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D2.3 The Health Consequences of the Twin Transition

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Abstract: This report examines the health implications of the green, digital and twin transition across European regions. Using occupation-based measures of green, digital and hybrid (twin) jobs combined with SHARE and EHIS data, it analyses associations with both physical and mental health at the individual and regional level. Results show differentiated patterns: digital exposure is systematically linked to worse mental health and, for older cohorts, poorer physical health; green jobs are associated with poorer physical but more favourable mental health outcomes; twin-intensive environments tend to mitigate some adverse effects, particularly for mental health. Findings reveal marked educational and gender heterogeneity, highlighting potential intergenerational and territorial inequalities in the health consequences of structural transformation.



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1 Introduction

Reaching a sustainable transition is a fundamental and urgent objective for the European Union and its Member States. The greening of the economy has increasingly been associated with the digital transition, giving rise to the concept of the “twin transition” (European Commission, 2023). While the innovation processes underpinning these transitions offer growth opportunities for firms and organisations, their implications for labour markets, social conditions and people’s health remain comparatively underexplored. At the same time, the green and digital transformation is expected to improve environmental quality - through lower emissions, cleaner production processes and reduced exposure to air and water pollution - potentially generating significant physical health benefits at the population level.

For decades, the academic literature has investigated the relationship between innovation and individuals, focusing on the labour-related channel, highlighting how technological change can simultaneously generate productivity gains and employment disruptions (Autor & Dorn, 2013; Vivarelli, 2014). New technologies may create jobs through new products and services, while displacing others via automation or restructuring (Aghion et al., 2016; Davis et al., 1996). Such labour-market shocks have been shown to affect workers’ health, particularly mental health, through increased insecurity, stress and adjustment costs (Sullivan & von Wachter, 2009). As the Twin Transition relies on the introduction and adoption of new green and digital technologies, it may therefore influence health through similar channels.

However, unlike past episodes of technological change that primarily reshaped the occupational structure, the Twin Transition mainly operates by transforming task content, skill requirements and work organisation within existing occupations (Acemoglu & Autor, 2011; Autor, 2019). Digitalisation increases demand for non-routine, analytical, and interactive tasks while reducing the intensity of routine tasks (Acemoglu & Autor, 2011; Frey & Osborne, 2017). At the same time, the green transition promotes new technologies and production processes while inducing the decline or transformation of carbon-intensive industries (Turner et al., 2025). Green jobs typically require specialised competencies not demanded in non-green occupations (Consoli et al., 2016; Vona et al., 2018). When these two transitions occur simultaneously, skill requirements become more complex and potentially more demanding, giving rise to “twin” skill profiles (Trevisan et al., 2024).

Against this background, this report assesses whether the regional unfolding of the Twin Transition relates to the health of individuals, particularly workers. We capture the green, digital and Twin Transition relevance in European regions based on the prevalence of related occupations (exploiting the measures developed in Deliverable 1.3 of this same project: “The geography of the green, digital and twin occupations in Europe”), and we also consider the regional technological advancements in the same domains (exploiting patent-based metrics developed in Deliverable 1.2 of this same project: “The geography of the green, digital and twin technological and scientific specialisation in Europe”).

More specifically, the report addresses the following research question: how does the regional unfolding of the green, digital and twin transition relate to individuals’ physical and



mental health across European regions? To unpack this broad question, the analysis also explores a set of related sub-questions. First, do green, digital and twin transitions display different associations with physical and mental health outcomes? Second, do these relationships vary across population groups, particularly along education and gender dimensions? Third, do consistent patterns emerge when analysing these associations at both the individual and the regional level? Finally, does the combination of green and digital transformations (the Twin Transition) generate health implications that differ from those associated with each transition considered separately?

In addressing these questions, the report contributes to the emerging literature on the socio-economic consequences of the Twin Transition in several ways. First, it links the analysis of green and digital transformations with population health outcomes, an area that remains comparatively underexplored in the economic literature on technological and environmental transitions. Second, it combines novel indicators of regional exposure to green, digital and twin transitions - based on occupational skill content and technological specialization - with harmonised microdata on health conditions from large European surveys. Third, it examines heterogeneity in the health implications of these transformations across education and gender groups, highlighting potential distributional effects. By doing so, the report provides new empirical evidence on how the structural changes associated with the Twin Transition may shape health outcomes and inequalities across European regions.

The empirical analysis is articulated along three main dimensions. First, using microdata from the Survey of Health, Ageing and Retirement in Europe (SHARE) and the European Health Interview Survey (EHIS), we provide a descriptive analysis of the relationship between the regional prevalence of the green, digital and twin skills transitions and health outcomes, both at the individual level and across regions. Second, we conduct an econometric analysis at both the individual and the regional level to assess these relationships more systematically, controlling for individual characteristics and key socio-economic conditions at the regional level. In this part of the report, the main analysis focuses on transition relevance through occupation-based metrics, while results from technological embeddedness, measured by patents, are presented in the Appendix.

The descriptive evidence highlights clear and systematic patterns. Regions with stronger digital and twin employment intensity tend to display better physical health but worse mental health outcomes, while greener labour-market environments are associated with more favourable mental health profiles, though are accompanied by poorer physical health. These patterns already point to potential health trade-offs embedded in the Twin Transition and motivate a more rigorous econometric investigation.

Econometric analysis confirms and refines these descriptive insights by controlling for a set of confounders. Digital and green transitions are associated with adverse physical health outcomes, while green exposure is associated with better mental health outcomes. The unfolding of the Twin Transition in European regions is positively associated with people's mental condition and appears to have a different effect on physical conditions depending on whether the focus is on the general population or senior individuals. Importantly, the results reveal substantial heterogeneity along education and gender dimensions. This indicates that



the health implications of the Twin Transition are not evenly distributed and may reinforce existing disparities if left unaddressed.

The remainder of the report is organised as follows. Section 2 presents the literature background. Section 3 describes the data and the construction of the main variables. Section 4 provides a descriptive analysis of health outcomes and green, digital, and twin skills across European regions, focusing on the prevalence of related occupations. Section 5 describes the empirical approach and reports the econometric results at the individual and regional levels based on SHARE and EHIS data, with additional results provided in the Appendix. Section 6 concludes by summarising the main findings and outlining their implications for policies aimed at promoting a just and inclusive Twin Transition.



2 Background and Literature Review

The member states of the European Union have implemented measures to accelerate the transition towards a sustainable economy. Through the European Industrial Strategy (European Commission, 2020) and the Green Deal Industrial plan (European Commission, 2023), the green transition is coupled with the digital transformation to support the so-called “twin transition”. European policy frameworks emphasise the twin transition as a cornerstone of sustainable growth, competitiveness, and climate neutrality, while also recognising the need to ensure that this transformation is fair and inclusive (European Commission, 2020; 2023).

The literature provides evidence that the Twin Transition is an opportunity for firms to grow, thanks to the innovation processes required to sustain it (Montresor & Vezzani, 2023; Cicerone et al., 2023; Faggian et al., 2025). However, the transformations necessary to sustain the Twin Transition are broader in scope, with deep implications for labour markets, working conditions, and social outcomes. For a long time, the field of economics has investigated the relationship between innovation and labour, highlighting the gains that may come from new products and services and the potential job losses associated with changes in production processes, despite relevant compensation mechanisms may be in place (Harrison et al., 2014; Vivarelli, 2014; Arenas Díaz et al., 2025). Those mechanisms relate to the introduction and diffusion of new technologies, which can create new jobs and, consequently, displace existing ones (Aghion et al., 2016; Davis et al., 1996). These labour-market disruptions associated with structural change can have long-lasting health consequences, including increased mortality risk and sustained deterioration in mental health (Sullivan & von Wachter, 2009). However, the evidence is mixed; for example, Devaraj et al. (2020) find that labour market dynamics following the introduction of a new technology are negatively associated with the shares of physical and mental distress at the regional level. Dematerialisation and improved environmental conditions resulting from digital and sustainability transitions may positively influence both physical and mental health, even beyond labour-related dynamics. However, both sustainable and digital technologies, once introduced into the market, can have a job-displacement effect. The effect of the Twin Transition on employment is complex, though, and it may operate in more nuanced ways than net job creation or destruction. As the broad literature on the relation between technology and labour (which has mostly focused on automation) suggests, it can modify the structure of work by reshaping tasks, skill requirements, and forms of work organisation within existing occupations (Acemoglu & Autor, 2011; Autor, 2019).

The Twin Transition introduces both opportunities and risks for different groups of workers. A worker performing a specific occupation must carry out a series of tasks. However, those skills and tasks are not immutable and can change over time due to the introduction of new technologies enabled by digitalisation or a sustainable transition (Frank et al., 2019; Vitale, 2024). Digitalisation accelerates routine-biased technological change, increasing demand for non-routine, analytical, and interactive tasks, while reducing demand for routine tasks (Acemoglu & Autor, 2011; Frey & Osborne, 2017). As a consequence, workers whose skills are less adaptable face higher risks of displacement and job insecurity. The green transition



further reshapes labour demand by promoting new activities and technologies while inducing the decline or transformation of carbon-intensive sectors (Turner et al., 2025). Empirical evidence suggests that green jobs often require higher and more specialised skill sets, differing from non-green jobs in terms of task composition and human capital requirements (Consoli et al., 2016; Vona et al., 2018). However, when green and digital transformations occur simultaneously, skill requirements become more complex and interdependent (Trevisan et al., 2024). The complementarity between skills is a crucial factor in assessing the economic value of an occupation (Stephany & Teutloff, 2024). The growing importance of hybrid green–digital skill bundles may raise adjustment costs for workers unable to reskill or concentrated in occupations with limited transition pathways (Neffke et al., 2024; Nedelkoska, 2013). In this sense, as tasks continue to evolve, workers might experience a gap between their skills and those required by their jobs, a phenomenon known as skill mismatch (Acemoglu, 1997). Both overqualification and underqualification have been shown to reduce job satisfaction, increase stress, and negatively impact mental well-being (Wu et al., 2015). The Twin Transition amplifies the risk of skill mismatch by increasing demand for complex, combined green-digital competences (Consoli et al., 2016; Vona et al., 2018; Acemoglu et al., 2022; Acemoglu & Restrepo, 2020). For instance, involuntary occupational mobility, particularly when repeated or poorly supported by training policies, may further exacerbate psychological strain and health risks.

