0.4	-0.7	1.0	-0.1	0.1	0.3	-248%
FI	1.7	0.3	1.4	2.8	1.5	1.5	1.6	12%
FR	0.4	0.4	-1.4	1.1	0.3	0.5	0.7	33%
HR	-1.2	0.1	-1.4	-0.8	-1.3	-1.2	-1.2	-17%
HU	-0.9	0.3	-1.5	-0.5	-1.1	-0.9	-0.7	81%
IE	0.8	0.1	0.4	0.9	0.7	0.9	0.9	-28%
IT	-0.9	0.6	-2.2	0.7	-1.4	-0.8	-0.4	-64%
LT	-0.4	0.3	-0.9	0.2	-0.7	-0.4	-0.2	-108%
LU	1.2	0.0	1.2	1.3	1.2	1.2	1.3	13%
LV	-0.5	0.2	-0.8	-0.2	-0.7	-0.5	-0.4	-73%
MT	0.0	0.3	-0.4	0.4	-0.2	0.0	0.1	-201%
NL	1.2	0.2	0.7	1.7	1.1	1.2	1.3	81%
PL	-0.6	0.2	-1.2	0.0	-0.7	-0.6	-0.5	-32%
PT	0.1	0.2	-0.3	0.8	0.0	0.1	0.2	-209%
RO	-1.6	0.3	-2.7	-0.8	-1.8	-1.6	-1.4	-16%
SE	1.4	0.1	1.2	1.7	1.4	1.4	1.5	3%
SI	-0.1	0.1	-0.2	0.3	-0.2	-0.1	0.0	-50%
SK	-0.7	0.1	-1.0	-0.5	-0.8	-0.7	-0.6	16%

A1.12. Cooling days index

A) Relevance of the Indicator.

Cooling degree days index. Heating Degree Days (HDD) and Cooling Degree Days (CDD) are weather-based technical indices that describe the energy requirements of buildings for heating and cooling across a year (Eurostat, 2024). While cooling currently accounts for a small share of household electricity use—about 3% across the EU—it has grown rapidly in recent decades and is expected to increase further due to climate change (Andreou et al., 2020). These indices can be both understood as vital tools for monitoring and interpreting energy demand in response to changing weather patterns, and as measures climate liveability and consequently as factors of regional attractiveness. Research suggests that climate-related factors, including heating and cooling needs, play a noteworthy role in location decisions (Cragg & Kahn, 1997; Rappaport, 2007). As global warming alters temperature patterns, regions offering more moderate climates could see increased in-migration, while those experiencing amplified extremes may encounter challenges in maintaining competitiveness and quality of life.

B) Data, source, treatment and coverage.

Description:	Cooling degree days (CDD) index: the severity of the heat in a specific time period taking into consideration outdoor temperature and average room temperature (in other words the need for cooling). The calculation of CDD relies on the base temperature, defined as the highest daily mean air temperature not leading to indoor cooling. The value of the base temperature depends in principle on several factors associated with the building and the surrounding environment. By using a general climatological approach, the base temperature is set to a constant value of 24°C in the CDD calculation. If Tm ≥ 24°C Then [CDD = ∑iTim - 21°C)] Else [CDD = 0] where Tim is the mean air temperature of day i.
Indicator:	cooling
Unit of Measurement:	Index
Frequency	Annual
Source:	Eurostat. Cooling and heating degree days by NUTS 3 region - annual data.
DOI	https://doi.org/10.2908/NRG_CHDDR2_A

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.

- 1st. Regression: Regressing NUTS1 indicator over NUTS2. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
- 2nd. Regression: Regressing NUTS0 indicator over ip1. If ip1 exists, ip1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2=cooling

- Method 2. Relative change in last observation. Not applied
- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. Country data have been assigned to NUTS2 Portuguese regions of "PT20" and "PT30.
- Method 5. Completing time-series. There is no data for some countries even at country level so NUTS2 time-series have been completed forwards (backwards) with previous (next) non-missing observation.

Table A1.31. Cooling days-cooling- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2010	2022	2010	2022
BE	2010	2022	2010	2022	2010	2022
BG	2010	2022	2010	2022	2010	2022
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2022	2010	2022	2010	2022
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2022	2010	2022	2010	2022
ES	2010	2022	2010	2022	2010	2022
FI	2010	2022	2010	2022	2010	2022
FR	2010	2022	2010	2022	2010	2022
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2022	2010	2022	2010	2022
IT	2010	2022	2010	2022	2010	2022
LT	2010	2022	2010	2022	2010	2022
LU	2010	2022	2010	2022	2010	2022
LV	2010	2022	2010	2022	2010	2022
MT	2010	2022	2010	2022	2010	2022
NL	2010	2022	2010	2022	2010	2022
PL	2010	2022	2010	2022	2010	2022
PT	2010	2022	2010	2022	2010	2022
RO	2010	2022	2010	2022	2010	2022
SE	2010	2022	2010	2022	2010	2022
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

C) Basic Descriptive Analysis.

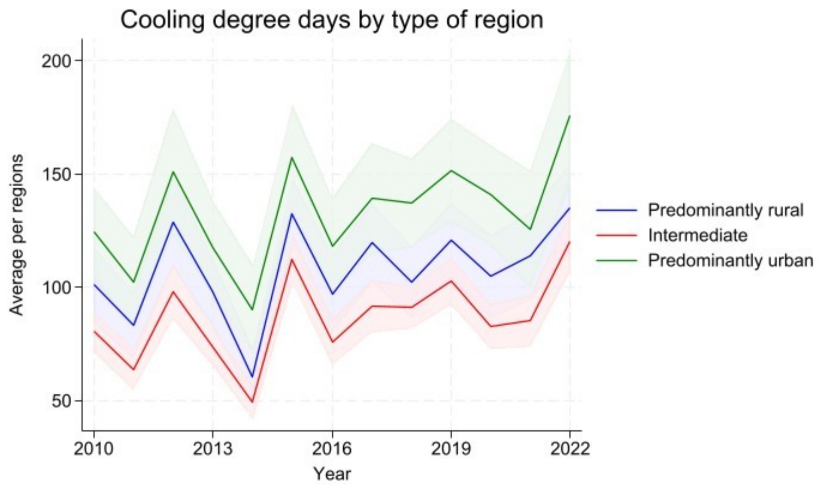

Figure A1.44. Cooling days index by type of region.

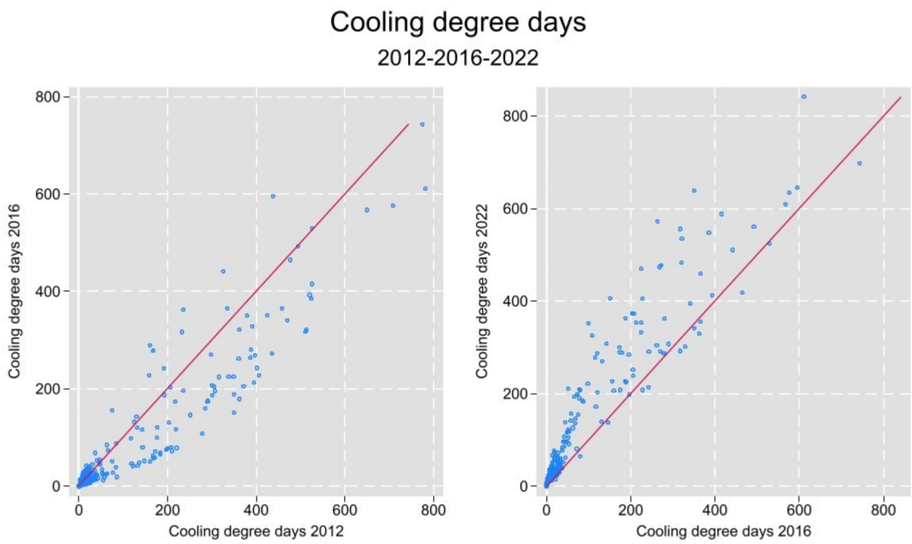

Figure A1.45. Dynamic scatterplot of Cooling days index.

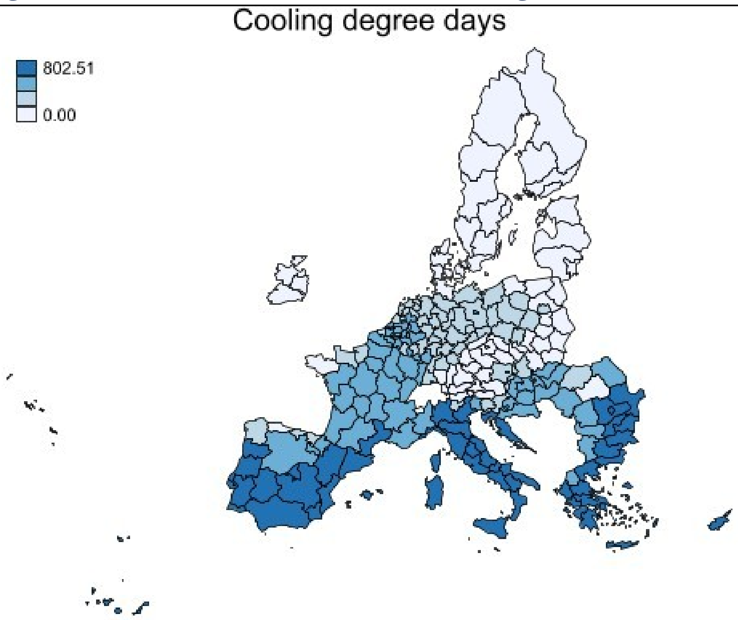

Figure A1.46. Geographical distribution of Cooling days index. Year 2020.

Table A1.32. Descriptive statistics. Cooling days index.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	45.6	60.3	0.0	283.3	5.7	20.8	53.9	6%
BE	23.7	14.9	0.3	60.2	10.6	20.5	35.2	47%
BG	177.7	70.3	31.7	371.3	128.6	176.1	225.2	8%
CY	726.6	52.6	634.2	812.2	687.3	732.5	754.0	-6%
CZ	32.3	28.3	0.1	155.9	11.7	26.0	40.4	1%
DE	27.9	22.2	0.0	109.8	11.2	22.3	38.7	7%
DK	2.2	4.1	0.0	18.6	0.0	0.5	2.3	534%
EE	12.4	14.7	0.0	43.0	1.5	6.4	16.5	-62%
EL	380.2	131.7	52.9	708.3	305.6	368.5	480.8	16%
ES	227.3	169.2	1.0	645.3	66.6	214.3	356.4	292%
FI	4.6	7.5	0.0	34.9	0.0	1.1	5.4	-83%
FR	55.4	49.4	0.0	352.4	21.5	44.0	75.2	976%
HR	151.2	63.2	30.1	290.3	101.0	157.1	196.0	66%
HU	126.2	52.0	32.8	230.2	81.4	121.3	170.5	67%
IE	0.0	0.1	0.0	0.5	0.0	0.0	0.0	
IT	226.9	133.9	0.4	572.5	131.8	232.3	321.0	106%
LT	20.6	17.8	0.8	66.5	7.4	16.4	25.0	-65%
LU	32.8	20.4	1.3	68.3	23.5	29.2	51.9	-15%
LV	14.0	15.5	0.9	49.0	4.1	8.1	14.9	-72%
MT	673.2	99.9	499.1	841.7	625.6	672.3	756.2	69%
NL	16.4	13.4	0.0	54.8	6.7	11.2	24.5	40%
PL	31.2	21.5	0.1	115.5	14.5	28.3	41.2	-12%
PT	197.7	76.2	43.2	362.6	143.3	190.5	263.1	8%
RO	135.6	83.1	5.5	360.4	67.5	135.1	197.5	14%
SE	1.8	4.2	0.0	28.4	0.0	0.1	1.4	95%
SI	61.6	27.7	10.8	109.2	43.0	64.2	83.0	85%
SK	65.8	44.6	5.4	191.3	34.9	51.8	98.6	44%

A1.13. Heating days index

A) Relevance of the Indicator.

Heating degree days index. Heating Degree Days (HDD) and Cooling Degree Days (CDD) are weather-based technical indices that describe the energy requirements of buildings for heating and cooling across a year (Eurostat, 2024). While cooling currently accounts for a small share of household electricity use—about 3% across the EU—it has grown rapidly in recent decades and is expected to increase further due to climate change (Andreou et al., 2020). These indices can be both understood as vital tools for monitoring and interpreting energy demand in response to changing weather patterns, and as measures climate liveability and consequently as factors of regional attractiveness. Research suggests that climate-related factors, including heating and cooling needs, play a noteworthy role in location decisions (Cragg & Kahn, 1997; Rappaport, 2007). As global warming alters temperature patterns, regions offering more moderate climates could see increased in-migration, while those experiencing amplified extremes may encounter challenges in maintaining competitiveness and quality of life.

B) Data, source, treatment and coverage.

Description:	Heating Degree Days (HDD) index: the severity of the cold in a specific time period taking into consideration outdoor temperature and average room temperature (in other words the need for heating). The calculation of HDD relies on the base temperature, defined as the lowest daily mean air temperature not leading to indoor heating. The value of the base temperature depends in principle on several factors associated with the building and the surrounding environment. By using a general climatological approach, the base temperature is set to a constant value of 15°C in the HDD calculation. If $T_m \leq 15°C$ Then [HDD = $\sum_i(18°C - T^i_m)$] Else [HDD = 0] where T^i_m is the mean air temperature of day i.
Indicator:	heating
Unit of Measurement:	Index
Frequency	Annual
Source:	Eurostat. Cooling and heating degree days by NUTS 3 region - annual data.
DOI	https://doi.org/10.2908/NRG_CHDDR2_A

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.

- 1st. Regression: Regressing NUTS1 indicator over NUTS2. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
- 2nd. Regression: Regressing NUTS0 indicator over ip1. If ip1 exists, ip1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2=cooling

- Method 2. Relative change in last observation. Not applied
- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. Country data have been assigned to NUTS2 Portuguese regions of "PT20" and "PT30".
- Method 5. Completing time-series. There is no data for some countries even at country level so NUTS2 time-series have been completed forwards (backwards) with previous (next) non-missing observation.

Table A1.33. Heating days-heating- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2010	2022	2010	2022
BE	2010	2022	2010	2022	2010	2022
BG	2010	2022	2010	2022	2010	2022
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2022	2010	2022	2010	2022
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2022	2010	2022	2010	2022
ES	2010	2022	2010	2022	2010	2022
FI	2010	2022	2010	2022	2010	2022
FR	2010	2022	2010	2022	2010	2022
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2022	2010	2022	2010	2022
IT	2010	2022	2010	2022	2010	2022
LT	2010	2022	2010	2022	2010	2022
LU	2010	2022	2010	2022	2010	2022
LV	2010	2022	2010	2022	2010	2022
MT	2010	2022	2010	2022	2010	2022
NL	2010	2022	2010	2022	2010	2022
PL	2010	2022	2010	2022	2010	2022
PT	2010	2022	2010	2022	2010	2022
RO	2010	2022	2010	2022	2010	2022
SE	2010	2022	2010	2022	2010	2022
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

C) Basic Descriptive Analysis.

