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The transition of brown regions: A matter of timing?

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Abstract

Green innovations aim to improve and reduce the environmental impact of economic activities. Thus far, research focus on the positive trajectories of green transition. Recent studies focus also on the speed of transition and on its effects on economic outcomes. Continuing in this direction we focus on brown regions (i.e. specialized in fossil-fuel technologies) and the challenges that they face to become sustainable. Taking as example German Labour Market Regions we identify brown regions and measure their transition using an innovative approach based on Social Network Analysis and Knowledge Spaces. We find that the earlier a region transitioned to green technologies, the better it is for both its social and economic outcomes. Our findings imply that the transition of brown regions has effects on socio-economic outcomes not yet accounted for in the sustainability transition literature.

Keywords: green transition, green technologies, knowledge spaces, network embeddedness, socio-economic development

JEL Classification: O32, O33, R11

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1 Introduction

The current economic system, which is essentially based on the use of fossil and non-renewable resources, faces immense structural challenges in the wake of climate change. This is even more true looking at the continuous increase of world population and finite natural resources (Imbert et al., 2017; Morone, 2016). Sustainable, also called green, innovations, which aim to reduce the environmental impact of human activities, have a key role in this change (Barbieri et al., 2020; Losacker et al., 2021; Montresor & Quatraro, 2020). In general, they are at the heart of efforts to combine economic and environmental goals to achieve sustainable growth - one of the main objectives of the European Green Deal (European Commission, 2019).

Nevertheless, despite the extraordinary ecological and economic opportunities, e.g. through the creation of new industrial sectors, the sustainability transition[1] also poses some challenges - especially for regions (Blažek et al., 2020; Hermans, 2018; Trippl et al., 2019). Particularly brown regions, e.g. coal regions, are facing the difficult task of sustainably transforming their established, and so far economically successful, industrial structure (Grillitsch & Hansen, 2019). While, previous research has almost exclusively focused on the positive trajectories of green transition (Blažek et al., 2020; Köhler et al., 2019), we are interested in the widely ignored transition patterns of brown regions and the corresponding objective (i.e. wages and employment) and subjective (i.e. life satisfaction) socio-economic consequences. Following recent calls (e.g. Geels, 2018; Köhler et al., 2019; Sovacool & Geels, 2016), we thereby focus on the corresponding speed on which the transformation happened. As the historical examples of post-communist countries' shift to market economies have been shown, the speed of transition shaped (to some extent) the different socio-economic development patterns (Dell'Anno & Villa, 2013; Roland, 2000). Although, it is still an ongoing debate whether a shock therapy, also called a big bang, approach is more beneficial than a more gradual approach (Dell'Anno & Villa, 2013; Foster & Stehrer, 2007; Merlevede & Schoors, 2007) this rather macro-economic literature stream emphasizes that the speed of transition is an crucial determinant of the socio-economic development. In the context of sustainability transitions, recently, it has been claimed that the speed of transition varies extremely between different regions, due to the heterogeneous regional contexts (Roberts et al., 2018). Despite the historical evidence and the recent calls for further research, so far it remains, however, unclear, particularly from an empirical point of view:

(1.) how the speed of sustainable transitions differs among regions, and

(2.) how these processes influence the subjective and objective socio-economic outcomes.

Building on the concepts of regional innovation systems (RIS) (Asheim & Isaksen, 2002; Cooke, 2001) as well as the anchoring concept (Elzen et al., 2012), we want to empirically address these two research questions by investigating the regional knowledge space[2] (Basilico et al., 2022; Basilico & Graf, 2020; Kogler et al., 2013). For each German labour market region, we build a knowledge space based on patent data for the time period from 1991 to 2018 (5 years moving windows). To identify green patents we follow previous studies (e.g. Kopka &

[1] We refer to "sustainability transition" and "green transition" as synonyms throughout the paper.

[2] Although, similar to previous studies (e.g. Santoalha & Boschma, 2021; van den Berge et al., 2020), our article only focuses on the technological dimension, which of course does not capture the entire socio-technical transition (Geels, 2002, 2011), we can still map an important part of a regional transition with the available data.

Grashof, 2022) and use the IPC Green Inventory (WIPO, 2021), while for the identification of brown patents we rely on the mixed-method strategy (CPC classification and text analysis) by EPO & IEA (2021). Based on this information, we then define brown regions as those that have an Revealed Technological Advantage (RTA) in brown technologies and no RTA in green technologies (in the period between 1995 and 1999). This means that these regions were patenting in polluting activities more and in sustainable activities less than the national average. In line with the underlying idea of the anchoring concept (Elzen et al., 2012) and the recent methodological approach by Basilico & Graf (2020), we propose a new measure for the green transition of regions that considers the embeddedness of green technologies in the regional knowledge space (compared with the national average), the so-called Revealed Technological Betweenness Centrality Advantage (RTBCA). Based on this measure, we then calculate our main independent variable, namely the time that the region needs to reach an RTBCA in green technologies. To determine our dependent variables, we use information provided by the INKAR database of the BBSR (Federal Institute for Building, Urban and Spatial Research) in the case of the objective outcomes (wage and employment) and the German Socio-Economic Panel (SOEP) in the case of subjective outcomes (life satisfaction).

In general, we contribute to the recent literature stream on the geography of sustainability transitions, integrating the literature on regional studies with the transition literature (e.g. Coenen & Truffer, 2012; Hansen & Coenen, 2015; Losacker et al., 2021), in three important aspects. First, we introduce a new measurement for the regional (technological) transition patterns that moves beyond the rather simplified perspective that standard specialisation indicators, such as Revealed Comparative Advantage, offer. Instead, our new indicator captures how well green technologies are embedded and connected to the rest of the regional knowledge space. This goes more in line with both the ideas of the niche-regime interactions, highlighted within the Multi-Level Perspective (MLP) (Geels, 2002) and the anchoring concept (Elzen et al., 2012). Second, we shift the so-far rather one-sided focus on the positive trajectories of green transition (Blažek et al., 2020; Köhler et al., 2019) to the transition patterns of brown regions which might entail rather negative outcomes in terms of objective and subjective socio-economic consequences. Third, by empirically investigating how the speed of sustainable transitions differs among regions and how this influences the corresponding subjective and objective socio-economic outcomes, we contribute to recent calls for further research (e.g. Geels, 2018; Köhler et al., 2019; Sovacool & Geels, 2016). Based on our empirical findings, policy implications could be derived aiming to support green transition in brown regions at the best pace, in order to maximize the socio-economic outcomes. Thus, contributing not only to green, but also, and more importantly, to a just transition (Høst et al., 2020; Velicu & Barca, 2020; European Commission, 2022).

The remainder of this paper is structured as follows: Section 2 reviews the corresponding literature and presents the underlying theoretical background. Section 3, describes the data and the empirical identification strategy for the regional transition. Thereafter, section 4 presents the econometric approach as well as descriptive statistics. The results are discussed in section 5. The paper ends with section 6 including final remarks, limitations and promising future research directions.

2 Theoretical background

2.1 Sustainability transitions, anchoring and regional knowledge spaces

Sustainability transitions refer to long-term and systemic transformation processes through which the current socio-technical system shifts to a more sustainable one (Markard et al., 2012). One prominent theoretical concept for understanding these transition processes is the multi-level perspective (MLP) (Elzen et al., 2012; Geels, 2002; Smith et al., 2010).[3] When using this concept, sustainability transitions are described through the dynamic processes within and between three levels of analysis: (1.) *Niches*, representing protected spaces, in which particular radical innovations can be developed, tested and deployed; (2.) *Socio-technical regimes*, which are institutional structures of existing systems that use a certain technology in a proven way and therefore lead to path dependencies and thus rather to incremental change processes; (3.) *Socio-technical landscape*, referring to exogenous (societal) events and developments (e.g. long-term trends such as demographic change or rapid shocks such as wars) that influence the socio-technical system (Geels, 2002; Geels & Schot, 2007; Rip & Kemp, 1998; Santner, 2017).

However, despite its popularity, the MLP has also been criticized (e.g. Genus & Coles, 2008; Smith et al., 2005). One of the most prominent criticisms of the MLP, refers to the geographical context, which has often been ignored (Binz et al., 2014; Coenen & Truffer, 2012; Hansen & Coenen, 2015). Only in recent years has this aspect gained considerable attention in the relevant literature (e.g. Losacker et al., 2021). As indicated by the concept of regional innovation systems (RIS), regions have different characteristics that need to be taken into account (Asheim & Isaksen, 2002; Asheim et al., 2016; Cooke, 2001). For instance, due to the existing localisation externalities (e.g. knowledge spillovers) (Marshall, 1920), the co-location in a regional cluster can contribute to an increased innovative performance (Baptista & Swann, 1998; Grashof et al., 2019; Grashof, 2021). Among the different categorizations of regions, (e.g. Kopka & Grashof, 2022) the distinction of Grillitsch & Hansen (2019) introducing the direction of industrial specialization as a new element is particularly suitable for our research. Specifically, in their work they distinguish between four types of regions (Grillitsch & Hansen, 2019):

(1.) Peripheral regions;

(2.) Regions specialized in a green industry;

(3.) Regions specialized in a dirty industry (in the following called brown regions);

(4.) Metropolitan regions.