A well-established body of literature in labour and health economics documents the strong association between labour market attachment and health outcomes. Stable employment, high-quality jobs, and predictable career trajectories are consistently linked to better physical and mental health, while unemployment, precarious employment, and involuntary job transitions are associated with deteriorating health conditions (Schmitz, 2011; Marcus, 2013). Importantly, this literature highlights that health effects are not limited to periods of unemployment. Job insecurity, uncertainty regarding future employment prospects, and repeated exposure to labour market shocks can negatively affect health even in the absence of actual job loss. Especially, the mental health conditions tend to be worse for workers under temporary job contracts (Hünefeld et al., 2020). Those workers have a higher probability of developing mental health problems needing medical support (Moscone et al., 2016). Evidence suggests that existing mechanisms of social protection, healthcare, and prevention are sufficient to support workers' full recovery within short periods after experiencing stress or mental health issues (Henseke, 2018). However, health outcomes often reflect cumulative exposure to adverse labour market conditions over long time periods. In this respect, workers' health can be interpreted as an integrative outcome that captures the longer-term consequences of labour market restructuring. Soffia et al. (2024) find both positive and negative effects of workers' exposure to various technologies (digital: artificial Intelligence and machine learning; manufacturing: robotics). On the one hand, exposed workers reported higher salaries, better career prospects, greater opportunities to influence decisions, and more consistent schedules. On the other hand, exposure to AI increased workers' perceived job insecurity, even if it does not predict actual unemployment, potentially affecting quality of life. Other consequences of exposure to digital technologies are longer working hours and poorer work-life balance, which could affect mental health (Piasna, 2024). Those findings are also supported by the literature investigating the quality of life of workers in the “gig



economy” (Apouey & Stabile, 2022). Berger et al. (2019) find that London Uber drivers enjoy the flexibility of their work, but they also show a higher level of anxiety. An increased risk to workers' physical health from digital technologies has been observed, especially there is an increased risk to develop physical health problems associated with repetitive hand or arm movements or painful postures (Piasna, 2024).

Regarding green occupations, they should not only be sustainable in terms of lowering the environmental impact but also provide decent jobs. An occupation which is exploitative or harmful may be at odds with a broader conception of sustainability (Renner et al., 2008). Nevertheless, in sustainable occupations, a higher risk of accidents or diseases has been observed, associated with lower organisational support at work (Moreira et al., 2018; Turner et al., 2025). For example, Christiansen et al. (2023) observed a higher incidence of dermatitis among Danish wind turbine workers exposed to epoxy (a resin used to increase the efficiency of wind turbine blades). Merging the green and digital spheres, the Twin Transition, which may increase uncertainty and alter employment trajectories, is likely to have significant health implications, even when aggregate labour market indicators appear stable.

Beyond labour-market mechanisms, digitalisation, the green transition, and especially their joint combination within the Twin Transition are expected to generate environmental improvements, including lower air and water pollution and reduced exposure to harmful emissions. A large body of evidence in environmental and health economics documents the substantial physical health gains associated with pollution abatement, ranging from lower mortality to reduced morbidity and hospital admissions (Chay and Greenstone, 2003; Giaccherini et al., 2021). Improvements in air quality have been shown to translate into measurable health benefits and productivity gains (Graff Zivin & Neidell, 2012; Holub & Thies, 2023). To the extent that green and digital technologies facilitate dematerialisation, cleaner production processes, and more efficient resource use, the Twin Transition may therefore exert indirect but meaningful positive effects on population physical health through environmental channels. However, these potential gains may be partly offset if the same transformations generate labour-market disruption, job insecurity, or intensified work patterns that adversely affect physical and mental health.

Taken together, these considerations highlight the inherently dual nature of the Twin Transition. On the one hand, it can improve environmental quality and thus enhance physical health at the population level; on the other hand, its adoption reshuffles the skill content of occupations (Frank et al., 2019), alters employment trajectories and reshapes working conditions, with potential consequences for both physical and mental health. The European Commission (2020; 2023) frames the Twin Transition as a process that should be just and equitable; understanding whether its health effects are evenly distributed, or instead reinforce existing inequalities, is therefore central for informing appropriate policy intervention.

Saint-Martin et al. (2018) call policy makers to raise awareness, improve coordination among stakeholders, and direct financial investments toward firms that can improve working conditions, considering labour market changes driven by the digitalisation of the economy. Similarly, Vitale et al. (2024) show that green jobs span a wide range of occupational sectors



and have a significant impact on society and the economy, raising concerns about workers' health and safety. Given limited knowledge of those risks, they suggest improving risk assessment tools to better protect workers' health and rights (Turner et al., 2025). These processes are occurring amid increasing economic inequality and fear of unemployment driven by widespread technological adoption. However, a lack of high-quality data to assess the evolution and the future of work is also observed (Frank et al., 2019). In this sense, we shed light on the relationship between Twin Transition and workers' health (both physical and mental), focusing specifically on the distribution of those effects across individuals and territories, matching innovative data. We analyse health as a key channel through which the Twin Transition might exacerbate existing inequalities or generate new ones.



3 Data and main variables

The analysis draws upon different data sources: the European Skills, Competences and Occupations classification (ESCO) and Labour Force Survey (for flagging and regionalise twin skills), PATSTAT, REGPAT and USPTO databases (for flagging and regionalise twin patents), Survey of Health, Ageing and Retirement in Europe (SHARE) and European Health Interview Survey (EHIS) (to assess the physical and mental health of workers). For the controls at the regional level, we use various datasets from Eurostat and the United Nations Educational, Scientific and Cultural Organization (UNESCO).

3.1 Skills and technological embeddedness variables

3.1.1 Skills variables

We use the European Skills, Competences, Qualifications and Occupations classification (ESCO) and the European Labour Force Survey (EU-LFS) in the same fashion as performed in Deliverable 1.3 (“The geography of the green, digital and twin occupations in Europe. Mapping Digital and Green Occupations and Twin Skill Readiness in EU Regions”). First, using the ESCO dataset (version 1.2.0) to ascertain how each occupation incorporates digital, green and twin skills. We worked on the ESCO classification at the 5-digit level to ensure granularity in our dataset (e.g. “3D modeller”, code 2166.1), considering only attributes classified as “skill/competence”. In this sense, we can isolate the competences required for each occupation. Moreover, by classifying digital and green skills provided by ESCO, we can determine the green and digital content of each occupation in the dataset. For the case assessing the content of twin skills for each occupation, we have considered only those which have at least one digital and one green skill. If an occupation has only one green (digital) skill and no digital (green) skills, it would score zero.

After computing the share of green, digital, and twin skills for each occupation at the ESCO 5-digit level, we aggregated those scores to the ISCO 3-digit level. This is done to enable the analysis of the distribution of green, digital, and twin skills across European NUTS-1 regions¹ using the EU-LFS database. We aggregated 1,795 ESCO 5-digit occupations into 125 ISCO 3-digit categories, calculating the average share for green, digital and twin skills. Afterwards, we link those results with EU-LFS employment counts to produce regional measures of skill embeddedness. These regional-level employment counts weighted by the individual sampling coefficients provided in the EU-LFS are obtained through a two-step procedure. First, we compute the share of workers employed in a given ISCO 3-digit occupation relative to the total regional employment. Second, we multiply this share by the corresponding ESCO-derived score for the occupation to obtain a reliable score of the embeddedness of green, digital and twin skills in the region.

¹ The NUTS-1 regional specification has been chosen to ensure the link with health data, see below.



3.1.2 Patent variables

In a secondary set of analyses (reported in Appendix A1), which complements those based on the direct measurement of the labour-related relevance of green, digital and Twin Transitions (See Section 3.1.1), we employ technology-based metrics. We use the indicators for green, digital and twin technological embeddedness as already built in Deliverable 1.2 (“The geography of the green, digital and twin technological and scientific specialization in Europe”).

To identify digital technologies, the PILLARS project dataset (Horizon 2020 GA: 101004703) was used to identify Digital Automation Technologies (DAT).² The query to retrieve those patents is based on a combination of IPC codes and keywords to reliably identify digital patents (Prytkova et al., 2022). For green technologies, patents were collected using the methodology proposed by Favot et al. (2023). The ENV-TECH and Y02/Y04S tagging schemes (i.e. Y02: “Technologies or applications for mitigation or adaptation against climate change”, Y04S: “Systems integrating technologies related to power network operation, communication or information technologies for improving the electrical power generation, transmission, distribution, management or usage, i.e. smart grids”) were used to flag green patents and categorise those linked to environmental and climate change mitigation technologies. The Cooperative Patent Classification (CPC) codes resulting from both classifications were manually reorganised to reflect the European Green Deal and the Circular Economy Action Plan policy priorities. Patents flagged as twin were identified using a two-step procedure. First, the patent families overlapping between green and digital patents were flagged as twin patents. Second, to flag patents with a shared knowledge base, co-citation patterns between green, digital and twin patents were considered; those patents were also flagged as twin patents. All digital, green and twin patents were regionalised using the REGPAT and USPTO databases.³

3.2 Health variables

3.2.1 SHARE (Survey of Health, Ageing and Retirement in Europe)

The SHARE dataset, managed by the European Research Infrastructure Consortium (ERIC), is a multidisciplinary, cross-national survey providing microdata on health, socio-economic status, and social and family relations of individuals aged 50 and over across European countries. It is designed as a longitudinal panel, allowing the analysis of individual trajectories over time, with repeated observations across waves. The survey ensures national representativeness through calibrated cross-sectional and longitudinal weights, adjusted for sampling design and non-response. Regional identifiers are available at the NUTS1 level for

² Those patents can be identified in the broad technological categories comprehending robotics, data acquisition and management, computing, artificial intelligence, intelligent information systems, additive manufacturing, networking and user interfaces.

³ This enabled the geo-localisation of patents across 271 NUTS-2 regions in 27 EU countries. To align with our variables on health outcomes, we followed a two-step procedure. First, we count the number of patents corresponding to each category and NUTS-1 region. Second, we weight this number by dividing it by the total population of the same NUTS-1 region.



baseline samples.⁴ SHARE is particularly suited for analysing ageing-related health outcomes, inequalities, and policy-relevant dynamics over time. Its harmonised design across countries makes it a key data source for comparative analysis of the elderly in Europe.

For this analysis, we use release 9.0 of the SHARE survey. Data are analysed both at the individual level and, after aggregation, at the NUTS-1 level, where individual observations are averaged to construct regional measures, which are then merged with regional indicators. The dataset covers 21 European countries and 80 NUTS-1 regions.⁵ To ensure temporal comparability, we restrict the sample to interview years 2017, 2020 and 2022, after consolidating partial interview years into the corresponding survey waves. The final sample consists of 100,368 observations, corresponding to approximately 45,000 individuals. Around 35% of respondents are observed in all three waves, while an additional 18% are observed twice, resulting in an unbalanced panel structure.

Health outcomes capture both physical and mental dimensions. Physical health is measured using a self-perceived health status scale, which asks respondents to rate their overall health on a five-point ordinal scale ranging from excellent to poor. We construct a binary indicator of poor physical health, equal to one when respondents report poor health (the lowest category of the scale), and zero otherwise. This measure captures severe perceived health limitations and has been shown to be strongly associated with objective health outcomes such as morbidity, functional decline and mortality (Idler and Benyamini, 1997; DeSalvo et al., 2006).

