The impact of the six European Key Enabling Technologies (KETs) on regional knowledge creation

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Assessing the importance of KETs' structural relevance in knowledge spaces

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Abstract

The European Commission summarized six young General Purpose Technologies (GPTs) under the label of European Key Enabling Technologies (KETs) in 2009. GPTs are broad, pervasive and widely diffused technologies that enable knowledge creation and economic growth. This study analyzes to what extent the KETs' structural relevance within their regional knowledge bases leads to regional knowledge creation. Additionally, we analyze whether the structural relevance and the regional knowledge presence in KETs interact with regards to regional knowledge creation. The 'structure' of a regional knowledge base describes the relation of all knowledge being present within a given region, while 'structural relevance' describes a technology's impact on the structure. Our analysis focuses on the time period from 1986-2015 and includes Germany's 141 Labor Market Regions (LMRs) as regional spatial units. Our database consists of patent data from which we map the structure of the regional knowledge bases, by constructing technological spaces based on technology co-occurrences on patents. The structural relevance is operationalized with the help of Social Network Analysis (SNA), by measuring the changes that the removal of KETs causes in the structure of technological spaces. Our findings indicate that KETs enable knowledge creation in different ways. They show that the effects of KETs on regional knowledge creation activities are KET-specific. Furthermore, it proves essential to distinguish between 'knowledge presence' and 'structural knowledge relevance' when addressing the innovation-spawning function of KETs. Thus, for both further research and for policy-making, it is a fundamental requirement to address KET-driven knowledge creation in particular KET-specific ways.

Keywords

General purpose technologies, GPT, key enabling technologies, KET, regional innovation, regional knowledge base, knowledge space, technological space, technological integration, German regions

JEL codes

O31, O33, R11, R58

1 Introduction

Recently, a group of young and emerging technologies became prominent at the level of European politics: Advanced Materials, Advanced Manufacturing Technology (AMT), Industrial Biotechnology, Micro- and Nanoelectronics (MNE), Nanotechnology, and Photonics. These six technologies were summarized under the concept of "Key Enabling Technologies" (KETs) by the European Commission (EC) in 2009 to attract particular attention to the foreseen economic and societal role of these technologies (European Commission 2009b, 2009a, 2012). Although KETs are horizontal technologies and comprise different technology fields (see Tab. 1), they share the same core features as young General Purpose Technologies (GPTs) (e.g., Aschhoff et al. 2010; Montresor & Quatraro 2017; Evangelista et al. 2018). GPTs are enabling technologies characterized by pervasive use across many sectors, scope for their own technological improvement, and innovational complementarities, the last of which are triggered as important components of innovations (Bresnahan & Trajtenberg 1995; Helpman & Trajtenberg 1996). Furthermore, they are widely diffused across the economy (Bresnahan & Trajtenberg 1995). Classical examples of GPTs are the steam engine, electricity, the internal combustion engine, semi-conductors, and ICTs (Bresnahan & Trajtenberg 1995; Lipsey et al. 1998).

The concept of KETs entails their characteristics as emerging GPTs, their applicability in a variety of sectors, and an enabling function to spur innovations. The (political) designation of the KET label was followed by several studies focusing on the group of six KETs and also on the effects of these KETs at the regional level (e.g., Montresor & Quatraro 2015; Corradini & de Propris 2017; Montresor & Quatraro 2017; Evangelista et al. 2018, 2019; Montresor & Quatraro 2019; Wanzenböck et al. 2020; Janssen & Abbasiharofteh 2021).

The present paper contributes to a better understanding of the structure underlying the effects of KETs and further provides important policy implications regarding the promotion of KETs at the regional level. We extend the scarce literature on KETs within a regional context by investigating the impact of the structural importance of KETs in regional knowledge bases on regional innovation. For this purpose, we first examine the question as to how the (regional) structural relevance of knowledge in one KET within a regional knowledge base acts as a driver of regional knowledge creation. Our underlying assumption is that regional innovation activities depend more on the structural role of KETs within the regional knowledge base than on the amount of KET knowledge present in the region. Second, we analyze how the impact of the structural relevance is mediated by the amount of KET-specific knowledge in the region, as we assume a substitution effect between the structural importance and the amount of KET knowledge in a region. Our questions are based on the (potential) effects of KETs as innovation-spawners and are posed against the backdrop of

KETs being technologies that have received much political attention. They are considered to be boosters of Europe's re-industrialization, or more specifically to be suppliers of technological building blocks for solutions that target major societal challenges (such as climate change or the ageing of the society) (European Commission 2009b, 2009a, 2012).

In our analysis, we assess each KET individually to advance the understanding of the specifics of each KET. As EU-policies often refer to the regional level, we analyze KETs from a regional perspective. The 141 German Labor Market Regions (LMRs) were chosen as spatial units of analysis. The LMRs are functionally defined regions that are larger than cities/counties and take commuter traffic into account (Kosfeld & Werner 2012). To address the structural relevance of KETs and the KET-specific dimensions, we use patent data to construct regional knowledge spaces (knowledge-/technology networks mapping the relatedness of technologies) (e.g., Hidalgo et al. 2007; Neffke et al. 2011; Boschma et al. 2015) and apply measures of social network analysis (SNA). Finally, we analyze the impact of the structural relevance of KETs and the amount of KET knowledge on the regional innovation output by applying a set of linear panel regression models.

The remainder of our paper is structured as follows. Section 2 provides a brief overview on the literature background of KETs and derives the hypotheses based on the theory. Section 3 describes our data and methodology. Our results are depicted and described in section 4 and discussed in section 5. Lastly, we conclude with a summary and show the limitations as well as research and policy implications of our results in section 6.

2 Background

2.1 General Purpose Technologies (GPTs)

The term 'General Purpose Technology' (GPT) evolved in the 1990s and is rooted in the work of Bresnahan & Trajtenberg (1995). Although a large body of literature addresses GPTs, no coherent definition or way of identifying GPTs exists, as Cantner & Vannuccini (2012) show. However, at its core, a GPT can generally be described as a breakthrough technology (e.g., Youtie et al. 2008) that is radical in nature (e.g., Cantner & Vannuccini 2012). These technologies are particularly dynamic (Bresnahan & Trajtenberg 1995) and mainly characterized by pervasiveness in their use across various sectors, by an ongoing technological improvement, and by innovation-spawning effects that are based on complementary innovation (Bresnahan & Trajtenberg 1995; Helpman & Trajtenberg 1996). Furthermore, GPTs (can) diffuse across the whole economy after their first occurrence (Bresnahan & Trajtenberg 1995). These characteristics bestow an enabling function, in the sense that GPTs pave the way for *"new opportunities rather than offering complete, final solutions"* (Bresnahan & Trajtenberg 1995, p. 84). This results in GPTs being transformative and being potential boosters of economic growth (Bresnahan & Trajtenberg 1995; Lipsey et al. 1998). Popular examples of GPTs comprise the steam engine, electricity, the internal combustion engine, semi-conductors, and ICTs (Bresnahan & Trajtenberg 1995; Lipsey et al. 1998). Recent additions to the group include biotechnology (e.g., Lipsey et al. 1998), nanotechnology (e.g., Lipsey et al. 1998; Youtie et al. 2008; Shea et al. 2011) and artificial intelligence (Cockburn et al. 2019), which are considered to be at least possible or emerging GPTs. As Cantner & Vannuccini (2012) point out, some studies use a rather narrow definition of GPTs, considering them to be "*singularities or extreme cases of radical innovations*" (p. 5). Aghion & Howitt (1998), for instance, refer to the steam engine, the electric dynamo, the laser, and the computer, and Rosenberg & Trajtenberg (2004) mainly consider the steam engine, electricity, and information technologies as GPTs. Other scholars use a broader understanding of GPTs (e.g., Carlaw & Lipsey 2011). As Cantner & Vannuccini (2012) further outline, two generations of GPT-based models exist: While models from the first generation (e.g., Aghion & Howitt 1998) allow one GPT at a time, in models of the second generation several GPTs can co-exist (e.g., van Zon et al. 2003; Carlaw & Lipsey 2006, 2011). The present study follows the broader understanding and the idea of the co-existence of GPTs.

