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Key Enabling Technologies (KETs): Firms' Key to Radical Innovation?

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Abstract

This study analyses the influence of Key Enabling Technologies (KETs) on radical innovation at the firm-level in 27 EU countries. KETs are a group of six technologies that are considered to be promising for Europe's industrial competitiveness and innovativeness because they are horizontal and widely combinable, representing properties of General Purpose Technologies. We test this by investigating whether KET knowledge promotes the emergence of radical innovation in firms and whether regional specialization in KETs can moderate this relationship. Based on a unique firm-level database, our results show that KETs generally facilitate the emegence of radical innovation and that firms lacking KET knowledge in particular can benefit from being located in regions specialised in KETs. However, when focusing on the six individual KETs, the results get markedly heterogeneous and point to differences in the influence of engineering-oriented and science-based KETs. Our results therefore call for tailored, KET-specific, approaches – both in research and policy.

Keywords

Radical innovation, recombinant novelty, knowledge creation, general purpose technologies, key enabling technologies, firm-level

JEL Classifications

L25; O31; O33; R10

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1 Introduction

Key Enabling Technologies (KETs) are a group of horizontal and widely applicable technologies that were summarised under the label of KETs by the European Commission (EC) in 2009. They comprise advanced materials, advanced manufacturing technologies (AMT), industrial biotechnology, micro- and nanoelectronics (MNE), nanotechnology and photonics. The policy-emphasis was put on KETs due to their foreseen role in tackling contemporary challenges, such as Europe's industrial competitiveness, an ageing society, and climate change (European Commission 2009b). Indeed, KETs affected European policy priorities soon after their designation and became, for example, an important pillar of Smart Specialization Strategies (S3) (Foray et al. 2009, 2011).

The growing policy prominence of KETs has been accompanied by a developing academic literature examining their impact, for example, on economic growth (e.g., Evangelista et al. 2018) and innovation (e.g., Wessendorf et al. 2021). As this literature highlights, KETs' economic potential is based on the features shared with General Purpose Technologies (GPTs), which is the underlying reason for policy-makers' interest. Here, the bridging function of KETs is central as it renders them 'platforms' that can link various different and formerly distant technologies (Corradini & de Propris 2017). This bridging function has also recently been shown to give KETs an important role in recombinant innovation[1] (Weitzmann 1998), as it not only enables technological innovation at the regional level in general (Wessendorf et al. 2021), but also promotes radical innovation[2] at the regional level (Montresor et al. 2022). In contrast to incremental innovation, radical innovation results from the synthesis of previously unconnected knowledge pieces (Weitzmann 1998; Fleming 2001; Nerkar 2003). Due to its potential for huge economic benefits (Ahuja & Lampert 2001; Castaldi et al. 2015), radical innovation has received increasing attention from academics (e.g., Knuepling et al. 2022; Grashof & Kopka 2023) and policy makers (e.g., Joint European Disruptive Initiative

[1] Recombinant innovation is defined as '*(…) the way that old ideas can be reconfigured in new ways to make* new ideas.' (Weitzman, 1998, p. 333).

[2] In line with (Castaldi et al. 2015), the terms 'innovation' and 'invention' are used interchangeably in this study because the theoretical framework of recombinant innovation also uses the term 'innovation'. However, it is important to note that this study concentrates on technological achievements rather than successful commercialization.

(JEDI) 2023; SprinD GmbH 2023[3]).

However, despite the high expectations about KETs, particularly from policy makers, and one important exception on the regional level (e.g., Montresor et al. 2022), there has been limited research on the relationship between KETs and radical innovation – especially from a firm-level perspective. In a first step, this study therefore aims to contribute to the recent literature stream on KETs and innovation by empirically investigating whether firms with KET knowledge have a higher likelihood to generate radical innovation. While previous studies have taken an aggregated view of KETs, thereby ignoring potential differences between the six specific KETs, we will take a more nuanced view of KETs and also differentiate the possible influence of the six specific KETs on the emergence of radical innovation.

Beyond examining the influence of firms' KET knowledge on the creation of radical innovation, we also consider the corresponding regional context. Following previous studies (e.g., Turkina et al. 2019; Grashof 2021), it is argued that contextual factors of heterogeneity are often overlooked in the examination of firm innovative performance. However, ignoring these contextual influences can lead to potential misinterpretations (Frenken et al. 2015; Grashof & Fornahl 2021). Therefore, following the current discussion on the role of regional clusters in the context of radical innovation (e.g., Grashof et al. 2019), in a second step we empirically investigate the extent to which regional specialization in KETs can moderate the relationship between firms' KET knowledge and the emergence of radical innovation. Like in the previous case, we assess this question for all KETs together, but also for each KET individually.

To empirically address these two research gaps, we combine several databases: ORBIS IP for information on firm-specific characteristics, PATSTAT, to identify radical patents and KET patents at the firm-level, OECD Regpat to enrich PATSTAT data with regionalised patents, and Eurostat to include information on the regional economic structure. The resulting database is an unbalanced panel of 67.476 unique firms that applied for any patent between 2013 and 2018, located in 27 different EU countries, also comprising patent-, firm-, and regional-specific information. To analyse our research questions, we follow previous studies (e.g., Schlegel & Backes-Gellner 2023) and use Poisson pseudo-maximum likelihood regressions with firm and year fixed-effects (with

[3] The recently launched JEDI initiative at the European level and the German federal agency Sprin-D both focus on promoting the generation of radical innovations (Joint European Disruptive Initiative (JEDI) 2023; SprinD GmbH 2023).

robust standard errors), since our dependent variable is a non-negative count variable that suffers from over-dispersion.

By empirically investigating the two underlying research questions, this study extends previous research on KETs and innovation in terms of (i.) a more fine-grained level of analysis (i.e. the firm-level), (ii.) a more nuanced perspective on KETs (i.e. differentiating between the six individual KETs), and (iii.) to a better understanding of the relevance of the regional context in studying the influence of KETs on firms' (radical) innovative performance. In addition to this, it also provides pragmatic insights for (regional) policy makers on the differentiated influence of KETs across the individual technology groups and regional contexts, thereby harnessing the potential of KETs to generate radical innovation.

The remainder of this paper is structured as follows: The next section presents the theoretical background on KETs and radical innovation before deriving the hypotheses. Section 3 describes our data basis and the methodological approach. The empirical results are presented and discussed in section 4, before section 5 concludes (including limitations and promising future research endeavors).

2 Theoretical Background

2.1 KETs and Radical Innovation at the Firm-Level

Innovation has been shown to drive economic growth (e.g., Rosenberg 2004; Verspagen 2005). It emerges from a cumulative process (Arthur 2007), in which existing knowledge pieces are recombined in new ways and knowledge relations are reconfigured (Schumpeter 1939; Weitzmann 1998; Fleming 2001). However, their novelty and impact vary widely on a range between 'ordinary' and 'exceptional' innovation types (Kovacs et al. 2019; Knuepling et al. 2022). The majority of innovations is ordinary, and frequently labeled 'incremental' (Dewar & Dutton 1986; Arts et al. 2013; Hesse 2020a), but a few ones attract attention by their exceptionality (Arts & Veugelers 2015). Among the different labels for exceptional innovation, 'radical' is most frequent (Kovacs et al. 2019; Knuepling et al. 2022). Despite ambiguities between innovation labels (Gopalakrishnan & Damanpour 1997; Knuepling et al. 2022; Shkolnykova & Kudic 2022), radical innovation is usually associated with a high degree of novelty and a remarkable impact (Knuepling et al. 2022). Similar to previous studies (e.g., Fleming 2001; Castaldi et al. 2015; Verhoeven et al. 2016), our study focuses on novelty and considers radical innovation as a recombination of distant and previously uncombined knowledge. Radical innovation is based on exploratory search processes (March 1991) and occurs only sporadically (Fleming 2001; Castaldi et al. 2015; Hesse & Fornahl 2020). If successful, it can drive change at the technological, industrial, and societal levels (Schoenmakers & Duysters 2010) and potentially results in a paradigm shift, as technological trajectories are created and technological paradigms may emerge through radical innovation (Dosi 1982; Ahuja & Lampert 2001; Verhoeven et al. 2016), generating economic growth in the long run (Ahuja & Lampert 2001). Considering the organisational level, the search processes for radical innovation and its emergence are usually risky and highly uncertain (e.g., Ayres 1988; O'Connor 1998; Fleming 2001). Consequently, the abilities and capabilities to combine distant knowledge are an important prerequisite. One set of technologies that may facilitate knowledge recombination and support the emergence of radical innovation in organisations are KETs, as they play a capabilities-enhancing role in exploratory search (Montresor & Quatraro 2020).

The European Commission (EC) grouped six multidisciplinary technologies under the label of 'Key Enabling Technologies' (KETs) in 2009: Advanced manufacturing technologies (AMT), advanced materials, industrial biotechnology, micro- and nanoelectronics – including semi-conductors (MNE), nanotechnology, and photonics (European Commission 2009b, 2009a, 2012). Subsequently, KETs gained prominence in the scientific literature and in policy-making. The EC defined KETs as highly relevant technology fields that are horizontal, pervasive, and cross-cutting (European Commission 2009a), but did not deliver a distinct conceptualisation. A closer look at KETs reveals features of General Purpose Technologies (GPTs) and their nature as enabling technologies (Teece 2018; Martinelli et al. 2021; John et al. 2022). GPTs are pervasive, innovation-spawning technologies that possess opportunities for further improvement and innovational complementarities. They spread across the whole economy, driving economic growth (Helpman & Trajtenberg 1994; Bresnahan & Trajtenberg 1995; Helpman 1998). Following Teece (2018), enabling technologies are 'junior GPTs'. They may not have an economy-wide impact (yet), but trigger complementary innovation and have the potential for technological improvement, fulfilling two of the three GPT-characteristics (Teece 2018). From a technological viewpoint and in the horizontal perspective, KETs play a vital role as bridging platforms, i.e. they can connect distant and unrelated knowledge, as links can be established between KETs and various other technologies (Corradini & de Propris 2017). The innovational and technological complementarities coming along with KETs add a vertical dimension to their horizontal nature (van de Velde et al. 2015; Corradini & de Propris 2017; Teece 2018).

