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Methodological and Ideological Options

The role of geographical scales in sustainability transitions: An empirical investigation of the European industrial context

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ABSTRACT

The journey towards sustainability has become paramount to industry, government and research. To date, the main contributions have proposed valuable theoretical models to study the transitions to sustainability. However, a quantitative examination of the phenomenon is still limited. In this paper, we exploit a multilevel-growth model to empirically explore the relevance of different geographical scales in studying sustainability transitions. By analysing a novel, 9-year longitudinal dataset that covers European carbon emission intensity data on four different scales (from specific districts to whole states), we show whether and how multiple geographical scales support the study of sustainability transition pathways. Drawing on our analysis, we contribute to the debate on economic geography, sustainability transition and carbon emission intensity, as well as discuss implications for sustainability policy, strategy and research.

1. Introduction

Transitions are gradual processes, where long periods of relative stability are followed by shorter phases of structural change (Fuenfschilling and Binz, 2018; Tushman and Anderson, 1986). Amidst these complex processes of "creative destruction" (Schumpeter, 1934), changes occur based on the presence of and the interconnections among multiple actors, who generally operate at different scales (Geels, 2002). In particular, Sustainability Transitions (ST) represent fundamental shifts of entire sectors towards new and sustainable levels of development (Skellern et al., 2017). These shifts encompass technological, material, organisational, institutional, political, economic and socio-cultural dimensions (Davies, 2013; Davies and Mullin, 2010; Foxon, 2011; Geels and Schot, 2007; Lindberg et al., 2019; Markard et al., 2012; Pisano et al., 2014; Vona et al., 2018).[1]

Previous studies have made considerable progress towards understanding the nature of ST, particularly on the basis of systemic-based conceptualizations, which emphasise the long-time horizon, multi-actor and multi-scalarity nature of the process (Geels, 2002; Geels and Schot, 2007; Loorbach, 2007; Schot and Geels, 2008). However, any theoretical model aiming to analyze complex systems tends to be subjective and abstract, especially because these systems are simplified representations that hardly find a precise correspondence in reality (Loorbach, 2007). Thinking in terms of systems should imply a clear definition of their boundaries, but these boundaries are often treated by previous works as arbitrary. From a methodological standpoint, the lack of a shared vision on the concept of boundaries generates high difficulties in their operationalisation. As a consequence, previous works have mainly investigated this phenomenon in qualitative terms (Heiberg et al., 2020), avoiding to translate theoretical concepts in measurable constructs. Almost all studies are, indeed, based on theoretical argumentations or use qualitative empirical methods (Berggren et al., 2015;

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[1] The best-known example of ST concerns the decarbonization of energy and transport systems (Verbong and Geels, 2007). Other examples are the biodiversity and food security in the agriculture sector (Spaargaren et al., 2012) or water management, waste management and urban development (Brown, 2008; Truffer et al., 2010).

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Bolton and Hannon, 2016; Geels, 2002; Geels et al., 2016; Köhler et al., 2009; Murphy, 2006), but generally lack quantitative data for explaining the evolution of transition pathways at different scales (see Hipp and Binz, 2020 as an exception).

In order to offer a more explanatory basis for societal and policy debate, researchers have sought to integrate geography into previous theoretical models. By definition, ST are spatial processes (Coenen and Truffer, 2012) where changes originate partly as a result of interventions at various geographical scales: urban, regional, national, and global. This idea has been conceptualised as multi-scalarity (Coenen et al., 2012). Furthermore, by linking the geographical dimension to the concept of multi-scalarity, the economic geography perspective (Martin, 2001; Martin and Sunley, 2006) proposes a definition of scale that can be used to identify boundaries for the study of ST. The concept of geographical scales, indeed, "[…] can be regarded as a territorial level at which significant relationships exist between actors: these relationships acquire a dynamic of their own through repeated interaction and that dynamic is distinctive from interactions at different scales" (Coenen et al., 2012: 972).

Our paper aims to join this conversation on geographical multi-scalarity by testing, with empirical data, *whether and how multiple geographical scales contribute to the interpretation of ST pathways*. In addressing this issue, we quantitatively assess the geographical unevenness of transition processes among scales in order to better understand "place-specific impacts on sustainability transitions" (Cohen et al., 2012, p.973). Until now, most research has focused on transformation processes in specific countries or on the comparison among a limited number of countries (Geels et al., 2016; Hodson and Marvin, 2012; Maassen, 2012; Späth and Rohracher, 2012); the implicit assumption is that ST primarily occur at the national level (Heiberg et al., 2020; Smith et al., 2010). Only a few studies, to our knowledge, have tried to go beyond an excessive emphasis on context-sensitivity by proposing a global lens (see Binz and Truffer, 2017; Fuenfschilling and Binz, 2018)—where forces operating at and between not only national, but also international and transnational levels play relevant roles (Bauer and Fuenfschilling, 2019; Frangenheim et al., 2020; Fuenfschilling and Binz, 2018; Sengers and Raven, 2015). With our approach, we intend to contribute to this line of research. More precisely, we study ST at different geographical scales and empirically validate Loorbach's cue that "local or regional sustainability does not necessarily mean national or global sustainability and vice versa" (Loorbach, 2007, p.23).

The scope of our paper is the industrial sector (IPCC, 2018), which we investigate through the development of a novel longitudinal dataset that covers the carbon emission intensity (CEI) data of European regions at four different geographical scales over a 9-year timespan (2008–2016). With these data, we contribute to three main streams of research: First, we add to the ST literature by quantitatively modelling ST trajectories across EU. Second, we contribute to the economic geography literature by empirically describing ST pathways that occur at different geographical scales. Finally, we supplement the carbon emission intensity debate by integrating the existing analyses at the national scale with more fine-grained investigations at sub-national scales. Additionally, this research may represent a bridgehead for the study of the impact of Phase III of the European Emissions Trading System (EU ETS) policy on carbon intensity dynamics in Europe (Teixidó et al., 2019).

The remainder of the paper is organised as follows: Section 2 discusses the theoretical background of the study. Section 3 presents the context of our paper, while Section 4 outlines the research design and the methods applied. We then present the results in Section 5 and conclude in Section 6 with policy implications and streams for future research.

2. Theoretical background

2.1. The complex nature of sustainability transitions

Markard et al. (2012, p.956) referred to ST as "long-term, multi-dimensional, and fundamental transformation processes through which established socio-technical systems shift to more sustainable modes of production and consumption". The governance of ST requires an interplay among different actors—from businesses to governments to society at large.

In order to capture such complexity, extant research in ST has evolved into four main streams (Markard et al., 2012). First, the Multi-Level Perspective (MLP) proposes a transition process deriving from the interactions among three levels. The first level is populated by niches; the second level hosts the incumbent regime, and the third level represents the landscape (Geels, 2002; Geels and Schot, 2007; Rip and Kemp, 1998; Smith et al., 2010).[2] According with this framework, radical innovations and learning processes are generated in the niches. If accepted by powerful actors and networks, these developments can result in new and stable socio-technical configurations at the regime level. The regime concept is, finally, understood at the landscape level as an interpretative concept encompassing norms and values. Second, the Transition Management (TM) framework suggests that the transition represents a process of structural societal change between two relatively stable states (punctuated equilibrium) through the co-evolution of different macro-factors (markets, networks and policies) and micro-factors (technologies, institutions and individuals) (Rauschmayer et al., 2015; Rotmans et al., 2001). Third, the Strategic Niche Management (SNM) approach argues that the study of niche development needs to be coupled with an analysis of the role of social networks, learning processes (Schot and Geels, 2008) and especially the guiding vision (Kemp et al., 1998). Finally, the Technological Innovation Systems (TIS) framework studies transitions by focusing on emerging technologies and their impact on the technical system through an entrepreneurial lens (Markard and Truffer, 2008).

The development of this composite fabric of frameworks shows the difficulties in defining an overall theory that can grasp the complexity of the ST phenomenon. Each of the above frameworks contributes to depicting ST, emphasising particular aspects or components while leaving others in the background. In particular, while the temporal dimension characterises all the four frameworks and captures the conceptualisation of transitions as processes of change over time, the spatial dimension is left more abstract and vague. The MLP, for instance, only considered global and local processes without paying attention to geographical aspects (Geels and Deuten, 2006), while the TIS generally referred to a global opportunity set without further specifying the spatial demarcations.

Economic geography supports the theory of ST by filling this gap.

