

## Regional capabilities in the European automotive industry: Relatedness, complexity and lock-ins in the transition to electric vehicles

Tim Becker<sup>a,\*</sup>, Sebastian Losacker<sup>a,c</sup>, Margherita Russo<sup>b</sup>

<sup>a</sup> Justus Liebig University Giessen, Department of Geography, Giessen, Germany

<sup>b</sup> University of Modena and Reggio Emilia, Marco Biagi Department of Economics and CAPP - Research Centre for the Analysis of Public Policies, Modena, Italy

<sup>c</sup> CIRCLE – Centre for Innovation Research, Lund University, Lund, Sweden

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### ABSTRACT

The shift toward battery electric vehicles (EVs) represents the most profound disruption in the automotive industry in over a century, with far-reaching consequences for European automotive regions. For decades, incremental improvements in internal combustion engine (ICE) technologies have served as the dominant decarbonization pathway, and many regions have built strong innovation systems around these legacy technologies. To assess how European NUTS2 regions are positioned for the transition to electric mobility, we analyze regional technological capabilities using technology-specific relatedness and knowledge complexity to investigate how EV- and ICE-related capabilities affect regional EV innovation. Using patent data from the OECD REGPAT database, we map regional innovation potentials and estimate econometric models to assess how these capability structures affect EV patenting. We find that higher relatedness density to EV technologies is positively associated with EV patenting, while relatedness to ICE improvements also shows a significant but weaker positive association, indicating that ICE capabilities do not necessarily impede EV innovation. However, when ICE-related capabilities substantially outweigh EV-related ones, we observe a negative effect on EV patenting, pointing to emerging lock-in risks. This effect is markedly stronger in low-complexity regions. Interregional co-patenting analysis shows that regions with low complexity and low EV-relatedness are doubly disadvantaged, as they are weakly positioned internally and less integrated into innovation networks. Focusing on four regions of this type, we illustrate how targeted partnerships could unlock untapped potentials. The results inform a policy discussion highlighting the need for place-sensitive innovation strategies addressing both emerging and legacy capability structures.

### 1. Introduction

The need to reduce CO<sub>2</sub> emissions has led governments around the world to embark on policy programs to achieve zero emissions from passenger cars. For decades, improvements in internal combustion engine (ICE) technologies represented the main pathway for reducing emissions from road transport. Through incremental innovation focused on enhancing fuel efficiency, many European regions developed strong technological capabilities and deeply embedded industrial structures around ICEs – supporting competitiveness, employment, and emissions reductions without requiring disruptive change (Näsman & Ballor, 2024; Pavlínek, 2022a).

In contrast, battery electric vehicles (hereafter EVs) represent a disruptive shift in the automotive industry, with the abandonment of the

production of internal combustion engines that have characterized the last 120 years of development in the automotive industry. This shift entails profound transformations in manufacturing processes and trade patterns, critical raw materials, the location of production facilities, and the technological capabilities required, thereby enabling entry for new actors and intensifying global competition, particularly evident in the rise of China, where firms have achieved technological leadership in batteries and electric drivetrains (Altenburg et al., 2022; Gong et al., 2024; Lema et al., 2024; Russo et al., 2022, 2023; Schwabe, 2020b; Wuttke & Whitfield, 2025). This places pressure on the European automotive industry to accelerate EV innovation and adapt to the new technological paradigm, thereby shaking European regions specialized in automotive production, especially those supplying components and parts for the ICE powertrain. The consequences can be significant: some

\* Corresponding author.

E-mail address: [tim.becker@geogr.uni-giessen.de](mailto:tim.becker@geogr.uni-giessen.de) (T. Becker).

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13 million Europeans work in the automotive sector, accounting for 11.5 % of all manufacturing jobs in the EU and generating more than 7 % of the EU's GDP, €374.6 billion in tax revenues for European governments, a €101.9 billion trade surplus for the EU, and accounting for a significant share of total R&D spending at €59.1 billion, almost a third of the EU total (ACEA - European Automobile Manufacturers' Association, 2023; European Commission, 2025; Jaramillo et al., 2022). The European Competitiveness Report (European Commission, 2024) highlights this challenge and stresses the need for coordinated, EU-level responses across policy fields to enhance EV innovation.

Against this backdrop, it becomes increasingly important to understand how regions are positioned to navigate the transition to electric mobility, examining the capabilities that enable regions to generate innovation in this domain. The economic geography literature shows that regional innovation is fundamentally shaped by the accumulation, combination, and recombination of capabilities, determining which technologies can emerge and evolve in a region (Boschma, 2017; Frenken et al., 2023). The *capability framework* conceptualizes regional development as a process driven by locally embedded knowledge, skills, and competences, which define not only production possibilities but also a region's capacity for technological innovation (Balland et al., 2019; Boschma, 2017; Frenken et al., 2023). Within this framework, relatedness plays a central role, as innovation is more likely in technological domains that share underlying capabilities with a region's existing knowledge base, resulting in path-dependent innovation trajectories (Boschma, 2017; Hidalgo et al., 2018). Ample empirical evidence shows that regions tend to diversify into related technologies, and that such related diversification supports regional innovation and technological upgrading (Balland et al., 2019; Boschma, 2017; Rigby, 2015). Knowledge complexity, in contrast, captures the breadth and sophistication of a region's capability set which may enable "long jumps" into unrelated technological spaces. Empirical studies show that higher knowledge complexity facilitates innovation and supports transitions into newly emerging technologies (Antonelli et al., 2022; Balland & Rigby, 2017; Balland et al., 2019, 2022; Hidalgo & Hausmann, 2009). At the same time, with regard to the automotive industry, the legacy of past trajectories, particularly deep-rooted regional innovation systems built around ICE technologies, must not be overlooked. These legacy structures may continue to shape regional innovation dynamics, potentially reinforcing existing paths and creating risks of capability lock-ins. Economic geography has long demonstrated that historically accumulated regional capability configurations generate path-dependent development trajectories which, in turn, may constrain the ability of regions to reconfigure and redeploy their capabilities in response to disruptive technological shifts (Boschma, 2017; Geels, 2025; Hassink, 2010; Martin & Sunley, 2006; Martin, 2010). While these literature streams have extensively demonstrated the relevance of regional capabilities and path dependence for innovation and transformation across various industries (Boschma, 2017; Frenken et al., 2023), the capability framework has so far been only limitedly applied to the automotive sector, especially with regard to how capabilities associated with legacy ICE technologies interact with those underpinning the emergence of EV technologies at the regional level. Initial evidence is provided by Ferloni et al. (2024), who show that EV patents are increasingly co-located with ICE inventions despite limited technological relatedness, indicating that existing automotive capability structures continue to shape emerging EV innovation; however, ICE-related experience supports EV patenting only in traditional automotive cities already specialized in both domains. This raises the central research question: *How are European regions positioned in terms of their technological capabilities for the transition toward electric mobility, and to what extent do legacy trajectories in ICE technologies influence their transition potential?*

In order to shed light on this question, we draw on the literature on regional diversification and economic complexity (Balland et al., 2019, 2022; Boschma, 2017; Frenken et al., 2023) and map the technological capabilities of European automotive regions for the two key

technological pathways that define decarbonization in the automotive sector – battery electric vehicles (including also hybrid vehicles) and internal combustion engine improvements. This mapping enables us to discuss the risk of capability lock-ins, particularly in regions with high legacy in ICE technologies that may hinder the emergence of EV innovation. To do so, we use regional (NUTS2 level) patent data from the OECD REGPAT database for the period 2005–2022, covering the EU27 countries plus the UK. We compute relatedness density with respect to the technologies for decarbonization and regional knowledge complexity, and position regions within this capability space. We then estimate negative binomial models to assess how relatedness density to these domains affects regional EV patenting.

We find that higher regional relatedness density to EV technologies is positively associated with EV patenting, while relatedness to ICE improvements shows a weaker positive effect, implying no general risk of lock-in when both capability types coexist. However, when ICE relatedness density substantially exceeds that of EVs, we observe a negative effect on EV patenting, indicating potential lock-in risks – higher in low-complexity regions, which appear more vulnerable to legacy path dependency. In addition, we analyze interregional co-patenting as a mechanism to enhance regional innovation potential and find that regions with low complexity and low EV relatedness are doubly disadvantaged – being both weakly positioned internally and less integrated into innovation networks. To illustrate how targeted partnerships with promising external collaborators could help bridge these capability gaps, we compare four structurally constrained regions, i.e., regions characterized by a dominance of ICE-related technological capabilities over EV-related ones: Jihovýchod (CZ06), Rheinhessen-Pfalz (DEB3), Lorraine (FRF3), and Herefordshire, Worcestershire, and Warwickshire (UKG1).

The paper is structured as follows. Section 2 discusses decarbonization pathways for the automotive industry, reviews the literature on relatedness and economic complexity, and discusses potential capability lock-ins. Section 3 describes the data and methods to map automotive regions' technological potential, Section 4 presents the results, Section 5 discusses policy implications, and Section 6 concludes.

## 2. Decarbonizing the automotive industry

### 2.1. ICEs improvements and EVs

Two main paths characterize the economic and political debate on the transition to low-carbon road transport: reducing emissions from internal combustion engines or moving towards electric mobility.<sup>1</sup> Due to the EU ban on ICEs from 2035 and competition from China, Japan and Korea, increasing market shares of electric vehicles is the most likely pathway. In the literature on the transition to EVs, much attention is paid to the impact on labour, the skills and competencies needed to support battery production, the infrastructure for charging EVs, national/EU sovereignty over raw materials, energy and technologies needed for the production of EVs and appropriate policy responses (Fredriksson et al., 2018; Gong & Hansen, 2023; Gong et al., 2024; Klier & Rubenstein, 2024; Luetkehaus, 2025; Pardi, 2021; Pavlínek, 2022b, 2023; Schade et al., 2022; Schwabe, 2020a, 2020b). On the other hand, improvements to ICE technologies have long been regarded as the main path for reducing emissions from road transport. Incremental advances targeting fuel efficiency gains enabled significant emission reductions without disrupting existing industrial structures (Näsman & Ballor, 2024). Many European regions built strong technological and industrial capacities around ICEs, forming deeply embedded supply chains and

<sup>1</sup> While hydrogen is considered a viable option for transport by selected stakeholders (Shin et al., 2019), it has yet to achieve the global acceptance, market uptake and significant development path of the other two technologies for light vehicles.