Mental health is proxied using the EURO-D depression scale, a validated instrument for measuring depressive symptomatology in older European populations (Prince et al., 1999; Castro-Costa et al., 2007). The scale is based on twelve items covering affective, cognitive and somatic symptoms of depression, including depressed mood, pessimism, irritability, loss of interest, sleep disturbances, fatigue, feelings of guilt and concentration problems. Each item is coded as a binary indicator, and the overall score ranges from 0 to 12. In the descriptive analysis, we define poor mental health using a binary indicator equal to one if at least one depressive symptom is reported. This operationalisation captures the presence of mental health vulnerability rather than only clinically severe depression, allowing us to identify early and diffuse mental health costs potentially associated with exposure to green, digital and twin transitions (Börsch-Supan et al., 2013; Cygan-Rehm et al., 2017).

To explore heterogeneity and distributional implications, the analysis conditions on gender and educational attainment, which is proxied by years of education and grouped into low (less than 10 years), medium (10-12 years) and high (more than 12 years, broadly corresponding to tertiary education).

⁴ The survey is not designed to be representative at the sub-national level. Nevertheless, calibrated cross-sectional weights include adjustments by age and sex and, in some countries, additional calibration by NUTS1 population margins.

⁵ The included countries in the analysis are the following: Austria, Belgium, Cyprus, Czech Republic, Germany, Denmark, Estonia, Greece, Spain, Finland, France, Croatia, Hungary, Italy, Lithuania, Luxemburg, Poland, Portugal, Romania, Sweden and Slovakia.



3.2.2 EHIS (European Health Interview Survey)

The analysis based on EHIS data relies on the European Health Interview Survey, a harmonised health survey coordinated by Eurostat and designed to produce nationally representative cross-sectional data on health status, health determinants and healthcare use for the general population. EHIS follows a repeated cross-sectional design, with three waves conducted across EU Member States, and provides high-quality and comparable health indicators aligned with European statistical standards. Survey weights correct for sampling design and non-response and are intended to ensure representativeness at the national level.

Unlike SHARE, EHIS covers individuals aged 15 and above, allowing the analysis to extend to younger and prime-age cohorts who are likely to be more directly exposed to ongoing green and digital labour-market transformations. At the same time, the cross-sectional nature of the survey prevents individuals from being tracked over time, limiting the scope for analysing within-individual dynamics.

We use EHIS Wave 3, administered in 2019, which is the most recent wave providing harmonised regional identifiers and detailed socio-economic information. Sub-national identifiers in EHIS are subject to anonymisation rules and are available in a limited, heterogeneous manner across waves and countries, with NUTS-level information available only for selected countries in Wave 3. Accordingly, the analysis is restricted to countries and regions for which consistent NUTS-1 identifiers can be constructed and matched to regional indicators of green, digital and twin transition.⁶ As in the SHARE analysis, all regional variables are defined at the NUTS-1 level and merged with individual-level EHIS observations. While EHIS supports robust national-level inference, sub-national results should be interpreted as descriptive rather than representative.

Health outcomes in EHIS capture both physical and mental dimensions. Physical health is measured using a self-assessed health question on a five-point ordinal scale ranging from very good to very bad. In line with the SHARE-based analysis, we construct a binary indicator of poor physical health equal to one when respondents report bad or very bad health, and zero otherwise. Mental health is measured using self-reported depressive symptoms over a recent reference period. We define a binary indicator of poor mental health that equals one if depressive status is reported within the past 12 months. This measure captures mental health vulnerability beyond clinically severe depression.

To examine heterogeneity and inequality dimensions, the EHIS analysis conditions on a set of individual characteristics closely aligned with those used in the SHARE analysis. Educational attainment is grouped into low, medium and high levels based on ISCED categories. Gender is included to account for differential exposure and responses to labour-market restructuring.

All models are estimated using calibrated EHIS survey weights to account for sampling design and non-response. As in the SHARE-based analysis, results based on regional aggregation are

⁶ The countries included when using EHIS are: Austria, Belgium, Czech Republic, Germany, Denmark, Estonia, Spain, Finland, Croatia, Hungary, Ireland, Italy, Lithuania, Poland, Portugal, Sweden and Slovakia.



interpreted as indicative of broad territorial patterns rather than precise causal estimates at the sub-national level.

3.2.3 Other data

In addition to individual-level information from SHARE and EHIS, the empirical analysis incorporates a set of regional-level control variables derived from Eurostat to account for broader socio-economic and demographic conditions that may correlate with both labour-market structure and health outcomes.

First, regional population size is included to control for differences in scale, settlement patterns and potential urbanisation effects across NUTS-1 regions. Population dynamics are relevant for capturing variations in access to services, labour-market density and congestion-related factors that may influence health outcomes independently of the Twin Transition.

Second, regional economic development is proxied by gross domestic product per capita expressed in purchasing power parity (GDP per capita, PPP). This measure allows us to control for differences in average income levels and economic resources across regions, net of price-level differences, and captures a broad set of factors related to material living conditions, welfare infrastructure and overall economic performance.

Finally, to account for differences in human capital beyond the specific green, digital and twin job indicators, we include the share of the working-age population with tertiary education, defined as individuals with ISCED levels 5-8. This variable captures the overall educational endowment of the regional labour force and helps isolate the role of green and digital (and twin) employment structures from more general human-capital effects.

All regional controls are measured at the NUTS-1 level and sourced from Eurostat, ensuring consistency and comparability across countries and over time. They are merged with individual-level data using NUTS1 regional identifiers and included in all the empirical specifications. Table 1 presents descriptive statistics for all the relevant variables.

Table 1 - Descriptive statistics for all included variables.

| Variables | Mean | S.D. | Min. | Max. |
|-------------------------------|-------------|-------------|-------------|-------------|
| Health status - SHARE | | | | |
| Poor physical health | 0.11 | 0.31 | 0 | 1 |
| Poor mental health | 0.24 | 0.42 | 0 | 1 |
| Age | 69.57 | 10.20 | 50 | 108 |
| Female | 0.57 | 0.49 | 0 | 1 |
| Low education | 0.23 | 0.46 | 0 | 1 |
| Medium education | 0.33 | 0.47 | 0 | 1 |
| High education | 0.34 | 0.47 | 0 | 1 |
| Employed | 0.22 | 0.42 | 0 | 1 |
| Total financial assets (Euro) | 7,851.18 | 21,408.88 | 0 | 5,439,000 |



| | | | | |
|---|-----------|-----------|--------|---------|
| Digital competence | 0.33 | 0.47 | 0 | 1 |
| Health status - EHIS | | | | |
| Poor physical health | 0.09 | 0.28 | 0 | 1 |
| Poor mental health | 0.073 | 0.26 | 0 | 1 |
| Age 20-29 | 0.096 | 0.29 | 0 | 1 |
| Age 30-44 | 0.20 | 0.40 | 0 | 1 |
| Age 45-59 | 0.26 | 0.37 | 0 | 1 |
| Age 60-69 | 0.18 | 0.38 | 0 | 1 |
| Age 70+ | 0.22 | 0.41 | 0 | 1 |
| Female | 0.55 | 0.50 | 0 | 1 |
| Low Education | 0.32 | 0.46 | 0 | 1 |
| Medium Education | 0.37 | 0.48 | 0 | 1 |
| High Education | 0.30 | 0.46 | 0 | 1 |
| Employed | 0.47 | 0.50 | 0 | 1 |
| Retired | 0.30 | 0.46 | 0 | 1 |
| Above 4th income quintile | 0.38 | 0.49 | 0 | 1 |
| Skill Indicators | | | | |
| Digital skills | 0.03 | 0.01 | 0.02 | 0.09 |
| Green skills | 0.07 | 0.01 | 0.04 | 0.11 |
| Twin skills | 0.02 | 0.012 | 0.02 | 0.03 |
| Controls (Eurostat) | | | | |
| Population | 6,836.49 | 35,458.02 | 162.9 | 422,038 |
| GDP per capita | 31,161.33 | 11,026.26 | 13,400 | 90,500 |
| Working pop with tertiary education (%) | 0.42 | 0.11 | 0.16 | 0.77 |

Notes: SHARE sample includes 100,371 observations and 39,450 individuals in 2017, 2020 and 2022. EHIS sample includes 213,776 observations and 189,575 individuals in 2019.



4 Descriptive analysis

4.1 Patterns on green, digital and twin occupations, and health

Figure 1 presents descriptive evidence on the relationship between regional prevalence of green, digital and twin occupations and workers’ health, distinguishing between physical and mental health outcomes. The figures are based on individual SHARE data and show conditional associations that account for individual age and gender, while also absorbing NUTS1 fixed effects. As a result, the patterns reflect within-region correlations over time rather than cross-sectional differences across regions.

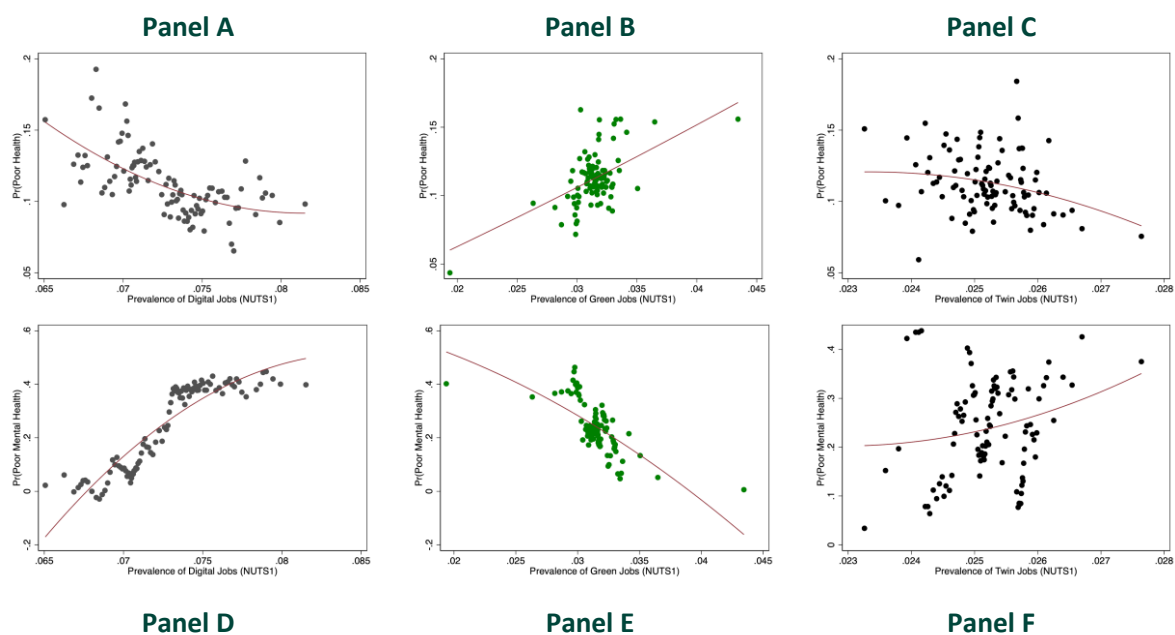


Figure 1 - Correlation between physical and mental health, and exposure to green, digital and twin jobs

The first set of panels documents a differentiated relationship between occupational composition and physical health. Panel A shows that a higher regional prevalence of digital jobs is associated with a lower probability of reporting poor physical health. Individuals living in more digitally intensive regions appear to experience better physical health outcomes, consistent with the concentration of digital employment in occupations characterised by lower physical strain, safer working conditions, and higher job quality. A similar, though weaker, pattern is observed in Panel C for twin jobs. Regions experiencing a stronger embedding of combined green and digital skills tend to show slightly lower rates of poor physical health. This suggests that twin occupations may partially replicate the protective effects on physical health observed for digital jobs, likely reflecting their higher skill content and reduced exposure to physically demanding tasks.

