Progress in Economic Geography 2 (2024) 100009

Contents lists available at ScienceDirect

Progress in Economic Geography

journal homepage: www.journals.elsevier.com/progress-in-economic-geography

The emergence of electric vehicle transition in cities: a case of technological and spatial coevolution?

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ARTICLE INFO

Keywords:
Transition
Electric Vehicle
Cities
Coevolution
Innovation
Relatedness

ABSTRACT

The transition towards Electric Vehicles (EVs) is connecting previously unrelated technologies. We combine an approach to transitions with economic geography, to explore how colocation can support the emergence of coevolution between EV-related sectors. We study technological and geographical relatedness between electric vehicle, battery, smart grid, and combustion engine inventions between 1980 and 2020. Geographical colocation of related technologies can signal coevolution between firms and inventors, that is specifically visible in some classes of cities that we identify. Finally, we fit a multiple regression to estimate the impact of cities' patenting in related technologies on EV patents. Results show increased relatedness inside cities and growth of colocation in time between electric vehicle, battery, and smart grid patents, demonstrating that relatedness is dynamically evolving during transitions. We also find that combustion engine capabilities are still relevant to support this transition, suggesting path interdependence between cities' innovative sectors.

1. Introduction

Contemporary transitions such as the one towards Electric Vehicles (EVs), involve interactions and complementarities among different technologies, including renewable energy generation, grid management, and vehicle recharge (Markard, 2018). Such complementarities are evident at the diffusion phase but also exist in invention and production (Malhotra et al., 2021). The creation and exchange of knowledge to invent and produce EVs is likely favored by geographical proximity between inventors and the applicant firms that employ them (Boschma, 2005). Therefore, the EV transition can be accompanied by new geographical centralities of invention: cities and regions that are better endowed with EV-related knowledge, or more capable to acquire it, might lead the way while those where incumbent technologies are prevalent could experience job losses and the challenge of converting their production base (Rodríguez-Pose & Bartalucci, 2023). Revealing the multi-sectoral and spatial interdependencies of transitions can help evaluate their social consequences and design improved multi-level policies to support them (Tödtling et al., 2022).

Evolutionary economic geographers and transition scholars have asked for more integration between both literatures in the investigation of regional diversification (Boschma et al., 2017). We pick up this invitation and propose an original coevolutionary perspective on transitions, which explores how the colocation of EV-related technologies in cities evolves in time as different sectors become increasingly connected. We integrate insights from the multi-sectoral perspective (Andersen et al., 2020), and the geography of transitions (Binz et al., 2020), to frame transitions as geographically emergent processes that involve interactions between previously disconnected technologies. By doing so, we advance our understanding of the geography of multi-sectoral recombinations in transitions, and we contribute to economic geography by exploring a dynamic perspective on relatedness.

In this article we provide empirical evidence at the world scale from 1980 to 2020 on the coevolution of EV patents with battery, smart grid, and combustion engine technologies, in the concerned cities that are defined in a comparable way. By this approach, we expand upon Ferloni (2022) by including all patents drawn from the most important global jurisdictions, thus providing a wider overview that is not only explorative but also amenable to the application of quantitative methods to measure coevolution of technologies linked to EV in all the cities of the world. In fact, we examine technological and geographical relatedness between these patent codes, before classifying cities in four different groups according to their patent scores. By doing so, we can discuss how cities differ in their relative technological specializations and the extent to which they could support coevolutionary interactions. Finally, we build a multiple regression model to estimate the impact of related

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https://doi.org/10.1016/j.peg.2024.100009
Received 13 March 2023; Received in revised form 22 December 2023; Accepted 16 January 2024
Available online 24 January 2024

technologies on EV patenting.

2. Theoretical framework

The main theoretical issues in developing a coevolutionary perspective on the emergence of innovations in transitions, consist in introducing the link between our empirical case and the literature on multi-sectoral interactions (2.1) and in wondering how the concept of relatedness from economic geography can be used to better understand the geography of transitions (2.2). Then, we elaborate on technological complementarities and geographical coevolution in 2.3, before summarizing the argument and raising three research questions in section 2.4.

2.1. Multi-sectoral interactions and the transition to electric vehicles

Innovation involves combining existing technologies in new ways (Arthur, 2009). During transitions, the combinatorial process that leads to regime-changing innovations is facilitated by landscape changes (Geels, 2002), such as the environmental crisis, which make some technological solutions become more desirable and likely to emerge, thus growing related, and others less so, becoming unrelated. If we apply this reasoning to EVs, we see that at the end of the 19th century electric cars were more diffused than fuel ones, in many European and US cities (Larminie & Lowry, 2012). Back then, electric engines and batteries were more related to cars than combustion engines. However, when oil allowed vehicles to travel long distances, cars became more related to combustion engines and less to batteries and electric motors. During the 20th century, alternatives to fuel cars were developed, including hybrid, fuel cell and battery-powered vehicles. Following cycles of hype and disillusion (Dijk et al., 2016), relatedness between vehicle technologies and various types of propulsion systems has also evolved in time following the ups and downs of different acceptable solutions.

Individual technologies are arranged into a modular and hierarchical architecture made of several levels, in which many sectors interact. For example, an Electric Vehicle is a technology composed of many individual technologies acting together (battery, electric motor, control unit). EVs are produced by the automotive sector which is “an aggregation of actors having similar production competences and outputs” (Stephan et al., 2017, p. 711), which interacts with the chemical, electronics, and textile sectors to receive components such as e.g., software, batteries, leather, plastics (Golembiewski et al., 2015; Markard, 2018). Thus, studying transitions involves considering the complementarities that form around a main technology, and the intersectoral connections that these imply.

Research on transitions has mostly focused on single technologies and sectors (Rosenbloom, 2020). Exceptions include the work of Raven & Verbong (2007), who focused on interactions between the natural gas and electricity sectors, or Papachristos et al. (2013) that discussed the case of functional foods as combination of food and pharmaceutical. Previous work had developed a typology of technological interactions that can be complementary but also in competition (Pistorius & Utterback, 1997). Recent contributions applied this approach to investigate interactions between different powertrain technologies including combustion, hydrogen, or battery (Mirzadeh Phirouzabadi et al., 2020). Transition scholars are increasingly aware of the importance of technological interrelatedness and complementarities (Markard & Hoffmann, 2016), and that making sense of this complexity calls for novel methods and approaches including modeling and simulations (Papachristos, 2014). This recognition has resulted in a coherent multi-sectoral perspective which aims to identify mechanisms of complementarity formation across technologies and domains of applications, such as the electricity sector (Andersen & Markard, 2020) or coastal shipping (Mäkitie et al., 2022).

New technological complementarities can result in the emergence of cross-sectoral knowledge and competences, which could benefit from geographical proximity. Recent studies have shown that increased relatedness between EV and batteries at the diffusion phase influenced the focus of battery inventions, which became more tailored to EV necessities (Malhotra et al., 2021). It follows that EV inventors might also find it increasingly necessary to integrate knowledge of battery, recharge, and smart grid, to be innovative. Following this reasoning, growing technological complementarity is likely to be accompanied by some degree of geographical proximity between inventors and firms in different sectors, to facilitate the creation of new multi-sectoral knowledge. The advantages of localization economies and knowledge spillovers are known to provide positive feedback to co-located agents, that could become increasingly embedded in local networks and institutions. In other words, it is important to understand to what extent geographical concentration can favor the creation of new complementarities during transitions.

2.2. Relatedness and the geography of transitions

A literature on the geography of transitions has emerged in recent years to remedy the lack of spatial sensitivity of earlier studies (Binz & Truffer, 2017; Binz et al., 2020). This literature focuses on the specificities of cities and developing countries (Köhler et al., 2019), but it also inquires into the role of local resources, production systems and institutions in enabling transitions, and of the involvement of different geographical scales in this process. This approach to transitions can benefit from the insights of economic geography on how different forms of proximity promote innovation, on the interplay between “local buzz and global pipelines” (Bathelt et al., 2004), and on the role of relatedness in regional diversification (Boschma, 2017).

The concept of relatedness refers to the observation that products, economic sectors, or technologies can have varying degrees of complementarity with each other, or of similarity in the inputs that are required to generate them (Jaffe, 1986; Hidalgo et al., 2018; Farinha et al., 2019). Inputs can be tangible (raw materials, machinery) or intangible (knowledge, skills), and they are typically not available everywhere. Relatedness is a staple in smart specialization approaches that postulate that regions should concentrate policy efforts in promoting innovative sectors that are related to existing ones (Balland et al., 2019). Relatedness has become a key methodological tool to measure local economic development and identify diversification opportunities, but several issues about its definition and measurement remain unresolved (Boschma, 2017). Among them, we focus on how relatedness can dynamically evolve: what happens when unrelated technologies become related over time (Castaldi et al., 2015)?

