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The twin innovation transitions of European regions

Giorgio Fazio[a,b], Sara Maioli[a,c] and Nirat Rujimora[a]

ABSTRACT

We investigate the spatial distributions and transitions of European regions' innovative orientation to information and communication technology (ICT), green technology or twin technologies. Using a transition probability approach and spatial methods, we estimate the probability of regions becoming innovative in either or both technologies and assess the role of spillovers.

ICT-oriented regions are more likely to make a twin transition than the green-oriented regions, and non-innovative regions are likely to stay so. Weak and strong twin innovators are persistently clustered in space, with few positive spillovers on single innovators. Innovation policies should avoid supporting green innovation without also supporting ICT innovation and aim at increasing positive spatial spillovers.

KEYWORDS

Twin transition; regional disparities; regional innovation; exploratory spatio-temporal data analysis (ESTDA)

JEL O31, O33, R11, R58

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1. INTRODUCTION

The pandemic has accelerated the efforts of governments from around the world, including Europe, to foster the transition of the economy towards both digitalisation and environmental sustainability.[1] While, ideally, the two agendas should overlap, leading to the so-called 'twin transition' of the economy, in reality digitalisation and transition to net zero could also conflict with each other. On one hand, digital technologies create new business models, provide workers with new skills, increase productivity (Shahnazi, 2021) and offer clean technology solutions that enable the green transition (Horner et al., 2016; Nilsson et al., 2018). On the other, they may be energy intensive, use scarce resources and create waste (IEA, 2017; Røpke, 2012). Hence, the extent to which digitalisation helps or not in the green transition has been part of an extensive debate (see, Avgerinou et al., 2017; Coroama and Hilty, 2014; Lange et al., 2020; Lange and Santarius, 2020; OECD, 2015, 2017; Schwartz et al., 2020; Strubell et al., 2019). In recent interventions, European policymakers have addressed the problem by highlighting the digital sector both as a source of solutions and as a target for carbon footprint reduction (COM, 2020a, 2021, 2022).

Uncovering the relationship between the two is clearly important and a growing literature has recently concentrated the efforts in this direction. Some authors have emphasised the importance of non-digital non-green technologies and green-complementary technologies for the development of green technologies (Barbieri et al., 2021; Montresor & Quatraro, 2020). Others have argued how technologies, like artificial intelligence (AI), exert a positive effect on the development of green technologies only if regional green specialisation pre-exists, and a negative effect otherwise (Cicerone et al., 2022). A similar role for AI on green technology is found at the firm-level (Montresor & Vezzani, 2023).

Understanding the above relationship, however, also needs to consider the role of heterogeneity and polarisation of knowledge across space, along the lines of the vast innovation and regional science literature on the role played by regional embeddedness, regional innovation systems and spatial externalities, or spillovers. Yet, there is a paucity of studies looking at the role of regional spatial spillovers and how regions transition towards becoming twin innovators, especially in relation to their starting innovative position.

Hence, this paper contributes to this area of research by looking at the intersection between twin innovation and

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regional studies to fill the gap in the evidence base on the structural shift towards digitalisation and sustainability at the European regional level. With this aim in mind, we focus on the information and communication technology (ICT) and green innovative orientation of 259 European regions over the period 1977-2018.[2] Specifically, we look at both the innovative orientation and specialisation of regions and use spatial statistics methods to answer the following three questions and test the related hypotheses. Are ICT-innovation-oriented regions or green-innovation-oriented regions more likely to transition towards becoming twin-innovation oriented? Does the distribution of twin-innovators depend on spatial proximity or socio-economic similarity? Is the probability of becoming a twin specialised region (or not) over time influenced by spatial proximity or socio-economic similarity?

To answer the above questions, we first measure and map the innovative orientation of regions in these technologies using an indicator of 'revealed technological advantage' along the lines of Cicerone et al. (2022). Then, we compute the unconditional Markov transition probabilities that regions change their innovative orientation from one technology to the other or both (twin transition). Finally, we look at the role of spillovers on the distribution of twin innovative orientation and specialisation of regions and on the temporal transitions of the twin-orientation of regions by performing both static and dynamic exploratory spatial data analyses (ESDA and ESTDA), where we condition transition probabilities on the geographical neighbours and on the role of socio-economic similarity with other regions emphasised by previous regional literature (Cartone et al., 2022; Conley & Topa, 2002; Ertur & Koch, 2007; Keller, 2002; Rodríguez-Pose & Di Cataldo, 2015). Finally, we also obtain inference on the impact of super-innovator regions. To the best of our knowledge, this is the first study characterising the spatio-temporal twin-innovation transitions of regions.

Several interesting results emerge from the analysis. First, we find that ICT-innovative oriented regions are more likely to become twin-innovative oriented than green innovative-oriented regions. Second, non-innovative regions are highly likely to remain so. Furthermore, we find evidence that twin innovative regions are spatially clustered and tend to remain so over time. We find weak evidence on the role of socio-economic similarity. Removing from the sample regions that are super-innovators and highly specialised regions strengthens the evidence on spatial dependence, indicating that these regions may be less influenced by spatial spillovers and 'play more on their own'. Finally, the above-mentioned spatial association is also reflected in the local indicators of spatial association (LISA) Markov chain transition probabilities, where a high degree of spatial persistence can be observed at the high and low end of the twin-innovative orientation of regions. For the intermediate cases, regions are more likely to be 'pulled down' by neighbours toward less twin-innovation oriented clusters than 'lifted up' toward more twin-innovation oriented clusters. On average, the probability of a region transitioning from low to high twin innovative orientation does not seem much related to the orientation of geographical and socio-economic neighbours.

The rest of the paper is organised as follows. The next section provides a discussion of the related literature to give the background for the research questions addressed in the paper. Section 3 presents the empirical strategy, including a description of the data and the methods of analysis. This is followed by the discussion of the results in Section 4. Finally, Section 5 summarises our conclusions and discusses the policy implications of our work.

2. RELATED LITERATURE

2.1. Green ICT vs ICT for green

The research on digital and green innovation is related to the earlier concepts of 'Green ICT' and 'ICT for Green' (Faucheux & Nicolaï, 2011). The first refers to the environmental efficiency of the ICT sector and the second to the ICT role on greening other sectors. According to some authors, ICTs may clash with the twin transition of the economy, as digitalisation uses electricity, and many ICTs are resource-intensive (including the exploitation of rare materials) and create waste (Lange & Santarius, 2020). The debate in the literature is open. For the case of data centres, for example, Coroama and Hilty (2014) and Avgerinou et al. (2017) find that they greatly increased their energy efficiency and Salahuddin and Alam (2016) and Koot and Wijnhoven (2021) find, instead, that data centres have increased their energy consumption and predict they will keep increasing it in the future. For new technologies, such as AI and natural language processing (NLP), Strubell et al. (2019) argue that they are environmentally unfriendly and Schwartz et al. (2020), instead, that they reduce energy consumption.

According to the ICT for Green hypothesis, ICTs can drive green innovation in non-ICT sectors by facilitating the efficient flow of information and knowledge among various players in the economic system (Zhang & Wang, 2019). Digital technologies can also enable the green transition by reducing the carbon footprint through the virtualisation of production and consumption (Horner et al., 2016; Nilsson et al., 2018), especially if digital technologies are energy-efficient and circular (Muench et al, 2022). Other studies (Lange et al., 2020; OECD, 2015, 2017) recognise that digitalisation is part of the structural change process where economic activity shifts away from agriculture and manufacturing towards services, hence reducing the energy intensity of the economy. This reduction, however, happens only if the new digitally enabled services are less energy intensive than traditional services (Mulder et al., 2014). In general, such reduction does not take place at the same speed across countries (EIT, 2022).

A fast-growing strand of papers has started investigating the above controversial relationship, and the role of ICT for Green, along the lines of the literature on technology (Acemoglu et al., 2016; Pichler et al., 2020; Taalbi, 2020), specifically the relationship between green technologies and non-green non-digital technologies

(Barbieri et al., 2021; Montresor & Quatraro, 2020). Montresor and Quatraro (2020) uncover that key enabling technologies (KETs) support the acquisition of new technological specialisation in green technology and that pre-existing knowledge of non-green technologies has a larger impact on green technologies than pre-existing green knowledge. Barbieri et al. (2021) use worldwide patent data and corroborate that green technology is driven by both complementary non-green patents and other subclasses of green patents.

Whether the development of green technologies significantly benefits from AI technologies has been investigated by Cicerone et al. (2022), who find that local AI knowledge helps regions keep their green technology specialisation, but only if they already have it, which may be due to the fact that both AI and green technologies are still in their infancy. However, Montresor and Vezzani (2023) investigate within-firm relationships and argue that the impact of digital technologies on firm's green innovation is mainly driven by AI technologies, but when digital technologies are unpacked this relationship depends selectively on the type of technology.

Our study builds on this growing strand of the literature by considering whether technological innovation interdependencies at the regional level are associated with structural shifts towards both digitalisation and sustainability. In particular, we ask whether ICT-innovation oriented regions or green-innovation oriented regions are more likely to transition towards becoming twin-innovation oriented.