By contrast, Panel B reveals an opposite association for green jobs. Increases in the local prevalence of green employment are associated with higher probabilities of poor physical



health. This pattern highlights the heterogeneous nature of green occupations, which include a substantial share of manual, physically demanding jobs, such as agriculture, waste management, and environmentally related construction activities.

The second set of panels focuses on mental health outcomes and reveals markedly different associations. Panel D shows a positive and non-linear relationship between the prevalence of digital jobs and the probability of poor mental health. Within regions, periods of higher exposure to digital employment are associated with increased risks of depressive symptoms, consistent with concerns in the literature about psychosocial stress, work intensity, and cognitive demands in digitally intensive work environments.

In contrast, Panel E documents a negative association between green-job prevalence and poor mental health. Individuals living in regions with a stronger green employment base are less likely to experience poor mental health. This may reflect higher job meaningfulness, stronger perceived social contribution, or more stable employment trajectories associated with green activities, which can act as protective factors for mental well-being.

Finally, Panel F shows a mild positive association between twin-job prevalence and poor mental health. While the association is weaker than for purely digital jobs, the results suggest that twin occupations may still involve higher mental strain. The need to simultaneously master green and digital skills can increase cognitive demands and adaptation efforts, potentially reducing or neutralising some of the mental health advantages typically associated with higher-quality, higher-skilled jobs.

4.2 Regional patterns on green, digital and twin occupations, and health

To represent the maps, we have calculated thresholds corresponding to the average green, digital, and twin skill endowment in NUTS1 regions. Those thresholds were also calculated for the average physical and mental health across all considered waves of SHARE. Then, to study the relationship between the endowment of different skill typologies and physical (mental) health, we have assigned a colour to each NUTS1 region based on whether it meets one or both thresholds, or none of them.

Figure 2 shows the relation between the endowment of digital skills and the average physical health across NUTS1 regions in Europe. The regions scoring high in digital skills and having poor physical health are just a few. Those are mainly located in Eastern Europe and in some metropolitan areas, such as Berlin and Madrid. The regions of central Europe have a high endowment of digital skills but better physical health. In general, this map shows a low association between digital skills and poor physical health, apart from a few specific cases.



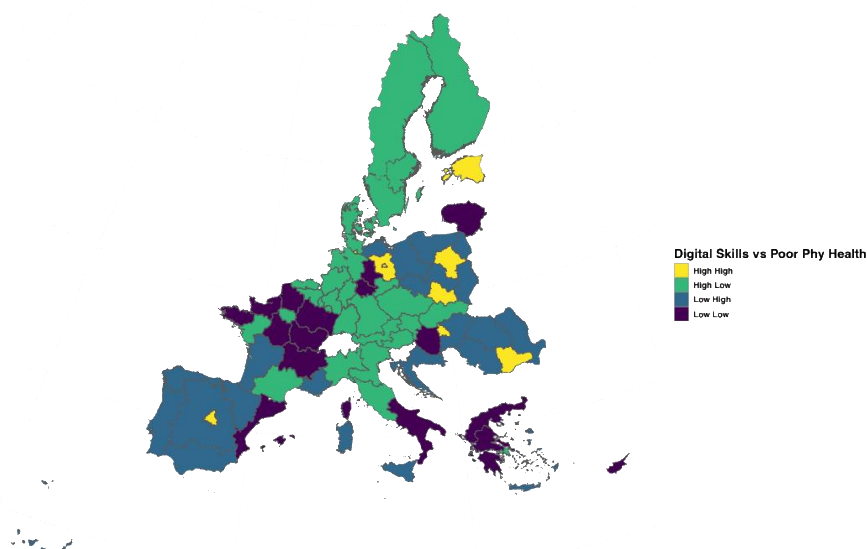


Figure 2 – Digital skills endowment vs average physical health across NUTS1 regions in Europe.

Figure 3 shows the relation between the endowment of green skills and poor physical health. The regions scoring high on both variables are those in Eastern Europe, including Romania and Poland. Another country with regions that have very high scores on both variables is Spain. The most economically developed areas of Europe, located in Germany, Northern Italy, France and Scandinavia, are scoring low in both indicators. From Deliverable 1.3, we know that the regions located in Eastern Europe are highly specialised in low-skilled green occupations. Thus, we observe a spatial co-occurrence between low-skilled green jobs and poor physical health.

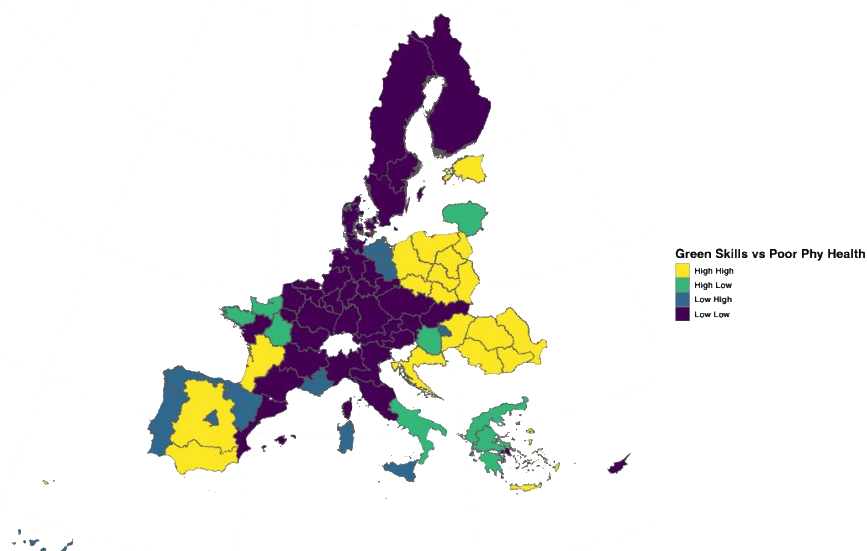


Figure 3 – Green skills endowment vs average physical health across NUTS1 regions in Europe.

Figure 4 shows the relationship between the endowment of twin skills and physical health across NUTS1 European regions. In general, the regions that showed a correlation between



green skills and poor physical health also show a high correlation for twin skills. However, some regions in central Europe have a high level of twin skills but better physical health, unlike green skills, which scored low on both variables. Regions that score low in twin skills are usually specialised in low-skilled occupations, as shown in Deliverable 1.3. Thus, the endowment of low-skilled green occupations also triggers the specialisation in twin occupations, which is associated with poor physical health.

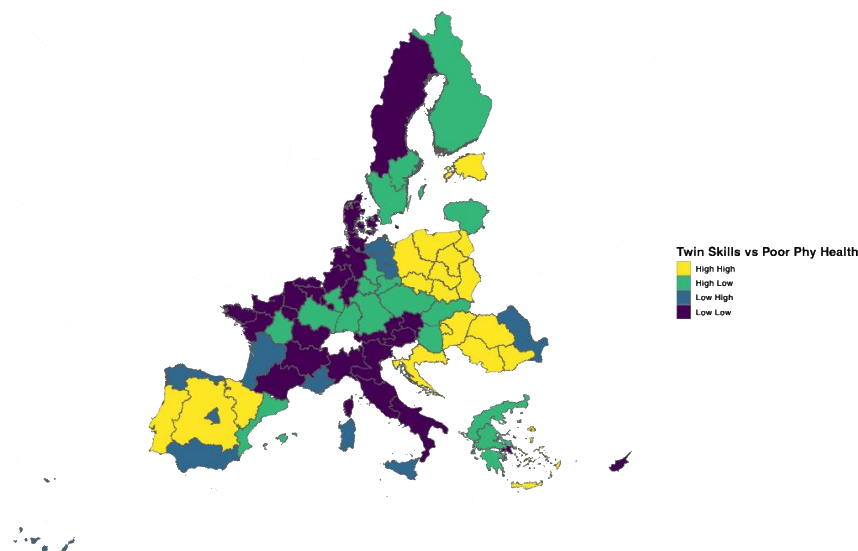


Figure 4 – Twin skills endowment vs poor physical health across NUTS1 regions in Europe.

Figure 5 shows the relation between the endowment of green skills and poor mental health. Regions with high green skills endowment and poor mental health are mainly in Poland and Romania, with a few exceptions in rural regions of Spain and France. Regions in the Mediterranean area, from Italy and Greece, have a high endowment of green skills but better mental health than other regions. In general, the correlation between green skills and poor mental health is weaker than that between green skills and poor physical health.



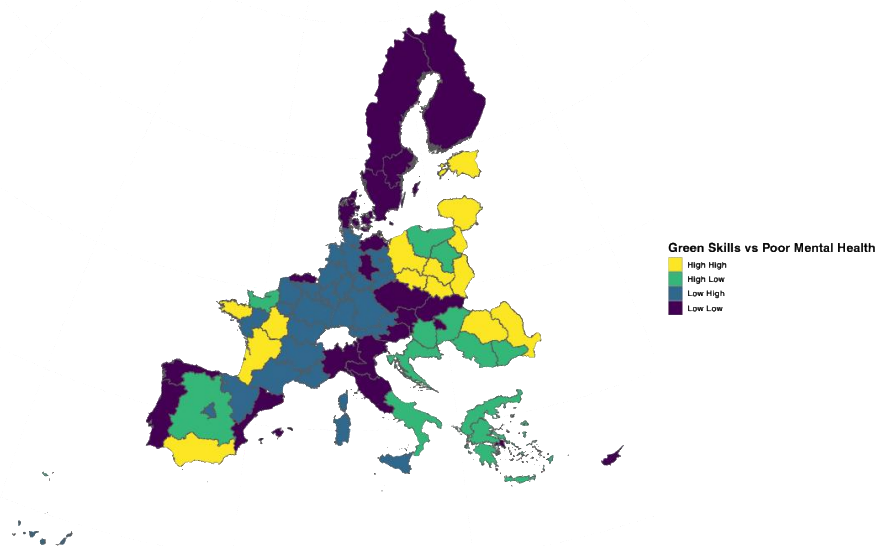


Figure 5 - Green skills endowment vs poor mental health across NUTS1 regions in Europe.