specialized labour markets (Pavlínek, 2022a). For a long time, this trajectory was seen as a realistic and economically grounded way to address environmental concerns while preserving regional competitiveness and employment. However, as the climate crisis intensified and electric mobility gained prominence as a zero-emission solution, ICE-related pathways gradually lost attention in both policy and academic debates. The focus shifted toward electrification, battery production, and related infrastructure as the core elements of a sustainable transport transition (Näsman & Ballor, 2024). More recently, the ICE pathway has regained political support in certain contexts. In Germany, policymakers and industry representatives advocate for technology neutrality and the continued use of synthetic e-fuels, particularly for high-performance or long-distance vehicles (Birel et al., 2024). Similar positions have emerged in Central and Eastern Europe, where regions with strong ICE-related industries highlight the potential disruption of a rapid shift to EVs. In Italy, opposition to a full ICE phase-out reflects concerns over SMEs competitiveness and the country's specialization in performance vehicle components. This renewed support raises concerns, as continued investment in ICE technologies may create lock-ins and increase uncertainty about the direction of the transition, hindering regional shifts toward EV-related sectors. Such ambiguity complicates investment decisions and coordination across the industry, leaving ICE-dependent regions at risk of falling behind in capability development and facing structural disadvantages in a decarbonizing sector. Therefore, it is crucial to consider both paths when investigating the transition towards EVs. For this transition, the regional level is crucial, given the regional, specialized cluster structures in the automotive industry (Pavlínek, 2020; Sturgeon et al., 2008) and the spatial footprint of environmental innovation and its diffusion (Losacker, Hansmeier, et al., 2023; Losacker, Horbach, et al., 2023). Besides, technological developments in the automotive industry are highly path-dependent, as firms benefit from regional knowledge spillovers from exposure to EV or ICE innovations of other firms and their innovation activities in the past (Aghion et al., 2016; Ferloni et al., 2024). In light of these considerations, we distinguish between the two technological domains, ICEs vs. EVs, and examine the transition at the regional level. This allows us to identify distinct development paths and specializations as a basis for assessing regional technological potentials and uncovering potential lock-ins, helping to derive appropriate policy responses. Policy responses may cover dimensions that extend beyond the scope of innovation policy and touch upon broader industrial policy concerns (Altenburg & Rodrik, 2017; Juhász et al., 2024; Uyarra et al., 2020). While innovation policy typically focuses on supporting R&D, capability building, and technological upgrading, industrial policy encompasses the strategic direction of entire sectors, including production location decisions, employment preservation, and value chain restructuring. A growing body of work argues for a more integrated approach that bridges these traditionally separate domains, emphasizing the need for coordinated policy frameworks to address long-term societal challenges (Altenburg & Rodrik, 2017; Edler & Fagerberg, 2017; Mazzucato, 2018; Schot & Steinmueller, 2018). In this perspective, industrial and innovation policies are increasingly understood as complementary instruments for shaping transformative change, aligning technological development with strategic missions such as the decarbonization of the mobility sector (Uyarra et al., 2020).

## 2.2. Regional capabilities for EV innovation

A central insight of economic geography is that regional diversification is a path-dependent process in which regions are more likely to develop new technologies related to their existing knowledge base, enabled by shared capabilities. Relatedness has become an established concept to explain economic, scientific and technological diversification, upgrading and growth. A large body of literature shows that regions tend to diversify into activities, industries and technologies related to their existing ones, and that related diversification fosters

technological and industry growth (Balland et al., 2019; Boschma et al., 2015, 2022; Boschma, 2017; Frenken et al., 2007, 2023; Hidalgo et al., 2018; Li & Neffke, 2024; Neffke et al., 2011; Otto et al., 2025; Whittle & Kogler, 2020).

When new technological fields are related to a region's existing capabilities, the likelihood of successful diversification increases due to lower adjustment costs, reduced uncertainties, and the ability to build on accumulated knowledge and infrastructure. Accordingly, higher relatedness can be interpreted as greater potential for new technological fields (Bachtrögler-Unger et al., 2023; Balland & Boschma, 2021b; Balland et al., 2019).

Rigby (2015) pioneered the study of regional technological diversification by operationalizing and measuring technological relatedness, using the repeated co-occurrence of technology classes on patent documents as an indicator of proximity in the technology space and a proxy for the underlying regional capability structure. The role of technological relatedness has since been empirically demonstrated across a wide range of technological domains, including eco-technologies, fuel cells, nanotechnologies, and biotechnologies, in European regions and U.S. metropolitan areas, showing that new technologies are more likely to emerge where they are related to a region's existing knowledge base (Boschma et al., 2014, 2015; Colombelli et al., 2014; Heimeriks & Boschma, 2014; Kogler et al., 2013; Rigby, 2015; Tanner, 2014, 2016; Van Den Berge & Weterings, 2014).

In the automotive case, for instance, regions specialized in mechanical engineering and thermodynamics may find it easier to move into advanced emissions control systems, whereas regions with strong capabilities in electrochemistry or materials science may be better positioned to develop battery technologies for electric vehicles.

Another central insight of the literature concerns the role of knowledge complexity. In contrast to relatedness, knowledge complexity captures the breadth and sophistication of a region's capability set and reflects its capacity to recombine diverse knowledge bases, thereby enabling "long jumps" into previously unrelated technological spaces. Empirical studies show that higher levels of knowledge complexity facilitate innovation and support transitions into newly emerging technologies (Antonelli et al., 2022; Balland & Rigby, 2017; Balland et al., 2019, 2022; Hausmann et al., 2024; Hidalgo & Hausmann, 2009). Drawing on these contributions, we consider regional knowledge complexity an additional crucial factor in shaping future technological developments in the automotive industry.

Bringing these two dimensions together, Balland et al. (2019) propose the relatedness–complexity space as a tool to inform regional diversification strategies within Smart Specialisation (S3) policy. This framework integrates the proximity of new activities to a region's existing capabilities (relatedness) with the strategic value or sophistication of those activities (complexity). It is designed to help policymakers identify diversification opportunities that are both feasible – because they build on existing capabilities – and desirable – because they contribute to long-term technology upgrading. In its original formulation, this space is used to map technologies relative to one another. In this paper, we adapt this framework to map regions rather than technologies, positioning them in the relatedness–complexity space with respect to two distinct technological fields ICEs vs. EVs. This shift in perspective offers an analytically and policy-relevant contribution. Instead of assessing the diversification value of individual technologies, we assess the diversification potential of regions towards either ICE or EV technologies. The combination of relatedness density and knowledge complexity offers a comprehensive view of a region's potential in technological fields and supports place-sensitive policy design. Together, these dimensions help policymakers assess which regions are better prepared for specific technological pathways and design targeted interventions that align regional strengths with long-term strategic objectives. This regionalized use of the relatedness–complexity space provides a valuable tool for identifying both the direction and depth of transformative potential across regions.

While the relatedness–complexity space provides a useful lens to identify feasible and desirable regional diversification paths, it also invites reflection on potential risks of technological lock-in arising from regional capability structures that reinforce path dependency. High levels of relatedness may support short-term gains but can limit the scope for exploration into more distant and potentially transformative technologies (Boschma, 2017; Martin & Sunley, 2006; Martin, 2012). In such cases, path-dependent regional development trajectories risk reinforcing existing strengths at the expense of renewal, particularly in less diversified regions where the set of accessible future options remains limited (Balland et al., 2019; Otto et al., 2025). This risk is especially pronounced in the automotive sector, where regions with deep specialization in ICE technologies may remain locked into these trajectories even as global industrial and regulatory dynamics are shifting toward EVs. It is further underlined by insights from Luetkehaus (2025), who shows that strong commitments to legacy technologies constrain the ability of incumbents to respond to transformative policy mixes. Crucially, those actors most in need of external incentives – due to high inertia – are also the least responsive to them, placing them at risk of being caught in a double trap of technological lock-in and policy ineffectiveness. At the regional level, particularly in areas with dense clustering in the automotive industry, this double trap risks manifesting as a form of collective rigidity, reinforcing development paths that are increasingly misaligned with broader industrial and policy transitions (Gong & Truffer, 2024). However, findings by Hansmeier et al. (2025) indicate that sectoral greening can occur even in established automotive regions, such as Wolfsburg, Munich, Ingolstadt, and Stuttgart, challenging the notion that strong industrial legacies inevitably hinder transformative environmental innovation. The degree of regional knowledge complexity might become central in this context, as more complex regions are better equipped to break out of lock-in by recombining capabilities and exploring more distant technological paths – making long jumps in the technology space (Balland et al., 2022; Hausmann et al., 2024; Hidalgo & Hausmann, 2009).

However, regions do not innovate in isolation. A growing body of literature highlights the importance of interregional collaboration for accessing non-local knowledge and compensating for locally missing capabilities (Bachtrögler-Unger et al., 2023; Balland & Boschma, 2021a; Calignano et al., 2024; Frenken et al., 2023; Kogler et al., 2023). Particularly in the context of technological transitions, such collaborations can support regional diversification into more distant, less related fields. These dynamics unfold within broader multi-scalar (global) innovation systems, in which technologies are shaped by transnational actor networks and dominant global regime logics that influence transition trajectories beyond regional and national borders (Binz & Truffer, 2017; Mazzoni et al., 2025). Interregional knowledge networks nevertheless remain a key analytical focus, as they serve both as channels for spillovers and as mechanisms to expand the technological opportunity space of regions (Kogler et al., 2023; Wanzenböck et al., 2014). Recent evidence shows that external collaborations, particularly those involving multilocation firms, can substitute for weak local relatedness by introducing diverse and complementary knowledge inputs (Frigon & Rigby, 2022; Kogler et al., 2023). In the context of the automotive transition, this implies that regions with high relatedness to ICE technologies but low relatedness to EVs may mitigate the risk of lock-in by collaborating with regions specialized in EV technologies that provide complementary capabilities absent in the focal region. This is even more crucial for regions with low knowledge complexity, as their limited internal capacity to recombine diverse capabilities makes external knowledge inputs essential for accessing more advanced technological domains. In doing so, interregional collaboration not only strengthens a region's position within each development path but also expands its strategic options beyond what local capabilities alone would permit.

However, interregional cooperation in patenting remains relatively sparse and strongly constrained by national borders, limiting regions' ability to access capabilities from other EU regions (Bachtrögler-Unger

et al., 2023; Lalanne & Meyer, 2024). To reveal a region's full potential, it is therefore crucial to consider its existing linkages and to understand the drivers shaping them. This, in turn, can inform policy strategies aimed at overcoming barriers and fostering new connections with regions where complementary capabilities can be accessed, thereby increasing a region's innovation potential (Wanzenböck & Piribauer, 2018; Wanzenböck et al., 2014, 2015). By providing a method for uncovering regions' untapped potential, Bachtrögler-Unger et al. (2023) demonstrate how cooperation between regions can enhance their potential in new fields.

Overall, the literature highlights that a region's potential to transition into new technological fields is shaped by the relatedness and complexity of its existing knowledge base, its established collaborative networks, and may be constrained by path dependencies rooted in legacy technologies. In the empirical part of this paper, we build on these factors to assess the ability of European regions to transition toward electric mobility, thereby addressing our central research question.

### 3. Empirical analysis

In this section, we identify automotive regions and outline the methodology for measuring technological potentials by mapping regional capabilities in the two technological domains: EVs and ICE improvements. To assess how regional capabilities in these domains shape innovation performance in EVs, we estimate negative binomial models of EV patenting. These models examine how regional relatedness density to EVs and ICE improvements (and their difference) affect the number of EV patents, thereby providing a lens on the risk of capability lock-ins. Furthermore, we present a methodology to uncover technological specificities in cross-regional collaborations and estimate potentially beneficial future collaborations to mitigate capability lock-in situations.

#### 3.1. Data

##### 3.1.1. Identification of automotive regions

To select automotive regions, we consider employment data at NUTS2 level (2021 rev.) and 2-digit of the NACE Rev. 2 (Eurostat, 2024), representing the most disaggregated figures available for NUTS2 regions. The sectoral unit of analysis is the division *Manufacture of motor vehicles, trailers and semi-trailers* (code 29, herein: C29): it provides a broad picture of the activities in the automotive supply chain co-located at a regional level, as it is the case of most tier-1 and tier-2 suppliers that need to be located close to the OEMs' plants to provide components and parts for just-in-time production in the car assembly line.