Due to their specific characteristics, the scarce scientific literature on KETs has grown in recent years (publications include e.g., Montresor & Quatraro 2017; Wanzenböck et al. 2020; Wessendorf et al. 2021; Antonietti et al. 2023). However, while most scientific publications in this literature stream focus on the regional level, and thus ultimately overlook specific processes at the micro-level, they can still provide insights that are helpful in deriving our hypotheses. For example, KETs can enhance a region's capabilities for knowledge recombination and hybridisation and for exploratory search (Montresor & Quatraro 2020). They can also increase the regional innovation output (Wessendorf et al. 2021), and promote the generation and adoption of radical innovations at the regional level (Montresor et al. 2022). Based on these insights, we argue that KETs also enhance firms' abilities to combine technology fields. The recombinant potential of KETs in firm's knowledge base should provide firms with a higher likelihood for radical innovation. Moreover, KETs' presence as bridging platforms increases the innovation potential, based on possible inter-sectoral technology spillovers, technological synergies and the potential for technological integration across distant, unrelated technology fields (Corradini & de Propris 2017). In this context, insights from the GPT-literature are also helpful. Particularly, Grashof & Kopka (2023) find evidence for the bridging function of a young GPT, namely artificial intelligence (AI), and the emergence of radical innovations associated with it. This supports our argument that KETs increase a firm's likelihood of creating radical innovation. Consequently, we propose the following hypothesis:

(H1a) The amount of KET knowledge in the knowledge base of firms positively influences the emergence of radical innovation in firms.

However, KETs are multidisciplinary technologies (European Commission 2012). Previous studies at the regional level found evidence of KET-specific differences in the strength and variety of their effects (e.g., Montresor & Quatraro 2017; Wanzenböck et al. 2020; Wessendorf et al. 2021). The literature unfortunately remains superficial on the reasons for KET-specific effects and their varying enabling nature. As emphasised by Wanzenböck et al. (2020) and as reflected in European Commission reports (e.g., Aschhoff et al. 2010), a rough distinction between KETs can be made as follows: AMT, advanced materials and photonics are more engineering- and industry-oriented, while industrial biotechnology and nanotechnology are more science-based (Wanzenböck et al. 2020). The tendency of MNE is the least clear in this context: Wanzenböck et al. (2020) describe Microelectronics to be engineering-oriented, while other studies underline the science-based nature of semi-conductors[4] (Pavitt 1984; Ponds et al. 2010). Despite the lack of a clear pattern in the variety of KET effects in the literature, it can be stated that AMT and advanced materials have the most pronounced GPT-features (e.g., Aschhoff et al. 2010; Montresor & Quatraro 2020; Antonietti et al. 2023). Particularly AMT can function as a core enabler that also enables other KETs (European Commission 2009b; van de Velde et al. 2012; de Heide et al. 2013). In general, we thus propose the following hypothesis:

(H1b) The influence of engineering-oriented KET knowledge on the emergence of radical innovation in firms is particularly pronounced**.**

2.2 KETs and Radical Innovation at the Firm-Level: Does the Regional Context Matter?

Agglomerations and firm performance were intensively studied in the past decades (e.g., Knoben et al. 2016; Grashof & Fornahl 2021) – recently also in the case of radical innovation (e.g., Grashof et al. 2019). Already one century ago, Marshall (1920) highlighted that firms can benefit from spatially co-locating with firms from the same industry. Amongst other externalities, the literature considers knowledge exchange and spillovers as key advantages for learning and knowledge generation in firms (e.g., Marshall 1920; Jaffe et al. 1993). Besides these positive externalities, firms might, however, also experience negative knowledge spillovers or knowledge leakages (Hervas-Oliver et al. 2018; Grashof 2021). In this realm, authors like Shaver & Flyer (2000) highlight the role of unintentional knowledge spillovers between firms/competitors that can be beneficial for the recipient of the spillovers (and harmful to the firm from which the unintentional spillovers originate, because of the potential loss of competitive advantage (e.g., Nooteboom 2000; Shaver & Flyer 2000)). Particularly, firms at a lower technological level (referred to as 'poor technology') may benefit from being located in geographic proximity to firms with an advanced knowledge base (referred to as 'good technology'). Following the notion of such an adverse selection effect (Shaver & Flyer 2000), we argue that firms with relatively little KET knowledge should profit more from

[4] The KET micro- and nanoelectronics (MNE) includes semi-conductors (European Commission 2009a).

being located in a KET-related regional cluster than firms with an already strong KET knowledge base, provided there is adequate absorptive capacity (Cohen & Levinthal 1990). This type of firm has greater opportunities to learn something new, due to unintentional knowledge spillovers (Shaver & Flyer 2000) that also include tacit knowledge, which is highly relevant for radical innovation (Mascitelli 2000). Therefore, these firms can benefit more from being located in a region that is highly specialised in KETs when it comes to generating radical innovation. Consequently, we suggest the following hypothesis:

(H2a) The regional specialisation in KETs negatively moderates the effect of a *firm's* KET knowledge stock on the generation of radical innovation, i.e. *'technology poor' firms gain more from being located in such a* specialised region.

As discussed previously, KETs are a very heterogeneous group of technologies (European Commission 2012). Studies considering the six individual KETs found KET-specific differences in their effects (e.g., Wessendorf et al. 2021), which can at least partly be explained by their different orientation (science-based vs. engineering-based). In terms of the knowledge base of KETs, engineering- and application-oriented KETs rely more on the exchange of tacit and informal knowledge, while the science-based KETs rely more on explicit knowledge (Wanzenböck et al. 2020). Since geographical proximity within regional clusters facilitates the exchange of tacit knowledge in particular (Daft & Lengel 1986), we expect the adverse selection effect (Shaver & Flyer 2000) to be stronger in the case of regional specialisation in engineering-oriented KETs than in science-driven KETs. Therefore, we propose the following hypothesis:

(H2b) The negative influence of regional specialisation on the effect of a firm´s KET knowledge stock on the generation of radical innovation is particularly pronounced in the case of engineering-oriented KETs.

3 Data and Methodological Approach

3.1 Data

To empirically investigate our hypotheses, we use four large data sources. For firm-level data, we use the extensive ORBIS IP database of Bureau van Djik (BvD), which provides information on firm-specific characteristics, like the number of employees, and patent information. Similar to Grashof & Kopka (2023), we combine this database via the application id with our second main database: PATSTAT, which is used to identify radical as well as KET patents on the firm-level. Lastly, we enrich this data with regionalised patent information from OECD REGPAT and further regional structural characteristics from Eurostat (both on a NUTS-3 level). The resulting unique database is an unbalanced panel of 67.476 unique firms that are located in 27 different EU countries and applied for any patent between 2013 and 2018, entailing patent- and firm-specific information.[5]

3.2 Variables

Based on the previously described diverse information sources, we create our variables of interest. Since our conceptual focus lies on the emergence (or novelty) of radical innovations (see Section 2), we use new technological combinations on a patent as proxy for the emergence of radical innovations, thereby following previous studies (e.g., Verhoeven et al. 2016; Arant et al. 2019; Grashof et al. 2019). To construct the underlying reference dataset for these new combinations, we use all patents from applicants located within the EU since 1981.[6] The technological combinations are in this context measured on the 4-digit CPC-level. Following previous studies (e.g., Hesse & Fornahl 2020; Mewes & Broekel 2020), it is argued that this patent classification level offers the best trade-off between a maximum number of technologies and a sufficiently large number of patents in each of these patent classes. Finally, we calculate our dependent variable by counting the number of these radical patents in each firm based on the DOCDB patent family ids. Consequently, patents from the same patent family are only counted once per firm (Grashof & Kopka 2023). Moreover, similar to Grashof & Kopka (2023), we assume that if a radical patent is attributed to more than one company, the knowledge of this patent is not exclusive and therefore attribute a full (radical) patent

[5] Unfortunately, we lose more or less half of our observations in our regression models (see Tables 2 and 3), because of all zero outcomes in the case of our dependent variable.

[6] The chosen time frame is thereby in line with previous studies (e.g., Grashof et al. 2019; Hesse & Fornahl, 2020; Verhoeven et al. 2016).

to all applicant companies. Thus, radical knowledge is proxied by the number of radical patents in each firm.

Our main independent variables of interest refer to the KET-related knowledge in firms and regions. For the former, we use again PATSTAT and identify KET patents based on technological classes, which is in line with previous studies (e.g., Wessendorf et al. 2021; Montresor et al. 2022). Since KETS are broad and horizontal technologies that share 'natural overlaps' (Larsen et al. 2011; van de Velde et al. 2012; Butter et al. 2014), we use a fine-grained list of the full-digit technology codes of the international patent classification (IPC) for the identification of KETs, as provided by van de Velde et al. (2012) (see Appendix 1). Unlike most other studies, all six KETs are considered individually in our analysis (see Hypothesis 1b). Similar to our dependent variable, we capture the KET-related knowledge by counting the number of KET patents filed by the corresponding firms, being in line with previous studies (e.g., Montresor et al. 2022). However, on the regional-level, we are more interested in the specialisation patterns in KETs. Hence, based on the regionalised patent information from the OECD REGPAT database we follow previous studies (e.g., Rigby 2015; Grashof & Basilico 2023) and calculate the revealed comparative advantage (RCA) in the following way:

$$RCA\_KET = \frac{patents^t_{r,i} / \sum_i patents^t_{r,i}}{\sum_r patents^t_{r,i} / \sum_r \sum_i patents^t_{r,i}} > 1 \qquad (1)$$

where $patents^t_{r,i}$ is the number of patents in region r in a KET-related technological class at a specific time t, $\sum_i patents^t_{r,i}$ is the total number of patents in region r at a specific time t. $\sum_r patents^t_{r,i}$ is the sum of all KET patents in every region at time t, and $\sum_r \sum_i patents^t_{r,i}$ is the sum of all patents for each region at time t. Based on this information, we create a dummy variable (RCA_KET_Dummy), which equals one if a region has an above-average share of KET patents compared to the cumulated share of KET patents over all regions (Kopka & Grashof 2022). Similar to the firm-level, we calculate this measure for all aggregated KETs and for each individual KET. To avoid a bias towards regions with very little patenting activity, we only consider regions in our empirical analysis that account for at least 5% of the distribution of patents over the entire study period, following previous studies (e.g., Grashof & Basilico 2023).