2.2. The role of space

Knowledge creation is heterogenous across space and, often, geographically polarised (Christ, 2010; Kemeny et al., 2022). A vast innovation literature has emphasised the role of regional embeddedness and regional innovation systems for the dynamics and spatial distribution of innovation (Aronica et al., 2022; Cooke, 1992; Cooke et al., 1997; Franco et al., 2014; Quatraro, 2009; Rodríguez-Pose & Crescenzi, 2008). Additionally, the importance of spillovers is emphasised in the regional science literature (Boschma, 2005; McCann, 2007). The existence of externalities due to spatial proximity makes the diffusion of technology geographically localised (Keller, 2002) and, as theoretically derived by Ertur and Koch (2007), a country's stock of knowledge spills on to other countries with an intensity which decreases with geographical distance. While geographical distance may already capture cultural similarity and knowledge flows via trade, other types of proximity may also affect cross-regional learning processes, e.g., social (Boschma, 2005; Ertur & Koch, 2007), ethnic (Conley & Topa, 2002), industrial (Cartone et al., 2022), institutional (Rodríguez-Pose & Di Cataldo, 2015), social norms (Corradini, 2022) and social capital (Fazio & Lavecchia, 2013; Kobeissi et al., 2023). Investigations usually confirm the importance of spatial interactions but with stronger evidence for the role of geography (Cartone et al., 2022; Conley & Topa, 2002). Along the lines of the above literature, in this paper we consider the role of spatial dependence, through geographical and socio-economic similarity, for the twin-innovative oriented transitions of European regions.

3. DATA, VARIABLES AND EMPIRICAL STRATEGY

3.1. Dataset and variables

Our study is based on 259 regions from 28 European Union countries observed over 42 years between 1977 and 2018.[3] In line with other papers, we measure innovation as the count of patents from the European Patent Office sourced from the OECD REGPAT (Maraut et al., 2008; OECD, 2022). Usual caveats apply when measuring innovation via patents, but, on balance, this approach makes it easier to compare our results with previous literature.[4] Regional data on ICT, environmental and total patents were reconstructed at the Eurostat NUTS2 level of aggregation (originally available at NUTS3 level) to bring the analysis in line with the level considered by EU cohesion policies and to avoid an excessive number of zeros in the data.[5]

In Table A2, Figure A1, and Figure A2 in the Appendix in the online supplemental data, we present some descriptive statistics, frequency distributions and maps of ICT and green patents at the beginning, middle and end of the period. For both types of patents, the median is zero at the beginning and becomes positive later. While many regions do not record a single patent, few regions record many patents. Overall, the evidence is that ICT and green patents are unequally distributed in space, in line with the previous evidence on other technological patents (Christ, 2010),[6] but there is also increasing diffusion/decreasing spatial concentration of ICT and green patents over time, as it can be seen from the decreasing coefficient of variation.

Next, following Cicerone et al. (2022), we compute three indicators of 'innovative orientation' (or 'revealed technological advantage', RTA) of region r in country c at time t in ICT, green and both (twin) technologies, as follows:[7]

$$Green_{rct} = \frac{Green\ Patents_{rct} / \sum_r Green\ Patent_{rct}}{Total\ Patents_{rct} / \sum_r Total\ Patent_{rct}} \quad (1)$$

$$ICT_{rct} = \frac{ICT\ Patents_{rct} / \sum_r ICT\ Patent_{rct}}{Total\ Patents_{rct} / \sum_r Total\ Patent_{rct}} \quad (2)$$

$$Twin_{rct} = \frac{Twin\ Patents_{rct} / \sum_r Twin\ Patent_{rct}}{Total\ Patents_{rct} / \sum_r Total\ Patent_{rct}} \quad (3)$$

where $Twin\ Patents = (Green\ Patents + ICT\ Patents)$. Cicerone et al. (2022) then dichotomise the above RTA into 'innovation specialisation' indicators based on whether the RTA is larger than one.[8] Here, in the first part of our analysis, we look at transitions from one innovative orientation to the other (or both), and do not dichotomise indicators (1) to (3). We use, instead, as alternative thresholds to denote a transition, the national median, the mean and one. The latter returns the (transition) probability of specialisation in each or both technologies similarly to Cicerone et al. (2022). Our approach, however, allows us to also consider outliers, e.g., regions with exceptional innovative orientation, or 'super-innovators' (largely exceeding one).

Later, however, we focus on twin innovation and consider both twin innovative orientation and a twin specialisation indicator, defined as follows:

$$Twin\_Specialisation_{rct} = \begin{cases} 1 \; if \; Green_{rct} > 1 \; and \; ICT_{rct} > 1 \\ 0 \; otherwise \end{cases} \tag{4}$$

Also, differently from Cicerone et al. (2022), we compute the above regional indicators in relation to the national values rather than the global values, as they do. This allows us to partly 'filter out' the effect of national innovation systems that we would not otherwise take into account in our approach and may well have an effect on the differences across countries. As a robustness check, however, we have replicated the analysis without this correction and results are substantially unchanged (see Appendix D). Also, while we are not explicitly looking at the regional determinants of innovation, the transition probability and spatio-temporal analysis of one innovative orientation will be conditional on the regional outcomes in terms of the other type of technology and the innovation orientation of other regions. Still, we wish to emphasise that our approach does not allow us to make claims that would require controlling for endogeneity to unmask the effects of policy interventions over the observed period.

The distributions of the above indicators are reported in Figure A3, where it can be observed how, for all innovative measures, the centre of the distribution moves rightward whilst the number of regions with zero innovative orientation decreases and that of specialised regions increases over time. Interestingly, the distribution of $Twin_{rct}$ seems to be dominated by that of ICT_{rt}. Figure A4 in the Appendix also shows the distributions in 1977, 1997 and 2018 when 'super-innovators', i.e., regions with innovative-orientation above two, are excluded.

3.2. Unconditional (a-spatial) transition probabilities

We first look at the single and twin transitions of regions calculating *unconditional* Markov chain probabilities of regions transitioning from one innovative orientation to the other or both. Following Ibe (2009, pp. 56–58), we define P^m as a discrete-time Markov chain matrix with m transition steps, i.e., in our case the 41 steps from 1977 to 2018. Since the Markov transition process is 'memoryless' and 'time-homogenous', we can break our analysis into sub-periods and gauge the existence of structural changes over time (two 20-year periods in our case).

The ijth entry of the matrix, $p_{ij}(m)$, gives the probability of transitioning from state i to state j after m steps. If the number of transitions between i and j is given, the probability can be defined as (Bickenbach & Bode, 2003):

$$p_{i,j}(\mathrm{m}) = \frac{r_{i,j}}{\sum_{j=1}^{k} r_{i,j}} \tag{5}$$

where r_{ij} is the number of transitions from state i to state j, $\sum_{j=1}^{k} r_{i,j}$ is the row summation of total transitions from state i to all state j, and k is the last column of the transition matrix. Moreover, as m approaches infinity, the steady-state probability, π, is given by:

$$\pi P^m = \lambda \pi = \pi \tag{6}$$

where π is a row eigenvector, λ is an eigenvalue equal to one, P^m is the m-steps transition matrix, and $\sum_{j=1}^{k} \pi_j = 1$. Then, element π_j of π denotes the long-run probability of a region transitioning into state j irrespective of the starting state (Ibe, 2009, pp. 61–63).

We graphically exemplify our approach in Figure 1, where the $Green_{rct}$ and ICT_{rct} scores are on the horizontal and vertical axis, respectively, and the four quadrants are drawn by considering the yearly median of the RTAs (as explained previously, in the analysis we also use the mean and one).

Going anti-clockwise 'Q.1: HG&HI' indicates the high green- and high ICT-innovative oriented regions, or twin innovators; 'Q.2: LG&HI' refers to the low green- but high ICT-innovative oriented regions; 'Q.3: LG&LI' denotes the regions with low innovative orientation in both green and ICT technologies; finally, 'Q.4: HG&LI' indicates those regions with high green-innovative orientation but low ICT-innovative orientation. The arrows capture transition in the innovative orientation of regions. Horizontal transitions capture changes in green but not ICT orientation, vertical transitions capture changes in ICT but not green orientation, and diagonal transitions capture the twin transitions. For example, $p_{3,1}(m)$ indicates the probability that a low green/low ICT region will transition to high green/high ICT after m steps.