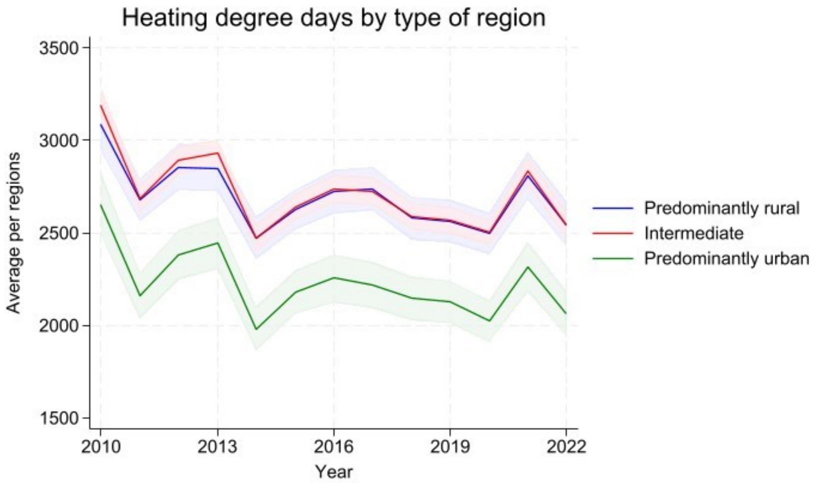

Figure A1.47. Heating days index by type of region.

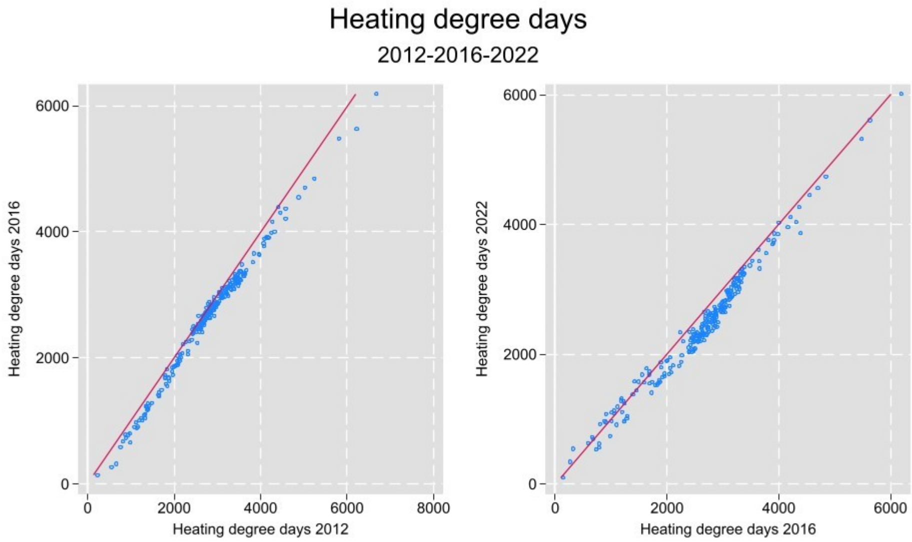

Figure A1.48. Dynamic scatterplot of Heating days index.

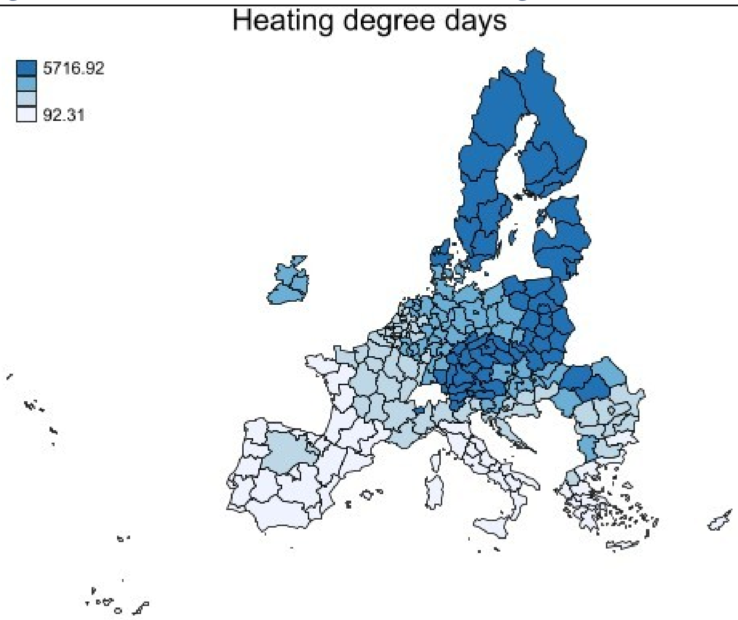

Figure A1.49. Geographical distribution of Heating days index. Year 2020.

Table A1.34. Descriptive statistics. Heating days index.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	3330.0	609.9	2048.2	4818.5	2833.1	3336.6	3799.7	-18%
BE	2582.6	308.0	2036.9	3484.8	2350.3	2523.9	2787.9	-26%
BG	2425.2	253.6	1791.4	3044.2	2300.6	2449.5	2587.4	-8%
CY	660.4	109.4	470.8	817.0	609.8	693.1	720.8	40%
CZ	3205.2	276.7	2588.1	3917.8	3007.3	3155.8	3387.8	-19%
DE	2948.4	318.6	2201.3	3967.4	2721.6	2906.4	3127.4	-25%
DK	3176.2	287.1	2799.3	4080.7	3000.4	3104.3	3317.1	-24%
EE	4151.1	331.3	3554.4	4887.2	4064.6	4143.2	4209.6	-16%
EL	1379.1	488.7	430.1	2622.0	993.6	1345.6	1738.3	19%
ES	1474.2	629.0	42.1	2668.8	1051.7	1661.4	1956.4	-13%
FI	4661.1	704.1	3402.7	6507.7	4199.9	4513.0	5070.8	-16%
FR	2308.3	376.8	1236.4	3182.1	2073.6	2317.0	2532.3	-26%
HR	2312.2	252.3	1683.7	2803.9	2121.1	2333.3	2509.3	-16%
HU	2634.7	202.3	2196.1	3078.7	2490.6	2651.0	2778.7	-14%
IE	2790.7	189.7	2424.1	3333.6	2660.1	2765.2	2870.5	-20%
IT	2040.0	919.5	885.7	4902.0	1389.6	1737.5	2388.6	-15%
LT	3805.9	284.1	3292.5	4418.1	3679.6	3800.4	3915.5	-14%
LU	2856.4	259.5	2515.7	3344.5	2666.8	2850.7	2962.6	-20%
LV	3968.3	311.0	3402.7	4636.0	3862.2	3997.4	4036.8	-13%
MT	472.5	96.3	322.4	662.4	401.9	465.9	543.6	35%
NL	2634.2	293.1	2043.1	3490.1	2428.4	2594.1	2763.7	-28%
PL	3281.1	304.0	2711.1	4192.6	3055.3	3247.1	3460.4	-18%
PT	1068.2	321.9	531.5	1836.2	816.5	1064.8	1307.3	-26%
RO	2815.1	336.9	2175.1	3613.6	2574.0	2758.5	3036.8	-11%
SE	4366.6	1018.2	2932.6	7011.1	3605.6	3948.3	5084.5	-21%
SI	2754.8	195.0	2339.3	3147.3	2634.3	2755.4	2846.7	-16%
SK	3041.8	346.7	2326.4	3701.8	2782.6	3012.6	3329.4	-14%

A1.14. Air quality

A) Relevance of the Indicator.

Air quality index. Air quality significantly shapes regional attractiveness, influencing both residential and business decisions as well as tourism flows. Poor air quality deters potential in-migrants and investors, while cleaner environments foster a healthier quality of life (Kahn, 2006). Empirical evidence from China shows that higher air quality raises property values and increases in-migration (Zheng & Kahn, 2013). In tourism, air quality is crucial, especially for nature-based destinations or when travelling with children (Eusébio et al., 2022; Łapko et al., 2020). Integrating air quality measures into regional development and destination management is thus vital for sustaining both resident and visitor appeal.

B) Data, source, treatment and coverage.

Description:	Air pollution population weighted average.
Indicator:	airqua
Unit of Measurement:	ug/m3 of air pollutant PM2.5
Frequency	Annual
Source:	University of Helsinki. MOBITIWN DATASET based on data of the European Environmental Agency https://www.eea.europa.eu.
DOI	https://doi.org/10.5281/zenodo.14228376

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression. Not applied
- Method 2. Relative change in last observation. Not applied
- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. Not applied
- Method 5. Completing time-series. Observation for 2022 has been filled with data for 2021

Table A1.35. Air Quality-airqua- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT					2010	2021
BE					2010	2021
BG					2010	2021
CY					2010	2021
CZ					2010	2021
DE					2010	2021
DK					2010	2021
EE					2010	2021
EL					2010	2021
ES					2010	2021
FI					2010	2021
FR					2010	2021
HR					2010	2021
HU					2010	2021
IE					2010	2021
IT					2010	2021
LT					2010	2021
LU					2010	2021
LV					2010	2021
MT					2010	2021
NL					2010	2021
PL					2010	2021
PT					2010	2021
RO					2010	2021
SE					2010	2021
SI					2010	2021
SK					2010	2021

C) Basic Descriptive Analysis.

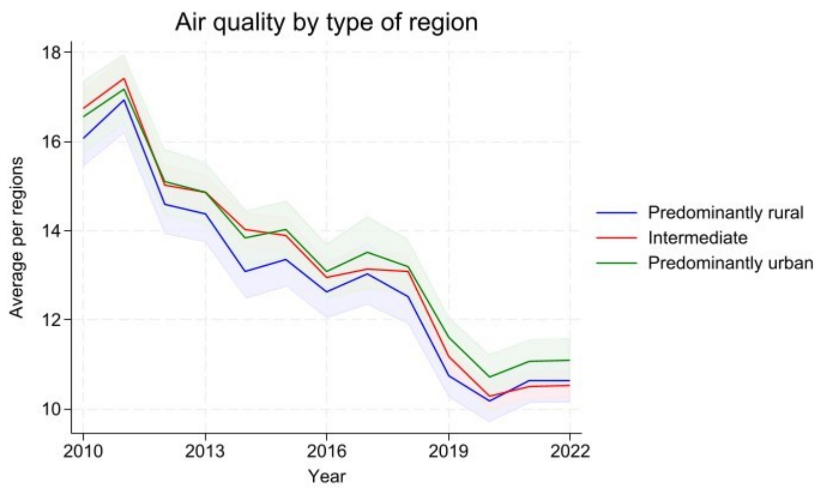

Figure A1.50. Air quality by type of region.

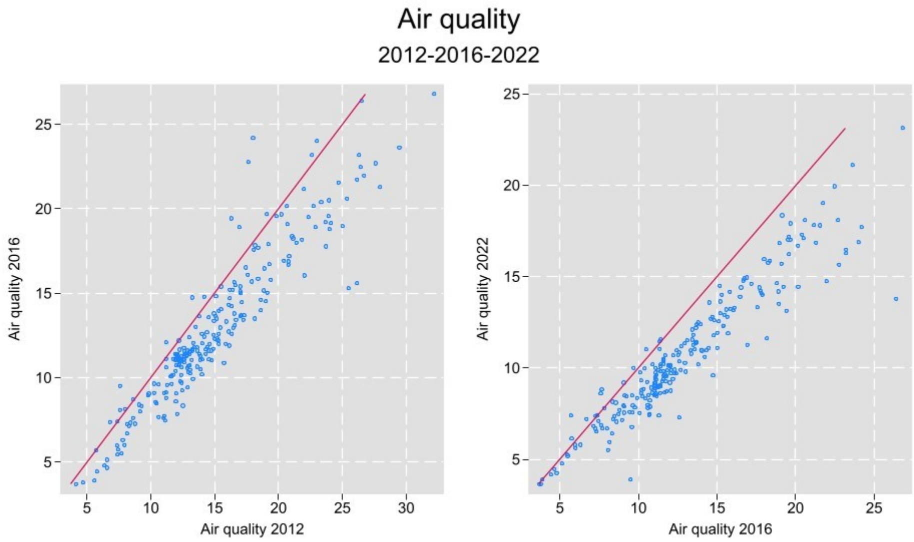

Figure A1.51. Dynamic scatterplot of Air quality.

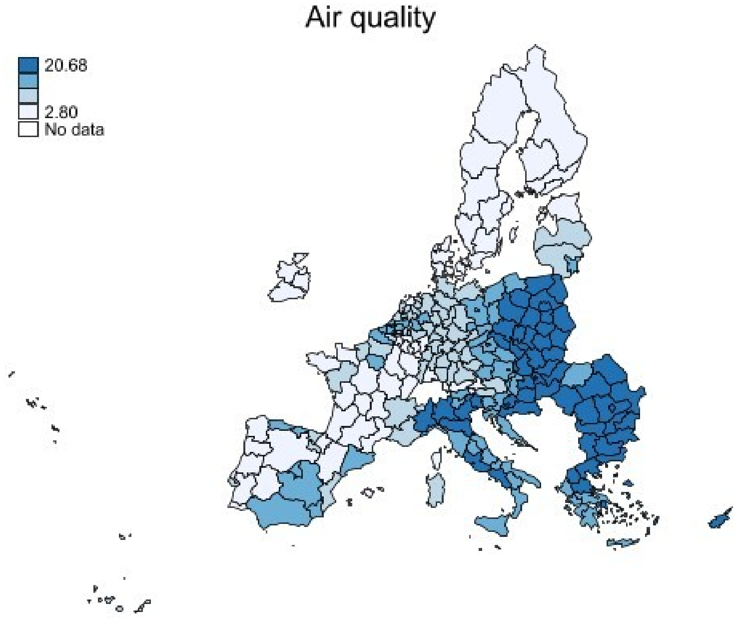

Figure A1.52. Geographical distribution of Air quality. Year 2020.

Table A1.36. Descriptive statistics. Air quality.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	12.0	3.4	6.4	23.4	9.6	11.4	14.3	-45%
BE	12.9	3.2	6.3	20.4	10.4	12.3	15.3	-45%
BG	20.9	5.0	13.5	36.1	16.5	20.7	24.8	-42%
CY	17.3	3.9	14.0	25.5	14.5	15.7	17.7	-36%
CZ	16.9	4.3	10.0	33.3	13.9	16.7	18.7	-37%
DE	12.1	2.5	6.8	19.9	9.9	12.0	13.8	-43%
DK	9.8	1.9	6.5	14.7	8.4	9.6	10.6	-32%
EE	6.8	1.4	5.2	9.1	5.6	6.9	7.9	-38%
EL	17.2	4.7	10.6	39.5	13.5	16.3	20.0	-30%
ES	10.3	2.2	5.4	16.2	8.7	10.2	12.1	-25%
FI	5.6	1.5	3.2	8.6	4.3	5.4	6.6	-36%
FR	10.8	2.9	6.2	19.4	8.6	10.2	12.7	-43%
HR	17.3	3.6	10.8	24.2	14.2	17.6	19.8	-29%
HU	17.5	3.1	12.3	27.0	15.3	17.3	19.3	-30%
IE	7.6	1.3	5.3	10.5	6.5	7.5	8.8	-33%
IT	14.2	3.6	8.5	27.2	11.7	13.3	16.2	-22%
LT	13.0	2.2	9.4	18.3	11.4	12.9	14.8	-32%
LU	11.0	2.9	7.3	15.9	8.1	11.3	12.8	-53%
LV	11.0	1.7	8.5	14.4	10.0	10.6	11.9	-30%
MT	12.1	1.1	10.1	14.7	11.5	12.0	12.2	-14%
NL	12.4	2.7	7.8	18.6	10.4	11.9	13.9	-45%
PL	20.2	4.5	11.0	37.0	17.0	19.8	22.9	-30%
PT	7.8	2.0	3.9	12.7	6.4	7.4	9.2	-23%
RO	17.3	3.4	11.3	28.3	14.6	16.9	19.1	-17%
SE	5.9	1.9	2.8	11.7	4.2	5.7	7.2	-34%
SI	14.9	2.8	11.1	20.7	12.0	15.0	17.0	-39%
SK	18.2	3.5	12.7	26.7	15.5	18.0	20.7	-31%

A1.15. Broadband coverage

A) Relevance of the Indicator.

