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Key enabling technologies (KETs) in the technological space: embeddedness and regional knowledge creation

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ABSTRACT

This study investigates the impact of European Key Enabling Technologies (KETs) on regional innovation. KETs are a group of six technologies that share features with General-Purpose Technologies and are anticipated to contribute to innovation, Europe's industrial competitiveness, and tackling grand societal challenges. As previous studies show innovation-driving effects of KETs, we are interested in the role of KETs in the regional technological space and its effect on innovation within a region. We analyse data from 141 German Labor Market Regions (LMRs) over a 15-year period and find varying and even negative impacts of individual KETs on regional knowledge creation. These findings emphasize KETs' heterogeneity and the need for tailored regional policies.

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1. Introduction

In the past decade, a group of six technologies gained prominence at the level of European politics, as they were summarized under the umbrella term of 'Key Enabling Technologies' (KETs) by the European Commission (EC) in 2009: Advanced materials, advanced manufacturing technology (AMT), industrial biotechnology, micro- and nanoelectronics (MNE), nanotechnology, and photonics. These horizontal technologies are enabling technologies (Martinelli, Mina, and Moggi 2021; Teece 2018), i.e. they have a high transformative potential and share at least two features of General-Purpose Technologies (GPTs): The potential for continuous technological improvement and technological/innovational complementarities (John et al. 2022; Martinelli, Mina, and Moggi 2021; Teece 2018). KETs potentially occur pervasively across many sectors because of their broad applicability (Corradini and de Propris 2017; European Commission 2009a, 2009b; Martinelli, Mina, and Moggi 2021; Teece 2018; van de Velde et al. 2015). As the concept of KETs entails GPT-features, they are expected to be key technologies in tackling grand societal challenges, like the climate change or an ageing society,

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and to significantly increase successful regional economic development (European Commission 2009a, 2009b, 2012). Moreover, KETs function as bridging platforms (Corradini and de Propris 2017), i.e. they serve as an interface for the recombination of various technologies, which enables innovation. Their recombinant potential and co-invention opportunities also rendered them central to smart specialization strategies (Foray, David, and Hall 2009; Montresor and Quatraro 2017). The main aspect of KETs, therefore, is their innovation-driving force through their function as bridging knowledge brokers. Janssen and Abbasiharofteh (2022) found, for example, that for a collaborative R&D process in KET topics, cognitive proximity is less important for tie formation, highlighting their linking effect of distant knowledge sources.

The political designation of the KET-label was followed by several studies on the group of KETs at the regional level that primarily focus on their potential effects and largely confirm them. Topics include KETs in the context of smart specialization and regional branching (Montresor and Quatraro 2017, 2019), regional diversification trajectories (Antonietti and Montresor 2021), regional knowledge creation in R&D networks (Wanzenböck, Neuländtner, and Scherngell 2020), KETs' impact on specialization and regional economic growth (Evangelista, Meliciani, and Vezzani 2018, 2019), the impact of KETs on occupation, tasks, and skills at the regional level (Antonietti et al. 2023), and KETs' impact on radical innovation (Montresor, Orsatti, and Quatraro 2022; Wessendorf and Grashof 2023). All of these studies have in common, that they focused mainly on the presence of KETs when assessing their effects, usually analysing them based on the number or the share of KET patents (e.g. Montresor, Orsatti, and Quatraro 2022; Wanzenböck, Neuländtner, and Scherngell 2020), by considering patent citations (e.g. Antonietti and Montresor 2021; Ardito, Natalicchio, and Messeni Petruzzelli 2023; Corradini and de Propris 2017), or by constructing specialization indicators, such as a revealed technological advantage (RTA) (e.g. Evangelista, Meliciani, and Vezzani 2018; Montresor and Quatraro 2017; Montresor and Quatraro 2019).

Thus, these studies lack the notion of the importance of KET knowledge within the regional knowledge structure, as a key mechanism of the innovation-spawning effect of KETs is their bridging function (Corradini and de Propris 2017). Consequently, the components of the embeddedness of KETs into the knowledge base at the regional level remain largely unexplored. This study, therefore, focuses on the network position of KETs within the regional knowledge base and its innovation-driving force, based on KETs' bridging properties. The bridging function of KETs may shape regional knowledge bases by generating links between different technology fields and by making the knowledge base more cohesive. They further could contribute to a better flow of ideas and knowledge throughout the regional knowledge base. Thus, it is assumed that KETs occupying a central role in the knowledge base enhance the potential for recombinant innovation. Therefore, this study investigates whether KETs have a stronger impact on the regional innovation output when they occupy central positions in the regional knowledge base and, thus, are structurally relevant. The 141 German Labor Market Regions (LMRs), as defined by Kosfeld and Werner (2012), serve as spatial units of analysis for this study. LMRs are functionally defined and larger than municipalities (NUTS3) but more fine-grained than the federal state level (NUTS2). Their critical feature for our analyses is that they consider commuter traffic (Kosfeld and Werner 2012). By using LMRs, the analyses, thus, incorporate that the knowledge relevant for innovations is embedded in persons that may reside in a wider area around their municipality of employment (Kosfeld and Werner 2012). To address the structural relevance of KETs and the KET-specific dimensions, a regional knowledge space is constructed based on patent data (knowledge/technology networks mapping the relatedness of technologies) (e.g. Boschma, Balland, and Kogler 2015; Hidalgo et al. 2007; Neffke, Henning, and Boschma 2011) and measures of social network analysis (SNA) are applied.

The remainder of this paper is structured as follows: Section 2 provides the literature background and hypotheses. Section 3 describes the data used and methodology applied. The results are presented in Section 4 and discussed in Section 5. Section 6 concludes.