3.3. Spatial dependence, twin innovative-orientation and spatial transitions

We are interested in assessing the role of spillovers in determining the twin innovative orientation and transitions of regions. We thus concentrate on the $Twin_{rct}$ and $Twin\_Specialisation_{rct}$ indicators and perform static and dynamic exploratory spatial data analyses (ESDA and ESTDA). We use both geographical and socio-economic weight matrices as alternatives to assess the role of different types of proximity.[9] For robustness, we use distance-based weight matrices (inverse Euclidean distance between centroids from the Eurostat GISCO database, 10-nearest-neighbours (10NN) and 5-nearest-neighbours (5NN)) and contiguity-based matrices (queen and rook). All matrices are row-standardised to obtain neighbour averages (converted into binary for the case of (local)

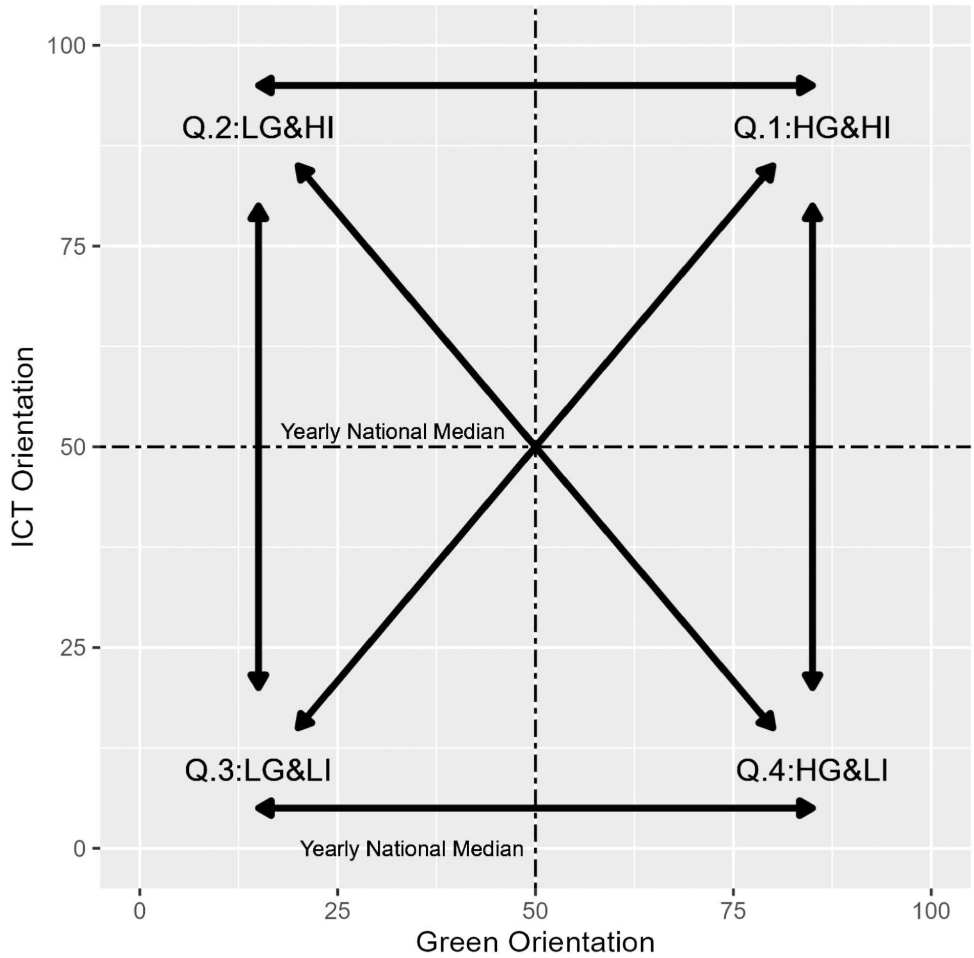

Figure 1. Twin transition.
Note: Q.1 = HG&HI (high green and high ICT orientation), Q.2 = LG&HI (low green but high ICT orientation), Q.3 = LG&LI (low green and low ICT orientation), Q.4 = HG&LI (high green but low ICT orientation). The arrows also indicate changes of twin orientation where horizontal transitions capture changes in green but not ICT orientation, vertical transitions capture changes in ICT but not green orientation. And finally, diagonal transitions capture changes in both (twin transition).

join count statistics, see below). Socio-economic proximity is based on the row-standardised inverse Euclidean distance (Cartone et al., 2022; Conley & Topa, 2002) of a purposefully constructed indicator of socio-economic quality. The latter is measured in two alternative ways: (1) the quality of government (QoG) index by Charron et al. (2022), similarly to Barbero et al. (2022) and Rodríguez-Pose and Di Cataldo (2015) and (2) the first component of a time-varying principal component analysis of four variables: life expectancy, HRST (employment rate in science and technology), NEET rate (young people not in employment and not in education and training – aged 15–29), rate of leavers from education and training (see Appendix C for detail of weight construction). When we use the socio-economic quality matrix, we use a reduced sample due to data availability (more details in Appendix C).

We then begin by assessing the spatial correlation via Global Moran's I statistic (Cliff & Ord, 1973, pp. 11–21):

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (7)$$

where n is number of regions, w_{ij} is a weight matrix between region i and region j where $i \neq j$, and x_i and x_j are $Twin_{rct}$ with $r = i,j$. Global Moran's I gives the overall degree of linear association between a region and its neighbours. Larger positive values indicate stronger clustering and larger negative values indicate stronger dispersion of the twin innovative oriented regions. The null hypothesis of no spatial autocorrelation is tested against its alternative. For the binary measure of $Twin\_Specialisation_{rct}$, we calculate the join count statistic (Cliff & Ord, 1973, p. 23):

$$BB = \frac{1}{2}\sum_{i}\sum_{j} w_{ij}x_i x_j \quad (8)$$

where, w_{ij} is a binary weight matrix between region i and region j where $i \neq j$, and x_i and x_j are $Twin\_Specialisation_{rct}$ with $r = i,j$. If region i and region j both have $Twin\_Specialisation_{rct} = 1$, their corresponding BB is equal to one which implies clustering of the twin innovation technologies and zero otherwise.

Next, we calculate the local indicators of spatial association (LISA), in particular the Local Moran's I, defined as

(Anselin, 1995, p. 99):

$$I_i = \frac{(x_i - \bar{x})}{\sum_{i=1}^{n}(x_i - \bar{x})^2/n}\sum_{j=1}^{n} w_{ij}(x_j - \bar{x}) \tag{9}$$

The null hypothesis of no spatial association of each region can be tested to infer the statistical significance of a spatial pattern for each region i. It should be noted that Local Moran's I and Global Moran's I are linked (see Anselin, 1995). Figure 2 and its corresponding note help with the interpretation of the global and Local Moran's I statistics. We also calculate the local join count statistic (Anselin & Li, 2019) for $Twin\_Specialisation_{rct}$:

$$BB_i = x_i \sum_j w_{ij}x_j \tag{10}$$

This is a local count statistic of any $x_i = 1$ with a count of neighbours where $x_j = 1$. This indicator assesses if a twin-innovation specialised region is surrounded by more twin-innovation specialised regions than under spatial randomness or no spatial autocorrelation.

Finally, we use exploratory spatio-temporal data analysis (ESTDA) methods to assess the spatial dynamics and spillovers of the twin-innovative orientation of regions through geographical and socio-economic proximities (this approach requires a continuous variable and cannot be used for the specialisation indicators). We follow Rey (2001) to compute the LISA Markov transition probability matrix for $Twin_{rct}$ as an outcome variable. Figure 2 graphically explains this approach using a Moran's scatterplot with $Twin_{rct}$ on the horizontal axis and its neighbour's value on the vertical axis. The graph is divided into four quadrants using the yearly national median as threshold for the transitions (later we also use the mean for robustness).

Going anti-clockwise, 'Q.1: HH' indicates the high twin-oriented regions with high twin-oriented neighbours; 'Q.2: LH' indicates the low twin-oriented regions with high twin-oriented neighbours; 'Q.3: LL' denotes low twin-oriented regions with low twin-oriented neighbours; and 'Q.4: HL' indicates high twin-oriented regions with low twin-oriented neighbours. Having allocated each region into one of these quadrants, we compute the LISA (Markov) transition probability matrix by applying Equation (5). In this case, $p_{3,4}(m)$, denotes the probability of transitioning from 'Q.3: LL' to 'Q.4: HL' after m steps, i.e., from low twin-orientation to high twin-orientation while the neighbours remain low twin-oriented. Equation (5) is also applied for steady-state probability in this context.

Finally, two-sided hypothesis tests, i.e., the null hypothesis of no spatial autocorrelation, of Global Moran's I, join count statistics, Local Moran's I, and local join count statistics, are all permutation-based tests with pseudo-P-value. This approach is more reliable for spatial data which is not normally distributed. Tests for Local Moran's I, and local join count statistics rely on the Benjamini-Hochberg method to derive the corrected P-value, which mitigates the problem of multiple significance tests by controlling for the 'false discovery rate'.

4. RESULTS

4.1. Unconditional transitions

Figure 3 provides maps of the position of regions in the quadrants of Figure 1 at three different points in time and using three different thresholds: the annual mean and median of ICT and green innovative orientation of regions and the value of one (values above one represent specialisation). From these maps, it is evident how the spatial distribution of ICT, green or twin innovative-oriented regions evolves from a strong concentration at the beginning of the sample in 1977 of highly innovative-oriented regions in central and northern Europe to greater dispersion later in the sample of all innovative types (see also the total number of patents in Figure A2 in Appendix A). Such an observation is irrespective of the threshold, even though, naturally, the identification of the innovative orientation and specialisation of regions will change. This pattern is in line with previous studies also showing decreasing concentration (Christ, 2010; Kemeny et al., 2022).[10]

Moreover, some degree of volatility in the innovative orientation of regions emerges from the data (see, also, Figures A5 and A6 for the regional transition corresponding to Figure 1). Regions can switch their innovative orientation, become less innovative-oriented or specialised, or become twin innovative oriented/specialised. However, those starting from a twin innovative-oriented status seem to struggle to maintain such status.