Moreover, the predominant focus of the MLP approach on one specific technology and how it is able to subsequently challenge the incumbent technology has also been criticized (Andersen & Markard, 2020; Sutherland et al., 2015), since it ignores the fact that technological change is a rather cumulative process, involving multiple technologies (Arthur, 2007; Basalla, 1988). Related to this narrow focus, the linking processes between niches and regime are also poorly understood in the MLP (Elzen et al., 2012; Smith, 2007), which prompted Elzen et al. (2012)

[3] Another frequently used concept refers to the Technological Innovation System (TIS), which examines both the structure and functions of the technological innovation system (Bergek et al., 2008; Hekkert et al., 2007; Köhler et al., 2019).

to introduce the anchoring concept. In their advancement of the MLP, they define anchoring as: "(...) the process in which a novelty becomes newly connected, connected in a new way, or connected more firmly to a niche or a regime. The further the process of anchoring progresses, meaning that more new connections supporting the novelty develop, the larger the chances are that anchoring will eventually develop into durable links." (Elzen et al., 2012, p.3). In other words, the anchoring concept focuses on the process of alignment of a novelty[4] to the mainstream structures, i.e. on the interactions between the niche and the regime. These linkages can thereby lead to both adaptation of the novelty in the regime and adaptation of the novelty in the niche, e.g. due to lack of compatibility/resistance of the regime (Elzen et al., 2012; Santner, 2017). Based on the classical analytical dimensions from the MLP literature (e.g. Geels, 2002), Elzen et al. (2012) differentiates between three forms of anchoring:

(1.) *Technological anchoring*, referring to the further definition and specification of the technology, i.e. further development of the technology according to the needs of the regime;

(2.) *Network anchoring*, meaning that the network of actors carrying the novelty changes, not only in terms of simple expansion of the network, but also with respect to an increasing interdependence;

(3.) *Institutional anchoring*, dealing with the institutional characteristics of the novelty, referring either to values, beliefs and identities (interpretative institutions), to formal and informal rules (normative institutions) or to market rules and arrangements, such as contracts (economic institutions).

In general, these three forms represent different aspects of the anchoring concept. While technological and institutional anchoring describe *what* is actually anchored, network anchoring deals with *whom* the novelty anchors (Elzen et al., 2012; Santner, 2017; Sutherland et al., 2015). Building from the form of *Technological anchoring*, we assume that technological change is a rather cumulative process, where existing knowledge is combined in unique ways to create something new (Arthur, 2007; Basalla, 1988; Jaffe, 1989). We follow a relational approach looking at innovation as a result of components recombination rather than a process made in isolation (Nelson & Winter, 1982; Henderson & Clark, 1990). As such, the concept of knowledge spaces, operationalized by creating a network of interrelated technologies, helps to identify such recombination processes (Breschi et al., 2003; Basilico & Graf, 2020; Kogler et al., 2013; Balland et al., 2019). In line with the anchoring concept explained above, we are interested in how green technologies become more embedded within in the regional knowledge space (Elzen et al., 2012).

While previous studies have conceptualised the evolutionary trajectories of regions in a rather positive form, i.e. creation of a new regional growth path (Blažek et al., 2020; Köhler et al., 2019), we are interested in the widely ignored sustainability transition patterns of brown regions. Due to their already existing, rather dirty, technological and industrial structure these regions face the challenge of transforming their RIS in a sustainable way. This transformation process entails, possibly, also negative trajectories, which might ultimately cause social and political problems (Blažek et al., 2020; Grillitsch & Hansen, 2019; Rodríguez-Pose, 2018).

[4] Novelty can be seen as a new technology, a new technical concept or a new socio-technical practice (Elzen et al., 2012).

Figure 1, shows the transition patterns of regions through the analysis of the embeddedness of green technologies over time in regional knowledge spaces. In the case of phase 1, the socio-technical regime and the niche are clearly distinct in the knowledge space. Moreover, the green technologies in the niche are rather independent from each other. In the case of phase 2, some clustering between the green technologies in the niches is visible. Such phenomenon is potentially induced by some exogenous landscape factors, such as long-term trends (e.g. demographic change) or rapid shocks (e.g. wars) (Geels, 2002; Geels et al., 2017). However, as in phase 1, the network of green technologies is still rather isolated from the rest of the regional knowledge space. In phase 2 the corresponding region would be considered specialized in these green technologies, following the literature about regional diversification (e.g. Boschma et al., 2014). Nevertheless, in terms of the anchoring concept, we would not describe phase 2 as when a successful transition happened since the specialization in green technologies is rather isolated from the rest of the regional knowledge space. There are basically no interactions between the niche and the regime (i.e. missing process of alignment of the novelties in the niche to the mainstream structures), making the sustainability transition of that specific region highly unlikely. In phase 3, the niche of green technologies develops some linkages with other technologies in the regional knowledge space. In this phase, presumably, some conflicts emerge between the incumbent technologies and the green technologies. A process that could possibly harm the conclusion of a successful transition process. Lastly, in phase 4 green technologies are now highly embedded and anchored in the regional knowledge space. Thus, phase 4 shows the successful transition of the regional knowledge space to green technologies[5].

2.2 Speed of transition and socio-economic consequences

After conceptualising the sustainability transition process on the regional level, we now address the corresponding speed of these processes and its socio-economic implications. The timing and pace of these transitions are at the center of a current debate in the literature on sustainability transitions, resulting in calls for further research (Geels, 2018; Köhler et al., 2019; Sovacool & Geels, 2016; Sovacool, 2016). In this context, the relevance of the regional-level has been stressed. Depending on the specific regional context the speed of transition might differ greatly between regions (Roberts et al., 2018; Wesche et al., 2019). We want to contribute to this ongoing discussion, by considering the pace of transition as well as its socio-economic impacts, following recent conceptual elaborations by Geels (2018) and Kivimaa et al. (2021).

To derive our underlying hypotheses, we use insights from historical examples (Grubler, 2012).[6] One prominent example, where the speed of transition played a quite relevant role, refers to the transitions of post-communist countries to market economies (Dell'Anno & Villa, 2013; Roland, 2000).[7] While the characteristics of the post-communist countries' transition patterns were relatively similar, encompassing, i.e., macroeconomic stability, liberalisation of prices and trade, as well as privatisation (Fischer & Gelb, 1990; Havrylyshyn et al., 1999; IMF,

[5] Although related (e.g. Andersen & Markard, 2020; Iammarino & McCann, 2006; Neffke et al., 2011), the technological dimension might differ from the industrial dimension.

[6] Although sustainability transitions might be slightly (but not necessarily) different from previous transitions (e.g. Geels, 2011, 2018), historical examples offer an instructive understanding of what one might expect, especially in terms of socio-economic outcomes (Grubler, 2012).

[7] For the purpose of our study, we consider only the economic and not the political transformation.