2.2. The spatial dimension of sustainability transitions: economic Geography and the role of multi-scalarity

As Dainton asserted (2001, p.10), "think[ing] clearly about space is not easy". For instance, within economic geography, there are different conceptualisations of space: namely, institutional, evolutionary, and relational.[3] According to institutional economic geography, space involves the presence of formal (i.e., rules, laws and regulations) and informal (i.e., culture, norms and values) institutions and the

[2] It is important to note that niche, regime and landscape levels do not correspond to micro-, meso- and macro-levels of socio-technical transformations, which are often misrepresented.

[3] Among these three conceptualizations, the institutional economic geography is the one which more closely overlaps with the ST frameworks previously described.

interactions among them (Martin, 2000). In this sense, the institutional setting (which derives from the interplay among these factors) determines the definition and evolution of a specific context. Evolutionary economic geography (Boschma and Frenken, 2006; Boschma and Martin, 2007) instead links space to the distribution of organisational routines in an area (Nelson and Winter, 1982). The emergence of an industrial, economic and technological pathway is determined by the presence of historical contingencies and their self-reinforcing effects. Thus, this perspective emphasises the concept of path dependency, which captures the interconnected role of both time and space (Martin and Sunley, 2006). Finally, relational economic geography considers space as a social construction characterised by networks of relations among actors (Amin, 2002; Sunley, 2008). Accordingly, space is not defined by precise geographical boundaries, but rather by the flow of capital, knowledge and people.

Recent scholars have demonstrated that ST are, in fact, spatial processes related to specific places (Coenen and Truffer, 2012), which has enhanced the value of geography in capturing the broad variety of transition pathways and the relevance of the context in describing ST processes (Coenen et al., 2012; Hansen and Coenen, 2015). This is a huge contribution with respect to the previous research (Hassink et al., 2019). Moreover, as space can be analysed at different degrees of aggregation (local, national, global), ST trends should not be interpreted as homogeneous.[4] Moved by the goal of considering these different degrees of aggregation, researchers applying economic geography to ST have introduced the concept of scales and, in particular, multi-scalarity (Brenner, 2001; Coenen et al., 2012; Truffer, 2016) as a key feature to characterise the uneven development of ST phenomena (Binz et al., 2020).

Two main approaches have been suggested. The first approach is conceptual and draws from the MLP, TM, SNM and TIS theoretical frameworks, as well as from relational economic geography. It focuses on the relationships among the *abstract* levels of niches-regimes-landscapes and actors (Berggren et al., 2015), all of which are linked by a variety of cultural, economic and power relationships (Bauer and Fuenfschilling, 2019). The second approach is more methodologically nuanced and moves forward by postulating that multi-scalarity defines relationships among *physical* territorial boundaries (e.g., urban-regional-national-global), which host societal systems and become the spaces for ST (Binz et al., 2020; Loorbach, 2007). However, the absence of a clear methodology for measuring scales limits the opportunities for comparative analyses among ST processes. Pushed by this evidence, our paper intends to operationalise the concept of multi-scalarity in order to create a methodological basis for the empirical investigation of the role played by multiple geographical scales in studying ST pathways. However, as there exist different and heterogeneous types of ST (e.g., energy, agriculture, mobility, urban and industry), a comprehensive measure of multi-scalarity could be ineffective and have weak explanatory power if different types of ST are analysed together. For this reason, our work focuses on the specific context of industrial ST, which represents one of the most relevant forms of transition nowadays (Fischedick et al., 2014). Consequently, in the following sections, we will characterise such a context (Section 3.1) and introduce Carbon Emission Intensity (CEI) as the measure to study industrial ST (Section 3.2).

[4] In the photovoltaic industry, for instance, Germany has seemingly been the market leader since the early 2000s when compared to other countries. However, an analysis at the federal level reveals an interesting heterogeneity in terms of market development, with the Bavaria and Baden Württemberg areas growing two times above the national average (Dewald and Truffer, 2012).

3. The context of our paper

3.1. Industrial sustainability transition

Extant literature in the field has proposed five different transition pathways towards sustainability (IPCC, 2018). Transitioning energy systems involves reconfiguring energy supply and distribution systems, maximizing the role of renewable sources and innovating the distribution network (Kern and Smith, 2008; Geels et al., 2016; Lindberg et al., 2019; Späth and Rohracher, 2012). Transitioning agriculture and land use requires shortening the supply chains, introducing new raw materials (e.g., insects, algae), and improving the end-consumer distribution to ensure biodiversity conservation and food security (Darnhofer, 2014; UN, 2015). Debates over mobility transition (Köhler et al., 2009) revolve around not only innovative automotive technologies (Dijk et al., 2016), but also shared mobility platforms and individual behaviours (Bork et al., 2015; Mullen and Marsden, 2016). Because of the close interdependence between mobility and urbanity, their transitions have often been approached together (Canitez, 2019; Hoogma et al., 2002; Lin et al., 2018). Urban transition implies an effort to create "smart cities" where citizens at the centre of the urban ecosystem and technological innovations are integrated into the household, mobility and energy fields (Audretsch et al., 2020; Bulkeley and Castán Broto, 2011; Ponta et al., 2018; Zheng et al., 2010).

Meanwhile, the industrial sector plays a significant role in ST, as it is responsible for a third of total global greenhouse gas emissions (Fischedick et al., 2014). The deep decarbonisation required by the EU policy, with emission reduction targets of 80–95% by 2050 compared to 1990, can only be accomplished by a radical system innovation (Wesseling et al., 2017). Thus, cleaner productions and resource savings are crucial elements for industrial ST (Skellern et al., 2017). Prior literature has often investigated industrial ST by analysing the different aspects involved, such as innovation (Krammer, 2009), environmental regulations (Wang and Sun, 2019), socio-technical systems (Skellern et al., 2017) and barriers towards ST (Geels, 2011). However, extant research has focused only on specific industrial sectors (Bauer and Fuenfschilling, 2019) and still lacks a wider empirical modelling of the phenomenon (Wesseling et al., 2017; Tsai, 2018).

3.2. Carbon emission intensity

CO2 equivalent (CO2e) emissions are widely regarded as a reliable proxy for measuring the effectiveness of ST-promoting actions and policies. This indicator accounts for not only direct CO2 emissions, but also for other greenhouse gases (GHGs) (Dogan and Seker, 2016) that are directly responsible for global warming and, consequently, climate change. GHGs are typically modelled in terms of CO2e to mimic their effect on the global temperature equilibrium and facilitate assessments (e.g., Carbon footprint, LCA, etc.) for products, processes or programs (IPCC, 2014).

Nevertheless, CO2e may not be sufficient to describe industrial ST, which encompass complex scenarios related to not only reducing environmental impacts, but also fostering economic growth (UNEP, 2011, 2017). Emissions reduction may be triggered by sustainability-oriented policies, but also by contingent elements such as economic crises, depopulation, or global health diseases.[5] For this reason, studies need a composite indicator that considers both environmental and economic perspectives. Based on the aforementioned literature and the necessity of normalizing the CO2e data among different geographical areas, we choose industrial Carbon Emission Intensity (CEI) as a proxy for industrial ST. Calculated as the ratio between CO2e and GDP, CEI is widely

[5] This study from the Centre for Clean Air reports the effects of the Coronavirus on CO2 emissions reduction in China https://www.carbonbrief.org/analysis-coronavirus-has-temporarily-reduced-chinas-co2-emissions-by-a-quarter

recognised as a robust indicator for evaluating the sustainable performance of countries, regions, and value chains in different sectors (Acquaye et al., 2018; Cai et al., 2016; Dong et al., 2018; Wang et al., 2017, 2018).

4. Method and data

4.1. Towards an operationalisation of geographical scales

As a first step in achieving our study purpose, we operationalised geographical scales.

At the EU level, historical data related to demography, economy, labour market and education are reported by EUROSTAT (2018, p.7) “for the collection, development and harmonization of the European Union’s regional statistics” and for “targeting political interventions at a regional level” (2018, p.4). In particular, the Nomenclature of Territorial Units for Statistics (NUTS) is the reference point for coding geographical space through data (Herz and Varela-Irimia, 2020). NUTS are drawn based on population thresholds and organised in different levels, where each EU Member State (NUTS 0) is divided into NUTS 1 (i.e., major socio-economic regions), which are consequently subdivided into NUTS 2 (i.e., basic regions for the application of regional policies) and then further into NUTS 3 (i.e., small regions for specific diagnoses). NUTS correspond to different administrative structures across European countries, following, where possible, existing administrative configurations or, alternatively, aggregating smaller administrative units. For instance, for the former case, NUTS 2 overlaps with *Communidades autónomas* in Spain, *Regiony soudržnosti (cohesion regions)* in Czech Republic and *Regioni* in Italy; for the latter case, *Regierungsbezirke/non-administrative aggregations* constitutes NUTS 2 in Germany (EUROSTAT, 2018).