2. Background

Technological innovation has been acknowledged as an important factor for economic growth (Rosenberg 2004; Verspagen 2005). It is generally described as a cumulative process, where existing knowledge is combined in new ways (Arthur 2007; Basalla 1988). This notion of recombining existing knowledge to generate new knowledge was coined as 'recombinant innovation' by Weitzmann (1998). Factors that influence the successful emergence of innovations have been discussed extensively in the literature. A central mechanism to access (complementary) knowledge that is beneficial for innovation processes are knowledge spillovers. These can occur unintentionally, for instance, through leakages and informal face-to-face contacts, or intentionally, through formal collaborations, like strategic alliances (Baptista and Swann 1998; Bathelt, Malmberg, and Maskell 2004; McCann and Folta 2011; Shaver and Flyer 2000). It is generally accepted that actors involved in innovation need an optimal degree of proximity to be able to successfully recombine knowledge elements. Different concepts of proximity have been addressed in the literature: Geographical, organizational, cognitive, social, and institutional proximity (Boschma 2005). Addressing these forms of proximity separately would go beyond the scope of this paper, but we want to highlight that, overall, a lack of proximity between actors in these dimensions (i.e. a too large distance) may impede the combination of knowledge elements. In contrast, if the proximity is too high, a recombination of knowledge will lack the necessary novelty[1] (Boschma 2005; Nooteboom 2000). Within a regional knowledge space, consisting of the region's technological knowledge and the connections within a region, so-called bridging platforms can help facilitate recombinant innovation growth through combining previously unconnected knowledge artifacts (Corradini and de Propris 2017). In other words, by linking knowledge elements, bridging platforms can increase the proximity between different knowledge bases that would otherwise be too distant for knowledge recombination to succeed.[2] Consequently, bridging platforms increase the possibility for knowledge spillovers (Corradini and de Propris 2017), thereby creating important prerequisites for the emergence of innovation. Therefore, regions with well-embedded bridging technologies should experience a higher innovation output.

The European Commission (EC) grouped the following six technology fields in the concept of Key Enabling Technologies (KETs)[3] in 2009: Nanotechnology, micro- and nano-electronics (including semi-conductors) (MNE), industrial biotechnology, photonics, advanced materials, and advanced manufacturing technologies (AMTs) (European Commission 2009b, 2012). These six technologies were selected by the EC based on their projected economic power. Their development, application and commercialization are fostered in order to strengthen the EU's industrial competitiveness and to tackle its societal challenges (European Commission 2009a, 2009b, 2012; Evangelista, Meliciani, and Vezzani 2018). In subsequent years, KETs attracted growing attention from policy makers (Corradini and de Propris 2017) and found prominence in EU-industrial and in EU-cohesion policies.[4] This attention was paralleled by the development of academic literature on KETs, which is still evolving. While the concept of European KETs was brought forward as an industrial policy approach without a clear-cut theoretic conceptualization, publications on KETs usually emphasize that KETs possess features of General-Purpose Technologies (GPTs) (Antonietti and Montresor 2021; Aschhoff et al. 2010; Corradini and de Propris 2017; Evangelista, Meliciani, and Vezzani 2018; Martinelli, Mina, and Moggi 2021; Montresor and Quatraro 2017; Montresor, Orsatti, and Quatraro 2022). As Teece (2018) further outlines, enabling technologies (like KETs) share particularly the wide applicability, innovational complementarities, and their potential for technological improvement with GPTs[5] (Bresnahan and Trajtenberg 1995; Martinelli, Mina, and Moggi 2021; Teece 2018). KETs combine a vertical dimension in the sense that they trigger complementary innovation with a horizontal dimension, as they are widely applicable across many technology fields, thanks to their multidisciplinary character (Corradini and de Propris 2017; European Commission 2009a, 2009b). Their wide applicability opens up many different opportunities in recombinant innovation and enables KETs to act as knowledge brokers that can connect distant parts of the regional knowledge base (Basilico and Graf 2023; Corradini and de Propris 2017). The ability to link previously unconnected or even isolated knowledge elements provides KETs with a bridging function (Corradini and de Propris 2017) that is, besides their innovational complementarities, at the core of their enabling function. Within the regional knowledge base this bridging function indicates a distinctive position of KETs that shapes the relations between knowledge elements and, thus, the whole knowledge base.

When KETs fulfil their role as well-linked bridging technologies, they can facilitate the flow of ideas and knowledge within the knowledge base. However, previous research on KETs mainly focused on the presence of KET knowledge within a region or it focused on regional specialization to assess the innovation spawning effect of these technologies. Nevertheless, due to KETs' bridging function, KET knowledge that occupies a central position within the regional knowledge space should foster regional innovation through recombinant knowledge growth. Therefore, the following hypothesis is formulated:

> (H1) The knowledge growth of a region is higher, if KETs have a central position within the region's technological spaces.

Scientific results regarding KETs remain rather ambiguous and research highlights the need to account for the differences in KETs characteristics. Researching the R&D networks of KETs, Wanzenböck, Neuländtner, and Scherngell (2020) provide a first loose classification for differences in the effects of KETs and their characteristics by dividing the six technologies into two groups, namely 'science-based' and 'engineering-oriented'. They highlight the importance of network embeddedness in the case of science-based KETs, while the knowledge creation process in engineering-oriented KETs is more informal. Therefore, a distinction between these two groups of KETs seems necessary, when

Table 1. Science-based and engineering-oriented KETs as suggested by Wanzenböck, Neuländtner, and Scherngell (2020), own modification.

	Science-based		Engineering-oriented
Industrial biotechnology	x		
Nanotechnology	x		
Adv. manufacturing technologies (AMTs)			x
Advanced materials			x
Photonics			x
Micro- and nanoelectronics (MNE)		x	

addressing the effects of KETs on the innovation output of regions. Table 1 provides an overview of the different KETs and how they position themselves in the distinction of science-based and engineering-oriented technologies.[6] As the tendency of MNE is the least clear in this context, we treat it as a special case.

For science-based KETs, a high regional network connectedness is considered to be more important than for engineering-oriented KETs. Know-how in these technological fields is more generic/codified and, therefore, less geographically bound to on-site production (Wanzenböck, Neuländtner, and Scherngell 2020). They draw more on scientific inputs than engineering-oriented KETs. The influence of network embeddedness is lower for engineering-oriented KETs, as knowledge generation is based more on informal processes (European Commission 2015; Wanzenböck, Neuländtner, and Scherngell 2020). Therefore, science-based technologies might depend more on the global structure of the regional knowledge base to harness positive effects on innovation output by being connected to many different fields of the regional knowledge space. Engineering-oriented technologies, on the other hand, should have a bigger effect on regional innovation output when they are locally more embedded into the knowledge base. They are much more dependent on field-specific and application-oriented knowledge that enables accumulating knowledge growth through adding onto already existing knowledge aspects in a less formalized way. Thus, raising the distinction between the local position and the global position of KETs in the regional technological space and differentiating science-based from engineering-oriented KETs, the following hypotheses are proposed:

(H2a) The knowledge growth of regions is higher, if science-based KETs have a globally central position within their technological space.