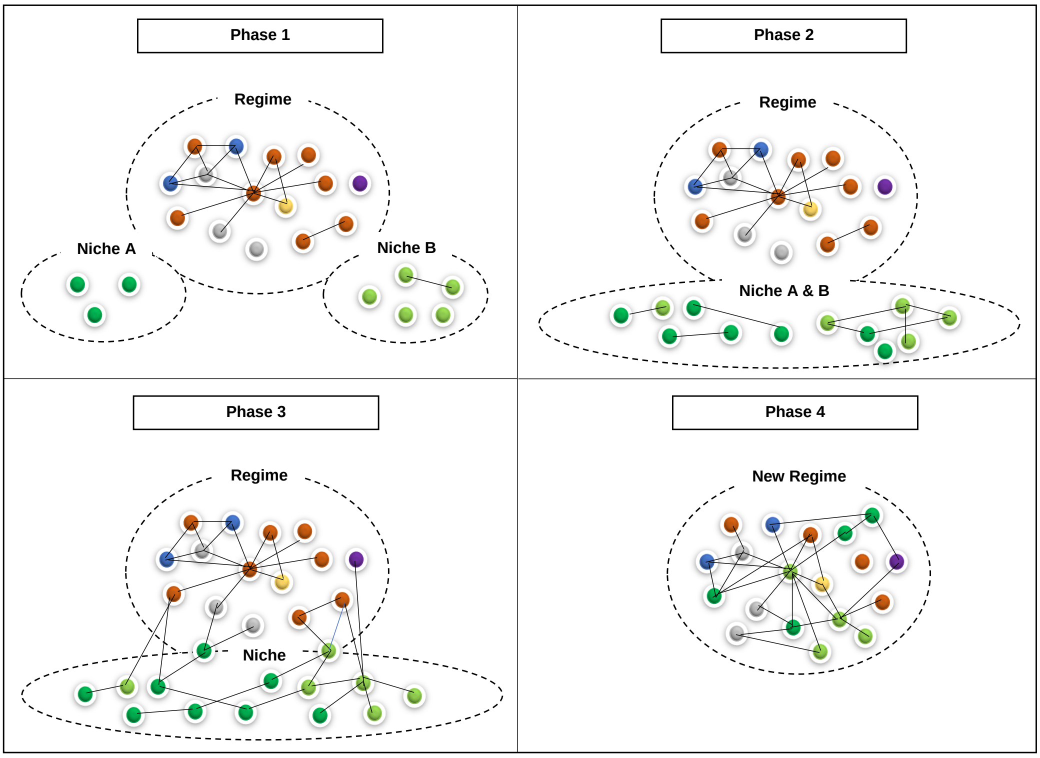


Figure 1: The different phases of green transition

2000), the speed and intensity of the respective implementation varied considerably. In general, the pace and strength of economic transition can be distinguished between two different forms: the gradual approach and the shock therapy, also called the big bang approach (Dell'Anno & Villa, 2013; Giannaros et al., 2008). The former is characterised by a gradual implementation of reforms spread through many years (Giannaros et al., 2008). The latter is, characterised by an immediate and profound change of the economic system towards a free market economy. This typology of transition was for a long time the prevailing approach of the International Monetary Fund and the World Bank, reflected by the Washington Consensus (Babb, 2013; Burki & Erikson, 2004). The corresponding literature shows that there are positive and negative examples in both approaches (e.g. Dell'Anno & Villa, 2013; Feltenstein & Nsouli, 2003; Roland, 2000). Thus, there is still no unanimous opinion on which of the two approaches achieved better economic results (Dell'Anno & Villa, 2013; Foster & Stehrer, 2007; Merlevede & Schoors, 2007). Despite this mixed evidence, for our specific research case, we assume that the speed of transition has a positive association with regional economic development. We thereby follow previous empirical studies which are in favour of the shock therapy (e.g. Dell'Anno & Villa, 2013; Fischer & Sahay, 2000). Although rapid change can lead to economic dislocation in the short term (Dell'Anno & Villa, 2013), it is generally assumed that it brings benefits, such as first-mover advantages (e.g. Lieberman & Montgomery, 1988). Thus, we propose the following hypothesis:

Hypothesis 1 *The pace of the sustainable (technical) transition has a positive influence on the regional economic development.*

Previous research on sustainability transition has largely overlooked the effects on subjective well-being[8], although the discontent within regions might likely cause severe social and political problems (Rodríguez-Pose, 2018; Rodríguez-Pose et al., 2021). For instance, a low life satisfaction among voters significantly drives the rise of populist political parties (Herrin et al., 2018; Nowakowski, 2021). As such, apart from focusing on the regional economic development, we also consider the non-economic aspect of subjective well-being. Due to the speed of change, it is conceivable that not all people can participate equally in this transformation or that the (political) communication of these changes is not effective enough. As a result, the population may feel overwhelmed by the (relatively) rapid changes, which is then expressed by rather negative attitudes towards the underlying technological developments. Thus, ultimately resulting to a decrease in the subjective well-being (De Ruyter et al., 2021; Heidenreich et al., 2016; Hinks, 2021). Therefore, we propose the following hypothesis:

Hypothesis 2 *The pace of the sustainable (technical) transition has a negative influence on the life satisfaction in regions.*

3 The empirical identification of the regional transition process

3.1 Data

We use EPO PATSTAT (Autumn 2020) as our source to detect innovative activities. We use patents filed between 1995 and 2018 with 5 year moving windows. A mix between CPC classification and text analysis is adopted to identify fossil-fuel patents (EPO & IEA, 2021). For the identification of green patents we use the WIPO green inventory (WIPO, 2021), including a catalogue of environmental-friendly technologies that has its roots in a list of the United Nations Framework Convention on Climate Change (Kopka & Grashof, 2022). A patent is classified as brown or green if one of its CPC classes falls in one of the two aforementioned inventories. For the knowledge space reconstruction we use the CPC classification at four digits level. The knowledge space is constructed following a co-occurrence method with CPC 4-digits classes as nodes and patents that co-classify at least two different CPC classes as edges.

Patent-based research have been proven as a valuable source of information since patents are associated with different technological domains (Breschi et al., 2003; Kogler et al., 2013; Boschma et al., 2014; Balland et al., 2019; Whittle & Kogler, 2019). Nonetheless, patents embed also some well-known limitations (Griliches, 1990). These analyses are limited to inventions that can be patented, omitting non-patentable inventions from industries with a lower propensity to patent (e.g. softwares or services). Moreover, our analysis is based on the patent classification system, assuming that patents in the same CPC class are similar but different from those in other classes. Since the classification is performed by patent offices for other purposes than this type of analysis, this might not hold true (Basilico et al., 2022).

To consider the geographical boundaries of knowledge spaces, we assign a patent to a region if at least one inventor resides in that area (Cantner & Graf, 2006). The approach based on the inventor location is performed because large companies have the tendency to file patents at their headquarters, which is not where the invention is initially originated (Graf, 2017). Consequently,

[8]However, it has been emphasized that the MLP should not only consider the ecological sustainability, but also the social sustainability (Geels, 2019; Røpke, 2016).

this could create large imbalances in the number of patents assigned to each region, since most of them would be assigned to large cities.

We consider Labour Market Regions (LMRs) as regional boundaries. LMRs are an aggregation of NUTS3 regions, designed to account for commuting patterns. By using LMRs instead of NUTS3 regions we better capture patents of inventors that reside in suburban areas and commute everyday to their workplace in larger cities (Basilico et al., 2022). Following the definition of Kosfeld & Werner (2012), there are 141 LMRs in Germany each comprehending the main city and the surrounding area. Our units of observation are those LMRs that successfully passed from being specialized in brown technologies to embed green ones.

3.2 Brown regions identification

The following methodological approach is applied to identify which regions in Germany are specialized in polluting activities at the beginning of the considered period. Similarly to Kopka & Grashof (2022), an indicator called Revealed Technological Advantage (RTA) is adopted (Balland et al., 2019). The RTA is a specialization index inspired by the Balassa indicator and it is operationalised as follows (Hidalgo et al., 2007):

$$brown = \frac{patents^t_{r,b} / \sum_i patents^t_{r,i}}{\sum_r patents^t_{r,b} / \sum_r \sum_i patents^t_{r,i}} \geq 1 \tag{1}$$

Where $patents^t_{r,b}$ is the number of patents in a region which have at least one CPC class identified as brown in time t, $\sum_i patents^t_{r,i}$ is the total number of patents in a region in time t, $\sum_r patents^t_{r,b}$ is the sum of all patents in every region which have at least one CPC class identified as brown in time t and $\sum_r \sum_i patents^t_{r,i}$ is the sum of the total number of patents for each region in time t.

A region r is classified as a brown region if it has a technological advantage in brown technologies b at a specific period t (all patents filed between 1995 and 1999). In other words, to be classified as brown, the region must have above average share of brown patents compared to the share of brown patents over all regions ($brown \geq 1$).

Moreover, with the same methodology explained above, we calculated the specialization in green technologies of regions. A region r is classified as a green region if it has a technological advantage in green technologies g at a specific period t (all patents filed between 1995 and 1999). Since it is difficult to assign them to one of the two categories, the regions that have in the period between 1995 and 1999 both specializations (in green and brown technologies) are excluded from the sample. At the end of this selection process, 23 regions have been identified as brown out of the 141 German LMRs.

3.3 A new measure for green transition: RTBCA

One of the most commonly used methods in economic geography to construct knowledge spaces is based on the concept developed by Hidalgo et al. (2007) of “product space”. This concept is commonly used to measure relatedness between technologies (e.g. Boschma et al., 2014; Kogler et al., 2013). The fundamental idea behind such approach is to build a network considering all the related products (in our case would be technologies) in one time period and then check how regions move inside of it over time based on the products in which they are specialized.

The network structure is thereby assumed as given because it is only measured in the first time period. Even if this method is adopted and accepted by the literature it does not fit our specific purposes. Our purpose is to investigate how green technologies are integrated and recombined in the knowledge space of brown regions. In order to achieve this objective it is necessary to construct knowledge spaces for each region and each time period. In this sense, we are able to track how green technologies become interconnected with other technologies and how the knowledge space changes. As showed by Basilico & Graf (2020) the underlying measures derived from this second approach are significantly different from the classic specialization indexes.

We assume that a region identified as brown should make use of their actual technological capabilities in order to embed and move to green technologies, such that a broad transformation of the regional knowledge space can succeed. Therefore, in line with our conceptual framework (see Figure 1) and similarly to Basilico & Graf (2020), we propose a relative measure that considers the embeddedness of green technologies in the regional knowledge space and we calculate to which degree this embeddedness differs from other regions.