We define regional specialization in the automotive industry by relying on two metrics: the normalized coefficient of location<sup>2</sup> – indicating specialization and increasing importance of the presence of the automotive industry from 0 to 1 – and the top quartile distribution of employment. Given that the location coefficient measures the relative importance of an industry in the region, it does not indicate its absolute size. Consequently, small regions such as Cantabria in Spain (with around 3000 employees in C29) would be included, while larger regions like Emilia-Romagna in Italy (with around 17,000 employees in C29) would be excluded. A complementary metric based on the quartile distribution of employment in C29 allows to identify automotive regions also all NUTS2 regions with employment  $L_{it}$  in C29 higher than the third

<sup>2</sup> The location coefficient,  $Q$ , in region  $r$  at time  $t$  (2018, in our dataset) is the employment ( $L$ ) share in sector  $k$  (here C29) at time  $t$  in region  $r$ , divided by the employment share in sector  $k$  at time  $t$  across all regions (EU27 and UK in our dataset). The normalized location coefficient value is  $q = (Q - 1)/(Q + 1)$ . We exclude missing values in employment data to compute the location coefficient.

quartile value (10,327.2).<sup>3</sup> Based on these two indicators, we identify 57 regions meeting both criteria, 17 additional regions based solely on the location coefficient, and 13 more regions based solely on the employment threshold. To ensure comprehensive coverage, we cross-reference our selection with the EU Automotive Regions Alliance – a political network of regions that identify themselves as automotive regions and support the transition of the European automotive and supply industry (EU Automotive Regions Alliance, 2023). Our metrics already capture 41 of the 57 Alliance regions. To reflect the political and strategic relevance of the remaining Alliance members, where the automotive industry likely plays a significant role despite not meeting the quantitative thresholds, we include 16 additional regions. In total, we identify 103 NUTS2 automotive regions (Fig. 1), representing around one-third of all NUTS2 regions and encompassing almost 86 % of employment in C29.

### 3.1.2. Patents

To measure regional technological capabilities in the fields of ICE improvements and EVs, we rely on patent data from OECD REGPAT (January 2024) and consider patent applications filed to the EPO, using Cooperative Patent Classification (CPC) at three-digit level (version 2023.02) (OECD, 2024). We use fractional counts by inventor share (inventor location) and aggregate patent counts to NUTS2 regions. The time frame for our analysis is the period 2005–2022. We start with patents classified in Y02T and identify relevant EV and ICE patents by filtering and splitting patents into two subgroups.<sup>4</sup> These represent the two largest technological fields in Y02T and are relatively equal in size (YIC: 9225 patents; YEV: 9321 patents). This classification allows us to look broadly into climate change technologies in the automotive industry and distinguish between the two dominant technological trajectories at the regional level. In particular, the two subclasses encompass ICE improvements, e.g., efficiency, alternative fuels, engine management systems (henceforth, YIC), and the development of battery-powered vehicles and accompanying technologies: hybrid and electric vehicles, electric machine technologies, batteries, enabling technologies, e.g., electric charging stations, systems integrating technologies related to power network operation (henceforth, YEV).

## 3.2. Methods

### 3.2.1. The relatedness density – complexity space

We approximate technological potentials by referring to knowledge complexity as well as relatedness, based on the patent data at the NUTS2 level for the period 2005–2022. We compute the regional knowledge complexity index by applying the Fitness-Complexity method (Tacchella et al., 2012) to a binary-valued network, connecting NUTS2 regions with the CPC classes at three-digit (i.e. 130 technological domains) in which the regions have a relative technological advantage (RTA).<sup>5</sup> RTA is here a binary variable (0 or 1) indicating whether a region  $r$  has a larger share of patents in technology class  $i$  than the average in the overall group.

To measure regional relatedness density to YIC (YICrd) and YEV (YEVrd), we follow the method applied, for example, by Balland et al. (2019) and implemented in the EconGeo package in R (Balland, 2017). First, we filter patents (all patents, regardless of regional origin) on which multiple CPC classes appear and create a weighted co-occurrences matrix ( $CPC\ classes \times CPC\ classes$ ) that indicates how often CPC classes co-occur on patents. This matrix is used to calculate the relatedness of any pair of CPC classes. The co-occurrences matrix is normalized by the total number of patents on which these CPC classes appear, and the

technological relatedness is converted into a binary value. The resulting matrix indicates whether two CPC classes are related (1) or not (0). A second matrix, ( $regions \times CPC\ classes$ ), is then computed, indicating in which CPC classes a region  $r$  has an RTA. Using these two matrices, relatedness density can be calculated. Technological relatedness density of a region  $r$  to a technology  $i$  is measured by the share of technology classes in which region  $r$  has an RTA to the technologies that are related to this technology class.

For each of the two groups of codes – YIC and YEV – we elaborate on the relatedness density at the NUTS2 level and plot this measure against the knowledge complexity of the regions. The combination of these two measures is elaborated to support policy design: relatedness density outlines the feasible options of a region in the two specified technological fields; regional technological knowledge complexity indicates to which extent a region's already available technological knowledge might be adequate to support a new combination. Importantly, examining not only YEV-related capabilities but also those linked to YIC is crucial for identifying risks of technological lock-in and regional path dependence.

### 3.2.2. Negative binomial model

To examine the regional drivers of electric vehicle innovation, we estimate negative binomial models to explain the annual number of EV patents (YEV) per NUTS2 region across all regions. Our primary aim is to assess how a region's relatedness density to EV technologies (YEVrd) and to internal combustion engine improvement technologies (YICrd) influences EV innovation outcomes. We estimate two model specifications. The first includes both YEVrd and YICrd individually, allowing us to observe the distinct and potentially opposing contributions of each technological domain. The second specification includes their difference (YICrd – YEVrd) to directly capture situations in which YIC-related capabilities dominate over YEV capabilities. This allows us to explore whether strong technological embeddedness in YIC – potentially reflecting structural inertia – acts as a barrier to a regional EV transition, consistent with the notion of technological lock-in. In the first case, we can assess whether YICrd hinders EV patenting per se; in the second, we examine how this relationship behaves when YICrd dominates YEVrd – together providing a more nuanced understanding of potential lock-in threats. Given our considerations in 2, we expect that higher YEVrd is positively associated with YEV patenting, whereas higher YICrd is expected to have a negative effect. We also expect a negative effect for a higher difference between YICrd and YEVrd.

We estimate the models using a negative binomial (NB) regression with a log-link function. The negative binomial model is particularly suited for overdispersed count data, where the conditional variance exceeds the mean – a condition that holds in our dataset. In contrast, Poisson models assume equidispersion and would therefore yield inefficient estimates and biased standard errors under overdispersion (Cameron & Trivedi, 2013; Hilbe, 2011). We additionally tested a zero-inflated negative binomial model to account for excess zeros in regional YEV patenting. However, the zero-inflation component was statistically insignificant, indicating that the standard negative binomial model already provides an adequate fit. We therefore rely on the standard NB specification for both parsimony and interpretability.

To account for differences in regional size, we include the logarithm of population as an offset. This effectively transforms the dependent variable into a per-capita intensity measure while preserving the count data structure and allowing the model to estimate patenting rates conditional on population size.

The key explanatory variables – YEVrd and YICrd – are calculated from full-count patent data at the inventor-region level using the OECD REGPAT database. We construct 5-year moving averages of patent activity in each domain, starting from 2001 (to compute relatedness density from 2005 onward). To mitigate potential endogeneity concerns, we lag these variables by one year in the model. The dependent variable – the annual number of YEV patents – is limited to the period 2005–2020

<sup>3</sup> We replaced NA values for 25 regions in 2018 with values that were available in 2016, 2017, or 2019.

<sup>4</sup> A list of codes can be found in Appendix Table A1.

<sup>5</sup> The implementation was done in R (version 4.2.1) using the package “economic complexity” (Vargas, 2020).

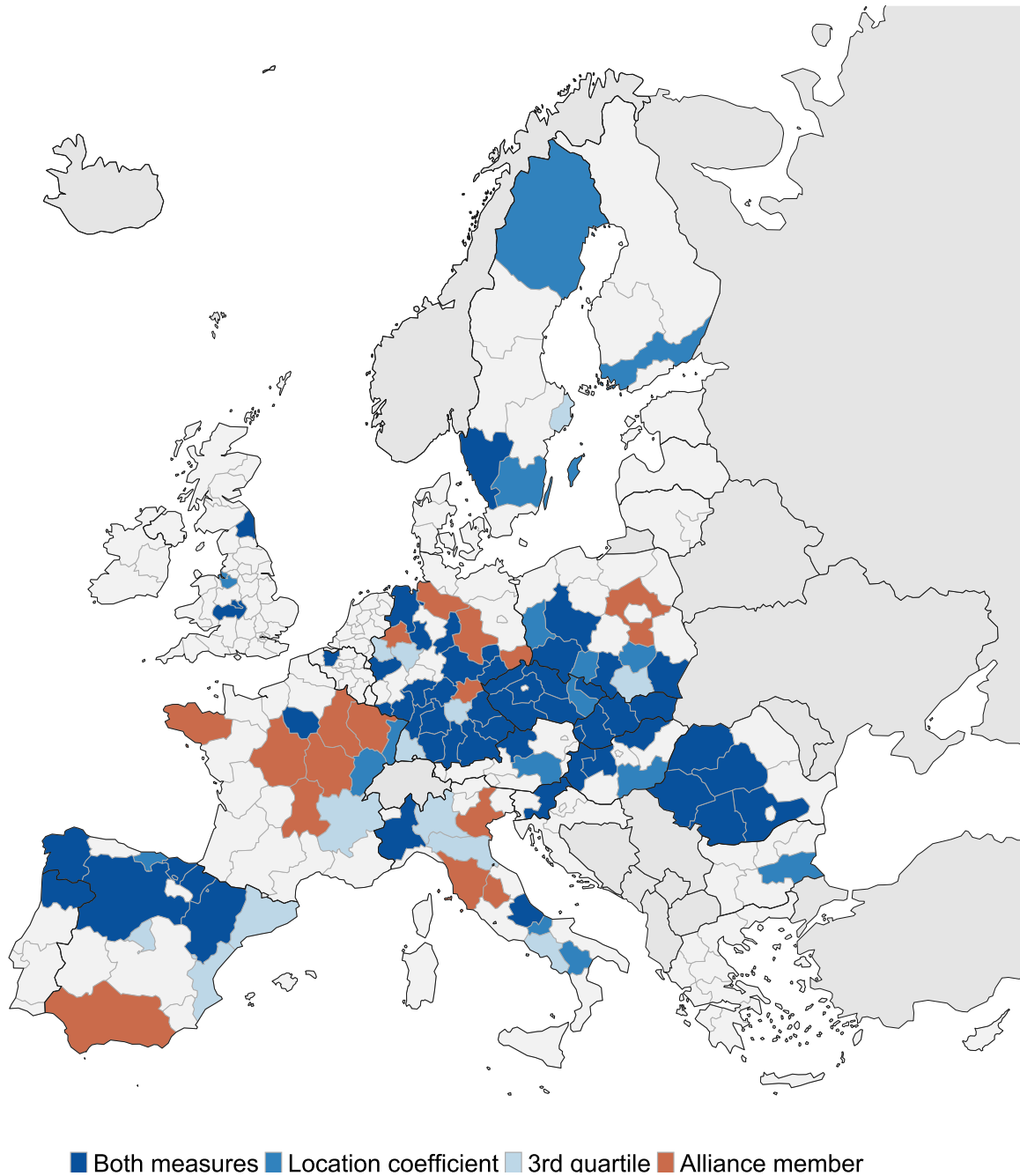


Fig. 1. Automotive regions in the EU27 and UK.

to avoid data sparsity due to patent publication delays.