Economic geographers have usually seen relatedness as static, but recent contributions are beginning to challenge this view (Juhász et al., 2021). The literature on socio-technical transitions allows to contextualize technological change as being constantly influenced by landscape trends (Geels, 2002) such as e.g., the environmental crisis or geopolitical conflicts that promote the emergence of certain combinations over others. As such, it provides a suitable background to understand how changes in relatedness between technologies can shift the whole foundations and goals of innovative activities. This article mobilizes the concept and methodologies of relatedness from economic geography, to understand how multi-sectoral complementarities emerge in space during the EV transition. We do so, using a coevolutionary perspective.

2.3. Complementarities, coevolution, and path dependence

Coevolution can be used in two main ways: to indicate specific interactions between technologies, economic actors, or other entities, or to designate wider system-level influences (Schamp, 2010; Gong & Hassink, 2018). We broadly define coevolution as a process of “coupled, deforming landscapes where the adaptive moves of each entity alter the landscape of its neighbors in the ecology or technological economy” (Kauffman & Macready, 1995:27). This definition states that for coevolution to occur we need distinct populations of actors whose independent actions affect each other, but it remains agnostic as to what research objects it should be applied to, and at which level of aggregation.

We consider technological and geographical relatedness as two different dynamics (Fig. 1). On the one hand, during transitions, previously disconnected technologies become increasingly related, when they are combined through new multi-sectoral applications (upper part of the figure). On the other hand, technologies can become co-located in the same urban regions, so that their geographical relatedness increases (bottom part of the figure). This could be because two technologies become complementary, or because they both benefit from being co-located with a third technology, or for different forms of local resources or synergies. Yet when growing technological relatedness is accompanied by an increase in technological colocation, as in Fig. 1, we have a stronger indication that specific coevolutionary interactions might be emerging locally between inventors, firms, and institutions in the form of business networking, knowledge exchange and policy initiatives. We are aware that to identify coevolution, we would need to show specific interactions between urban actors (Murmann, 2013). However, we believe that colocation trends in time can be a reasonable proxy for it, especially when considering many cities simultaneously alongside technological relatedness trends.

The advantage of our coevolutionary framework is that it permits to combine a multi-sectoral perspective with a geographical one, to study *which* technological complementarities are forming during transitions, and *where* the interactions that support them are emerging. By focusing on the spatial embeddedness of socio-technical change, we must consider how existing specializations in incumbent sectors can support or hinder the development of new ones. For example, in Fig. 1 we can see that region 1 has retained the presence of a main sector but is not able to attract new sectors or technologies. Region 2 has diversified its technology base, but the existing sector has declined and a new one has not formed yet. Region 3 is the only one that has maintained an existing specialization, attracted a new sector, and diversified its technologies. A coevolutionary perspective acknowledges that productive paths can persist, disappear, or emerge, and illuminates the role of *path interdependence* between different technological trajectories (MacKinnon et al., 2019; Chlebna et al., 2022).

Our article only studies technologies, but this framework can be used to investigate coevolution across institutions, policies, discourses, and many more socio-technical dimensions. Once we know that a new structure of technological or geographical connections is emerging, we might focus on how different socio-technical dimensions enable or hinder them. For example, we could explore institutional support to EVs and compare policies across urban regions. Then, we might select some locations and conduct a detailed analysis of the specific coevolutionary interactions that are involved. The geography of transitions involves complex multi-sectoral linkages. A coevolutionary approach can help understand how these complementarities are spatially contingent and the extent to which they benefit of geographical concentration.

2.4. Conceptualization and research questions

We apply this coevolutionary approach to four technologies: Electric Vehicle, battery, smart grid, and Internal Combustion Engine (ICE). These technologies are interdependent: EVs require batteries, and smart grid systems can use EVs for vehicle-to-grid arrangements to stabilize loads. Yet they are also independent, because batteries are used for many other applications (e.g., e-bicycles, laptops, toothbrushes) and smart grid devices can be used to integrate renewable energy sources. Thus, these four technologies can be assumed as developing along separate trajectories and becoming increasingly related. A coevolutionary dynamic between them is apparent at the diffusion phase, where interfaces such as recharge stations involve EVs along with many different artifacts including chargers, plugs, transformers, grid connections, and photovoltaic panels among others. While we acknowledge that diffusion dynamics can feed back to invention (Malhotra et al., 2021), we limit ourselves to the invention phase. We use patent data to measure technological and geographical relatedness:

– Patent co-classification, or the presence of two patent codes in the same document provides a measure of technological relatedness
– Patent colocation, or the presence of two patent codes in the same urban region, indicates geographical relatedness.

Increased technological and geographical relatedness are taken as proxies for the existence of technological complementarities and spatial coevolution. The goal of this paper is to gain insights on the dynamics of coevolution of EV-related technologies and their geographical emergence. Accordingly, we formulate the following research questions:

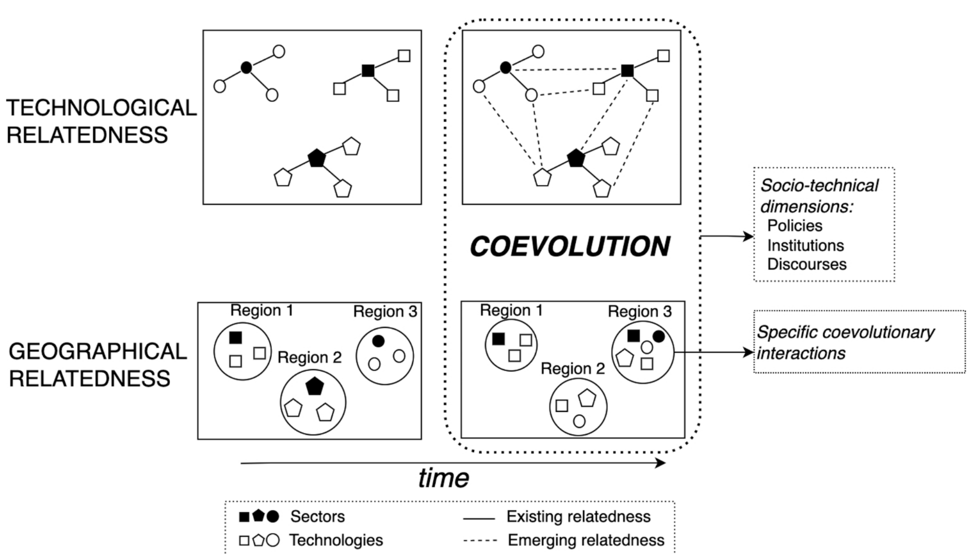

Fig. 1. A coevolutionary framework to explore technological relatedness and colocation. Sectors are aggregations of actors with similar or complementary competences. Identical shapes suggest similarities between technologies, and association to a main sector.

1. To what extent is technological complementarity between EV, battery, smart grid, and ICE technologies, accompanied by geographical coevolution?
2. What do technology colocation patterns across different groups of cities suggest about EV coevolution with other sectors?
3. Does patenting in battery, smart grid, or ICE influence EV patenting, and does path dependence play a role?

We expect to find increased technological and spatial relatedness between these EV, battery, and smart grid, but we expect ICE patents to become less related to EV ones, as fully electric capabilities became more important than hybrid ones. We also anticipate that these technologies are not evenly localized, but that some urban regions — particularly those with long-lasting automotive capabilities — will display relevant EV patenting skills. As a result, we expect path dependence, particularly with respect to ICE capabilities, to play a significant role in EV patenting. Furthermore, we expect battery, smart grid, and ICE patenting to positively influence EV invention.

3. Methods

Despite their notorious limitations, patents are well-established indicators to measure innovation (Griliches, 1990). Patent codes can disclose relevant information to identify technological capabilities and track their evolution and recombination in time (Strumsky et al., 2012). We studied all patents classes, but among them, we specifically focused on four Cooperative Patent Classification (CPC) codes, at the four-digit level, to identify the technologies of Electric Vehicle (EV), battery, smart grid, and Internal Combustion Engine (ICE). These technology codes are (EPO, 2022):

– For EV, Code B60L: “Propulsion of electrically propelled vehicles”.
– For battery, code H01M: “Processes or means, e.g., batteries, for the direct conversion of chemical energy into electrical energy”.
– For Smart Grid, the tag Y04S was considered, that refers to “Systems integrating technologies related to power network operation, communication or information technologies […], i.e., smart grids”.
– For Internal Combustion Engine (ICE), code F02B: “Internal-Combustion piston engines; combustion engines in general.”

It should be noted that there is not a precise one-to-one correspondence between these codes and the technologies they aim to measure. Also, codes are at a rather aggregate level of the CPC classification (the subclass, which comprises 656 codes that appear across all our periods) and as such they include more inventions than those we were interested in. However, they were recurrently identified as central, both in the literature (Golembiewski et al., 2015; Borgstedt et al., 2017) and in our first explorative analyses. Including many codes, or choosing a more detailed level (more than four digits), would have provided an accurate identification but it would have raised issues of representativeness (which and how many codes to choose to define a technology) and escalated the number of combinations between them. The choice of this level of aggregation was backed by similar studies in which the analysis of IPC/CPC knowledge networks is often conducted at the four or even three-digit level (Kogler et al., 2013; Leydesdorff et al., 2017; Yan & Luo, 2017; Song et al., 2019; Li & Rigby, 2022;).