Firstly, to calculate this embeddedness measure we reconstruct the regional knowledge space of the identified brown regions using a co-occurrence method on CPC 4-digits level. When a patent is co-classified in two different technology classes a connection between them is formed. Secondly, we classify the CPC classes in which a region is active among green, brown or other technologies. A single 4-digit CPC class could contain patents identified as brown, as green and/or as belonging to other technologies because both methodologies to identify green and brown patents are based on more granular level. Thirdly, we calculate a measure of betweenness centrality (Wassermann & Faust, 1994). Betweenness centrality measures how many times a node is in the shortest path between two other nodes. If a node is only highly connected with another node it would score high in other measures developed in the field of Social Network Analysis (like for example degree centrality) even though it is unconnected with the rest of the network (Basilico & Graf, 2020; Graf, 2017). Another advantage of using Betweenness centrality instead of other measures is that it takes into account all the indirect connections with other nodes. Thus, if a node with high betweenness centrality disappears, the connectedness of the whole network drops sharply (Basilico et al., 2022). Betweenness centrality of a node i is defined by:

$$WB_i^C = \sum_{j<k} s_i \times \frac{g_{jik}}{g_{jk}}, \forall i \neq j, k \tag{2}$$

with i, j, k as distinct nodes, g_{jk} is the number of geodesics between j and k and g_{jik} is the number of geodesics between j and k passing through i (Wassermann & Faust, 1994). We add to the original formulation of betweenness centrality the indicator s_i which is the share of patents identified as green, brown or others in each node (CPC 4-digits class) i. This measure provides both how well a technology is embedded in the knowledge space and how strong the support for brown, green or other technologies is for each single CPC 4-digits class.

To understand how well green and brown technologies are embedded in the regional knowledge space, we sum the betweenness centrality calculated in the previous step for green and brown technologies:

$$SBC_{rst} = \sum_{i \in s} WB_i^C \tag{3}$$

where s is one of the two macro-technologies (either green or brown). Finally, we calculate the Revealed Technological Betweenness Centrality Advantage (RTBCA) which measures how well green and brown technologies are embedded in the knowledge space of a single region r compared to all other regions. Therefore, to be classified as green, the region must have above average betweenness centrality in green technologies compared to the betweenness centrality in green technologies over all regions ($RTBCA_{rst} \geq 1$):

$$RTBCA_{rst} = \frac{SBC_{rst} / \sum_{r=1}^{n} SBC_{rst}}{\sum_{s=1}^{m} SBC_{rst} / \sum_{r=1}^{n} \sum_{s=1}^{m} SBC_{rst}} \times \frac{N_r}{N_g} \geq 1 \tag{4}$$

$RTBCA_{rst}$ ranges between 0 and $+\infty$. An $RTBCA_{rst} = 1$ means that the level of betweenness centrality of green or brown technologies in a region is the same as on the national level. An $RTBCA_{rst} < 1$ indicates that the level of betwenness centrality in that specific technology in the respective region is lower than in the rest of Germany.

To the original formulation by Basilico & Graf (2020) we add N_g which represents the number of nodes of the German knowledge space and N_r which represents the number of nodes of each regional knowledge space. The fraction N_r/N_g shows the share of CPC 4-digits classes that a region has compared to Germany as a whole. Since the German knowledge space contains a higher number of CPC 4-digits classes than the regional knowledge space, without this procedure the betweenness centralities are on two completely different levels and are not comparable. However, by considering this fraction, it is possible to account for the size effect: The higher the number of nodes contained in a knowledge space, the higher the probability that a node falls in the shortest path between two other nodes. To further check that this advantage is not just random, to be classified as a region that transitioned to green technologies the RTBCA must be repeated for two consecutive periods[9]. From the 23 regions previously selected and identified as brown, only 12 scored an RTBCA higher than 1 within the considered period (from 2000 to 2018), providing already a first indication of the challenges these regions face in sustainably transforming. Among the regions that failed to embed green technologies in their knowledge space are especially regions from East Germany. Whereas 59% of the regions from West Germany (10 out of 17 regions) could successfully anchor green technologies in their knowledge space, only 33% of East German regions (2 out of 6 regions) could achieve this. For these regions, which have already experienced enormous socio-economic change with the reunification, an additional challenge is apparently faced by successfully perform the green transition. Figure 2 shows the brown regions (colored) that successfully transitioned to embed green technologies against the regions (in gray) that were not successful in the transition process.

The regions that successfully transitioned to embed green technologies in their regional knowledge space are the following (in parenthesis, the number of years that the region needed for the transition): Altötting (16 years), Augsburg (9 years), Bremen (2 years), Darmstadt (15 years), Dortmund (2 years), Dresden (3 years), Frankfurt am Main (11 years), Heilbronn (16 years), Ingolstadt (4 years), Leipzig (8 years), Ludwigshafen (14 years) and Münster (3 years).

[9]When referring to “period” it is meant a time length of 5 years in which all the patents issued within this time frame are included.

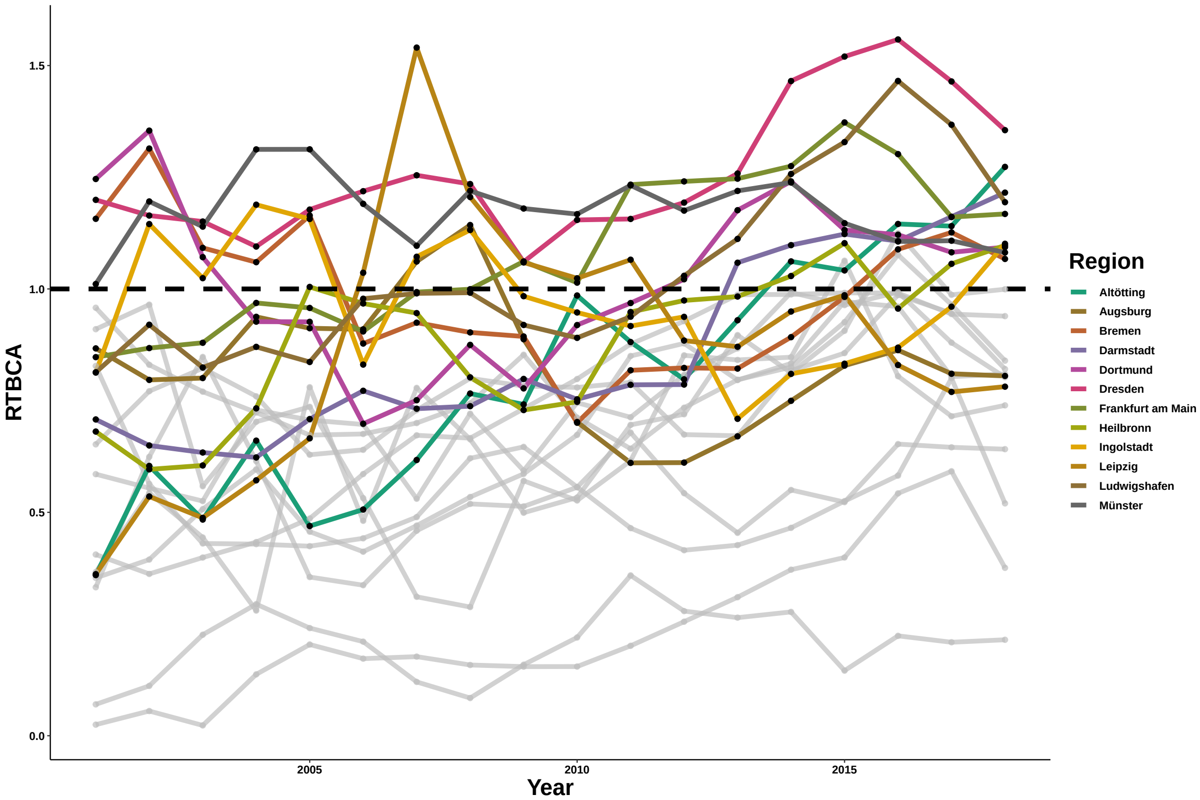


Figure 2: Brown regions that transitioned to green technologies (coloured) and brown regions that did not (in gray) in terms of $RTBC$

The speed of transition differs in some cases substantially from each other. To better understand the different transition patterns, we therefore extend our descriptive analysis by dividing the regions in three groups:

(1.) the fast transitioning regions (Bremen, Dortmund, Dresden, Ingolstadt and Münster),

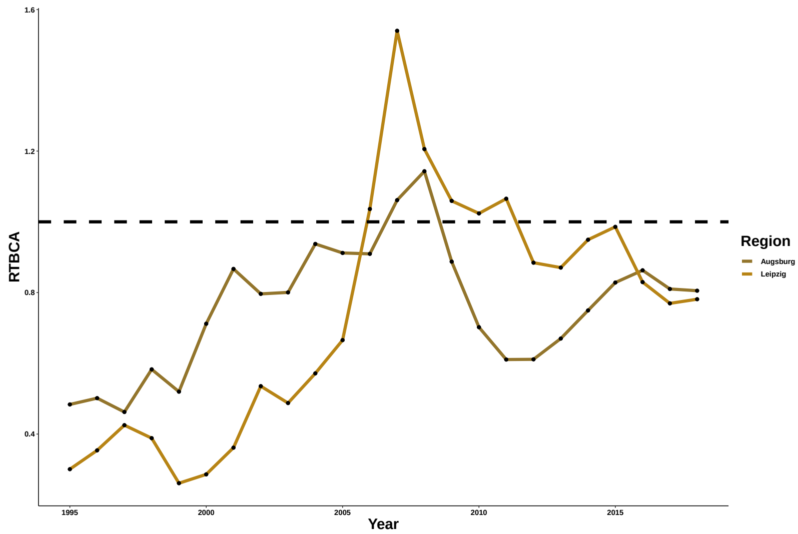
(2.) the medium transitioning regions (Augsburg and Leipzig)

(3.) the late transitioning regions (Altötting, Darmstadt, Frankfurt am Main, Heilbronn and Ludwigshafen).