Figure 6 shows the correlation between the endowment of digital skills and poor mental health. Regions with poor mental health and high levels of digital skills are mainly located in Germany and in some capital cities, such as Madrid and Paris. This map shows how highly developed areas, which are benefiting from digitalisation, are also suffering from poor mental health. There are also regions from Italy and Scandinavian countries showing a high endowment of digital skills, but better mental health. All in all, the correlation between the endowment of digital skills and poor mental health is strong apart from the exceptions noted above.

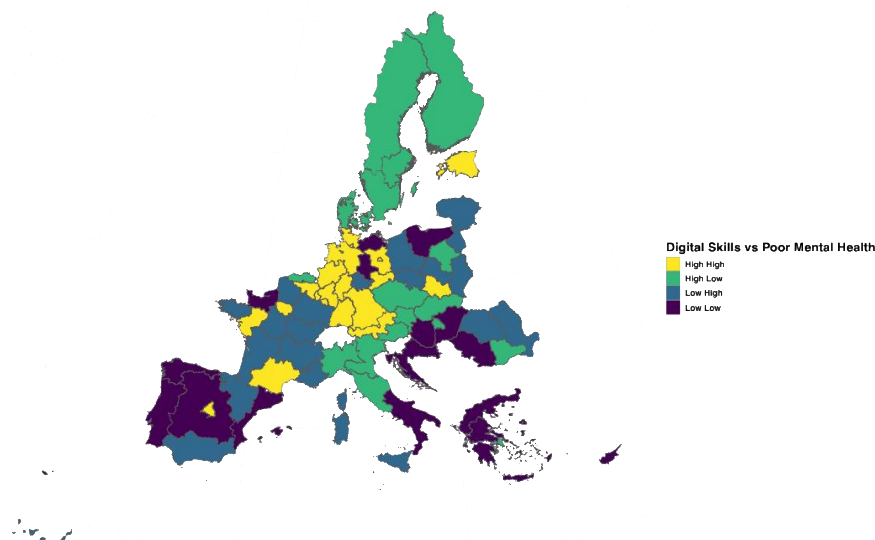


Figure 6 – Digital skills endowment vs poor mental health across NUTS1 regions in Europe.

Figure 7 shows the relationship between twin-skill endowment and poor mental health in NUTS1 regions in Europe. Regions with both a high endowment of twin skills and poor mental



health are mainly in Central Europe (Germany) and Eastern Europe (Poland). Thus, in the case of twin skills and mental health, the relationship involves both advanced and lagging regions. Those results show that, depending on whether the endowment of green and digital skills triggers the endowment of twin skills, the correlation with mental health differs.

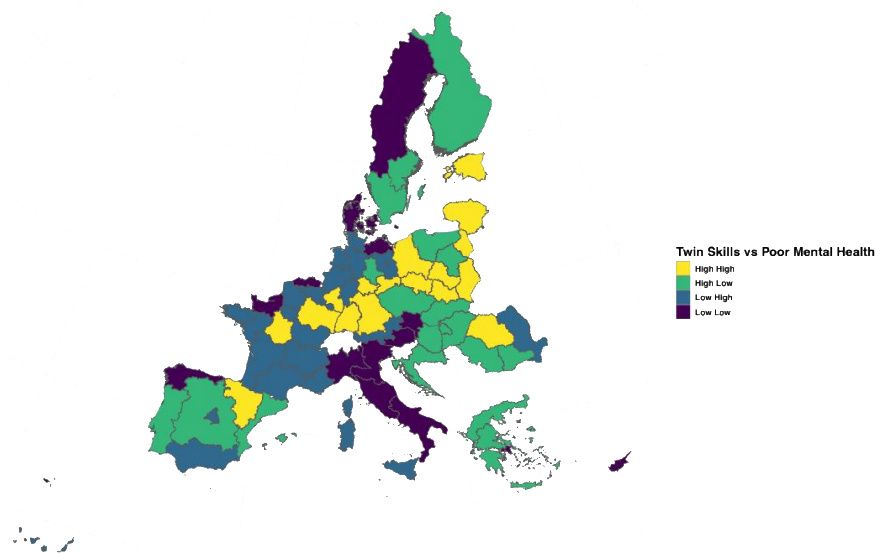


Figure 7 – Twin skills endowment vs average mental health across NUTS1 regions in Europe.



5 Econometric analysis

5.1 Empirical approach

The empirical analysis combines data from SHARE and EHIS to exploit their complementary strengths. SHARE provides longitudinal information on individuals aged 50 and above, allowing us to analyse within-individual changes in health in relation to regional exposure to green, digital and twin labour-market transitions. Its panel structure enables control for unobserved individual heterogeneity, strengthening the interpretation of dynamic associations over time.

EHIS complements SHARE by extending the analysis to the full adult population. Although EHIS is based on repeated cross-sections rather than panel data, it covers all age groups and offers broader population representativeness, particularly for younger and prime-age workers who are more directly exposed to emerging labour-market transformations.

Together, the two datasets provide a more complete picture of the health implications of the Twin Transition across the life cycle. SHARE captures adjustment processes among older workers, while EHIS assesses whether similar patterns emerge in the wider working-age population. Consistency across the two sources strengthens the robustness and policy relevance of the results, while divergences help identify age-specific mechanisms and intergenerational inequalities associated with the health-twin transition nexus.

The empirical analysis is designed to assess the relationship between regional exposure to green, digital and twin transitions and workers' health outcomes, while accounting for both individual-level heterogeneity and territorial dynamics using both SHARE and EHIS data sources. To this end, we adopt a dual empirical strategy, combining individual-level panel models with complementary analyses based on aggregated NUTS-1 data. This approach allows us to jointly exploit within-individual variation over time and to explore whether consistent patterns emerge when health outcomes are analysed at the regional-average level.

At the individual level, we estimate linear probability models of the following form:

$$H_{irt}^f = \beta TT_{rt} + X_{it}'\gamma + Z_{rt}'\delta + \alpha_{it} + \lambda_t + \varepsilon_{it}$$

where H_{irt}^f denotes a binary health indicator with $f = \{\text{physical health, mental health}\}$ for individual i , living in region r at time t . The variable TT_{rt} captures regional exposure to the Twin Transition, proxied by the share of digital, green, or twin jobs in the regional labour market. X is a vector of time-varying individual controls, including age and employment status, while Z includes time-varying regional controls such as population size, GDP per capita, and the share of the working population with tertiary education. The specification includes individual fixed effects (α_{it}), which absorb all time-invariant individual characteristics, and year fixed effects (λ_t), capturing common macroeconomic and institutional shocks. In the case of EHIS, the absence of a panel structure prevents the



inclusion of these fixed effects; however, the model controls for the same individual characteristics (five age classes, sex, and employment status).

This specification identifies the effect of changes in regional exposure to green, digital and twin jobs on health outcomes by exploiting within-individual variation over time. As such, it isolates the association between changes in the local labour-market environment and changes in individual health status, net of stable individual traits and common time trends. All models are estimated using survey probability weights, and standard errors are clustered at the NUTS1 level.

To explore heterogeneity, the baseline specification is extended by interacting regional exposure variables with two key individual characteristics, including education level and gender. Given the inclusion of individual fixed effects, these interaction terms capture differential responses to regional exposure along dimensions that are either time-varying or interact with time-varying regional conditions.

In parallel, we estimate analogous models at the NUTS-1 level by aggregating individual health outcomes into regional averages. These regional-level regressions relate changes in average health outcomes to changes in regional exposure to green, digital and twin jobs, controlling for regional characteristics and including year fixed effects. This set of models do not exploit individual-level variation. However, they provide a useful robustness check and allow us to assess whether the individual-level findings translate into consistent regional patterns. Nevertheless, a drop in the statistical power due to the limited number of observations and the above-mentioned implications arising from representativeness issues should be considered.

It should be noted that our baseline evidence focuses on the relation between labour-related metrics and health conditions. We leave the analysis based on patent indicators to Appendix A1. Indeed, this set of indicators does not allow us to consider the actual adoption of technologies, but rather their development. Compared to the labour-related measures of transition prevalence, this latter appears to be only marginally related to the health of individuals, and a clear set of mechanisms is more difficult to define a priori.

5.2 Results with individual SHARE data

Table 2 reports the baseline individual-level estimates for physical and mental health outcomes for individuals aged 50 and above.

For physical health, a higher regional prevalence of digital jobs is significantly associated with a greater probability of reporting poor physical health (Column 1). Green job exposure shows an even stronger positive association with poor physical health, suggesting that physically demanding activities embedded in parts of the green economy may play a dominant role (Column 2). As already observed in Deliverable 1.3, occupations with a high share of green skills pertain to Elementary occupations and Skilled agricultural, forestry and fishery (ISCO 1-digit), which are commonly regarded as labour-intensive, traditional sectors. By contrast, twin



job exposure is significantly associated with better physical health outcomes (Column 3), indicating a protective relationship.

The pattern partly reverses for mental health. Digital exposure is positively and strongly associated with poor mental health (Column 4), confirming that digitally intensive labour-market environments are linked to higher risks of depressive symptoms. Green exposure, in contrast, is significantly associated with better mental health outcomes (Column 5), aligning with the greater meaningfulness and intangible valuation associated with green occupations (e.g., Landini et al., 2025). Twin exposure also shows a strong negative association with poor mental health, with a magnitude larger than that of green exposure (Column 6).

Table 2 – Individual level estimates: SHARE.

| | Poor Physical Health | | | Poor Mental Health | | |
|------------------------------|----------------------|----------|-----------|--------------------|-----------|-----------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share of Digital Jobs | 1.361*** | | | 2.739*** | | |
| | (0.439) | | | (0.709) | | |
| Share of Green Jobs | | 2.016*** | | | -2.629*** | |
| | | (0.473) | | | (0.565) | |
| Share of Twin Jobs | | | -5.860*** | | | -9.911*** |
| | | | (1.314) | | | (1.848) |
| Observations | 100,371 | 100,371 | 100,371 | 100,371 | 100,371 | 100,371 |
| R-squared | 0.648 | 0.648 | 0.648 | 0.576 | 0.576 | 0.576 |

Notes: All estimates control for individual age and employment status, regional GDP p.c., population and share of working population with tertiary education (NUTS-1 level). Estimates include individual and year fixed effects. Standard errors, in parentheses, are clustered at the NUTS1 level. Statistical significance: * 10%; ** 5%; *** 1%.

Takeaway

#1

The results highlight a sharp difference in the relation between health and the twin transition realms. Digitalisation is associated with worse mental health and poorer physical health. Green jobs relevance is associated with worse physical but better mental health. Twin exposure, instead, is associated with better outcomes in both physical and mental health dimensions, suggesting that, for older cohorts, hybrid green–digital labour-market environments may combine elements that mitigate some of the health costs observed for the individual components separately. Overall, the results highlight that different components of the transition affect physical and mental health in distinct and asymmetric ways.