(H2b) The knowledge growth of regions is higher, if engineering-oriented KETs have a locally central position within their technological space.

Nevertheless, the distinction between science-based and engineering-oriented KETs also raises the question of the mode of innovation at place. An important distinction can be made between a scientific and technologically-based innovation (STI) mode and a learning-by-doing, by-using, and by-interacting (DUI) mode of innovation. As the DUI mode is based on informal learning processes and experience-based know-how, it characterizes a non-formalized R&D process based on knowledge application. The STI mode of innovation draws from codified scientific knowledge, its usage, and its development, leading to a formalized R&D process (Jensen et al. 2016; Parrilli and Alcalde Heras 2016). Given the above-mentioned distinction between science-based and engineering-oriented KETs, we argue that the different KETs benefit more from either STI or DUI mode. Because of their usage of codified knowledge and formalized R&D processes (Wanzenböck, Neuländtner, and Scherngell 2020), science-based KETs are expected to be more STI-oriented . This allows inventors within these technological fields to use globally available codified knowledge. Nevertheless, given the recombinant nature of knowledge creation (Weitzmann 1998), an embeddedness into the regional (scientific) knowledge space seems very important in the case of science-based KETs. Engineering-oriented KETs, on the other hand, are based more on 'hands-on' knowledge, which implies less dependence on knowledge networks. At the same time, there is a need for an accumulation of knowledge within that field to enable learning by doing/using innovations. Therefore, regions that specialize in engineering-oriented KETs should experience an increase in innovation output, while a strong embeddedness of these KETs in the regional knowledge space should be less important. On the other hand, in the case of science-based KETs, a strong embeddedness in the regional knowledge base should be important for an increase in innovation output. Thus, the following hypotheses are formulated:

(H3a) The importance of network embeddedness of KETs for the regional knowledge growth is higher in the case of science-based KETs.

(H3b) The importance of regional specialization in KETs for the regional knowledge growth is higher in the case of engineering-oriented KETs.

3. Data and methods

3.1. Data

To proxy the regional knowledge base, inventor-based patent data (REGPAT, 2024 version) is used, as inventors carry the knowledge relevant in the innovation process. Each patent is regionalized based on the inventor's residence addresses. Patents with co-inventors in different regions are equally assigned to all of the respective regions.[7] The KET patents are identified via a list of IPC codes provided by van de Velde et al. (2012) (see online Supplementary material Appendix, Table A). All six KET-fields are considered individually in our analysis. The study focuses on the period from 1995–2017 and the analysis is based on the application of 5-year annually moving windows (e.g. 1995–1999, 1996–2000, etc.). Germany is selected as the focal country, since it is strong in KET-patenting and in KET-based products compared to other EU-countries (Butter et al. 2014). This ensures enough cases with a high KET occurrence and embeddedness. The approach further allows to regionalize the patent data in 141 German Labor Market Regions (LMRs), as defined by Kosfeld and Werner (2012), which are functionally classified spatial entities between the NUTS-2 and NUTS-3 level, considering commuter traffic (Kosfeld and Werner 2012). Thus, LMRs act as structurally cohesive areas instead of artificial policy borders. Observations with less than 10 patents in any given region-year incidence are omitted from the sample.

3.2. Operationalization

To proxy the regional innovation output, two approaches are employed to capture different dimensions of innovation. First, to assess the overall innovation strength, we use the 5-year moving average of inventor-based patent counts within non-KET patents as our dependent variable. We apply this moving average to circumvent distortions in yearly patent applications particularly in less innovative regions, where a low number of patents may significantly shape the innovative landscape. Furthermore, as this study is based on the regional level, we assume that the dissemination of newly created knowledge (reflected by the number of patents) takes time within the region. Therefore, we argue that the knowledge creation process is influenced by KETs not only directly after the patent application. This approach follows other studies that use a 5-year moving window to calculate the regions' revealed technological advantages (RTAs) (e.g. Montresor and Quatraro 2017) and other cross-sectional studies that also aggregate the patent count as a dependent variable (e.g. Pintar and Scherngell 2022; Reher, Runst, and Thomä 2024). Second, to assess the diversification of the knowledge base through the bridging function of KETs, we calculate the number of RTAs (e.g. Balland et al. 2019). We employ the RTA as a binary variable, measuring if a region r in a specific time period generated a new comparative advantage in a specific technology t. To calculate the RTA, the following formula is used, where X_{rt} is a rectangular matrix that contains the number of patents in the region:

$$\mathrm{RTA}_r = \frac{\left(\frac{X_{rt}}{\sum_{t'} X_{rt'}}\right)}{\left(\frac{\sum_{r'} X_{r't}}{\sum_{r't'} X_{r't'}}\right)} > 1$$

Thus, the RTA measures whether the share of KET patents in a region is higher than the share of KET patents in Germany. If the RTA value is greater than 1, indicating a comparative advantage, we set the binary RTA variable for this KET in this year to 1. Then, the number of RTAs in a region in any given five-year period is calculated and used as a proxy for diversification. If the number of RTAs in a region increases, it is assumed that the regional knowledge base has become broader. Thus, the patent count measures cumulative and vertical growth of regional knowledge output, while the RTA count measures the horizontal growth of regional knowledge output.

To analyse the embeddedness of KETs within the knowledge base of German LMRs, regional technological spaces[8] based on co-occurrences of 4-digit IPCs in patents are constructed. They map the relatedness of technological knowledge (Boschma, Balland, and Kogler 2015), making them a useful tool to analyse the structure of technological relations within regions (Kogler, Rigby, and Tucker 2013; Neffke, Henning, and Boschma 2011). Patents function as edges and IPC-codes as nodes in this network. To measure the proximity of two different (4-digit IPC) technologies, the count of their co-occurrences in patents is used. The relatedness is then measured by the probability index (Balland 2017), which is an extension of the association strength (van Eck and Waltman 2009).