Additionally, we control for several firm- and regional-specific characteristics. Since firm size plays a role in the emergence of radical innovations (e.g., Grashof et al. 2021), we capture it via the number of employees. As the underlying distribution is skewed, the logged number of employees (Employess_ln) is used. Moreover, the total non-KET patent count is included (Pat_nonket) to control for the general knowledge stock of firms, making it more likely to find new technological combinations. Furthermore, we consider a firm´s technological diversity as a relevant control variable. We assume that greater technological diversity positively impacts the emergence of radical innovations because it facilitates the exploration of complementarities and novel combinations (Quintana-García & Benavides-Velasco 2008; Hesse 2020b). To assess a firms' technological diversity, we utilise the inverse Herfindahl-Hirschman Index, based on CPC 4-digit codes (e.g., Garcia-Vega 2006; Leten et al. 2007; Grashof & Kopka 2023). A firm with a more diverse range of CPC-codes will therefore exhibit higher technological diversity. The index is computed by tallying the individual patents of each 4-digit CPC in each firm over a five-year moving window (including the year of observation and the previous four years) and then calculating the proportion of each 4-digit CPC within the total. These proportions are squared, summed and then inversed to create the inverse Herfindahl-Hirschman Index (Inv_HHI). Additionally, also control variables for the structural characteristics of regions are considered. Based on data from Eurostat on the NUTS-3 level (following e.g., Montresor et al. 2022) we include GDP per capita to account for the local economic strength (GDPpc) as well as the population density (Popdens) to control for potential urbanisation economies.

Table 1 shows the corresponding descriptive statistics for all main variables.[7] In line with previous research (e.g., Verhoeven et al. 2016; Grashof et al. 2019) it becomes obvious that radical innovations constitute a rather rare event, while the overall non-KET patenting activities of firms are generally more widespread. Moreover, regarding the KETs we observe differences between the six KETs (with the highest average number of patent activities in advanced materials and AMT) as well as a relatively large variance in general. On the regional-level, we see that almost 44% of the firms in our sample are located in regions that are specialised in at least in one KET. In combination with the relatively high average population density of the regions in which the firms in our sample are located (Germany's overall average was 236 persons/km² in 2022), it seems that on average the firms in our sample tend to be located in small to medium-sized cities. Given our focus on patents, this average location pattern seems quite understandable.

[7] The pairwise correlation matrix for all variables is presented in Appendix 2.

Table 1: Descriptive Statistics *(Source: Authors' own computations)*

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
Rad	539808	0.026	0.373	0	64
Pat_ket	539808	0.155	3.366	0	408
Pat_advmat	527075	0.048	1.478	0	252
Pat_amt	528277	0.041	0.97	0	166
Pat_biotech	525844	0.025	0.521	0	71
Pat_micronano	524719	0.04	1.806	0	394
Pat_nanotech	521507	0.002	0.147	0	47
Pat_photo	525260	0.031	1.324	0	257
RCA_ket_dummy	518903	0.436	0.496	0	1
RCA_advmat_dummy	518903	0.521	0.5	0	1
RCA_amt_dummy	518903	0.554	0.497	0	1
RCA_biotech_dummy	518903	0.638	0.481	0	1
RCA_micronano_dummy	518903	0.641	0.48	0	1
RCA_nanotech_dummy	518903	0.876	0.33	0	1
RCA_photo_dummy	518903	0.644	0.479	0	1
Employees_ln	329357	3.541	1.949	0	13.407
Pat_nonket	539808	6.944	127.299	0	18502
Inv_HHI	539808	0.042	0.175	0	0.993
GDPpc	519628	34556.965	17541.956	2800	184200
Popdens	518587	914.2	2155.859	1.9	21490

3.3 Methodological Approach

Since our dataset has an unbalanced panel structure (from 2011 to 2018), we conduct a panel regression approach at the level of EU-based companies. In this context, following the results of the robust Hausman test (e.g., Wooldridge 2002; Schaffer & Stillman 2010), we use a fixed effect panel regression. Our dependent variable is a non-negative count variable (i.e. number of radical patents of each firm in each year) and suffers from over-dispersion (i.e. the variance is greater than the mean). In order to account for that, we follow previous studies (e.g., Grashof & Kopka 2023; Schlegel & Backes-Gellner 2023) and use Poisson pseudo-maximum likelihood regressions (PPML) with firm and year fixed effects as well as robust standard errors[8], remaining stable in the presence of over-dispersion (Fally 2015). The stylised models adopt the following form:

(2) $$Rad_{it} = \alpha + \beta_1 Pat\_Ket_{it-1} + \beta_2 Employees\_ln_{it-1} + \beta_3 Pat\_nonket_{it-1} + \beta_4 Inv\_HHI_{it-1} + \beta_5 GDPpc_{it-1} + \beta_6 Popdens_{it-1} + \omega_i + \delta_t + \varepsilon_{it}$$

(3) $$Rad_{it} = \alpha + \beta_1 \mathrm{Pat\_Ket}_{it-1} + \beta_2 \mathrm{RCA\_Ket}_{it-1} + \beta_3 (\mathrm{Pat\_Ket\ x\ RCA\_Ket})_{it-1} + \beta_4 \mathrm{Employees\_ln}_{\mathrm{it-1}} + \beta_5 \mathrm{Pat\_nonket}_{\mathrm{it-1}} + \beta_6 \mathrm{Inv\_HHI}_{\mathrm{it-1}} + \beta_7 \mathrm{GDPpc}_{\mathrm{it-1}} + \beta_8 \mathrm{Popdens}_{\mathrm{it-1}} + \omega_i + \delta_t + \varepsilon_{it}$$

where Rad_{it} corresponds to the number of radical patents in company i at time t, Pat_Ket_{it-1} to the number of KET patents, RCA_Ket_{it-1} to the regional KET-specialisation. In addition to this aggregated view, we differentiate between the six specific KETs. Our control variables are indicated by $Employees\_ln_{it-1}$, Pat_nonket_{it-1}, Inv_HHI_{it-1}, $GDPpc_{it-1}$, $Popdens_{it-1}$. Both our main independent variables and our control variables are lagged by one year to mitigate potential endogeneity problems. In addition, firm (ω_i) and year (δ_t) fixed-effects are included to control for unobserved heterogeneity. Finally, ε_{it} is the error term.[9]

[8] For the estimation, we use the Stata command ppmlhdfe from Correia et al. 2020.

[9] Given the claimed robustness of the fixed-effects Poisson model to the fixed-effects negative binomial model (Wooldridge 1999), and in line with previous studies (e.g., Anzenbacher & Wagner 2020; Ganco et al. 2020), as a robustness check we also estimate our models using fixed-effects Poisson panel models with robust standard errors. The corresponding results remain stable and are presented in Appendix 3 and 4.

4 Results and Discussion

In the following, we present and discuss the results of our econometric analysis in two steps. First, we investigate the relationship between firms' knowledge in KETs and the emergence of radical innovation (see equation 2) thereby differentiating between the six KETs. Second, we examine the potential moderating role of the regional context by introducing interaction effects with the specialisation in regions (see equation 3).

4.1 KETs and Radical Innovation at the Firm-Level

In the case of the first regression series (see Table 2), we find a significant positive influence of the number of KET patents (Pat_ket). Thus, the amount of KET knowledge fosters the generation of radical innovation in firms, confirming H1a. This result complements previous findings on the regional impact of KETs (e.g., Wessendorf et al. 2021; Montresor et al. 2022) by adding a micro-level dimension. It also shows that KETs improve the ability of firms to link previously unconnected technologies (see section 2), for which the bridging function of GPTs (Grashof & Kopka 2023) or KETs (Corradini & de Propris 2017) is critical.

Additionally, the results in Table 2 indicate KET-specific differences in their influence on the emergence of radical innovation. Partly in line with H1b, we detect a highly significant effect in the cases of advanced materials (Pat_advmat) and photonics (Pat_photo). However, the coefficient for AMT (Pat_amt) is statistically insignificant, although with a p-value of 0.130 only slightly above the standard threshold of 0.1. Regarding the remaining KETs, the more science-based industrial biotechnology (Pat_biotech), and nanotechnology (Pat_nanotech), show insignificant effects. Also, micro- and nanoelectronics (MNE) (Pat_micronano) is insignificant. Consequently, although we cannot fully accept H1b, the results show that engineering-oriented KET knowledge, especially in the fields of advanced materials and photonics, tends to drive the emergence of radical innovation in firms, which can be explained, for example, by their more pronounced GPT-features (e.g., Montresor & Quatraro 2020).

Table 2: PPML Regression Results of KETs Influence

(Source: Authors' own computations)

	Dependent variable: Number of radical patents t+1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pat_ket	0.005*** (0.002)						
Pat_advmat		0.008*** (0.003)					
Pat_amt			0.005 (0.003)				
Pat_biotech				0.004 (0.009)			
Pat_micronano					-0.002 (0.003)		
Pat_nanotech						0.012 (0.016)	
Pat_photo							0.009*** (0.003)
Employees_ln	0.126** (0.043)	0.098** (0.042)	0.181*** (0.046)	0.153*** (0.049)	0.164*** (0.049)	0.121** (0.048)	0.127** (0.050)
Pat_nonket	0.001*** (0.0002)	0.0004** (0.0002)	0.001*** (0.0002)	0.001*** (0.0003)	0.001*** (0.0003)	0.001* (0.0004)	0.001*** (0.0003)
HHI	0.136** (0.058)	0.206*** (0.063)	0.118* (0.062)	0.228*** (0.069)	0.152** (0.065)	0.213*** (0.072)	0.156** (0.065)
GDPpc	0.00002** (9.65e-06)	0.00003*** (0.00001)	0.00003*** (0.00001)	0.00002 (0.00001)	0.00003*** (0.00001)	0.00002* (0.00001)	0.00003** (0.00001)
Popdens	0.0003 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0004 (0.0003)	0.0003 (0.0002)	0.0002 (0.0003)	0.0002 (0.0003)
Fixed-Effects							
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observ.	18,693	16,201	16,374	15,409	15,473	14,646	15,558
Number of groups	3,307	3,010	3,048	2,865	2,910	2,751	2,902
Pseudo R2	0.3044	0.2881	0.2954	0.2502	0.2647	0.1981	0.2666
Wald chi-square	64.65***	50.03***	47.95***	45.23***	39.24***	23.84***	44.88***
BIC	24714.44	20693.15	21113.02	18992.63	19366.1	17555.17	19485.75

Note: Robust standard errors in parentheses; p<0.1, ** p<0.05, *** p<0.01*

Regarding the control variables, in line with previous studies (e.g., Grashof et al. 2021), we can observe a significant and positive influence of firm size, indicating that larger firms tend to innovate more radically than smaller firms. Moreover, the technological diversity of firms also plays a significant role in the emergence of radical innovation by facilitating the exploration of complementarities and novel combinations (Quintana-García & Benavides-Velasco 2008; Hesse 2020b). Additionally, non-KET patent activities significantly promote the generation of radical innovation in firms, showing the path dependence and cumulativeness of knowledge accumulation (Grashof & Kopka 2023). Finally, we also find evidence of a significant positive influence of the regional economic strength on the creation of radical innovation in firms.