Next, we quantify the unconditional probabilities of these changes. Table 1 reports the Markov chain transition probabilities (and total transitions in parentheses) associated with the transitions between the four quadrants in Figure 1 for two sub-periods and the three thresholds.[11] The results show how regions starting from LG&HI (ICT oriented) are more likely to become twin-oriented (move to HG&HI) than regions starting from green orientation HG&LI (around 25% versus 10%). This confirms the evidence purported in previous studies that previous ICT orientation is more likely associated with twin orientation, i.e., 'ICT for green'. This result is confirmed across periods and thresholds. More importantly, regions starting from LG&HI could equally become twin-oriented (HG&HI) and lose ICT orientation (move to LG&LI), with around 20% probability. In contrast, regions in HG&LI are more likely to transition to lower green innovative-orientation, i.e., LG&LI, than become a twin innovative-oriented region (HG&HI), with ~35% versus 10% probability. This evidence addresses our first question and is in line with the hypothesis that green oriented innovators are more likely to lose their status than become twin-oriented. ICT-oriented innovators, instead, are equally likely to become twin-oriented or lose their ICT-oriented status.

The east–west diagonal indicates the probability of persistence, i.e., keeping the same innovative orientation. These probabilities are not particularly high, confirming (and quantifying) the above-mentioned volatility in Figure 3 and Figure A6. There is, however, a substantial degree of persistence of low innovative-oriented regions

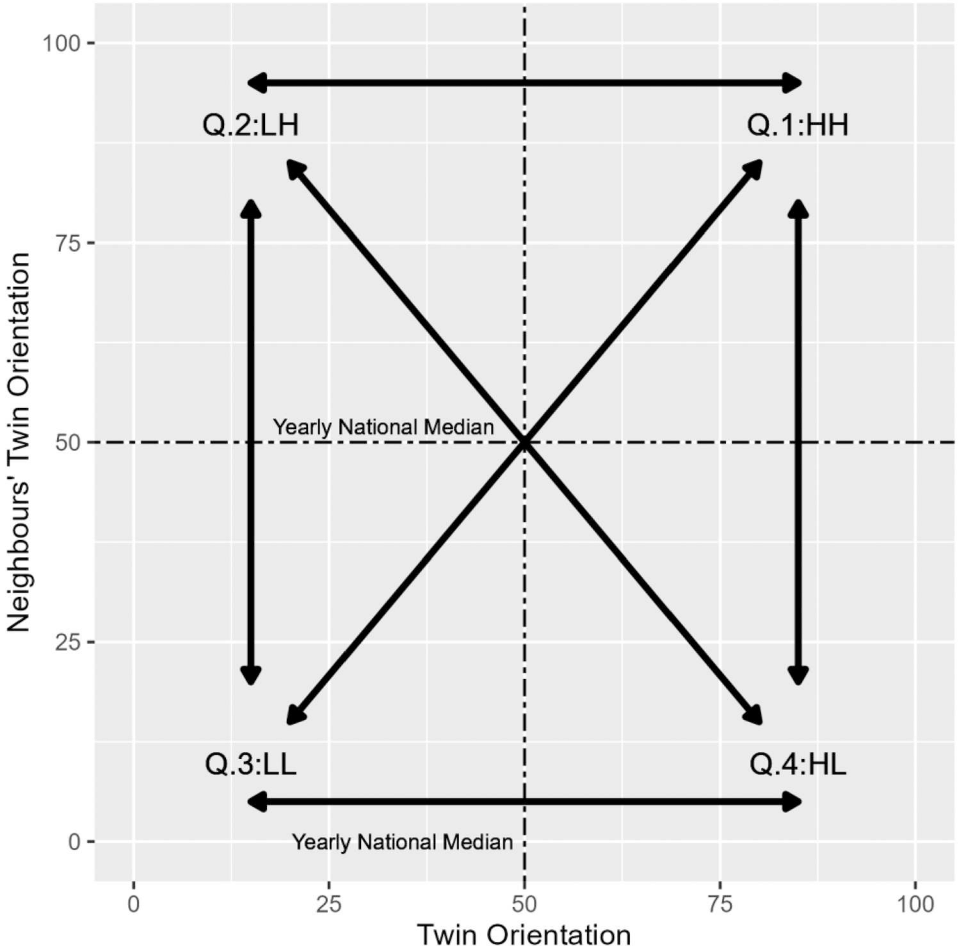

Figure 2. Moran's scatterplot (LISA Markov transition of twin orientation).
Note: Q.1 = HH (high region's twin and high neighbours' twin orientation), Q.2 = LH (low region's twin but high neighbours' twin orientation), Q.3 = LL (low region's twin and low neighbours' twin orientation), Q.4 = HL (high region's twin but low neighbours' twin orientation). Regions with positive Local Moran's I are in Q.1: HH and Q.3: LL (indicating clusters), and in Q.2: LH and Q.4: HL for regions with negative Local Moran's I (indicating dispersion). The arrows also indicate changes of twin orientation where horizontal transitions capture changes in region's twin but not neighbours' twin, vertical transitions capture changes in neighbours' twin but not region's twin and finally, diagonal transitions capture changes in both.

(LG&LI) across all panels, with around 60–70% probability of starting from low green and low ICT innovative-orientation and not transitioning into any other (better) quadrant. This suggests that lagging innovators struggle to escape from being trapped in such a position. Indeed, the steady-state probabilities show that around 40% of European regions would be stuck in the LG&LI position in the long term, irrespective of the starting position. Drawing a parallel with the literature on the left-behind places (Pike et al., 2023; Rodríguez-Pose et al., 2023), these regions can be considered as 'left behind' in the innovation process. Along the lines of that literature, it would be worth investigating why they are not subject to internal innovation nor spillovers.

Starting from the HG&HI quadrant, regions have ~30% probability of worsening their Green innovative-orientation while keeping high ICT innovative-orientation (transitioning into LG&HI), which is double the probability of moving in the opposite direction (~15% of moving into HG&LI). Hence, it is easier to retain a knowledge advantage in ICT than green technologies. Starting from LG&LI, regions have only slightly different probabilities of becoming ICT innovation-oriented (around 10%) or green innovation-oriented (around 15%). Our results are generally robust to using a smaller time window of 5-years (see Table A5); the probabilities of transitioning into the HG&HI quadrant from LG&LI quadrant are slightly higher in the 2014–2018 period, in line with the evidence of greater regional dynamism in Figure 1.[12]

4.2. Twin innovative orientation, spatial dependence and transitions

We begin the ESDA of twin innovative oriented regions (those with innovation above the median) by estimating the spatial autocorrelation and spatial local association with the Global and Local Moran's I statistics. Join count and local join count statistics are also provided.

Table 2 reports the Global Moran's statistics (Equation 6) of $Twin_{rct}$ in Panel A and Panel B, and join count statistics (Equation 7) of $Twin\_Specialisation_{rct}$ in Panel C for some representative years based on both geographical and socio-economic weights and for a smaller