5.2.1 Heterogeneity: educational attainment

Table 3 examines heterogeneity by educational attainment, distinguishing between low, medium (reference group) and high education levels. The results show that education moderates both physical and mental health effects, although the patterns differ across the three components of the Twin Transition.



For poor physical health, digital occupation prevalence is positively and significantly associated with worse outcomes for the reference education group (Column 1). The interaction terms indicate no statistically significant differences across education groups, suggesting that the physical health penalty associated with digital exposure is broadly shared and does not vary systematically by educational attainment.

Green job relevance is also positively and significantly associated with poor physical health for the reference group. However, the interaction with low education is positive and statistically significant, suggesting that the adverse association with physical health is considerably stronger among low-educated individuals. No significant difference emerges for highly educated individuals (Column 2). This indicates that the physical strain associated with green-intensive labour markets may disproportionately affect those with lower formal education. This may be the condition characterising regions with a high concentration of low-skilled and manual workers engaged in remedial activities in highly polluting or dirty sectors (as already explained at the beginning of this subsection).

Twin job exposure, by contrast, is negatively associated with poor physical health for the reference group, indicating a protective effect. The interaction with low education is strongly negative and statistically significant, implying that the protective association is substantially larger for low-educated individuals. No significant differential effect is found for highly educated workers (Column 3). Overall, when older cohorts are considered in relation to the physical health dimension, the clearest educational gradient emerges for twin exposure, with low-educated individuals showing comparatively better outcomes in twin-intensive environments. A tentative explanation for this evidence lies in the types of regions that may be characterised by this relation: possibly, these are healthy areas where the high prevalence of twin jobs derives from the joint post-industrial (with a high level of digitally-driven dematerialisation) and sustainable nature of the economy.

Educational heterogeneity is more pronounced for mental health outcomes. Digitalisation is positively and significantly associated with poor mental health for the reference group. The interaction with low education is positive and strongly significant, indicating that the adverse mental health effect is significantly amplified among low-educated individuals. No significant difference emerges for highly educated individuals (Column 4). This suggests that lower educational attainment increases vulnerability to the psychosocial pressures associated with digital labour-market environments.

For green jobs relevance, the baseline coefficient is negative but not statistically significant. However, the interaction with low education is negative and highly significant (Column 5), suggesting that green exposure is strongly protective of mental health only among low-educated individuals. No significant differential effect is observed for highly educated individuals.

Twin job exposure shows a strongly negative and statistically significant association with poor mental health for the reference group. The interaction with low education is positive and



highly significant, indicating that the protective effect is substantially weakened, and in magnitude largely offset, among low-educated individuals (Column 6). No significant difference is observed for highly educated workers. Thus, unlike the physical health dimension, the mental health benefits associated with twin exposure are less pronounced for those with lower education.

Table 3 – Individual level estimates by educational attainment: SHARE.

| | Poor Physical Health | | | Poor Mental Health | | |
|---|----------------------|----------|-----------|--------------------|-----------|------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share of Digital Jobs | 1.276** | | | 1.817** | | |
| | (0.488) | | | (0.812) | | |
| Education Low X Share of Digital Jobs | 0.404 | | | 2.667*** | | |
| | (0.553) | | | (0.753) | | |
| Education High X Share of Digital Jobs | -0.113 | | | 0.320 | | |
| | (0.461) | | | (0.713) | | |
| Share of Green Jobs | | 1.573*** | | | -0.474 | |
| | | (0.563) | | | (0.732) | |
| Education Low X Share of Green Jobs | | 1.430* | | | -5.667*** | |
| | | (0.788) | | | (0.920) | |
| Education High X Share of Green Jobs | | -0.534 | | | 0.333 | |
| | | (0.734) | | | (0.964) | |
| Share of Twin Jobs | | | -3.057* | | | -13.643*** |
| | | | (1.834) | | | (2.648) |
| Education Low X Share of Twin Jobs | | | -7.514*** | | | 18.720*** |
| | | | (2.811) | | | (3.636) |
| Education High X Share of Twin Jobs | | | -1.936 | | | -4.611 |
| | | | (2.208) | | | (3.411) |
| Education Low | -0.026 | -0.047* | 0.190*** | -0.185*** | 0.196*** | -0.465*** |
| | (0.041) | (0.028) | (0.071) | (0.055) | (0.035) | (0.093) |
| Education High | -0.006 | 0.002 | 0.035 | 0.001 | 0.015 | 0.134 |



| | | | | | | |
|---------------------|---------|---------|---------|---------|---------|---------|
| | (0.034) | (0.026) | (0.056) | (0.052) | (0.036) | (0.087) |
| Observations | 100,368 | 100,368 | 100,368 | 100,368 | 100,368 | 100,368 |
| R-squared | 0.648 | 0.648 | 0.648 | 0.576 | 0.576 | 0.576 |

Notes: All estimates control for individual age and employment status, regional GDP p.c., population and share of working population with tertiary education (NUTS-1 level). Estimates include individual and year fixed effects. Standard errors, in parentheses, are clustered at the NUTS1 level. Statistical significance: * 10%; ** 5%; *** 1%.

Takeaway #2

In the physical dimension, low-educated individuals are more adversely affected by the green transition, while they benefit more strongly from twin-intensive environments. In the mental health dimension, lower education amplifies the adverse effects of digital exposure and attenuates the protective effect of twin exposure, while strengthening the protective association of green jobs.

5.2.2 Heterogeneity: gender

Table 4 reports gender-specific estimates and reveals differentiated patterns across physical and mental health outcomes. Starting with physical health (Column 1), digital jobs prevalence is positively associated with poor physical health for men, but the interaction term shows that this adverse association is significantly weaker for women. Although intensive digitalisation remains detrimental overall, its effect is substantially attenuated among women, indicating relative female resilience in digitally intensive environments.

A different pattern emerges for the relevance of green jobs (Column 2): while the association with poor physical health is weak for men, women exhibit a significantly stronger positive association. This suggests that the physical burden linked to green-intensive labour markets may disproportionately affect women in this age group.

For twin jobs exposure (Column 3), the baseline effect indicates better physical health outcomes, and the interaction term is not statistically significant. This implies that the protective association of hybrid green–digital environments does not differ meaningfully across genders in the physical health dimension.

The gender contrast is considerably sharper for mental health. Digitalisation of the regional labour market is associated with worse mental health for men and the effect becomes dramatically stronger for women (Column 4), indicating a sizeable gender gap in the psychosocial costs of digital labour-market environments. Green jobs’ relevance (Column 5) shows the opposite pattern: it is associated with worse mental health among men but becomes strongly protective among women. For twin jobs (Column 6), the association is strongly protective for men, but this advantage disappears for women, for whom the relationship turns adverse and significant.

Table 4 – Individual level estimates by gender: SHARE.

| | | |
|--|-----------------------------|---------------------------|
| | Poor Physical Health | Poor Mental Health |
|--|-----------------------------|---------------------------|



| | (1) | (2) | (3) | (4) | (5) | (6) |
|--------------------------------|-----------|----------|----------|-----------|------------|------------|
| Share of Digital Jobs | 2.116*** | | | -6.888*** | | |
| | (0.509) | | | (0.801) | | |
| Female X Share of Digital Jobs | -1.370*** | | | 17.477*** | | |
| | (0.478) | | | (0.714) | | |
| Share of Green Jobs | | 0.507 | | | 4.095*** | |
| | | (0.683) | | | (0.788) | |
| Female X Share of Green Jobs | | 2.773*** | | | -12.358*** | |
| | | (0.893) | | | (1.038) | |
| Share of Twin Jobs | | | -4.137** | | | -18.368*** |
| | | | (1.907) | | | (2.617) |
| Female X Share of Twin Jobs | | | -3.186 | | | 15.638*** |
| | | | (2.497) | | | (3.529) |
| Observations | 100,371 | 100,371 | 100,371 | 100,371 | 100,371 | 100,371 |
| R-squared | 0.648 | 0.648 | 0.648 | 0.580 | 0.577 | 0.576 |

Notes: All estimates control for individual age and employment status, regional GDP p.c., population and share of working population with tertiary education (NUTS-1 level). Estimates include individual and year fixed effects. Standard errors, in parentheses, are clustered at the NUTS1 level. Statistical significance: * 10%; ** 5%; *** 1%.

Takeaway

#3

Gender heterogeneity is modest for physical health but pronounced for mental health. Women display greater resilience than men in the physical health dimension of digitalisation, but are significantly more vulnerable in the mental health dimension, in digitally and twin-intensive contexts. At the same time, greener labour-market environments appear to offer women comparatively stronger mental health benefits. These findings highlight that the Twin Transition interacts with gender not only in magnitude but also in the direction of its health implications.

5.3 Results with SHARE data at the NUTS1 level

Appendix Table A2.1 reports the results of the analysis conducted at the NUTS-1 level, where individual health outcomes are aggregated into regional averages. This approach necessarily abstracts from individual-level heterogeneity and reduces statistical power, so it should be taken with caution. Despite the caveats, we observe weaker physical health effects; these, somehow confirms the negative relation between the green jobs intensity and physical health. By contrast, the mental health patterns are more distinct. Digital and green exposure show no statistically robust associations, despite for the latter the evidences confirms the sign. In line with the granular baseline evidence, twin job intensity is strongly associated with better average mental health at the NUTS1 level.



5.4 Results with individual EHIS data

Tables 5 to 7 present results from EHIS data, extending the analysis to the full adult population. Although EHIS is based on repeated cross-sections and therefore does not allow for the inclusion of individual fixed effects, it provides an important robustness check of the SHARE findings and helps assess whether the main patterns identified among older individuals also hold for younger and prime-age workers.

Table 5 reports the baseline estimates based on EHIS data. For physical health, EHIS results are broadly aligned with SHARE for digital (Column 1) and green (Column 2) jobs intensity, both of which are positively and significantly associated with poor physical health. However, a notable difference concerns twin jobs prevalence (Column 3), which, in the case of EHIS data, is positively and significantly associated with poor physical health. This divergence suggests that the physical health implications of twin-intensive labour markets may differ across age groups - leading to less healthy conditions for young workers - or reflect methodological differences between panel and cross-sectional designs.

The analysis of mental health conditions is qualitatively overlapping with that emerging from SHARE. Digitalisation, captured through the regional relevance of digital jobs, is positively and significantly associated with poor mental health (Column 4), indicating worse mental well-being in digitally intensive labour-market environments. Green jobs intensity is negatively and significantly associated with poor mental health (Column 5), again in line with SHARE, suggesting a protective association. Twin job exposure is also negatively associated with poor mental health (Column 6), confirming the favourable mental health pattern observed in SHARE, although the magnitude is smaller.

Overall, the comparison shows strong consistency across datasets in the mental health dimension, while some divergence emerges for physical health, particularly regarding the role of twin jobs.