3.1. Patents and geo-localization

We use the REGPAT patent database (OECD, 2022; Maraut et al., 2008), that includes information about the geographical location of inventors and applicants at the regional level, for patents submitted to the European Patent Office (EPO) and internationally via the Patent Co-operation Treaty (PCT-WIPO), from 1980 to 2020. The address of inventors is used to geolocate patents, as it is usually considered the most reliable indicator to this end (OECD, 2009). While data for European regions are precise at the NUTS 3 level, and US data are identified at the County level, the OECD defines regions in other countries such as China and India at a higher level of aggregation.[1] To mitigate this uneven delineation, we account for the fact that inventors gravitate around major metropolitan areas by aggregating smaller urban locations into LURs or Large Urban Regions (Rozenblat, 2020). LURs are defined all over the world on the notion of Mega-city region (Hall & Pain, 2009), and describe the fact that economic dynamics transcend municipal administrative boundaries forming large regional systems of workers and firms around urban agglomerations.

OECD regional codes have been matched to LURs in different ways. European and US data have been matched by NUTS and County, using a correspondence table with LURs (Rozenblat, 2020). In some cases, multiple NUTS or counties have been aggregated into LURs, which are usually larger units. Conversely, for countries such as China, India or Japan, several LURs could be present for one OECD code. In these cases, we attributed manually patents to the most representative LUR.[2] Finally, few patents (less than 2 %) were not regionalized in the REGPAT database and therefore were not attributed to LURs (Table 1).

3.2. Relatedness and specialization

We use patents to construct a technology space, or network of technological relatedness between any two codes i and j, which measures the strength of the connection, or the proximity between technologies. There are different ways to measure technological proximity (Engelsman & van Raan, 1994; Yan & Luo, 2017): co-classification measures how often two codes appear together in a patent, while citation indicators measure when codes cite each other or are cited together (co-citations). Furthermore, colocation measures consider that two codes are related if they appear together in the same spatial unit (here LURs). Studies on technological relatedness have applied alternatively measures of co-classification (Balland et al., 2019; Balland & Boschma, 2021), colocation (Boschma et al., 2015) or citation (Rigby, 2015).

In this paper, we calculate and compare measures of co-classification and colocation, conceptualizing them as *technological relatedness* and *geographical relatedness* respectively. The comparison between these two forms of relatedness is the background against which we contextualize technology coevolution and urban specialization. Accordingly, we construct two square matrices of 656 CPC codes, across four non-overlapping periods of 10 years from 1980 to 2020, and we calculate the frequency of two patent codes i and j appearing together in the same patent (*technological relatedness)*, or of two patent codes being located in the same LURs (*geographical relatedness)*. Then, we normalize these scores using the well-established cosine similarity index (Yan & Luo, 2017). The cosine formula equals the ratio between the number of times when codes i and j appear together and the geometric mean of the number of times each code is observed, and it takes values between 0 (two technologies are never together) and 1 (they are always together):

$$\cos(i,j) = \frac{\sum_{p\in P}\mathbf{1}_i(p)\mathbf{1}_j(p)}{\sqrt{\left(\sum_{p\in P}\mathbf{1}_i(p)\right)\left(\sum_{p\in P}\mathbf{1}_j(p)\right)}}, \tag{1}$$

[1] As a comparison, EU countries such as Italy or France have each 111 and 102 regional units identified, while China has 36 and India 37.

[2] These are usually the capital cities of states or provinces. For example, for the OECD region of Rajasthan (India), patents were attributed to Jaipur, which is the capital and largest city of the state. Other LURs are present in Rajasthan such as Jodhpur, Udaipur, or Kota, but address data from REGPAT were not precise enough to attribute patents to these LURs in the absence of a subregional code.

Table 1
Patent locations in Large Urban Regions (LURs), (1980–2020).

	NUTS (EU+EFTA)	USA	Japan	South Korea	China	India	Hong Kong	Taiwan	Total
Total patents (EPO + WIPO)	2,297,426	1,680,753	1,033,510	251,283	413,028	66,271	12,763	35,066	5,790,100
Patents matched to LURs	2,256,249	1,646,715	1,014,356	250,187	410,660	65,284	12,763	35,066	5,691,280
% Of patents matched to LURs	98.2	98.0	98.1	99.6	99.4	98.5	100	100	98.3
Distinct LURs	329	113	29	9	31	28	1	1	541

where P is the set of all patents, and $\boldsymbol{I}_i(p)$ is equal to 1 if patent p has code i and 0 otherwise. Following Balland & Boschma (2021), we calculated the concentration of patent codes in LURs, to check the extent to which a city's inventive activity is specialized. Hence, we calculate patent counts, and we measured the RTA or Revealed Technological Advantage (Soete & Wyatt, 1983) for each technology i, in region r, at time t ($r = 1, \ldots, n$; $i = 1, \ldots, k$). $RTA^t_{r,i}$ is expressed as the ratio between the share of technology i in the patent production of LUR r, and the share of technology i in the patent production of all LURs (patent jurisdictions in Table 1). If a LUR has $RTA^t_{r,i} > 1$ it can be considered as specialized in i at time t:

$$RTA^t_{r,i} = \frac{N^t_{r,i} \Big/ \sum_{j\in T} \quad N^t_{r,j}}{\sum_{r\in R} N^t_{r,i} \Big/ \sum_{r\in R}\sum_{j\in T} \quad N^t_{r,j}} \tag{2}$$

where $N^t_{r,i}$ is the number of patents of technology i, produced in LUR r at time t, T is the set of all technologies and R the set of all LURs. Given the RTA, we also calculate a diversity index to measure the extent to which a LUR is capable to invent in several different technology fields. The diversity of LUR r is measured as the sum of technologies i in which r is specialized ($RTA^t_{r,i}>1$):

$$Diversity^t_r = \left|\left\{ i \in T | RTA^t_{r,i} > 1 \right\}\right| \tag{3}$$

3.3. City classifications and the role of related specializations

To analyze patent trends and differences across LURs, we applied correspondence analysis (Sanders, 1989), that allows to simplify variability and identify similarities across observations. Applied on temporal data, it allows to cluster the LURs' trajectories (Pumain et al., 2015). LURs are grouped into different clusters according to similarities in the trajectories of their absolute patents scores in EV, battery, smart grid, and combustion engine technologies patents. Correspondence analysis allows to appreciate the extent to which each group of cities produce inventions in a specific technology or a combination of them. City groups are also used to account for average specialization paths by group and technology.

After classifying cities, we constructed two regression models to estimate the effect of specialization in battery, smart grid, or combustion engine on specialization in EVs. We included data for 175 urban regions (LURs) across four ten-year periods, for a total of 700 observations. We removed LURs with a score of 0 in all technologies, and we added 1 to technology scores to avoid issues when calculating logarithms, ending up with a total of 655 observations (Table 2). We added patent counts to control for the effect of big LURs' diverse environments and sheer patenting size.

Then, we fit the following model using OLS:

$$\begin{aligned}\log\left(N_{t,r,EV}+1\right) = \alpha_t \quad & + \beta_{BA,t}\log\left(N_{t,r,BA}+1\right) + \beta_{SG,t}\log\left(N_{t,r,SG}+1\right) \\ & + \beta_{ICE,t}\log\left(N_{t,r,ICE}+1\right) + \beta_{Div,t}\log\left(Diversity_{t,r}\right) \\ & + \beta_{t,r,ALL}\log\left(N_{t,r,ALL}\right) + \varepsilon_{t,r}\end{aligned} \tag{4}$$

For the second model, we use a quasi-Poisson specification, to control for possible heteroskedasticity in the OLS model (Santos Silva & Tenreyro, 2006). Thus, we have:

$$\begin{aligned}\mathbb{E}\left[N_{t,r,EV}\right] = \exp\big(A_t \quad & + \beta_{BA,t}\log\left(N_{t,r,BA}+1\right) + \beta_{SG,t}\log\left(N_{t,r,SG}+1\right) \\ & + \beta_{ICE,t}\log\left(N_{t,r,ICE}+1\right) + \beta_{Div,t}\log\left(Diversity_{t,r}\right) \\ & + \beta_{t,r,ALL}\log\left(N_{t,r,ALL}\right)\big)\end{aligned} \tag{5}$$

where $N_{t,r,EV}, N_{t,r,BA}, N_{t,r,SG}, N_{t,r,ICE}, N_{t,r,ALL}$ are the number of patents in EV, battery, smart grid, combustion engine and total patents produced by each LUR at each time period t.