This structure fits the concept of geographical multi-scalarity, as it allows us to relate different territorial boundaries and provides a more concrete base for assessing geographical scales, as presented in the theoretical section of the paper.

4.2. Operationalizing industrial sustainability transition through carbon emission intensity

Data on CO2e were retrieved from the EU ETS register.[6] Established in 2005, EU ETS is the world’s first international emissions trading system (European Parliament and the Council of the European Union, 2003). It remains the biggest one to date (Bocklet et al., 2019; Naegele and Zaklan, 2019), accounting for over three-quarters of international carbon trading and about 45% of the EU GHGs emissions. The trading system has been set up for industrial emissions, treating GHGs emissions as a commodity (Verbruggen et al., 2019) and delineating specific emissions quotas and reduction targets for GHGs (Marcu et al., 2017). Emissions data are consequently registered and made publicly available at the level of the single industrial plant. In this study, data on CO2e at the plant level have been aggregated at NUTS 3. We then considered the nested structure of NUTS (i.e., NUTS 0–1–2-3) in order to assess CO2e in different European geographical contexts. The EU ETS regulation provides four stages of application (Phase I, 2005–2007; Phase II, 2008–2012; Phase III, 2013–2020, Phase IV 2021–2030), with increasing limitations in GHGs emissions. It is currently concluding its Phase III of application, spanning from 2013 to 2020. Therefore, our dataset includes emissions data from the whole Phase II and the first 4 years of Phase III.

Secondly, we gathered GDP data from the Eurostat database[7] at the NUTS 3 level. GDP data for NUTS 0-1-2 derived from the aggregation of the original data at NUTS 3. The CEI data were then calculated by dividing CO2e data by GDP data at NUTS 3. Therefore, our final dataset consists of longitudinal data on CEI from 2008 to 2016, covering four different scales (i.e., NUTS 0-1-2-3).

Overall, the dataset contains data on 28 NUTS 0, 103 NUTS 1, 279 NUTS 2 and 1248 NUTS 3, ultimately accounting for 14,433 observations. Table 1 provides details on the number of observations in the dataset at different NUTS levels.

Our structured panel dataset considers all NUTS levels across the same years (2008–2016). However, the dataset is unbalanced because not all the units have measurements of CEI in each of the nine observed years. This is due to two main reasons. First, different countries gained membership into the EU ETS at different times; therefore, some countries (i.e., Czech Republic) started reporting on EU ETS later than others (i.e., Germany, Italy). Second, the NUTS nomenclature was revised in 2015,[8] which has resulted in changes in territorial definition in some countries (i.e., France and Poland).

4.3. Multilevel-growth model

The nested structure of our dataset implies that, at each NUTS level, every unit is characterised by a specific temporal pattern in its CEI levels, and it can differ among units belonging to the same geographical scale. In other words, the analysis of the overall average pattern is not sufficient to draw conclusions on the ST in these European countries if NUTS level-specific (individual) ST trends at different scales are heterogeneous and systematically differ from the overall average pattern. In order to account for both these temporal and spatial sources of dependence in our data, we chose a multilevel-growth model (Tasca et al., 2009). This model is known for its ability to estimate overall developmental trajectories of constructs across time (Curran and Hussong, 2003), while simultaneously accounting for between-individual differences that can stem from systematic factors affecting the variable under investigation (Byrne and Crombie, 2003). Thus, compared to conventional repeated measures analyses, multi-level growth models can provide more adequate information about temporal changes in a specific variable in the presence of nested structures.

Furthermore, multilevel-growth modelling is one of the most powerful and informative approaches for analysing unbalanced repeated measures (Byrne, 2012; Curran et al., 2012). Thus, it perfectly fits with our database where several units have missing observations in 1 or more years.

In our specific case, the multilevel growth model technically involves specifying an overall average ST trajectory common to the whole EU and then analysing at which geographical scale the ST pathways deviate from that overall mean trajectory. Once it is evaluated that the unit trajectories at one specific level differ from the overall mean pattern, the model can be extended to identify systematic factors that drive the ST patterns at each level.

Based on our data, we should estimate a five-level (i.e., NUTS 0–1–2-3 and Time) growth model for CEI over time (Curran et al., 2012). However, given the large number of observations in the dataset (see Section 4.2), the estimation of a five-level model is computationally unfeasible. Hence, we tested three four-level models: NUTS 1–2-3 and Time (Model 1); NUTS 0–1-2 and Time (Model 2); and NUTS 0–2-3 and Time (Model 3). By jointly analysing the variability of the ST dynamic at each geographical scale in every model, it is possible to evaluate the level at which the individual ST trajectories become heterogeneous. This step is important for identifying potential systematic factors that may drive the behaviour of these ST patterns.

[6] https://ec.europa.eu/clima/policies/ets_en

[7] https://ec.europa.eu/eurostat/web/regions/data/database

[8] Commission Regulation (EU) No 1319/2013 entered into force on 31 December 2013 and applied, with regard to the transmission of data to the Commission (Eurostat), from 1 January 2015.

Table 1
Number of observations at different NUTS levels.

Year	2008	2009	2010	2011	2012	2013	2014	2015	2016
NUTS 0	27	27	27	27	27	28	28	28	28
NUTS 1	102	102	102	102	102	103	103	103	103
NUTS 2	276	276	276	276	276	279	279	279	279
NUTS 3	1195	1195	1192	1196	1194	1207	1197	1197	1195

Formally, the four-level growth model can be specified in reduced form as follows:

$$(1)\quad y_{tjki} = \underbrace{\gamma_0 + \gamma_1 t}_{\text{Fixed effects}} + \underbrace{r_{0jki} + r_{1jki}t + s_{0ki} + s_{1ki}t + u_{0i} + u_{1i}t}_{\text{Random effects}} + e_{tjki}$$

$$t = 2008, \dots, 2016;\ j = 1, \dots, N_{ki};\ k = 1, \dots, N_i;\ i = 1, \dots, N$$

with t representing the time, and j, k, and i representing the different NUTS levels taken into consideration. y_{tjki} is the CEI measured at time t for:

- NUTS 3j nested in NUTS 2k nested in NUTS 1i for Model 1;
- NUTS 2j nested in NUTS 1k nested in NUTS 0i for Model 2;
- NUTS 3j nested in NUTS 2k nested in NUTS 0i for Model 3.

In terms of main results, a multilevel-growth model provides the "fixed effects" and the "random effects" as indicated in Eq. (1). The "fixed effects" of the model estimate the expected common trajectory for the overall sample, which we assume to be linear on the entire time span. Hence, this common trajectory is identified by estimating the expected intercept of the CEI in 2008, denoted by γ_0, and the expected slope, γ_1, for the whole EU. On the other hand, the "random effects" estimates, for each geographical scale included in the model, if the individual trajectories at that specific level significantly differ from the overall one. Thus, looking at the p-values of the corresponding random effects, we can see if there is significant variability at each geographical scale included in the model—either in the initial value of the trajectory (intercept), through r_{0jki}, s_{0ki}, and u_{0i},or in the transition (slope) through r_{1jki}, s_{1ki}, and u_{1i}.

In order to choose the best model for our data, we used common model selection criteria such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Lower values of AIC and BIC signal a better fit between the data and model.

In cases where the individual trajectories at one or more geographical scale significantly differ from the overall mean pattern, the model can be extended to account for potential systematic factors that may affect the individual ST trajectories. In this regard, we have developed a further set of analyses to deeply investigate the association between decreasing CEI levels and actual structural change in the EU industrial sector. To distinguish different underlying mechanisms in CEI dynamics and to discriminate actual transitions from just incremental process innovations, we were interested in identifying sharp drops in CEI figures over a short period of time. This would indicate a potential change in the manufacturing approach that more likely represents an actual transition pathway. Moreover, sharp drops in CEI may also be due to the decommissioning of plants; hence, the data have to be controlled for this effect in order to make the argument about transitions more robust. We thus deconstructed the processes that lie below the CEI dynamics by introducing two covariates into the multilevel-growth model.