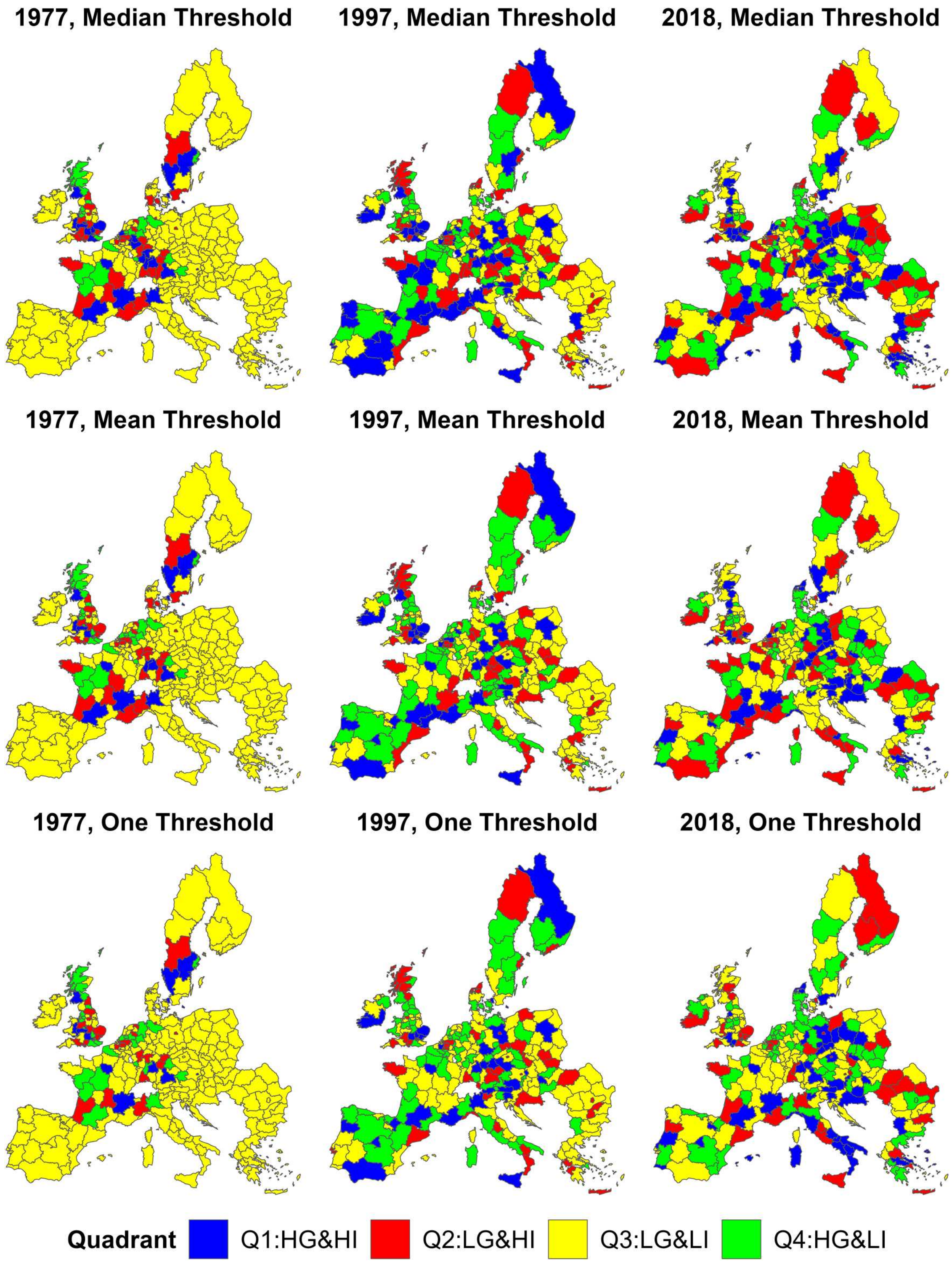

Figure 3. Evolution of regions' quadrant in 1977, 1997 and 2018.

Note: $n = 259$. Q.1 = HG&HI (high green and ICT orientation), Q.2 = LG&HI (low green but high ICT orientation), Q.3 = LG&LI (low green and ICT orientation), Q.4 = HG&LI (high green but low ICT orientation). 'Mean Threshold' denotes the quadrants defined by the annual national mean for each orientation. 'Median Threshold' denotes the quadrants defined by the annual national median for each orientation. 'One Threshold' denotes the quadrants defined by a value of one, which represents the benchmark of no specialisation.

set of regions due to data availability). Panel A presents statistics calculated using the original sample and Panel B after removing the super-innovators.

We can see how there is evidence of positive and statistically significant spatial autocorrelation, or clustering, between twin innovative oriented regions based on the 10NN, 5NN, queen and rook matrices. The correlations in panel A, however, tend to first decrease over time, becoming statistically insignificant in the mid-period and then significant again at the end of the period.

Table 1. Transition probabilities of Green and ICT orientations (1977–2018).

Panel A: median-threshold quadrant								
	Panel A1:1977–1997				Panel A2:1997–2018			
Quadrant	HG&HI (Q.1)	LG&HI (Q.2)	LG&LI (Q.3)	HG&LI (Q.4)	HG&HI (Q.1)	LG&HI (Q.2)	LG&LI (Q.3)	HG&LI (Q.4)
HG&HI (Q.1)	0.49 (478)	0.27 (258)	0.11 (105)	0.13 (129)	0.55 (703)	0.25 (315)	0.09 (118)	0.11 (141)
LG&HI (Q.2)	0.26 (265)	0.40 (407)	0.21 (212)	0.12 (121)	0.22 (296)	0.50 (655)	0.18 (232)	0.10 (136)
LG&LI (Q.3)	0.05 (125)	0.11 (260)	0.69 (1585)	0.14 (325)	0.08 (127)	0.14 (222)	0.57 (928)	0.21 (348)
HG&LI (Q.4)	0.14 (130)	0.12 (107)	0.33 (304)	0.41 (369)	0.14 (166)	0.10 (126)	0.27 (332)	0.49 (594)
Steady-state	0.20	0.20	0.41	0.18	0.24	0.24	0.29	0.22
Panel B: mean-threshold quadrant								
	Panel B1:1977–1997				Panel B2:1997–2018			
Quadrant	HG&HI (Q.1)	LG&HI (Q.2)	LG&LI (Q.3)	HG&LI (Q.4)	HG&HI (Q.1)	LG&HI (Q.2)	LG&LI (Q.3)	HG&LI (Q.4)
HG&HI (Q.1)	0.41 (287)	0.30 (213)	0.15 (105)	0.14 (99)	0.45 (430)	0.31 (291)	0.12 (116)	0.12 (114)
LG&HI (Q.2)	0.20 (214)	0.45 (467)	0.24 (248)	0.11 (117)	0.21 (280)	0.51 (680)	0.18 (244)	0.10 (127)
LG&LI (Q.3)	0.05 (118)	0.11 (280)	0.70 (1770)	0.15 (368)	0.07 (132)	0.13 (248)	0.61 (1205)	0.19 (377)
HG&LI (Q.4)	0.12 (104)	0.12 (106)	0.37 (331)	0.39 (353)	0.10 (123)	0.10 (121)	0.33 (389)	0.47 (562)
Steady-state	0.14	0.21	0.46	0.18	0.18	0.25	0.36	0.21
Panel C: one-threshold quadrant								
	Panel C1:1977–1997				Panel C2:1997–2018			
Quadrant	SG&SI (Q.1)	NG&SI (Q.2)	NG&NI (Q.3)	SG&NI (Q.4)	SG&SI (Q.1)	NG&SI (Q.2)	NG&NI (Q.3)	SG&NI (Q.4)
SG&SI (Q.1)	0.38 (200)	0.30 (155)	0.16 (83)	0.16 (84)	0.49 (394)	0.25 (198)	0.12 (96)	0.14 (115)
NG&SI (Q.2)	0.19 (157)	0.45 (364)	0.25 (206)	0.10 (85)	0.19 (198)	0.51 (528)	0.19 (195)	0.10 (106)
NG&NI (Q.3)	0.03 (92)	0.08 (232)	0.71 (1962)	0.17 (477)	0.05 (108)	0.09 (196)	0.63 (1341)	0.22 (470)
SG&NI (Q.4)	0.08 (91)	0.07 (81)	0.40 (431)	0.44 (480)	0.08 (119)	0.07 (106)	0.31 (469)	0.54 (800)
Steady-state	0.11	0.17	0.51	0.22	0.15	0.19	0.38	0.27

Note: $n = 259$. The total number of transitions is reported in parentheses. HG&HI = high green and ICT orientation, LG&HI = low green but high ICT orientation, LG&LI = low green and ICT orientation, HG&LI = high green but low ICT orientation. SG&SI = specialisation in green and ICT, NG&SI = no-specialisation in green but specialisation in ICT, NG&NI = no-specialisation in green and ICT, SG&NI = specialisation in green but no-specialisation in ICT. 'Mean-threshold' denotes the quadrants defined by the annual national mean for each orientation. 'Median-threshold' denotes the quadrants defined by the annual national median for each orientation. 'One-threshold' denotes the quadrants defined by a value of one, which represents the benchmark of no specialisation.

Table 2. Global Moran's I statistics and join count statistics.

Panel A: $Twin_{rct}$: Global Moran's I statistics

Variable	10NN (inverse distance) (row-standardised)	5NN (inverse distance) (row-standardised)	Queen (row-standardised)	Rook (row-standardised)	Socio-economic (PCA), (inverse distance) (row-standardised)	Variable	Socio-economic (QoG), (inverse distance) (row-standardised)
Twin	0.185 (0.00)	0.18 (0.00)	0.237 (0.00)	0.237 (0.00)			
1977	[0.029]	[0.039]	[0.043]	[0.043]			
Twin	0.059 (0.05)	0.08 (0.05)	0.056 (0.17)	0.056 (0.17)			
1987	[0.028]	[0.039]	[0.043]	[0.042]			
Twin	0.001 (0.80)	0.008 (0.71)	0.019 (0.57)	0.019 (0.57)			
1997	[0.029]	[0.039]	[0.043]	[0.043]			
Twin	0.043 (0.12)	0.040 (0.24)	0.022 (0.49)	0.022 (0.49)	−0.051 (0.12)		
2000	[0.029]	[0.039]	[0.043]	[0.043]	[0.033]		
Twin	0.086 (0.01)	0.11 (0.01)	0.099 (0.02)	0.099 (0.02)	−0.023 (0.61)	Twin	0.049 (0.09)
2007	[0.03]	[0.039]	[0.044]	[0.043]	[0.035]	2010	[0.031]
Twin	0.084 (0.01)	0.099 (0.02)	0.017 (0.47)	0.017 (0.47)	−0.020 (0.48)	Twin	0.007 (0.67)
2018	[0.025]	[0.033]	[0.037]	[0.037]	[0.029]	2017	[0.033]

Panel B: $Twin_{rct}$: Global Moran's I statistics (without super-innovators)