Furthermore, we estimated a second model in which we calculated the effect of battery, smart grid and ICE patents at period t, on EV specialization at period $t+1$. We fitted a logistic regression to estimate the probability of a certain LUR to specialize (entry model) or lose its specialization (exit model) in EV in period $t+1$ given its patent scores in battery and smart grid in period t. We added again LURs' diversity and size in terms of patents. The entry model writes:

$$\begin{aligned}&\log\left(\frac{P\left(RTA_{EV,(t+1)} > 1 | RTA_{EV,t} \le 1\right)}{1-P\left(RTA_{EV,(t+1)} > 1 | RTA_{EV,t} \le 1\right)}\right) = \alpha_t \quad + \beta_{BA,t}\log\left(N_{t,r,BA}+1\right) \\ & + \beta_{SG,t}\log\left(N_{t,r,SG}+1\right) + \beta_{ICE,t}\log\left(N_{t,r,ICE}+1\right) + \beta_{Div,t}\log\left(Diversity_{t,r}\right) \\ & + \beta_{t,r,ALL}\log\left(N_{t,r,ALL}\right) + \varepsilon_{t,r}\end{aligned} \tag{6}$$

The exit model writes:

$$\begin{aligned}&\log\left(\frac{P\left(RTA_{EV,(t+1)} \le 1 | RTA_{EV,t} > 1\right)}{1-P\left(RTA_{EV,(t+1)} \le 1 | RTA_{EV,t} > 1\right)}\right) = -\alpha_t \quad - \beta_{BA,t}\log\left(N_{t,r,BA}+1\right) \\ & - \beta_{SG,t}\log\left(N_{t,r,SG}+1\right) - \beta_{ICE,t}\log\left(N_{t,r,ICE}+1\right) - \beta_{Div,t}\log\left(Diversity_{t,r}\right) \\ & - \beta_{t,r,ALL}\log\left(N_{t,r,ALL}\right) - \varepsilon_{t,r}\end{aligned} \tag{7}$$

We adopt the sign convention in Eq. (7) to have a consistent way of interpreting the sign of the coefficients across the different equations. Using this convention, positive coefficients in (7) are associated with a higher probability for LURs to preserve their specialization in EV. By estimating the contemporaneous and the lagged models, we can make sense of two dynamics: models 4 and 5 show *simultaneous* technological coevolution, as the effects of related specializations operate within each 10-year period. Instead, models 6 and 7 show *path dependence*, or the effect of previous specializations on subsequent EV specialization. By combining them we can have insights about coevolution in different periods and as a path-dependent process.

Table 2
Summary statistics for regression models.

Statistic	N	Mean	St. Dev.	Min	Max
EV score	655	50.6	209	1	3791
Battery score	655	146.6	611.4	1	10,930
Smart grid score	655	21.7	67.3	1	1222
ICE score	655	43.3	113.4	1	1678
Diversity	655	196.0	59.2	5	381
Tot. patents LUR	655	18,895.144	44,487.2	7	748,291

4. Results

4.1. The evolution of technological and geographical relatedness to EVs

The first question we asked was to what extent technological complementarity between EV, smart grid, battery, and ICE was accompanied by geographical coevolution. We examine here relatedness to EVs, and we assess the evolution of both measures separately, before comparing their dynamics.

4.1.1. Technological relatedness

Fig. 2 shows the evolution of technological relatedness in the past four decades through the ego-networks[3] constructed around EV technology within the whole space of all technologies. The red-encircled nodes represent the four studied technologies, while the colors inside the nodes indicate the general patent sections to which codes belong. Nodes' sizes are proportional to the share of a code on total patents, while link size denotes the intensity of technological relatedness.

This figure shows that the relative weight of machine and engine-related patents drops constantly in time, as smaller node sizes indicate a decreasing proportion on total patents. Besides, this group of codes is becoming increasingly peripheral, as shown by weaker tie strength and fewer connections to sections other than the F one (machines, engines). Conversely, battery and smart grid codes become connected to many other technology codes from the B (transporting vehicles), H (electric elements) and G (measuring/digital data). The growing importance of these sections, particularly the electric elements and digital technologies ones, is apparent in the growing number of different codes and their size in terms of patents.[4] In the evolution of this knowledge space, it is interesting to note the role of recharge technologies.[5] This category of technologies is very related to smart grid and battery since the first periods, and in the last period it becomes the most related technology to EVs. Recharge technologies arguably play a strategic role of interfaces that enable complementarities between technologies and infrastructure (electric grid, local energy generation, batteries, appliances).

4.1.2. Geographical relatedness

Fig. 3 shows the evolution of the EV ego-network for geographic relatedness, or the extent to which two technologies appear in the same cities.[6] Smart grid patents are absent from this graph because they are not enough related to EV, and battery patents appear only in the third period. Contrary to Fig. 2, we don't see a clear growth of the G (measuring/digital data) and H (electric elements) sections, but they are stable or decreasing in time (particularly the former). Engine and machine-related patents of the F section increase in relative importance (size) and connections, instead of declining as in Fig. 2. Overall, geographical relatedness is more evenly distributed than technological one, so that tie strength is more homogeneous than the technological relatedness. Also, the network of geographical relatedness is more stable because the technological capabilities that are located in some large urban regions in the activities of inventors and their applicant firms, have a certain degree of geographical stickiness and inertia. Considering this, the presence of engine-related patents until the final period suggests that the LURs where motor-related patents are invented are also the places where EV-related inventions are created.

4.1.3. Does geographical relatedness reflect technological one?

We can now combine the evolution of technological and geographic relatedness for 152 technology codes that are the most related to EVs (Fig. 4). Codes have been clustered into five groups that display similar trends, using a k-means algorithm, to provide a clearer visualization, and Table 3 summarizes their composition and main technology codes. Then, we compared the average relatedness to EVs of these five groups of technologies with that of battery, smart grid, and combustion engine technologies.

While clusters 1, 2 and 3 feature very diverse patent codes and technologies, the most related clusters to EV technology are 4 and 5. Cluster 4 includes codes that have to do with electricity distribution/recharge, and cluster 5 comprises technologies related to vehicle propulsion/assembly. Smart grid and battery patents are among the most related technologies to EVs, both in technological and geographical terms, and this trend increases in time. Most other patent codes are much less related to EVs, particularly technologically, and only patents in groups 4 and 5 score equally high. On the other hand, combustion engine patents become less related to EVs technologically, but more related geographically.

The trajectory of battery and smart grid patents is coherent with our coevolutionary hypothesis that increased technological proximity might be reflected by growing colocation. In contrast, combustion engine technologies become increasingly co-located with EVs despite their decreasing technological relatedness, and this could be explained by path dependence: traditional automotive producers are mostly responsible for innovating in ICE, but they also participate more and more in EV innovation so even though patent documents show decreasing proximity between EV and ICE, they continue to be invented in the same urban regions.

To sum up, the evolution of technological relatedness to EVs has indicated that combustion engine technologies have lost importance while electric and digital technologies have taken center stage, particularly those related to recharge. The comparison of technological and geographical relatedness has nuanced this by showing that ICE patents are less related technologically but more co-located with EV ones. We can answer the first research question saying that for battery and smart grid, growing complementarity is accompanied by coevolution, but not for ICE. This suggests that, despite a general common trend, distinguishing these two forms of relatedness helps to disclose insightful exceptions.

4.2. City specialization clusters: technological trajectories and spatial proximities

After providing a general context on relatedness dynamics, we now want to know if the analysis of patent locations can suggest the existence of different coevolution patterns across groups of cities. We performed a correspondence analysis on cities according to their specialization in the four technologies during the four periods. It yielded four groups of cities according to their relative proximity to each technology in time. Based on this, we could map the trajectories with respect to the four technologies in Fig. 5, one for each city — LUR (gray arrows) and the average trajectory by group (colored arrows). Red triangles show the position of the four technologies, or the average of cities' specialization during the whole period. Thus, the proximity of each group trajectory to the red triangles indicates how much their patent output is specialized in the

[3] The ego-networks for technological relatedness are built by selecting from the whole knowledge space, the top 25 % most (technologically) related technologies to EVs, and the links between them. For the sake of clarity, only links involving EV, battery, smart grid or ICE codes have been included.

[4] A general description of patent codes and their rankings in terms of node size (code counts on total counts) can be found in the supplementary material, for both technological and geographic relatedness.

[5] This code is H02J and is defined as: "Circuit arrangements or systems for supplying or distributing electric power" (EPO, 2022).

[6] The ego-networks for geographic relatedness are built by selecting the top 5 % most geographically related codes to EV. Unlikely technological relatedness, geographical one is much more evenly distributed. Therefore, we had to proceed to an extra filtering: we used the top 5 % most related codes to select links that contained them in the whole network. For each code, we selected the top 5 % of their most related links. Finally, we select from the resulting network only the ego-network of EV patents, which includes the connections of EV and their links. Only links to EV, battery, smart grid, or combustion engine codes have been included.