The first covariate is related to the idea that the mean CEI trajectory over time may not be linear and smooth, but rather characterised by a discontinuity, representing a sharp drop in CEI over a shorter time span. We thus applied a piecewise model, where the final trajectory is assumed to present a discontinuity. Such a discontinuity corresponds to a change in the regulation due to the introduction of the Phase III of the EU ETS in 2013. This approach responds to a call for research aimed at evaluating the impact of the new policies that accompanied Phase III, such as the auctioning mechanism for allocation, the cancellation of free allowances, and the tightening of actions to fight the carbon leakage (Teixidó et al., 2019). Therefore, the final model is composed of two linear trajectories that specifically align with each sub-period of observation (i.e., 2008–2012 and 2013–2016).

The second covariate considers the decommissioning of plants during the whole period. Thus, within the aforementioned piecewise model, we included an additional covariate constructed as a three-level categorical variable representing the groups of regions experiencing a decrease, an increase, and an invariance in the number of plants reporting into the EU ETS. The reference group (Decomm-1) represents the decommissioning scenario, where the number of plants decreased over the entire period of analysis. The second group (Decomm+1) corresponds to regions that increased the number of plants. The last group (Decomm0) represents regions for which the number of plants remained unchanged. Section 5.4 reports the results of these analyses.

5. Findings

In this section, we detail the five main results of our analyses: 1. CEI shows an overall decline in the proposed timespan; 2. Different geographical scales show different transition patterns; 3. The initial level of CEI influences the trajectory of CEI over time; 4. The influence of geographical scales on CEI shows statistically significant differences across the different states analysed; 5. Regulations produce a steep drop on CEI dynamics and their effect overcomes the impact produced by the decommissioning of plants.

5.1. Descriptive statistics: the decline of carbon emission intensity over time

Table 2 shows the trends of CEI over time for the sample as a whole. We observe a decreasing pattern, for both the mean and the median, with roughly equal standard deviations.

Table 3 and Fig. 1 show our data at NUTS 0. In particular, Table 3 summarises that, for each country, the percentage of CO2e in 2016 was comparable to the EU total, the variation of CO2e in the period 2008–2016, the variation of CEI in the period 2008–2016, and CEI in 2016 with respect to the EU average. Considering CO2e (column A), our

Table 2
Summary measures of CEI from 2008 to 2016 for the entire sample.

	2008	2009	2010	2011	2012	2013	2014	2015	2016
Mean CEI	162.97	151.74	150.59	143.47	137.85	137.21	125.83	119.26	114.67
Median CEI	50.32	46.92	46.79	41.270	36.874	37.44	37.921	34.544	35.131
St dev CEI	802.05	746.62	767.71	818.90	778.53	739.47	729.03	689.79	651.29

Table 3
CO2e in 2016, CEI variation in the period 2008–2016, CEI variation in respect to the EU average and the CEI trends for each country in the period of analysis.

Rank	Country (NUTS 0)	A	B	C	D
		CO2e 2016 (%)	Variation of CO2e 2008–2016 (%)	Variation of CEI 2008–2016 (%)	CEI 2016 vs. EU average (%)
1	Germany	26.6%	−4.3%	−22%	24.9%
2	Poland	11.6%	−2.9%	−23%	304.7%
3	Italy	9.1%	−29.9%	−32%	−20.2%
4	United Kingdom	7.8%	−46.2%	−56%	−51.4%
5	Spain	7.2%	−24.4%	−25%	−3.7%
6	France	6.0%	−18.1%	−33%	−60.3%
7	Netherlands	5.4%	11.4%	−3%	14.5%
8	Czech Republic	3.9%	−16.0%	−23%	232.8%
9	Greece	2.7%	−33.6%	−9%	128.5%
10	Belgium	2.6%	−21.3%	−34%	−10.3%
11	Romania	2.3%	−37.5%	−46%	103.7%
12	Bulgaria	2.0%	−12.8%	−33%	505.1%
13	Austria	1.7%	−9.9%	−26%	−29.3%
14	Finland	1.6%	−24.4%	−32%	9.7%
15	Portugal	1.5%	−13.2%	−17%	18.8%
16	Slovakia	1.2%	−15.9%	−32%	128.3%
17	Sweden	1.2%	−1.7%	−25%	−62.9%
18	Hungary	1.1%	−28.6%	−32%	48.5%
19	Ireland	1.0%	−12.9%	−8%	−13.6%
20	Denmark	0.9%	−36.3%	−47%	−51.1%
21	Estonia	0.8%	−0.7%	−24%	440.9%
22	Croatia[a]	0.5%	−5.9%	−12%	54.6%
23	Slovenia	0.4%	−26.9%	−31%	40.0%
24	Lithuania	0.4%	4.9%	−12%	35.5%
25	Cyprus	0.3%	−16.6%	−14%	119.3%
26	Latvia	0.1%	−17.8%	−20%	−25.2%
27	Luxembourg	0.1%	−28.4%	−49%	−75.4%
28	Malta	0.0%	−71.3%	−83%	−51.1%
	European Union	100.0%	−18.34%	−29.6%	

[a] Data since 2013

data showed a high concentration in a limited number of countries (the first five countries generated more than 60% of the total emissions). In terms of variation in the period of analysis (column B), all countries were characterised by a decline, except for the Netherlands and Lithuania. Similarly, the CEI trends (column C) showed a decline in all countries in the period 2008–2016, with a reduction in the whole EU of almost 30%. However, each country tended to show a different CEI pattern, both in terms of variation and in relation to the EU average (column D). Poland showed a CEI three times higher than the EU average, while France and the UK showed 2016 CEI values that were 60% and 51% lower than the EU average, respectively.

Furthermore, Fig. 1 reports the empirical growth curves of CEI at NUTS 0 for the different EU countries, acknowledging the linear[9] decreasing patterns for all countries, except for Greece and Bulgaria.

[9] This pattern confirms the possibility of describing the phenomenon through a linear model over the entire time span (2008–2016), and thus the appropriateness of a linear multilevel-growth model in the subsequent statistical analyses.

5.2. The multilevel-growth model: the relevance of multi-scalarity and path dependency

Table 4 shows the fixed effects for the three proposed models (Model 1 including NUTS 1–2-3; Model 2 including NUTS 0–1-2, and Model 3 including NUTS 0–2-3), as well as the fit indexes. It highlights two important elements: the average starting point of CEI at EU level (i.e., intercept γ_0), and the growth rate of CEI over time (i.e., slope γ_1). These values suggest the significance of both intercept and slope in all three models (p-value <.001) and confirm that the mean trajectory of CEI declines over time (b= −8.672 for Model 1, −9.822 for Model 2 and −9.810 for Model 3). As for the fit measures, it is evident that Model 3 better fits with the data, showing the lowest values of the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC).

Table 5 reports the significance levels of the random effects for the three models for each of the geographical scales considered. With our findings, we confirm the important role played by countries (NUTS 0) in studying ST, as both models including this scale (i.e. Model 2 and Model 3) signal its statistical significance, in terms of the starting point of CEI and the variation over time. However, we also integrate previous research by showing that local scales (NUTS 1, 2 and 3) have additional informative power in studying ST, in the sense that the corresponding individual trajectories significantly vary with respect to the corresponding overall mean trajectory estimated in Table 4.

In order to better capture these results, Figs. 2 and 3 visualise European maps of CEI reported at the different scales (NUTS 0–1–2-3) for 2016 (Fig. 2) and for the period of analysis 2008–2016 (Fig. 3). It is interesting to note that, when considering well-performing countries, analyses at local scales show differences that are extremely relevant (Fig. 2). This issue becomes apparent when examining some examples in more detail. Consider, for instance, the regions within Germany, which is performing well at NUTS 0: The analysis at NUTS 2 scale shows relevant differences in areas such as Düsseldorf and Sachsen-Anhalt, which display CEI values ten times higher than Mecklenburg-Vorpommern and Tübingen, respectively. Similarly, when analysing CEI over time and considering the UK at NUTS 0, we show one of the most relevant declines in the EU. However, important differences emerge when investigating NUTS 2, with some areas (e.g., West Wales and The Valleys) performing worse than others (e.g., Dorset and Somerset) by two orders of magnitude.