4.2 KETs and Radical Innovation: Moderating Role of the Regional Context

Focusing on the regional influence in the second set of models, Table 3 displays a highly significant negative interaction term between the regional specialisation in KETs and the amount of KET- knowledge in firms. In other words, a regional specialisation in KETs substitutes for the amount of KET knowledge in firms, thereby supporting H2a. Thus, in line with the adverse selection effect (Shaver & Flyer 2000), firms with a relatively strong knowledge base in KETs do not benefit as much from being located in a highly KET-specialised region as firms with a relatively weak knowledge base in KETs.

Regarding the main effects, we do not find a significant direct effect of regional KET-specialisation on the number of radical patents in firms (when Pat_ket = 0). However, similar to the first series of models (see Table 2), we observe a significant positive effect of KET knowledge in firms' knowledge bases on radical innovation generation (in this case, when RCA_ket_dummy = 0). Hence, KET knowledge seems to be particularly important for firms being located outside a region specialised in KETs (at the aggregate KET level). Moreover, the absence of KET knowledge in firms can be compensated by being located in a KET-specialised environment. At the same time, it should be noted that firms with strong knowledge of KETs located in a region specialised in KETs have a lower likelihood of KET-driven radical innovation.

Table 3: PPML Regression Results of Regional Influence

(Source: Authors' own computations)

	Dependent variable: Number of radical patents t+1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pat_ket	0.008*** (0.002)						
RCA_ket_dummy	0.007 (0.039)						
*RCA_ket_dummy*Pat_ket*	-0.004** (0.002)						
Pat_advmat		0.011*** (0.004)					
RCA_advmat_dummy		0.095** (0.039)					
*RCA_advmat_dummy*Pat_advmat*		-0.005 (0.005)					
Pat_amt			0.012** (0.004)				
RCA_amt_dummy			0.060* (0.035)				
*RCA_amt_dummy*Pat_amt*			-0.007** (0.003)				
Pat_biotech				-0.001 (0.027)			
RCA_biotech_dummy				-0.027 (0.042)			
*RCA_biotech_dummy*Pat_biotech*				0.005 (0.026)			
Pat_micronano					0.0002 (0.003)		
RCA_micronano_dummy					-0.049 (0.039)		
*RCA_micronano_dummy *Pat_micronano*					-0.002 (0.001)		
Pat_nanotech						0.0002 (0.025)	
RCA_nanotech_dummy						-0.042 (0.059)	
*RCA_nanotech_dummy*Pat_nanotech*						0.013 (0.022)	
Pat_photo							0.008 (0.006)
RCA_photo_dummy							0.097** (0.038)
*RCA_photo_dummy*Pat_photo*							0.001 (0.005)

(continued on next page)

(Table 3, continued from previous page)

Dependent variable: Number of radical patents t+1

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employees_ln	0.137*** (0.044)	0.113*** (0.043)	0.186*** (0.047)	0.163*** (0.050)	0.176*** (0.051)	0.134*** (0.049)	0.140*** (0.051)
Pat_nonket	0.001*** (0.0002)	0.0004** (0.0002)	0.001*** (0.0002)	0.001*** (0.0003)	0.001*** (0.0003)	0.001* (0.0004)	0.001*** (0.0003)
HHI	0.138** (0.059)	0.204*** (0.064)	0.131** (0.062)	0.233*** (0.069)	0.150** (0.066)	0.221*** (0.073)	0.164** (0.066)
GDPpc	0.00002* (9.70e-06)	0.00003** (0.00001)	0.00003*** (0.00001)	0.00002 (0.00001)	0.00003*** (0.00001)	0.00002* (0.00001)	0.00003** (0.00001)
Popdens	0.0003 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0004 (0.0003)	0.0003 (0.0002)	0.0002 (0.0003)	0.0002 (0.0003)
Fixed-Effects							
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observations	17,991	15,556	15,749	14,791	14,859	14,033	14,935
Number of groups	3,211	2,918	2,958	2,775	2,821	2,663	2,812
Pseudo R2	0.3071	0.2915	0.2987	0.2534	0.2679	0.2010	0.2700
Wald chi-square	71.74***	59.06***	66.93***	56.89***	47.91***	26.57***	55.20***
BIC	24091.97	20113.22	20548.8	18445.04	18819.75	17011.37	18926.14

Note: Robust standard errors in parentheses; p<0.1, ** p<0.05, *** p<0.01*

At the disaggregate level, however, the analysis of the six different KETs in the second series of models shows heterogeneous results (see Table 3). In line with our KET-specific results presented in Table 2, we find no statistically significant influence of science-driven KETs, i.e. industrial biotechnology, and nanotechnology, and of MNE, on the emergence of radical innovation in firms. However, in contrast to H2b, the results for engineering-oriented KETs do not provide a consistent picture. Only in the case of AMT (see Model 3) we find evidence for the expected substitution effect between the regional specialisation and firms' knowledge stock. As expected, firms lacking AMT-knowledge particularly benefit from being located in a region specialised in AMT. The isolated significant effect of Pat_amt highlights AMTs' relevance for radical knowledge generation and underlines the importance of AMT-knowledge in firms located outside a region specialised in AMT. This also highlights, to a certain extent, the recombinant potential of AMTs. As the most heterogeneous technology field among the KETs (Aschhoff et al. 2010), AMT is partly dependent on developments in other KETs (Aschhoff et al. 2010), but can also advance other KETs (van de Velde et al. 2012). While the effect of the number of AMT-patents is just slightly outside the significance level in the first set of calculations (see Table 2), it becomes significant in the second set (Table 3). Given the regional focus of the second series of models, we interpret this finding as AMT's tendency to unfold their effect in rather technologically weak regions. However, the influence of the two remaining engineering-oriented KETs differs in this context. For advanced materials we find that both variables (Pat_advmat, RCA_advmat_dummy) in Model 2 positively and statistically significantly influence the number of radical patents in firms. Amplifying the evidence from the first set of computations (see Table 2), advanced materials drive radical innovation at the firm-level. Thus, firms with advanced materials-knowledge are more likely to innovate radically, probably due to their pronounced GPT-nature (Aschhoff et al. 2010; Antonietti et al. 2023). Furthermore, we also find evidence for significant positive influence of a regional specialisation in advanced materials on the emergence of radical innovation in firms, while we only observe an insignificant negative interaction effect between firms' knowledge in advanced materials and the regional specialisation in advanced materials. Consequently, the results highlight the driving role of advanced materials in the emergence of radical innovation. As no substitution effect exists between a regional advanced materials specialisation and advanced materials-knowledge in firms, a firm with strong competencies in advanced materials located in such a spatial environment specialised in this KET is not necessarily impeded in radical innovation processes. In other words, we find no evidence for an adverse selection effect (Shaver & Flyer 2000), but instead knowledge in advanced materials (in firms and regions) acts as driver of radical innovation in firms. As a heterogeneous technology field (Aschhoff et al. 2010; de Heide et al. 2013), and in line with its core KET-properties, advanced materials appear to be broad enough to generate radical innovation in various settings, by providing pieces of knowledge that are sufficiently distant from other knowledge pieces to generate an entirely new recombination. Lastly, in the case of photonics we only observe a significant influence of the regional specialisation on the emergence of radical innovation in firms. While the effect of photonics on radical innovation is significant in the first regression (see Model 7 in Table 2), its isolated effect turns insignificant in the second series. The comparison of the results between the two models is not straightforward due to the inclusion of the interaction term in the second series of models. Hence, the second finding is only valid in absence of a photonics-RCA (RCA_photo_dummy = 0), i.e. regions not specialised in this technology. Consequently, we continue regarding photonics as a significant driver of radical innovation in firms. Moreover, we observe that a regional photonics specialisation (RCA_photo_dummy) exerts a significantly positive effect on radical innovation at the firm-level. Hence, a firm with no photonics patents (Pat_photo = 0) benefits from being located in a region specialised in photonics. This again highlights the role of knowledge spillovers in spatial proximity. Although it can be assumed that a sufficient absorptive capacity (Cohen & Levinthal 1990) and skills to absorb and recombine photonics-related knowledge via firm-external linkages (formal or informal) is needed. In general, cluster policies seem to be most important for photonics, in comparison to other KETs, as usually actors along the value chain are involved in (complex) recombinant activities (Aschhoff et al. 2010). Nevertheless, we find no significant interaction effect between Pat_photo and RCA_photo_dummy, so there is no robust evidence of a substitution effect. Rather, the effect of photonics-knowledge on radical innovation generation depends on the specific setting in terms of the firm's knowledge base and the spatial environment.

The results for our control variables remain robust and largely the same as those already discussed and presented in Table 2.

5 Concluding Remarks

Despite its potential economic relevance (e.g., Castaldi et al. 2015), radical innovation remains understudied in the literature stream on Key Enabling Technologies (KETs) – especially at the firm-level. Due to their unique characteristics, KETs however carry the potential to drive radical innovation as they may facilitate knowledge recombination. The present study therefore focuses on the effects of KETs on the emergence of radical innovation in firms. In addition, and in line with previous studies (e.g., Turkina et al. 2019; Grashof 2021), we also consider the corresponding regional context by empirically investigating the extent to which regional specialisation in KETs can moderate the relationship between KET knowledge and the generation of radical innovation in firms. Since KETs are relatively heterogenous (e.g., European Commission 2012) in both cases, we examine all KETs together and individually.

Regarding the aggregated perspective (i.e. KETs are not differentiated), the findings validate our assumptions. First, a higher amount of KET knowledge in firms promotes the generation of radical innovation. Our results show the high potential of KETs in recombinant innovation and also underscores that KETs are characterised by features of General Purpose Technologies (GPTs) and are enabling technologies (Teece 2018; Martinelli et al. 2021; John et al. 2022). Thanks to its horizontal, multidisciplinary nature, KET knowledge is broadly combinable with knowledge from various other fields (European Commission 2009b, 2009a; Corradini & de Propris 2017; Montresor &

Quatraro 2017). Our findings further suggest that KETs possess a bridging function in firms' knowledge bases, due to which they enable links between formerly distant and unconnected technologies (see e.g., Corradini & de Propris 2017). Because of these capabilities-enhancing properties exploratory search is enabled (Montresor & Quatraro 2020) and KETs can promote radical innovation. Second, this positive effect is negatively moderated by a regional KET-specialisation, indicating a substitution effect between the amount of KET knowledge within a firm and a regional specialisation in KETs. Thus, firms located outside a region specialised in KETs benefit more from being active in KETs themselves, while firms located within a KET-specialised region can benefit from knowledge spillovers that substitute for missing KET knowledge. However, if a firm strong in KETs is located in a KET-specialised region, a negative effect of the specialisation on radical innovation emergence at the firm-level arises. Moreover, the observed substitution effect implies that firms with little KET knowledge benefit more from regional knowledge spillovers than firms active in KETs – this is in line with the adverse selection effect highlighted by Shaver & Flyer (2000).