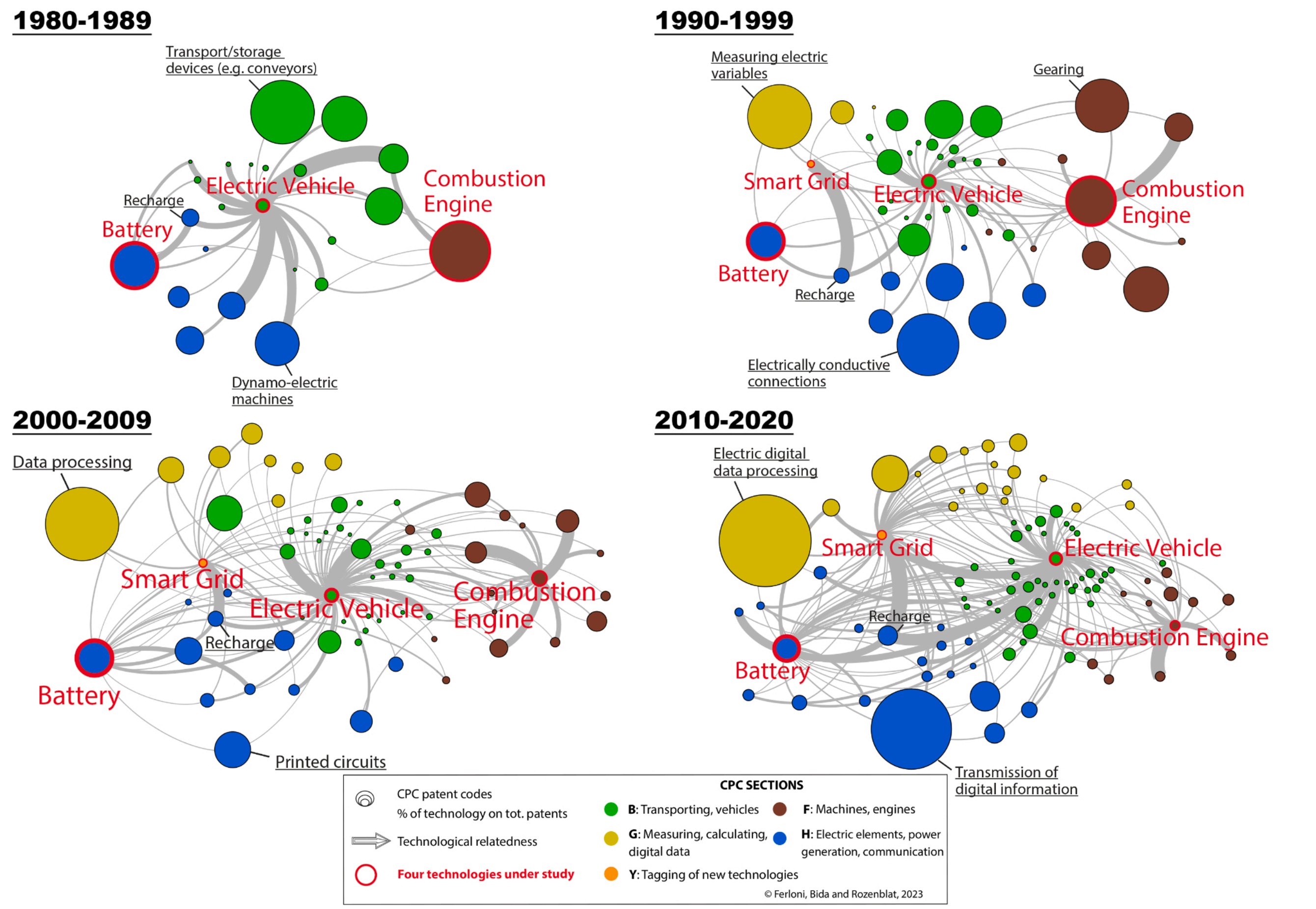

Fig. 2. the evolution of technological relatedness to EVs.

four technologies under study.

Cities' trajectories show a generalized distancing from internal combustion patents, towards EV, battery, and smart grid ones. Groups 1 and 2 are close to battery inventions and group 3 to smart grid ones, while group 4 is the closest to ICE patents. This figure permits to visualize the overall patent trajectories of city clusters and to situate them with respect to technologies. Before analyzing the composition of these cities' groups more in detail in Table 4, we can already announce their general characteristics: cluster 1 is composed of emerging innovation hubs, most of them located in Asian countries. Cluster 2 includes major global cities, while cluster 3 reunites several leaders in new technologies. Finally, cluster 4 contains established automotive cities. We now analyze the specialization patterns of these groups of cities more in detail.

In Fig. 6 we see the evolution of group specialization in EV, battery, smart grid, and ICE. While we used absolute patent scores in our four technologies to build Fig. 5, here we use RTA scores. Thus, these trajectories are relativized according not only to the four technology groups of patents, but to the overall patents' production of each city (averaged by cluster) and by global patent outputs for each technology (see Eq. 2). The most specialized groups in EV are numbers 1 and 4. However, group 1 displays a dramatic growth of specialization in time, while the latter remains stable. About ICE specialization, cities in group 4 are the only ones to be set on an increasing path while all others decrease. Besides, cities in group 1 are rather specialized in battery and smart grid, while those in group 4 are not, and they do not grow in these technologies. Group 3 appears particularly specialized in smart grid, while group 2 mostly shows an unspecialized dynamic across technologies.

Table 4 shows the most relevant cities, in terms of patent numbers, for each cluster. Group 1 features several Asian cities, some of which experienced strong economic growth in recent decades (Shenzhen, Shanghai, Taipei). Apart from Tokyo, all of them including to some extent European cities such as Brussels and Grenoble, can be considered as emerging innovation hubs. Conversely, cities in group 4 such as Paris, Nagoya, Stuttgart, or Detroit are established automotive centers. This suggests that automotive cities have a significant specialization in EVs because of their experience in traditional automotive production, and this is confirmed by the fact that their specialization in ICE patents grows more than that in EVs. Conversely, cities in cluster 1 are not at all specialized in ICE, their specialization in EVs is growing and this dynamic is accompanied by growth in the related sectors of battery and smart grid. Cities in cluster 2 are major global centers that do not display significant specialization trends, while cities in cluster 3 are technological leaders such as S. Francisco, S. Diego, Seattle or Dallas and their increasing specialization in smart grid is matched by growing EV specialization in the most recent period.

Accordingly, we answer the second question by saying that EV coevolution is most likely in emerging innovation hub cities of cluster 1 that, despite not having a strong automotive heritage, are those where the related technologies of battery and smart grid are growing the most. Automotive cities are likely to retain their innovative capabilities for some time, but the fact that their specialization in related technologies is stagnating puts their capability to maintain an innovative edge into question. Global and unspecialized urban areas such as New York or Frankfurt are not expected to be significant coevolutionary *milieus*, but rather global platforms in support of technological diversity and financial networking. Finally, technological leaders such as San Francisco could become important hubs of EV innovation and coevolution, but that will depend on the relative importance of digital technologies in general, and smart grid ones in particular, to EV innovation.