2.2 Key Enabling Technologies (KETs)

Regarding younger and co-existing GPTs, the European Commission (EC) introduced the concept of Key Enabling Technologies (KETs)[1] for the European Union (EU) in 2009, in which the following six technology fields were grouped: Nanotechnology, Micro- and Nano-Electronics (including semi-conductors) (MNE), Industrial Biotechnology, Photonics, Advanced Materials, and Advanced Manufacturing Technology (AMT) (European Commission 2009b, 2012). Although the concept of European KETs was brought forward as an industrial policy approach without a clear-cut theoretic conceptualization, the six KETs are young or even potentially emerging GPTs (Aschhoff et al. 2010; de Heide et al. 2013; Montresor & Quatraro 2017; Evangelista et al. 2018; Antonietti & Montresor 2021). The term 'key' addresses the (assumed) importance of these technologies for the European knowledge economy and for tackling societal challenges, such as an ageing society or climate change (e.g. the need to reduce carbon emissions). 'Enabling' refers to their features as GPTs, especially relating to industrial processes and with respect to their role in laying the foundation for further innovation (European Commission 2009b, 2009a, 2012;

[1] When we use the term 'Key Enabling Technologies' (KETs), we refer to the technologies summarized under this label by the European Commission. The term itself is not exclusive to the European KETs.
However, in the present context 'KETs' is mainly used within EU-policies and rather sparsely by policy makers beyond the level of the EU commission. Only a few EU-members adopted the term, such as Germany, Austria or Belgium (de Heide et al. 2013; Butter et al. 2014). Examples for other technology-oriented approaches are the Technologies Clés (France), Platform Technologies (USA) or Industrial Technologies (China) (de Heide et al. 2013).

Montresor & Quatraro 2015). The KET concept was introduced to emphasize the foreseen potential of the six technology fields and to foster their development, application and commercialization, in order to enhance the EU's industrial competitiveness and to tackle the EU's societal challenges (European Commission 2009a, 2009b, 2009a, 2012). Hence, it is also expected that KETs will increase the economic development and success at the regional level (European Commission 2009b). Based on their economic potential and the potential for diverse solutions to societal challenges, the six technologies were selected by the European Commission (EC) (European Commission 2009b; Evangelista et al. 2018) and defined as follows:

> *"KETs are knowledge intensive and associated with high R&D intensity, rapid innovation cycles, high capital expenditure and highly-skilled employment. They enable process, goods and service innovation throughout the economy and are of systemic relevance. They are multidisciplinary, cutting across many technology areas with a trend towards convergence and integration."* (European Commission 2009b, p. 1)

Due to their foreseen potential, KETs have drawn much attention from policy makers in the past years (Corradini & de Propris 2017) and enjoy prominent status in EU-industrial and in EU-cohesion policies. For instance, they play an important role in the Horizon 2020 framework program or in smart specialization strategies (European Commission 2012; Butter et al. 2014; Montresor & Quatraro 2017).[2] In the following paragraph we derive three stylized facts from the main KET features, regarding their role within regional knowledge bases.

2.3 Stylized facts of KETs in regional knowledge bases

To be able to assess the importance of KETs in regional knowledge bases, we consider the regional structural relevance of KETs, which we define as the degree of the importance of KETs within the regional knowledge structure and its impact on it. We assess the regional knowledge structure through the relations of all technologies (as a proxy for knowledge) within the region to each other. To prepare for our analysis, we derive three stylized facts regarding the 'behavior' of KETs within the regional knowledge structure, based on the GPT-characteristics of KETs from the literature.

Innovations are combinations of pre-existing knowledge (Schumpeter 1947; Arthur 2007), thus each innovation establishes or strengthens a link within its inherent pre-existing knowledge. Hence, in KET-based innovations, KET knowledge is linked with other knowledge (from other KETs or non-KETs). Since KETs (as GPTs) function as core building blocks of innovations and are broadly applicable across many fields (see sections 2.1 and 2.2), we expect KETs to be remarkably linked

[2] See Table Appendix A for an overview on the six KETs, which also indicates their multidisciplinary and cross-sectional character.

to other technologies within the knowledge base. Presumably, this results in a high number of linkages from KETs to other technologies within a knowledge base, from which we derive:

(S1) In terms of technological linkages, the knowledge base is structurally focused on KETs.

Further, Antonietti & Montresor (2021) stress the importance of KETs for regional diversification and prove that a larger number of KETs within a region enhances the region's probability for unrelated diversification if KET knowledge is combined with the knowledge of other technologies during the innovation process. From our point of view, this indicates that KETs possess a bridging function. Leaving aside the regional perspective and regarding the technological one, Corradini & de Propris (2017) provide evidence for the bridging function of KETs. According to them, KETs function as bridging platforms and can couple unrelated and more distant technologies/knowledge. Bridging platforms are nodes of technologies (e.g., KETs) that are very pervasive in respect to different technology fields. These nodes connect to other technologies and "[form] *a platform that allows the technological integration across seemingly unrelated technologies by bridging the gaps across different knowledge landscapes*" (Corradini & de Propris 2017, p. 198). This enables the coupling of two formerly unrelated technologies, which especially raises the potential for radical innovations (Corradini & de Propris 2017). Based on this idea that KETs link otherwise unconnected technologies and on the understanding that KETs embody the GPT characteristic of setting the stage for further innovation (Bresnahan & Trajtenberg 1995), we derive the following stylized fact:

(S2) In terms of linkages that bridge knowledge gaps, the knowledge base is structurally focused on KETs.

Derived from the pervasiveness, wide diffusion and bridging function of KETs (see section 2.2), as well as from the combination of linking distant knowledge and at the same time being connected to many different knowledge fields, we expect that KETs essentially contribute to the knowledge base's cohesiveness. By connecting otherwise unconnected technologies (S2), KETs can also connect otherwise unconnected technology fields or different groups of related technologies. Thus, if the knowledge base is mapped as a technological space (see section 3.2), KETs act as a 'connector' of network components, making the structure more cohesive and less fragmented.

(S3) KETs substantially ensure the structural cohesiveness of knowledge within the knowledge base.

2.4 Regional KET-based innovativeness

Extant scientific literature on the group of KETs at the regional level focuses mainly on the effects of KETs. Addressed topics include KETs in the context of smart specialization (Montresor & Quatraro 2017, 2019), regional diversification (Antonietti & Montresor 2021), regional branching (Montresor & Quatraro 2017), regional knowledge creation in R&D networks (Wanzenböck et al. 2020), or the KETs' impact on relatedness and regional economic growth (Evangelista et al. 2018, 2019). We extend the literature by focusing on the underlying structural prerequisites of the effect of KETs within the regional knowledge base with a special emphasis on the innovation-spawning effect of these technology fields. KETs, as GPTs (see section 2.2.), not only possess the potential to enable (complementary) innovation (Bresnahan & Trajtenberg 1995) in general, but can positively affect regional branching in a more exploratory manner, lowering the importance of relatedness at the same time (Montresor & Quatraro 2017). This could be, among other aspects, a consequence of the bridging function of KETs that Corradini & de Propris (2017) point out.

Following the notion of recombinant innovation (Schumpeter 1947; Arthur 2007), the combination of KET knowledge with other knowledge represents the core of the innovation-spawning effect of KETs. They seem to be prone to spawn innovation via their structural characteristics, since they establish links to many other technologies, they link otherwise unconnected technologies, and they function as bridges between groups of (related) technology fields. Given this structural role of KETs (see also the three stylized facts in 2.3), we assume that the positive effect of KETs not only relies on the presence of KET-related knowledge in the region, but particularly on its structural relevance within the regional knowledge pool. Considering regional innovation generally, we hypothesize:

(H1) An increase in the structural relevance of each KET in a region's knowledge base leads to an increase of the total innovation output of the region.

Although we assume that the structural relevance of KETs plays an essential role for regional innovativeness, we also expect that a high structural relevance in combination with a very strong focus on knowledge accumulation and knowledge creation in a specific KET tendentially reduces the enabling role of this KET. Since KETs are knowledge- and R&D intensive (European Commission 2009b, 2009a), we presume that knowledge creation in KETs binds resources at the cost of knowledge creation in other technology fields. Furthermore, if a KET is too dominant in the sense of a knowledge base highly focused on a KET, from our point of view this potentially diminishes the possibilities for knowledge combination between KETs and non-KETs and could even lead to a regional lock-in. However, considering the idea of recombinant innovation again (Schumpeter 1947; Arthur 2007), we assume that the specific KETs can only unfold their enabling function when they possess a structurally important role within the knowledge base without too much knowledge in the respective KETs being present, which leads us to deriving the following hypothesis:

(H2) The impact of the structural relevance of each KET in the regional knowledge base on the general level of innovativeness within the region is negatively moderated by the amount of KET-specific knowledge in the region.