Table 5 - Individual level estimates: EHIS.

| | Poor Physical Health | | | Poor Mental Health | | |
|------------------------------|----------------------|---------------------|---------------------|---------------------|----------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share of Digital Jobs | 0.356*** (0.083) | | | 1.005*** (0.103) | | |
| Share of Green Jobs | | 1.741*** (0.174) | | | -1.721*** (0.171) | |
| Share of Twin Jobs | | | 3.244*** (0.342) | | | -0.932** (0.375) |
| Observations | 213,776 | 213,776 | 213,776 | 213,776 | 213,776 | 213,776 |
| R-squared | 0.066 | 0.066 | 0.066 | 0.018 | 0.018 | 0.017 |

Notes: All estimates include individual controls for 5 age classes (20-29, 30-44, 45-59, 60-69, 70+) and employment status, along with regional GDP p.c., population and share of working population with tertiary education (NUTS-1 level). Standard errors, in parentheses, are clustered at the NUTS1 level. Statistical significance: * 10%; ** 5%; *** 1%.



Takeaway**#4**

The health implications of the green, digital and twin transition appear to be similar between different age cohorts, suggesting limited intergenerational differences. A notable exception concerns the physical health conditions linked to the joint green-digital transition: in this respect, the evidence suggests worsening conditions for the younger cohorts.

5.4.1 Heterogeneity: educational attainment

Table 6 examines heterogeneity by educational attainment. Once again, the results appear to be generally aligned with those emerging from SHARE. Digitalisation is positively associated with poor physical health across the board (Column 1); differences across education groups are not evident. The greening of regional economies worsens physical conditions, and this is even more true for less educated individuals (Column 2). Twin job intensity is associated with worse physical conditions (Column 3), though there is an education-related heterogeneity that favours highly educated workers. This is in line with Table 5 and with the analysis for older individuals using SHARE data shown in Table 3, although the results appear different in the section related to twin jobs, where the evidence is contrasting.

Digitalisation is associated with worse mental health across groups, but the adverse effect is significantly stronger among individuals with lower education, indicating greater vulnerability in this group (Column 4). The greening of regional economies links with better mental health on average; however, the protective effect is significantly weaker among highly educated individuals (Column 5). This differs from the evidence presented in Table 3. With the caveat associated with the different methodology, this may suggest worse mental conditions among young and high-skilled workers. By contrast, twin job exposure does not exhibit a statistically robust educational gradient in mental health (Column 6).

Table 6 – Individual level estimates by educational attainment: EHIS.

| | Poor Physical Health | | | Poor Mental Health | | |
|---|----------------------|----------|-----|--------------------|-----------|-----|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share of Digital Jobs | 0.701*** | | | 1.389*** | | |
| | (0.139) | | | (0.166) | | |
| Education Low X Share of Digital Jobs | 0.462 | | | 2.242*** | | |
| | (0.551) | | | (0.747) | | |
| Education High X Share of Digital Jobs | -0.123 | | | 0.385 | | |
| | (0.461) | | | (0.713) | | |
| Share of Green Jobs | | 1.538*** | | | -1.669*** | |
| | | (0.248) | | | (0.246) | |
| Education Low X Share of Green Jobs | | 2.839*** | | | -0.275 | |
| | | (0.494) | | | (0.511) | |
| Education High X Share of Green Jobs | | -0.463 | | | 0.806** | |
| | | (0.303) | | | (0.335) | |



| | | | | | | |
|--|----------|-----------|-----------|---------|-----------|---------|
| Share of Twin Jobs | | | 5.183*** | | | 0.446 |
| | | | (0.518) | | | (0.580) |
| Education Low X Share of Twin Jobs | | | -0.637 | | | -1.029 |
| | | | (0.940) | | | (1.019) |
| Education High X Share of Twin Jobs | | | -2.555*** | | | -0.487 |
| | | | (0.658) | | | (0.763) |
| Education Low | 0.042*** | -0.057*** | 0.045* | 0.040** | 0.033* | 0.052** |
| | (0.016) | (0.016) | (0.023) | (0.019) | (0.017) | (0.025) |
| Education High | -0.003 | -0.003 | 0.048*** | 0.017 | -0.035*** | 0.002 |
| | (0.011) | (0.010) | (0.017) | (0.013) | (0.012) | (0.020) |
| Observations | 210,114 | 210,114 | 210,114 | 210,114 | 210,114 | 210,114 |
| R-squared | 0.069 | 0.071 | 0.070 | 0.021 | 0.021 | 0.020 |

Notes: All estimates include individual controls for 5 age classes (20-29, 30-44, 45-59, 60-69, 70+) and employment status, along with regional GDP p.c., population and share of working population with tertiary education (NUTS-1 level). Standard errors, in parentheses, are clustered at the NUTS1 level.

Statistical significance: * 10%; ** 5%; *** 1%.

Takeaway

#5

Some evidence suggests the presence of intergenerational differences in health outcomes associated with the Twin Transition. In particular, highly educated young workers appear to experience weaker mental health outcomes when residing in areas characterised by strong greening dynamics. Labour markets marked by an intense integration of digital and green processes may therefore exhibit education-related inequalities as younger cohorts enter the workforce.

5.4.2 Heterogeneity: gender

Table 7 presents gender-specific estimates and reveals differentiated patterns across physical and mental health dimensions. Starting with physical health (Column 1), digital exposure is positively and significantly associated with poor physical health for men. The interaction term is negative and significant, indicating that this adverse association is substantially attenuated for women. Although digital exposure remains detrimental overall, women appear relatively more resilient in the physical health dimension. This aligns with what we found for older cohorts (Table 4).

Green exposure is also strongly associated with worse physical health (Column 2). When extending the analysis to the entire adult population, this result does not seem to be affected by gender. Another difference across cohorts emerges: twin jobs intensity is associated with worsening conditions across genders (Column 3).

The mental health patterns are sharper, more asymmetric and somehow more different from those emerging when focusing only on the older cohorts of the population (Table 4). Digital exposure is positively and strongly associated with poor mental health, and the interaction term is positive and significant (Column 4), indicating that the adverse effect is significantly larger for women. Regional greening dynamics are negatively associated with poor mental



health (Column 5), and this protective effect is significantly stronger for women, as shown by the negative and significant interaction. For twin jobs, no statistically significant association is observed for men (Column 6). However, the interaction term is negative and marginally significant, indicating that twinning processes become protective for women.

Table 7 – Individual level estimates by gender: EHIS.

| | Poor Physical Health | | | Poor Mental Health | | |
|---------------------------------------|----------------------|---------------------|---------------------|---------------------|----------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share of Digital Jobs | 0.567*** (0.113) | | | 0.830*** (0.134) | | |
| Female X Share of Digital Jobs | -0.412*** (0.158) | | | 0.328* (0.193) | | |
| Share of Green Jobs | | 1.489*** (0.236) | | | -1.245*** (0.228) | |
| Female X Share of Green Jobs | | 0.483 (0.317) | | | -0.964*** (0.332) | |
| Share of Twin Jobs | | | 3.767*** (0.470) | | | -0.400 (0.490) |
| Female X Share of Twin Jobs | | | -1.026 (0.655) | | | -1.188* (0.721) |
| Female | 0.031*** (0.011) | -0.013 (0.010) | 0.028* (0.016) | 0.003 (0.013) | 0.055*** (0.011) | 0.056*** (0.018) |
| Observations | 213,776 | 213,776 | 213,776 | 213,776 | 213,776 | 213,776 |
| R-squared | 0.066 | 0.066 | 0.066 | 0.021 | 0.021 | 0.020 |

Notes: All estimates include individual controls for 5 age classes (20-29, 30-44, 45-59, 60-69, 70+) and employment status, along with regional GDP p.c., population and share of working population with tertiary education (NUTS-1 level). Standard errors, in parentheses, are clustered at the NUTS1 level. Statistical significance: * 10%; ** 5%; *** 1%.

Takeaway

#6

When extending the analysis to the whole adult population, some gender-related imbalances remain. A main change concerns the greening of the regional economies, which does not appear to be worsening the physical health of women more than that of men. In addition, women improve their mental health conditions in relation to the Twin Transition.

5.5 Results with EHIS data at the NUTS1 level

Appendix Table A2.2 presents NUTS1-level estimates using EHIS data. The very limited number of observations, the lack of individual variation and representativeness at the NUTS1 level call for extreme caution in commenting on this set of results. However, the aggregate evidence by and large aligns with the individual analysis based on EHIS data shown above.

The physical health effects are present but relatively modest in magnitude. All three exposures - digital, green and twin - are positively and significantly associated with poor physical health, indicating worse average outcomes in more transition-intensive regions. In particular, the positive coefficient on green jobs is consistent in sign with the evidence



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observed for older individuals in SHARE, where greener regions are also associated with worse physical health, although the SHARE effects are generally stronger and more precisely estimated.

The mental health patterns are more differentiated. Green and twin job intensity are both strongly and significantly associated with lower probabilities of poor mental health, pointing to better average mental well-being in greener and hybrid-intensive regions. This is broadly consistent with SHARE, where twin exposure at the regional level is also linked to better mental health among the older population. By contrast, digital exposure is positively signed but not statistically significant for mental health, aligning with the weaker and less robust digital association found in the regional SHARE estimates. Overall, for the full adult population, the regional EHIS evidence confirms the adverse physical health association of green intensity and highlights a more pronounced and protective role of green and twin exposure in the mental health dimension, in line with the patterns identified for the elderly in SHARE.



6 Conclusion

This report provides systematic evidence that the Twin Transition has measurable and differentiated health implications across individuals and regions in Europe. We provided a novel analysis that uses detailed information on the prevalence of green-, digital-, and twin-related workers across European regions as a proxy for the (joint) uptake of digitalisation and environmental sustainability. In addition, we sought to provide a complementary analysis of regional inventive activity in these domains. We linked these metrics with detailed information on the health of individuals in NUTS1 European regions.

We first provided preliminary descriptive evidence pointing to differential impacts of green, digital, and twin transitions on health conditions. We then employed econometric methods to better ascertain the presence of robust correlations, controlling for key individual characteristics. We find that digitalisation is typically associated with worse mental health and poorer physical health. The greening of regional economies is associated with worse physical but better mental health. This suggests the coexistence of social meaning or valuation attributed to sustainability with physically demanding tasks. Instead, the combination of digitalisation and sustainability leads to better mental health.

By working with data focusing on different age cohorts, we also notice some intergenerational differences. The magnitude of the mental health effects tends to be stronger in SHARE than in EHIS, suggesting that older individuals - either still active in the labour market or recently retired - may experience the psychosocial pressures of digital restructuring more intensely than younger cohorts. More striking is the evidence of the physical health consequences of the Twin Transition, which are negative for young people. This divergence may indicate that younger or prime-age workers are more exposed to the physically demanding components of hybrid green-digital environments, while older individuals may be positively selected into less physically intensive tasks or occupational positions. Overall, older cohorts appear more sensitive to its mental health implications, especially in digitally intensive contexts; the physical health burden of green and hybrid restructuring may fall more heavily on younger or working-age individuals. A deeper understanding of these age-related disparities is crucial for assessing whether the Twin Transition generates uneven health consequences across generations.