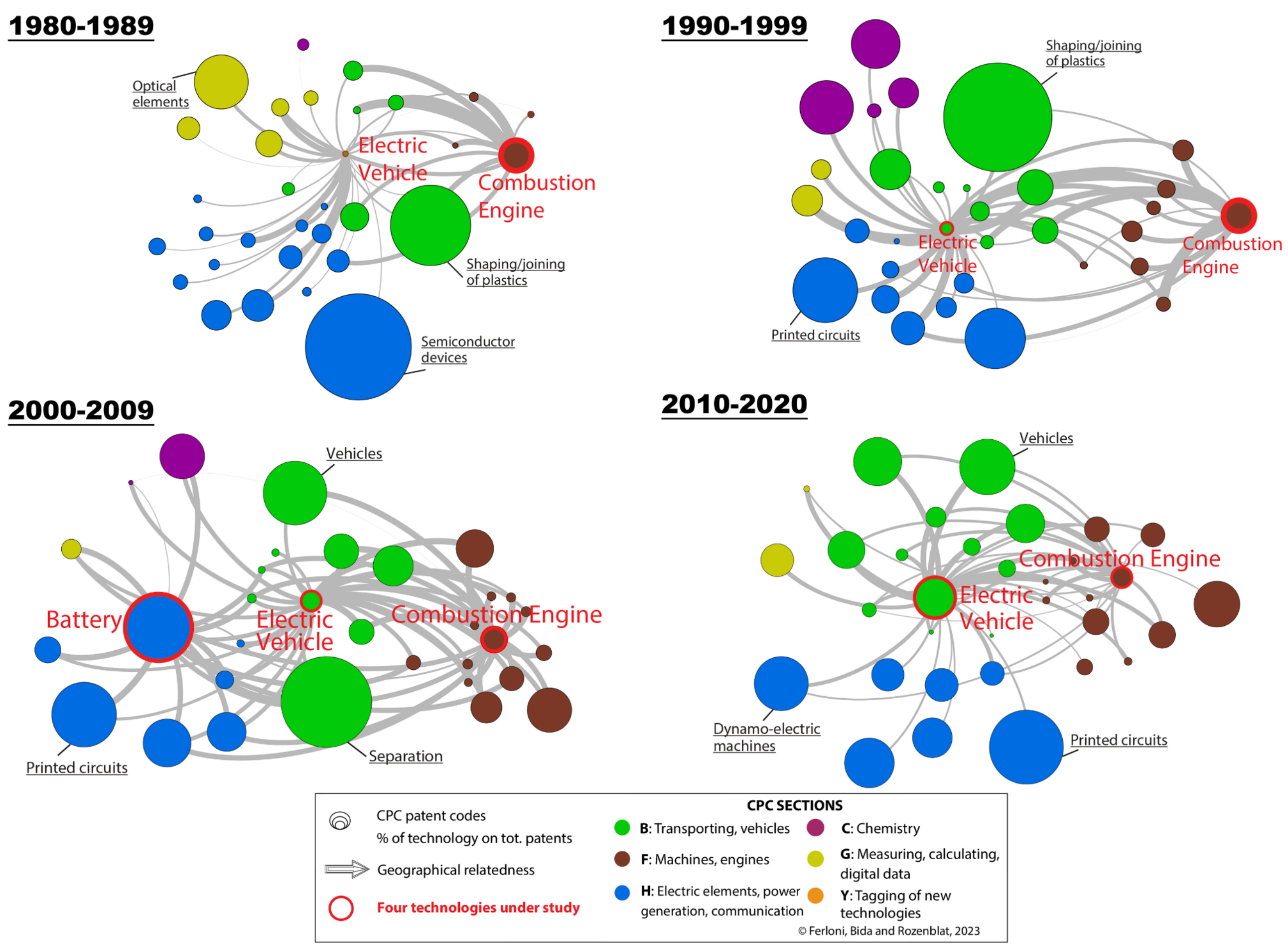

Fig. 3. the evolution of geographical relatedness to EVs (1980–2020).

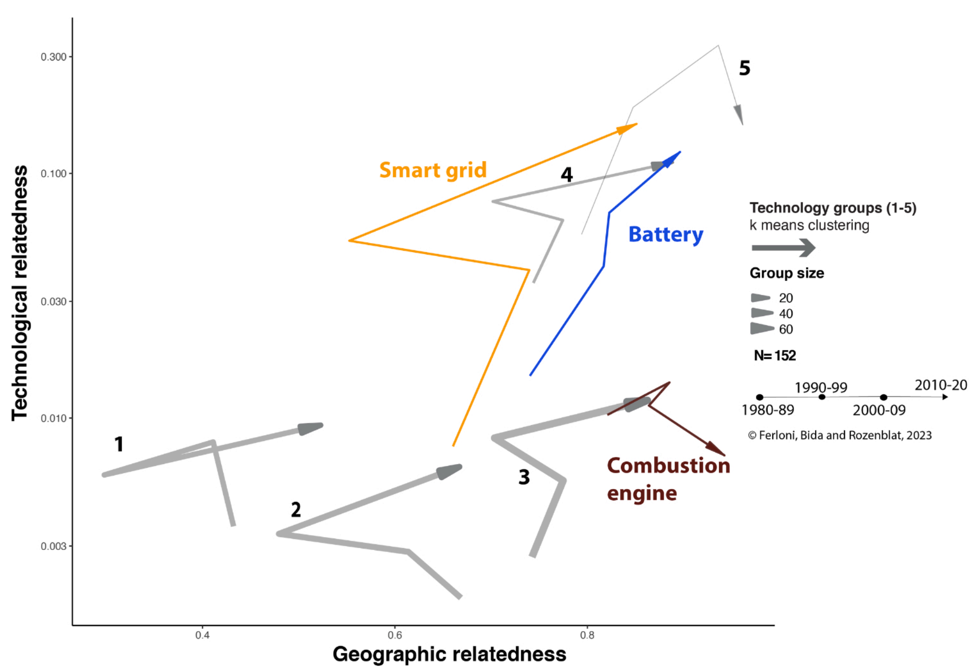

Fig. 4. The evolution of technological and geographic relatedness to EVs (1980–2020).

Table 3
Size of technology clusters and their main technologies.

Cluster	Number of codes	Main technologies
1	32	Vehicles, railway, aircraft, domestic cleaning.
2	42	Digital data, transmission of information, medical preparations.
3	64	Semiconductor devices, measuring variables, vehicle components.
4	8	Distributing electric power, dynamos, converters.
5	2	Mounting propulsion units in vehicles. Control of vehicle subunits.

4.3. The effect of related technologies on EV patenting

The third question asked if being inventive in battery, smart grid or ICE impacted EV invention, and whether path dependence played a role in this. To answer, we show the results of multiple regressions where we consider the effect of battery, smart grid, and internal combustion engine patenting on EV invention. We add a measure of the total number of inventions and a measure of diversity, to account for the role of large cities and of possessing diversified innovative capabilities. The models show the results of multiple cross-sectional regressions calculated for every time period. The first model is a simple OLS regression, while the second one uses a quasi-Poisson distribution which provides an heteroskedasticity-robust fitting (Santos Silva & Tenreyro, 2006).

Results indicate that:

- In the PPML model, coefficients for each period are significant and increasing, starting from period 2 (1990–1999), and show a trend of increasing specialization in EVs in time.
- Battery patents are significant and increasing across periods, suggesting increased coevolution between battery and EV technologies.
- Smart grid patents are important in periods 1 and 2 (1980–1999), their effect decreases in period 3 (2000–2009) before recovering in period 4 (2010–2020). This suggests that smart grid played a role in the first generations of EV patenting and that this role is again important in recent years.
- The effect of ICE patents is increasing until period 3 (2000–2009) for both models, before decreasing its effect in period 4 (2010–2020). This suggests that specializing in combustion engine technologies is important to EV patenting, but that its effect is decreasing.

Table 4
Most patenting cities (LURs) by cluster.

Cluster 1	Cluster 2	Cluster 3	Cluster 4
Tokyo	Osaka	S. Francisco	Paris
Seoul	New York	S. Diego	Nagoya
Shenzhen	Boston	Eindhoven	Stuttgart
Guangzhou	Frankfurt	Nuremberg	Munich
Shanghai	Los Angeles	Seattle	London
Cincinnati	Philadelphia	Basel	Chicago
Taipei	Houston	Washington	Düsseldorf
Brussels	Milano	Berlin	Zurich
Grenoble	Copenhagen	Dallas	Detroit
Münster	Geneva	Helsinki	Stockholm
N = 39	**N = 40**	**N = 43**	**N = 53**

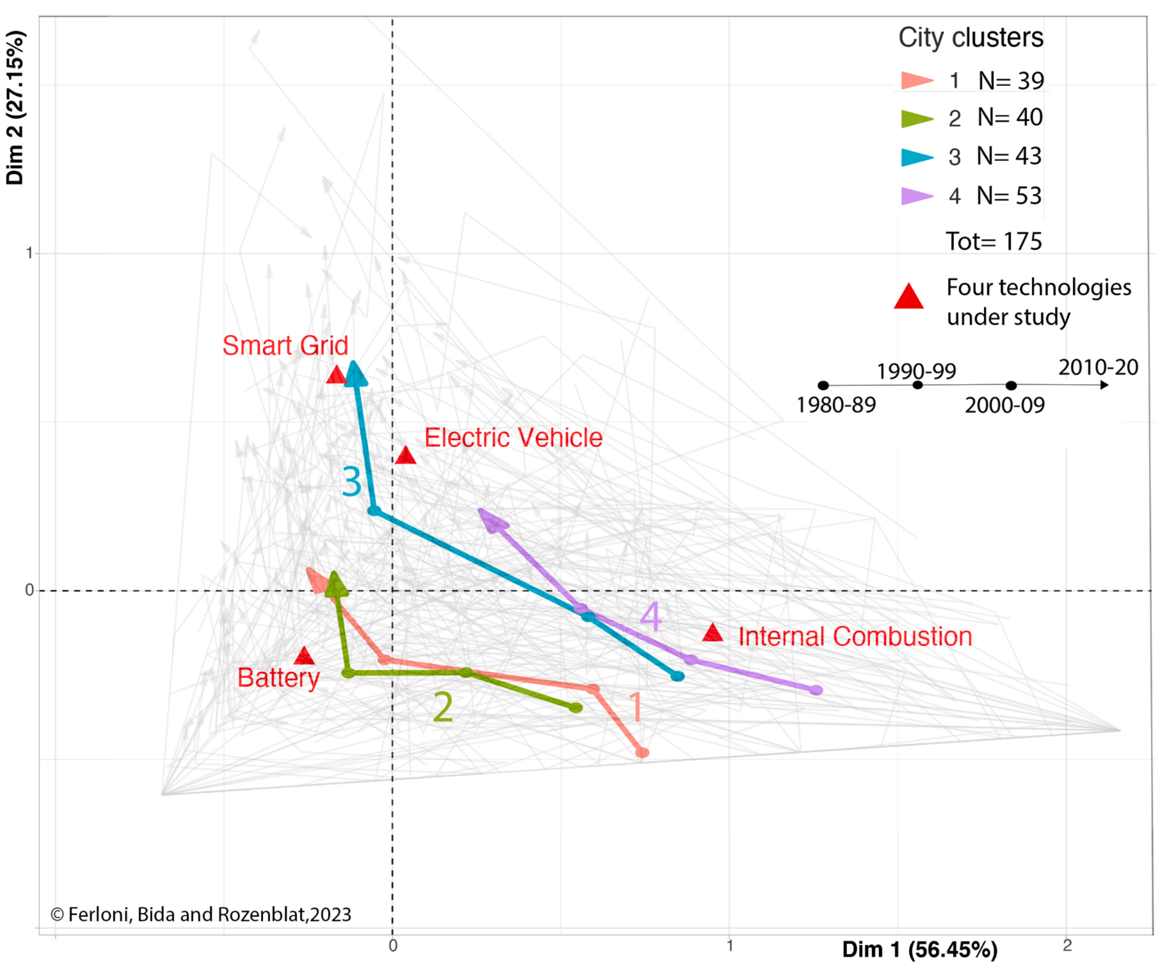

Fig. 5. the trajectories of city clusters with respect to technologies (1980–2020).