In the following section, we describe the data used, our operationalization of the presented concepts, and our method of analysis.

3 Data and methods

3.1 Data basis

Our data basis consists of patent data obtained from the European Patent Office's (EPO) database PATSTAT (2017b version) for Germany from 1986 to 2015.

We select inventor-based patent data to proxy regional knowledge presence. As inventors possess the relevant knowledge and apply it in the innovation process, they serve as an indicator as to where the knowledge is located geographically. The patents are regionalized based on their inventors' residence addresses. If co-inventors of a patent are located in different regions, the patent is assigned to all of the respective regions[3]. KET patents are identified as patents that have at least one technology code assigned to one of the KETs. As KETs are broad and horizontal technologies that share 'natural overlaps' due to an unsharp delineation from another (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 B). All six KET fields are considered individually in our analysis.

Our study focuses on the 30-year-period from 1986-2015 and the analysis is based on the application of 5-year annually moving windows (1986-1990, 1987-1991 etc.). We choose Germany as our focal country, since it is very strong in KET patenting and in KET-based products, compared to other EU-countries (Butter et al. 2014). To regionalize, we choose the level of the 141 German Labor Market Regions (LMRs), as defined by Kosfeld & Werner (2012), that are functionally classified spatial entities between the NUTS-2 and NUTS-3 level, considering commuter traffic (Kosfeld & Werner 2012). Regions without any KET patents throughout the focal 30-year period are omitted from the sample. For each LMR and 5-year moving window, we construct regional technological spaces as described in the following section.

[3] We therefore assume that all inventors share the knowledge of a patent, as knowledge is non-exclusive.

3.2 Operationalization

Technological Spaces

In the current study we operationalize different knowledge via different technologies and construct so-called technological spaces to analyze the structural relevance of KETs in German LMRs. The technological spaces are networks functioning as relational maps of the knowledge bases. In the present case, nodes in these networks represent different technologies and links between the nodes incorporate the relatedness of the technologies. Technological spaces, also known as knowledge spaces (Kogler et al. 2013), can be constructed at any spatial scale and are based on the concept of product spaces by Hidalgo et al. (2007) (Neffke et al. 2011; Boschma et al. 2015; Vlčková et al. 2018). Product spaces are networks representing an economy, with products as nodes and their degree of relatedness as links (Hidalgo et al. 2007), whereas technological spaces map the relatedness of technologies instead of products (Boschma et al. 2015). Knowledge spaces/technological spaces can be utilized, for instance, to assess the specialization of regions in specific technologies (Vlčková et al. 2018). Furthermore, they are an important tool to analyze the structure of the relations of technologies within regions (Neffke et al. 2011; Kogler et al. 2013). As these characteristics show, the term 'space' should be understood in a relational way. In our context, we construct regional technological spaces based on technology-patent co-occurrences. The nodes, in the form of technologies (IPC-codes), are linked by the patents in which they appear together. To account for the frequency of the co-occurrence of two different technologies, our networks are edge-weighted; the more often two technologies co-occur in patents, the higher the edge-weight and the more proximate the two technologies. We divide the edge-weight by 1, as we use a distance-based network indicator. As a higher co-occurrence explains a higher proximity, we need to invert the proximity to assess the distance of technologies.

Assessing the structural relevance of KETs

To investigate the role of KETs within regional knowledge bases, we evaluate their technological spaces' network centralization and network cohesion with the help of three global network indicators. Regarding the network centralization, we compute the degree centralization and the betweenness centralization. Considering network cohesion, we compute the connectedness.

Degree centralization is employed as a measurement, since we assume that the regional technological spaces are structurally centralized on KETs, in terms of linkages between technologies (**S1**). Betweenness centralization is used as we assume that the technological spaces are centralized on KETs when it comes to the bridging function of technologies (**S2**). Connectedness is used as a cohesiveness-indicator, since we assume that KETs substantially ensure the technological spaces' cohesiveness (**S3**).

Based on (Freeman 1978), network centralization is a measurement at the level of the whole network and related to different node centralities, such as degree centrality and betweenness centrality. It is the sum of the differences between the maximum value of a node centrality and the centrality value of each other node in the network, divided by the maximum possible sum of differences in node centrality, which Freeman (1978, p. 228) formulates as follows.

$$C_X = \frac{\sum_{i=1}^{n}[C_X(p^*) - C_X(p_i)]}{max\ \sum_{i=1}^{n}[C_X(p^*) - C_X(p_i)]}$$

$C_X(p_i)$ represents the respective node centrality (in our case degree centrality or betweenness centrality), of which the maximum value in the network is $C_X(p^*)$. Accordingly, $max\ \sum_{i=1}^{n}[C_X(p^*) - C_X(p_i)]$ stands for the highest possible sum of differences in the node centrality within a network of *n* nodes. In other words, degree centralization indicates whether the network consists only of a few nodes with many links (and many nodes with only a few links), or if the number of links is more evenly distributed. Betweenness centralization indicates to what extent the network comprises nodes that have a high betweenness centrality, meaning they have a link that bridges to a network component that would be unconnected without this link. If all nodes possess equal centralities, centralization is 0. A star network with only one very central node possesses the maximum possible centralization, represented by the value 1. This is valid for both betweenness and degree centralization (Freeman 1978). We use the centralization measures to determine to what extent a network depends on specific (central) nodes.

The connectedness measures the network cohesion. It generally describes the share of nodes that belong to the same component and thus specifies how well a network is connected, following Graf (2017). The connectedness is calculated using the following formula, where r_{ij} is 1 if nodes *i* and *j* are in the same component and 0 if both nodes are part of different components, while *n* is the total number of nodes in the network.

$$Connectedness = \frac{\sum_{i \neq j} r_{ij}}{n(n-1)}$$

For each region, each KET, and each time period, we compute the values of these three network indicators, subsequently remove all KET patents of one KET type from the network, recompute the network indicators, and determine the differences to which the indicators' values were changed by the KET-removal (inspired by Buarque et al. 2020). The omission-based differences in the indicators describe the structural changes in the networks caused by the omission of KETs and hence the structural relevance of the omitted KET in the original network.

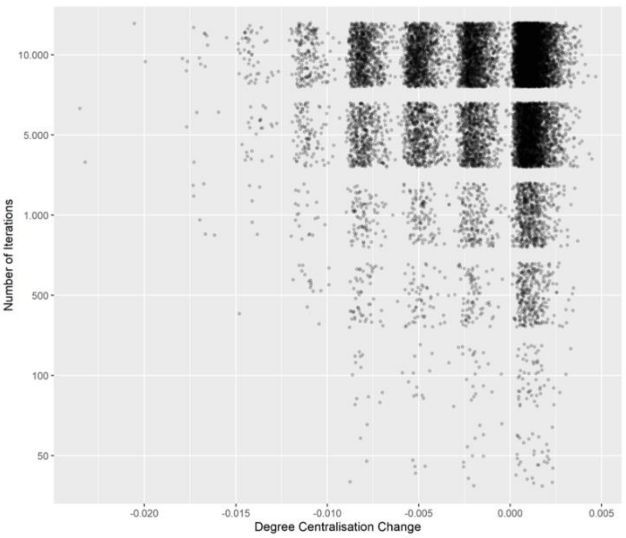

Fig. 1: Distribution of the structural impact of omitting random patents on the degree centralization in the technological space of the LMR Soest. (Own computation)

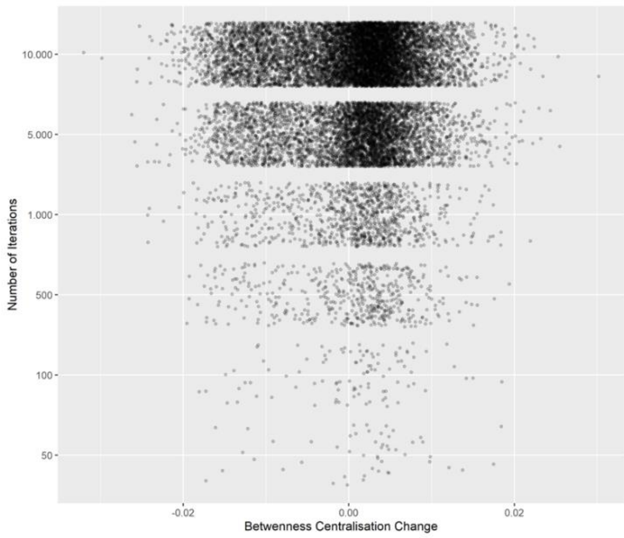

Fig. 2: Distribution of the structural impact of omitting random patents on the betweenness centralization in the technological space of the LMR Soest. (Own computation)