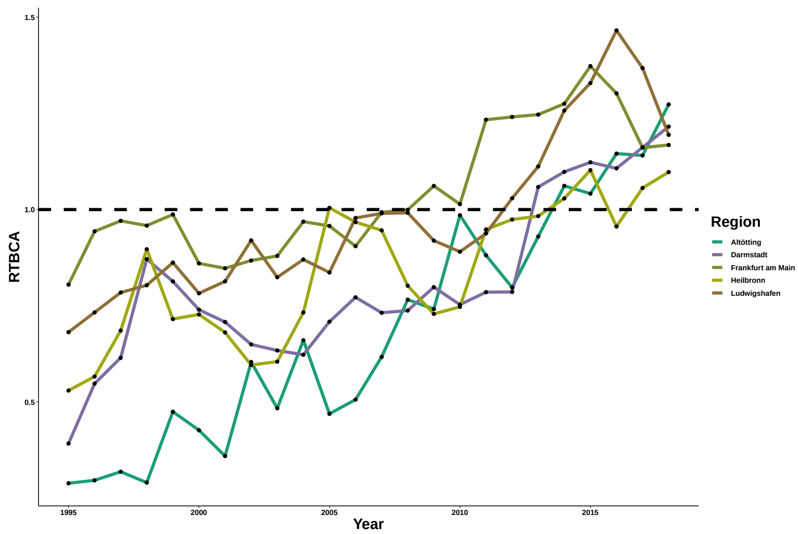
In the following, we show if different regions stay or not above the German level in terms of betweenness centrality after they reached this level at least for two consecutive time periods.

Figure 3a shows the trends in $RTBCA_{rst}$ for the fast transitioning regions. Not all the regions that rapidly transitioned to green technologies maintained this advantage over time. Only Münster and Dresden stayed constantly in a position of advantage with respect to the German average ($RTBCA_{rst} \geq 1$). Figure 3b shows the trends in $RTBCA_{rst}$ for the regions that transitioned in the middle of the period under consideration. In this case, both Augsburg and Leipzig achieve an advantage only for few periods of time (6 periods for Augsburg and 2 periods for Leipzig). Figure 3c shows the trends in $RTBCA_{rst}$ for the late transitioning regions. In this case all the regions maintained a position of advantage until the end of the considered period (this can also be explained by the relatively short observation period for these late transitioning regions).

(a) Fast transitioning regions



(b) Medium transitioning regions



(c) Late transitioning regions

Figure 3: Regional trends in terms of Revealed Technological Betweenness Centrality Advantage (RT-BCA)

This first descriptive analysis shows that actually not all regions were also able to maintain such an advantage once they achieved it. This could, eventually, bias the results of the econometric model. Therefore, in Appendix C we provide robustness checks both on the economic and social outcomes removing these dubious cases from the sample. The final results are similar to those when the entire sample of regions is considered, confirming the goodness of our study.

4 Econometric Approach

In this section, we present our variables, their data sources and some descriptive statistics. Furthermore, we show the estimation strategy that we used to understand how the transition speed in brown regions affects the objective and subjective socio-economic outcomes.

4.1 Dependent, independent and control variables

The variables used for measuring the regional economic outcomes are *Employment* and *log(Wage)*[10], which have both been used previously to investigate the impact of regional diversification (e.g. Barbieri & Consoli, 2019; Cortinovis et al., 2022). We construct them by using the median employment and median income wage, both available in the INKAR (in German: "Indikatoren und Karten zur Raum- und Stadtentwicklung") database of the BBSR (in German: "Bundesamt für Bauwesen und Raumordnung"). In this sense, we measure both the impact of the transition on the occupation and on the wealth of a region. Furthermore, in line with previous studies (e.g. Dolan & Metcalfe, 2012), the impact of the transition on the subjective well-being is measured through *Life Satisfaction*. This variable is identified based on the German Socio-Economic Panel (SOEP). This is an average score (going on a scale from 1 to 10) of how the people living in the region are satisfied by their life[11]. A transition towards a green economy can cause drastic changes both on the economic (job loss or reshuffling) and on the social side (uncertainty about the future and protests) of people residing in the affected area. Therefore, we capture both dimensions in our regression models.

The main independent variable used for both regressions is the *Transition Speed*. *Transition Speed* captures the speed in which a region transitioned to embed green technology better than the rest of Germany, i.e. $RTBCA_{rst} \geq 1$ for two consecutive periods. A value equal to zero is referred to the period in which the transition happened, negative consecutive values are referred to the periods before the transition happened and positive consecutive values are referred to the periods after the transition happened. This is the most important variable for our model specification, because it permits us to calculate exactly in which period the transition to green technology happened and how persistent the transition over time is.

As control variables we use *RTBCA*, *Population Density*, *Proportion of Students*, *Average Age Population*, *Nr. of Non-Green Patents*, *Percentage School Leavers* and *Connectedness*. *RTBCA* is exactly the measure showed in equation 4. This variable does not capture the number of periods since the region performed the transition, but "just" if in one period the region embeds green technology better than Germany. Therefore, it does not relate to the timing in which the

[10] For wage, we use the logarithmic form since there are few regions with low wage and many with high. This is done to reduce the differences.

[11] The exact question from the SOEP questionnaire can be translated as follows: "How satisfied, all things considered, are you with your life at present?"

transition happened. Instead, it just controls for the fact that the *RTBCA* became higher than 1, but not for two consecutive periods as captured by the *Transition Speed* variable, so it is less restrictive and subject to a higher variation. This entails that if the region gets in one period an *RTBCA* higher than 1, it may be driven by the data and not by a successful green transition.

We included *Population density* as an additional control variable. We assume that the higher the *Population Density* in a region is, the higher is the concentration of both polluting and green technologies. Such regions are highly dynamic for two reasons. On one side, if the urban agglomeration is high, the probability to have a non-optimal distribution of resources and the probability to produce polluting activities increases (Lu et al., 2021). On the other side, to develop green technologies specific high-level skills are necessary and big cities attract people with such capabilities (Bacolod et al., 2009). Related to the second aspect, we also control for the proportion of students per 100 inhabitants aged between 18 and 25 in one region (*Proportion of Students*). We assume that a regional population with a higher educational level has high-level skills valuable for regional entities that would like to undergone through a sustainability transition process (Consoli et al., 2016). Hence, to capture the more general educational structure of regions, we additionally consider the proportion of school leavers without secondary level qualifications as a percentage of total school leavers (*Percentage School Leavers*). Moreover, since younger people tend to care more about climate change (e.g. Milfont et al., 2021), we also control for the regional age structure by considering the average age of the population (*Average Age Population*). Furthermore, the variable *Nr. of Non-Green Patents* is included to control for the fact that the higher the number of patents produced in other industries, the higher is also the possibility to have a high embeddedness in green technologies due to an indirect effect on cross-fertilization. Finally, *Connectedness* is included to assess how well connected a regional knowledge space is. In fact, the more connected the regional knowledge space is, the higher is the probability that green technologies are well-embedded.

Table 1 contains all variables used for the regressions together with short descriptions. Table 2 presents the descriptive statistics for both models. The number of observations in the case of the social outcomes model drops from 216 of the economic outcomes model to 204. This happens because the data for the year 2018 in the case of *Life Satisfaction* is not available yet in the SOEP database. Correlations are presented in Appendix A.

To better understand how the dependent variables vary before and after the transition happened, we perform a first descriptive analysis, the results of which are shown in figure 4. In general, it is clear that the median increased in all three cases after the transition happened. Moreover, in the case of *Employment Rate* and *Life Satisfaction* the Wilcoxon Rank Sum Test shows a p-value lower than 0.05 allowing us to reject the null hypothesis which implies that the means are not significantly different. In the case of *log(Wage)*, the mean difference is statistical significant only at 10% level.