In addition to technological relatedness, we include a set of region-level control variables capturing innovation inputs and economic context. We include knowledge complexity, computed as described in the previous section using the Fitness–Complexity algorithm (Tacchella et al., 2012). This measure captures the sophistication of a region’s knowledge base and allows us to empirically assess whether the relatedness-complexity mapping holds in the EV domain – i.e., whether more complex regions indeed patent more in EVs and are therefore better positioned. We lag knowledge complexity also by one year. Further, we include R&D intensity (R&D expenditure as a share of GDP) and human capital (measured as regional tertiary education share) as proxies for innovation inputs (Audretsch & Feldman, 2004; Griliches, 1979). To account for general economic development and agglomeration effects, we add GDP per capita and population density, respectively

(Carlino & Kerr, 2015). All regional control variables are obtained from Eurostat. The model is specified as:

$$\mathbb{E}[YEV_{r,t}] = \exp(\beta_0 + \beta_1 \log(YEVrd_{r,t-1}) + \beta_2 \log(YICrd_{r,t-1}) + \beta_3 \log(\text{complexity}_{r,t-1}) + X_{r,t} \beta + \log(\text{pop}_{r,t}))$$

where  $YEV_{r,t}$  is the count of EV patents in region  $r$  and year  $t$ ,  $YEVrd_{r,t-1}$  and  $YICrd_{r,t-1}$  the respective relatedness densities to YEV and YIC, and  $X_{r,t}$  a vector including R&D intensity, tertiary education, GDP per capita, and population density.  $\log(\text{pop}_{r,t})$  is an offset term equal to the logarithm of the population of region  $r$  in year  $t$ , used to scale the count model and convert it into per-capita intensity. In the alternative model specification, the difference term  $(\log(YICrd_{r,t-1}) - \log(YEVrd_{r,t-1}))$  replaces the separate inclusion of the two relatedness variables:

$$\mathbb{E}[YEV_{r,t}] = \exp(\beta_0 + \beta_1(\log(YICrd_{r,t-1}) - \log(YEVrd_{r,t-1})) + \beta_2 \log(\text{complexity}_{r,t-1}) + X'_{r,t} \beta + \log(\text{pop}_{r,t}))$$

### 3.2.3. Inter-regional linkages & untapped potential

To support the transition to electric vehicles and address potential capability lock-ins, we identify patents co-invented across NUTS2 borders to uncover cross-regional collaboration patterns and estimate untapped potential. We conduct the analysis for both technology classes to explore potential differences in the drivers of inter-regional collaboration, focusing on the period 2013–2022 to capture more recent dynamics. Of all YIC and YEV patents, 2867 involve inventors from at least two regions and this share is highly similar for YIC (1269 inter-regional patents) and YEV (1629 inter-regional patents) with around 27.5 % and 25.5 % respectively. We construct an undirected spatial network, where a link exists between two regions if inventors from both appear on the same patent. Patents with more than two inventors are broken into one-to-one cross-regional inventor combinations.

To explain the drivers of inter-regional linkages, we estimate a linear (OLS) model in log-log form, following the approach of [Bachtrögler-Unger et al. \(2023\)](#). The dependent variable is the number of cross-regional inventor links (edge weight) between region pairs ( $i, j$ ) in domain  $k$  (YIC or YEV). Our primary interest lies in the role of technological relatedness and knowledge complexity in shaping cross-regional collaboration. We include the average relatedness density (avgRD) and relatedness density distance (relDensDist), as well as their counterparts for knowledge complexity, to assess how technological proximity and divergence in capabilities influence cross-regional collaboration. We control for established drivers of regional linkages: geographic distance ([Broekel et al., 2014](#)) measured in kilometers between regions  $i$  and  $j$ , innovation mass (total patents in  $i$  and  $j$ ), and a country dummy indicating whether both regions are in the same country, accounting for the barrier posed by national borders ([Bachtrögler-Unger et al., 2023](#)).

To identify promising cross-regional collaborations in the EV domain, we follow [Bachtrögler-Unger et al. \(2023\)](#) and re-estimate the YEV model using standardized variables. We then predict untapped potentials by substituting the same-country effect with pairwise complementarity, following [Balland and Boschma \(2021a\)](#). We measure complementary interregional linkages as how much relatedness density a region  $r$  adds by connecting to another region that is specialized in technologies related to the focal technology class (YEV), but in which region  $r$  is not specialized. This substitution allows us to simulate an idealized EU network that overcomes national borders while accounting for factors such as spatial constraints and the pull effect of innovation mass. We compute the difference between rescaled predicted and observed linkages, normalized between 0 and 100, where higher values indicate greater untapped potential.

## 4. Results

The results of the empirical analysis address the research question by examining regional knowledge complexity and relatedness density toward YEV and YIC. This allows us to map regions in the relatedness density–complexity space and, through the joint perspective, identify those at risk of capability lock-ins. We then examine co-patenting patterns and their drivers to assess the potential of inter-regional linkages, highlighting opportunities to access complementary capabilities that can support regional transitions toward electric mobility.

### 4.1. Mapping the potential of EU automotive regions in the transition towards YEV and YIC domains

For each technological domain, YEV and YIC, we examine the position of European regions by plotting relatedness density and technological knowledge complexity of NUTS2 regions in the RD-complexity space. For illustrative purposes, we use data aggregated over the period

2013–2022 to capture recent positioning while ensuring comparability across regions with differing patenting intensities. Results based on other time periods show similar patterns, confirming the robustness of the observed regional structure. The aim is to identify the extent to which regional capabilities exist to develop and advance these technologies, and explore how regions are positioned in relation to both legacy (YIC) and emerging (YEV) technological domains.

To interpret the relatedness density–complexity space we first outline nine partitions that map the level of challenge for regions based on their capabilities in a single technological domain (either YEV or YIC), without considering their interrelation. This provides an initial rationale for policy intervention with respect to region-specific factors (see [Fig. 2](#), where the level of regional challenge is indicated in capital letters). For the relatedness density, the partition rule creates three groups of regions,<sup>6</sup> according to the level of relatedness density: those with an relatedness density (RD) greater than 50 %, the ones with an RD above 25 % and below 50 %, and the regions with an RD below 25 %. These three partitions highlight, respectively, "appropriate", "modest", and "not appropriate" regional technological knowledge that would be required to support the transition towards the respective technological class. The threshold of 25 % is higher than the average region in the sample, while the threshold of 50 % might be considered a general high value in the literature (as in [Balland et al., 2019](#)), supported by the fact that, in our dataset, it is a high value for automotive regions (corresponding to a level of RD for automotive regions above the third quartile). For regional knowledge complexity, we refer to the threshold of the interquartile range (IQR, which is computed on automotive and non-automotive regions) as relative measures to rank regions by knowledge complexity.

All things being equal, the combination of these thresholds helps in summarizing the challenges for the regional policies on a scale of increasing difficulties in their implementation, from "easy" to "moderate", "difficult", "very difficult", and "extremely difficult".

In [Fig. 3](#), we map the spatial distribution of regional potentials in each of the two technological domains under analysis. The cross-map comparison shows some regions with different resulting positions for the two technological domains, as in the case of Lombardia (ITC4) in Italy, which is very well positioned in terms of YIC, but weakly positioned towards YEV. In contrast, there are a couple of regions where the opposite holds, and which seem to be very well positioned towards YEV but weaker in YIC. This is the case for Oberösterreich (AT31) in Austria, the País Vasco (ES21) in Spain and Västsverige (SE23) in Sweden. Some regions find themselves very well positioned in both domains, such as Piemonte (ITC1) in Italy and Stuttgart (DE11) in Germany. On the other hand, several regions appear to be weakly positioned in both technological domains, for example regions such as Abruzzo (ITF1) and Campania (ITF3) in southern Italy, some Spanish regions, as well as Yugoiztochen (BG33) in Bulgaria and the Polish regions of Wielkopolskie (PL41) and Świętokrzyskie (PL72). Eastern European automotive regions in general seem to be somewhat weaker positioned in YEV, but there are also some regions such as Małopolskie (PL21) in Poland, Jihozápad (CZ03) in the Czech Republic, Sud-Muntenia (RO31) in Romania that seem to have relevant regional capabilities for this technological domain. There are also several regions that are positioned intermediately in both technological domains, which implies a less clear scenario for the regional technological development trajectory. A prominent example is the region of Emilia-Romagna (ITH5) in Italy, known for its innovative capacity and a strong automotive industry presence. Other examples of regions with intermediate regional capabilities in both technological domains include important automotive regions such as Střední Čechy (CZ02) in the Czech Republic, Braunschweig (DE91) in Germany, Dolnośląskie (PL51) in Poland and

<sup>6</sup> Quartile values considered in the partition rule of the combination of relatedness vs. complexity are the following (Q1, Q3): YIC (20, 40); YEV (20, 46.67); complexity (0.8, 1.23).

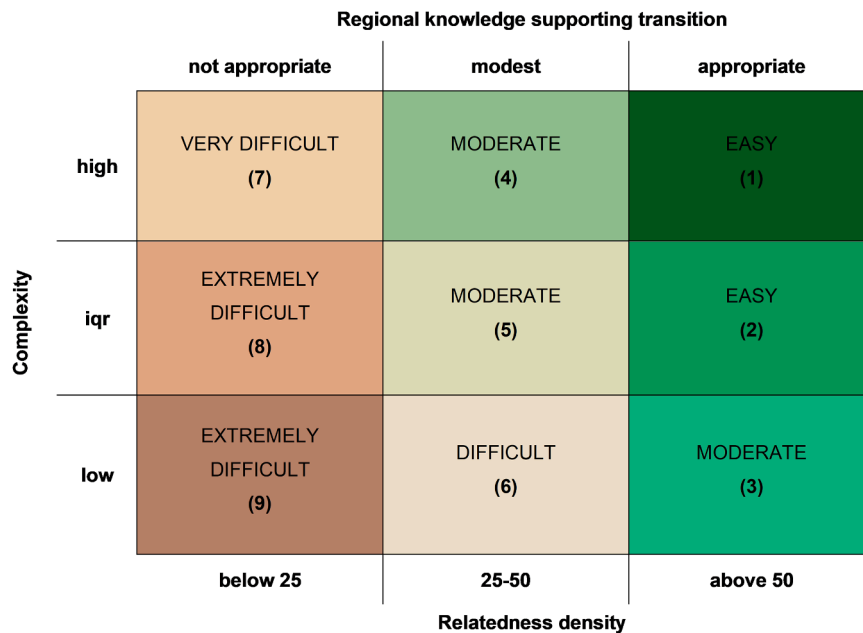


Fig. 2. Mapping regional transition challenges in the knowledge complexity and relatedness density space. The level of regional transition challenge is indicated in capital letters.

Northumberland and Tyne and Wear (UKC2) in the United Kingdom.

#### 4.2. Negative binomial model

To examine the regional drivers of electric vehicle innovation, we estimate negative binomial models explaining the annual count of EV patents per NUTS2 region (Table 1). Our main explanatory variables are the region’s relatedness density to EV (YEVrd) and ICE improvement (YICrd) technologies, along with their difference (YICrd – YEVrd) as an alternative specification. This allows us to assess whether embeddedness in legacy ICE capabilities constrains regional EV innovation through a lock-in effect. To account for time-specific events that uniformly affect all regions, such as technological trends or EV-related policy shifts, year fixed effects are included in Models (2) and (4). Given the prevalence of structural zeros and sparse patenting across regions, we refrain from including region fixed effects to preserve meaningful cross-sectional variation and avoid dropping entire regions from the sample.