Variable	10NN (inverse distance) (row-standardised)	5NN (inverse distance) (row-standardised)	Queen (row-standardised)	Rook (row-standardised)	Socio-economic (PCA) (row-standardised)	Variable	Socio-economic (QoG) (row-standardised)
Twin	0.243 (0.00)	0.268 (0.00)	0.297 (0.00)	0.297 (0.00)			
1977	[0.03]{$n=243$}	[0.041]{$n=243$}	[0.046]{$n=233$}	[0.046]{$n=233$}			
Twin	0.289 (0.00)	0.303 (0.00)	0.295 (0.00)	0.295 (0.00)			
1987	[0.031]{$n=245$}	[0.041]{$n=245$}	[0.047]{$n=238$}	[0.047]{$n=238$}			
Twin	0.122 (0.00)	0.098 (0.02)	0.084 (0.06)	0.084 (0.06)			
1997	[0.03]{$n=247$}	[0.041]{$n=247$}	[0.046]{$n=240$}	[0.046]{$n=240$}			
Twin	0.204 (0.00)	0.226 (0.00)	0.194 (0.00)	0.195 (0.00)	0.07 (0.03)		
2000	[0.03]{$n=246$}	[0.041]{$n=246$}	[0.045]{$n=236$}	[0.046]{$n=236$}	[0.034]{$n=207$}		
Twin	0.1 (0.00)	0.1 (0.02)	0.112 (0.01)	0.112 (0.01)	0.033 (0.27)	Twin	0.086 (0.01)
2007	[0.03]{$n=250$}	[0.041]{$n=250$}	[0.045]{$n=242$}	[0.045]{$n=242$}	[0.036]{$n=212$}	2010	[0.032]{$n=167$}
Twin	0.09 (0.01)	0.11 (0.01)	0.109 (0.02)	0.109 (0.02)	0.034 (0.28)	Twin	−0.004 (0.91)
2018	[0.03]{$n=248$}	[0.041]{$n=248$}	[0.046]{$n=241$}	[0.046]{$n=241$}	[0.036]{$n=210$}	2017	[0.033]{$n=164$}

	Panel C: *Twin_Specialisation*$_{rct}$: join-count statistics			
Variable	**10NN (binary)**	**5NN (binary)**	**Queen (binary)**	**Rook (binary)**
Twin	5.5 (0.14)	3 (0.20)	4 (0.06)	4 (0.06)
1977	[1.563]	[1.103]	[1.14]	[1.139]
Twin	17.5 (0.22)	10 (0.17)	10 (0.13)	10 (0.13)
1987	[3.146]	[2.229]	[2.41]	[2.412]
Twin	22.5 (0.22)	10 (0.65)	10 (0.44)	10 (0.44)
1997	[3.623]	[2.55]	[2.799]	[2.798]
Twin	13.5 (0.09)	7 (0.32)	5 (0.21)	5 (0.22)
2000	[3.715]	[2.615]	[2.873]	[2.872]
Twin	36.5 (0.19)	18.5 (0.30)	15 (0.64)	15 (0.63)
2007	[4.568]	[3.171]	[3.546]	[3.543]
Twin	57.5 (0.01)	30 (0.02)	24 (0.21)	24 (0.20)
2018	[5.163]	[3.601]	[4.12]	[4.113]

Note: For Panel A and Panel C, $n = 259$ for 10NN and 5NN, $n = 250$ for queen and rook, $n = 219$ for socio-economic (PCA), $n = 171$ for socio-economic (QoG). 10NN and 5NN refer to 10-nearest-neighbours and 5-nearest-neighbours. Socio-economic (PCA) is available between 2000–2018 while socio-economic (QoG) only in 2010, 2013 and 2017. Two-sided hypothesis testing is permutation-based with permutation number equal to 9999. Permutation-based P-values are reported in parentheses. Standard errors are reported in square brackets. For Panel B, super-innovators with *Twin*$_{rct}$ larger than two are excluded and the corresponding number of regions are reported in curly brackets. In line with the literature, socio-economic distance is calculated between regions over the EU to assess if socio-economic similarities across the EU have shaped patterns in terms of twin innovation. Thus, in this context, it is not converted into binary and not applied for the case of join count statistics.

They are statistically significant in Panel B when the super-innovators are removed. This evidence could signal that these regions have a lower degree of spatial association with their neighbours and 'play more on their own'. When we look at time-varying socio-economic distance, there is no evidence of statistically significant correlations in Panel A for both the PCA and QoG indicators, but only in Panel B and for the years 2000 (PCA) and 2010 (QoG), when the super-innovators are removed. In Panel C, there is, however, positive, and statistically significant, spatial autocorrelation only in 2018. Despite different indicators and methods, this evidence is in line with the previous finding that the most specialised regions seem to exercise extensive spillovers on their neighbours.

Overall, the Global Moran's I coefficients indicate statistically significant spatial autocorrelation ranging between 0.05 and 0.29 depending on the type of weight matrix and year. In contrast, the join count statistics give evidence of spatial autocorrelation only in 2018.

Overall, these results give support to the hypothesis that twin innovation is positively spatially correlated across European regions. There is only mild evidence, however, that their twin innovative status is associated with time-varying socio-economic similarity. Although results from geographical and socio-economic neighbours should not be directly compared, it should be noted that weaker evidence of spatial association derived from the socio-economic distance is consistent with previous findings (Cartone et al., 2022; Conley & Topa, 2002). Our results are, however, in contrast with the statistically insignificant Global Moran's I statistics found by Cicerone et al. (2022) for most of the years in their sample when looking at AI knowledge and green technology specialisation among the EU-28 regions. This difference could be due to the different innovation indicators used.

The above global spatial analysis may miss the existence of local spatial clusters. We therefore turn to the LISA indicators and local join count statistics.

Figure 4 presents the map of LISA clusters based on Equation 8 (or the quadrants defined by the yearly national median corresponding to Figure 2) in some representative years (geographical: 1977, 2000, 2018, PCA: 2000, 2018, QoG: 2010, 2017). White cells denote insignificant regions at the 5%. For all types of geographical proximities, there is no local cluster in 1977 but most clusters are in LL in later years (low twin innovation specialisation for both a region and its neighbours). These clusters are not stable: they tend to be located in the Eastern European regions in 2000 but then disappear in 2018. For socio-economic proximity, LL clusters also appear in 2000 for PCA only when super-innovators are removed (see Figure A7) before disappearing in 2018, but there are no clusters for QoG. Overall, there is no evidence of HH clusters

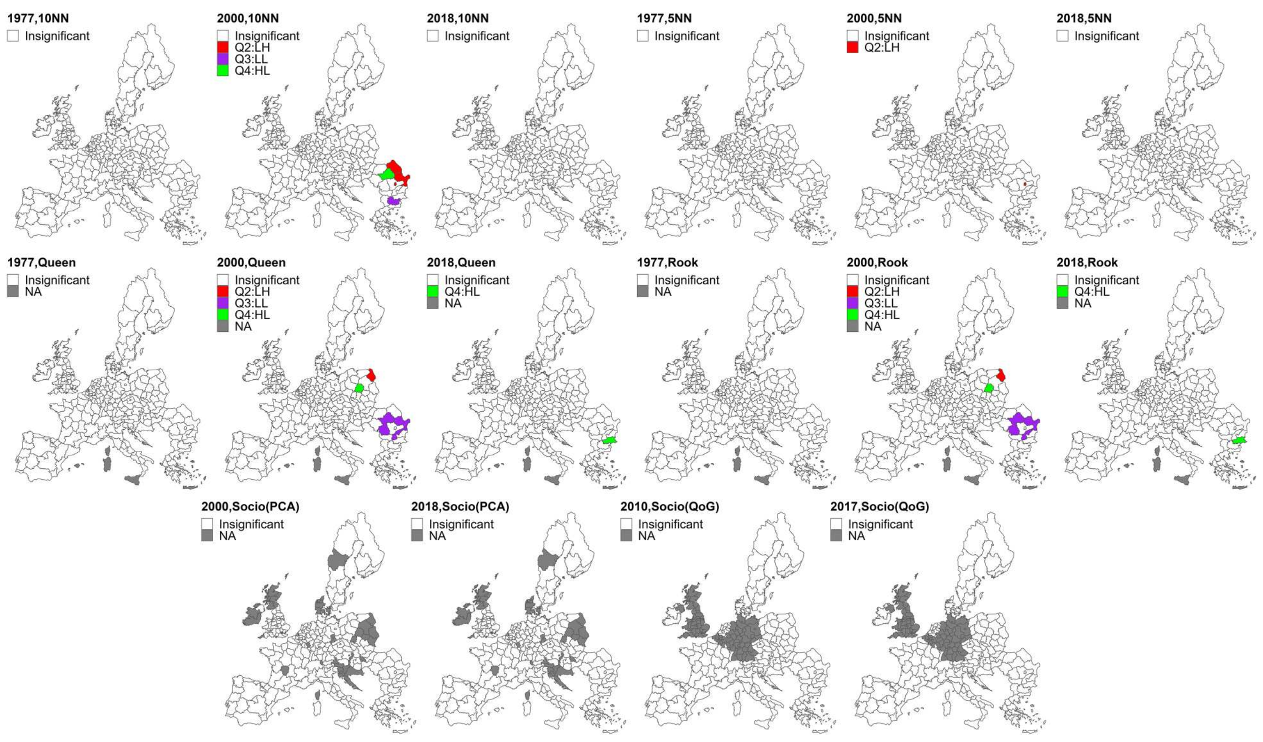

Figure 4. LISA clusters in 1977, 2000 and 2018 across different weights with median threshold.
Note: $n = 259$ for distance and 5NN. $n = 250$ for queen and rook. $n = 219$ for socio-economic PCA. $N = 171$ for socio-economic QoG. HH = high region's and high neighbours' innovation, LH = low region's but high neighbours' innovation, LL = low region's and low neighbours' innovation, HL = high region's but low neighbours' innovation. Insignificant regions indicate Benjamini-Hochberg corrected P-value > 0.05 relying on median threshold. The two-sided hypothesis testing is permutation-based with permutation number equal to 9999. Permutation-based Benjamini-Hochberg corrected P-value is applied to control for the false discovery rate.

across years and weights and the existence of LL clusters is robust across thresholds (Figure A8 and Figure A9).