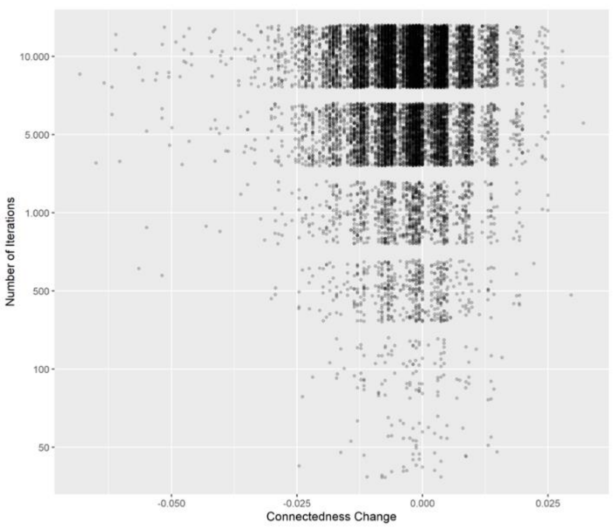

Fig. 3: Distribution of the structural impact of omitting random patents on the connectedness in the technological space of the LMR Soest. (Own computation)

The following formula describes the structural change *StrChg* regarding network indicator *i* in the technological space of region *r* with respect to the omitted KET *k*. The value of indicator i is represented by v for the complete network and by c for the network where KET k was omitted:

$$StrChg_{rik} = v_{ir} - c_{irk}$$

As this process does not reveal if a change in the network structure traces to the structural role of the omitted KET in the respective network or if the difference occurs due to the simple reduction of network edges, we perform a robustness check. We compute the impact of the removal of a random sample of patents for each region. The number of patents in the random sample is identical with the number of omitted KET patents. This process is repeated 1,000 times and only the structural changes within a 95%-interval are used to account for the randomness of the process, starting from the lower 2.5% to the upper 97.5%. We then compare this range to $StrChg_{rik}$. If the structural change $StrChg_{rik}$ lies within this distribution we set it to zero as it can be explained by removing random network edges. The above-described process is repeated for each specific KET in each 5-year window in each region. Regarding the described robustness check, figures 1-3 exemplify the distribution of the structural impact of omitting random patents, measured by the change in each of the three network indicators in the technological space of the LMR 'Soest'[4]. To make the arbitrary number of 1,000 samples comprehensible, the distributions for 50, 100, 500 and 1,000 random samples are displayed (each point is one iteration). As can be seen, we observe no change in the general distribution after 1,000 iterations. After the computation of the structural change $StrChg_{rik}$, we construct a composite indicator that describes the structural relevance of KETs in the technological space by combining the three global network indicators. We label this index *Structural Technology Impact Index (STII)*. The STII consists of the sum of normalized[5] structural changes $StrChg_{norm}$ in the technological space of region *r* with respect to technology (KET) *k*, and the different network indicators *bet* (betweenness centralization), *deg* (degree centralization) and *con* (connectedness), divided by the number *n* of network indicators used (in our case 3).

$$STII_{rk} = \frac{StrChg_{norm,deg,r,k} + StrChg_{norm,bet,r,k} + StrChg_{norm,con,r,k}}{n}$$

In general, our procedure has two distinct advantages over the use of common node-level indicators. First, computing network indicators on a node-level based on co-occurrences on patents leads to a dependence of these indicators on the size of the analyzed technology. Consequently, a simple comparison of these node-level indicators would be a pitfall if technologies of different sizes (e.g., KETs) are compared, since a technology with many patents naturally has a higher degree centrality. Second, when analyzing technologies in the technological space, often a 4-digit CPC/IPC-level network is constructed. This complicates the comparison of finer grained technologies or of technologies that comprise more than one 4-digit class, as these would skew the indicators in their favor. Our method applies the analysis at the level of the patent and thus is independent from the classification level of the technology. As all the indicators are positively correlated (if we remove a KET, we expect the values for all three indicators to drop), the changes do not offset each other in the $STII_{rk}$ construction. Needless to say, the use of a composite indicator leads to information losses. Considering all three network indicators separately for each of the six KETs in our investigation, however, would lead to an overload of information. This would make the interpretation of the results nearly impossible as three indicators are considered for each of the six KETs, all with their own interaction effects. For this reason, and as we aim to provide basic insightsfor further research on the innovation-spawning effect of KETs, we focus on the $STII_{rk}$ and provide more detailed results on the single network indicators in appendix D.

[4] Soest was chosen randomly to illustrate our procedure.

[5] We normalized the indicators for each time-period and KET on a scale of -1 and 1, keeping the structure of the distribution. The absolute max. value is used to 0-1-normalize all negative and all positive values of the indicator.

Variables

To assess our derived hypotheses, we use the annual regional inventor-based patent count[6] as our dependent variable in order to proxy the regional innovation activities. We are aware of the pitfalls and constraints that patent data entails, as not all innovations which are employed in processes or products are patented (e.g., Griliches 1990). We assume that, nevertheless, the cumulated annual patent count in a region acts as a good proxy for the general innovativeness.

Both the $STII_{rk}$ and the regional number of KET patents are plugged into our analysis as independent variables (see 'model specification' below). Regarding the control variables, we include the regional knowledge complexity, the size of the technological space and the number of patents in the previous period. Since regions with a higher complexity are assumed to be more innovative (Antonelli et al. 2020), we control for regional complexity by using an indicator that is grounded on the methods of reflections (Hidalgo & Hausmann 2009) and on the revealed technological advantages (RTAs) of regions. It considers regional diversity and technological ubiquity (Balland & Rigby 2017). We calculate the regional complexity based on the same 5-year moving window that we used to compute the $STII_{rk}$.

We use the number of different technologies (4-digit IPC codes) to measure the size of the regional technological space based on the 5-year moving windows. The number of different technologies equals the number of nodes in the technological space and is important to include, since we presume the omission of patents (links) to cause a stronger structural effect in smaller networks. As innovative regions usually keep up their high number of patents, we take the regional innovativeness from the previous time period into account. The descriptive statistics of the variables described above are reported in Appendix C.

Model specification

Following this, our data now consists of a panel data set ranging over 26 5-year windows within the focal period 1986-2015 in all 141 LMR. In order to test our hypotheses H1 and H2, a set of regression models is calculated. We conduct an OLS panel regression analysis over all 5-year-windows with the logged regional patent count as the dependent variable. The independent variables are (a) the STIIs per KET, (b) their respective patent count (H1), and the interaction effect between these two (H2). The robust Hausman test (e.g., Hausman 1978; Wooldridge 2002) allows for a random effects panel regression, which we thus use in our analysis. Furthermore, we use a random effects model, as it assists in controlling for unobserved heterogeneity. The stylized model adopts the following form:

[6] A patent was assigned to multiple regions if its inventors resided in more than one region.

$$LogPat_{rt} = \alpha + \beta 1STII_{krt-5} + \beta 2Count_{krt-5} + \beta 3STII_{krt-5}XCount_{krt-5} + \beta 4PatentCount_{rt-5} + \beta 5Control_{rt} + u_{rt} + \varepsilon_{rt}$$

where *LogPat* corresponds to the logged number of patents in a region, *STII* to our Structural Technology Impact Index, *Count* to the number of patents in a specific KET, and *PatentCount* to the number of patents in a region (5-year lagged) to control for path-dependence in knowledge creation. *Control* describes the remaining control variables. *k* denotes the specific KET, *r* the respective labor market region (LMR), *t* the 5-year-period, u_{rt} the between-entity error, and ε_{rt} the within-entity error. The variance inflation factor indicates that our regression does not suffer from multicollinearity issues (Belsley et al. 1980).

4 Results

This section reports the results of the regression analysis in two parts. First, the direct impact of the structural relevance of KETs in the technological space on the innovativeness of regions is analyzed (H1), together with the effect of the regional presence of KET knowledge on regional innovativeness. Second, the stated interaction effect is described and analyzed, both statistically and visually. While our analysis is based on the use of our composite indicator *STII*, we provide further details by attaching the results based on the three single network indicators in appendix D.