4.2 Descriptive statistics by transition group

In this subsection, we show some descriptive statistics for the different regions divided by the three groups based on when the transition happened. This rather descriptive analysis provides some first insights about the relationship between the pace of transition and the socio-economic outcomes, which we will explore more thoroughly and robustly in our subsequent econometric

Table 1: Variables used in the regressions

Variable Name	Description
	Dependent Variable
Employment	Employment rate in each Labour Market Region
log(Wage)	Logarithm of the gross average monthly wage in each Labour Market Region
Life Satisfaction	Average life satisfaction on a scale between 1 and 10 in each Labour Market Region
	Independent Variable
Transition Speed	The speed in which the Labour Market Region transitioned to embed green technologies better than the rest of Germany, 0 is referred to the year in which the transition happened
	Control Variables
RTBCA	Dummy variable that takes the value of 1 when the RTBC is higher than 1
Population Density	Population density in each Labour Market Region
Proportion of Students	Number of students present in each Labour Market Region divided for 100
Average Age Population	Average age of the population in each Labour Market Region
Nr. of Non-Green Patents	Number of patents identified as not green for each Labour Market Region
Percentage School Leavers	Percentage of people that left school before graduating in each Labour Market Region (on average)
Connectedness	Connectedness of the knowledge space of each Labour Market Region

approach.

Figure 5 shows the difference before and after the transition happened of all three dependent variables, broken down by transition group. The group of regions which transitioned faster do not show a significant[12] difference before and after the transition happened in the three dependent variables. However, in the case of *Life Satisfaction* the regions that transitioned faster show a lower median after the transition happened. For the *Medium* and *Late* transitioning groups the difference is always significant and the median is always higher after the transition happened for all three dependent variables. Thus, these results hinter that there is a overall positive effect for all the considered regions for each dependent variable. The only exception in this context refers to the case of *Fast* transitioning regions and *Life Satisfaction*, where we observe a negative (even though not significant) trend. Especially this aspect should be investigated more closely in order to check if by introducing control variables the negative trend becomes statistically significant, meaning that there is a negative effect on social outcomes for fast transitioning regions.

However, descriptive statistics do not provide a full picture of the possible effects of green transition on social and economic outcomes. Thus, it is difficult to draw any statistically mean-

[12]As previously for Figure 4, the performed significance test is a Wilcoxon Rank Sum Test.

Table 2: Descriptive statistics for the models

Variable Name	N	Mean	SD	Min	Max
	Dependent Variables				
Employment Rate	216	53.786	5.005	42.667	66.407
log(Wage)	216	7.765	0.150	7.450	8.143
Life Satisfaction	204	7.091	0.229	6.296	7.491
	Independent Variable				
Transition Speed	216	1.917	7.545	-14.000	17.000
	Control Variables				
RTBCA	216	0.398	0.491	0.000	1.000
Population Density	216	717.747	433.420	136.633	1751.700
Proportion of Students	216	28.853	22.000	0.000	100.430
Average Age Population	216	42.553	1.538	38.903	45.937
Nr. of Non-Green Patents	216	2023.639	1543.555	275.000	6497.000
Percentage School Leavers	216	7.096	2.182	3.208	13.320
Connectedness	216	0.820	0.096	0.406	0.977

ingful conclusion. This is why we proceed by using an econometric approach introducing variables to control for specific regional characteristics that matter when the region is undergoing a transition process.

4.3 Estimation strategy

In all the models presented and for the two different typologies of outcomes, we calculated both a linear[13] and fixed effect model over regions[14]. Fixed effects are included to control for unobservable regional characteristics that could affect our results. The model used for the analysis is the following:

$$EO/SO_{t,r} = \beta_0 + \beta_1 TrSp_{t,r} + \beta_2 Controls_{t,r} + \alpha_t + \alpha_r + \mu_{t,r} \quad (5)$$

Where $EO/SO_{t,r}$ are either the economic outcomes *Employment* or *log(Wage)*, or the social outcomes, *Life Satisfaction*, for each region (r) and each period (t). $TrSp_{t,r}$ is the main independent variable *Transition Speed*. $Controls_{t,r}$ is the set of controls already presented in subsection 4.1 which potentially influence our main dependent variables. α_r is the regional invariant variable for the fixed effect model. Finally, μ represents the residuals.

5 Regression Results

Table 3 shows the results for both the economic outcomes and the social outcomes. Column 1 shows the results for *Employment*, column 2 shows the results for *log(Wage)* and column 3 shows the results for *Life Satisfaction*.

Columns 1 and 2 show that the variable *Transition Speed* has a positive and significant effect both on *Employment* and *log(Wage)*. This result means that the sooner a region transitioned to green technologies, the better are their economic outcomes. In fact, the higher the *Transition Speed* gets, the earlier the region transitioned to green technology. These results on the economic

[13]The results of the linear model are included in the Appendix B in table 6, here we present only the results for the fixed effect model.

[14]The year fixed effects are not included in the analysis since they are highly correlated with our main independent variable *Transition Speed* which is already a time variable and differs among observations.

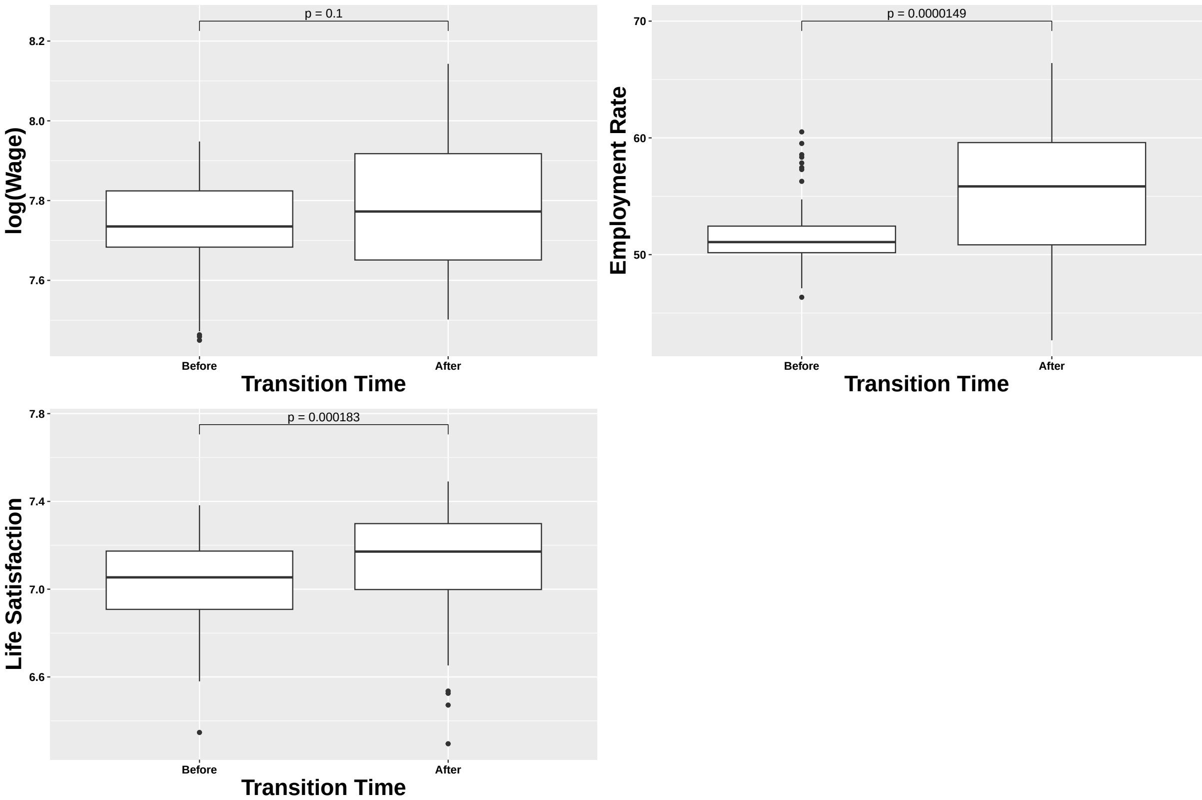


Figure 4: Boxplots representing the mean differences among the three main dependent variables (*Wage*, *Employment Rate* and *Life Satisfaction*)

outcomes confirm what was observed in figures 4 and 5 with a positive effect on the main dependent variables. The earlier the transition happened, the better it is for both wage and employment in the considered regions.