Figure 5 presents the map of twin clusters derived from local join count statistics (equation 9) in 1977, 2000 and 2018. The white refers to an absence of local join (cluster) or $BB_i = 0$. The red, pink and blue refer to regions with $BB_i > 0$ and significant at 5%, 10% and insignificant at the 10%, respectively. There are very few clusters of $Twin\_Specialisation_{rct}$ and most of them are blue (insignificant) with a small number in 1977, before spreading across European regions in 2018. Interestingly, only Italian regions appear to be significant in 2018 across different weight matrices, albeit pink. Lacking significant clusters of specialised regions in twin innovation supports the finding of no HH cluster in Figure 4.

Moving from static ESDA to dynamic ESTDA, Table 3 reports LISA transition probabilities of $Twin_{rct}$ over the periods 1977–2018 for geographical proximity, 2000–2018 for socio-economic (PCA) proximity, and 2010–2017 for socio-economic (QoG) proximity where LISA quadrants are defined by the year-varying national median.

Based on geographical proximity (10NN, 5NN, queen and rook), regions starting from LH and LL could equally become high twin innovation-oriented regions (transition probabilities LH to HH versus LL to HL are both around 15%). Also, regions starting in either LH or HL are more likely to be negatively influenced by lowly innovative neighbouring regions and thus move into an LL cluster (around 25–30% probability) than to be positively influenced by neighbouring regions and move to an HH cluster (around 15% probability). Thus, all geographical proximities are more frequently associated with regions going out of their twin innovative specialisation rather than moving into it, as transitioning into LL clusters is more likely than into HH clusters. This is confirmed by the steady-state probabilities, where the highest value is for LL, at about 30%. These results are against the hypothesis of a positive role of spatial spillovers in the 'off-diagonal' transition probabilities: regions could become high twin innovators regardless of their neighbours. Also, regions are more likely to be pulled down to an LL cluster than pulled up to an HH cluster. This is robust to different alternatives (see Tables A6, A7 and A8).

However, regions starting from HH and LL are likely to stay in the same position (around 55–65% probability). Geographical clusters of twin innovation specialised regions are highly persistent both at the high and low end of the spectrum.

When we consider the role of socio-economic similarity on the twin transition probabilities (Panels E (PCA) and F (QoG), Table 3), we do not find substantively different results. First, the probability of transitioning from LH to HH is similar (slightly lower) than that of LL regions moving to HL (around 15% versus 18%) and that LH and HL regions are more likely to become LL than HH, evidencing negative spillovers. Second, diagonal clusters are still persistent for both PCA and QoG. Lastly, in the long run, it is equally likely for a region to be in any innovation status except for the HH status (around 20%), irrespective of its starting position. Overall, it indicates that socio-economic and geographical proximity play roughly the same role in influencing regional twin transition, albeit the information considered is different and

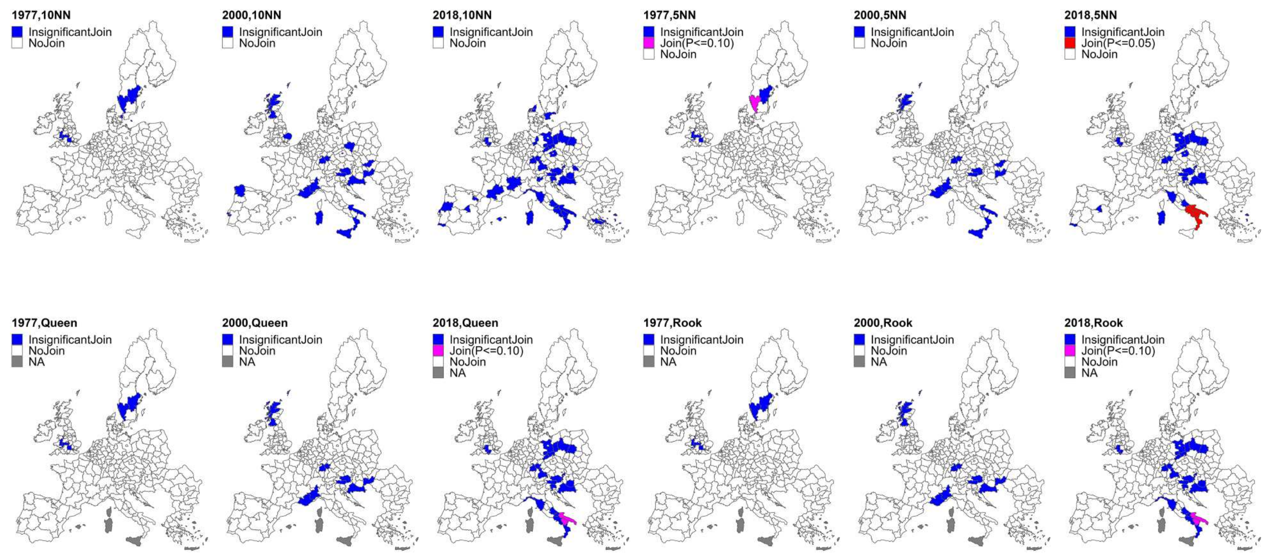

Figure 5. Local join count statistics in 1977, 2000 and 2018 across different weights.
Note: $n = 259$ for distance and 5NN. $n = 250$ for queen and rook. The blue indicates regions with $BB_i > 0$ but insignificant at the 10%. The red and pink refer to $BB_i > 0$ and significant at 5% and 10%, respectively. The two-sided hypothesis testing is permutation-based with permutation number equal to 9999. Permutation-based Benjamini-Hochberg corrected P-value is applied to control for the false discovery rate. In line with the literature, socio-economic distance is calculated between regions over the EU to assess if socio-economic similarities across the EU have shaped patterns in terms of twin innovation. Thus, in this context, it is not converted into binary and not applied for the local join count statistics.

Table 3. LISA transition probabilities of $Twin_{rct}$ (median-threshold quadrant).

	10-Nearest-neighbours (inverse distance, row-standardised)								5-Nearest-neighbours (inverse distance, row-standardised)							
	Panel A1: 10NN (1977-1997)				Panel A2: 10NN (1997-2018)				Panel B1: 5NN (1977-1997)				Panel B2: 5NN (1997-2018)			
	HH (Q.1)	LH (Q.2)	LL (Q.3)	HL (Q.4)	HH (Q.1)	LH (Q.2)	LL (Q.3)	HL (Q.4)	HH (Q.1)	LH (Q.2)	LL (Q.3)	HL (Q.4)	HH (Q.1)	LH (Q.2)	LL (Q.3)	HL (Q.4)
HH	0.56	0.19	0.07	0.18	0.66	0.17	0.03	0.14	0.55	0.18	0.07	0.19	0.64	0.17	0.03	0.16
(Q.1)	(542)	(189)	(67)	(173)	(865)	(219)	(43)	(179)	(548)	(180)	(73)	(194)	(850)	(222)	(43)	(205)
LH	0.13	0.49	0.27	0.12	0.16	0.54	0.18	0.12	0.14	0.50	0.25	0.12	0.17	0.53	0.19	0.11
(Q.2)	(189)	(727)	(393)	(173)	(212)	(713)	(241)	(153)	(197)	(701)	(345)	(163)	(223)	(693)	(248)	(141)
LL	0.04	0.25	0.56	0.15	0.04	0.15	0.65	0.17	0.05	0.23	0.59	0.14	0.04	0.15	0.65	0.16
(Q.3)	(69)	(415)	(945)	(258)	(55)	(234)	(991)	(253)	(81)	(399)	(1035)	(248)	(56)	(230)	(1008)	(253)
HL	0.18	0.15	0.22	0.45	0.15	0.11	0.21	0.54	0.18	0.14	0.24	0.44	0.16	0.12	0.20	0.52
(Q.4)	(186)	(158)	(226)	(470)	(189)	(138)	(265)	(689)	(186)	(145)	(242)	(443)	(202)	(149)	(251)	(665)
Steady-state	0.20	0.29	0.31	0.21	0.25	0.24	0.28	0.23	0.20	0.27	0.32	0.21	0.25	0.24	0.28	0.23
	Queen (row-standardised)								Rook (row-standardised)							
	Panel C1: Queen (1977-1997)				Panel C2: Queen (1997-2018)				Panel D1: Rook (1977-1997)				Panel D2: Rook (1997-2018)			
	HH (Q.1)	LH (Q.2)	LL (Q.3)	HL (Q.4)	HH (Q.1)	LH (Q.2)	LL (Q.3)	HL (Q.4)	HH (Q.1)	LH (Q.2)	LL (Q.3)	HL (Q.4)	HH (Q.1)	LH (Q.2)	LL (Q.3)	HL (Q.4)
HH	0.58	0.19	0.07	0.17	0.64	0.16	0.04	0.16	0.58	0.19	0.07	0.17	0.64	0.16	0.04	0.16
(Q.1)	(550)	(182)	(66)	(158)	(820)	(203)	(55)	(198)	(550)	(182)	(66)	(158)	(815)	(203)	(55)	(198)
LH	0.14	0.50	0.24	0.12	0.16	0.54	0.19	0.11	0.14	0.50	0.24	0.12	0.16	0.55	0.19	0.11
(Q.2)	(180)	(665)	(323)	(154)	(198)	(675)	(235)	(135)	(180)	(666)	(322)	(154)	(198)	(682)	(233)	(135)
LL	0.04	0.22	0.59	0.15	0.04	0.15	0.65	0.16	0.04	0.22	0.60	0.15	0.04	0.15	0.65	0.16
(Q.3)	(67)	(377)	(1017)	(263)	(68)	(226)	(978)	(243)	(67)	(376)	(1018)	(263)	(67)	(224)	(975)	(244)
HL	0.17	0.13	0.25	0.46	0.17	0.11	0.21	0.52	0.17	0.13	0.25	0.46	0.17	0.10	0.21	0.52
(Q.4)	(169)	(125)	(245)	(459)	(201)	(128)	(251)	(636)	(169)	(125)	(245)	(459)	(202)	(128)	(251)	(640)
Steady-state	0.20	0.27	0.32	0.21	0.25	0.23	0.29	0.23	0.20	0.27	0.32	0.21	0.25	0.23	0.29	0.23