Nevertheless, these results mainly hold true for the aggregate KET-level. When focusing on the six particular KETs, the effects become quite heterogeneous, which is similar to previous studies examining the disaggregate level of KETs (e.g., Wanzenböck et al. 2020; Wessendorf et al. 2021). In general, however, our results tend to support the differentiation made by Wanzenböck (2020). We find evidence of differences in the influence between rather engineering-oriented KETs, i.e. advanced materials, photonics and AMT, and rather science-based KETs, i.e. industrial biotechnology, and nanotechnology, and MNE[10]. While the results of the latter stay insignificant, we find a significant influence of advanced materials and photonics on the emergence of radical innovation. Although AMT stays slightly below the threshold p-value of 0.1, when considering the regional specialisation, we do detect a statistically positive influence, showing the tendency of AMT to unfold its influence in regions with a rather weak specialisation in this technology field. Moreover, in the case of AMT, we also discover a substitution effect between firms' knowledge base and the regional specialisation, implying that the adverse selection process (e.g., Shaver & Flyer 2000) is particularly pronounced in the case of AMT, being the most heterogenous technology field among

[10] MNE is not clearly assigned to a science- or engineering-based nature, as described in section 2. However, semi-conductors, which are included in MNE tend to be rather science-based (Ponds et al. 2010; Pavitt 1984).

the KETs (Aschhoff et al. 2010).

Nevertheless, some limitations to our study need to be considered, providing opportunities for future research. First, in line with previous studies (e.g., Wessendorf et al. 2021), we use patent data, which have some known drawbacks (Griliches 1990). For instance, while patents indicate a commercial intention, not all inventions are patented and not all patents might be commercially exploited. Future research could therefore consider using non-patent-based measures coming from surveys (e.g., Hervas-Oliver et al. 2019) and/or web scraping (e.g., Kinne & Lenz 2021). Second, by measuring radical innovation through the recombination of previously unconnected knowledge pieces, we only focus on the novelty side, following other studies (e.g., Grashof et al. 2019). Future research could therefore investigate alternative patent-based measures that rather capture the impact, such as forward citations (e.g., Trajtenberg et al. 1997). Third, while we provide some reasoning for the heterogenous results with respect to the influence of individual KETs on radical innovation, future research is needed to further investigate the underlying mechanisms in more detail. In depth case studies might be useful in this regard.

Despite these limitations, our study contributes to previous research on KETs and innovation in three ways. First, we provide a more fine-grained level of analysis than previous studies (e.g., Montresor et al. 2022) by going on the firm-level. Second, our results offer more nuanced insights on KETs and their relationship with radical innovation by differentiating between the six individual KETs. Third, we contribute to a better understanding of the relevance of the regional context in studying the influence of KETs on the emergence of radical innovation in firms. In addition, our findings also bear rather practical implications for policy makers. While we do find evidence for an all overall stimulating influence of KETs on the generation of radical innovation in firms, the heterogenous results of the individual KETs call for a more technology-specific approach that differentiates between the six KETs. Moreover, our results suggest that it is crucial to be informed in advance about the specific geographic context in which a firm is located, since it may be beneficial for one firm type ('weak' firms in KETs) while detrimental for another firm type ('strong' firms in KETs). Overall, it can therefore be concluded that KETs can be one way to enable radical innovation, although they may not be the key to radical innovation for every firm.

References

Ahuja, G., Lampert, C. M. (2001): Entrepreneurship in the large corporation: A longitudinal study of how established firms create breakthrough inventons. Strat. Mgmt. J., 22 (6-7), pp. 521–543. DOI: https://doi.org/10.1002/smj.176.

Antonietti, R., Cattani, L., Gambarotto, F., Pedrini, G. (2023): Education, routine, and complexity-biased Key Enabling Technologies: evidence from Emilia-Romagna, Italy. Industry and Innovation, 30 (1), pp. 103–134. DOI: https://doi.org/10.1080/13662716.2022.2045910.

Antonietti, R., Montresor, S. (2021): Going beyond Relatedness: Regional Diversification Trajectories and Key Enabling Technologies (KETs) in Italian Regions. Economic Geography, 97 (2), pp. 187–207. DOI: https://doi.org/10.1080/00130095.2021.1920390.

Anzenbacher, A., Wagner, M. (2020): The role of exploration and exploitation for innovation success: effects of business models on organizational ambidexterity in the semiconductor industry. International Entrepreneurship and Management Journal, 16 (2), pp. 571–594. DOI: https://doi.org/10.1007/s11365-019-00604-6.

Arant, W., Fornahl, D., Grashof, N., Hesse, K., Söllner, C. (2019): University-industry collaborations—The key to radical innovations? Rev Reg Res, 39 (2), pp. 119–141. DOI: https://doi.org/10.1007/s10037-019-00133-3.

Arthur, W. B. (2007): The structure of invention. Research Policy, 36 (2), pp. 274–287. DOI: https://doi.org/10.1016/j.respol.2006.11.005.

Arts, S., Appio, F. P., van Looy, B. (2013): Inventions Shaping Technological Trajectories: Do Existing Patent Indicators Provide a Comprehensive Picture? Scientometrics, 97. DOI: https://doi.org/10.2139/ssrn.2178373.

Arts, S., Veugelers, R. (2015): Technology familiarity, recombinant novelty, and breakthrough invention. Ind Corp Change, 24 (6), pp. 1215–1246. DOI: https://doi.org/10.1093/icc/dtu029.

Aschhoff, B., Crass, D., Cremers, K., Grimpe, C., Rammer, C., Brandes, F. et al. (2010): European Competitiveness in Key Enabling Technologies: Summary Report. Centre for European Economic Research (ZEW). Mannheim.

Ayres, R. U. (1988): Barriers and breakthroughs: an “expanding frontiers” model of the technology-industry life cycle. Technovation, 7 (2), pp. 87–115. DOI: https://doi.org/10.1016/0166-4972(88)90041-7.

Bresnahan, T. F., Trajtenberg, M. (1995): General purpose technologies ‘Engines of growth’? Journal of Econometrics, 65 (1), pp. 83–108. DOI: https://doi.org/10.1016/0304-4076(94)01598-T.

Butter, M., Fischer, N., Gijsbers, G., Hartmann, C., de Heide, M., van der Zee, F. (2014): Horizon 2020: Key Enabling Technologies (KETs), Booster for European Leadership in the Manufacturing Sector. European Parliament, Directorate General for Internal Policies, Policy Department A: Economic and Scientific Policy. Brussels.

Castaldi, C., Frenken, K., Los, B. (2015): Related Variety, Unrelated Variety and Technological Breakthroughs: An analysis of US State-Level Patenting. Regional Studies, 49 (5), pp. 767–781. DOI: https://doi.org/10.1080/00343404.2014.940305.

Cohen, W. M., Levinthal, D. A. (1990): Absorptive Capacity: A New Perspective on Learning and Innovation. Administrative Science Quarterly, 35 (1), p. 128. DOI: https://doi.org/10.2307/2393553.

Corradini, C., de Propris, L. (2017): Beyond local search: Bridging platforms and inter-sectoral technological integration. Research Policy, 46 (1), pp. 196–206. DOI: https://doi.org/10.1016/j.respol.2016.09.017.

Correia, S., Guimarães, P., Zylkin, T. (2020): Fast Poisson estimation with high-dimensional fixed effects. The Stata Journal, 20 (1), pp. 95–115. DOI: https://doi.org/10.1177/1536867X20909691.

Daft, R. L., Lengel, R. H. (1986): Organizational Information Requirements, Media Richness and Structural Design. Management Science, 32 (5), pp. 554–571. DOI: https://doi.org/10.1287/mnsc.32.5.554.

Dewar, R. D., Dutton, J. E. (1986): The Adoption of Radical and Incremental Innovations: An Empirical Analysis. Management Science, 32 (11), pp. 1422–1433. DOI: https://doi.org/10.1287/mnsc.32.11.1422.

Dosi, G. (1982): Technological paradigms and technological trajectories. A suggested interpretation of the determinants and directions of technical change. Research Policy, 11 (3), pp. 147–162. DOI: https://doi.org/10.1016/0048-7333(82)90016-6.

European Commission (2009a): Current situation of key enabling technologies in Europe. Commission of the European Communities. Brussels (SEC(2009) 1257 final).

European Commission (2009b): Preparing for our future: Developing a common strategy for key enabling technologies in the EU. Commission of the European Communities. Brussels (COM(2009) 512 final). Available online at https://eur-lex.europa.eu/legal-content/en/TXT/?uri=CELEX:52009DC0512, checked on 9/24/2023.

European Commission (2012): A European strategy for Key Enabling Technologies – A bridge to growth and jobs. Commission of the European Communities. Brussels (COM(2012) 341 final). Available online at https://eur-lex.europa.eu/LexUriServ/LexUriServ.do?uri=COM:2012:0341:FIN:EN:PDF, checked on 9/24/2023.

Evangelista, R., Meliciani, V., Vezzani, A. (2018): Specialisation in key enabling technologies and regional growth in Europe. Economics of Innovation and New Technology, 27 (3), pp. 273–289. DOI: https://doi.org/10.1080/10438599.2017.1338392.

Fally, T. (2015): Structural gravity and fixed effects. Journal of International Economics, 97 (1), pp. 76–85. DOI: https://doi.org/10.1016/j.jinteco.2015.05.005.

Fleming, L. (2001): Recombinant Uncertainty in Technological Search, 47 (1), pp. 117–132. DOI: https://doi.org/10.1287/mnsc.47.1.117.10671.

Foray, D., David, P. A., Hall, B. H. (2009): Smart Specialisation: The Concept. In: European Commission (Ed.): Knowledge for Growth. Prospects for science, technology and innovation. Brussels.

Foray, D., David, P. A., Hall, B. H. (2011): Smart specialization: From academic idea to political instrument, the surprising career of a concept and the difficulties involved in its implementation. Lausanne, Switzerland (MTEI Working Paper) (2011-01).

Frenken, K., Cefis, E., Stam, E. (2015): Industrial Dynamics and Clusters: A Survey. Regional Studies, 49 (1), pp. 10–27. DOI: https://doi.org/10.1080/00343404.2014.904505.