Fig. 6. The evolution of specializations of city clusters by technology.

- Diversity appears to have no effect on EV patents.
- LUR size is not significant. Only in period 3 for the PPML model, it has a significant negative effect on EV patents.

4.3.1. *Acquiring or losing EV specialization: an exploration*

After estimating the effect of related specializations on EV within each period, we explore the effect of patenting in battery, smart grid, or ICE in period *t*, on developing a specialization in EV in period $t+1$. Thus, we keep only three time periods because we check for effects of independent variables on subsequent periods. We then fit a logit and probit model for each period, and we do this exercise for entry (acquiring a specialization that is new to the region) and exit (losing a specialization that was once present). For entry and exit, the dependent variable is 0 when regions do not develop EV specialization or lose it respectively. It is 1, when regions become specialized in EV, or they maintain EV specialization respectively.

The results of the entry model suggest that ICE patents have a positive effect on developing a specialization in EV, for the first two periods, while in the third period this is no longer the case. On the other hand, battery patents are not significant, while smart grid ones have a significant and negative effect in the second period. Contrary to the previous models, diversity appears to have a positive effect on developing a specialization in EVs, and this effect grows in the latest period. Interestingly, this effect appears unrelated to city size, because the overall patent output affects EV specialization negatively, especially in the last period.

For the exit models, we find that ICE patenting across periods has a positive effect on retaining an existing specialization in EV. In the last period, however, this effect decreases. This could mean that as EV innovation became more diffused and important, LURs with automotive competences were finding it easier to retain it. Some form of path dependence could provide an advantage in EV patenting to automotive regions, but the coefficient declines in the last period, which suggests that in the future this might not be the case anymore.[7]

To answer the third research question, we can say that the quantitative models support our coevolutionary hypothesis by showing that battery, smart grid, and combustion engine patents have a strong effect on EV patent scores, when they are considered within the same 10-year periods. However, when the effects of patenting in these technologies are assessed on the development of EV specializations in the following 10 years, we found no role for battery and a negative role for smart grid. Instead, we found that diversity played an increasingly relevant role in the emergence of EV technology. Besides, being specialized in ICE patents can help to develop a new EV specialization or not to lose an existing one, even though the effect is decreasing in the last period.

5. Discussion: increased EV coevolution, but not everywhere

This article set out to explore to what extent growing technological complementarities during transitions are linked to geographical colocation. We found that battery and smart grid patents are some of the technologies that are most related to EVs, while ICE and machine-related patents decreased their importance. However, EV patents are increasingly co-located with ICE inventions, despite being less related technologically. These discrepancies between measures can disclose significant insights and contribute to the debate on different relatedness indicators and their application (Farinha et al., 2019).

When analyzing city groups, we found that the experience of urban inventors and firms in ICE technologies, is an important factor in

[7] This result should be interpreted with caution given the small number of observations for the exit model, compared to the entry one, resulting from the limited number of EV-specialized regions.

Table 5
Ordinary Least Squared and Poisson Pseudo Maximum Likelihood models for estimating the effects of the independent variables on EV patent scores of cities (1980–2020).

Dependent variable: EV patent scores		
Independent Variables	**OLS**	**PPML**
Intercept — period 1 (1980–1989)	-0.054	-0.33667
	(0.493)	(0.84518)
Intercept — period 2 (1990–1999)	-1.202	-2.34812*
	(0.778)	(1.34857)
Intercept — period 3 (2000–2009)	-1.444	0.454422***
	(1.157)	(1.67489)
Intercept — period 4 (2010–2020)	-1.840	2.34922*
	(1.678)	(1.38330)
Battery scores (1980–1989)	0.131**	0.15885**
	(0.066)	(0.07452)
Battery scores (1990–1999)	0.225***	0.25127***
	(0.067)	(0.09914)
Battery scores (2000–2009)	0.306***	0.63961***
	(0.064)	(0.08054)
Battery scores (2010–2020)	0.413***	0.47060***
	(0.071)	(0.05397)
Smart Grid scores (1980–1989)	0.285***	0.23965***
	(0.097)	(0.08841)
Smart Grid scores (1990–1999)	0.253***	0.22877**
	(0.090)	(0.09914)
Smart Grid scores (2000–2009)	0.055	0.18594**
	(0.070)	(0.08852)
Smart Grid scores (2010–2020)	0.188**	0.20542**
	(0.081)	(0.08045)
ICE scores (1980–1989)	0.238***	0.39600***
	(0.069)	(0.07241)
ICE scores (1990–1999)	0.361***	0.44124***
	(0.064)	(0.06816)
ICE scores (2000–2009)	0.366***	0.67242***
	(0.057)	(0.05986)
ICE scores (2010–2020)	0.328***	0.45228***
	(0.059)	(0.04568)
Diversity (1980–1989)	-0.179	-0.16161
	(0.163)	(0.17832)
Diversity (1990–1999)	0.265	0.30469
	(0.166)	(0.20155)
Diversity (2000–2009)	0.058	-0.32794
	(0.173)	(0.23951)
Diversity (2010–2020)	0.326	-0.14750
	(0.200)	(0.16455)
Tot. patents (1980–1989)	0.097	0.08838
	(0.099)	(0.10663)
Tot. patents (1990–1999)	-0.044	0.04682
	(0.088)	(0.11538)
Tot. patents (2000–2009)	0.144	-0.53518***
	(0.097)	(0.13276)
Tot. patents (2010–2020)	0.049	-0.18198
	(0.133)	(0.11261)
R^2	0.851	
Adj. R^2	0.845	
Observations	655	655

Standard Errors in parentheses (robust estimation for PPML model)
All dependent variables are log-transformed.
The independent variable is also log-transformed in the OLS model.
* $p < 0.1$;
** $p < 0.05$;
*** $p < 0.01$

producing EV patents, but only for traditional automotive cities that were already specialized in both ICE and EV patents. In fact, cities that have recently acquired a specialization in EV patents have done so while increasing or stabilizing their smart grid and battery specializations and decreasing ICE one. This leads to question whether automotive firms will be capable of retaining their leadership on EV inventions, or if firms with competences in digital technologies, electronics or other sectors will become the main innovators in EVs, relegating automakers to a role of assemblers (Alochet et al., 2022; Ferloni, 2022).

The econometric analysis has shown that battery, smart grid, and EV patents are increasingly found in the same urban regions at the same time. However, battery and smart grid patents do not appear to support the development of a new EV specialization, or the conservation of an existing one, but this effect might become more apparent in the future, as coevolutionary interactions among these technologies become stronger. ICE patents have a relevant effect on EV ones, but this effect decreases in the most recent period. Finally, the economic diversity of cities has a significant positive effect in promoting EV specialization, particularly in the last period. Results suggest that coevolutionary interactions around EV technology are increasingly likely, but more research is needed to identify them in detail.

These findings contribute to economic geography in several ways. First, they suggest that relatedness changes in time, so debates on regional diversification and smart specialization should be framed within an evolutionary perspective. Second, technological relatedness and colocation are not the same thing: we need to further refine our tools for measuring these two kinds of relatedness. Third, by focusing on transitions, economic geographers can conceptually distinguish groups of related innovations according to the processes of socio-technical change in which they are bundled up together. This means embracing geographical *path interdependence* (MacKinnon et al., 2019) and considering not only the emergence of a main technology of interest, in our case Electric Vehicles, but also those that could be coevolving with it. If we had focused only on EV patent scores, we would have found mainly that traditional automotive cities retain a key role. Instead, we could highlight another group of emerging urban regions that experienced a rapid growth in EV patents and smart grid, but which also specialized in batteries, while at the same time abandoning ICE inventions.