Starting with the effect of KET knowledge on the regional patent activity, table 2 reports the regression results and displays five models. Model 1 consists of the control variables and acts as a baseline. Here, we observe an interesting behavior of the regional knowledge complexity. It does not significantly impact the logged total number of patents in a region. This seems to be surprising, given the literature that highlights the importance of knowledge complexity in the creation of new knowledge (Antonelli et al. 2020). However, as other studies found, the connection between complexity and innovation can be ambiguous as more complex knowledge is harder to build upon (Balland & Rigby 2017). The other two control variables behave as expected. Given that knowledge is path-dependent (Dosi 1988) and can be geographically sticky (von Hippel 1994; Lundvall & Johnson 1994; Balland & Rigby 2017), it is not surprising that the 5-year lagged total patent number of a region positively impacts the present patent count. Furthermore, the general size of the regional technological space indicates a diversified knowledge base which positively impacts the total number of patents in a region. This could also be an explanation for the insignificance of the regional knowledge complexity, as it inherently describes a similar phenomenon, even though the variance inflation factor does not indicate multicollinearity issues (with a value of 1.17). Model 2 includes the patent count of each KET and model 3 includes the structural relevance of each KET in the technological space. In the fourth model these variables are combined. Our first observation is that the independent variables are very robust over the first four models. Thus, our indicator (STII) describes aspects of regional KET knowledge that are inherently different from the total regional patent count of each KET. In the following, we concentrate on model 4.

Starting with photonics, we can observe a significant positive impact of its structural relevance on the regional patent activity. The structural relevance of AMT also positively impacts the regional innovativeness. Nanotechnology shows an impact, but on a lower alpha (<0.1). The p-value of the coefficient is very close to 0.05 (0.05009), which is why we believe it is valid to interpret the results. The impact of nanotechnology is weaker (0.069) in comparison to photonics and AMT. Hence, we can partially accept hypothesis H1, which states that an increase in the structural relevance of each KET within the knowledge base leads to an increase of the total number of regional innovations. AMT, photonics, and nanotechnology exhibit the expected behavior, while the structural relevance of MNE, advanced materials, and industrial biotechnology shows no significant effect on the regional patent activity. Furthermore, it seems that KETs that impact the regional innovativeness by their patent count are not always the ones that impact the regional patent activity by their structural relevance. This shows differences in (a) the relevance of specific KETs and (b) the effect of the amount of knowledge in a region and its importance for the regional knowledge structure. Even though this is not part of the hypotheses, we observe a positive impact of the patent count in photonics and advanced materials. The effect of photonics is only marginally significant ($p<0.1$). Interestingly, there even is a negative impact of the patent numbers in Micro- and Nanoelectronics and AMT on the regional innovativeness, while nanotechnology and industrial biotechnology show no significant impact. From a KET-specific perspective, the combination of the (non-)existing impacts of the dimensions 'structural knowledge relevance' and 'knowledge presence' on the regional innovation output differs from KET to KET. These surprising results highlight the need for (a) a differentiated view on KETs and (b) the second part of our analysis, in which we assume a mediating effect of the number of KET patents on the impact of the structural relevance of KETs on the regional patent output. Model 5 shows the results of this analysis. Furthermore, to ease the interpretability of our results, the interaction effects are visualized based on the marginal effects of the structural relevance, given different patent counts (fig. 4 and fig. 5). Starting with the model results, we only observe two interaction effects that are significant on a 0.05 alpha and we find negative interaction effects both for AMT and nanotechnology. This indicates a substitution effect between the patent count of the respective KET and its structural relevance in a region on the regional logged patent activity. Figures 4 and 5 display the marginal effects of both KETs over their respective patent count in a region. Note, that the predicted patent numbers are transformed back from their logged format. Starting with AMT, (a) we find a strong indication for an increase of the positive effect with a higher structural relevance when fewer AMT patents are present in a region. Additionally, we can observe that even with a weak structural relevance (-0.5) and a high patent count (500) the effect is higher than with a few patents and a high structural relevance, the confidence interval is much larger enclosing the whole confidence intervals of both other marginal effects (with 10 and 100 patents). Thus, although we find some indications that a higher patent count is more important than a high structural relevance, no statistical significance exists in this observation. We, therefore, derive that focusing structural relevance should be more robust in its effect on the regional innovativeness for AMT. Nanotechnology is the second KET with a significant interaction effect and reveals a similar behavior. With an increase of the patent count of nanotechnology in a region, the region's predicted patent number based on the structural relevance of nanotechnology decreases with an increasing structural relevance. Furthermore, with a very low

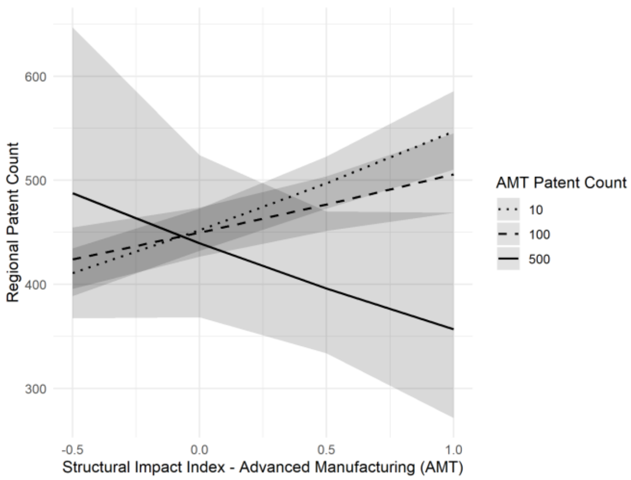

Fig. 4: Marginal effects of the Structural Technology Impact Index (STII) for different patent numbers in Advanced Manufacturing Technology (AMT) on the patent output in German Labor Market Regions (LMR) (Authors' own computation).

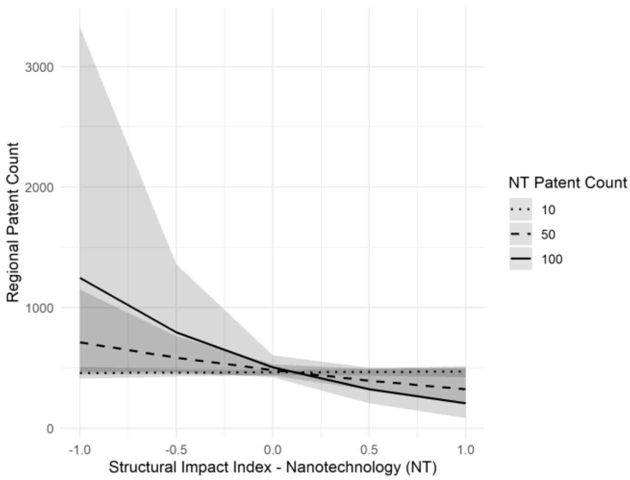

Fig. 5: Marginal effects of the Structural Technology Impact Index (STII) for different patent numbers in Nanotechnology (NT) on the patent output in German Labor Market Regions (LMR) (Authors' own computation).

number of patents in a region, the slope of the marginal effects is near zero and thus nanotechnology depends on the number of its patents to have an effect in the region. Furthermore, we also observe that the confidence intervals of the marginal effects with a higher regional nanotechnology patents number are larger. Thus, we derive that even though a low structural relevance with a high number