Regarding our control variables, our models show that *Population Density* has a negative effect on both economic outcomes, but also on the social outcome (see column 3). The higher the population density in the region is, the lower is the wage, the employment rate and the life satisfaction. Since the sample of German regions considered in this study is limited (i.e. not all regions in Germany are included, but only brown regions) and regions in former GDR experienced high growth rates this result differs in part from previous studies (Beaudry & Schiffauerova, 2009) and has to be interpreted cautiously. The results on the *Number of Students per 100* show a positive effect on all the three dependent variables. This means that the regions with a higher number of students have a positive and significant impact on both the economic and social outcomes, which goes in line with recent findings about the regional impact of universities (e.g. Janzen et al., 2022; Marrocu et al., 2022). Moreover, our results indicate that *Average Age Population* has a negative and significant effect on *Employment* as well as on *log(Wage)*. This means that the older the population is, the lower is the average employment and average wage in the region. A result that is not surprising since having a older population in the region means to have a higher share of retirees. The *Percentage of School Leavers* is positive and significant only in the case of *Employment*, indicating that the more people leave school early, the higher is the number of people employed in the region. This rather surprising result can potentially be explained by the fact that if population leaves early school by searching immediately for a job they contribute to the employment rate of the region. Whereas, people with a higher educational

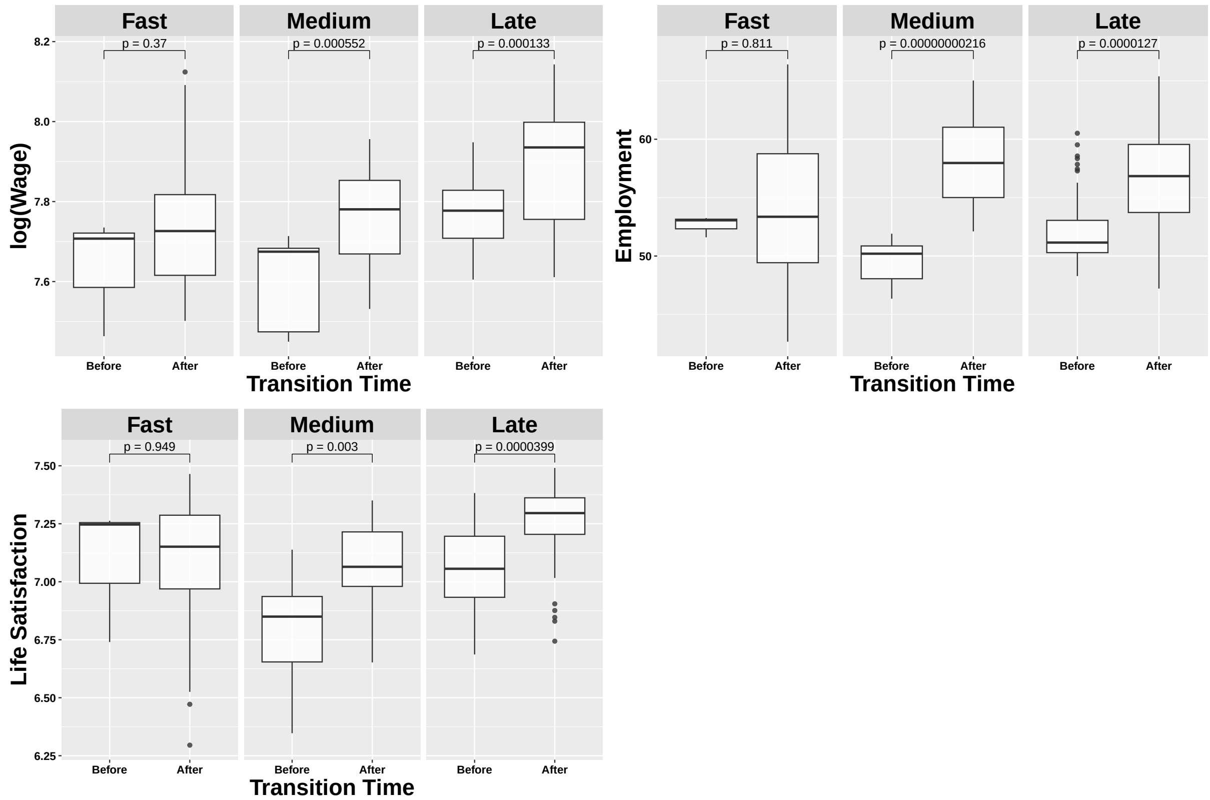


Figure 5: Boxplots representing the mean differences among the three main dependent variables (*Wage*, *Employment Rate* and *Life Satisfaction*) divided among regions with different speed of transition

degree enter the job market later, although with a higher probability of earning a better salary.

Column 3 shows the results for the social outcomes model which in general confirm what was observed in figure 5, where the regions show a positive and significant trend in terms of *Life Satisfaction*. In fact, the variable *Transition Speed* has a positive and significant effect on *Life Satisfaction*. This means that the sooner the region transitioned to green technologies, the higher is the average life satisfaction of the people living in that specific area. This result is in line with the results from the economic outcomes. It suggests that the positive effect on the economic outcomes is also directly reflected on how people perceived the shift. Higher wages and a higher employment rate are directly translated to higher living standards in the fast transitioning regions. In other words, in the regions that transitioned earlier there was not only a positive effect in economic terms, but also a positive effect on the social sphere. Therefore, hypothesis number 2 is rejected.

To check empirically for that, we show the results in Appendix C of the social outcomes model using as dependent variables *Life Satisfaction on the Job* and *Fear of Jobloss*[15] both taken from the SOEP. The results show, a positive coefficient in the case of *Transition Speed*. Thus, the earlier the region transitioned the better are both outcomes. This result confirms that the people which were living in fast transitioning regions did not suffer from this rapid change.

As a further robustness check, we performed the same econometric models on the regions that transitioned to green and have not reduced their Revealed Technological Betweenness to a

[15] *Fear of Jobloss* is a numeric variable with a minimum value of 1 and a maximum value of 3. The person with the highest fear of loosing the job assigns a value 1. Whereas, the individual with the lowest fear of loosing the job assigns a value of 3.

Table 3: Results for economic and social outcomes fixed effect models

	Dependent variable:		
	Emp	log(Wage)	Life Satis
	(1)	(2)	(3)
Transition Speed	1.022***	0.031***	0.020**
	(0.074)	(0.001)	(0.008)
RTBCA	−0.046	−0.005	0.033
	(0.256)	(0.005)	(0.027)
Population Density	−0.004***	−0.00004***	−0.0002***
	(0.0005)	(0.00001)	(0.0001)
Proportion of Students	0.056***	0.001**	0.004**
	(0.020)	(0.0004)	(0.002)
Average Age Population	−1.654***	−0.070***	−0.010
	(0.361)	(0.007)	(0.040)
Nr. of Non-Green Patents	0.0004	0.0001***	−0.0001**
	(0.001)	(0.00001)	(0.0001)
Percentage School Leavers	0.288***	0.001	−0.004
	(0.103)	(0.002)	(0.011)
Connectedness	6.381**	0.103***	0.334
	(2.482)	(0.037)	(0.270)
Observations	216	216	204
R^2	0.937	0.979	0.709
Adjusted R^2	0.931	0.977	0.679
Residual Std. Error	1.314 (df = 196)	0.023 (df = 196)	0.130 (df = 184)
F Statistic	153.820*** (df = 19; 196)	478.775*** (df = 19; 196)	23.584*** (df = 19; 184)
Note:			*p<0.1; **p<0.05; ***p<0.01

value lower than one. The results are available in the Appendix C in table 7. In general, they confirm positive effects on both economic and social outcomes for *Transition Speed*.

6 Conclusions

The challenge put forward by the increase of the world population and finite natural resources requires structural changes to introduce green innovations in the economic system (Barbieri et al., 2020; Imbert et al., 2017; Losacker et al., 2021; Montresor & Quatraro, 2020). Even if, there are economic opportunities to reshape and create new industrial sectors, the sustainability transition also produces some threats, especially to brown regions (e.g. coal regions). These regions need to transform their established, and rather non-ecologically oriented, economic structure towards sustainability (Grillitsch & Hansen, 2019; Blažek et al., 2020; Trippl et al., 2019). Whereas, previous research focused on the positive opportunities put forward by green transition (Köhler et al., 2019; Blažek et al., 2020), we concentrate our research on the socio-economic consequences of the transition patterns of brown regions. Following recent calls (e.g. Geels, 2018; Sovacool & Geels, 2016), we thereby focus on how the speed of transition could influence such social and economic outcomes.

Firstly, we identify brown regions as the ones that have a Revealed Technological Advantage in brown patents in the period between 1995 and 1999. Secondly, based on the literature about

RIS and the anchoring concept, we propose a novel measure for green transition that study the embeddedness of green technologies in the regional knowledge space. We call it Revealed Technological Betweenness Centrality Advantage (RTBCA) (Basilico & Graf, 2020; Elzen et al., 2012). It is important to consider not only if a green technology is present in the region but also, and more importantly, if it is well-amalgamated in the region looking at its previous specializations. Thirdly, based on this last measure we calculate the number of years that a region takes to reach for the first time a RTBCA. Fourthly, using an econometric approach we determine how the speed of transition influences economic (wage and employment) and social (life satisfaction) outcomes.

Our descriptive analysis shows that the economic outcomes (employment rate and wage) have a positive trend in all the regions regarded as brown after the transition happened. The same results are shown in the case of the social outcomes (life satisfaction), where these regions also have a positive trend in the period after the transition happened. From the econometric approach we find that the earlier a brown region transitions to green technologies, the better are both the economic and social outcomes. In other words, this means that a fast transition to green technologies is beneficial for both the economic and social outcomes in previously brown regions. For regional and national policy makers, these findings first of all imply that previously brown regions can also successfully realize a sustainability transition. Apart from strengthening already existing green regional clusters, brown regions should therefore not be disregarded in order to maximize the ecological and economic opportunities as well as to avoid the creation of potentially new left-behind places. However, our results also emphasize the need of support, since almost half of the identified brown regions have not managed to achieve such a green transition. In this context, we can show that particularly a fast transition appears to be beneficial for the socio-economic outcomes of these regions. Hence, large-scale support programs, such as the Structural Strengthening Act Coal Regions in Germany [in German: Strukturstärkungsgesetz Kohleregionen][16], are needed to enable and accelerate the sustainability transition in brown regions.