Broadband coverage. Broadband connectivity is a key factor in regional attractiveness: High-speed internet supports business operations, remote work, e-learning, and telemedicine, making regions with reliable broadband more appealing to residents and investors (European Commission, 2022). Poor connectivity, in contrast, creates a digital divide, reducing regional competitiveness and opportunities for development (OECD, 2020). Studies show that robust broadband networks attract skilled workers and businesses, fostering balanced growth between urban and rural areas (Van Dijk et al., 2018). Thus, broadband access is essential for driving economic, social, and technological progress in regions.

B) Data, source, treatment and coverage.

Description:	Percentage of households with broadband access
Indicator:	broadaccess
Unit of Measurement:	Percentage of households (%)
Frequency	Annual
Source:	Eurostat. Households with broadband access
DOI	https://doi.org/10.2908/ISOC_R_BROAD_H

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.
    - 1st. Regression: Regressing NUTS1 indicator over NUTS2. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
    - 2nd. Regression: Regressing NUTS0 indicator over ip1. If ip1 exists, ip1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2= broadaccess.
    - 3rd. Regression: Regressing NUTS0 indicator over NUTS1. It NUTS1 exists, NUTS1 value assigned, otherwise, adjusted regression value is assigned. New indicator ip3. So ip3=broadaccess for all Greek and German NUTS2 regions and Grad Zagreb (HR05) and Sjeverna Hrvatska (HR06) NUTS2 regions.
- Method 2. Relative change in last observation. Not applied
- Method 3. Mean Adjacent observations. Not applied

- Method 4. Aggregated nuts level value. Country data applied to Åland (FI20) Finnish region.
- Method 5. Completing time-series. Observation for 2022 has been filled with data for 2021.

Table A1.37. Households with broadband access-broadaccess- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2021	2010	2021	2010	2021
BE	2010	2021	2010	2021	2010	2021
BG	2010	2021	2010	2021	2010	2021
CY	2010	2021	2010	2021	2010	2021
CZ	2010	2021	2010	2021	2010	2021
DE	2010	2021	2010	2021		
DK	2010	2021	2010	2021	2010	2021
EE	2010	2021	2010	2021	2010	2021
EL	2010	2021	2010	2021		
ES	2010	2021	2010	2021	2010	2021
FI	2010	2021	2010	2021	2010	2021
FR	2010	2021	2010	2021	2014	2021
HR	2010	2021	2010	2021	2010	2021
HU	2010	2021	2010	2021	2010	2021
IE	2010	2021	2010	2021	2018	2021
IT	2010	2021	2010	2021	2010	2021
LT	2010	2021	2010	2021	2018	2021
LU	2010	2021	2010	2021	2010	2021
LV	2010	2021	2010	2021	2010	2021
MT	2010	2021	2010	2021	2010	2021
NL	2010	2021	2010	2021	2010	2021
PL	2010	2021	2010	2021		
PT	2010	2021	2010	2021	2010	2021
RO	2010	2021	2010	2021	2010	2021
SE	2010	2021	2010	2021	2010	2021
SI	2010	2021	2010	2021	2015	2021
SK	2010	2021	2010	2021	2010	2021

C) Basic Descriptive Analysis.

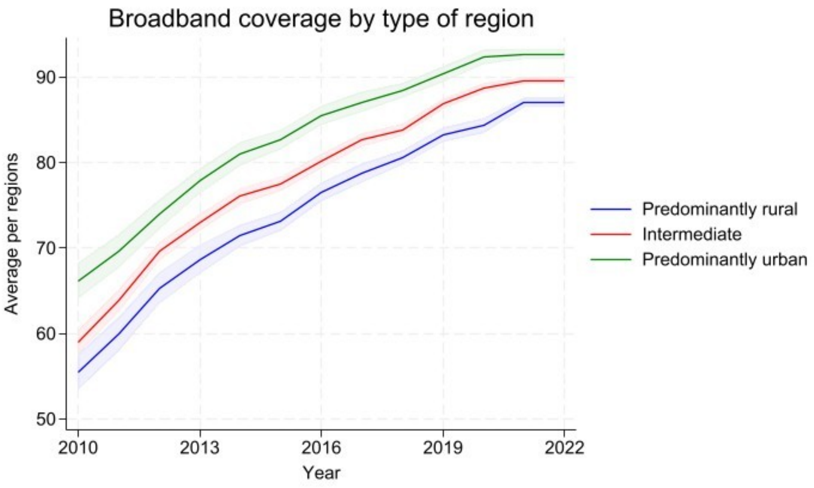

Figure A1.53. Broadband coverage by type of region.

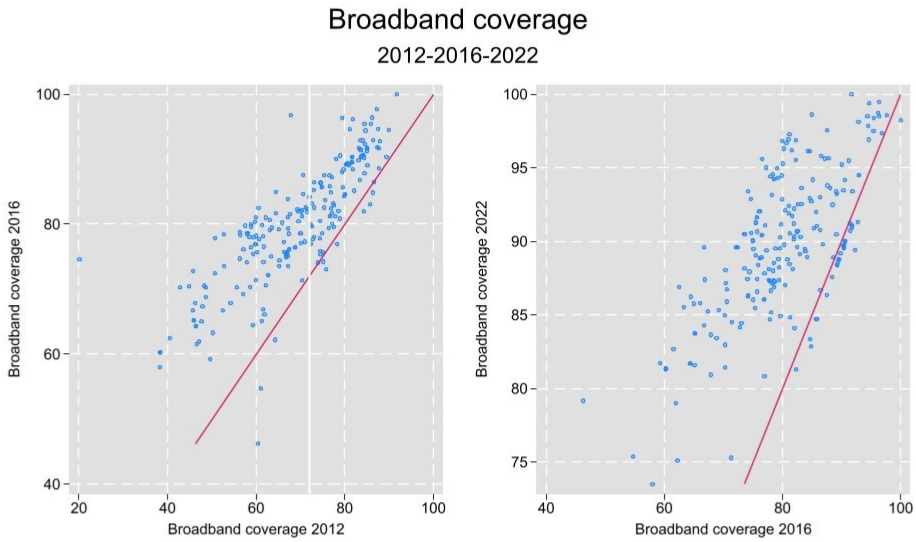

Figure A1.54. Dynamic scatterplot of Broadband coverage.

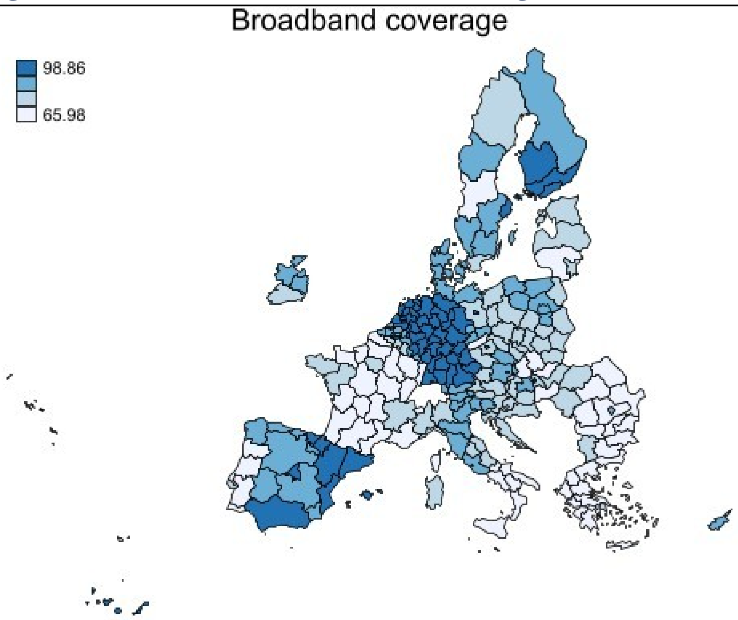

Figure A1.55. Geographical distribution of Broadband coverage. Year 2020.

Table A1.38. Descriptive statistics. Households with broad band access.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	82.3	8.5	57.1	93.6	78.2	84.5	89.1	44%
BE	82.5	7.7	62.9	96.1	77.2	83.4	87.3	32%
BG	60.5	17.8	16.7	86.2	49.6	63.4	73.9	259%
CY	75.3	14.8	50.7	93.4	64.4	74.2	89.4	84%
CZ	77.5	11.7	46.5	94.7	67.9	79.5	87.5	68%
DE	86.8	6.4	59.6	97.3	83.3	88.5	91.1	19%
DK	88.1	4.7	75.6	94.5	85.0	89.3	92.0	16%
EE	82.4	9.6	63.6	90.9	78.4	86.9	89.3	43%
EL	62.3	16.5	26.7	90.7	50.9	64.1	75.1	154%
ES	78.9	13.9	44.5	98.9	67.1	80.1	91.7	74%
FI	89.5	6.1	71.9	97.8	86.5	91.2	94.5	25%
FR	74.7	9.6	36.6	94.2	69.6	76.6	81.0	45%
HR	73.1	11.9	49.1	88.3	63.6	76.0	83.4	75%
HU	75.7	13.2	40.6	95.6	66.7	77.7	86.3	84%
IE	79.4	19.0	20.1	95.2	74.6	86.4	91.4	20%
IT	73.0	14.2	33.9	92.9	61.2	77.0	84.3	85%
LT	72.5	10.9	50.6	87.4	63.2	72.9	80.9	55%
LU	87.2	12.8	67.7	97.3	70.3	93.6	96.8	38%
LV	75.2	11.2	52.6	89.5	70.1	75.1	83.3	70%
MT	82.1	6.5	69.3	90.5	78.0	81.2	85.9	31%
NL	92.6	6.9	70.6	100.0	87.4	95.6	98.0	26%
PL	75.7	10.7	51.6	94.2	68.6	75.4	83.7	60%
PT	70.3	12.5	41.7	90.1	60.0	72.3	81.3	70%
RO	65.7	21.4	15.5	94.5	52.3	70.2	84.5	303%
SE	87.9	5.1	74.9	100.0	84.4	88.2	91.2	11%
SI	80.3	10.1	57.8	95.3	72.3	79.9	89.9	50%
SK	76.1	12.1	42.7	96.1	72.7	77.7	83.9	82%

A1.16. High-tech employment

A) Relevance of the Indicator.

High-tech employment. The availability of ICT specialists and high-tech jobs is crucial for regional attractiveness, fostering innovation and economic growth. Skilled labour attracts businesses and drives digital transformation, enhancing competitiveness (European Commission, 2022). High-tech employment also offers career opportunities, boosting a region's appeal to talent while supporting economic resilience and diversification (OECD, 2020). Research indicates that the employment of ICT specialists and use of digital technologies can improve firm productivity by about 23% (Cette et al., 2020). ICT agglomeration promotes high-tech innovation, particularly in regions with ICT specialization, and inter-sectoral and inter-regional spillovers contribute to innovation development (Sergio et al., 2023).

B) Data, source, treatment and coverage.

Description:	Percent of Employed in High-technology sectors (high-technology manufacturing and knowledge-intensive high-technology services)
Indicator:	hightech
Unit of Measurement:	Percentage of employed (%)
Frequency	Annual
Source:	Eurostat. Employment in technology and knowledge-intensive sectors by NUTS2 region and sex (from 2008 onwards, NACE Rev. 2)
DOI	https://doi.org/10.2908/HTEC_EMP_REG2

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.
    - 1st. Regression: Regressing NUTS1 indicator over NUTS2. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
    - 2nd. Regression: Regressing NUTS0 indicator over ip1. If ip1 exists, ip1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2= hightech.
    - 3rd. Regression: Regressing NUTS0 indicator over NUTS1. It NUTS1 exists, NUTS1 value assigned, otherwise, adjusted regression value is assigned. New indicator ip3. So ip3= hightech for all Greek and

German NUTS2 regions and Grad Zagreb (HR05) and Sjeverna Hrvatska (HR06) NUTS2 regions.

- Method 2. Relative change in last observation. As there are some NUTS2 regions with some data but enough for applying regression techniques the change of each observation with the last available observation has been obtained for the aggregated level and then, apply this change to the following level if it has been needed. This is the case of the Greek NUTS2 region of Ipeiros (EL54) and Algarve (PT15) in Portugal.

- Method 3. Mean Adjacent observations. Not applied

- Method 4. Aggregated nuts level value. As there is no data for NUTS2 level, NUTS1 data value have been assigned in the cases of Greek regions of Voreio Aigaio (EL41), Dytiki Makedonia (EL53) and Ionia Nisia (EL62). In the case of Spain this procedure has been applied to Ciudad de Ceuta (ES63) and Ciudad de Melilla (ES64). Finally, this method has been also applied to the Italian region of Valle d'Aosta/Vallée d'Aoste (ITC2).

  In absence of NUTS1 data, country data have been assigned to the Finnish region of Åland (FI20) and the Portuguese NUTS2 of Região Autónoma dos Açores (PT20) and Região Autónoma da Madeira (PT30).

- Method 5. Completing time-series. Not applied

Table A1.39. Employment in High-technology sectors -hightech- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2010	2022	2010	2022
BE	2010	2022	2010	2022	2010	2022
BG	2010	2022	2010	2022	2010	2022
CY	2010	2022	2010	2022	2010	2022
CZ	2010	2022	2010	2022	2010	2022
DE	2010	2022	2010	2022	2010	2022
DK	2010	2022	2010	2022	2010	2022
EE	2010	2022	2010	2022	2010	2022
EL	2010	2022	2010	2022	2010	2022
ES	2010	2022	2010	2022	2010	2022
FI	2010	2022	2010	2022	2010	2022
FR	2010	2022	2010	2022	2010	2022
HR	2010	2022	2010	2022	2010	2022
HU	2010	2022	2010	2022	2010	2022
IE	2010	2022	2010	2022	2012	2022
IT	2010	2022	2010	2022	2010	2022
LT	2010	2022	2010	2022	2013	2022
LU	2010	2022	2010	2022	2010	2022
LV	2010	2022	2010	2022	2010	2022

MT	2010	2022	2010	2022	2010	2022
NL	2010	2022	2010	2022	2010	2022
PL	2010	2022	2010	2022	2010	2022
PT	2010	2022	2010	2022	2010	2022
RO	2010	2022	2010	2022	2010	2022
SE	2010	2022	2010	2022	2010	2022
SI	2010	2022	2010	2022	2010	2022
SK	2010	2022	2010	2022	2010	2022

C) Basic Descriptive Analysis.

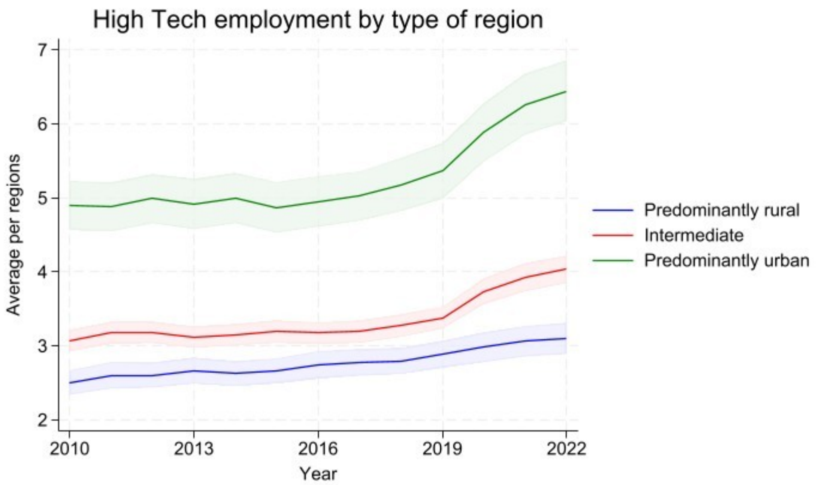

Figure A1.56. High tech employment by type of region.