Table 5 reports an additional result of our study: All three models produced highly negative correlations between the intercept and slope at all scales, suggesting that high-emitting geographical areas show greater declines in CEI over time compared to lower-emitting areas. Stated differently, the initial value of CEI affects the evolution of CEI over time, according to a path dependence logic, leading to greater declines in CEI for scales displaying higher starting points and, conversely, lower declines of CEI for scales showing lower starting points.

In order to further support these results, Fig. 4 shows the correlation between the estimated intercept and slope of CEI at NUTS 0. What clearly emerges from the graph is a negative relationship between the two, so that higher levels of intercept correspond to steeper negative slopes.

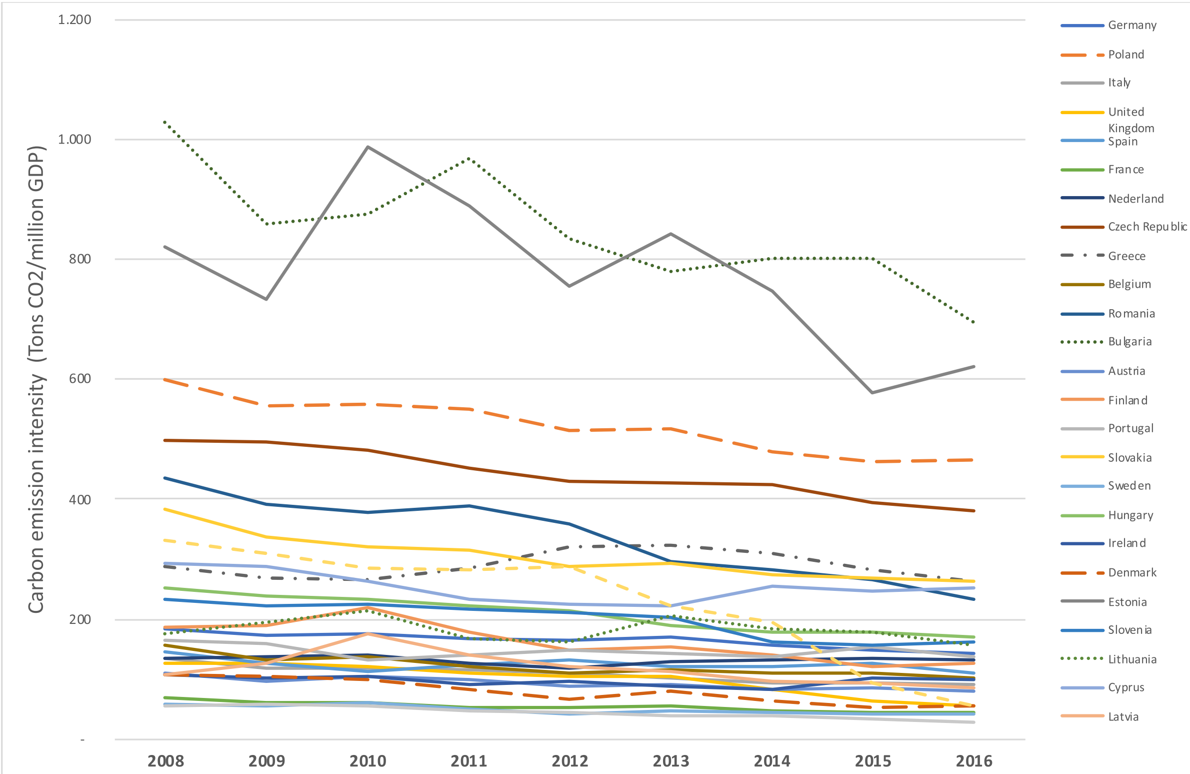

Fig. 1. Empirical curves of CEI at NUTS 0.

Table 4
Fixed effects into the three models proposed and fit indexes; *** p-value < .001; ** p-value < .01; * p-value < .05.

	Model 1 (NUTS 1–2-3)		Model 2 (NUTS 0–1-2)		Model 3 (NUTS 0–2-3)	
	Estimate (SE)	t-value	Estimate (SE)	t-value	Estimate (SE)	t-value
Intercept	359.336 (46.112)	7.793***	413.81 (76.17)	5.432***	427.453 (71.155)	6.007***
Slope (variation over time)	−8.672 (1.647)	−5.266***	−9.810 (2.87)	−3.418**	−9.822 (2.184)	−4.498***
Fit indexes						
Df	12		12		12	
AIC	125,235		152,573		125,217	
BIC	125,321		152,659		125.303	
LogLik	−62,605		−76,274		−62,597	
Deviance	125,211		152,549		125,193	
Chi sq.			0		27.355	
Pr>(Chi sq.)			1		<2e-16 ***	

Table 5
Random effects for the three models proposed, in terms of intercept and slope; *** p-value < .001; ** p-value < .01; * p-value < .05; n.s. Not Significant.

	Model 1 (NUTS 1–2-3)			Model 2 (NUTS 0–1-2)			Model 3 (NUTS 0–2-3)		
	Intercept	Slope	Cor.	Intercept	Slope	Cor.	Intercept	Slope	Cor.
NUTS 0				*	*	−1.00	*	*	−0.68
NUTS 1	*	*	−0.88	n.s.	n.s.	−1.00			
NUTS 2	***	***	−1.00	***	***	−1.00	***	***	−1.00
NUTS 3	***	***	−0.69				***	***	−0.70

5.3. *The significance of different scales for different states*

So far, we have highlighted the importance of multi-scalarity in studying ST. However, this opens up the question: Is this evidence consistent across different states or, conversely, does it show an uneven pattern that can be explained by geographical specificities? In this section, we employ the results of Model 1 from our previous analyses to explore this issue. In particular, Table 6 presents the significance of the random effects model at different NUTS, for the EU's top ten emitting states.

We show that the NUTS 3 scale is statistically significant in most states (p-value <.001) for both intercept and slope. For NUTS 2, the results are significant for France (p-value <.001), The Netherlands (p-value <.001) and Czech Republic (p-value <.01) in terms of intercept, and for Greece (p-value <.001) in both intercept and slope. The NUTS 1 results are significant for Germany (intercept, p-value <.05) and Spain