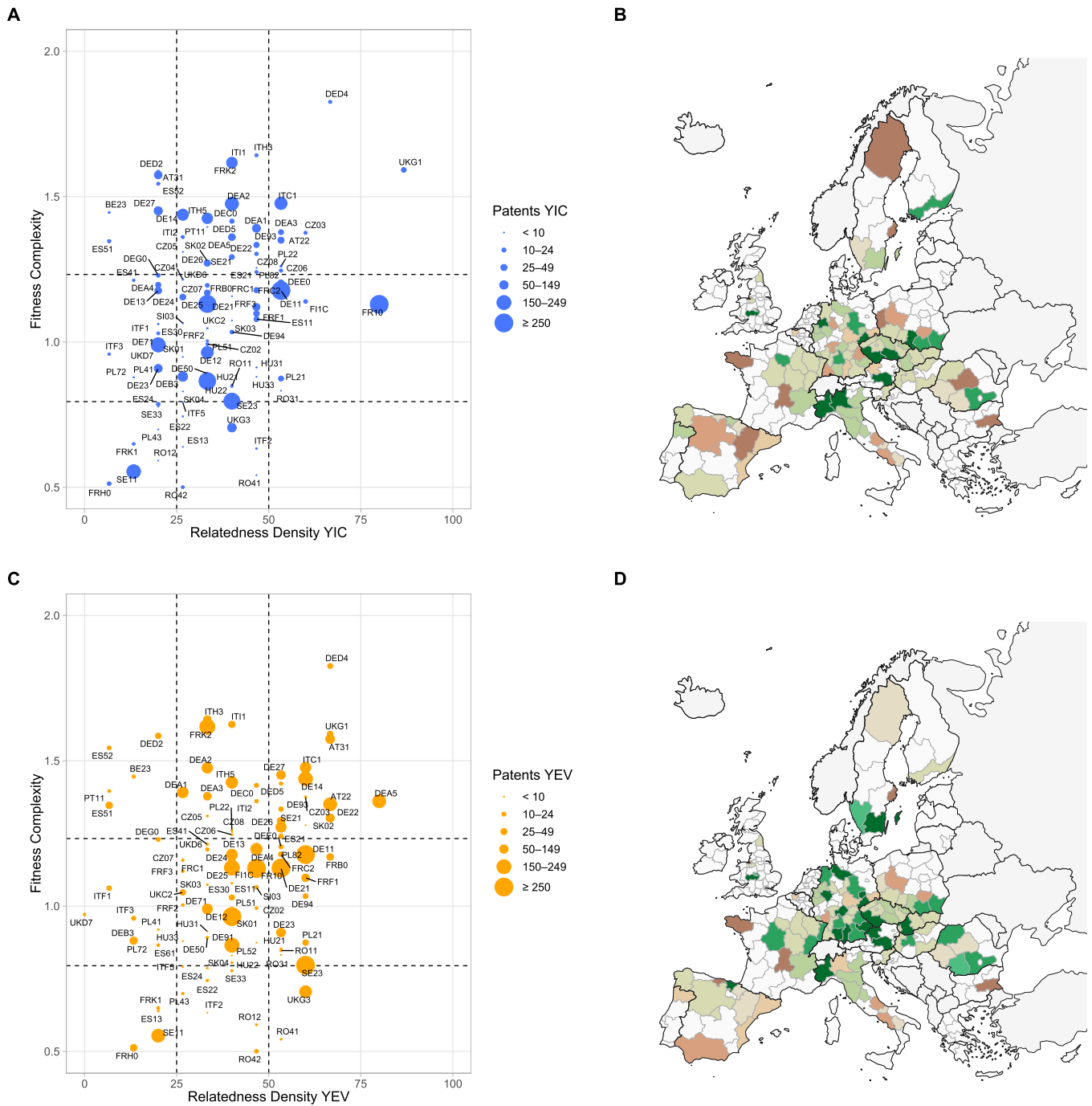
The results in Table 1 support the expected role of YEVrd as a key enabler of EV innovation, with a positive and statistically significant effect across both models (Models 1 and 2). The magnitude of this effect is substantial with a 10 % increase in relatedness density to YEV technologies corresponds to an approximate 5.3 % increase in expected YEV patenting. While this impact is smaller than that of R&D intensity – a well-established innovation input whose estimated effect is more than twice as large – it nonetheless remains economically meaningful, highlighting that technological relatedness is strongly associated with EV patenting alongside conventional inputs. Knowledge complexity is also positively and statistically significantly associated with EV patenting across all models, suggesting that regions with more sophisticated knowledge bases tend to exhibit higher EV innovation activity. The effect is slightly stronger than that of EV-relatedness, with a 10 % increase in complexity corresponding to an approximate 8.9 % rise in expected EV patenting. This lends additional support to the RD–complexity space as a useful framework for mapping and assessing regional innovation potential in the EV domain. These findings are in line with previous studies across technological domains, such as Balland et al. (2019), who find that relatedness and complexity are positively and significantly associated with technological growth at the regional level.

The coefficient on YICrd is also positive and statistically significant,

albeit smaller in magnitude than YEVrd, suggesting that ICE-related capabilities do not necessarily impede EV innovation and may even provide complementary technological spillovers. This aligns with findings by Ferloni et al. (2024) and Hansmeier et al. (2025), who show that established automotive regions are capable of innovating in EV technologies and appear to partially draw on their existing ICE-related capabilities in doing so. However, the relatedness difference specification (Models 3 and 4), which captures the extent to which ICE capabilities dominate over EV capabilities, reveals a negative and significant effect. This implies that regions where the legacy orientation toward ICE technologies structurally outweighs EV-related capabilities are less likely to patent in EV technologies, consistent with the notion of technological lock-in. In other words, while some degree of ICE expertise may support EV innovation, an overdominance of ICE-related capabilities appears to constrain a region’s ability to transition toward EV technologies. To our knowledge, this asymmetric effect of technological relatedness, whereby legacy dominance becomes a structural barrier to innovation in emerging technologies, has not yet been explicitly identified in the existing relatedness literature, which has largely emphasized its enabling role and typically does not distinguish between technology-specific interactions of relatedness. Our results therefore provide novel empirical evidence that technological relatedness can shift from an enabling to a constraining force when strong regional dominance in legacy capabilities reinforces declining technological paradigms. This offers new insights into the conditions under which regional capability structures may hinder, rather than support, processes of technological transition.

The remaining control variables behave largely as expected. R&D intensity and GDP per capita are positively associated with EV patenting, highlighting the role of regional innovation inputs and economic development. In contrast, tertiary education and population density show negative effects, possibly reflecting structural differences between urban and industrial regions or a weaker alignment between broad educational attainment with technological outputs, particularly given that the automotive industry often concentrates in specialized engineering hubs rather than in service-oriented, highly educated urban centers.

Overall, the findings support that both relatedness density to EV technologies (YEVrd) and knowledge complexity are important enablers



**Fig. 3.** EU27 and UK regions: position in the relatedness density – knowledge complexity space, by technological domains YIC (A and B) and YEV (C and D). Legend for B and D is Fig. 2.

of regional EV innovation. At the same time, technological inertia rooted in ICE capabilities may act as a barrier when those capabilities dominate the regional knowledge base.

To investigate whether the effect of ICE dominance varies by regional knowledge complexity, we split the dataset into high-complexity regions (top 25 % of the complexity distribution) and low-complexity regions (bottom 25 %) and estimate separate binomial regressions for each group. This quartile-based split allows us to contrast regions with the most advanced and diversified knowledge bases with those that are structurally weaker and more constrained in their capability endowments. To ensure comparability of effect sizes across groups, the key explanatory variable – the difference between

relatedness density to YIC and YEV – is z-standardized. Results reported in Table 2 show that greater dominance of ICE over EV technologies is negatively associated with YEV patenting in both region types, although the strength of this effect differs markedly. Specifically, the constraining effect of ICE dominance is almost twice as strong in low-complexity regions as in high-complexity regions.

This suggests that while capability dominance in legacy technologies restricts innovation in emerging technologies across all regions, those with more complex knowledge bases display greater resilience to lock-ins and are better able to make long-jumps into emerging technological fields even when legacy systems remain strong. By contrast, regions with low knowledge complexity appear substantially more vulnerable to

**Table 1**  
Negative binomial regression results for regional EV patenting.

	Dependent variable: YEV patents			
	RD model (1)	RD model (2)	RD diff model (3)	RD diff model (4)
YEVrd, t-1	0.567*** (0.053)	0.532*** (0.052)		
YICrd, t-1	0.112** (0.044)	0.110*** (0.042)		
RD difference, t-1			-0.122*** (0.042)	-0.106*** (0.040)
Complexity, t-1	0.810*** (0.076)	0.893*** (0.074)	1.018*** (0.079)	1.109*** (0.077)
R&D intensity	1.256*** (0.102)	1.301*** (0.100)	1.354*** (0.106)	1.391*** (0.103)
Human capital	-0.345*** (0.120)	-0.671*** (0.122)	-0.616*** (0.122)	-0.966*** (0.124)
Population density	-0.189*** (0.028)	-0.183*** (0.027)	-0.266*** (0.028)	-0.254*** (0.027)
GDP per capita	1.426*** (0.097)	1.358*** (0.094)	1.467*** (0.099)	1.384*** (0.096)
Constant	-30.556*** (0.905)	-29.775*** (0.890)	-27.637*** (0.890)	-26.820*** (0.874)
Observations	2811	2811	2811	2811
Fixed effects	No	Yes	No	Yes
Log Likelihood	-4113.4	-4036.0	-4182.2	-4100.9
AIC	8244.8	8118.0	8380.4	8245.7

Note: Standard errors in parentheses. \*p < 0.1; \*\*p < 0.05; \*\*\*p < 0.01.

**Table 2**  
Negative binomial regression results for EV patenting in high- and low-complexity regions (quartile split).

	Dependent variable: YEV patents			
	Low complexity (5)		High complexity (7)	
RD difference, t-1	-0.317** (0.149)	-0.291* (0.152)	-0.163*** (0.038)	-0.154*** (0.037)
R&D intensity	0.399 (0.728)	0.322 (0.759)	1.645*** (0.122)	1.839*** (0.119)
Human capital	-0.108 (0.489)	-1.185** (0.566)	-0.709*** (0.182)	-0.953*** (0.171)
Population density	-0.186 (0.198)	-0.214 (0.185)	-0.273*** (0.041)	-0.218*** (0.038)
GDP per capita	1.172*** (0.317)	1.205*** (0.323)	1.836*** (0.209)	1.244*** (0.213)
Constant	-26.273*** (2.832)	-23.278*** (2.946)	-30.128*** (1.886)	-24.832*** (1.928)
Observations	822	822	836	836
Fixed effects	No	Yes	No	Yes
Log Likelihood	-260.2	-238.4	-2470.1	-2410.6
AIC	534.4	520.8	4954.3	4865.2

Note: Standard errors in parentheses. \*p < 0.1; \*\*p < 0.05; \*\*\*p < 0.01.

lock-in dynamics and face greater difficulty in reorienting towards unrelated technological trajectories.

This moderating role of knowledge complexity is consistent with the literature, which shows that more complex regional knowledge bases support diversification and innovation (Antonelli et al., 2022; Balland & Rigby, 2017; Balland et al., 2019, 2022). However, our analysis goes beyond this established insight by demonstrating that the effect of complexity interacts with technology-specific relatedness dominance. When ICE-related capabilities structurally outweigh EV-related ones, even complex regions begin to experience constraints, although to a lesser degree, while low-complexity regions appear far more severely locked into legacy trajectories. In these regions, the lack of breadth and sophistication in the regional capability base limits their ability to overcome dominant legacy structures and reorient towards emerging technologies. To the best of our knowledge, this asymmetric and technology-specific lock-in effect of relatedness dominance across

different complexity levels has not previously been empirically demonstrated, thereby providing novel evidence on how regional capability structures can shift from enabling to constraining forces, and how this dynamic is reinforced by underlying differences in knowledge complexity in the context of technological transition.