After the construction of the regional knowledge spaces, the centrality of the KETs within the network is evaluated, based on two specific indicators from social network analysis (SNA). The first indicator is the betweenness centrality, in order to measure the global position within the regional knowledge space. The second indicator is the constraints and determines the local embeddedness within the knowledge base. Betweenness centrality measures how often a node lies on the shortest paths between all other nodes in the network (Freeman 1978). The betweenness centrality, therefore, is a global network measure, as it entails information on the whole network and the position of the specific technology within that network. KETs with a high global embeddedness act as knowledge brokers at the global network scale. The second indicator, constraints, is based on the local (or ego) network of the technology. It measures the local knowledge broker function of technologies, as it considers all nodes a technology is directly related to, and it determines how many otherwise not directly connected technologies are connected via the specific node (Burt 2004). KETs as knowledge brokers should have higher constraints than other technologies. Lastly, to measure the specialization of regions in KETs, their specific RTA is measured (e.g. Balland et al. 2019).

Since regions with a higher complexity are assumed to be more innovative (Antonelli, Crespi, and Quatraro 2022), we additionally control for regional complexity (Balland and Rigby 2017). The regional complexity is calculated based on the same 5-year moving window that is used to compute the regional knowledge spaces. Additionally, to capture the diversity of the regional knowledge base, the Herfindahl-Hirschman Index (HHI) of patent concentration is calculated, based on 4-digit IPC codes (see, for example, Garcia-Vega 2006; Grashof and Kopka 2023; Kang and Park 2019; Wang, Guo, and Zou 2022). As the HHI is a concentration measure, the inverse of the HHI is used to identify regional knowledge diversity. Lasty, we include GDP per capita to account for the local economic strength. Descriptive statistics of the variables are reported in Table 2.

We can observe that based on the mean of the RTAs, regional specialization in KETs is rather scarce. In the case of nanotechnology, only 12.8% of all region-time observations show a specialization. Industrial biotechnology as well as advanced materials have the highest incidence of specialization. These differences between KETs can also be observed for the constraints as well as betweenness centralities. Industrial biotechnology, for

Table 2. Descriptive statistics.

Statistic	N	Mean	St. Dev.	Min	Max
$RTACount_{rt+5}$	3,162	132.668	45.789	12	244
Pat_{rt+5}	3,162	1,317.065	1,892.494	8	15,424
$Betweenness_{AdvMat,rt}$	3,162	0.013	0.017	0.000	0.260
$Constraints_{AdvMat,rt}$	3,162	0.265	0.256	0.000	1.223
$RTA_{AdvMat,rt}$	3,162	0.343	0.475	0	1
$Betweenness_{AMT,rt}$	3,162	0.080	0.052	0.000	0.437
$Constraints_{AMT,rt}$	3,162	0.197	0.206	0.000	1.235
$RTA_{AMT,rt}$	3,162	0.405	0.491	0	1
$Betweenness_{Photonics,rt}$	3,162	0.023	0.023	0.000	0.193
$Constraints_{Photonics,rt}$	3,162	0.285	0.262	0.000	1.125
$RTA_{Photonics,rt}$	3,162	0.328	0.469	0	1
$Betweenness_{MNE,rt}$	3,162	0.001	0.002	0.000	0.034
$Constraints_{MNE,rt}$	3,162	0.241	0.337	0.000	1.343
$RTA_{MNE,rt}$	3,162	0.275	0.446	0	1
$Betweenness_{IndBio,rt}$	3,162	0.015	0.020	0.000	0.202
$Constraints_{IndBio,rt}$	3,162	0.306	0.236	0.000	1.243
$RTA_{IndBio,rt}$	3,162	0.317	0.465	0	1
$Betweenness_{NanoTech,rt}$	3,162	0.001	0.004	0.000	0.106
$Constraints_{NanoTech,rt}$	3,162	0.227	0.293	0.000	1.125
$RTA_{NanoTech,rt}$	3,162	0.249	0.432	0	1
KCI	3,162	−0.007	0.187	−1.613	0.738
$GDPc$	3,162	26.480	7.728	11.112	70.026
$HHIinv$	3,162	0.978	0.016	0.804	0.994

example, has a comparatively low betweenness centrality, while at the same time it has the highest constraints among all KETs. This is in line with previous research that discovered differences in the nature and the technological characteristics of KETs (e.g. Wessendorf and Grashof 2023). This analysis brings a new dimension into this discussion, introducing a network-specific point of view.

3.3. Model specification

Our panel data set ranges over 5-year moving windows within the period of 1995–2017 in all 141 LMR with an unbalanced structure. Following the results of the robust Hausman test (e.g. Schaffer and Stillman 2010; Wooldridge 2002), we use a fixed effects panel regression. As both independent variables are non-negative count variables (i.e. number of patents and number of RTAs in a region in a specific year) and both variables suffer from overdispersion, a Negative Binomial Fixed Effects Panel Regression is applied, using the R package 'fixest' (Bergé 2018). To address possible temporal and spatial correlations (and, thereby, also potential geographic spillover effects), standard errors are corrected using the Driscoll-Kraay approach (Driscoll and Kraay 1998; Millo 2017). Further, a small sample correction adjusted for clusters, accounting for all fixed-effects coefficients, is done (Bergé 2018). A time-lag between our dependent variables and all independent variables of five years is included.

The model adopts the following stylized form, in which the model formula is shortened because each KET-specific variable is included simultaneously in the final model but only considered once in the presented formula:

$$Pat_{rt+5} = \alpha + \beta_1 Betweenness_{krt} + \beta_2 Constraints_{krt}$$

$$+\beta_4 RTA_{rt} + \beta_5 Control_{rt} + \delta_{rt} + \varepsilon_{rt}$$

$$RTACount_{rt+5} = \alpha + \beta_1 Betweenness_{krt} + \beta_2 Constraints_{krt}$$

$$+\beta_4 RTA_{rt} + \beta_5 Control_{rt} + \delta_{rt} + \varepsilon_{rt}$$

Pat corresponds to the number of patents in a region, and *RTACount* represents the number of RTAs in a region. *Betweenness* describes the betweenness centrality, while *Constraints* corresponds to the calculated constraints of each KET. *RTA* is the regional specialization in KETs. *Control* describes the remaining control variables, namely the regional complexity (*KCI*), the GDP per capita (*GDPc*), the regional knowledge diversity (*HHIinv*), and the non-leading patent count (*Pat*) as well as RTA count (*RTACount*). Furthermore, k denotes the specific KET, r the respective labour market region (LMR), t the 5-year-period, δ_{rt} the year fixed-effect, and ε_{rt} is the error term.[9]

4. Results

The results of our econometric analysis are presented in the following section. We investigate the impact of KETs' network embeddedness and regional specialization in KETs – first, on the diversification and broadening of the regional knowledge base and, second, on the general regional patent stock (and, thus, the cumulative regional knowledge growth).