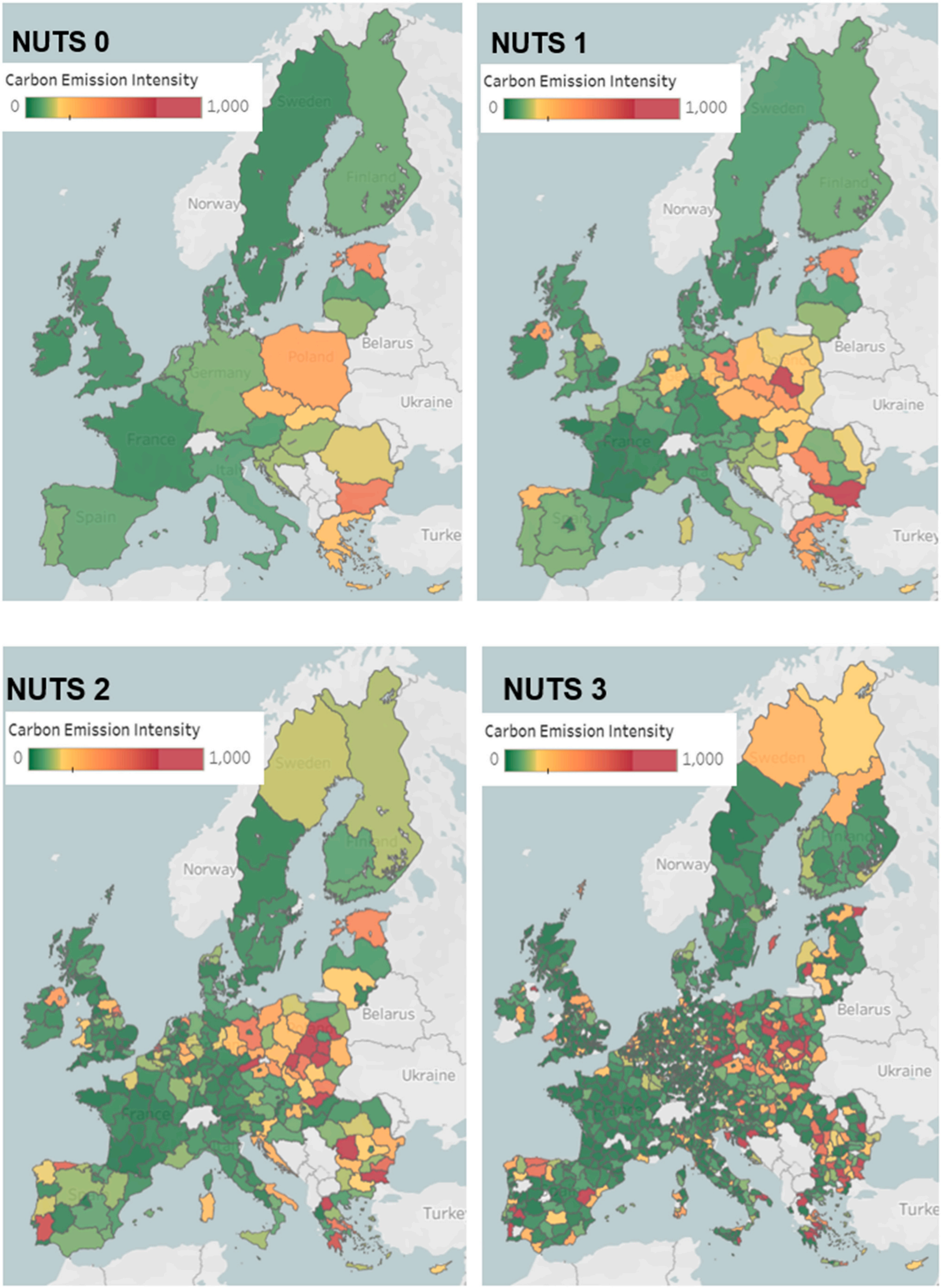

Fig. 2. Carbon Emission Intensity (tons of CO2e/million €) for the year 2016 for NUTS 0-1-2-3

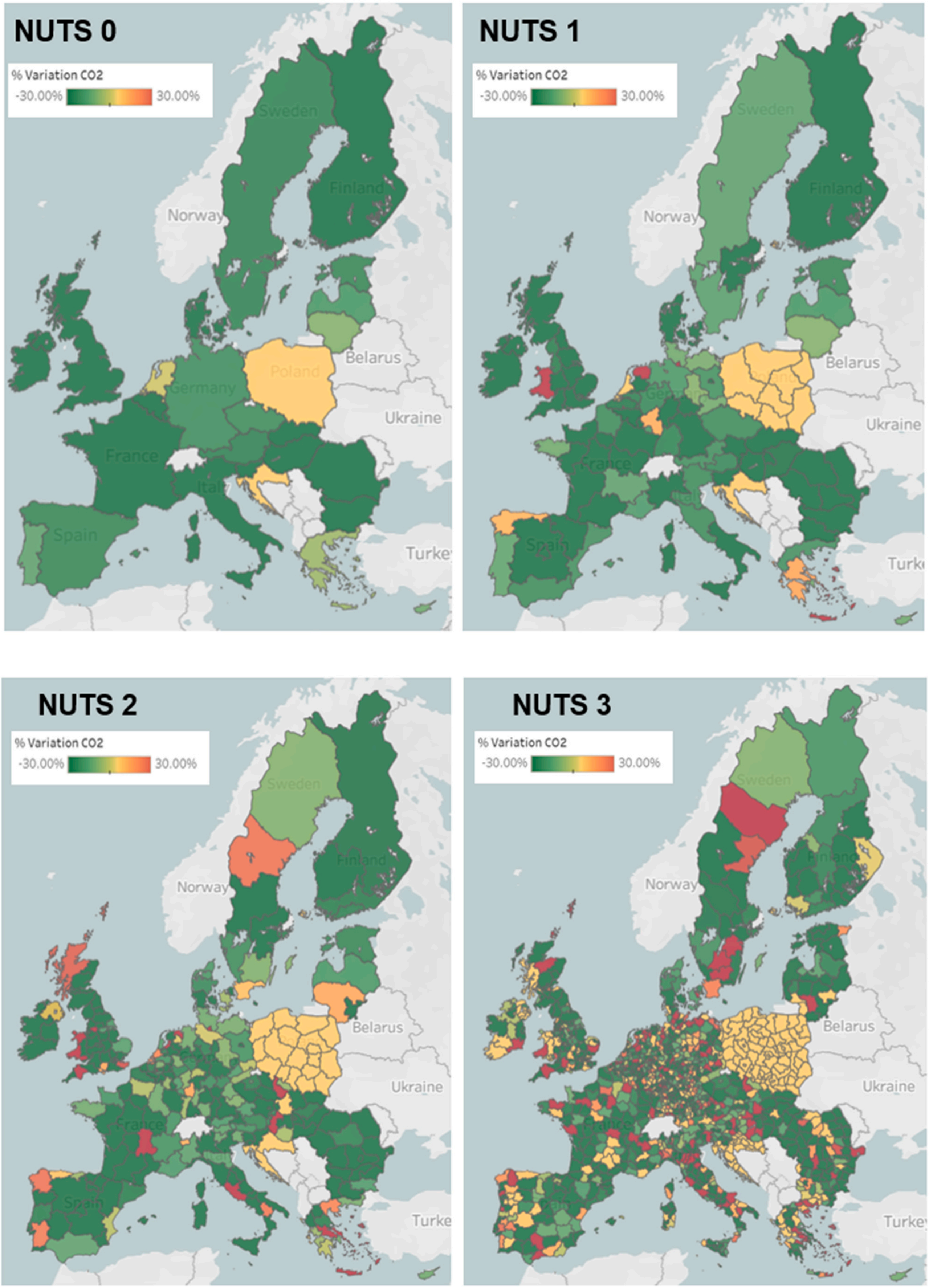

Fig. 3. Variation of Carbon Emission Intensity (tons of CO2e/million €) between 2008 and 2016 for NUTS 0-1-2-3.

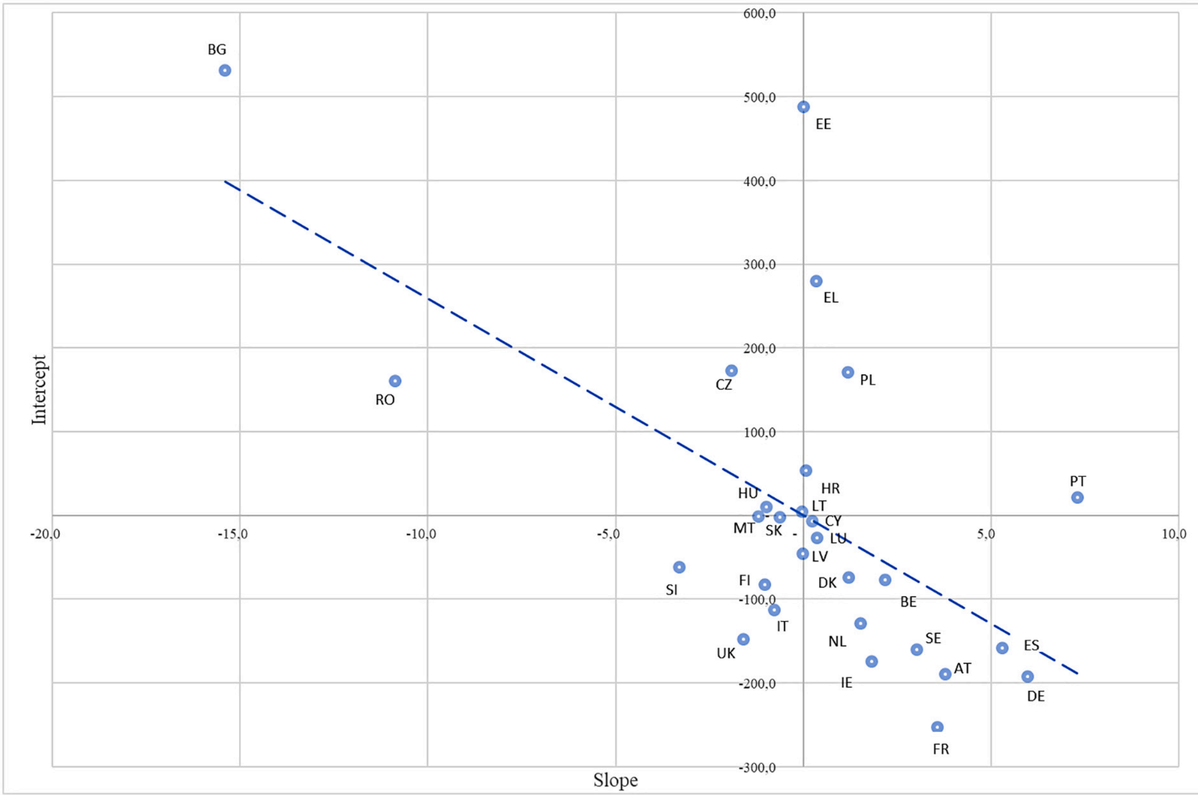

Fig. 4. Plot of the correlation between intercept and slope of Carbon Emission Intensity for each country, derived from the multilevel-growth model.