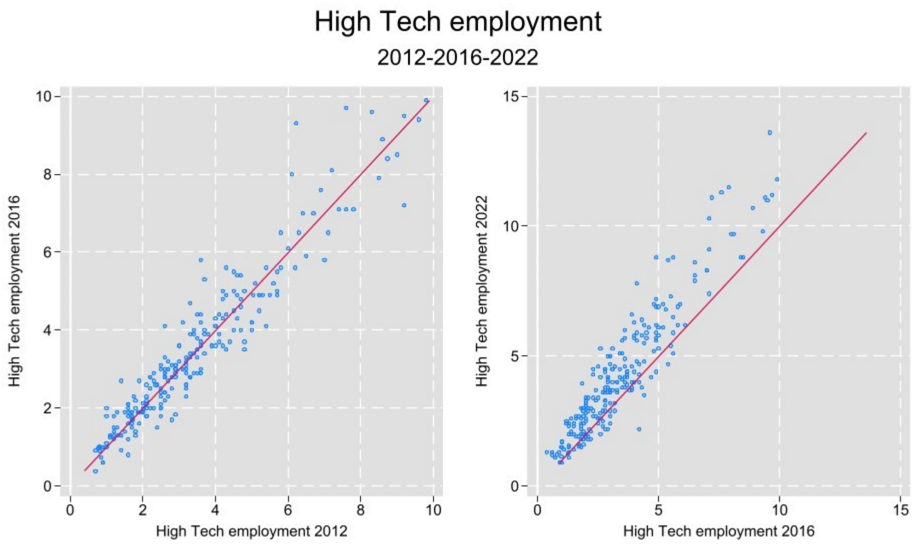

Figure A1.57. Dynamic scatterplot of High-tech employment.

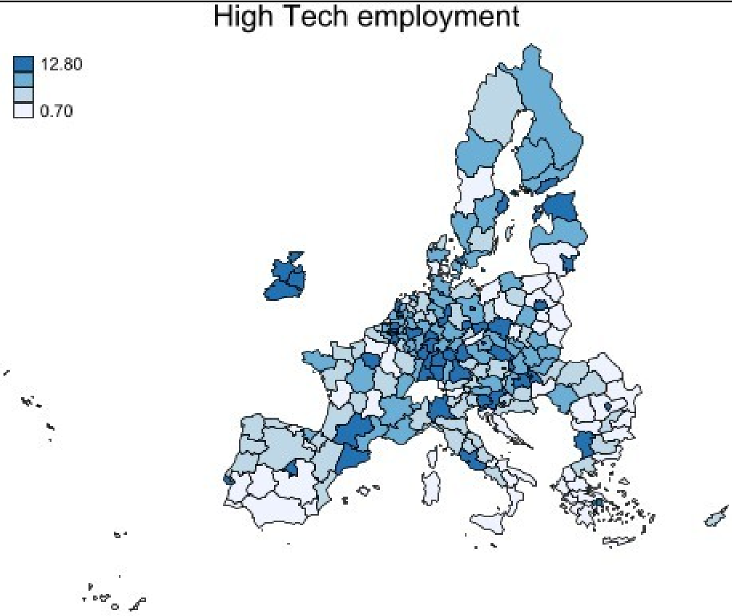

Figure A1.58. Geographical distribution of High-tech employment. Year 2020.

Table A1.40. Descriptive statistics. High technology employment.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	3.7	1.4	2.1	8.6	2.8	3.3	3.9	41%
BE	4.9	1.9	2.3	11.1	3.3	4.6	6.2	31%
BG	2.8	2.2	1.0	9.7	1.5	1.9	2.6	32%
CY	3.1	0.6	2.2	4.7	2.9	3.0	3.2	114%
CZ	4.7	2.1	1.7	13.2	3.7	4.2	5.0	21%
DE	4.1	1.6	1.4	10.8	2.9	3.7	5.1	29%
DK	4.8	2.6	2.2	11.1	2.8	4.0	5.4	1%
EE	5.0	1.0	3.4	6.8	4.1	5.2	5.6	100%
EL	1.4	1.2	0.4	6.1	0.8	1.1	1.4	70%
ES	2.8	1.6	1.1	9.0	1.9	2.3	3.0	39%
FI	5.6	2.3	3.4	11.0	4.0	4.4	6.1	5%
FR	2.9	1.5	0.8	8.5	1.8	2.6	3.6	18%
HR	3.7	2.9	1.5	11.2	1.9	2.1	5.3	54%
HU	5.0	2.5	1.7	13.6	3.2	4.3	6.6	15%
IE	7.7	2.1	4.6	11.9	5.6	7.8	9.7	27%
IT	2.9	1.3	0.8	8.2	2.0	2.7	3.5	31%
LT	3.6	2.5	0.9	8.8	1.4	3.4	5.1	146%
LU	4.3	0.6	3.6	6.0	3.9	4.2	4.3	46%
LV	3.5	0.7	2.5	5.3	3.1	3.3	3.6	66%
MT	5.8	0.3	5.1	6.2	5.7	5.9	6.1	22%
NL	3.7	1.4	0.9	8.2	2.6	3.7	4.4	37%
PL	2.7	1.9	0.9	9.7	1.6	2.1	3.2	37%
PT	2.7	1.5	0.8	8.7	1.7	2.2	3.3	102%
RO	2.8	2.6	0.6	11.3	1.0	1.5	3.1	62%
SE	4.3	2.1	1.9	11.5	2.8	4.0	4.9	28%
SI	5.7	1.7	3.1	8.7	4.3	5.8	6.7	27%
SK	5.0	2.7	2.4	12.5	3.1	3.8	6.1	44%

A1.17. Internet interaction with authorities

A) Relevance of the Indicator.

Internet use for interaction with authorities. Regions with a digitally skilled population attract businesses reliant on advanced technologies, driving competitiveness and economic development (European Commission, 2022; Tran et al., 2023). Enhanced digital skills also benefit less-developed areas, enabling them to diversify technologically (Castellacci et al., 2019). Digital skills and ICT specialists correlate strongly with economic growth, highlighting their importance in regional digital transformation strategies (Barinova et al. 2022). Additionally, regions investing in digital upskilling programs improve labour market prospects, quality of life, and institutional environments, which are key factors for attracting professionals and sustaining long-term advantage. We proxy the digital skills of the population by means of several indicators and this is the first one.

B) Data, source, treatment and coverage.

Description:	Percentage of Individuals who declared internet use for interaction with public authorities (last 12 months)
Indicator:	int_public
Unit of Measurement:	Percentage of individuals (%)
Frequency	Annual
Source:	Eurostat. Individuals who used the internet for interaction with public authorities
DOI	https://doi.org/10.2908/ISOC_R_GOV_I

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.
    - 1st. Regression: Regressing year over NUTS2 indicator. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
    - 2nd. Regression: Regressing year over NUTS1 indicator. If NUTS1 value exists, NUTS1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2.
    - 3rd. Regression: Regressing year over NUTS0 indicator. If NUTS0 value exists, NUTS0 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip3.
    - Finally, if ip1 exists, ip1 is assigned, otherwise ip2 or ip3 is assigned.
- Method 2. Relative change in last observation. Not applied

- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. Country data has been assigned to Finnish region of Åland (FI20)
- Method 5. Completing time-series. Observation for 2022 has been filled with value for 2021

Table A1.41. Internet interaction with authorities -int_admin- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2021	2011	2021	2011	2021
BE	2010	2021	2011	2021	2011	2021
BG	2010	2021	2011	2021	2011	2021
CY	2010	2021	2011	2021	2011	2021
CZ	2010	2021	2011	2021	2011	2021
DE	2010	2021	2011	2021		
DK	2010	2021	2011	2021	2011	2021
EE	2010	2021	2011	2021	2011	2021
EL	2010	2021	2011	2021		
ES	2010	2021	2011	2021	2011	2021
FI	2010	2021	2011	2021	2011	2021
FR	2010	2021	2011	2021	2014	2021
HR	2010	2021	2011	2021	2011	2021
HU	2010	2021	2011	2021	2011	2021
IE	2010	2021	2011	2021	2018	2021
IT	2010	2021	2011	2021	2011	2021
LT	2010	2021	2011	2021	2018	2021
LU	2010	2021	2011	2021	2011	2021
LV	2010	2021	2011	2021	2011	2021
MT	2010	2021	2011	2021	2011	2021
NL	2010	2021	2011	2021	2011	2021
PL	2010	2021	2011	2021		
PT	2010	2021	2011	2021	2011	2021
RO	2010	2021	2011	2021	2011	2021
SE	2010	2021	2011	2021	2011	2021
SI	2010	2021	2011	2021	2015	2021
SK	2010	2021	2011	2021	2011	2021

C) Basic Descriptive Analysis.

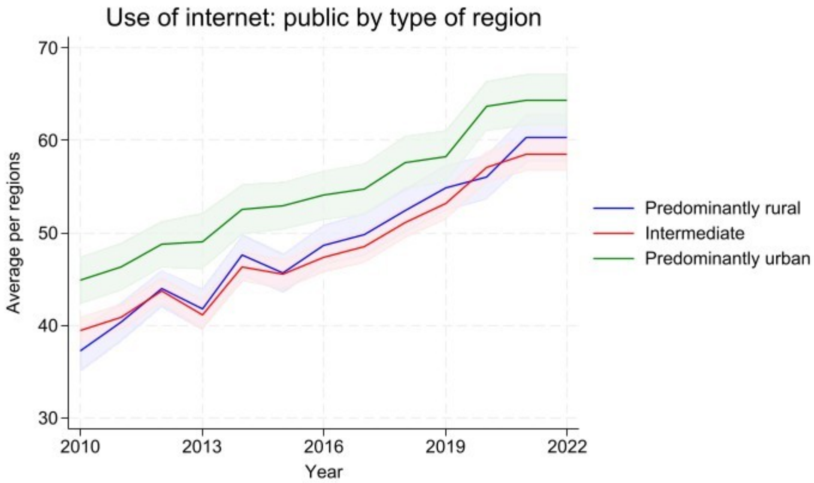

Figure A1.59. Internet interaction with authorities by type of region.

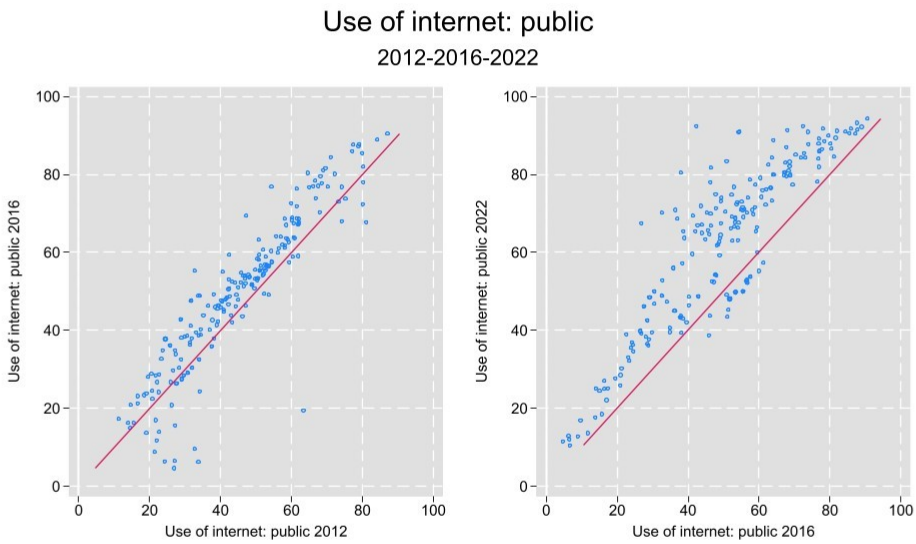

Figure A1.60. Dynamic scatterplot of Internet interaction with authorities.

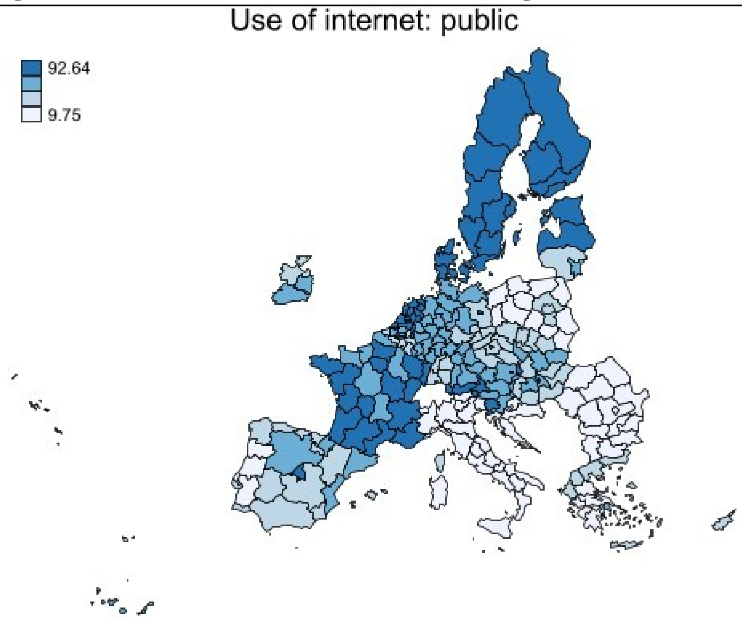

Figure A1.61. Geographical distribution of Internet interaction with authorities. Year 2020.

Table A1.42. Descriptive statistics. Internet interaction with authorities.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	60.3	9.0	45.3	80.0	52.3	58.9	68.8	44%
BE	55.8	9.4	35.8	79.8	48.7	55.3	61.6	55%
BG	21.7	6.8	9.8	41.0	17.3	20.3	25.2	9%
CY	40.8	11.0	25.4	57.3	30.2	41.5	50.3	125%
CZ	44.3	15.5	15.6	80.5	31.4	43.3	53.8	208%
DE	53.3	5.7	36.7	72.6	49.6	52.5	55.6	1%
DK	86.8	5.2	74.4	94.3	83.2	88.4	90.9	19%
EE	68.9	14.6	48.4	81.9	53.0	78.0	80.3	64%
EL	38.2	12.9	7.5	66.5	31.6	40.7	46.0	397%
ES	51.3	11.2	20.7	81.8	43.2	50.3	59.2	87%
FI	79.3	9.0	62.9	93.2	73.9	80.2	86.4	33%
FR	63.6	10.9	33.4	85.1	56.3	63.3	72.3	53%
HR	32.6	8.6	17.4	47.4	25.7	33.0	37.3	134%
HU	49.1	14.3	25.7	88.8	38.6	45.6	59.0	118%
IE	55.9	17.7	23.8	92.4	46.7	52.6	61.0	180%
IT	25.4	6.9	11.2	46.9	20.4	25.1	28.9	52%
LT	47.9	12.9	19.0	66.4	39.9	49.6	58.0	145%
LU	67.4	7.6	56.2	78.2	61.5	66.8	75.1	16%
LV	59.5	15.2	35.4	77.4	47.3	65.6	69.6	94%
MT	46.1	9.7	31.8	63.4	40.7	44.8	50.0	70%
NL	76.8	8.8	52.4	91.0	71.0	77.4	84.2	37%
PL	33.1	8.6	19.3	56.0	26.3	30.6	39.8	71%
PT	38.9	9.2	12.8	61.1	34.2	38.1	42.1	111%
RO	12.0	8.4	2.6	63.4	6.9	10.6	12.8	79%
SE	79.7	8.1	58.7	94.2	73.5	81.0	86.1	36%
SI	53.8	10.3	38.7	73.1	46.8	51.6	62.3	56%
SK	52.4	10.0	31.5	76.8	47.2	52.3	57.0	13%

A1.18. Internet use for selling purposes

A) Relevance of the Indicator.