Ganco, M., Miller, C. D., Toh, P. K. (2020): From litigation to innovation: Firms' ability to litigate and technological diversification through human capital. Strat. Mgmt. J., 41 (13), pp. 2436–2473. DOI: https://doi.org/10.1002/smj.3203.

Garcia-Vega, M. (2006): Does technological diversification promote innovation?: An empirical analysis for European firms. Research Policy, 35 (2), pp. 230–246. DOI: https://doi.org/10.1016/j.respol.2005.09.006.

Gopalakrishnan, S., Damanpour, F. (1997): A review of innovation research in economics, sociology and technology management. Omega, 25 (1), pp. 15–28. DOI: https://doi.org/10.1016/S0305-0483(96)00043-6.

Grashof, N. (2021): Spill over or Spill out? – A multilevel analysis of the cluster and firm performance relationship. Industry and Innovation, 28 (10), p. 1298. DOI: https://doi.org/10.1080/13662716.2021.1967728.

Grashof, N., Basilico, S. (2023): The dark side of green innovation? Green transition and regional inequality in Europe. Utrecht (Papers in Evolutionary Economic Geography (PEEG)) (23.14).

Grashof, N., Fornahl, D. (2021): "To be or not to be" located in a cluster?—A descriptive meta-analysis of the firm-specific cluster effect. Ann Reg Sci, 67 (3), pp. 541–591. DOI: https://doi.org/10.1007/s00168-021-01057-y.

Grashof, N., Hesse, K., Fornahl, D. (2019): Radical or not? The role of clusters in the emergence of radical innovations. European Planning Studies, 27 (10), pp. 1904–1923. DOI: https://doi.org/10.1080/09654313.2019.1631260.

Grashof, N., Kopka, A. (2023): Artificial intelligence and radical innovation: an opportunity for all companies? Small Bus Econ, 61 (2), pp. 771–797. DOI: https://doi.org/10.1007/s11187-022-00698-3.

Grashof, N., Kopka, A., Wessendorf, C., Fornahl, D. (2021): Industry 4.0 and clusters: complementaries or substitutes in firm's knowledge creation? Competitiveness Review: An International Business Journal, 83 (1), pp. 83–105. DOI: https://doi.org/10.1108/CR-12-2019-0162.

Griliches, Z. (1990): Patent Statistics as Economic Indicators: A Survey. Journal of Economic Literature, 28 (4), pp. 1661–1707.

de Heide, M., Butter, M., Kappen, D., Thielmann, A., Braun, A., Meister, M. et al. (2013): Vision and characteristics of multi KETs pilot lines. Intermediary report (Draft 5.0).

Helpman, E. (1998): General purpose technologies and economic growth. Cambridge, Mass.: MIT Press.

Helpman, E., Trajtenberg, M. (1994): A Time to Sow and a Time to Reap: Growth Based on General Purpose Technologies. Cambridge, MA, USA (NBER Working Paper Series) (4854).

Hervas-Oliver, J.-L., Sempere-Ripoll, F., Estelles-Miguel, S., Rojas-Alvarado, R. (2019): Radical vs incremental innovation in Marshallian Industrial Districts in the Valencian Region: what prevails? European Planning Studies, 27 (10), pp. 1924–1939. DOI: https://doi.org/10.1080/09654313.2019.1638887.

Hervas-Oliver, J.-L., Sempere-Ripoll, F., Rojas Alvarado, R., Estelles-Miguel, S. (2018): Agglomerations and firm performance: who benefits and how much? Regional Studies, 52 (3), pp. 338–349. DOI: https://doi.org/10.1080/00343404.2017.1297895.

Hesse, K. (2020a): Drivers and mechanisms of the emergence and diffusion. Dissertation at the University of Bremen.

Hesse, K. (2020b): Related to whom? The impact of organisational and regional capabilities on radical breakthroughs (Bremen Papers on Economics & Innovation) (2005). Available online at https://media.suub.uni-bremen.de/bitstream/elib/4238/4/ierp%20working%20paper_Hesse_n.pdf.

Hesse, K., Fornahl, D. (2020): Essential ingredients for radical innovations? The role of (un-)related variety and external linkages in Germany. Pap Reg Sci, 99 (5), pp. 1165–1183. DOI: https://doi.org/10.1111/pirs.12527.

Jaffe, A. B., Trajtenberg, M., Henderson, R. (1993): Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. THE QUARTERLY JOURNAL OF ECONOMICS, 108 (3), pp. 577–598. DOI: https://doi.org/10.2307/2118401.

John, N., Wesseling, J. H., Worrell, E., Hekkert, M. (2022): How key-enabling technologies' regimes influence sociotechnical transitions: The impact of artificial intelligence on decarbonization in the steel industry. Journal of Cleaner Production, 370, p. 133624. DOI: https://doi.org/10.1016/j.jclepro.2022.133624.

Joint European Disruptive Initiative (**JEDI) (2023):** JEDI. The European ARPA. Edited by Joint European Disruptive Initiative (JEDI). Joint European Disruptive Initiative (JEDI). Available online at https://www.jedi.foundation/, updated on 2023, checked on 20th April 2023.

Kinne, J., Lenz, D. (2021): Predicting innovative firms using web mining and deep learning. PloS one, 16 (4), e0249071. DOI: https://doi.org/10.1371/journal.pone.0249071.

Knoben, J., Arikan, A. T., van Oort, F., Raspe, O. (2016): Agglomeration and firm performance: One firm's medicine is another firm's poison. Environment and Planning A: Economy and Space, 48 (1), pp. 132–153. DOI: https://doi.org/10.1177/0308518X15602898.

Knuepling, L., Wessendorf, C., Basilico, S. (2022): Revisiting innovation typology: A systemic approach. Jena (JENA ECONOMIC RESEARCH PAPERS) (2022-22).

Kopka, A., Grashof, N. (2022): Artificial intelligence: Catalyst or barrier on the path to sustainability? TECHNOLOGICAL FORECASTING AND SOCIAL CHANGE, 175, p. 121318. DOI: https://doi.org/10.1016/j.techfore.2021.121318.

Kovacs, A., Marullo, C., Verhoeven, D., van Looy, B. (2019): Radical, Disruptive, Discontinuous and Breakthrough Innovation: more of the same? FEB Research Report. KU Leuven (Management, Strategy and Innovation (MSI), MSI_1904).

Larsen, P. B., van de Velde, E., Durnick, E., Piester, H. N., Jakobsen, L., Shapiro, H. (2011): Cross-sectoral Analysis of the Impact of International industrial Policy on Key Enabling Technologies. Within the Framework Contract Sectoral Competitiveness ENTR/06/054. Final Report - 28th May, 2011. With assistance of Danish Technological Institute (DTI), IDEA Consult. Edited by European Commission, DG Enterprise and Industry. European Commission. Copenhagen, Denmark.

Leten, B., Belderbos, R., van Looy, B. (2007): Technological Diversification, Coherence, and Performance of Firms. Journal of Product Innovation Management, 24 (6), pp. 567–579. DOI: https://doi.org/10.1111/j.1540-5885.2007.00272.x.

March, J. G. (1991): Exploration and Exploitation in Organizational Learning. Organization Science, 2 (1), pp. 71–87.

Marshall, A. (1920): Principles of Economics. 8th ed. London: Macmillan.

Martinelli, A., Mina, A., Moggi, M. (2021): The enabling technologies of industry 4.0: examining the seeds of the fourth industrial revolution. Industrial and Corporate Change, 30 (1), pp. 161–188. DOI: https://doi.org/10.1093/icc/dtaa060.

Mascitelli, R. (2000): From experience: harnessing tacit knowledge to achieve breakthrough innovation. J Prod Innov Manag, 17 (3), pp. 179–193. DOI: https://doi.org/10.1016/S0737-6782(00)00038-2.

Mewes, L., Broekel, T. (2020): Subsidized to change? The impact of R&D policy on regional technological diversification. Ann Reg Sci, 65 (1), pp. 221–252. DOI: https://doi.org/10.1007/s00168-020-00981-9.

Montresor, S., Orsatti, G., Quatraro, F. (2022): Technological novelty and key enabling technologies: evidence from European regions. Economics of Innovation and New Technology, 97 (2), pp. 1–22. DOI: https://doi.org/10.1080/10438599.2022.2038147.

Montresor, S., Quatraro, F. (2017): Regional Branching and Key Enabling Technologies: Evidence from European Patent Data. Economic Geography, 93 (4), pp. 367–396. DOI: https://doi.org/10.1080/00130095.2017.1326810.

Montresor, S., Quatraro, F. (2020): Green technologies and Smart Specialisation Strategies: a European patent-based analysis of the intertwining of technological relatedness and key enabling technologies. Regional Studies, 54 (10), pp. 1354–1365. DOI: https://doi.org/10.1080/00343404.2019.1648784.

Nerkar, A. (2003): Old Is Gold? The Value of Temporal Exploration in the Creation of New Knowledge. Management Science, 49 (2), pp. 211–229. DOI: https://doi.org/10.1287/mnsc.49.2.211.12747.

Nooteboom, B. (2000): Learning by Interaction: Absorptive Capacity, Cognitive Distance and Governance. Journal of Management and Governance, 4, pp. 69–92. DOI: https://doi.org/10.1023/A:1009941416749.

O'Connor, G. C. (1998): Market Learning and Radical Innovation: A Cross Case Comparison of Eight Radical Innovation Projects. Journal of Product Innovation Management, 15 (2), pp. 151–166. DOI: https://doi.org/10.1016/s0737-6782(97)00078-7.

Pavitt, K. (1984): Sectoral patterns of technical change: towards a taxonomy and a theory. Research Policy, 13, pp. 343–373.

Ponds, R., van Oort, F., Frenken, K. (2010): Innovation, spillovers and university–industry collaboration: an extended knowledge production function approach. Journal of Economic Geography, 10 (2), pp. 231–255. DOI: https://doi.org/10.1093/jeg/lbp036.

Quintana-García, C., Benavides-Velasco, C. A. (2008): Innovative competence, exploration and exploitation: The influence of technological diversification. Research Policy, 37 (3), pp. 492–507. DOI: https://doi.org/10.1016/j.respol.2007.12.002.

Rigby, D. L. (2015): Technological Relatedness and Knowledge Space: Entry and Exit of US Cities from Patent Classes. Regional Studies, 49 (11), pp. 1922–1937. DOI: https://doi.org/10.1080/00343404.2013.854878.