This research also contributes to transition studies. First, by confirming that we need more research on the geography of socio-technical change: even though the EV transition has a global reach and impact, it is a selective process that involves specific technologies and emerges differently across cities. Regional economies can experience path dependence, path creation, or path destruction: today, the competences of incumbent actors — in our case automotive producers — appear crucial to support transitions, but their dependence on ICE technologies might slow down the growth of battery and electric technologies in traditional motor regions. Conversely, regions that are less dependent on an automotive heritage might be freer to create the kind of disruptive innovations that might be at the core of the EV transition or even of a post-automobile paradigm. Second, but related to the previous point, transitions also imply path destruction, or the phasing out of entire sectors that sustain some regional economies: this can have heavy social consequences, heighten competition between territories and fuel discontent (Rodríguez-Pose & Bartalucci, 2023). A multi-sectoral perspective can help address these issues by allowing to trace the relatedness potential between incumbent and emergent sectors across value chains (Andersen & Gulbrandsen, 2020). Showing how these complementarities are organized in space would add much explanatory power, and it could be achieved with a more systematic engagement with economic geographic insights. Third, this paper illustrates the interest of a mixed methodological stance combining explorative and quantitative methods. Transition studies could take advantage of formal modeling approaches (Papachristos, 2014), and economic geographers might engage more in appreciative studies. We believe that our methodological proposal centered around networks is a step in this direction.

This research is not exempt from limitations. First, we identified some representative patent codes, but several others could be used to delimit each technology more in detail. Second, we have used patent data to infer coevolution at an aggregate level, but we could not trace specific interactions between agents. Future research may study interdependencies of innovative actors at the micro level to confirm our findings. Third, we only addressed the phase of invention, but coevolution takes place also in production and diffusion, with feedbacks across these phases. The analysis of coevolution could be widened to

Table 6
Logit and probit models for estimating the effect of independent variables, in period t, on entry or exit of cities in or from EV specialization in period t + 1 (1980–2020). Coefficients in each period influence entry or exit in the following one. All dependent variables are log-transformed.

	Dependent variable: entry in or exit from EV specialization (binary)					
	Logit			Probit		
	Period 1 (1980–1989)	Period 2 (1990–1999)	Period 3 (2000–2009)	Period 1 (1980–1989)	Period 2 (1990–1999)	Period 3 (2000–2009)
Entry Models						
(Intercept)	-7.585*	-1477	-3.181	-4.097*	-1.022	-1.489
	(4.450)	(2.794)	(5.409)	(2.290)	(1.553)	(2.940)
Battery	0.476	0.490	0.396	0.286	0.243	0.216
	(0.305)	(0.393)	(0.340)	(0.177)	(0.210)	(0.183)
Smart grid	-0.038	-1.094*	0.391	-0.031	-0.657*	0.192
	(0.469)	(0.616)	(0.359)	(0.275)	(0.340)	(0.197)
ICE	0.586*	0.864**	0.164	0.352*	0.445**	0.073
	(0.316)	(0.374)	(0.325)	(0.183)	(0.205)	(0.181)
Diversity	1.929**	0.773	2.239**	1.074**	0.409	1.118**
	(0.981)	(1.006)	(1.086)	(0.531)	(0.537)	(0.557)
All patents	-0.716	-0.819	-1.422***	-0.431*	-0.400	-0.741**
	(0.439)	(0.531)	(0.547)	(0.250)	(0.281)	(0.292)
AIC	*112.719*	*88.375*	*116.601*	*112.892*	*88.514*	*116.969*
BIC	*128.410*	*104.299*	*134.033*	*128.583*	*104.438*	*134.400*
Log Likelihood	*-50,359*	*-38.188*	*-52.300*	*-50.446*	*-38.257*	*-52.484*
Deviance	*100.719*	*76.375*	*104.601*	*100.892*	*76.514*	*104.969*
Num. obs.	*101*	*105*	*135*	*101*	*105*	*135*
Exit Models						
(Intercept)	8.882	-0.289	9.757	5.447	-0.681	5.609
	(7.202)	(7.449)	(10.195)	(4.039)	(4.099)	(5.908)
Battery	-0.341	-0.456	0.954	-0.223	-0.293	0.577
	(0.384)	(0.518)	(0.736)	(0.233)	(0.296)	(0.425)
Smart grid	0.491	-0.304	-0.105	0.313	-0.136	-0.028
	(0.495)	(0.518)	(0.554)	(0.297)	(0.302)	(0.323)
ICE	0.895*	2.179***	1.581***	0.552**	1.238***	0.938***
	(0.458)	(0.720)	(0.555)	(0.273)	(0.372)	(0.302)
Diversity	-1.548	0.857	-0.106	-0.956	0.552	0.042
	(1.467)	(1.360)	(2.207)	(0.852)	(0.762)	(1.257)
All patents	-0.311	-1.128	-1.873	-0.185	-0.616	-1.164*
	(0.735)	(0.798)	(1.168)	(0.444)	(0.437)	(0.661)
AIC	*65.159*	*64.758*	*45.872*	*65.008*	*64.864*	*45.611*
BIC	*75.999*	*76.802*	*55.853*	*75.848*	*76.908*	*55.592*
Log Likelihood	*-26.579*	*-26.379*	*-16.936*	*-26.504*	*-26.432*	*-16.485*
Deviance	*53.159*	*52.758*	*33.872*	*53.008*	*52.864*	*33.611*
Num. obs.	*45*	*55*	*39*	*45*	*55*	*39*

*** $p < 0.01$;
** $p < 0.05$;
* $p < 0.1$

other phases and account for these interactions. Fourth, we only studied technology, but the social, institutional, organizational dimensions are key to the EV transition: future research could use our coevolutionary framework to investigate how socio-technical change impacts them. Fifth, this research could also be expanded by studying inter-urban interactions to account for distant networking. Finally, a full-scale replacement of conventional cars is still far. New developments — e.g., the hydrogen car, or new battery technologies — might radically change technological equilibria, which would require considering different sectors and coevolutionary relations altogether.

6. Conclusion

As environmental and social challenges become urgent, scholars have called for a critical approach to innovation focusing on transformative change or on "challenge-oriented innovation systems" (Schot & Steinmueller, 2018; Tödtling et al., 2022). This means that we should increasingly focus on innovation as a trigger of socio-technical transformations beyond its role as engine of economic growth. We identify three frontiers of transformative research that a coevolutionary approach could help investigate, and we elaborate on the policy implications.

First, a coevolutionary approach can help identifying how specific green technologies interact. Economic geographers are bringing evidence on the drivers of green innovation (Perruchas et al., 2020; Losacker et al., 2022). However, these contributions have largely "green boxed" very diverse technologies, juxtaposing them to non-green ones. Recent studies are shedding light on the interplay between green and brown innovations (Barbieri et al., 2022), but a coevolutionary approach could help do justice to the complexity of contemporary transitions and to specify which technologies interact around new multisectoral domains of application.

Second, and related to the previous point: coevolution can help frame regional diversification opportunities beyond the green/non-green dichotomy. The green transition will likely have a negative impact on less developed or peripheral regions, and on those where "dirty" sectors are dominant (Rodríguez-Pose & Bartalucci, 2023). Yet some parts of "dirty" value chains might be related to emerging sectors (Andersen & Gulbrandsen, 2020). Besides, peripheral regions might realize large jumps in development by acquiring competences in emerging sectors for which localized support structures are not yet present (Gong et al., 2023). Social networks, political interests, cultural or institutional factors could all contribute to leapfrogging, and a coevolutionary framework is well positioned to include them into the analysis.

Third, coevolution can help investigate the role of multi-scalar configurations into the analysis. In economic geography, the role of extra-regional linkages in diversification has received limited treatment

(Balland & Boschma, 2021). Transition scholars have found that external knowledge sources can help anchor unrelated activities in developing regions (Binz & Anadon, 2018) and are increasingly studying multi-scalar innovation networks (Miörner & Binz, 2021). A coevolutionary approach can help include not only institutional and socio-technical factors but also to conceptualize multi-sectoral interactions across geographical scales.

Finally, our results can allow to propose some general policy indications about innovation and regional diversification. Smart specialization policies should become more attentive to the challenges and opportunities provided by transitions. Related diversification is a relevant starting point, but socio-technical change might enable new multi-sectoral complementarities. Incumbent sectors are likely to remain influential for some time, especially in capital-intensive industries such as automotive, but emerging technologies are increasingly crucial. Local institutions should therefore maintain a strategic and proactive attitude, not only to support the most related sectors today, but to nurture and explore more unrelated capabilities for tomorrow. In times of climate urgency and uncertainty, we need more studies to understand coevolution across the energy, digital, and mobility sectors, to promote public debates and better-informed regional innovation policies.

Declaration of Competing Interest

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

Acknowledgements

This paper was presented and benefitted from discussions with colleagues at the "Geoinno 2022" conference in Milan. The authors wish to thank Frank Neffke for his advice on the econometric models. We also acknowledge the editors and two anonymous referees for their insightful and constructive remarks. The first author gratefully acknowledges the financial support of Société Académique Vaudoise (SAV).

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