Other sources of inequalities in the transition-health nexus relate to the education level and gender. As far as the former is concerned, lower education translates into more severe physical conditions in areas characterised by intense greening dynamics, and worse mental health conditions in areas with high digitalisation. Gender inequality seems to play a role as well. Women are better off in terms of physical health consequences arising from digitalisation processes and mental health consequences of the green transition. Nevertheless, they face more severe physical consequences when the greening of regional economies is factored in. Some intergenerational differences emerge when considering the gender imbalances, though.



A series of policy implications emerges. The evidence suggests that the Twin Transition entails health trade-offs that go beyond aggregate employment outcomes. Policies promoting green and digital restructuring should therefore integrate a health-sensitive perspective, with particular attention to mental health support, training and reskilling, and targeted interventions for vulnerable groups. Embedding occupational health considerations into transition strategies would help ensure that the shift towards sustainability and digitalisation remains not only economically efficient, but also socially inclusive, equitable and healthy. More in detail, policy should consider new forms of occupational risks associated with the mental health consequences, in particular, implying stress and anxiety deriving from sharp disruptions in the labour markets. In addition to recognising mental health as an important element of quality jobs, policy should implement targeted cushioning measures. For instance, these may take the form of training older people facing sharp changes associated with digitalisation, or protecting young workers from the physical strain of twin jobs, with health and safety regulations enforced, particularly among temporary workers. Training and increased participation in formal education may reduce the health-related education gap we observe. Women would benefit from organisational settings where digital transformation is not accompanied by expectations of constant connectivity and permanent availability. Limiting such “always-on” practices may alleviate work-family conflict, which continues to disproportionately affect women due to unequal care burdens.

This report is subject to several limitations that should be considered when interpreting the results. First, although SHARE provides calibrated survey weights and these are used throughout the analysis, they do not guarantee representativeness at the NUTS-1 regional level. The weights mainly rebalance the sample with respect to age and gender composition, while the survey itself is designed to be representative primarily at the national level. As a consequence, regional estimates should be interpreted with caution, as they may still reflect sampling imbalances across territories. Second, the EHIS analysis relies on a single cross-sectional wave (2019), which prevents the observation of individual dynamics over time and limits the possibility of analysing health adjustments associated with the unfolding of the Twin Transition. Third, the indicators used to measure exposure to the green, digital and twin transitions present inherent measurement limitations. Occupation-based metrics capture the skill content of jobs rather than individuals’ direct exposure to specific technologies, while patent-based indicators reflect the development of technological knowledge rather than its diffusion, adoption, or effective use in regional labour markets. Fourth, the SHARE analysis covers the period up to 2022 and therefore overlaps with the COVID-19 pandemic, which likely influenced both the adoption of digital technologies and individuals’ physical and mental health conditions. Although time effects are included in the empirical models, the pandemic may still represent an important unobserved factor that is only partially captured by the estimates. More broadly, the analysis cannot fully account for other potentially relevant unobserved factors, such as local exposure to environmental pollution or the presence of particularly vulnerable communities within regions. This issue is compounded by the use of NUTS-1 regions, which are relatively large territorial units and may encompass substantial internal heterogeneity that remains unobserved in the data. Taken together, these limitations highlight the need for more granular and spatially detailed data to better



understand the relationship between population health and the ongoing green and digital transitions.



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Appendix I. Results based on patent indicators and SHARE data

The tables reported in this Appendix complement the main analysis by replacing skill-based indicators of green, digital and twin labour-market exposure with measures of technological embeddedness based on patent applications. Patent-based indicators capture local inventive activity rather than actual adoption or changes in the economic structure and labour markets. That said, Table A1 1 confirms the results on the improved physical conditions associated with the twin green-digital transformations (Column 3) and mental health deriving from a higher focus on environmental sustainability (Column 5). Table A1 2 further reinforces the evidence on improved mental health conditions emerging from the greening of the economy (Column 5), which is possibly the most stable of our evidence.

Tables A1 3 and A1 4 replicate the analysis using EHIS data. In this case, the results differ from the ones observed in the main analysis. As mentioned above, in addition to difference in the age cohorts consider we should factor in the lack of longitudinal structure in the data that hampers the possibility to control for individual non observable heterogeneity. We notice an improvement of physical health conditions in regions characterised by technological developments in the green realm. We observe a negative relation between healthy mental conditions and technological development in the twin domains. When looking at aggregate results the detrimental relation between green technology and mental health disappears. To reiterate these results should be taken with caution since technological output (patenting) does not reflect actual adoption or use. They may derive from health conditions in innovation hubs whose compositional features (e.g., urban concentration, sorting into innovative areas, local cost-of-living or work intensity) differ from those areas actually using technologies.

Table A1 1 – Individual-level estimates using technological embeddedness: SHARE.

| | Poor Physical Health | | | Poor Mental Health | | |
|------------------------|----------------------|------------------|--------------------|--------------------|----------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Digital patents | -0.095 (0.103) | | | -0.120 (0.184) | | |
| Green patents | | 0.021 (0.064) | | | -0.371*** (0.109) | |
| Twin patents | | | -0.369* (0.205) | | | -0.036 (0.363) |
| Observations | 83,515 | 99,435 | 73,800 | 83,515 | 99,435 | 73,800 |
| R-squared | 0.670 | 0.650 | 0.671 | 0.587 | 0.577 | 0.587 |

Notes: All estimates control for individual age and employment status, regional GDP p.c., population and share of working population with tertiary education (NUTS-1 level). Estimates include individual and year fixed effects. Standard errors, in parentheses, are clustered at the NUTS1 level. Statistical significance: * 10%; ** 5%; *** 1%.



Table A1 2 – NUTS-1 level estimates using technological embeddedness: SHARE.

| | Poor Physical Health | | | Poor Mental Health | | |
|------------------------|----------------------|------------------|-------------------|--------------------|---------------------|------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Digital patents | -0.340 (0.220) | | | -0.730 (0.592) | | |
| Green patents | | 0.011 (0.135) | | | -0.682** (0.326) | |
| Twin patents | | | -0.027 (0.399) | | | 0.079 (1.112) |
| Observations | 204 | 233 | 173 | 204 | 233 | 173 |
| R-squared | 0.841 | 0.823 | 0.872 | 0.913 | 0.916 | 0.923 |

Notes: Patents are expressed as the total number of patents over total residence population in each NUTS1-year cell. All estimates control for individual age and employment status, regional GDP p.c., population and share of working population with tertiary education (NUTS-1 level). Estimates include individual and year fixed effects. Standard errors, in parentheses, are clustered at the NUTS1 level.
Statistical significance: * 10%; ** 5%; *** 1%.

Table A1 3 – Individual-level estimates using technological embeddedness: EHIS.

| | Poor Physical Health | | | Poor Mental Health | | |
|------------------------|----------------------|----------------------|------------------|--------------------|---------------------|---------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Digital patents | -0.001 (0.035) | | | -0.028 (0.047) | | |
| Green patents | | -0.044*** (0.014) | | | 0.122*** (0.020) | |
| Twin patents | | | 0.065 (0.105) | | | 0.937*** (0.143) |
| Observations | 209,857 | 209,857 | 190,929 | 209,857 | 209,857 | 190,929 |
| R-squared | 0.066 | 0.066 | 0.062 | 0.017 | 0.018 | 0.019 |

Notes: Patents are expressed as the total number of patents over total residence population in each NUTS1-year cell. All estimates include individual controls for 5 age classes (20-29, 30-44, 45-59, 60-69, 70+) and employment status, along with regional GDP p.c., population and share of working population with tertiary education (NUTS-1 level). Standard errors, in parentheses, are clustered at the NUTS1 level.
Statistical significance: * 10%; ** 5%; *** 1%.

Table A1 4 – NUTS-1 level estimates using technological embeddedness: EHIS.

| | Poor Physical Health | | | Poor Mental Health | | |
|------------------------|----------------------|----------------------|-------------------|--------------------|------------------|-------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Digital patents | -0.088 (0.077) | | | -0.087 (0.244) | | |
| Green patents | | -0.091*** (0.033) | | | 0.104 (0.073) | |
| Twin patents | | | -0.152 (0.271) | | | 0.896* (0.459) |
| Observations | 56 | 56 | 56 | 56 | 56 | 56 |
| R-squared | 0.300 | 0.345 | 0.328 | 0.227 | 0.255 | 0.315 |



Notes: Patents are expressed as the total number of patents over total residence population in each NUTS1-year cell. All estimates include individual controls for 5 age classes (20-29, 30-44, 45-59, 60-69, 70+) and employment status, along with regional GDP p.c., population and share of working population with tertiary education (NUTS-1 level). Standard errors, in parentheses, are clustered at the NUTS1 level. Statistical significance: * 10%; ** 5%; *** 1%.



Appendix II. Additional estimates at NUTS1 level

Table A2 1 - NUTS-1 level estimates: SHARE.

| | Poor Physical Health | | | Poor Mental Health | | |
|-----------------------|----------------------|---------------------|-------------------|--------------------|-------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share of Digital Jobs | -0.777 (0.974) | | | -2.229 (2.647) | | |
| Share of Green Jobs | | 2.680*** (0.892) | | | -2.322 (2.488) | |
| Share of Twin Jobs | | | -2.036 (2.320) | | | -15.289** (6.195) |
| Observations | 238 | 238 | 238 | 238 | 238 | 238 |
| R-squared | 0.830 | 0.839 | 0.830 | 0.897 | 0.897 | 0.901 |

Notes: All estimates control for regional GDP p.c., population and share of working population with tertiary education. Estimates include NUTS1 and year fixed effects. Standard errors, in parentheses, are clustered at the NUTS1 level. Statistical significance: * 10%; ** 5%; *** 1%.

Table A2 2 - NUTS-1 level estimates: EHIS.

| | Poor Physical Health | | | Poor Mental Health | | |
|-----------------------|----------------------|-------------------|-------------------|--------------------|----------------------|----------------------|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Share of Digital Jobs | 0.377* (0.211) | | | 0.792 (0.567) | | |
| Share of Green Jobs | | 0.733* (0.403) | | | -2.708*** (0.701) | |
| Share of Twin Jobs | | | 1.850* (1.012) | | | -4.491*** (1.509) |
| Observations | 59 | 59 | 59 | 59 | 59 | 59 |
| R-squared | 0.296 | 0.297 | 0.307 | 0.241 | 0.321 | 0.282 |

Notes: All estimates control for regional GDP p.c., population and share of working population with tertiary education. Estimates include NUTS1 and year fixed effects. Standard errors, in parentheses, are clustered at the NUTS1 level. Statistical significance: * 10%; ** 5%; *** 1%.