Table 6
Analysis of the top 10 CO2e emitting countries; *** p-value < .001; ** p-value < .01; * p-value<.05; § p-value<.1; N.S.= Not Significant; n.a.= not available.

State	NUTS 1			NUTS 2			NUTS 3		
	Obs.	Intercept	Slope	Obs.	Intercept	Slope	Obs.	Intercept	Slope
Germany	16	*	N.S.	38	N.S.	N.S.	361	***	***
Poland	7	N.S.	N.S.	17	N.S.	N.S.	73	***	***
Italy	5	N.S.	N.S.	21	N.S.	N.S.	105	***	***
Spain	7	§	§	19	N.S.	N.S.	59	***	***
UK	12	N.S.	N.S.	41	N.S.	N.S.	158	***	***
France	14	N.S.	N.S.	27	***	N.S.	192	n.a.	n.a.
The Netherlands	4	N.S.	N.S.	12	***	N.S.	78	n.a.	n.a.
Czech Republic	0	n.a.	n.a.	8	**	N.S.	14	***	***
Greece	0	n.a.	n.a.	12	***	***	40	**	**
Belgium	3	N.S.	N.S.	11	N.S.	N.S.	44	***	***

(intercept and slope, p-value <.1). Overall, these results suggest that, while NUTS 3 appears to always be relevant, the significance of NUTS 1 and NUTS 2 differs across states, highlighting the importance of place specificity in the study of ST. In fact, each national context shows specific geographical scales where CEI trajectories significantly differ from the average. This result suggests that ST should be addressed with regulations focusing on specific geographical scales in different states (Hansen and Coenen, 2015).

5.4. Potential drivers of industrial transition

The final set of analyses elaborates on the extent to which decreasing CEI is associated with actual structural changes in the EU industrial sector, as well as deconstruct the processes that underlie the CEI dynamics. We thus explore the potential drivers of industrial transition by considering the effects on CEI introduced by changes in EU ETS regulation and by the decommissioning of plants (see Section 4.3 for details).

The piecewise model allows us to consider the possibility that the trajectory of CEI is not necessarily smooth and linear over the entire time

Table 7
Fixed effects into the model proposed indexes; *** p-value < .001; ** p-value < .01; * p-value < .05.

	Model 3 (NUTS 0–2-3)	
	Estimate (SE)	t-value
Intercept	307.054 (52.276)	5.874***
Slope t1: period 2008–2012	−8.504 (2.122)	−4.008***
Slope t2: period 2013–2016	−13.996 (3.024)	−4.629***

span 2008–2016; instead, it could be characterised by a discontinuity in its overall mean path introduced by the regulation. The model encompasses two trajectories for the sub-periods of analysis (i.e., 2008–2012, Phase II EU ETS; and 2013–2016, Phase III EU ETS): Both sub-periods show statistically significant values of the linear slope corresponding to each of the two time periods considered (Table 7). Compared to the overall trajectory of the general model (NUTS 0–2-3), which had an average rate of change in CEI equal to −9.82, the piecewise model shows

Table 8
Fixed effects into the model proposed indexes; *** p-value < .001; ** p-value < .01; * p-value < .05.

		Model 3 (NUTS 0–2-3)	
		Estimate (SE)	t-value
Decomm-1	Intercept	241.850 (60.309)	4.010***
	Slope t1: period 2008–2012	−10.321 (2.197)	−4.697***
	Slope t2: period 2013–2016	−12.783 (3.859)	−3.317**
Decomm0	Intercept	49.565 (51.013)	0.972
	Slope t1: period 2008–2012	3.304 (1.685)	1.960
	Slope t2: period 2013–2016	−3.003 (4.944)	−0.607
Decomm+1	Intercept	187.223 (48.362)	3.871***
	Slope t1: period 2008–2012	3.998 (1.605)	−2.491*
	Slope t2: period 2013–2016	−2.305 (4.639)	−3.317

the rate of change of the CEI is equal to −8.504 in the first sub-period (2008–2012) and −13.996 in the second (2013–2016), while both values of the slope are statistically significant (p-value < .001). This result shows that the change in EU ETS regulation helped to accelerate the decreasing average CEI pattern and thus might represent an actual transition pathway.

In light of the decommissioning variable, the coefficients of the reference case (i.e., Decomm-1, representing the decommissioning scenario) were all significant, while the slope in the second sub-period showed a steeper decrease compared to the first sub-period (Table 8). These analyses confirm the significance of the piecewise model in those NUTS that experienced the decommissioning of plants. Decomm+1, which characterises those NUTS where the number of plants increased, showed that the intercept is higher than in the reference case: It is equal to the sum of the reference model with the specific intercept generated by Decomm+1 (241.850 + 187.223 = 429.073). The slope in the sub-period t1 was significant and equal to −10.321 + 3.998 = −6.323, but it was not significant in the sub-period t2 (i.e., not significantly different from the reference case) and therefore remained equal to the reference case itself (−12.783). Finally, considering Decomm0, which characterises NUTS that did not vary the number of plants during the period, both the intercept and the slope in the sub-periods t1 and t2 were not statistically significant. Therefore, Decomm0 is not significantly different from Decomm-1.

Taken together, these results suggest that regulation triggers industrial transition dynamics, while decommissioning does not lead to any significant effect. In fact, NUTS in which the decommissioning took place behaved similarly to those in which decommissioning did not occur, especially in the sub-period t2. Fig. 5 shows the piecewise average trajectories for the three decommissioning scenarios.

6. Discussion and conclusion

The field of ST is gaining strong interest among academics and practitioners due to its high relevance for business and society. This trend is expected to increase, given the magnitude of sustainability challenges facing the world today. At the same time, ST is a research field characterised by high complexity: Transformational processes require the interactions of multiple actors in order to proceed, as highlighted by previous theoretical frameworks in the field (i.e., MLP, TM, SNM and TIS). However, the abstract conceptualisation of niches, regimes, and landscapes opened up the opportunity for the economic geography literature to contribute to the ST field with the introduction of space. This literature has made constructive comments and criticism on transition studies (Cooke, 2009; Hodson and Marvin, 2009; Shove and Walker, 2007; Truffer, 2008), particularly by introducing the concept of multi-scalarity (Coenen et al., 2012). However, further efforts to empirically measure the concept of space would benefit the field's progression. In our paper, we operationalise multi-scalarity in order to create a methodological basis for empirically investigating multiple geographical scales and performing comparative analyses of ST processes. This is a necessary – even urgent – step to explain the geographical unevenness of transition pathways, as well as concretely elaborate on how a spatial perspective on ST may be used to complement the existing literature and define more effective policies.

Beyond contributing to the ST literature in general, our study also adds insights to the specific literature on CEI by focusing on industrial sustainability transition. Current studies on carbon emissions (Pan et al., 2019; Turner et al., 2012) have mainly concentrated on the definition of mitigation policies through data collected at the national level (Hossain, 2011; Dogan and Seker, 2016; Wang et al., 2017; Zhang et al., 2014). However, as we have emphasised, a single measurement approach cannot address the complexities of and differences among countries; thus, we exploited a novel and comprehensive longitudinal dataset, where data on EU CEI were gathered at finer geographical aggregations. To our knowledge, this is the first study to exploit these data, which is surprising considering that they may support the adoption of a novel and more efficient approach to defining ST policies, based on different scales.

Moreover, our research contributes to the quantitative study of the drivers of ST. Our results delineate how changes introduced by the Phase III of EU ETS succeeded in decreasing CEI without causing unintended carbon leakages. In this way, we answer calls from the extant literature to study the effects of the Phase III, including issues related to the carbon leakages linked to the decommissioning of plants (Naegele and Zaklan, 2019; Teixidó et al., 2019).