Rosenberg, N. (2004): Innovation and Economic Growth. Paris: OECD.

Schaffer, M. E., Stillman, S. (2010): xtoverid: stata module to calculate tests of overidentifying restrictions after xtreg, xtivreg, xtivreg2 and xthtaylor. Available online at http://ideas. repec.org/c/boc/bocode/s456779.html, checked on 10/4/2023.

Schlegel, T., Backes-Gellner, U. (2023): The role of fields of study for the effects of higher education institutions on regional firm location. Small Bus Econ. DOI: https://doi.org/10.1007/s11187-023-00742-w.

Schoenmakers, W., Duysters, G. (2010): The technological origins of radical inventions. Research Policy, 39 (8), pp. 1051–1059. DOI: https://doi.org/10.1016/j.respol.2010.05.013.

Schumpeter, J. A. (1939): Business Cycles. New York: McGraw-Hill Book Company, Inc.

Shaver, J. M., Flyer, F. (2000): Agglomeration economies, firm heterogeneity, and foreign direct investment in the United States. Strat. Mgmt. J., 21 (12), pp. 1175–1193. DOI: https://doi.org/10.1002/1097-0266(200012)21:12<1175::AID-SMJ139>3.0.CO;2-Q.

Shkolnykova, M., Kudic, M. (2022): Who benefits from SMEs' radical innovations - empirical evidence from German biotechnology. Small Bus Econ, 58 (2), pp. 1157–1185. DOI: https://doi.org/10.1007/s11187-021-00464-x.

SprinD GmbH (2023): SPRIN-D. Federal Agency For Disruptive Innovation. A home for people with radical new ideas. Edited by SprinD GmbH. SprinD GmbH. Available online at https://www.sprind.org/en/, updated on 2023, checked on 20th April 2023.

Teece, D. J. (2018): Profiting from innovation in the digital economy: Enabling technologies, standards, and licensing models in the wireless world. Research Policy, 47 (8), pp. 1367–1387. DOI: https://doi.org/10.1016/j.respol.2017.01.015.

Trajtenberg, M., Henderson, R., Jaffe, A. (1997): University Versus Corporate Patents: A Window On The Basicness Of Invention. Economics of Innovation and New Technology, 5 (1), pp. 19–50. DOI: https://doi.org/10.1080/10438599700000006.

Turkina, E., Oreshkin, B., Kali, R. (2019): Regional innovation clusters and firm innovation performance: an interactionist approach, 53 (8), pp. 1193–1206. DOI: https://doi.org/10.1080/00343404.2019.1566697.

van de Velde, E., Rammer, C., de Heide, M., Pinaud, F., Verbeek, A., Gehrke, B. et al. (2012): Feasibility study for an EU Monitoring Mechanism on Key Enabling Technologies. Edited by European Union. IDEA Consult; Center for European Economic Research (ZEW); TNO; CEA, checked on 12/11/2020.

van de Velde, E., Rammer, C., Schliessler, P., Gehrke, B., Wassmann, P., de Heide, M. et al. (2015): Key Enabling Technologies (KETs) Observatory. Methodology Report.

Verhoeven, D., Bakker, J., Veugelers, R. (2016): Measuring technological novelty with patent-based indicators. Research Policy, 45 (3), pp. 707–723. DOI: https://doi.org/10.1016/j.respol.2015.11.010.

Verspagen, B. (2005): Innovation and economic growth. In: Fagerberg, J., Mowery, D. C., Nelson, R. R. (Eds.): The Oxford handbook of innovation. Oxford: Oxford University Press.

Wanzenböck, I., Neuländtner, M., Scherngell, T. (2020): Impacts of EU funded R&D networks on the generation of key enabling technologies: Empirical evidence from a regional perspective. Pap Reg Sci, 99 (1), pp. 3–24. DOI: https://doi.org/10.1111/pirs.12473.

Weitzmann, M. (1998): Recombinant Growth. THE QUARTERLY JOURNAL OF ECONOMICS, 113 (2), pp. 331–360.

Wessendorf, C., Kopka, A., Fornahl, D. (2021): The impact of the six European Key Enabling Technologies (KETs) on regional knowledge creation. Utrecht (Papers in Evolutionary Economic Geography (PEEG)) (21.27).

Wooldridge, J. M. (1999): Distribution-free estimation of some nonlinear panel data models. Journal of Econometrics, 90 (1), pp. 77–97. DOI: https://doi.org/10.1016/S0304-4076(98)00033-5.

Wooldridge, J. M. (2002): Econometric analysis of cross section and panel data. Cambridge, Mass: MIT Press.

Appendix

Appendix 1: List of KETs - International Patent Classification (IPC) codes

Nano-tech.	**Photonics**	**Industrial Biotech.**	**Advanced Materials**	**Micro- & Nano-electr. (MNE)**	**Advanced Manufacturing Technology (AMT)**		
B82Y	F21K	C02F 3/34	B32B 9	G01R 31/26	B01D 15	C04B 11/028	C21C 5/52
B81C	F21V	C07C 29	B32B 15	G01R 31/27	B01D 67	C04B 35/622	C21C 5/54
B82B	F21Y	C07D 475	B32B 17	G01R 31/28	B01J 10	C04B 35/624	C21C 5/56
	G01D 5/26	C07K 2	B32B 18	G01R 31/303	B01J 12	C04B 35/626	C21C 7
	G01D 5/58	C08B 3	B32B 19	G01R 31/304	B01J 13	C04B 35/653	C21D
	G01D 15/14	C08B 7	B32B 25	G01R 31/317	B01J 14	C04B 35/657	C22B 11
	G01G 23/32	C08H 1	B32B 27	G01R 31/327	B01J 15	C04B 37	C22B 21
	G01J	C08L 89	B82Y 30	G09G 3/14	B01J 16	C04B 38/02	C22B 26
	G01L 1/24	C09D 11	C01B 31	G09G 3/32	B01J 19/02	C04B 38/10	C22B 4
	G01L 3/08	C09D 189	C01D 15	H01F 1/40	B01J 19/08	C04B 40	C22B 59
	G01L 11/02	C09J 189	C01D 17	H01F 10/193	B01J 19/18	C04B 7/60	C22B 9
	G01L 23/06	C12M	C01F 13	H01G 9/028	B01J 19/20	C04B 9/20	C22C 1
	G01M 11	C12P	C01F 15	H01G 9/032	B01J 19/22	C07C 17/38	C22C 3
	G01P 3/36	C12Q	C01F 17	H01H 47/32	B01J 19/24	C07C 2/08	C22C 33
	G01P 3/38	C12S	C03C	H01H 57	B01J 19/26	C07C 2/46	C22C 35
	G01P 3/68	C07K 14/435	C04B 35	H01S 5	B01J 19/28	C07C 2/52	C22C 47
	G01P 5/26	C07K 14/47	C08F	H01L	B01J 20/30	C07C 2/58	C22F
	G01Q 20/02	C07K 14/705	C08J 5	H03B 5/32	B01J 21/20	C07C 2/80	C23C 14/56
	G01Q 30/02	C07K 16/18	C08L	H03C 3/22	B01J 23/90	C07C 201/16	C23C 16/54
	G01Q 60/06	C07K 16/28	C22C	H03F 3/04	B01J 23/92	C07C 209/82	C25B 9
	G01Q 60/18	C12N 15/09	C23C	H03F 3/06	B01J 23/94	C07C 213/10	C25B 15/02
	G01R 15/22	C12N 15/11	D21H 17	H03F 3/08	B01J 23/96	C07C 227/38	C25C
	G01R 15/24	C12N 15/12	G02B 1	H03F 3/10	B01J 25/04	C07C 231/22	C25D 1
	G01R 23/17	C12N 5/10	H01B 3	H03F 3/12	B01J 27/28	C07C 249/14	C30B 15/20
	G01R 31/308	C12P 21/08	H01F 1/0	H03F 3/14	B01J 27/30	C07C 253/32	C30B 35
	G01R 33/032	C12Q 1/68	H01F 1/12	H03F 3/16	B01J 27/32	C07C 263/18	C40B 60
	G01R 33/26	G01N 33/15	H01F 1/34	H03F 3/183	B01J 29/90	C07C 269/08	D01D 10
	G01S 7/481	G01N 33/50	H01F 1/42	H03F 3/21	B01J 31/40	C07C 273/14	D01D 11
	G01V 8	G01N 33/53	H01F 1/44	H03F 3/343	B01J 38	C07C 277/06	D01D 13
	G02B 5	G01N 33/68	H01L 51/30	H03F 3/387	B01J 39/26	C07C 29/74	D01F 9/133
	G02B 13/14	G01N 33/566	H01L 51/46	H03F 3/55	B01J 41/20	C07C 303/42	D01F 9/32
	G03B 42	C12N 1/19	H01L 51/54	H03K 17/72	B01J 47	C07C 315/06	D06B 23/20
	G03G 21/08	C12N 1/21		H05K 1	B01J 49	C07C 319/26	D21H 23/20
	G06E	C12N 1/15		B82Y 25	B01J 8/06	C07C 37/68	D21H 23/70
	G06F 3/042	C12N 15/00			B01J 8/14	C07C 4/04	D21H 23/74
	G06K 9/58	C12N 15/10			B01J 8/24	C07C 4/06	D21H 23/78
	G06K 9/74	C12P 21/02			B01J 10	C07C 4/16	D21H 27/22