Internet for selling purposes. Regions with a digitally skilled population attract businesses reliant on advanced technologies, driving competitiveness and economic development (European Commission, 2022; Tran et al., 2023). Enhanced digital skills also benefit less-developed areas, enabling them to diversify technologically (Castellacci et al., 2019). Digital skills and ICT specialists correlate strongly with economic growth, highlighting their importance in regional digital transformation strategies (Barinova et al. 2022). Additionally, regions investing in digital upskilling programs improve labour market prospects, quality of life, and institutional environments, which are key factors for attracting professionals and sustaining long-term advantage. We proxy the digital skills of the population by means of several indicators and this is the second one.

B) Data, source, treatment and coverage.

Description:	Percentage of individuals who declared Internet use for selling goods or services
Indicator:	int_sell
Unit of Measurement:	Percentage of individuals (%)
Frequency	Annual
Source:	Eurostat. Individuals who used the internet, frequency of use and activities
DOI	https://doi.org/10.2908/ISOC_R_IUSE_I

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.
    - 1st. Regression: Regressing year over NUTS2 indicator. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
    - 2nd. Regression: Regressing year over NUTS1 indicator. If NUTS1 value exists, NUTS1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2.
    - 3rd. Regression: Regressing year over NUTS0 indicator. If NUTS0 value exists, NUTS0 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip3.
    - Finally, if ip1 exists, ip1 is assigned, otherwise ip2 or ip3 is assigned.
- Method 2. Relative change in last observation. Not applied

- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. Not applied
- Method 5. Completing time-series. Observation for 2022 has been filled with value for 2021

Table A1.43. Internet use for selling goods or services -int_sell- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2011	2022	2011	2022
BE	2010	2022	2011	2022	2011	2022
BG	2010	2022	2011	2022	2011	2022
CY	2010	2022	2011	2022	2011	2022
CZ	2010	2022	2011	2022	2011	2022
DE	2010	2022	2011	2022		
DK	2010	2022	2011	2022	2011	2022
EE	2010	2022	2011	2022	2011	2022
EL	2010	2022	2011	2022		
ES	2010	2022	2011	2022	2011	2022
FI	2010	2022	2011	2022	2011	2022
FR	2010	2022	2011	2022	2014	2022
HR	2010	2022	2011	2022	2011	2022
HU	2010	2022	2011	2022	2011	2022
IE	2010	2022	2011	2022	2018	2022
IT	2010	2022	2011	2022	2011	2022
LT	2010	2022	2011	2022	2018	2022
LU	2010	2022	2011	2022	2011	2022
LV	2011	2022	2011	2022	2011	2022
MT	2010	2022	2011	2022	2011	2022
NL	2010	2022	2011	2022	2011	2022
PL	2010	2022	2011	2022		
PT	2010	2022	2011	2022	2011	2022
RO	2010	2022	2011	2022	2011	2022
SE	2010	2022	2011	2022	2011	2022
SI	2010	2022	2011	2022	2015	2022
SK	2010	2022	2011	2022	2011	2022

C) Basic Descriptive Analysis.

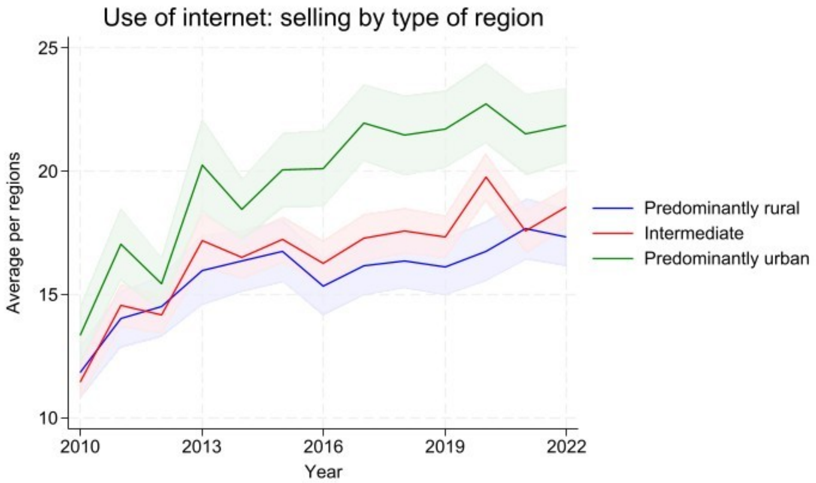

Figure A1.62. Internet use for selling goods or services by type of region.

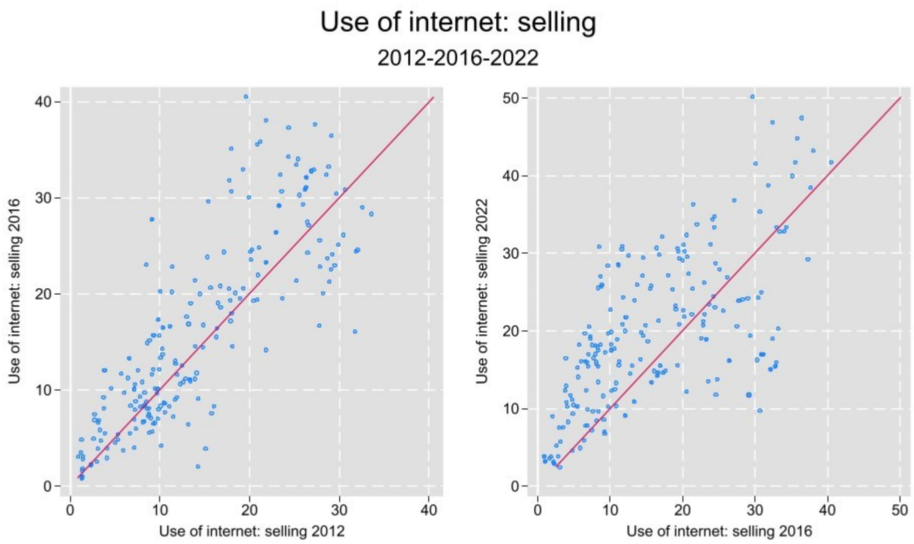

Figure A1.63. Dynamic scatterplot of Internet use for selling goods or services.

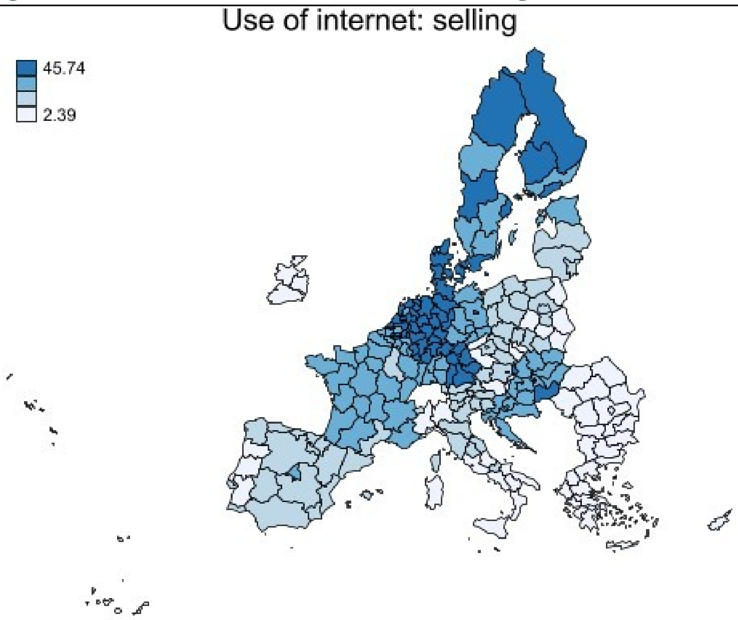

Figure A1.64. Geographical distribution of Internet selling goods or services. Year 2020.

Table A1.44. Descriptive statistics. Internet use for selling purposes.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	13.8	6.0	5.9	31.6	9.6	12.1	15.7	254%
BE	21.5	5.1	11.8	36.8	17.7	20.8	24.4	76%
BG	6.5	2.9	0.9	16.9	4.3	6.3	8.0	469%
CY	2.4	1.3	0.8	4.8	1.5	2.4	3.4	513%
CZ	12.6	4.2	5.1	25.4	9.1	12.6	14.8	91%
DE	26.3	6.8	8.6	37.4	21.8	27.6	31.7	-22%
DK	29.1	4.4	19.3	40.1	25.4	28.9	32.8	15%
EE	18.3	5.1	8.1	24.4	13.4	18.8	23.2	188%
EL	2.5	1.0	0.8	7.6	1.8	2.6	2.9	71%
ES	11.0	4.5	2.9	28.1	7.8	10.1	13.6	299%
FI	23.5	6.0	13.9	34.8	17.9	23.0	29.0	118%
FR	22.8	7.7	2.0	40.1	19.5	24.3	27.7	4%
HR	19.4	8.7	4.5	34.9	10.2	21.6	25.0	398%
HU	16.2	7.5	4.7	31.9	9.7	14.5	21.8	297%
IE	13.1	5.6	0.4	27.3	10.4	12.1	17.4	956%
IT	9.1	3.4	1.9	21.5	6.7	8.9	10.6	240%
LT	8.1	5.3	0.7	19.5	3.9	6.9	11.1	1277%
LU	16.7	3.3	11.2	23.4	14.2	16.0	18.1	46%
LV	7.4	3.4	2.4	13.4	4.6	7.8	9.6	330%
MT	25.0	7.8	13.3	36.3	20.8	24.5	30.2	174%
NL	34.5	8.6	15.4	54.1	27.5	34.9	40.7	70%
PL	11.2	3.9	1.2	17.3	8.7	12.0	14.3	141%
PT	6.6	2.9	1.1	13.4	4.7	6.8	8.4	472%
RO	3.0	1.8	0.3	10.8	1.5	2.5	3.9	486%
SE	20.4	5.8	9.0	35.0	16.2	19.4	25.2	35%
SI	22.2	6.4	14.8	38.1	16.8	20.4	27.7	-12%
SK	16.1	7.3	5.2	32.3	10.3	14.4	21.9	203%

A1.19. Internet use for banking purposes

A) Relevance of the Indicator.

Internet use for banking purposes. Regions with a digitally skilled population attract businesses reliant on advanced technologies, driving competitiveness and economic development (European Commission, 2022; Tran et al., 2023). Enhanced digital skills also benefit less-developed areas, enabling them to diversify technologically (Castellacci et al., 2019). Digital skills and ICT specialists correlate strongly with economic growth, highlighting their importance in regional digital transformation strategies (Barinova et al. 2022). Additionally, regions investing in digital upskilling programs improve labour market prospects, quality of life, and institutional environments, which are key factors for attracting professionals and sustaining long-term advantage. We proxy the digital skills of the population by means of several indicators and this is the third one.

B) Data, source, treatment and coverage.

Description:	Percentage of individuals who declared Internet use for internet banking
Indicator:	int_bank
Unit of Measurement:	Percentage of individuals (%)
Frequency	Annual
Source:	Eurostat. Individuals who used the internet, frequency of use and activities
DOI	https://doi.org/10.2908/ISOC_R_IUSE_I

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.
    - 1st. Regression: Regressing year over NUTS2 indicator. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
    - 2nd. Regression: Regressing year over NUTS1 indicator. If NUTS1 value exists, NUTS1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2.
    - 3rd. Regression: Regressing year over NUTS0 indicator. If NUTS0 value exists, NUTS0 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip3.
    - Finally, if ip1 exists, ip1 is assigned, otherwise ip2 or ip3 is assigned.
- Method 2. Relative change in last observation. Not applied

- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. Not applied
- Method 5. Completing time-series. Observation for 2022 has been filled with value for 2021

Table A1.45. Internet use for banking -int_bank- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2011	2022	2011	2022
BE	2010	2022	2011	2022	2011	2022
BG	2010	2022	2011	2022	2011	2022
CY	2010	2022	2011	2022	2011	2022
CZ	2010	2022	2011	2022	2011	2022
DE	2010	2022	2011	2022		
DK	2010	2022	2011	2022	2011	2022
EE	2010	2022	2011	2022	2011	2022
EL	2010	2022	2011	2022		
ES	2010	2022	2011	2022	2011	2022
FI	2010	2022	2011	2022	2011	2022
FR	2010	2022	2011	2022	2014	2022
HR	2010	2022	2011	2022	2011	2022
HU	2010	2022	2011	2022	2011	2022
IE	2010	2022	2011	2022	2018	2022
IT	2010	2022	2011	2022	2011	2022
LT	2010	2022	2011	2022	2018	2022
LU	2010	2022	2011	2022	2011	2022
LV	2010	2022	2011	2022	2011	2022
MT	2010	2022	2011	2022	2011	2022
NL	2010	2022	2011	2022	2011	2022
PL	2010	2022	2011	2022		
PT	2010	2022	2011	2022	2011	2022
RO	2010	2022	2011	2022	2011	2022
SE	2010	2022	2011	2022	2011	2022
SI	2010	2022	2011	2022	2015	2022
SK	2010	2022	2011	2022	2011	2022

C) Basic Descriptive Analysis.

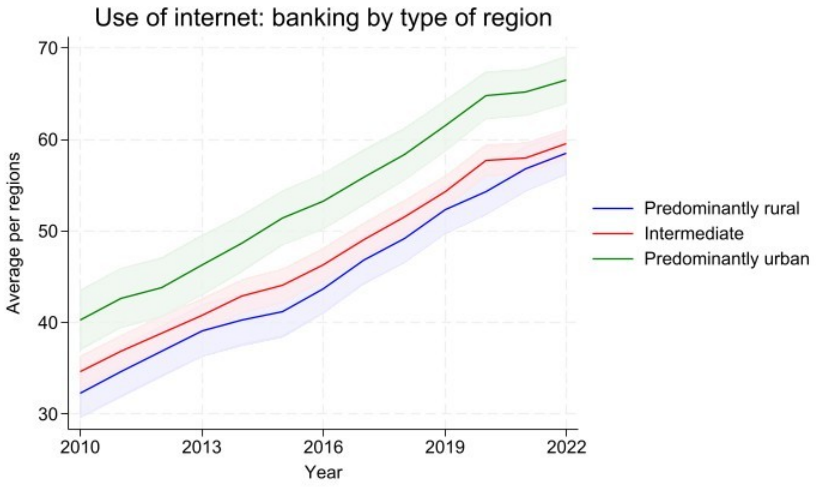

Figure A1.65. Internet use for banking by type of region.