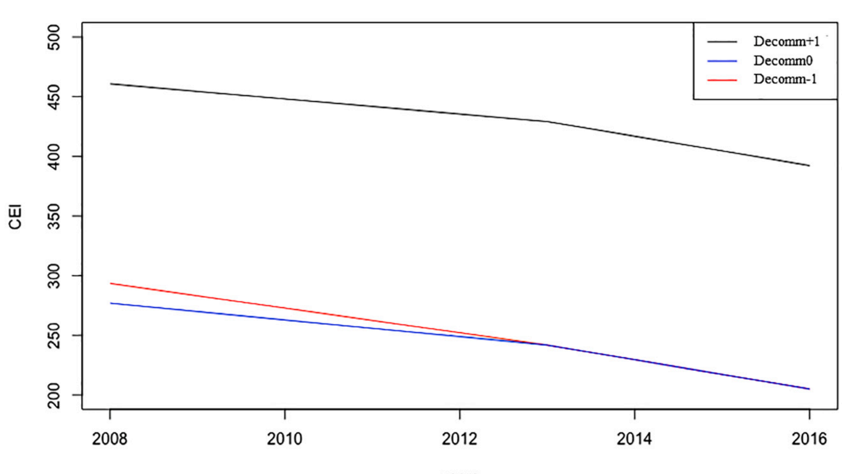

Fig. 5. Plot of CEI model for the three decommissioning scenarios, i.e., Decomm+1 representing the NUTS where the number of plants increased during the period of analysis; Decomm0 representing the NUTS that did not vary the number of plants; Decomm-1 representing the NUTS where the number of plants decreased.

6.1. Policy implications

Based on the aforementioned contributions, our results provide several policy implications. Firstly, we suggest that the mean trajectory of CEI in the EU decreased between 2008 and 2016. European and national policies have been crucial for triggering the process of ST (Lindberg et al., 2019), pushing European countries to be engaged in re-industrialization processes. To date, we are aware of differences among countries in their journey towards a less CO2-intensive, but wealthier, context. Our data show a general reduction of CEI in the timespan considered, indicating that the EU Commission's ETS policy (Directive 2003/87/EC) has had positive effects. However, we also suggest that the overall EU results (−18% CO2e) are far from reaching the targets set by the EU Green Deal[10] (−55% CO2e by 2030). This is probably because nowadays, policies to support ST are mainly defined at the national or European level. However, we suggest that a "one-size-fit-all" approach does not work in this complex context. An exploration of the finer aggregations of geographical boundaries is imperative to make processes of re-industrialization more effective in the future (Coe et al., 2004). While governments should have a comprehensive plan that defines general initiatives for their entire national contexts, they should also adopt specific policies built around the characteristics of each spatial dimension in which the transition is going to take place.

This leads to the paper's second finding: Different geographical scales (NUTS 0, 1, 2 and 3) all play a significant role in studying ST trajectories. The concept of geographical multi-scalarity has the potential to overcome the emphasis on the national scale that pervades extant research. This resonates with the debate, introduced by Brenner (2001) and further elaborated by Coenen et al. (2012), about the importance of considering different scales in order to fight the "tendency to create an ontological hierarchy in which the global is somehow more powerful than the local scale" (Coenen et al., 2012, p.75). In particular, focusing on micro-scales allows scholars to appropriately consider the specialization of competences and institutional structures as critical factors supporting ST processes. Local actors should be better equipped than national actors to design successful policies, thanks to their knowledge of local specific conditions and their ability to match policies to area peculiarities (Asheim et al., 2011).

Thirdly, our findings show that different starting points in CEI correspond to different decreasing trajectories, thereby depicting different ST patterns. In particular, geographical areas starting from a higher level of CEI show a more pronounced decline in CEI over time, while the opposite occurs for areas starting from lower values of CEI. The literature on evolutionary economic geography supports this orientation through the concept of path dependency, as the history and status quo of a place necessarily affect its transition pathway. At the firm-level, companies tend to be "locked-in" (Greco and di Fabbio, 2014) within specific geographical areas due to patterns of activities and resources, which impede the delineation of new pathways deviating from the initial conditions. The same can be said for regions. As ST is affected both by the processes related to the historical pathway and the features of the place itself, the proximity among actors creates a self-reinforcing mechanism that limits variations in context conditions (Coenen et al., 2010), while stimulating knowledge spill-overs and diversification in related (but not spatially distant) geographical areas. However, it is interesting to note that the negative relationships between intercept and slope derived from our data are not homogeneous along the ST pathway; instead, they tend to have a steeper decline in the initial phases and a flatter one as the pathway evolves. Countries that have played a leading role in ST (e.g., Germany, France, The Netherlands, Denmark) will face greater challenges in further sustaining their emission reductions, while countries just starting their pathway (e.g., Hungary, Czech Republic, Romania, Bulgaria) will obtain greater results. This is mainly due to the fact that the two groups occupy two distinct positions in the journey towards ST. Accordingly, policies will have to consider these differences when delineating country-specific actions in order to be fully effective.

Additionally, our results show that the significance of the geographical scales at NUTS 1, 2 and 3 changes based on the NUTS 0 considered. The natural variety of European contexts underscores the importance of studying ST from an institutional economic geography perspective (Martin, 2001; Martin and Sunley, 2006). We thus highlight the need to identify groups of geographical areas that share similar structural characteristics, institutional conditions and transition strategies. It is important to note that the grouping of these geographical areas does not have to exclusively follow the rule of geographical proximity, but can also aggregate areas that are distantly located from one another. This grouping may provide the basis for identifying more precise and fitting policies towards ST.[11]

Finally, our analysis confirms that in the early stages of the EU ETS, primarily incremental process innovations might have been introduced and resulted in a limited reduction of CEI. This would then not so much correspond to an actual "transition", but rather to incremental improvements due to (regulatory-) induced energy saving attempts. However, by conducting a piecewise analysis, we show that the introduction of Phase III in EU ETS resulted in a steeper decrease in CEI (compared to Phase II), which might signal a structural change in the overall energy-intensive industrial sector. This result confirms early studies in the field (Petrick and Wagner, 2014; Wagner et al., 2014). With our analytical framework, we also quantify the impact of regulations on the reduction of CEI, showing a significant change of trajectory before and after the introduction of the Phase III of EU ETS. Our findings as a whole suggest that the changes in EU ETS (e.g., a single GHGs emissions cap for the whole EU area, the expansion of the sectors covered and the emission allowances allocated by auctioning, instead of being granting for free) acted as a trigger for transition processes, but the different geographical areas have been able to leverage this impulse by carrying forward their own independent transition process. In addition, our analyses show that regions experiencing plant decommissioning display the very same CEI decrease as regions where the industrial ecosystem is stable or even growing. This result supports previous evidence about the effectiveness of EU ETS regulation in reducing carbon emissions, namely by promoting industrial transition without causing undesirable carbon leakages (Naegele and Zaklan, 2019).

6.2. Limitations and future research

This paper contains some limitations that reveal opportunities for further research. Firstly, our study focused on the industrial sector, although there are other forms of ST to explore, such as transitions in energy systems (Lindberg et al., 2019), mobility (Köhler et al., 2020), agriculture and food-chain (Adegbeye et al., 2020), and cities (Geng et al., 2019). Broadening the investigation to non-industrial transitions could provide a more comprehensive picture of the challenges and opportunities facing our societies. Secondly, we used CEI as a proxy of industrial ST. This study represents, to our knowledge, the first attempt to account for the hierarchical structure of CEI for a large pool of countries. Furthermore, the use of CEI data allowed us to analyze policy-induced transition pathways with incremental effects along time. Further research could adopt additional variables (e.g., total CO2 emissions, air pollution) in order to better represent structural changes with consequent more radical effects on ST.

Third, the EU ETS database that we used to collect data on industrial

[10] COM (2020) 562 final. Available at: https://eur-lex.europa.eu/legal-content/EN/TXT/PDF/?uri=CELEX:52020DC0562&from=EN

[11] We highlight that we do not test for spatial autocorrelations in our analyses, however, geographical proximity may represent a lens for interpreting our results.

CO2e emissions features missing values due to data collection issues or different countries' legislative shortcomings. Future studies could adopt different data sources for CO2e emissions by shifting from self-declarations data (as in the EU ETS register) to more objective data collected through satellites (e.g., EU Copernicus project), or by focusing on a broader panel of air quality data that integrates information from the European Pollutant Release and Transfer Register (*E*-PRTR).

Finally, our paper described the evolution of ST trajectories in terms of the interplay between time and space. Future research could more deeply investigate this topic by analysing the reasons why these pathways occur; that is, they could identify drivers of ST. The digital development of a region, its level of education, and its foreign direct investments could represent interesting examples of antecedents that explain the different ST pathways.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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