The control variables further underline this structural contrast. While R&D intensity exhibits a strong and statistically significant positive effect in high-complexity regions, it remains insignificant in low-complexity regions, suggesting that innovation inputs translate into EV patenting only where sufficient absorptive capacity and complementary capabilities are already in place. Human capital and population density display negative coefficients and are significantly negative in high-complexity regions, indicating that EV-related patenting is less concentrated in highly urbanized or service-oriented regions and instead more strongly associated with specialized industrial structures. GDP per capita, by contrast, shows a consistently positive and significant effect across both groups, pointing to a general alignment between higher levels of regional economic development and EV-related patenting, even when technological capabilities diverge.

Given the insights above, we can reconsider the RD-complexity space not only for each technology class individually, but also in terms of their combined effects – specifically, the negative implications of YICrd dominance over YEVrd. This perspective highlights the risk of potential capability lock-ins, where dominant regional capabilities in YIC may impede the transition toward YEV, particularly when reinforced by low levels of knowledge complexity. Several automotive regions are facing these conditions, and as discussed in Section 2, a potential pathway out lies in establishing extra-regional linkages that allow access to complementary capabilities. To illustrate the potential for regions to tap into underutilized external resources, we select four regions where these conditions – namely, a high dominance of YIC in terms of relatedness density – are present, and examine the estimated untapped potential derived from the co-patenting analysis in the next section. As example regions, we select Herefordshire, Worcestershire and Warwickshire (UKG1), Jihovýchod (CZ06), Rheinhessen-Pfalz (DEB3), and Lorraine (FRF3). All have a strong legacy in ICE-related innovation and host major industry actors such as Jaguar Land Rover, Škoda Auto, and Mercedes-Benz, along with a range of engineering and component firms that have long shaped the regional technological environment. While DEB3 and FRF3 exhibit relatively low knowledge complexity, CZ06 shows medium complexity, and UKG1 stands out with comparatively higher levels.

#### 4.3. Co-patenting & untapped potential

The cross-region linkages emerging from the co-patenting activities of inventors of different regions are mapped in Fig. 4 for the YEV and the YIC domains. In both domains, networks are centered on German regions, presenting the highest eigenvector centrality (details in Appendix Table A2), well above France and Italy, showing country-centered networks that are nonetheless connected to German regions, driving the overall patenting activity in Europe through their co-patenting with other regions. Central Eastern countries, Northern countries, and the UK appear to be linked to Germany in a significant co-patenting activity.

From the models implemented to explain the number of co-patenting connections by technological domain, we can draw insights regarding technology-specific determinants of interregional collaboration. Table A3 in the Appendix shows the results of the two baseline models for YIC and YEV as well as the models with centered and standardized variables (scaled specifications). We find that distance negatively influences co-patenting in both technologies, with a stronger effect for YIC. Patent mass has a positive effect on inter-regional co-patenting for both technologies, with the effect being nearly twice as strong for YEV. The country effect is positive in both models, indicating that being in the same country facilitates inter-regional cooperation, with a stronger impact for YEV, which likely reflects the higher technological maturity

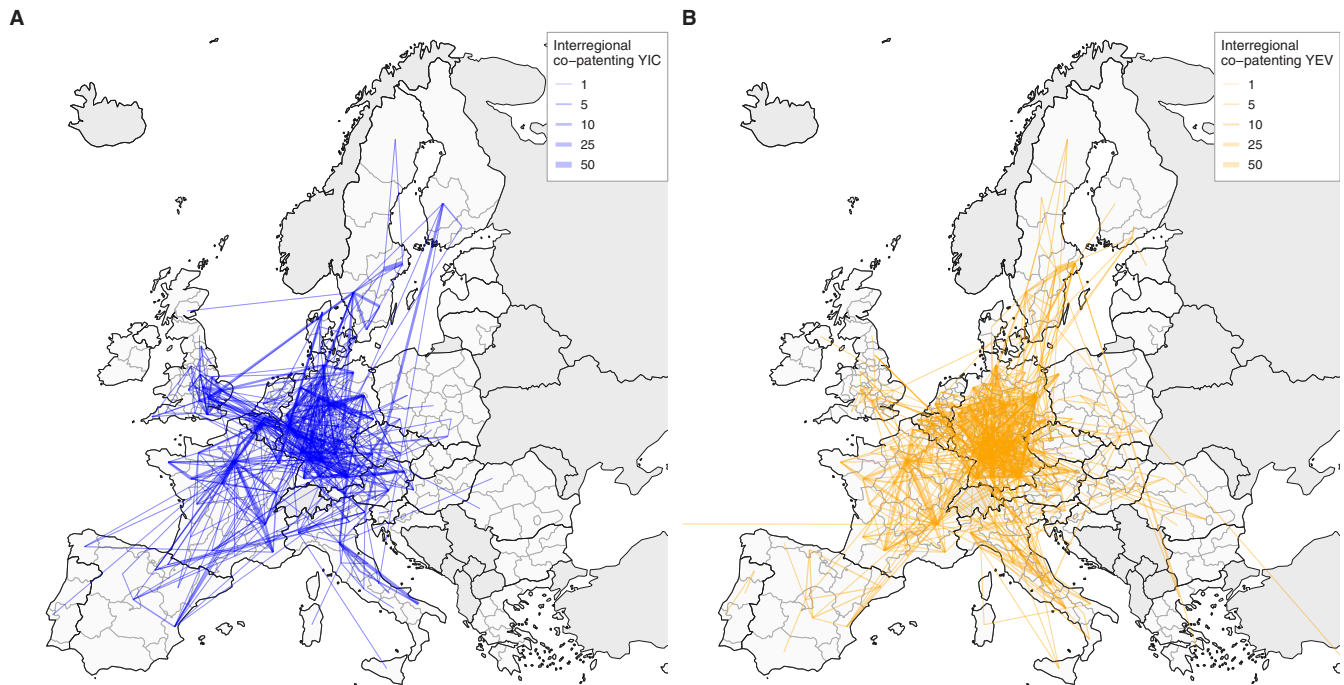


Fig. 4. Interregional co-patenting networks in the YIC (A) and YEV (B) domains.

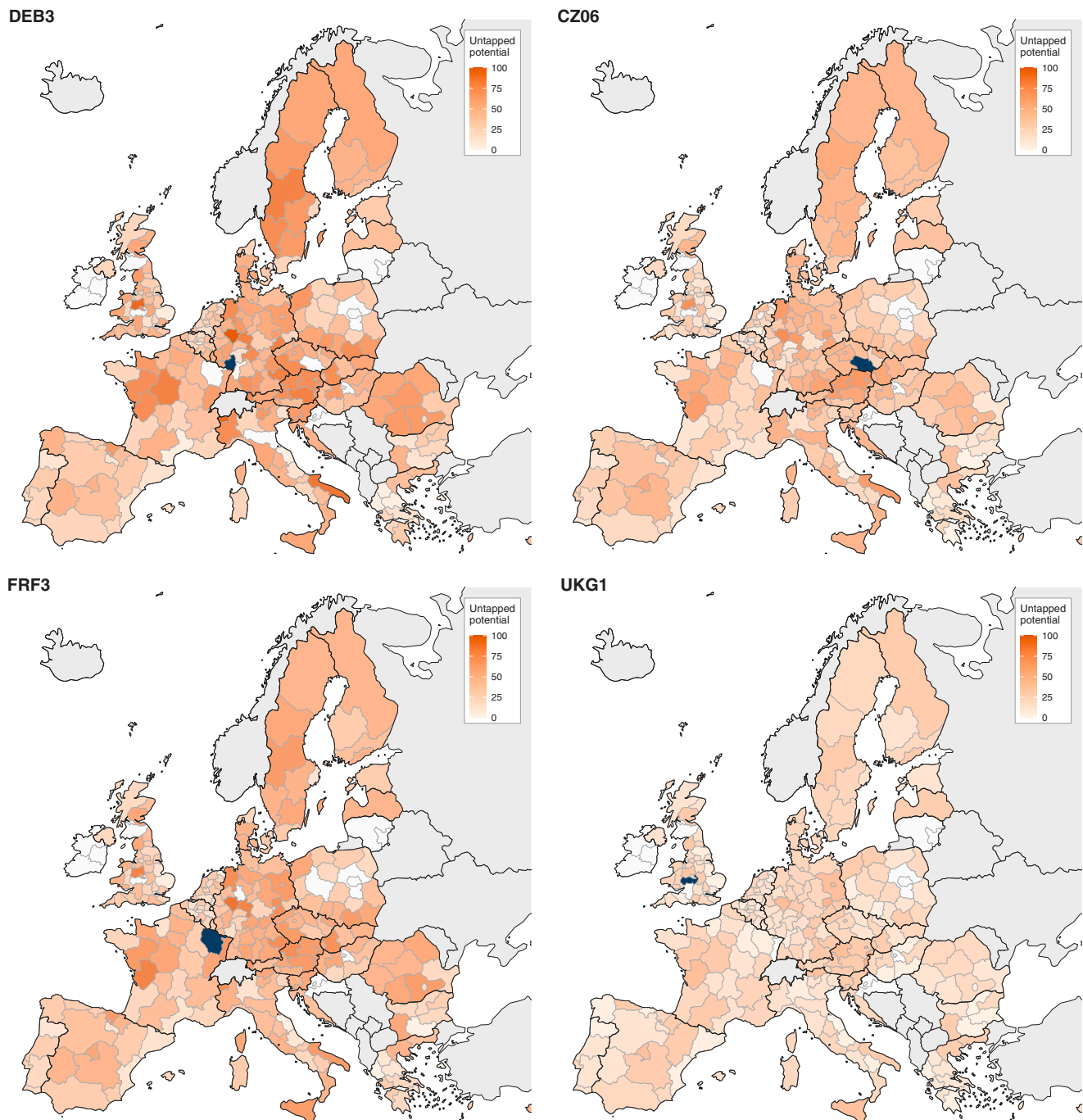
of YIC. This effect is considered in the second step, where we adjust the model by incorporating complementarity, following [Bachtrögler-Unger et al. \(2023\)](#), suggesting that an EU-level policy could mitigate the country effect to some extent.

Other variables, such as the average relatedness density between cooperating regions, distance in relatedness density, and similar measures for complexity, do not show significant effects across all models. However, greater distance in complexity appears to hinder inter-regional cooperation, as high-complexity regions may have fewer incentives to collaborate with structurally weaker partners. The average relatedness density is significant only for YEV, where regions with high relatedness density towards YEV cooperate more frequently. This might be driven by different levels of technological maturity, with YEV still being less mature than YIC. This implies that regions with low knowledge complexity and low relatedness to EV technologies are not only at risk of internal capability lock-ins, as discussed above, but are also less frequently engaged in inter-regional co-patenting. As a result, they face a double disadvantage, lacking both the internal capacity and the external connections needed to access complementary capabilities, thereby reinforcing a structural trap that limits their participation in emerging technological trajectories. We shall discuss the policy implications of these results in [Section 5](#). While our analysis offers valuable insights, some limitations should be noted. The regression includes only region pairs with at least one co-patent, introducing a potential selection bias by excluding distant or unconnected regions. Moreover, many observed interregional patents stem from inventors or subsidiaries within the same firm, meaning co-patenting often reflects internal corporate strategies rather than broader regional collaboration. Even when using applicant data, this concern remains, as co-patents involving different applicants frequently result from intra-firm collaborations across subsidiaries ([Meier et al., 2023](#)). Accordingly, the policy implications of these linkages should be interpreted with caution. However, for untapped potential, intra-firm collaboration is less of a concern. [Kogler et al. \(2023\)](#) show that interregional networks within multi-location firms can facilitate regional diversification into unrelated technologies, especially in non-metropolitan regions. These internal knowledge flows can compensate for missing local capabilities, suggesting that co-patents still reflect economically meaningful innovation

linkages and pathways for capability upgrading.