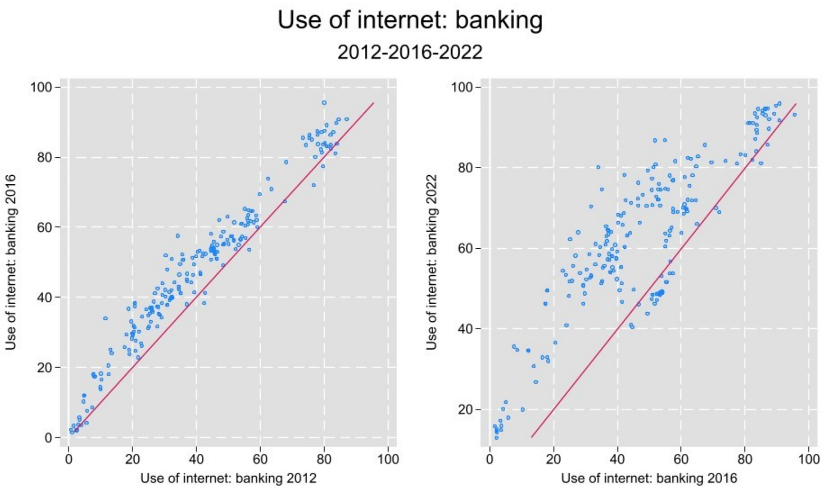

Figure A1.66. Dynamic scatterplot of Internet use for banking.

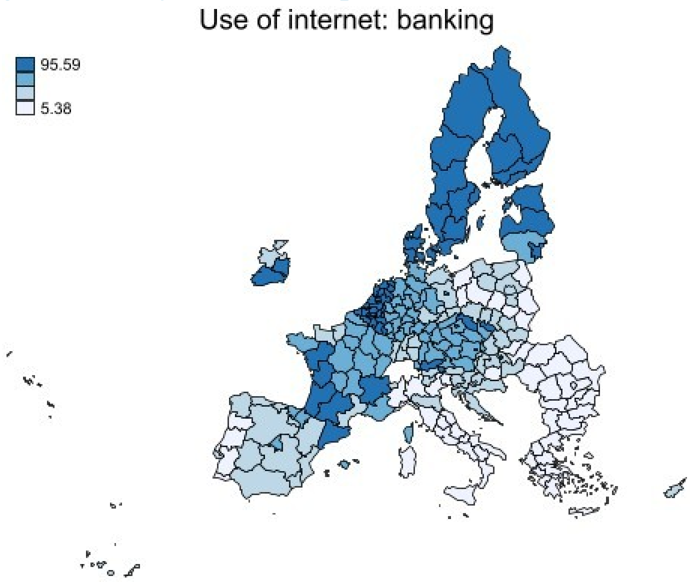

Figure A1.67. Geographical distribution of Internet use for banking. Year 2020.

Table A1.46. Descriptive statistics. Internet use for banking purposes.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	54.3	11.2	30.0	78.4	45.7	54.2	62.6	94%
BE	65.0	9.5	41.5	85.6	57.6	64.2	72.6	55%
BG	6.7	6.3	0.6	35.5	2.7	4.9	7.6	1178%
CY	33.6	16.6	17.5	64.7	21.0	27.6	40.5	266%
CZ	52.2	17.0	20.1	86.7	40.0	51.9	67.7	244%
DE	51.6	7.0	34.8	68.1	46.5	50.5	56.2	14%
DK	85.4	8.0	64.9	95.6	79.7	87.2	91.8	36%
EE	76.4	6.1	65.1	83.4	72.2	79.2	80.7	28%
EL	19.2	13.2	2.2	62.2	7.7	16.5	28.1	1138%
ES	43.4	15.6	7.9	80.1	30.9	41.2	56.0	224%
FI	86.5	5.8	72.8	96.5	83.1	86.3	91.0	24%
FR	56.3	11.1	18.3	77.3	51.3	57.9	63.8	53%
HR	35.2	13.8	15.6	58.0	20.7	33.3	47.6	189%
HU	36.7	14.7	11.5	80.1	25.8	34.5	47.8	238%
IE	54.0	16.9	17.4	86.8	42.4	53.9	66.6	182%
IT	30.2	12.7	6.6	60.9	20.8	29.2	38.4	200%
LT	56.6	13.0	36.6	81.6	45.4	55.9	64.6	107%
LU	67.0	5.6	56.4	76.4	63.5	67.7	70.6	24%
LV	63.4	11.7	47.1	82.4	54.9	62.1	71.6	74%
MT	49.8	8.8	37.7	66.3	43.2	47.5	53.9	76%
NL	85.6	5.3	73.2	95.5	81.8	86.5	89.8	17%
PL	37.9	11.4	11.4	63.1	30.1	35.7	47.7	164%
PT	32.5	13.1	12.3	66.3	21.7	29.5	42.5	219%
RO	7.5	6.2	0.7	34.8	3.1	5.2	10.7	669%
SE	81.0	5.0	68.5	95.0	77.6	81.5	84.4	11%
SI	39.8	10.8	25.1	62.7	31.6	37.1	50.9	99%
SK	46.7	10.0	28.9	71.4	37.8	47.7	54.4	44%

A1.20. Internet use for private purposes

A) Relevance of the Indicator.

Internet use for private purposes. Regions with a digitally skilled population attract businesses reliant on advanced technologies, driving competitiveness and economic development (European Commission, 2022; Tran et al., 2023). Enhanced digital skills also benefit less-developed areas, enabling them to diversify technologically (Castellacci et al., 2019). Digital skills and ICT specialists correlate strongly with economic growth, highlighting their importance in regional digital transformation strategies (Barinova et al. 2022). Additionally, regions investing in digital upskilling programs improve labour market prospects, quality of life, and institutional environments, which are key factors for attracting professionals and sustaining long-term advantage. We proxy the digital skills of the population by means of several indicators and this is the last involved indicator in this dimension.

B) Data, source, treatment and coverage.

Description:	Percentage of individuals who declared Internet use for personal purposes (last 3 months)
Indicator:	int_priv
Unit of Measurement:	Percentage of individuals (%)
Frequency	Annual
Source:	Eurostat. Individuals who used the internet, frequency of use and activities
DOI	https://doi.org/10.2908/ISOC_R_IUSE_I

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.
  - 1st. Regression: Regressing year over NUTS2 indicator. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
  - 2nd. Regression: Regressing year over NUTS1 indicator. If NUTS1 value exists, NUTS1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2.
  - 3rd. Regression: Regressing year over NUTS0 indicator. If NUTS0 value exists, NUTS0 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip3.
  - Finally, if ip1 exists, ip1 is assigned, otherwise ip2 or ip3 is assigned.
- Method 2. Relative change in last observation. Not applied

- Method 3. Mean Adjacent observations. Not applied
- Method 4. Aggregated nuts level value. Not applied
- Method 5. Completing time-series. Observation for 2022 has been filled with value for 2021

Table A1.47. Internet private -int_priv- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2022	2011	2022	2011	2022
BE	2010	2022	2011	2022	2011	2022
BG	2010	2022	2011	2022	2011	2022
CY	2010	2022	2011	2022	2011	2022
CZ	2010	2022	2011	2022	2011	2022
DE	2010	2022	2011	2022		
DK	2010	2022	2011	2022	2011	2022
EE	2010	2022	2011	2022	2011	2022
EL	2010	2022	2011	2022		
ES	2010	2022	2011	2022	2011	2022
FI	2010	2022	2011	2022	2011	2022
FR	2010	2022	2011	2022	2014	2022
HR	2010	2022	2011	2022	2011	2022
HU	2010	2022	2011	2022	2011	2022
IE	2010	2022	2011	2022	2018	2022
IT	2010	2022	2011	2022	2011	2022
LT	2010	2022	2011	2022	2018	2022
LU	2010	2022	2011	2022	2011	2022
LV	2010	2022	2011	2022	2011	2022
MT	2010	2022	2011	2022	2011	2022
NL	2010	2022	2011	2022	2011	2022
PL	2010	2022	2011	2022		
PT	2010	2022	2011	2022	2011	2022
RO	2010	2022	2011	2022	2011	2022
SE	2010	2022	2011	2022	2011	2022
SI	2010	2022	2011	2022	2015	2022
SK	2010	2022	2011	2022	2011	2022

C) Basic Descriptive Analysis.

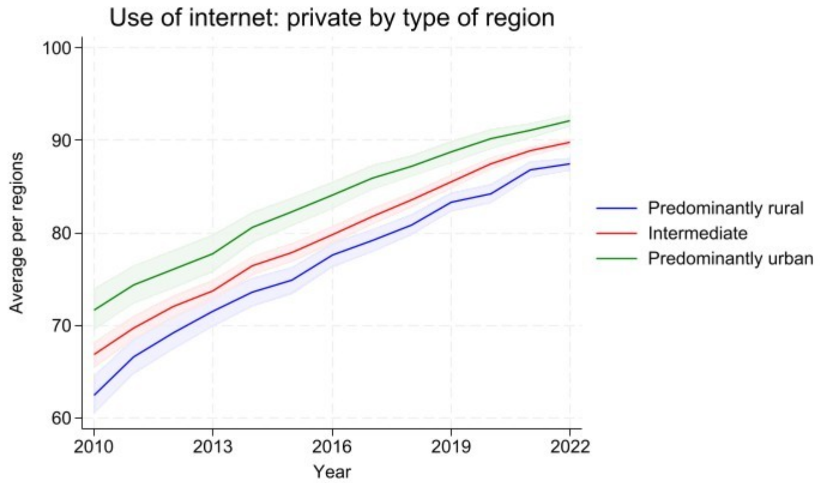

Figure A1.68. Internet use for private purposes by type of region.

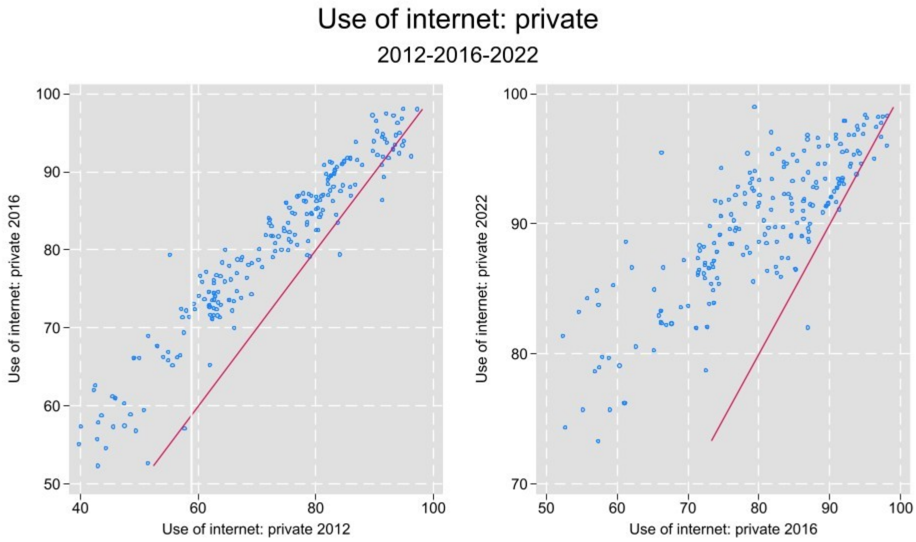

Figure A1.69. Dynamic scatterplot of Internet use for private purposes.

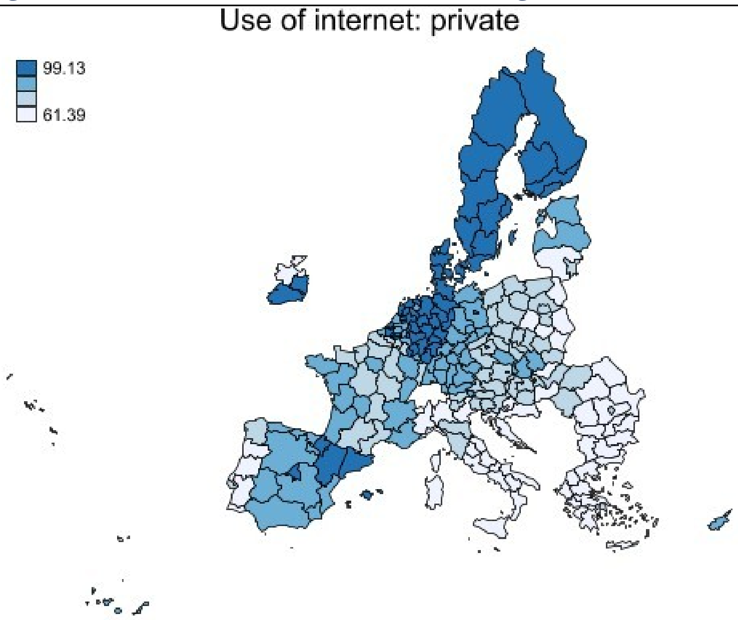

Figure A1.70. Geographical distribution of Internet use for private purposes. Year 2020.

Table A1.48. Descriptive statistics. Internet use for private purposes.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	84.2	6.1	69.2	96.6	80.4	84.7	88.5	26%
BE	86.4	5.8	70.4	96.6	82.2	86.8	90.6	20%
BG	59.0	12.2	32.4	84.9	49.3	60.3	67.1	96%
CY	75.0	13.4	52.2	90.8	65.4	75.9	86.1	72%
CZ	81.0	8.5	55.9	96.9	75.1	82.5	87.4	38%
DE	87.9	5.3	68.1	96.6	84.3	89.2	92.1	15%
DK	95.2	3.7	84.7	99.4	93.2	96.4	98.0	12%
EE	85.1	6.2	73.9	91.5	79.4	88.1	89.4	24%
EL	62.8	13.0	34.5	89.5	54.7	64.4	71.2	114%
ES	80.1	11.3	52.6	99.0	71.2	81.0	90.7	52%
FI	92.9	4.0	83.0	98.8	90.8	93.4	96.1	13%
FR	81.5	9.8	32.8	95.6	78.2	83.8	88.0	38%
HR	70.6	8.7	54.4	83.5	64.3	69.8	78.6	49%
HU	76.1	9.5	52.2	96.0	69.2	76.0	84.4	47%
IE	81.4	10.4	55.6	99.4	72.7	81.6	87.4	41%
IT	67.8	12.1	38.6	89.8	58.4	68.3	77.2	68%
LT	75.4	8.8	59.6	90.3	68.3	75.3	82.1	45%
LU	95.4	3.2	89.5	98.7	93.8	96.5	97.5	10%
LV	80.1	8.0	66.3	91.3	75.2	79.8	86.1	38%
MT	77.7	9.0	62.0	91.5	69.2	78.1	85.8	48%
NL	93.8	2.4	86.9	99.2	92.4	94.0	95.3	5%
PL	72.7	9.3	57.7	90.6	63.2	73.3	80.7	46%
PT	69.3	11.7	43.9	91.1	59.9	70.9	78.1	73%
RO	61.6	16.8	29.1	90.7	48.2	60.8	76.2	140%
SE	93.7	3.3	85.2	98.9	91.4	94.0	96.4	7%
SI	77.4	8.8	62.2	92.9	71.6	77.4	84.9	31%
SK	81.6	5.7	70.9	94.7	77.7	80.6	85.2	18%

A1.21. Greenhouse gas emissions

A) Relevance of the Indicator.

Greenhouse Gas (GHG) emissions. Greenhouse Gas emissions are a critical dimension of the green transition, serving as both a measure of environmental impact and a determinant of regional vulnerability. Regions with high GHG emissions, particularly those reliant on fossil fuels and carbon-intensive industries like mining, heavy industry, and road transportation, face significant challenges in adapting to the European Green Deal's low-carbon goals. These regions often experience economic disruptions, job losses, and increased costs associated with transitioning to greener energy and production methods.

The impact of GHG emissions on regional attractiveness is twofold. Regions capable of reducing emissions tend to attract greater investment, innovation, and skilled labour, enhancing their competitiveness. Conversely, regions with persistently high emissions may struggle to appeal to businesses and residents due to increased regulatory pressures and environmental degradation. Thus, addressing GHG emissions is essential for fostering sustainable development and improving regional attractiveness.