In general, the scientific contributions of this study to the current literature on green transition are manifold. Firstly, by introducing a new measurement for calculating the regional transition patterns, we move forward with respect to the standard specialization indicators widely used in literature. Our indicator goes well-along the literature about the Multi-Level Perspective (MLP) (Geels, 2002) and the anchoring concept (Elzen et al., 2012). In fact, we check how well green technologies are embedded in the regional knowledge space. Secondly, we change the research perspective already seen in previous studies on sustainability transition, focusing particularly on the positive effects of such patterns (Blažek et al., 2020; Köhler et al., 2019), by studying the transition patterns of brown regions and their potential socio-economic implications. Finally, through empirically studying the speed of sustainable transition patterns and their effects on socio-economic outcomes, we also contribute to recent calls for further research from the relevant literature (e.g. Geels, 2018; Sovacool & Geels, 2016).

Nevertheless, the present paper has certainly limitations due to the nature of the analysis. First, like many other studies focusing on regional knowledge space (e.g. Kogler et al., 2013;

[16]For more information about the program, please visit https://www.bundesregierung.de/breg-en/service/archive/kohleregionen-foerderung-1665150.

Basilico & Graf, 2020; Basilico et al., 2022; Boschma et al., 2014; Balland et al., 2019), we rely only on inventions that can be patented. Therefore, we do not consider all the inventions that usually are not patented, like services and software. Second, the analysis relies on the technological classification of the patent system which implies that a patent classified in a specific technology class is substantially different from the others. This assumption might not hold true, in the sense that such classification is introduced by patent offices for other reasons than this type of analysis. Third, other variables instead of rate of employment, wages and life satisfaction can be used for measuring socio-economic outcomes. Using different variables could consequently change the results substantially. This, together with the focus solely on Germany, limit the general applicability of the paper. Fourth, due to data constraints the industrial structure of the regions is not considered in the present study. Although the technological and industry structure are to some extent related (e.g. Pinheiro et al., 2022), the inclusion of the regional industrial structure could change the identification of brown regions and, subsequently, perhaps also affect the results. Finally, the choice of taking the 4-digit CPC level can be regarded as arbitrary and implies a not clear demarcation between green and brown technologies (a single 4-digit CPC class can be regarded as both green and brown). However, this level of cutting offers the best trade-off between sufficiently large number of patents in the classes and a maximum number of technologies (Mewes & Broekel, 2020).

However, the limitations described also provide the starting point for future scientific work. Apart from considering other countries and using additional data sources (e.g. employment data), further research could focus on the effects that green transition patterns have on the (regional) organizational level. Such disruptive events could reshape the regional innovation systems with the emergence of new private and public actors substituting other old ones not able to keep up with the regional transformation process.

Appendices

A Correlation tables

Table 4: Correlation table for economic outcomes model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Employment	-	0.63***	0.46***	0.15***	-0.33***	-0.02	0.50***	-0.03	-0.35***	0.35***
(2) log(Wage)		-	0.24***	0.05	-0.29***	0.19***	0.12***	0.49***	-0.60***	0.67***
(3) Transition Speed			-	0.41***	0.11	0.00	0.49***	-0.21***	-0.41***	0.35***
(4) RTBCA				-	0.17***	0.12***	0.22***	0.04	-0.13***	0.20***
(5) Population Density					-	0.02	0.38***	0.17***	0.38***	-0.11
(6) Proportion of Students						-	0.00	0.08	-0.21***	0.26***
(7) Average Age Population							-	-0.07	-0.01	0.19***
(8) Nr. of Non-Green Patents								-	-0.16***	0.58***
(9) Percentage School Leavers									-	-0.59***
(10) Connectedness										-

Note: *p ¡ 0.1; **p ¡ 0.05; ***p ¡ 0.01

Table 5: Correlation table for social outcomes model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Life Satisfaction	-	0.31***	0.04	-0.41***	0.12***	-0.04	0.22***	-0.63***	0.57***
(2) Transition Speed		-	0.41***	0.12***	-0.01	0.47***	-0.21***	-0.42***	0.33***
(3) RTBCA			-	0.19***	0.11	0.20***	0.03	-0.12***	0.16***
(4) Population Density				-	0.02	0.40***	0.16***	0.38***	-0.11
(5) Proportion of Students					-	0.00	0.08	-0.20***	0.26***
(6) Average Age Population						-	-0.05	-0.01	0.18***
(7) Nr. of Non-Green Patents							-	-0.16***	0.60***
(8) Percentage School Leavers								-	-0.59***
(9) Connectedness									-

Note: *p ¡ 0.1; **p ¡ 0.05; ***p ¡ 0.01

B Results linear model

Table 6: Results econometric approach for linear estimation with robust standard errors

	Dependent variable:		
	Emp	log(Wage)	Life Satis
	(1)	(2)	(3)
Transition Speed	0.212***	0.005***	0.008***
	(0.047)	(0.001)	(0.002)
RTBCA	0.043	−0.029*	−0.032
	(0.531)	(0.016)	(0.028)
Population Density	−0.008***	−0.0001***	−0.0002***
	(0.001)	(0.00002)	(0.00004)
Proportion of Students	−0.001	0.001***	0.0001
	(0.008)	(0.0003)	(0.001)
Average Age Population	2.052***	0.019***	−0.009
	(0.161)	(0.005)	(0.010)
Nr. of Non-Green Patents	0.001***	0.0001***	0.00002
	(0.0002)	(0.00001)	(0.00001)
Percentage School Leavers	0.089	−0.016***	−0.025***
	(0.118)	(0.004)	(0.007)
Connectedness	−3.966	0.052	0.596**
	(4.557)	(0.119)	(0.242)
Observations	216	216	204
R^2	0.642	0.644	0.530
Adjusted R^2	0.628	0.630	0.511
Residual Std. Error	3.052 (df = 207)	0.091 (df = 207)	0.160 (df = 195)
F Statistic	46.399*** (df = 8; 207)	46.779*** (df = 8; 207)	27.514*** (df = 8; 195)
Note:			*p<0.1; **p<0.05; ***p<0.01

C Robustness checks

Table 7: Results for both models including only the regions that permanently transitioned to green technologies.

	Dependent variable:		
	Fixed Effect Emp	Fixed Effect log(Wage)	Fixed Effect Life Satis
	(1)	(2)	(3)
Transition Speed	0.824***	0.026	0.011***
	(0.049)	(0.130)	(0.002)
RTBCA	−0.574	−0.004	−0.004
	(0.701)	(0.390)	(0.019)
Population Density	−0.004***	−0.00004	−0.0002***
	(0.001)	(0.001)	(0.00002)
Proportion of Students	0.054***	0.001	0.002***
	(0.007)	(0.026)	(0.0002)
Average Age Population	−0.457**	−0.037	0.054***
	(0.225)	(0.596)	(0.007)
Nr. of Non-Green Patents	−0.001***	0.00001	−0.0002***
	(0.0002)	(0.001)	(0.00001)
Percentage School Leavers	0.522***	0.007	0.009**
	(0.107)	(0.105)	(0.004)
Connectedness	13.182***	0.189	0.959***
	(4.848)	(3.523)	(0.169)
Observations	126	126	119
R^2	0.926	0.981	0.678
Adjusted R^2	0.916	0.979	0.635
Residual Std. Error	1.306 (df = 111)	0.021 (df = 111)	0.141 (df = 104)
F Statistic	98.758*** (df = 14; 111)	409.634*** (df = 14; 111)	15.667*** (df = 14; 104)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 8: Results for the social outcomes model using different dependent variables (*Life Satisfaction on the Job* and *Fear of Jobloss*)

	Dependent variable:	
	Fixed Effect Jobloss	Fixed Effect Fear Env
	(1)	(2)
Transition Speed	0.019***	−0.008
	(0.002)	(0.008)
RTBCA	−0.044*	0.032
	(0.027)	(0.025)
Population Density	−0.0001***	−0.0001**
	(0.00003)	(0.00004)
Proportion of Students	0.001***	0.002
	(0.0003)	(0.002)
Average Age Population	0.003	−0.002
	(0.010)	(0.039)
Nr. of Non-Green Patents	−0.0001***	−0.00003
	(0.00001)	(0.0001)
Percentage School Leavers	0.018***	0.007
	(0.006)	(0.007)
Connectedness	0.485**	0.241
	(0.239)	(0.253)
Observations	119	119
R^2	0.727	0.390
Adjusted R^2	0.691	0.308
Residual Std. Error (df = 104)	0.077	0.054
F Statistic (df = 14; 104)	19.826***	4.758***
Note:		*p<0.1; **p<0.05; ***p<0.01

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