	Dependent variable				
	log(Pat + 1)				
Independent variables	(1)	(2)	(3)	(4)	(5)
Constant	3.421*** (0.035)	3.414*** (0.035)	3.417*** (0.035)	3.408*** (0.035)	3.419*** (0.035)
$Complexity_{r,t}$	-0.004 (0.012)	-0.018 (0.013)	-0.005 (0.012)	-0.017 (0.013)	-0.018 (0.013)
$Pat_{r,t-5}$	0.0001*** (0.00001)	0.0001*** (0.00001)	0.0001*** (0.00001)	0.0001*** (0.00001)	0.0001*** (0.00001)
$TechSpace\ Size_{r,t}$	0.012*** (0.0001)	0.012*** (0.0001)	0.012*** (0.0001)	0.012*** (0.0001)	0.012*** (0.0001)
$Count_{Photonics,r,t-5}$		0.0004** (0.0002)		0.0004* (0.0002)	0.0003 (0.0002)
$Count_{AdvMat,r,t-5}$		0.001*** (0.0003)		0.001*** (0.0003)	0.001*** (0.0003)
$Count_{MNE,r,t-5}$		-0.003* (0.002)		-0.004* (0.002)	-0.003 (0.002)
$Count_{AMT,r,t-5}$		-0.0002 (0.0002)		-0.0004** (0.0002)	-0.0001 (0.0002)
$Count_{IndBio,r,t-5}$		0.0001 (0.0001)		0.0001 (0.0001)	0.00004 (0.0002)
$Count_{Nanotech,r,t-5}$		0.001 (0.001)		0.001 (0.001)	0.001 (0.001)
$STII_{Photonics,r,t-5}$			0.101*** (0.031)	0.103*** (0.031)	0.106*** (0.035)
$STII_{AdvMat,r,t-5}$			0.022 (0.032)	0.008 (0.032)	0.033 (0.035)
$STII_{MNE,r,t-5}$			-0.049 (0.040)	-0.038 (0.040)	-0.004 (0.055)
$STII_{AMT,r,t-5}$			0.168*** (0.028)	0.171*** (0.028)	0.199*** (0.030)
$STII_{IndBio,r,t-5}$			-0.024 (0.028)	-0.026 (0.028)	-0.038 (0.030)
$STII_{Nanotech,r,t-5}$			0.064* (0.035)	0.069* (0.035)	0.114*** (0.040)
$Count_{Photonics,r,t-5} X STII_{Photonics,r,t-5}$					-0.0001 (0.001)
$Count_{AdvMat,r,t-5} X STII_{AdvMat,r,t-5}$					-0.002* (0.001)
$Count_{MNE,r,t-5} X STII_{MNE,r,t-5}$					-0.011 (0.013)
$Count_{AMT,r,t-5} X STII_{AMT,r,t-5}$					-0.001** (0.0003)
$Count_{IndBio,r,t-5} X STII_{IndBio,r,t-5}$					0.001 (0.001)
$Count_{Nanotech,r,t-5} X STII_{Nanotech,r,t-5}$					-0.010** (0.005)
Observations	2,841	2,841	2,841	2,841	2,841
R^2	0.791	0.793	0.796	0.798	0.800
Adjusted R^2	0.791	0.792	0.796	0.796	0.799
F-Statistic	10,743.290***	10,829.330***	11,056.270***	11,123.520***	11,291.260***
Note:					*p<0.10, **p<0.05, ***p<0.01

Table 1*:* Regression results (Authors' own computations). (Knowledge complexity = *Complexity,* total number of regional patents = *Pat,* size of the techspace = *TechSpace Size*, number of KET patents = *Count*, structural technology impact index (structural relevance) = *STII,* advanced materials = *AdvMat*, micro- and nanoelectronics = *MNE*, advanced manufacturing technology = *AMT*, industrial biotechnology = *IndBio*, nanotechnology = *Nanotech*, photonics = *photonics,* region = *r*, focal time period = *t,* previous time period = *t-5*).

of nanotechnology patents predicts a higher patent count, the results for a lower number of patents and a higher structural relevance are much more robust. Summarizing these results, we can accept hypothesis H2 which states that the impact of the structural relevance of each KET in the regional knowledge base on the innovativeness within the region is negatively moderated by the amount of KET-specific knowledge in the region with respect to nanotechnology and AMT. The other KETs do not display a significant interaction effect. In summary, our results display a highly KET-specific pattern. For three KETs we find a positive impact of their structural relevance on the total regional patent activity and, even though this is beyond our hypothesis, we find an impact of the presence of KET knowledge on regional innovativeness for four KETs. There seems to be a major difference between the effect of the number of KET patents in a region and their structural relevance, which certainly calls for further research.

5 Discussion

This section discusses the results presented in section 4. Instead of a clear pattern, we find highly KET-specific results regarding the effects of KETs on regional knowledge creation. Our findings add to the suggestion by Montresor & Quatraro (2017), that the degree of the six KETs' enabling power differs between them. Considering the effect of the structural relevance of KETs in the regional knowledge base, we found that AMT, nanotechnology, and photonics positively affect regional knowledge creation. Hence, we can verify that these three KETs do enable innovation via their structural role. AMT holds the strongest effect, which is in line with the literature describing AMT as a core enabler for other technologies, including other KETs (European Commission 2009b; van de Velde et al. 2012; de Heide et al. 2013; Butter et al. 2014). The structural relevance of nanotechnology, on the contrary, only has a small but nevertheless significant effect. Here it may play a role that AMT is a rather engineering-based and manufacturing-oriented technology, while nanotechnology in comparison is more science-based and R&D-driven (Wanzenböck et al. 2020). Being aware that further research is required to explore the inter-KET differences in further detail, we suggest that this difference could be due to AMT having more application opportunities than nanotechnology, given that both are in comparable structurally relevant positions. Advanced Materials, similar to AMT, hold comparatively wide application opportunities, even among KETs (e.g., Aschhoff et al. 2010; Butter et al. 2014), and are rather application-oriented (Wanzenböck et al. 2020). Nevertheless, in contrast to AMTs, our results do not display any significant innovation-spawning effect of advanced materials via their structural relevance.

Generally, these results indicate that KETs do not only differ in their effects, but especially seem to rely on different mechanisms underlying their effects, which goes beyond the six technology fields being merely different types of technologies. This is furthermore supported by our surprising results with regards to the impact of the amount of KET knowledge, operationalized by the patent count of KETs. While the structural relevance of KETs either has a positive effect or no effect on regional knowledge creation, the amount of KET knowledge can either affect regional knowledge creation positively, not at all, or even negatively. The latter is the case for AMT and MNE and could be due to the fact that KETs are knowledge- and R&D-intensive technologies (European Commission 2009b, 2009a). For this reason, knowledge creation in KETs potentially binds resources at the cost of innovation in other fields. Especially AMTs seem prone to this effect; while their strong structural relevance has a positive effect, a high patent count in AMT negatively affects regional innovation activities. AMT fulfills the role of enabling production processes (European Commission 2009b; van de Velde et al. 2015), thus a structural relevance is more important than a vast amount of AMT knowledge in the region, as the latter could lead to focusing too much on the KET itself instead of its enabling functions. The results for AMT, photonics, and nanotechnology indicate that the respective KET's core features are especially prominent, such as functioning as a bridging platform and connecting distant, otherwise unconnected knowledge (Corradini & de Propris 2017).

Even though we did not analyze the regional specialization in KETs, our findings regarding photonics and advanced materials support the finding of Montresor & Quatraro (2017) that a specialization in KETs makes relatedness in the regional branching process less binding, meaning that formerly more distant knowledge could be combined when KETs are involved. In this sense, the significant positive effect of the patent count of photonics and advanced materials on regional innovativeness is likely to indicate that these KETs possess the ability to spawn innovation and enhance capabilities for more unrelated development paths by just being present in the region, independent from their structural relevance (and thus independent from a rather central or peripheral role within the knowledge base).

Generally, the results from the first part of our analysis emphasize the importance of distinguishing between the dimensions 'knowledge presence', meaning the pure quantity of knowledge in a specific KET, and 'structural knowledge relevance', meaning the structural role that a KET plays in the regional knowledge base. This distinction accentuates that KETs do not only differ in terms of their enabling power (Montresor & Quatraro 2017), but we suggest that their enabling power is based on different, KET-specific, ways of enabling and on differently working mechanisms underlying the effects of the different KETs.

In the second step of our analysis, we focus on the interaction effects between the presence of KET knowledge, proxied by the number of patents in the respective KETs and the structural relevance of KET knowledge, proxied by our *Structural Technology Impact Index (STII)*. In the cases of Advanced Manufacturing Technology (AMT) and nanotechnology, we found a negative moderating effect of the respective number of patents on the effect of the structural relevance of the respective KET on innovation. This indicates that both technologies may hamper regional innovation activities when they are too dominant in the region both structurally and nominally at the same time. An important structural role and at the same time a high amount of knowledge in the respective KET would mean that the region is too focused on both technologies in these cases. As indicated above, KETs are knowledge- and R&D intensive technologies (European Commission 2009b, 2009a). Being overly focused on AMT and nanotechnology would be likely to bind regional capacities which were necessary for innovation in other fields.