The analysis of untapped potential for regional collaboration, as depicted in the maps in [Figure 5](#), highlights partnership opportunities for our four example regions: Rheinhesen-Pfalz (DEB3), Jihovýchod (CZ06), Lorraine (FRF3), and Herefordshire, Worcestershire, and Warwickshire (UKG1). Untapped potential is measured as the difference between the predicted and realized number of inter-regional linkages for each technology class, normalized between 0 and 100, with high values indicating substantial unrealized collaboration potential. By using the scaled YIC and YEV models and substituting the impact of the same country with pairwise complementarity ([Balland & Boschma, 2021a](#)), we predict the number of interregional linkages under the assumption of a policy that actively supports the overcoming of national boundaries and enables access to complementary knowledge that is currently underutilized or absent. By focusing on YEV, we can identify partners that offer substantial complementary capabilities, even when accounting for factors such as distance and patent mass. This approach therefore allows us to move beyond observed collaboration patterns and reveal strategically relevant partners that could support regional upgrading in the EV domain under more integrated and coordinated European innovation policies.

[Fig. 5](#) shows the untapped potential for the four example regions for YEV. For Rheinhesen-Pfalz, the estimation identifies several regions with untapped potential for collaboration. The most promising partner is Arnsberg (DEA5), which benefits from a growing electromobility cluster focused on battery production, power electronics, and applied research in North Rhine-Westphalia. Rheinhesen-Pfalz could also strengthen ties with Shropshire and Staffordshire (UKG2), a region closely aligned with the UK's automotive transition efforts and home to major OEM R&D activities. Another valuable connection is Kassel (DE73), where automotive suppliers and research institutes are actively engaged in alternative powertrain development. Collaborating with these regions could help Rheinhesen-Pfalz to move beyond its current ICE-dominated profile by accessing EV-relevant knowledge bases and supporting diversification. Similarly, for Jihovýchod (CZ06), the analysis highlights strong complementarities with Arnsberg, providing access to the expanding electromobility ecosystem. Further opportunities lie in Niederösterreich (AT12) and Oberösterreich (AT31), both of which offer



**Fig. 5.** Untapped potential in YE for selected automotive regions: Rheinhessen-Pfalz (DEB3), Jihovýchod (CZ06), Lorraine (FRF3), Herefordshire, Worcestershire and Warwickshire (UKG1).

robust engineering capacities and growing support for clean mobility. Weser-Ems (DE94) also stands out with relevant expertise in electrification and automotive supply, making it a strategic partner for knowledge exchange and capability upgrading. For Lorraine (FRF3), Poitou-Charentes (FRI3) in Nouvelle-Aquitaine emerges as a promising partner, where regional initiatives in sustainable transport and battery innovation are emerging. FRF3 may also benefit from closer cooperation with Oberösterreich, known for its strong industrial base and EV-related R&D activities, while Arnsberg again features as a key complementary region. Lastly, for Herefordshire, Worcestershire, and Warwickshire (UKG1), collaboration prospects include Wien (AT13), which hosts a strong research environment and expanding electric mobility activities.

Additional links with Chemnitz (DED6), a Saxon region with a long automotive tradition and rising engagement in EV technologies, and Burgenland (AT11), where regional innovation strategies increasingly support clean transport, could further enhance UKG1's diversification potential.

Another important insight emerging from these example regions is that, as our model of inter-regional linkages reveals, the level of regional knowledge complexity significantly shapes the extent of existing co-patenting connections. More complex regions tend to be more deeply integrated into collaboration networks and already display dense interregional collaboration. In contrast, regions with lower complexity exhibit substantially higher levels of untapped potential, as illustrated

by DEB3 (Rheinessen-Pfalz) and FRF3 (Lorraine), which show markedly greater collaboration potential than CZ06 (Jihovýchod) and particularly UKG1 (Herefordshire, Worcestershire, and Warwickshire) (see Fig. 5). Overall, the identified partner regions offer strong complementarities that can meaningfully strengthen the regional innovation systems of our example regions. By strategically leveraging these partnerships, regions can activate previously untapped collaboration potential, and reduce the risk of capability lock-ins associated with legacy technological trajectories.

## 5. Discussion: what policies to what region?

The results of the empirical analysis reveal substantial variation in regional positioning with respect to EV and ICE technologies, indicating different levels of transition challenge and lock-in risks. Regions with high relatedness density to EV technologies are better positioned to innovate, whereas in regions where capabilities are heavily skewed toward ICE, EV innovation is significantly impeded – highlighting a risk of capability lock-ins in legacy automotive regions. Regions with low knowledge complexity and low relatedness density are particularly vulnerable, as they lack both strong internal capabilities and integration into interregional innovation networks. These findings have important implications for innovation policy. In particular, they underscore the need for differentiated, place-sensitive innovation policies that consider both the internal capability base and the legacy structure of regions. Innovation policy in the EU, particularly under frameworks such as Smart Specialisation Strategies (S3), has increasingly emphasized tailoring support to regional strengths and priorities (Balland et al., 2019; Foray, 2014; Otto et al., 2025). However, such policies have often focused more on reinforcing existing capabilities than on addressing structural challenges or transition risks. Our results suggest that a more nuanced calibration is needed – one in which innovation policy serves distinct functions across different regional types.

Regions with high complexity and high relatedness to YEV technologies, and without a strong dominance of YIC capabilities, are particularly well positioned for the EV transition. Examples include for instance the País Vasco (ES21), which exhibits strong YEV capabilities and limited ICE legacy. Another interesting case is Stuttgart (DE11), a traditional automotive hub with a strong legacy in ICE technologies. At the same time, Stuttgart also shows high relatedness to YEV and high knowledge complexity, making it one of the top EV patenting regions in Europe, with over 500 patents during the period under analysis. This combination reduces the risk of lock-in and reflects the potential for transformation within an established industrial region. These findings align with Hansmeier et al. (2025), who show that sectoral greening can occur even in incumbent-dominated automotive regions. In such cases, innovation policy could focus on leveraging the existing local capabilities – supporting scaling, boosting R&D intensity, and fostering leadership in green value chains. This type of region is well suited for policies that promote frontier innovation and consolidate competitive advantages.

Regions with similar relatedness structures but lower complexity can also hold significant potential for the EV transition. Västsverige (SE23) exemplifies this, with more than 300 EV patents during the study period and a solid foundation of supporting regional capabilities. The presence of Volvo Cars, owned by the Chinese Geely who is one of the most dynamic applicants in the EV domain (Russo et al., 2026; Wuttke & Whitfield, 2025), coupled with collaborative efforts as part of Sweden's regionally driven smart specialisation approach, has strengthened regional innovation capacity. In such contexts, innovation policy could focus on enhancing R&D capabilities and fostering knowledge exchange to accelerate complexity gains.

By contrast, regions with high complexity but low relatedness to EV technologies and a strong ICE dominance face a distinct set of challenges. While they possess sophisticated knowledge bases, as in the case of Lombardia (ITC4), these are often misaligned with the emerging

technological trajectory. In such contexts, innovation policy could move beyond incremental adjustments and actively support transformative change by directly targeting EV-related innovation, coupled with a strategic phase-out of support for ICE-oriented activities. Phase-out instruments, such as stepwise technology bans that can be issued at the EU level, may play a central role in the future and have been shown to strengthen the effectiveness of other policy instruments by credibly destabilizing legacy technologies (Luetkehaus, 2025).

In addition, regions with low complexity, low relatedness to YEV technologies, and strong ICE legacies – such as Rheinessen-Pfalz (DEB3), Jihovýchod (CZ06), or Lorraine (FRF3) – are structurally constrained and poorly positioned for the EV transition. These regions face a high risk of capability lock-in. Innovation policy in such contexts may need to move beyond traditional R&D support and focus on foundational investments in infrastructure, human capital, and the strengthening of basic innovation system functions. Strengthening cross-regional linkages can help establish learning channels and provide access to complementary capabilities, gradually expanding the range of options for engaging with EV innovation. A critical factor in such settings is the responsiveness of actors to policy interventions, given that strong incumbent capabilities and legacy commitments may limit their effectiveness (Luetkehaus, 2025). In some cases, industrial policy diversification beyond the automotive sector may offer a more viable development path than direct participation in the EV transition. This may require a more fundamental reorientation, in which regions disengage from the automotive industry altogether and redeploy existing capabilities rooted in ICE technologies toward adjacent sectors.

However, beyond regional capabilities, many other dimensions must be coped with by policymakers' agendas, at regional, national and at the EU levels – dimensions that extend beyond the scope of innovation policy and touch upon broader industrial policy concerns (Altenburg & Rodrik, 2017; Juhász et al., 2024; Uyerra et al., 2020) and interactions between private strategies and public policies. This overlap creates governance issues, especially in the context of the EV transition, where long-term technological change intersects with immediate industrial restructuring needs. One such dimension is the strategic behavior of OEMs. In some of the poorly or moderately well positioned regions, there is still a presence of dynamic OEMs that are investing heavily in the EV transition, thereby driving their local tier 1 and tier 2 producers – as in the case of Lamborghini and Ferrari in Emilia-Romagna (Italy). By contrast, Maserati, now owned by Stellantis, is downsizing production, with negative effects on the local supplier base.

Furthermore, a regional policy response cannot be viewed in isolation, as a bundle of policies at different levels affects the regional automotive industry and its technological developments. In the global race toward EVs, with China playing a leading role, EU decarbonization targets are pursued through an array of national policies that do not consistently leveraging regional technological potential. So far, no EU-wide strategy has effectively coordinated these efforts, an issue at the core of the critical considerations in the EU competitiveness report (European Commission, 2024), where countries have highly distinct national policies and strategies in place. Germany plays a crucial role through the announcement of several gigafactories located in the core regions (Klier & Rubenstein, 2024) with very high EV transition potential, the reconversion of existing plants to retain local automotive employment by reshoring parts and components, and the reskilling and upskilling of the workforce. These measures are coordinated across different policy levels, from the federal level to subnational levels (BMW, 2021, 2023). Overall, German regions are better positioned for the EV transition than for YIC improvements, although this trajectory has recently become politically contested. France combines demand-side and supply-side measures to support the EV transition, linking incentives to an eco-score based on a simplified Life Cycle Assessment and mobilizing public funds to attract investment in high-potential regions. This includes the development of four gigafactories within an integrated ecosystem aimed at creating 10,000 new

jobs in the automotive sector (Direction Générale des Entreprises). An example is Stellantis' recent investment in a gigafactory in Billy-Berclau-Douvain, located in the North-East, near the Picardie and Île-de-France regions, both of which are identified as having medium potential in the EV domain. Spain has focused on national policies to attract foreign investment for reconvert existing plants, with success in attracting Ford's EV production facility in Europe. Italy does not yet appear to pursue a coordinated policy aimed at enhancing the technological capabilities of its regions, as illustrated by Stellantis' announcement of another gigafactory in Termoli, in the Molise region, which exhibits very low knowledge complexity and is surrounded by regions with low potential. By contrast, regions such as Piedmont and Emilia-Romagna show greater innovation potential, but long-term structural investments are not yet reflected in plans made available to the public. Central and Eastern European countries show limited momentum in EV technologies (Pavlínek, 2022b, 2023). However, the potential of certain regions is significant, with Chinese and Korean firms increasingly targeting these areas for FDI, particularly for battery production (Klier & Rubenstein, 2024). These investments, especially in greenfield plants, are reshaping the regional automotive landscape by targeting regions in need of foreign direct investment (as documented by Klier & Rubenstein, 2024). In this context, macro-regional initiatives like the EU Strategy for the Danube Region (EUSDR) play an important role in advancing the automotive transition towards EVs in Central and Eastern Europe. The strategic relevance of this macro-region is underscored by the fact that one-quarter of Europe's cell production is located within the EUSDR, with 14 % from Samsung SDI's plant in Goed (north of Budapest), and 10 % from SK Innovation's plant in Komárom, Hungary, driven by national policies attracting FDI. Macro-regions can therefore contribute to moving beyond region- and country-based policies towards a more strategic perspective, fostering mutual learning within and across macro-regions to support European technological sovereignty in global competition.