	Socio-economic (inverse distance, row-standardised)							
	Panel E: PCA (2000-2018)				Panel F: QoG (2010-2017)			
	HH (Q.1)	LH (Q.2)	LL (Q.3)	HL (Q.4)	HH (Q.1)	LH (Q.2)	LL (Q.3)	HL (Q.4)
HH	0.58	0.17	0.05	0.20	0.51	0.20	0.09	0.20
(Q.1)	(480)	(139)	(45)	(169)	(112)	(45)	(20)	(44)
LH	0.12	0.57	0.20	0.11	0.14	0.48	0.20	0.18
(Q.2)	(130)	(599)	(212)	(116)	(44)	(154)	(64)	(57)
LL	0.06	0.21	0.55	0.18	0.06	0.23	0.52	0.18
(Q.3)	(58)	(213)	(558)	(177)	(19)	(71)	(159)	(55)
HL	0.16	0.10	0.18	0.56	0.13	0.14	0.18	0.55
(Q.4)	(168)	(103)	(189)	(586)	(47)	(49)	(62)	(195)
Steady-state	0.21	0.27	0.25	0.27	0.19	0.27	0.26	0.29

Note: $n = 259$ for distance and 5NN. $n = 250$ for queen and rook. $n = 219$ for socio-economic (PCA). $n = 171$ for socio-economic (QoG). LISA = local indicators of spatial association. The total number of transitions is reported in parentheses. HH = high region's and high neighbours' innovation; LH = low region's but high neighbours' innovation, LL = low region's and low neighbours' innovation, HL = high region's but low neighbours' innovation. Socio-economic PCA weight is available between 2000–2018 while socio-economic QoG weight is available only in 2010, 2013 and 2017.

the socio-economic matrix is time-varying. These results provide robust evidence of transition and spillovers.

5. CONCLUSION AND POLICY IMPLICATIONS

Recent policies focus on the twin transition of the economy towards digital and environmental transformation. Innovation is key to favour such transitions and an emerging, and a quickly growing, literature has investigated the interdependence between digital and green innovation. In this paper, we look at such interdependence using unconditional transition probability, ESDA and ESTDA methods, to look at the ICT and green innovation orientation of 259 European regions from 1977 to 2018 and their single and twin transitions with an additional focus on the role of proximity, especially for the twin transitions.

Several interesting results emerge from the analysis. First, the innovative orientation of regions is, in general, spatially unequal. Many regions have low ICT, green or twin orientation and very few have very high innovative orientation in each or both of these technologies. Some regions are super-innovators. Over the observed period this inequality decreases. Second, graphical analysis shows that the innovative orientation of regions seems unstable with regions switching their innovation orientation. We investigate these transitions by estimating the unconditional (a-spatial) probabilities of regions transitioning from one innovative orientation to the other or to both. Our evidence, broadly in line with recent studies, shows that ICT innovation-oriented regions are more likely than green innovation-oriented regions to become twin innovation-orientation, i.e., ICT-innovation seems a pre-condition for green innovation. This analysis also shows that non-innovative regions are highly likely to remain so, i.e., left behind from the innovation process.

Third, we find evidence of spatial association and clustering of twin innovators due to geographical proximity, with only moderate to little evidence of a role for socio-economic proximity. Interestingly, when we remove from the sample the super-innovators this strengthens the evidence on spatial dependence, possibly indicating that these super-innovators may reduce the overall strength of spatial spillovers and they may be playing more on their own than other less innovative regions. This interpretation could be in line with the idea that these regions have more powerful but also contained regional innovation systems. Fourth, the above-mentioned spatial association is also reflected in the LISA Markov chain transition probabilities showing strong spatial persistence at the two extremes of the specialisation spectrum, for the lowly and highly innovative clusters. For the intermediate cases, spatial spillovers seem to play an undesirable, slightly downward, role, also indicating that twin innovative orientation may be more precarious when not complemented by positive spillover effects.

These results have implications for the success of twin transition policies targeted at regional level, such as Smart Specialisation strategies (COM, 2010, 2012). Non-innovative and single-innovation oriented regions (especially those purely green oriented) will struggle to make a twin transition without innovation policies targeting digital technologies that can be leveraged towards their twin transition. Green transition especially can be precarious if left without the support of non-green innovation strategies. Another important challenge, especially from the regional cohesion standpoint, is the risk of regions being persistently left behind from the twin transition, with the process representing a new source of discontent that fuels the existing perception of a two-tier Europe (Dijkstra et al., 2020; McCann & Ortega-Argilés, 2021; Pike et al., 2023; Rodríguez-Pose, 2018; Rodríguez-Pose et al., 2023). Policies targeting regional knowledge exchange, especially around the super-innovator regions, may help activate the effects of positive spillovers and the diffusion and stability of twin transitions.

Future work could add some methodological improvements that go beyond the scope of this paper. First, our methodology is partly limited in addressing the role of regional determinants and uncovering the endogenous forces behind some of the evidence presented, and the role of policy interventions. Second, it would be interesting to explore a quantile approach that could potentially uncover more evidence on the role of space on the transitions from extreme values like zero. Finally, the approach could be extended to be made dynamic by considering lagged effects.

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NOTES

1. In March 2020, just before the pandemic, the European Commission announced the European Industrial Strategy (COM, 2020a) for the twin transition towards climate neutrality and digital leadership. The 'New Industrial Way for Europe' (COM, 2020a) endeavours to simultaneously promote investment in digital and green technologies and enable industrial transition, thereby

'shaping Europe's digital future' (COM, 2020b) and achieve the European Green Deal (COM, 2019; COM, 2021).

2. Our sample includes the UK, a member of the EU during the period considered, and also currently adopting policies to favour the twin transitions (see DCMS, 2022).

3. The dataset from OECD uses inventor(s)'s country (ies) of residence based on fractional count basis to identify the region(s) of patent corresponding to geographical boundary of NUTS 2013. Fractional count based on residence allows regions to have their patents recorded prior to their EPO's membership, for example, Romania joined the EPO in 2003 but our dataset has patents for regions in Romania in 1980. Noting that EPO is separate from the European Union (EU) and its membership is different.

4. Patent data indicates regional knowledge or innovative activities (Griliches, 1990). However, the use of patent statistics is subject to drawbacks, as not all inventions are patented, and patent applications differ across technological fields and countries (Pavitt, 1985; Basberg, 1987; OECD, 2009, pp. 27–29). See Appendix B and Table A1 for data description and sources.

5. See Appendix B for greater details of ICT-related patents and environment-related patents.

6. Christ (2010) showed that, by looking at 819 OECD TL3 regions of the EU-25, plus Switzerland and Norway, the patents across 32 technology fields are unequally distributed as around 50% of regions do not have a single patent application in the early 2000s. However, European patents saw a decreasing trend in spatial inequality or clustering as locational and spatial Gini coefficients for most technology fields have drastically declined between 1988 and 2004.

7. Using relative measures of specialisation, following the previous literature, is functional to addressing the issue of technological interdependence. Even though we find that a relative measure, such as innovative orientation, and absolute measures of innovation (patents) are similarly distributed, the approach may not be suitable to address whether and why one region becomes more innovative in absolute terms. We would like to thank an anonymous reviewer for making this point.

8. Please note that our notation is slightly different from Cicerone et al. (2022), as our definition of innovative orientation amounts to their definition of RTA.

9. Our spatial correlation analysis may be affected by the omission of national border effects, like those due to national culture and institutions (Naveed & Ahmad, 2016). Using innovation indicators that are relative to national values partially mitigates this issue.

10. Kemeny et al. (2022) found that between 1920 and 2010 in the US there was a high spatial clustering of patents for disruptive innovations during the industrial revolutions, but a dispersion in the subsequent periods. Disruptive innovation was also found to be positively associated with spatial output and income, thereby exacerbating spatial economic inequalities.

11. Our analysis is robust to quadrants defined by different thresholds including annual national mean, median and the value of one.

12. While we do not investigate these, as it is beyond the scope of our paper, some of these transitions could be linked to the recent adoption of smart specialisation strategies.

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