In the case of AMT, we find a substitution effect between the amount of knowledge and its structural relevance. Furthermore, as the specific results also suggest, the structural relevance is an important driver of regional innovativeness, while we find evidence that the presence of AMT knowledge causes a negative impact on regional innovativeness. The case of nanotechnology seems rather special: In comparison to AMT, nanotechnology could be more specialized, which would explain why a high structural relevance does not increase the regional patent activity as much. Nanotechnology could also bring the risk for regional over-specialization or lock-in effects. However, a region in which the structural relevance of nanotechnology is low but the number of nanotechnology patents is high does have a higher predicted patent count. This could be explained by regions attracting a higher human capital stock due to the R&D-intensity and complexity of nanotechnology, while - at the same time - not being overly focused on nanotechnology. We assume that the regions which drive these results are characterized by a high degree of openness, a high amount of human capital, and high R&D-funding. However, further research has to confirm these assumptions.

Summarizing these findings, we assume that even though all KETs share GPT-characteristics, the way they enable innovations is inherently different in structure. While some rather 'classical' GPT-like technologies are part of the the KET-classification (e.g., AMTs), generally the group of KETs is highly diverse. Some technologies are specialized and require a high degree of R&D (e.g., industrial biotechnology, nanotechnology), while others are more application-focused (e.g., advanced materials). These structural differences are one possible explanation for the highly diverse results of our analysis. Therefore, KETs cannot be analyzed as one technological group but have to be considered separately and uniquely.

6 Summary and conclusion

The aim of this paper is to extend the literature on European Key Enabling Technologies (KETs) with a special focus on their role in the regional knowledge base, mapped as technological space, and the effect of their structural position in the technological space on regional knowledge creation. The literature remains vague on the role 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., Montresor & Quatraro 2017; Evangelista et al. 2018; Wanzenböck et al. 2020; Antonietti & Montresor 2021). Nevertheless, to the best of our knowledge, no studies exist that focus on the structural relevance of KETs in the regional knowledge base as a key driver of regional innovativeness. Hence, we analyzed to what extent regional knowledge creation is driven by KET-knowledge and the structural relevance of KETs in their regional knowledge bases. We focused on a 30-year period, with German Labor Market Regions (LMR) as our observational entities, and we operationalized knowledge creation activities via the regional innovation output, proxied by patent applications. Given the results presented in section 4, we found evidence for the innovation-enabling role of (most) KETs.

However, the results especially point out an essential difference between the effect of the amount of specific KET-knowledge in a region and its structural relevance. Some KETs possess an enabling role via their structural relevance while other KETs can enable innovation by following the tendency that more knowledge in the specific KET also triggers more innovation at the regional level (advanced materials, photonics). Considering the knowledge presence, the effect can also be negative. Each KET has a different combination regarding the impacts of 'structural knowledge relevance' and 'knowledge presence'. Additionally, we found that in the two cases of nanotechnology and Advanced Manufacturing Technology (AMT) a substitution effect is in place between their structural relevance and the amount of technology-specific knowledge in the region. In general, this points out that KETs do enable regional knowledge creation – however in different ways. The results not only emphasize the inherent heterogeneity of KETs as multidisciplinary and cross-sectoral technologies, but in our view particularly imply the demand to be cautious when addressing the six technology fields as a single group (especially in the context of knowledge creation activities). This aspect should not get lost when addressing the impact of KETs.

KETs, as young GPTs, are seen as enablers for regional innovativeness and growth (Bresnahan & Trajtenberg 1995; European Commission 2009b, 2009a; Montresor & Quatraro 2017; Evangelista et al. 2018, 2019). Our results suggest that an undifferentiated approach for subsidizing KETs to facilitate innovativeness is unadvisable. The diverse results highlight the need for a specialized and targeted funding approach to the specific KETs in specific circumstances. Furthermore, the KET-specific effects on regional knowledge creation underline the importance to distinguish between the dimensions of 'structural relevance' and 'knowledge presence' when addressing the effects of KETs and their underlying mechanisms. KETs share GPT-characteristics, but obviously comprise different and diverse technology fields. This indicates for both further research and for policy making that the heterogeneities of KETs deserve a stronger focus than the shared GPT-characteristics under which they are framed.

Considering our results, a few limitations need to be discussed. First, our study is focused on patent data and consequently can only provide approximations regarding the applied indicators for the regional innovativeness or regarding the amount of KET knowledge within a region. This is due to the fact that not all innovations are patented (e.g., Griliches 1990). Second, a usage of more control variables at the regional level was not possible, due to data availability constraints linked to the long time period under investigation that even includes years before Germany's re-unification. Third, this study is centered on the structural relevance of KETs, but our results reveal that for some KETs it is (also) the amount of KET knowledge that is vital for the effect of these KETs on the general regional innovativeness. Hence, KET knowledge should be addressed in more detail. Fourth, considering the highly KET-specific results and the natural heterogeneities of KETs, it could prove useful to evaluate whether KETs could be more consistently grouped by subgroups across the KET fields, which share similar characteristics regarding the enabling function and their effects. Additionally, further research should evaluate the question as to which factors cause the (strong) differences in the effects of KETs.

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 at the core 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.

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Appendix A: Overview on the six European Key Enabling Technologies (KETs)

KET field	Summary of KET field	Examples for industries of application/fields of application/applications
Adv. Mat.	Broad field without a clear definition	***Examples for sectors/industries:*** All Manufacturing Industries ***Examples for applicational fields/applications:*** Semiconductors, Engineering, Aerospace, Automotive, Construction, Software, Medicine/health, Energy / environment
AMT	AMTs are a combination of various technology fields. They are employed in manufacturing processes which make processes faster, reduce resource consumption, waste, and costs.	***Examples for sectors/industries:*** Generally important in capital intensive industries and in industries where assembly processes are complex ***Examples for applicational fields/applications:*** Process technologies/production systems of relevance for production of KETs/process technologies; related to making manual labor obsolete; numerically controlled technologies, measuring technologies Related to automation, robotics, and computer integrated manufacturing
Ind. Biotech.	Industrial application of biotechnology, e.g., for industrial processes, chemicals, and fuel production	***Examples for sectors/industries:*** Chemical, pharmaceutical, food industries ***Examples for applicational fields/applications:*** Production of chemicals, plastics, detergent, food, biofuels; e.g., industrial application of micro-organisms (e.g., yeast, bacteria, mould), and enzymes
MNE	Semiconductor components and electronic subsystems which are highly miniaturized	***Examples for sectors/industries:*** Medical, automotive, transportation, aeronautics and spacecraft, markets for consumers or industrial equipment ***Examples for applicational fields/applications:*** Products and services in which some kind of smart control is needed. E.g.: Cameras, wireless technologies, a car's fuel efficiency control system
Nanotech.	Relates to structures/devices/systems at the nanometer scale	***Examples for sectors/industries:*** Wide range of industries, e.g.: manufacturing, chemical, electronics, automotive, textiles, healthcare, environmental sector, energy sector ***Examples for applicational fields/applications:*** Coatings (e.g., nano-structured coatings), microelectronics, telecommunication products (e.g., displays), medicine/health (e.g., nano cancer therapy)
Photonics	Related to light; encompasses the generation of light as well as the detection and management	***Examples for sectors/industries:*** Electronics, instruments, chemicals ***Examples for applicational fields/applications:*** Optical systems/components, consumer electronics, displays, solar energy, optical communications, medical/life science

Table Appendix A: Overview on KETs (Based on: European Commission 2009b, 2009a; Aschhoff et al. 2010; van de Velde et al. 2012; de Heide et al. 2013; van de Velde et al. 2015; Evangelista et al. 2018)

Appendix B: International Patent Classification (IPC) codes of Key Enabling Technologies (KETs)

Nanotechnology	Photonics	Industrial Biotechnology	Advanced Materials	Micro- and Nano-electronics (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

Nanotechnology	Photonics	Industrial Biotechnology	Advanced Materials	Micro- and Nano-electronics (MNE)	Advanced Manufacturing Technology (AMT)		
	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
	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

Nanotechnology	Photonics	Industrial Biotechnology	Advanced Materials	Micro- and Nano-electronics (MNE)	Advanced Manufacturing Technology (AMT)		
	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	

Table Appendix B: Technology codes of the International Patent Classification (IPC) which were assigned to the European Key Enabling Technologies (KETs). (Source: van de Velde et al. 2012)