The results for the first part of the analysis are reported in Table 3. Regarding the betweenness centrality, we observe that all coefficients, except for industrial biotechnology (IndBio), are statistically significant and positive. This indicates that regional knowledge diversification is indeed positively influenced by a higher regional embeddedness of KETs, highlighting the bridging function of (specific) KETs (see, e.g. Corradini and de Propris 2017). Nevertheless, an obvious distinction can be made between the global position and the local embeddedness of KETs: Considering the constraints, statistically significant positive results are observed for MNE and nanotechnology, while all coefficients of the other KETs are statistically significant and negative. Nearly all KETs impact the broadening of the regional knowledge space through their global regional knowledge network embeddedness. Nanotechnology and MNE additionally work through a higher local network embeddedness. Lastly, the regional specialization is addressed in this part of the analysis. Here, only MNE have a statistically significant and positive coefficient. Advanced materials (AdvMat) and AMTs even show a statistically significant negative coefficient.

Regarding the control variables, in line with previous studies, we find a positive impact of regional knowledge complexity on the number of technologies a region is specialized in. Further, the breadth and diversity of regional knowledge also have a statistically positive impact, albeit not in all models and only on a marginal significance level (0.1). The logged GDP per capita has a positive statistical influence on the number of regional technological specializations as well.

The second part of the analysis addresses the impact of the embeddedness of KETs on the cumulative regional knowledge growth (the growth of the regional patent stock). The results are reported in Table 4. Compared to the first part of the analysis, KETs show a different behaviour, as the impact of their network embeddedness shifts. The betweenness centrality of photonics does not present a statistically significant positive effect, while AMTs and industrial biotechnology even have a statistically significant negative impact. Regarding the remaining three KETs, a higher betweenness centrality shows a statistically significant positive impact. Considering the effect of constraints, all engineering-oriented KETs and industrial biotechnology show a statistically negative effect, while the coefficients of MNE and nanotechnology are statistically significant and positive. Lastly, the regional specialization of KETs is analysed. All engineering-oriented KETs as well as industrial biotechnology show a statistically significant and positive impact on the cumulative regional knowledge output. In the case of AMTs, this is in line with the results of Wessendorf and Grashof (2023), who found that a regional specialization in AMTs promotes radical innovation in firms.

Regarding the control variables, contrary to the findings from the first part of the analysis, we find no impact of the regional knowledge complexity on the regional patent output. Further, and in line with previous research, the breadth and diversity of the regional knowledge has a statistically positive impact, as well as the logged GDP per capita. Table 5 provides an overview of the findings.

In light of these findings, we can address the hypotheses derived in Section 2. First, no clear direct impact of regional KET embeddedness on the regional knowledge output can be observed, as we find both statistically positive and negative effects. Further, some of the KETs show no significant statistical influence on the regional knowledge output. Considering the distinction between science-based and engineering-oriented KETs and

Table 3. Regression results for RTA count.

	Dependent variable: RTA count					
	(1)	(2)	(3)	(4)	(5)	(6)
$Betweenness_{AdvMat,rt}$	3.86*** (0.463)					
$Constraints_{AdvMat,rt}$	−0.054** (0.017)					
$RTA_{AdvMat,rt}$	−0.021* (0.010)					
$Betweenness_{AMT,rt}$		0.236* (0.112)				
$Constraints_{AMT,rt}$		−0.611*** (0.079)				
$RTA_{AMT,rt}$		−0.020** (0.007)				
$Betweenness_{Photonics,rt}$			1.56*** (0.188)			
$Constraints_{Photonics,rt}$			−0.159*** (0.043)			
$RTA_{Photonics,rt}$			−0.001 (0.013)			
$Betweenness_{MNE,rt}$				7.67*** (2.00)		
$Constraints_{MNE,rt}$				0.111*** (0.015)		
$RTA_{MNE,rt}$				0.033* (0.014)		
$Betweenness_{IndBio,rt}$					0.045 (0.287)	
$Constraints_{IndBio,rt}$					−0.118*** (0.025)	
$RTA_{IndBio,rt}$					−0.013 (0.014)	
$Betweenness_{NanoTech,rt}$						13.3*** (3.62)
$Constraints_{NanoTech,rt}$						0.183*** (0.012)
$RTA_{NanoTech,rt}$						0.002 (0.011)
KCI	0.083* (0.038)	0.108** (0.036)	0.076. (0.041)	0.082. (0.047)	0.085. (0.045)	0.082* (0.034)
GDPc	0.535*** (0.029)	0.413*** (0.020)	0.511*** (0.025)	0.503*** (0.025)	0.535*** (0.029)	0.501*** (0.025)
HHIinv	15.5*** (1.17)	13.6*** (1.19)	15.5*** (1.37)	15.4*** (1.40)	15.5*** (1.41)	15.9*** (1.11)
Year	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Type	Drisc.-Kra. (L=2)	Drisc.-Kra. (L=2)	Drisc.-Kra. (L=2)	Drisc.-Kra. (L=2)	Drisc.-Kra. (L=2)	Drisc.-Kra. (L=2)
Obs.	3,162	3,162	3,162	3,162	3,162	3,162
Squared Cor.	0.67712	0.74429	0.69020	0.68901	0.68422	0.69037
Pseudo R^2	0.09509	0.11151	0.09421	0.09355	0.08963	0.09899
BIC	30,606.5	30,055.3	30,635.8	30,658.2	30,789.6	30,475.3
Overdispersion	23.047	29.283	23.169	23.046	21.910	24.282

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Table 4. Regression results for patent count.