The case of the automotive sector illustrates how regions with longstanding strengths in legacy technologies – such as internal combustion engines – can face capability lock-ins during disruptive transitions. Regional innovation systems built around ICE, supported by dense networks of suppliers, OEMs, universities, and institutions, have historically advanced incremental improvements such as emission reduction. However, the shift toward electric vehicles represents a disruptive change that challenges these established trajectories. When regional capabilities are heavily concentrated in legacy technologies and knowledge complexity is low, adaptation becomes more difficult. Similar dynamics can be observed in other industries, where sustainability efforts are giving rise to emerging technologies that differ substantially from legacy systems (as seen, for instance, in electricity generation with the shift to renewables, heating through the rise of heat pumps, and packaging & plastics via biobased solutions). Our framework is transferable to such sectors, as it jointly considers legacy and emerging technologies, evaluates the dominance of regional capabilities across both, and incorporates knowledge complexity as a key enabler for transformative change. By identifying where capability lock-ins are likely – particularly in regions with strong legacy orientation and low complexity – and by examining interregional connections as a potential pathway out, the framework provides a valuable tool for supporting targeted innovation strategies in other transitioning industries.

## 6. Conclusions

The shift to battery electric vehicles marks the most significant disruption in the automotive industry in over a century, posing far-reaching challenges for European automotive regions. As these regions seek to navigate the transition, their ability to innovate in EV technologies depends not only on existing capabilities but also on legacy structures shaped by decades of ICE-related development. Against this backdrop, we examined how European regions are positioned in terms

of their technological capabilities to support the transition toward electric mobility, and to what extent legacy trajectories in ICE technologies influence their transition potential.

Assessing regional capabilities through the lens of relatedness density and knowledge complexity, the empirical analysis sheds light on these dynamics. By mapping NUTS2 regions in the RD-complexity space for both battery electric vehicles and internal combustion engine improvements, we identify substantial variation in regional positioning that signals different levels of transition challenge and potential lock-in risks. Our analysis shows that regional relatedness density to electric vehicle technologies is strongly associated with EV patenting, while relatedness to internal combustion engine improvements exerts a weaker positive influence. Crucially, however, when regional capabilities are heavily skewed toward ICE technologies, EV innovation is significantly impeded, highlighting a risk of capability lock-ins in regions with a strong legacy in ICE development. This effect is even more pronounced in low-complexity regions, suggesting that while dominance in legacy technological capabilities limits EV innovation across all regions, those with more complex knowledge bases demonstrate greater resilience to lock-in and a stronger capacity to make long jumps into emerging technological fields, even when legacy systems remain strong. Further, we find that regions with low knowledge complexity and low relatedness density are particularly vulnerable, as they are both poorly positioned in terms of internal capabilities and only marginally embedded in interregional innovation networks. With these insights, our study contributes to the fields of regional diversification, the geography of environmental innovation, and sustainability transitions. Besides, these findings have important implications for innovation and industrial policies and open avenues for future research.

Our findings point to the need for differentiated, place-sensitive innovation and industrial policies that account for both existing regional capabilities and legacy technology orientations. Well-positioned regions can benefit from targeted support to consolidate (global) leadership, while ICE-dominated regions may require transformative policy mixes – including phase-out strategies – to overcome lock-ins. Weakly positioned regions, characterized by low complexity and strong legacy capability dominance, are particularly at risk of lock-in and would require foundational investments, tailored policy support, and stronger interregional linkages. At the same time, the effectiveness of such interventions depends on actor responsiveness, which may be constrained by entrenched incumbent structures. Addressing these challenges calls for improved coordination across innovation and industrial policy domains.

By providing insights into the technological positioning of European regions for the EV transition, this study opens several promising directions for future research. First, the role of extra-European innovation linkages – particularly in light of rising global interdependencies and geopolitical tensions – warrants closer examination. Understanding how regions connect to global EV knowledge networks, including Chinese, Korean, or US actors, could reveal important dynamics of technological upgrading and dependency. Second, future work should explore how regional technological positioning, as captured by relatedness and complexity, translates into tangible regional development outcomes. While patenting offers a valuable proxy for innovation, it tells us little about how these dynamics affect employment, economic growth, or the local adoption of electric vehicles. This calls for further research linking innovation patterns to broader transition outcomes (Breul et al., 2025).

## CRedit authorship contribution statement

**Tim Becker:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Sebastian Losacker:** Writing – review & editing, Writing – original draft, Validation, Supervision, Funding acquisition, Conceptualization. **Margherita Russo:** Writing – review & editing, Writing – original draft, Validation,

Supervision, Investigation, Funding acquisition, Formal analysis, Conceptualization.

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**Declaration of competing interest**

The authors declare that they have no known competing financial

**Appendix**

**Table A1**

Classification YIC vs. YEV.

COOPERATIVE PATENT CLASSIFICATION: Y02T		
Classification	CLIMATE CHANGE MITIGATION TECHNOLOGIES RELATED TO TRANSPORTATION	
YIC	Y02T 10/10	Internal combustion engine [ICE] based vehicles
	Y02T 10/12	Improving ICE efficiencies
	Y02T 10/30	Use of alternative fuels, e.g. biofuels
YEV	Y02T 10/40	Engine management systems
	Y02T 10/62	Hybrid vehicles
	Y02T 10/64	Electric machine technologies in electromobility
	Y02T 10/70	Energy storage systems for electromobility, e.g. batteries
	Y02T 10/7072	Electromobility specific charging systems or methods for batteries, ultracapacitors, supercapacitors or double-layer capacitors
	Y02T 10/72	Electric energy management in electromobility
	Y02T 10/90	Energy harvesting concepts as power supply for auxiliaries' energy consumption, e.g. photovoltaic sun-roof
	Y02T 10/92	Energy efficient charging or discharging systems for batteries, ultracapacitors, supercapacitors or double-layer capacitors specially adapted for vehicles
	Y02T 90/10	Technologies relating to charging of electric vehicles
	Y02T 90/12	Electric charging stations
	Y02T 90/14	Plug-in electric vehicles
	Y02T 90/16	Information or communication technologies improving the operation of electric vehicles
	Y02T 90/167	Systems integrating technologies related to power network operation and communication or information technologies for supporting the interoperability of electric or hybrid vehicles, i.e. smartgrids as interface for battery charging of electric vehicles [EV] or hybrid vehicles [HEV]

**Table A2**

Eigenvector centrality in the YIC and YEV domains of the top 40 EU27 and UK regions (by decreasing the order of their centrality).

NUTS2	Eigenvector centrality YIC	NUTS2	Eigenvector centrality YEV
DE11	1,0000	DE11	1,0000
DE12	0,9039	DE12	0,9581
DE14	0,5518	DE21	0,6653
DEB3	0,3772	DE13	0,4568
DE21	0,2621	DE14	0,4147
DE91	0,2393	DE25	0,3091
DE13	0,2283	DEB3	0,2978
DE92	0,2245	DE27	0,2126
DE71	0,1741	FRF1	0,2010
DEA2	0,1440	DE71	0,1969
DE27	0,1387	DEA5	0,1775
DEA1	0,1300	DED2	0,1605
DEE0	0,0989	DE22	0,1591
DE24	0,0853	DEA1	0,1566
DE26	0,0806	DE23	0,1482
DEA5	0,0728	DEA2	0,1401
DE30	0,0719	DE24	0,1356
DE25	0,0708	DEA4	0,1108
AT33	0,0638	DEA3	0,1043
DE23	0,0620	DE91	0,1026

(continued on next page)

Table A2 (continued)

NUTS2	Eigenvector centrality YIC	NUTS2	Eigenvector centrality YEV
DEB2	0,0559	DE30	0,0972
DEG0	0,0503	DE92	0,0872
DE73	0,0484	DE26	0,0855
CZ03	0,0443	PL42	0,0824
DEC0	0,0423	DEG0	0,0621
AT34	0,0416	DE40	0,0592
DE94	0,0375	DE72	0,0543
DEA4	0,0355	AT34	0,0533
AT31	0,0345	DED4	0,0508
DEB1	0,0336	DEE0	0,0485
DE93	0,0330	DE73	0,0438
DE22	0,0318	DEF0	0,0422
DEA3	0,0300	DEB1	0,0404
DED2	0,0280	FR10	0,0302
DED4	0,0263	DE60	0,0301
AT22	0,0251	DE94	0,0269
DE60	0,0240	AT22	0,0263
UKH2	0,0238	DECO	0,0254
FRF3	0,0220	ES52	0,0226
DED5	0,0218	BE21	0,0212

Table A3

Regression results inter-regional patenting.

	Dependent variable: Inter-regional connections (log)			
	YIC (1)	YIC scaled (2)	YEV (3)	YEV scaled (4)
Distance (log)	-0.326*** (0.042)	-0.348*** (0.045)	-0.280*** (0.038)	-0.278*** (0.038)
Mass (log)	0.191*** (0.036)	0.204*** (0.038)	0.334*** (0.031)	0.354*** (0.033)
Same country	0.151* (0.079)	0.176* (0.092)	0.342*** (0.069)	0.393*** (0.079)
AvgRD (log)	0.161 (0.100)	0.062 (0.039)	0.263*** (0.074)	0.116*** (0.033)
DistanceRD (log)	-0.003 (0.005)	-0.024 (0.037)	0.002 (0.004)	0.016 (0.032)
Avg complexity (log)	-0.195 (0.192)	-0.039 (0.038)	-0.243 (0.167)	-0.047 (0.033)
Distance complexity (log)	-0.053* (0.028)	-0.069* (0.037)	-0.042* (0.024)	-0.056* (0.032)
Constant	-0.016 (0.481)	-0.114 (0.070)	-2.082*** (0.405)	-2.267*** (0.062)
Observations	610	610	745	745
R <sup>2</sup>	0.184	0.184	0.257	0.257
Adjusted R <sup>2</sup>	0.175	0.175	0.250	0.250
Residual Std. Error	0.777 (df = 602)	0.908 (df = 602)	0.754 (df = 737)	0.866 (df = 737)
F Statistic	19.417*** (df = 7; 602)	19.417*** (df = 7; 602)	36.427*** (df = 7; 737)	36.427*** (df = 7; 737)

Note: Standard errors in parentheses.

\*p < 0.1.

\*\*p < 0.05.

\*\*\*p < 0.01.

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