Nano-tech.	Photonics	Industrial Biotech.	Advanced Materials	Micro- & Nano-electr. (MNE)	Advanced Manufacturing Technology (AMT)		
	G06N 3/067				B01L	C07C 4/18	F24J 1
	G08B 13/186				B04B	C07C 41/34	F25J 3
	G08C 19/36				B04C	C07C 41/58	F25J 5
	G08C 23/04				B32B 37	C07C 45/78	F27B 17
	G08C 23/06				B32B 38	C07C 45/90	F27B 19
	G08G 1/04				B32B 39	C07C 46/10	F27D 19
	G11B 7/12				B32B 41	C07C 47/058	F27D 7/06
	G11B 7/125				B81C 3	C07C 47/09	G01C 19/5628
	G11B 7/13				B82B 3	C07C 5/333	G01C 19/5663
	G11B 7/135				B82Y 35	C07C 5/41	G01C 19/5769
	G11B 11/03				B82Y 40	C07C 51/42	G01C 25
	G11B 11/12				C01B 17/20	C07C 51/573	G01R 3
	G11B 11/18				C01B 17/62	C07C 51/64	G11B 7/22
	G11C 11/42				C01B 17/80	C07C 57/07	H01L 21
	G11C 13/04				C01B 17/96	C07C 67/48	H01L 31/18
	G11C 19/30				C01B 21/28	C07C 68/08	H01L 35/34
	H01J 3				C01B 21/32	C07C 7	H01L 39/24
	H01J 5/16				C01B 21/48	C07D 201/16	H01L 41/22
	H01J 29/46				C01B 25/232	C07D 209/84	H01L 43/12
	H01J 29/82				C01B 31/24	C07D 213/803	H01L 51/40
	H01J 29/89				C01B 9	C07D 251/62	H01L 51/48
	H01J 31/50				C01C 1/28	C07D 301/32	H01L 51/56
	H01J 37/04				C01D 1/28	C07D 311/40	H01S 3/08
	H01J 37/05				C01D 3/14	C07D 499/18	H01S 3/09
	H01J 49/04				C01D 5/16	C07D 501/12	H01S 5/04
	H01J 49/06				C01D 7/22	C07F 7/20	H01S 5/06
	H01L 31/052				C01D 9/16	C07H 1/06	H01S 5/10
	H01L 31/055				C01F 1	C07K 1	H05B 33/10
	H01L 31/10				C01G 1	C08B 1/10	H05K 13
	H01L 33/06				C02F 11/02	C08B 17	H05K 3
	H01L 33/08				C02F 11/04	C08B 30/16	
	H01L 33/10				C02F 3	C08C	
	H01L 33/18				C03B 20	C08F 2/01	
	H01L 51/50				C03B 5/24	C09B 41	
	H01L 51/52				C03B 5/173	C09B 67/54	
	H01S 3				C03B 5/237	C09D 7/14	
	H01S 5				C03B 5/02	C09J5	
	H02N 6				C03C 21	C12M	
	H05B 33				C03C 29	C12S	

(Source: van de Velde et al. 2012)

Appendix 2: Pairwise Correlation Matrix

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Rad	1.000											
(2) pat_ket_all	0.539***	1.000										
(3) pat_ket_advanc~l	0.396***	0.675***	1.000									
(4) pat_ket_amt	0.415***	0.785***	0.490***	1.000								
(5) pat_ket_biotech	0.376***	0.567***	0.628***	0.551***	1.000							
(6) pat_ket_micro_~o	0.305***	0.762***	0.168***	0.760***	0.377***	1.000						
(7) pat_ket_nanotech	0.389***	0.594***	0.221***	0.648***	0.287***	0.536***	1.000					
(8) pat_ket_photon~s	0.384***	0.680***	0.123***	0.283***	0.316***	0.458***	0.377***	1.000				
(9) rca_dummy	-0.002	0.011***	0.009***	0.007***	0.016***	0.005***	0.000	0.006***	1.000			
(10) rca_dummy_adv~t	-0.020***	-0.011***	0.003**	-0.008***	-0.008***	-0.010***	-0.004***	-0.012***	0.274***	1.000		
(11) rca_dummy_amt	-0.016***	-0.006***	-0.005***	0.001	-0.005***	0.000	-0.001	-0.009***	0.270***	0.315***	1.000	
(12) rca_dummy_bio~h	-0.016***	-0.007***	-0.006***	-0.007***	0.010***	-0.002	-0.003**	-0.009***	0.197***	0.194***	0.261***	1.000
(13) rca_dummy_mic~o	-0.019***	-0.010***	-0.013***	-0.006***	-0.017***	0.000	0.001	-0.002	0.099***	0.243***	0.317***	0.161***
(14) rca_dummy_nano	-0.014***	-0.010***	-0.008***	-0.006***	-0.016***	-0.003**	-0.002	-0.005***	-0.057***	0.163***	0.173***	0.044***
(15) rca_dummy_photo	-0.015***	-0.007***	-0.012***	-0.007***	-0.013***	0.000	0.000	0.005***	0.099***	0.170***	0.216***	0.166***
(16) mitarbeiter_ln	0.125***	0.101***	0.079***	0.097***	0.074***	0.053***	0.040***	0.053***	-0.024***	-0.021***	-0.023***	-0.024***
(17) Pat_nonket_upd	0.579***	0.469***	0.322***	0.401***	0.329***	0.313***	0.566***	0.304***	-0.003**	-0.021***	-0.016***	-0.016***
(18) HHI	0.100***	0.084***	0.064***	0.079***	0.074***	0.047***	0.031***	0.048***	0.003**	-0.034***	-0.013***	-0.014***
(19) GDPpc	0.053***	0.043***	0.027***	0.034***	0.038***	0.028***	0.008***	0.022***	0.040***	-0.278***	-0.218***	-0.134***
(20) Popdens	0.034***	0.023***	0.023***	0.013***	0.036***	0.006***	0.003**	0.009***	0.135***	-0.111***	-0.060***	0.050***

(continued on next page)

(Appendix 2, continued from previous page)

Variables	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
(13) rca_dummy_mic~o	1.000							
(14) rca_dummy_nano	0.223***	1.000						
(15) rca_dummy_photo	0.330***	0.144***	1.000					
(16) mitarbeiter_ln	-0.042***	0.004**	-0.023***	1.000				
(17) Pat_nonket_upd	-0.018***	-0.017***	-0.013***	0.144***	1.000			
(18) HHI	-0.038***	-0.030***	-0.013***	0.152***	0.044***	1.000		
(19) GDPpc	-0.326***	-0.277***	-0.246***	0.045***	0.060***	0.034***	1.000	
(20) Popdens	-0.165***	-0.222***	-0.049***	0.071***	0.044***	0.018***	0.480***	1.000

(Source: Authors' own computations)

Appendix 3: Conditional Fixed-Effects Poisson Regression Results

	Dependent variable: Number of radical patents t+1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pat_ket	0.005** (0.002)						
Pat_advmat		0.008*** (0.003)					
Pat_amt			0.005 (0.004)				
Pat_biotech				0.004 (0.010)			
Pat_micronano					-0.002 (0.002)		
Pat_nanotech						0.012 (0.015)	
Pat_photo							0.009*** (0.002)
Employees_ln	0.126** (0.053)	0.098** (0.050)	0.181*** (0.058)	0.153*** (0.058)	0.164** (0.064)	0.121** (0.059)	0.127** (0.065)
Pat_nonket	0.001*** (0.0003)	0.0004* (0.0002)	0.001*** (0.0003)	0.001*** (0.0004)	0.001** (0.0004)	0.001 (0.001)	0.001*** (0.0003)
Inv_HHI	0.136* (0.072)	0.206*** (0.076)	0.118 (0.076)	0.228*** (0.081)	0.152* (0.078)	0.213** (0.087)	0.156** (0.078)
GDPpc	0.00002 (0.00001)	0.00003** (0.00001)	0.00003*** (0.00001)	0.00002 (0.00001)	0.00003** (0.00001)	0.00002 (0.00001)	0.00003** (0.00001)
Popdens	0.0003 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0004 (0.0004)	0.0003 (0.0003)	0.0002 (0.0003)	0.0002 (0.0003)
Fixed-Effects							
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observ.	18,693	16,201	16,374	15,409	15,473	14,646	15,558
Number of groups	3,307	3,010	3,048	2,865	2,910	2,751	2,902
Wald chi-square	105.60***	115.73***	89.96***	69.08***	90.21***	103.80***	131.21***
BIC	16892.25	13750.67	14052.65	12509.8	12730.94	11418.27	12854.64

*Note: Robust standard errors in parentheses; *p<0.1, ** p<0.05, *** p<0.01*

(Source: Authors' own computations)

Appendix 4: Conditional Fixed-Effects Poisson Regression Results with Regional Influence

	Dependent variable: Number of radical patents t+1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Pat_ket	0.008*** (0.002)						
RCA_ket_dummy	0.007 (0.045)						
*RCA_ket_dummy*Pat_ket*	-0.004*** (0.001)						
Pat_advmat		0.011*** (0.004)					
RCA_advmat_dummy		0.095** (0.045)					
*RCA_advmat_dummy * Pat_advmat*		-0.005 (0.004)					
Pat_amt			0.012** (0.005)				
RCA_amt_dummy			0.060 (0.040)				
*RCA_amt_dummy*Pat_amt*			-0.007** (0.003)				
Pat_biotech				-0.001 (0.035)			
RCA_biotech_dummy				-0.027 (0.049)			
*RCA_biotech_dummy * Pat_biotech*				0.005 (0.034)			
Pat_micronano					0.0002 (0.003)		
RCA_micronano_dummy					-0.049 (0.045)		
*RCA_micronano_dummy * Pat_micronano*					-0.002* (0.001)		
Pat_nanotech						0.0002 (0.020)	
RCA_nanotech_dummy						-0.042 (0.064)	
*RCA_nanotech_dummy * Pat_nanotech*						0.013 (0.019)	
Pat_photo							0.008 (0.006)
RCA_photo_dummy							0.097** (0.042)
*RCA_photo_dummy*Pat_photo*							0.001 (0.005)

(continued on next page)

(Appendix 4, continued from previous page)

	Dependent variable: Number of radical patents t+1						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Employees_ln	0.137** (0.054)	0.113** (0.051)	0.186*** (0.059)	0.163*** (0.059)	0.176*** (0.065)	0.134** (0.060)	0.140** (0.066)
Pat_nonket	0.001*** (0.0003)	0.0004* (0.0002)	0.001*** (0.0002)	0.001*** (0.0003)	0.001** (0.0003)	0.001 (0.001)	0.001*** (0.0004)
Inv_HHI	0.138* (0.073)	0.204*** (0.077)	0.131* (0.075)	0.233*** (0.081)	0.150* (0.079)	0.221** (0.088)	0.164** (0.079)
GDPpc	0.00002 (0.00001)	0.00003** (0.00001)	0.00003*** (0.00001)	0.00002 (0.00001)	0.00003** (0.00001)	0.00002 (0.00001)	0.00003** (0.00001)
Popdens	0.0003 (0.0002)	0.0001 (0.0002)	0.0001 (0.0002)	0.0004 (0.0004)	0.0003 (0.0003)	0.0002 (0.0003)	0.0002 (0.0003)
Fixed-Effects							
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of observ.	17,991	15,556	15,749	14,791	14,859	14,033	14,935
Number of groups	3,211	2,918	2,958	2,775	2,821	2,663	2,812
Wald chi-square	143.75***	125.44***	105.51***	84.20***	113.59***	118.16***	146.01***
BIC	16470.94	13363.27	13676.36	12149.51	12369.89	11058.37	12482.94

*Note: Robust standard errors in parentheses; *p<0.1, ** p<0.05, *** p<0.01*

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