	Dependent variable: PAT count					
	(1)	(2)	(3)	(4)	(5)	(6)
$Betweenness_{AdvMat,rt}$	2.277** (0.7101)					
$Constraints_{AdvMat,rt}$	−0.4697*** (0.0621)					
$RTA_{AdvMat,rt}$	0.0752*** (0.0157)					
$Betweenness_{AMT,rt}$		−2.031*** (0.4543)				
$Constraints_{AMT,rt}$		−1.362*** (0.1217)				
$RTA_{AMT,rt}$		0.1163*** (0.0279)				
$Betweenness_{Photonics,rt}$			0.2193 (0.6458)			
$Constraints_{Photonics,rt}$			−0.6345*** (0.0859)			
$RTA_{Photonics,rt}$			0.0767** (0.0239)			
$Betweenness_{MNE,rt}$				33.90*** (7.906)		
$Constraints_{MNE,rt}$				0.2676*** (0.0425)		
$RTA_{MNE,rt}$				0.0018 (0.0251)		
$Betweenness_{IndBio,rt}$					−2.619*** (0.6827)	
$Constraints_{IndBio,rt}$					−0.6149*** (0.0946)	
$RTA_{IndBio,rt}$					0.2184*** (0.0160)	
$Betweenness_{NanoTech,rt}$						49.16** (15.76)
$Constraints_{NanoTech,rt}$						0.7213*** (0.0469)
$RTA_{NanoTech,rt}$						0.0818 (0.0537)
KCI	−0.0163 (0.2153)	0.0155 (0.1767)	−0.0449 (0.2607)	−0.0171 (0.2695)	0.0117 (0.1655)	0.0095 (0.3708)
GDPc	2.085*** (0.0146)	1.813*** (0.0542)	2.019*** (0.0326)	2.099*** (0.0277)	2.038*** (0.0445)	3.246*** (0.0412)
HHIinv	5.690*** (1.212)	2.269 (1.207)	5.875*** (0.9154)	5.110*** (0.9176)	5.310*** (1.387)	19.82*** (1.957)
Year	Yes	Yes	Yes	Yes	Yes	Yes
S.E. Type	Drisco. -Kra. (L=2)	Drisco.-Kra. (L=2)	Drisco. -Kra. (L=2)	Drisco.-Kra. (L=2)	Drisco.-Kra. (L=2)	Drisco.-Kra. (L=2)
Obs.	3,162	3,162	3,162	3,162	3,162	3,162
Squared Cor.	0.84338	0.87670	0.84794	0.81088	0.86441	0.59065
Pseudo R^2	0.13365	0.14588	0.13615	0.13247	0.13839	0.07122
BIC	44,928.3	44,297.5	44,799.4	44,989.5	44,683.9	48,149.2
Overdispersion	49.476	60.180	51.418	48.455	53.364	19.523

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

Table 5. Overview of findings.

		Broadening Knowledge Output			Cumulative Knowledge Output		
		Global	Local	Specialization	Global	Local	Specialization
Engineering-oriented	Advanced Materials	+	–	–	+	–	+
	Advanced Manufacturing Technologies	+	–	–	–	–	+
	Photonics	+	–	**o**	**o**	–	+
(ambiguous)	Micro- and Nanoelectronics	+	+	+	+	+	**o**
Science-based	Industrial Biotechnology	**o**	–	**o**	–	–	+
	Nanotechnology	+	+	**o**	+	+	**o**

Note: This table does not include marginally significant effects (with an alpha between 0.05 and 0.1). Even though, we oppose the rather artificial cut-off of 0.05 as a significance level and call for awareness of edge cases with a *p* very close to 0.05, we think that in this case only robust results should be shown.

between local and global network embeddedness, we find indeed some interesting aspects – but no clear separation of science-based and engineering-oriented KETs is possible. Nevertheless, and contrary to our hypothesis 2b, it is apparent that engineering-oriented KETs have a positive influence on regional diversification through a higher global regional knowledge network embeddedness and a negative influence through a higher local regional knowledge network embeddedness. Lastly, in the case of regional specialization, we have to reject hypotheses 3a and 3b, as no clear distinction in the effect is possible. Further, we even find evidence for a negative impact of regional KET specialization on diversification (in two cases). In the following Section 5, these rather surprising and interesting findings are discussed and embedded in the current literature on KETs.

5. Discussion

In the following, the results of our econometric analysis are discussed and embedded in the literature. Overall, regarding KETs' effects on regional knowledge creation and diversification, our findings show results that differ between the individual KETs. Furthermore, a major difference between the effect of the embeddedness of KETs within a region and regional specialization in KETs exists, which certainly calls for further research. Generally, our findings support the suggestion by Montresor and Quatraro (2017), that the degree of the six KETs' enabling power varies. We find evidence for KETs' innovation-driving role and observe that the network embeddedness of all six KETs affects regional innovation, although in different ways. Their global embeddedness influences regional diversification either positively or not at all, but the cumulative regional knowledge output is negatively affected in some cases. The analysis reveals that some KETs drive innovation via their global network embeddedness, whereas most KETs hinder innovation when they are locally embedded in the regional knowledge base. Generally, AMTs and advanced materials exhibit pronounced GPT features (Antonietti et al. 2023; Aschhoff et al. 2010). In the present case, AMTs have positive effects on the broadening of the regional knowledge base through global embeddedness. Advanced materials unfold their impact through both global and local embeddedness. For AMTs, this is also consistent with the literature describing them as core enablers for other technologies and other KETs (Butter et al. 2014; de Heide et al. 2013; European Commission 2009b; van de Velde et al. 2012). Interestingly, a strong global embeddedness of AMTs supports the broadening of the regional knowledge base but negatively impacts the general knowledge growth of the region. Since AMTs are enablers of production processes (European Commission 2009b; van de Velde et al. 2015), a global embeddedness is more important than a local concentration of AMTs knowledge in the region, as the latter could indicate the lack of a sufficient number of actors adopting AMTs knowledge – impeding knowledge spread and acting as brokers in a negative way. One of the core features of GPTs is their pervasiveness and wide applicability across different sectors. A strong local embeddedness could mean that there is not enough spread or pervasiveness of AMTs knowledge in place. This falls in line with the idea that enabling technologies share the wide applicability with GPTs but are not necessarily disseminated across the economy to the same extent as GPTs (Teece 2018). In the case of advanced materials and AMTs, we further find that a specialization hinders the knowledge diversification of regions. In the case of photonics, we observe a similar pattern like in advanced materials and AMTs. A higher global regional knowledge network embeddedness affects regional diversification positively, while a high specialization positively impacts regional cumulative knowledge growth.