B) Data, source, treatment and coverage.

Description:	Emissions of GHG. CO2eq using Global Warming Potential Values (GWP-100) from IPCC AR5 and they include fossil CO2 only, CH4, N2O and F-gases
Indicator:	ghg
Unit of Measurement:	Kton (kilotonne)
Frequency	Annual
Source:	European Commission and Joint Research Centre (JRC)
DOI	https://doi.org/10.2908/ISOC_R_IUSE_I

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression. No applied.
- Method 2. Relative change in last observation. No applied.
- Method 3. Mean Adjacent observations. No applied.
- Method 4. Aggregated nuts level value. No applied.
- Method 5. Completing time-series. No applied.

Table A1.49. Greenhouse gas emissions -ghg- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT					2010	2022
BE					2010	2022
BG					2010	2022
CY					2010	2022
CZ					2010	2022
DE					2010	2022
DK					2010	2022
EE					2010	2022
EL					2010	2022
ES					2010	2022
FI					2010	2022
FR					2010	2022
HR					2010	2022
HU					2010	2022
IE					2010	2022
IT					2010	2022
LT					2010	2022
LU					2010	2022
LV					2010	2022
MT					2010	2022
NL					2010	2022
PL					2010	2022
PT					2010	2022
RO					2010	2022
SE					2010	2022
SI					2010	2022
SK					2010	2022

C) Basic Descriptive Analysis.

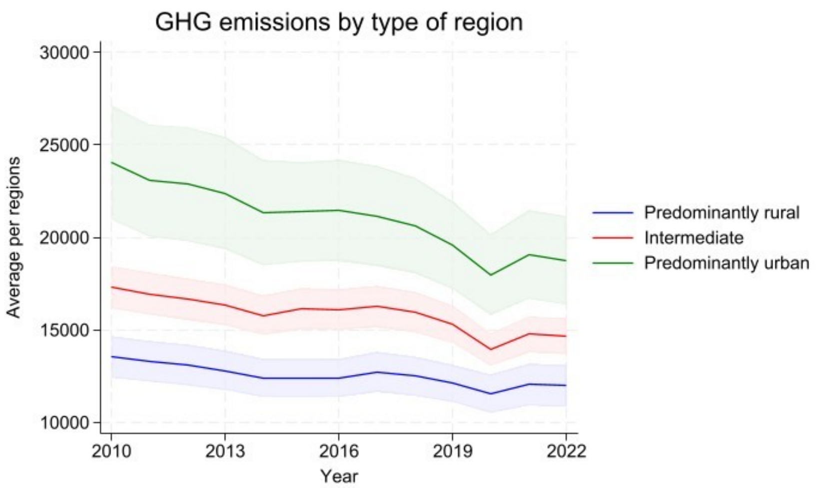

Figure A1.71. Greenhouse gas emissions by type of region.

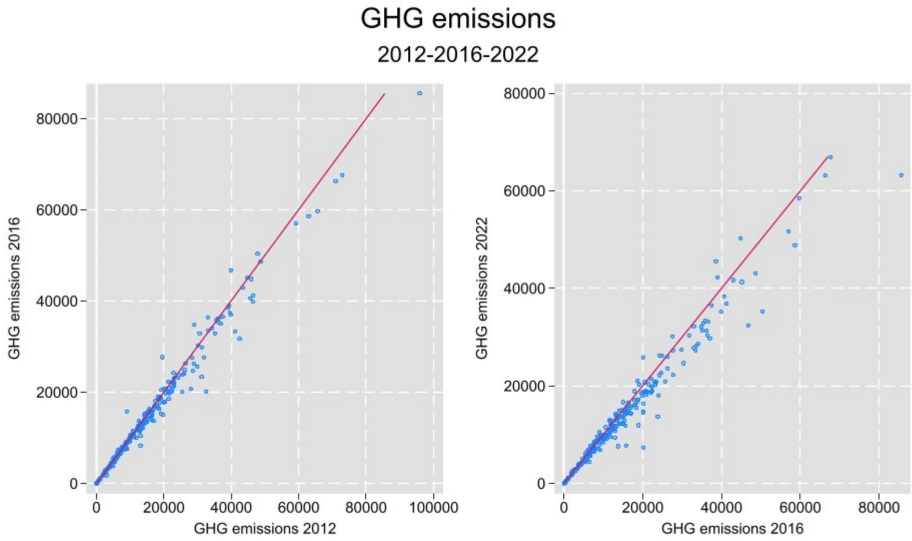

Figure A1.72. Dynamic scatterplot of Greenhouse gas emissions.

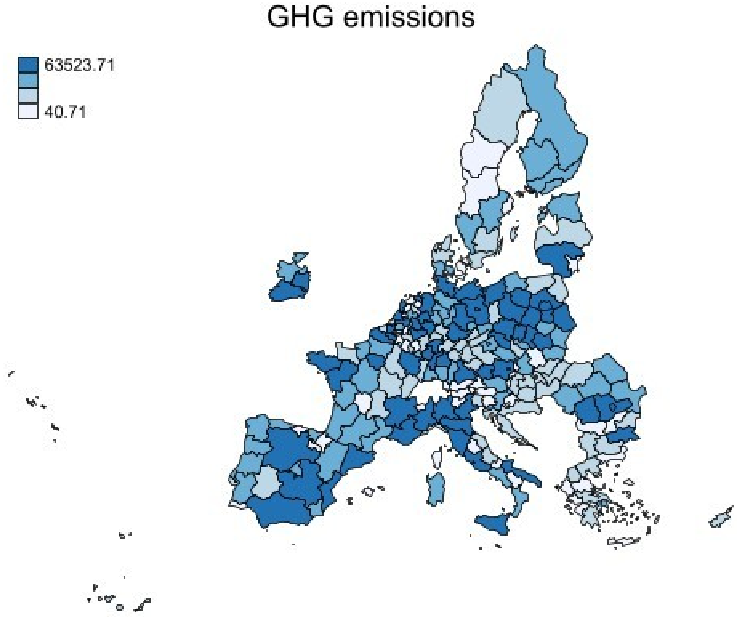

Figure A1.73. Geographical distribution of Greenhouse gas emissions. Year 2020.

Table A1.50. Descriptive statistics. Greenhouse gas emissions.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	9231.5	7663.1	1892.9	23963.2	4198.4	4846.2	15928.7	-14%
BE	11392.6	7493.8	2537.8	28071.2	4293.9	8976.9	18637.3	-20%
BG	10449.1	6239.8	4695.3	26308.5	5729.8	7950.1	11847.3	9%
CY	9307.7	729.5	8094.6	10595.0	8813.3	9412.6	9648.2	10%
CZ	16373.4	10869.3	4937.0	47887.2	10263.4	13053.3	17952.2	-11%
DE	22844.2	16390.3	4177.6	95896.1	10662.6	16812.1	30383.1	-14%
DK	10056.8	2703.0	4444.9	15334.8	8818.2	10029.6	12527.8	-29%
EE	22201.7	4904.0	13731.2	26644.6	18799.2	24359.3	25381.8	-45%
EL	6761.1	6267.7	807.5	32606.8	2561.5	4742.0	9614.4	-21%
ES	17617.5	15128.0	126.7	67010.4	6223.3	14695.9	25301.1	-14%
FI	14079.1	7700.4	86.3	25096.1	13107.4	15320.5	20061.7	-39%
FR	17193.7	13287.4	31.1	54206.6	6458.7	15141.5	23887.7	-12%
HR	6391.3	3352.7	1691.8	10741.3	3194.6	6718.6	9507.4	-14%
HU	8362.3	2176.0	5410.1	14257.4	6765.3	7583.1	9423.8	1%
IE	20915.6	7033.3	12551.5	32937.0	13359.5	20151.4	28053.7	-4%
IT	20173.9	17063.1	867.7	77948.2	6886.6	14912.4	32925.8	-22%
LT	11335.5	7345.7	3489.5	19388.7	3875.4	11334.8	18734.1	-18%
LU	10470.2	1127.7	8457.0	12160.0	9962.2	10414.6	11230.9	-30%
LV	11865.4	377.5	11058.2	12555.2	11616.3	11894.1	12038.2	-12%
MT	2354.4	460.1	1786.5	3063.3	2038.5	2090.0	2747.8	-28%
NL	16207.3	10818.1	4545.9	46767.3	6504.9	13765.1	24814.3	-24%
PL	23519.8	14735.0	6932.3	71901.9	12783.3	20640.5	28346.8	-3%
PT	9144.5	7563.9	416.9	23151.9	1092.0	9786.4	15238.0	-9%
RO	14526.4	5051.4	5623.5	27858.1	11697.1	14183.4	17461.8	1%
SE	8190.4	3592.5	2949.5	17143.1	6261.0	7088.0	10164.3	-22%
SI	9832.2	3545.2	5995.5	15007.5	6434.7	9425.6	13360.5	-15%
SK	11435.4	5452.3	4829.5	19211.0	6003.0	11260.3	16682.4	-7%

A1.22. Circular employment per 100k inhabitants

A) Relevance of the Indicator.

Circular economy employment. Circular economy employment is a key aspect of the green transition, driving sustainability through jobs in recycling, remanufacturing, and resource management. Regions adopting these practices attract investment and skilled labour, enhancing their competitiveness and economic resilience. Regions with strong governance and infrastructure benefit the most, boosting their appeal to businesses and residents. Peripheral regions, while offering potential in renewables, face challenges such as limited expertise and resistance to change. Addressing these gaps is essential to reduce regional inequalities and improve overall attractiveness.

B) Data, source, treatment and coverage.

Description:	The indicator uses Eurostat circular employment and Eurostat population data to interpolate Espon regional and obtaining circular employment per 100.000 inhabitants
Indicator:	c_emp_100k
Unit of Measurement:	Persons employed Full-time equivalent (FTE) per 100.000 inhabitants
Frequency	Annual
Source:	Espon DataBase Circular economy material providers (employment) (NUTS2). Eurostat: Persons employed in circular economy sectors (NUTS0) Eurostat. Population on 1 January by age, sex and NUTS2 region (NUTS2 and NUTS0)
Data	Espon circular employment: https://database.espon.eu/private-media/object/1064/ind_1064_cbm_emp_csv_JKzXRb4.zip
DOI	Eurostat circular employment: https://doi.org/10.2908/CEI_CIE011 Eurostat population: https://doi.org/10.2908/DEMO_R_D2JAN

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression. There are only two observations for nust2 level: for 2010 and 2015. As there are not enough regional observations for applying regression techniques, interpolation techniques against a trend for the period 2010-2015 has been used for filling time-series at NUTS2 level.

- Method 2. Relative change in last observation. Once the period 2010-2015 has been filled, the change in NUTS0 between each year and 2015 has been used for completing time-series from 2016 to 2022.

- Method 3. Mean Adjacent observations. Not applied.
- Method 4. Aggregated nuts level value. Not applied
- Method 5. Completing time-series. Not applied.

Table A1.51. Circular Employment per 100k -c_emp_100k- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2021			2010	2015
BE	2010	2021			2010	2015
BG	2010	2021			2010	2015
CY	2010	2021			2010	2015
CZ	2010	2021			2010	2015
DE	2010	2021			2010	2015
DK	2010	2021			2010	2015
EE	2010	2021			2010	2015
EL	2010	2021			2010	2015
ES	2010	2021			2010	2015
FI	2010	2021			2010	2015
FR	2010	2021			2010	2015
HR	2010	2021			2015	2015
HU	2010	2021			2010	2015
IE	2010	2021				
IT	2010	2021			2010	2015
LT	2010	2021				
LU	2010	2021				
LV	2010	2021			2010	2015
MT	2010	2021				
NL	2010	2021			2010	2015
PL	2010	2021			2010	2015
PT	2010	2021			2010	2015
RO	2010	2021			2010	2015
SE	2010	2021			2010	2015
SI	2010	2021			2010	2015
SK	2010	2021			2010	2015

C) Basic Descriptive Analysis.

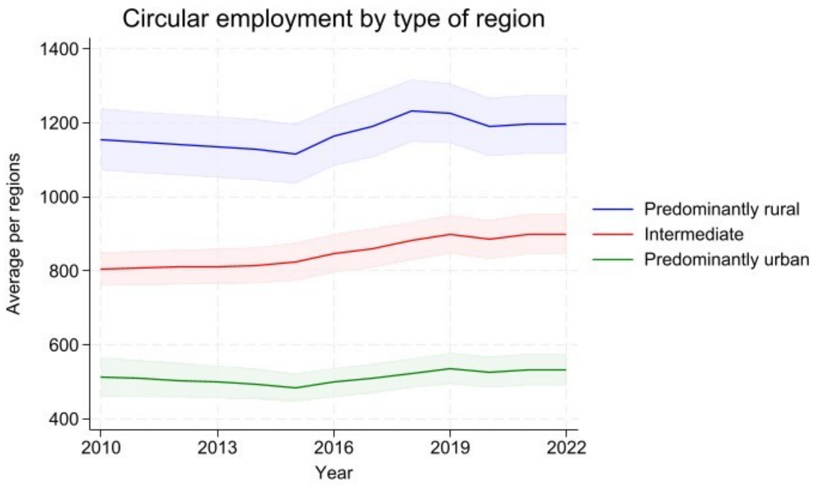

Figure A1.74. Circular employment per 100k by type of region.

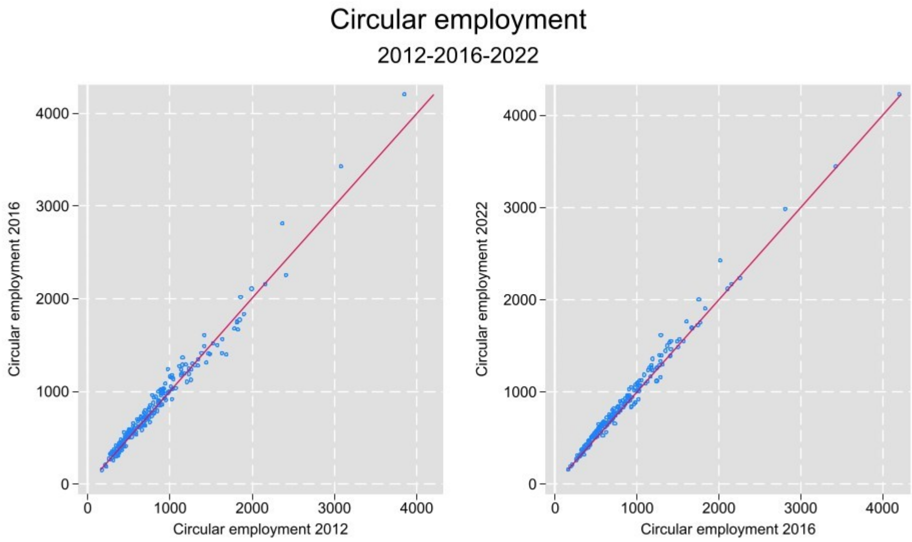

Figure A1.75. Dynamic scatterplot of Circular employment per 100k.