These results highlight the GPT characteristics of the engineering-oriented KETs. Due to their special features, these technologies are combinable on a much wider range than other technologies. A region with a high local embeddedness of KETs may lack the necessary broker function for technological progress and innovation. A regional specialization in these technologies may additionally come with a too high proximity in its various dimensions, preventing positive effects on diversification. As widely acknowledged, a successful innovation comprises the recombination of knowledge elements that are neither too distant nor too similar (Boschma, Balland, and Kogler 2015; Corradini 2019; Nooteboom 2000).

Regarding the distinction of science-based and engineering-oriented KETs, MNE are a special case (see Section 2). The effects observed for MNE resemble the effects of nanotechnology, indicating a similar structural behaviour regarding their influences on the knowledge creation process. Both nanotechnology and MNE favour regional cumulative knowledge growth, and they broaden the regional knowledge base through a higher global and local embeddedness. In comparison to the broad field of AMTs, nanotechnology as well as MNE seem to be more specialized technologies, which would explain why a dense local network embeddedness does increase the regional patent activity, as knowledge combinations involving a specialized technology could be more fruitful. As an R&D intensive technology (e.g. Ponds, van Oort, and Frenken 2010), MNE could also bear the risk for regional lock-in effects, as simultaneously specializing and accumulating knowledge in that technology could bind regional capacities, hindering the regional cumulative knowledge growth outside of the KET.

Finally, considering the strongly science-based industrial biotechnology, the results are the opposite from what we expected. It seems that its impact on the broadening of the regional knowledge space is limited and only happens through a local broker function of the technology. The influence of industrial biotechnology is much more pronounced in the case of cumulative knowledge growth. The science-driven nature of industrial biotechnology might demand a more specific context, in which the KET is embedded, to bridge the gap between scientific knowledge and its industrial application. The R&D-intensity of industrial biotechnology could lead to a high amount of resources necessary to innovate in this KET, dampening the growth of other technological areas and limiting the amount of possible knowledge spillovers due to its segregated impact.

Generally, these results suggest that the effects of KETs rely on different underlying mechanisms unconnected to the differences in the type of technology engaged. The results for advanced materials, AMTs, and photonics indicate prominent core features of KETs, like the bridging function that connects distant, otherwise unconnected knowledge (Corradini and de Propris 2017). However, these findings also suggest that different capacities, skills, and knowledge may be required at the regional level to exploit inventions in KETs or to involve them in explorative research. In summary, all KETs share GPT-characteristics, however, the way in which they enable innovations is inherently different in structure. While some more 'classical' GPT-like technologies are part of the KET-classification (e.g. AMTs), the group of KETs is highly diverse and generates a variety of innovation effects. Furthermore, relative to each other, some KETs are rather science-based and require a high level of R&D (e.g. industrial biotechnology, nanotechnology), while others are more application-focused (e.g. AMTs, advanced materials). Moreover, some KETs have broader application cases (e.g. AMTs) than others (e.g. industrial biotechnology). These structural differences and KET-specific demarcations of their associated technology subfields are one possible explanation for the highly diverse results of our analysis. We identify three different groups of KETs: (1) the engineering-oriented KETs with pronounced GPT features (AMT, AdvMat, Photonics), (2) the science-based KETs (MNE, NanoTech), and (3) industrial biotechnology as a science-based niche technology.

Therefore, researchers and policy-makers should consider KETs separately rather than as a single group. In addition to considering KETs as heterogeneous technology fields with different innovation-spawning mechanisms, a decision to invest in KETs must also be tailored to the KET-specific features in terms of the potential effects of the interaction between KET-knowledge in the region and the structural role of KETs within the knowledge base. A first step involves the analysis of KETs' role in the regional knowledge base. If KETs are well embedded, they may not need much support to generate the desired effects through their special function. In this context, it is particularly important to formulate clear objectives for policy approaches. It should be made clear whether the reason for addressing KETs is to increase either the regional knowledge diversification or the region's innovation output. As our study shows, the embeddedness of KETs affects the regional innovation scene in certain cases. For instance, even though our findings do not permit a clear distinction of science-driven and engineering-oriented KETs, it became obvious that particularly the engineering-oriented KETs drive regional knowledge diversification through their bridging function. Table 5 helps to inform policy decisions in this context: Depending on the way KETs unfold their effect, it can be helpful to support their global or local network embeddedness. The local embeddedness could be increased through supporting entities in establishing linkages around their core knowledge competences, for instance, in the same sector or at least in related fields. The global embeddedness in the region can be supported by promoting entities to cross-sectionally connect and exchange throughout the region. In both cases, spillovers can occur that eventually increase proximities between actors, strengthening their linkages. However, at the same time, it is crucial to be aware that a regional specialization in KETs is mostly helpful for the cumulative regional knowledge output but can also impede the broadening of the knowledge base. Thus, actions aiming to promote the embeddedness of KETs in the regional knowledge network should also consider that a certain diversification of the knowledge base seems necessary to not contradict the desired effects. Lastly, the question has to be raised, whether industrial biotechnology should be included in the group of KETs, as it seems to be a special case.