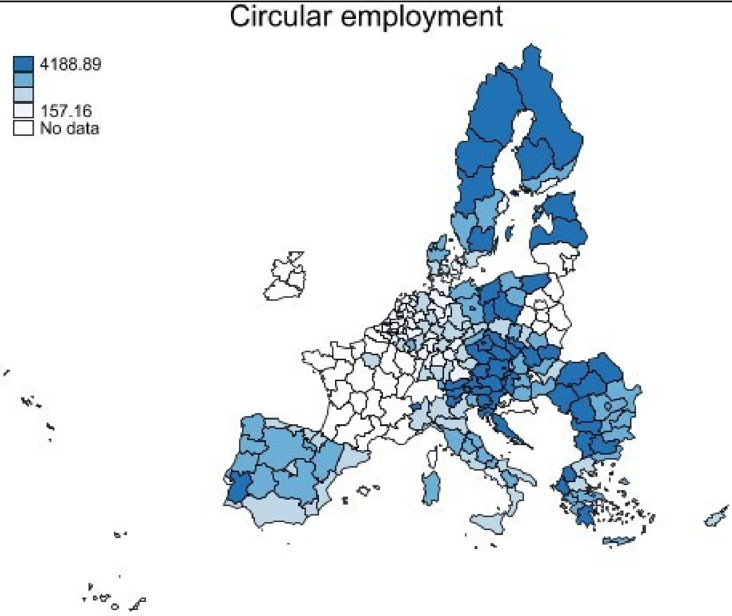

Figure A1.76. Geographical distribution of Circular employment per 100k. Year 2020.

Table A1.52. Descriptive statistics. Circular employment per 100k inhabitants.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	12152.0	7157.0	2984.3	24569.0	7099.2	9994.0	20582.8	-7%
BE	3176.6	1690.7	812.9	7083.7	1784.7	3246.0	4410.7	-16%
BG	10628.9	4565.4	6344.0	21187.0	7294.4	8056.1	15479.1	-2%
CY	6393.7	3501.0	4042.0	13014.3	4042.0	4042.0	10134.3	-26%
CZ	16229.7	4243.4	7443.9	25939.0	14087.1	15573.6	18727.2	-8%
DE	10107.8	4923.9	2368.0	29520.9	6495.5	8971.0	12680.9	37%
DK	4933.2	2223.7	1369.1	9358.7	2858.6	4705.6	6546.8	-42%
EE	27780.8	2930.3	22552.0	31312.6	26048.0	27750.0	30696.6	39%
EL	5125.2	2986.3	1517.0	12276.0	3050.0	5080.0	5939.0	-10%
ES	14016.9	14108.6	320.8	57831.4	4453.0	7994.2	19625.1	-5%
FI	16758.4	15290.6	315.2	76373.1	6574.0	13013.3	26959.6	-14%
FR	480075.4	87257.5	47088.4	524507.0	470463.0	488181.0	521357.0	10%
HR	46792.0	6452.0	17926.0	58574.0	42721.5	45261.0	51368.0	21%
HU	34764.4	44981.0	7958.0	140978.0	8719.6	9357.9	52662.4	-2%
IE	28305.0	4139.4	22354.0	33541.0	24219.0	28227.0	32165.0	50%
IT	19432.6	14303.9	1552.8	64759.2	8487.0	13874.4	29362.5	-9%
LT	34637.5	3719.0	27198.0	39115.0	33120.0	35211.0	37606.0	44%
LU	1921.5	183.8	1643.0	2158.0	1799.0	1924.0	2100.0	31%
LV	52230.5	3911.5	44951.0	56335.5	49885.7	53602.4	55300.4	25%
MT	4670.8	274.2	4359.0	5029.0	4393.0	4749.0	4949.0	12%
NL	5771.5	3972.8	1243.0	17563.9	2319.5	4629.4	8614.6	33%
PL	183203.6	194665.8	8375.0	441671.0	19368.6	28933.8	418033.0	10%
PT	11874.3	11006.5	1396.9	36723.3	2197.0	10027.7	22974.2	-3%
RO	28679.8	6080.1	19787.0	40623.0	23791.3	26245.3	35481.6	17%
SE	14756.7	3964.1	7816.0	23170.0	10386.8	14933.9	17570.9	13%
SI	14628.6	3716.0	7115.4	20477.0	11886.2	13016.6	17974.9	-13%
SK	16338.6	7114.4	4725.9	25826.3	10942.5	18182.5	20790.6	1%

A1.23. Mining and quarrying sector wages and salaries

A) Relevance of the Indicator.

Wages in the mining sector. Wages in the mining sector reflect the economic reliance of regions on extractive industries. High wage levels in mining indicate a significant contribution of this sector to regional GDP, making these areas economically vulnerable to decarbonisation policies under the European Green Deal. As mining-dependent regions transition away from fossil fuels, the reduction in mining activity and associated wages can lead to economic stagnation, unemployment, and outmigration, negatively impacting regional attractiveness.

Conversely, regions that manage to diversify their economies and invest in green technologies may offset these vulnerabilities. Supporting workforce retraining and leveraging green transition funding can mitigate the socioeconomic impacts of declining mining activities, improving long-term regional competitiveness and attractiveness.

B) Data, source, treatment and coverage.

Description:	Mining and quarrying sector wages and salaries per 10,000 inhabitants
Indicator:	wage_min_100k
Unit of Measurement:	Million euro by 100.000 persons
Frequency	Annual
Source:	Eurostat. SBS data by NUTS2 region and NACE Rev. 2 (2008-2020) and Population on 1 January by age, sex and NUTS2 region
DOI	Wages and Salaries. https://doi.org/10.2908/SBS_R_NUTS06_R2 Population. https://doi.org/10.2908/DEMO_R_D2JAN

Methods applied for filling NUTS2 time-series.

- Method 1. Simple Linear Regression.
    - 1st. Regression: Regressing NUTS1 indicator over NUTS2. If NUTS2 value exists, NUTS2 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip1.
    - 2nd. Regression: Regressing NUTS0 indicator over ip1. If ip1 exists, ip1 value is assigned, otherwise, adjusted regression value is assigned. New indicator: ip2= hightech.

- Method 2. Relative change in last observation. As there are some NUTS2 regions with some data but enough for applying regression techniques the change of each observation with the last available observation has been obtained for the aggregated level and then, apply this change to the following level if it has been needed. This is the case of the German NUTS2 of Koblenz (DEB1) and Trier (DEB2) and the Duch NUTS2 regions of Groningen (NL11), Friesland (NL12), Drenthe (NL13), Over Ijssel (NL21), Flevoland (NL23) and Utrecht (NL31).

- Method 3. Mean Adjacent observations. Not applied

- Method 4. Aggregated nuts level value. As there is no data for NUTS2 level and NUTS1 level, country data have been applied to German NUTS2 region of Berlin (DE30) and Dutch NUTS2 region of Noord-Holland (NL32).

  In absence of NUTS1 data, country data have been assigned to the Finnish region of Åland (FI20) and the Portuguese NUTS2 of Região Autónoma dos Açores (PT20) and Região Autónoma da Madeira (PT30).

- Method 5. Completing time-series. Lagged non missing values have been used for completing the period 2010-2020

Table A1.53. Mining and quarrying sector wages and salaries per 100k -wage_min_100k- Coverage by NUTS0 NUTS1 and NUTS2

Country	Nuts 0		Nuts 1		NUTS2	
	min	max	min	max	min	max
AT	2010	2020	2010	2020	2010	2020
BE	2010	2020	2010	2020	2010	2020
BG	2010	2020	2010	2020	2010	2020
CY	2010	2015	2010	2015	2010	2015
CZ	2010	2020	2010	2020	2010	2020
DE	2010	2020	2010	2020	2010	2020
DK	2010	2020	2010	2020	2010	2020
EE	2010	2020	2010	2020	2010	2020
EL	2010	2020	2010	2020	2010	2020
ES	2010	2020	2010	2020	2010	2020
FI	2010	2019	2013	2019	2010	2020
FR	2010	2020	2010	2020	2010	2020
HR	2014	2020	2014	2020	2014	2020
HU	2010	2020	2010	2020	2010	2020
IE	2010	2020	2010	2018	2016	2020
IT	2010	2020	2010	2020	2010	2020
LT	2010	2020	2010	2020	2016	2020
LU	2010	2020	2010	2020	2010	2020
LV	2010	2020	2010	2020	2010	2020
MT	2015	2020	2015	2020	2015	2020
NL	2010	2020	2010	2020	2010	2020

PL	2010	2020	2010	2020	2010	2020
PT	2010	2020	2010	2020	2010	2020
RO	2010	2020	2010	2020	2010	2020
SE	2010	2020	2010	2020	2010	2020
SI	2010	2020	2010	2020	2013	2020
SK	2010	2020	2010	2020	2010	2020

C) Basic Descriptive Analysis.

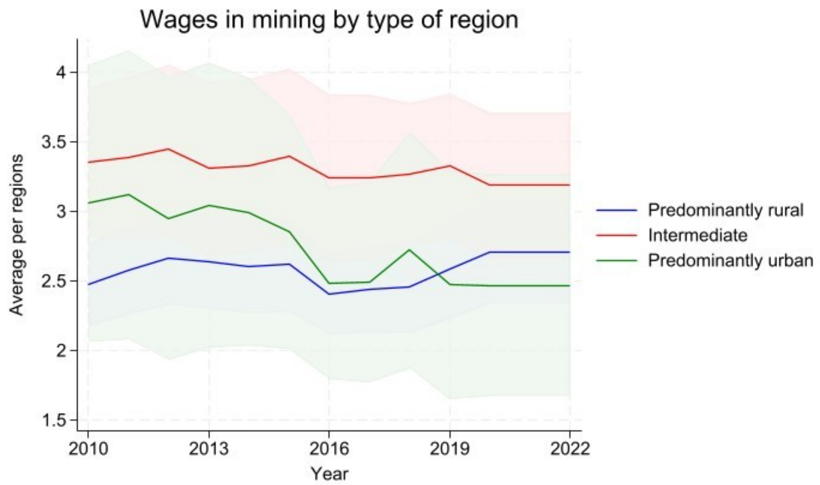

Figure A1.77. Mining and quarrying sector wages and salaries per 100k by type of region.

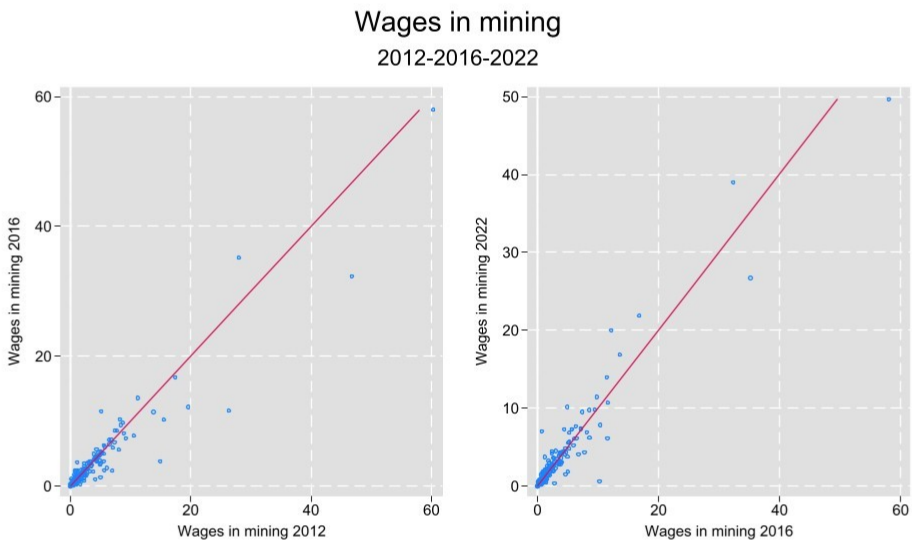

Figure A1.78. Dynamic scatterplot of Mining and quarrying sector wages and salaries per 100k.

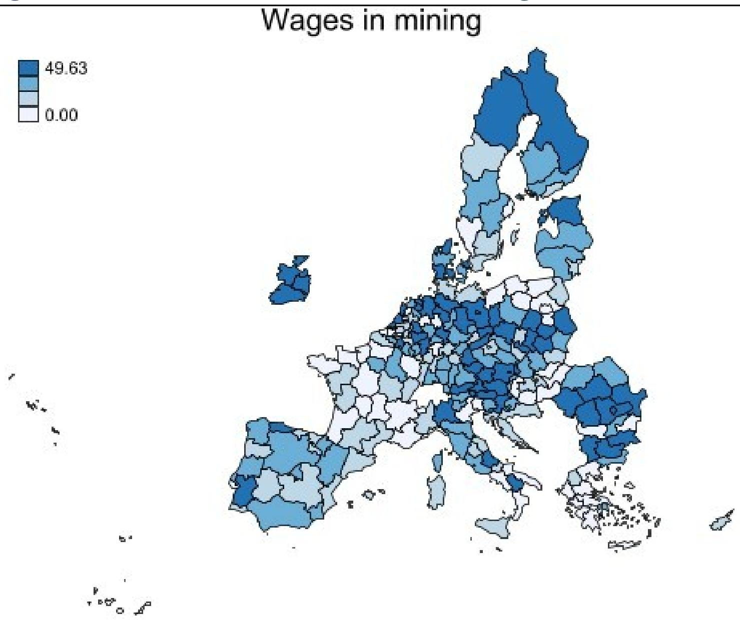

Figure A1.79. Geographical distribution of Mining and quarrying sector wages and salaries per 100k. Year 2020.

Table A1.54. Descriptive statistics. Mining and quarrying sector wages and salaries per 100k.

Country	Mean	SD	Min	Max	Q1	Q2	Q3	Growth
AT	4.0	1.8	0.7	7.8	2.7	4.1	5.5	12%
BE	1.2	1.3	0.0	6.1	0.2	0.8	1.7	44%
BG	2.9	2.9	0.2	9.8	0.6	2.2	3.6	138%
CY	1.5	0.1	1.3	1.8	1.4	1.4	1.4	-21%
CZ	4.7	6.1	0.4	26.3	1.0	1.7	6.6	-9%
DE	3.3	3.0	0.0	22.2	1.1	2.4	4.7	16%
DK	6.2	6.1	1.0	22.3	1.7	4.0	10.2	74%
EE	4.9	0.6	4.1	6.0	4.4	4.9	5.3	6%
EL	0.9	1.1	0.0	4.7	0.3	0.4	1.1	-12%
ES	1.6	1.8	0.0	13.2	0.8	1.2	1.8	-15%
FI	4.2	4.9	0.8	16.9	1.4	2.1	3.0	22%
FR	1.1	1.2	0.0	6.8	0.5	0.7	1.0	-27%
HR	3.9	4.3	0.4	15.0	1.1	2.3	4.3	-74%
HU	0.6	0.3	0.2	1.5	0.3	0.5	0.8	11%
IE	5.2	1.6	3.1	8.5	3.5	5.0	6.9	-5%
IT	1.5	1.5	0.2	7.6	0.6	1.0	1.7	15%
LT	0.9	0.6	0.2	2.1	0.4	0.8	1.2	194%
LU	2.5	0.3	2.2	3.3	2.3	2.4	2.5	-8%
LV	1.7	0.5	0.9	2.3	1.4	1.6	2.2	153%
MT	0.6	0.1	0.4	0.7	0.5	0.6	0.6	-8%
NL	5.2	7.9	0.0	39.9	1.0	2.2	5.6	40%
PL	5.7	9.9	0.2	46.8	0.5	2.1	5.0	11%
PT	2.2	3.3	0.2	11.9	0.4	0.9	1.7	-2%
RO	3.9	2.4	0.5	9.7	1.6	3.7	5.3	69%
SE	8.2	17.9	0.4	64.5	1.0	1.4	2.3	-23%
SI	3.3	1.6	1.4	5.3	1.7	3.4	4.8	-10%
SK	1.8	1.1	0.4	3.7	0.7	1.7	2.7	92%

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