6. Summary and conclusion

The aims of this paper are to extend the literature on European Key Enabling Technologies (KETs), as defined by the EU commission, and to distinguish the underlying mechanisms of KETs' innovation-driving role. We particularly focus on the role of the embeddedness of KETs in the regional technological space for knowledge creation in regions. The existing literature remains vague on the different effects of KETs in the regional knowledge creation process, even though the enabling role of KETs and certain positive effects of KETs on regional economic development have been verified (e.g. Antonietti and Montresor 2021; Evangelista, Meliciani, and Vezzani 2018; Montresor and Quatraro 2017; Montresor, Orsatti, and Quatraro 2022; Wanzenböck, Neuländtner, and Scherngell 2020). We focus on twelve five-year moving time windows with German Labor Market Regions (LMR) as our observational entities. Further, we operationalize knowledge creation activities via the regional innovation output, proxied by patent applications, and via the broadening of the regional knowledge base, proxied by the number of technological specializations. Given the results presented in Section 4, we find evidence for the innovation-enabling role of (most) KETs. However, the results display an essential difference between (a) the individual KETs themselves and (b) the broadening and the cumulative knowledge growth effect of KETs. Some KETs possess an enabling role via their network embeddedness, while they do not enable innovation through a regional KET specialization (with the exception of AMTs). Considering the cumulative knowledge growth, the effect of KETs' embeddedness can also be negative. Each KET shows a different combination regarding the impacts of their global and local embeddedness and the regional specialization. The results not only emphasize the heterogeneity of KETs as multidisciplinary and cross-sectoral technologies but, in our opinion, particularly imply the demand to be cautious when addressing the six technology fields as a single group in the context of innovation. KETs, as enabling technologies (Teece 2018), are expected to drive regional innovativeness and growth (Bresnahan and Trajtenberg 1995; European Commission 2009a, 2009b; Evangelista, Meliciani, and Vezzani 2018, 2019; Montresor and Quatraro 2017). Our results strongly suggest that labelling KETs as uniform innovation drivers is unadvisable. They are enabling technologies, sharing GPT-characteristics, but encompass different and diverse technology fields. Thus, for both further research and policy-makers, the heterogeneities of KETs deserve more attention than the shared GPT-characteristics under which they are framed. Our results further strengthen the request for a specialized and targeted funding approach to the individual KETs in specific circumstances to support the emergence of innovation. The inclusion of KETs in regional innovation policies should not be limited to the respective technology fields themselves. Rather, it is essential to integrate the insights of the individual innovation-driving nature of the different KETs. Policies should be network-centric, and they should focus on establishing links between firms to position those active in KETs at the core of the regional knowledge network. Our findings show that focusing on knowledge creation in KETs per se does not necessarily lead to a further knowledge creation effect within the region.

In view of our results, a few limitations need to be discussed. First, our study is based on patent data and, thus, can only provide approximations to the applied indicators for the regional innovativeness or regarding the amount of KET knowledge within a region. Because not all innovations get patented (e.g. Griliches 1990), future research should include non-patent related innovation indicators of KET knowledge and general regional knowledge creation. Second, this study is centred on the embeddedness of KETs, but our results reveal that for some KETs it is (also) the regional specialization in KET knowledge that is crucial for their effect on the overall regional innovativeness. Hence, this distinction should be addressed in more detail. One possible path for future research could be to analyse the interaction between these two characteristics. Third, considering the highly KET-specific results and KETs' heterogeneities, it could prove useful to evaluate whether KETs could be grouped differently. Future research could investigate whether it is possible to create consistent subgroups across different KET-fields that share similar characteristics regarding their enabling function and effects (e.g. in their scope of impact or their type of application, science-based and engineering-oriented). Another way could be to rethink the current classification of KETs also on the basis of their effects – in light of our findings, for example, a combination of nanotechnology and MNE could be considered. Also, it should be tested whether industrial biotechnology in its current classification should be regarded as a KET. Additionally, further research should evaluate which factors cause the (strong) differences in KETs' effects. Moreover, the present study is only focused on Germany, with a limited number of years in the panel. Future research needs to test whether our results also apply to other countries and to longer periods of time. In addition to the use of a different and more recent database, the narrower focus may also be an explanation why our results regarding the effects of a regional KET specialization on regional diversification differ from Montresor and Quatraro (2017). Lastly, the present study does not consider moderating factors of the regional context, which may have a significant altering impact on the functioning of KETs. Therefore, future studies should look into possible moderating characteristics of regions that could explain some of the contradicting findings (e.g. regarding industrial biotechnology).

Generally, our work contributes to the limited regional literature on European KETs and serves as an important orientation for future research on KETs. In this context, it addresses the scarcity of insights regarding the prerequisites of their enabling function and consequently expands the knowledge on KETs in a regional context. At the same time, our results call for awareness to consider the heterogeneities regarding the six KET-fields by illustrating that no clear and consistent impact of the different KETs on regional knowledge creation activities exists, which has to be considered by scholars and addressed by policy-makers alike.

Notes

1. Considering the example of cognitive proximity: If two actors are too proximate, it will be difficult to obtain new insights from one another. If, on the other hand, the distance between the two is too large, there will be a high risk of misunderstanding (or not understanding) each other (e.g., Nooteboom 2000).

2. As an example: Two organizations are active in two different technological fields, A and B. Knowledge spillovers provide access to a third technology C that is very broad and somewhat related to parts of A and parts of B. Although the organizations lack the cognitive abilities to absorb and process knowledge in A or B, respectively, they are able to understand and process parts of C and engage in this technology. This may lead them to discover opportunities to combine A, B, and C into new technological knowledge, potentially resulting in the convergence of all three technologies. In this example, not only the cognitive gap between the two organizations is diminished, but technology C might also increase the organizations' proximity in the organizational and institutional dimensions, for instance, through interaction and collaboration.
3. With 'Key Enabling Technologies' (KETs) we refer to the technologies summarized as KETs by the EC. The term is, however, not exclusive to the European KETs.
4. See, e.g.: European Commission (2009a, 2009b, 2014); van de Velde et al. (2015); European Commission (2015); Butter et al. (2014); van de Velde et al. (2012).
5. In contrast to GPTs, KETs are not necessarily (yet) spread across the whole economy (Teece 2018).
6. Micro- and nanoelectronics are an ambiguous case: Wanzenböck et al. categorize MNE as engineering-oriented. However, Pavitt (1984) and Ponds, van Oort, and Frenken (2010) consider semi-conductors (that are part of MNE, see European Commission 2009a, 2009b) to be science-driven. Hence, we refrain from explicitly assigning MNE into one category.
7. We assume that all inventors share the knowledge of a patent, as knowledge is non-exclusive.
8. Technological spaces are based on the concept of product spaces by Hidalgo et al. (2007).
9. Additional robustness checks are included in the (online Supplementary material Appendix). They show a smaller time window for the calculations of the technological space as well as moving averages of three years instead of five (Table B). Additionally, a robustness check without any timeframe is done with just the yearly data (Table C). Both robustness checks lengthen the time period (up to the most recent year 2022 in the case of the second robustness check).

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