Appendix C: Descriptive statistics of used variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
TechSpace Size$_{r,}$	2,841	236.910	121.908	11	135	335	550
Pat$_{r}$	2,841	1,173.598	1,710.810	7	215	1,463	13,277
Complexity$_{r}$	2,841	-0.006	0.271	-2.980	-0.113	0.101	1.455
Count$_{Photonics,r}$	2,841	32.499	57.172	0	3	37	581
Count$_{AdvMat,r}$	2,841	24.366	43.651	0	2	25	350
Count$_{MNE,r}$	2,841	2.073	4.504	0	0	2	47
Count$_{AMT,r}$	2,841	81.115	132.162	0	11	91	1,272
Count$_{IndBio,r}$	2,841	47.056	93.691	0	4	44	711
Count$_{Nanotech,r}$	2,841	5.082	11.125	0	0	5	106
STII$_{Photonics,}$	2,841	0.034	0.124	-0.441	-0.022	0.058	1.000
STII$_{AdvMat,r}$	2,841	0.043	0.118	-0	-0.01	0.1	1
STII$_{MNE,r}$	2,841	0.009	0.092	-1	-0.001	0	1
STII$_{AMT,r}$	2,841	0.082	0.140	-0.320	-0.008	0.135	0.990
STII$_{IndBio,r}$	2,841	0.047	0.136	-0.703	-0.017	0.068	0.979
STII$_{Nanotech,r}$	2,841	0.022	0.109	-1	-0.003	0.005	1
Count$_{Photonics,r,t-5}$	2,841	24.359	47.825	0	2	25	581
Count$_{AdvMat,r,t-5}$	2,841	19.018	38.634	0	1	18	350
Count$_{MNE,r,t-5}$	2,841	1.590	4.055	0	0	1	47
Count$_{AMT,r,t-5}$	2,841	66.927	120.024	0	7	72	1,272
Count$_{IndBio,r,t-5}$	2,841	40.094	86.646	0	2	36	711
Count$_{Nanotech,r,t-5}$	2,841	3.101	8.628	0	0	2	106
STII$_{Photonics,r,t-5}$	2,841	0.031	0.121	-0.441	-0.021	0.050	1.000
STII$_{AdvMat,r,t-5}$	2,841	0.038	0.117	-0.359	-0.010	0.050	1.000
STII$_{MNE,r,t-5}$	2,841	0.010	0.087	-0.559	0.000	0.000	1.000
STII$_{AMT,r,t-5}$	2,841	0.079	0.145	-0.495	-0.008	0.130	0.990
STII$_{IndBio,r,t-5}$	2,841	0.054	0.142	-0.703	-0.011	0.074	0.979
Count$_{Nanotech,r,t-5}$	2,841	0.018	0.101	-1	0	0	1
Pat$_{r,t-5}$	2,841	1,001.889	1,562.109	2	159	1,217	13,277

Table Appendix C: Descriptive statistics of variables employed in the regression analysis (see section 3) Source: Authors' own computations. (Size of the techspace = *TechSpace Size*, total number of regional patents = *Pat,* knowledge complexity = *Complexity,* number of KET patents = *Count*, structural technology impact index (structural relevance) = *STII,* advanced materials = *AdvMat*, micro- and nanoelectronics = *MNE*, advanced manufacturing technology = *AMT*, industrial biotechnology = *IndBio*, nanotechnology = *Nanotech*, photonics = *photonics,* region = *r*, focal time period = *t,* previous time period = *t-5*).

Appendix D: Detailed results of the analysis

	Dependent variable: log(Pat + 1)				
Independent variables	(1)	(2)	(3)	(4)	(5)
Constant	3.421*** (0.035)	3.414*** (0.035)	3.455*** (0.033)	3.447*** (0.034)	3.464*** (0.033)
$Complexity_r$	-0.004 (0.012)	-0.018 (0.013)	-0.003 (0.012)	-0.016 (0.013)	-0.018 (0.013)
Pat_r	0.0001*** (0.00001)	0.0001*** (0.00001)	0.0001*** (0.00001)	0.0001*** (0.00001)	0.0001*** (0.00001)
$Techspace\ size_r$	0.012*** (0.0001)	0.012*** (0.0001)	0.011*** (0.0001)	0.011*** (0.0001)	0.011*** (0.0001)
$Count_{Photonics,r}$		0.0004** (0.0002)		0.0004* (0.0002)	0.001** (0.0003)
$Count_{AdvMat,r}$		0.001*** (0.0003)		0.001*** (0.0003)	0.001*** (0.0003)
$Count_{MNE,r}$		-0.003* (0.002)		-0.003 (0.002)	-0.002 (0.002)
$Count_{AMT,r}$		-0.0002 (0.0002)		-0.0003* (0.0002)	-0.0001 (0.0002)
$Count_{IndBio,r}$		0.0001 (0.0001)		0.0001 (0.0001)	0.0002 (0.0002)
$Count_{Nanotech,r}$		0.001 (0.001)		0.0004 (0.001)	0.002* (0.001)
$Degree_{Photonics,r,t-5}$			0.054** (0.026)	0.057** (0.026)	0.062** (0.030)
$Betweeness_{Photonics,r,\ t-5}$			-0.005 (0.025)	-0.002 (0.025)	-0.002 (0.029)
$Connectedness_{Photonics,r,\ t-5}$			0.073*** (0.027)	0.068** (0.027)	0.058* (0.032)
$Degree_{AdvMat,r,\ t-5}$			-0.0003 (0.024)	-0.016 (0.024)	0.008 (0.028)
$Betweeness_{AdvMat,r,\ t-5}$			0.020 (0.027)	0.019 (0.027)	0.022 (0.032)
$Connectedness_{AdvMat,r,\ t-5}$			0.001 (0.031)	-0.002 (0.031)	-0.016 (0.037)
$Degree_{MNE,r,\ t-5}$			-0.018 (0.030)	-0.017 (0.030)	-0.002 (0.040)
$Betweeness_{MNE,r,t-5}$			0.031 (0.035)	0.039 (0.035)	0.040 (0.051)
$Connectedness_{MNE,r,t-5}$			-0.048 (0.034)	-0.052 (0.034)	-0.044 (0.048)
$Degree_{AMT,r,t-5}$			0.027 (0.021)	0.021 (0.021)	0.048** (0.023)
$Betweeness_{AMT,\ r,t-5}$			-0.044* (0.024)	-0.038 (0.024)	-0.099*** (0.029)
$Connectedness_{AMT,r,t-5}$			0.209*** (0.028)	0.208*** (0.028)	0.229*** (0.033)
$Degree_{\ IndBio,r,t-5}$			-0.051* (0.026)	-0.049* (0.026)	-0.065** (0.028)
$Betweeness_{IndBio,r,t-5}$			-0.013 (0.022)	-0.017 (0.022)	-0.028 (0.025)
$Connectedness_{IndBio,r,t-5}$			0.025 (0.026)	0.027 (0.026)	0.049* (0.029)
$Degree_{Nanotech,r,t-5}$			-0.010 (0.029)	0.001 (0.030)	0.039 (0.033)
$Betweeness_{Nanotech,r,t-5}$			0.020 (0.025)	0.023 (0.025)	-0.008 (0.032)
$Connectedness_{Nanotech,r,t-5}$			0.048 (0.031)	0.041 (0.031)	0.053 (0.038)

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$Count_{Photonics,r,t-5}XDegree_{Photonics,r,t-5}$					-0.0004 (0.0005)
$Count_{Photonics,r,t-5}XBetweeness_{Photonics,r,t-5}$					0.0003 (0.001)
$Count_{Photonics,r,t-5}XConnectedness_{Photonics,r,t-5}$					0.0003 (0.001)
$Count_{AdvMat,r,t-5}XDegree_{AdvMat,r,t-5}$					-0.001^{**} (0.001)
$Count_{AdvMat,r,t-5}XBetweeness_{AdvMat,r,t-5}$					0.001 (0.001)
$Count_{AdvMat,r,t-5}XConnectedness_{AdvMat,r,t-5}$					0.002 (0.002)
$Count_{MNE,r,t-5}XDegree_{MNE,r,t-5}$					-0.0005 (0.006)
$Count_{MNE,r,t-5}XBewtweeness_{MNE,r,t-5}$					-0.007 (0.013)
$Count_{MNE,r,t-5}XConnectedness_{MNE,r,t-5}$					0.002 (0.012)
$Count_{AMT,r,t-5}XDegree_{AMT,r,t-5}$					-0.001^{***} (0.0002)
$Count_{AMT,r,t-5}XBetweeness_{AMT,r,t-5}$					0.002^{***} (0.0003)
$Count_{AMT,r,t-5}XConnectedness_{AMTt,r,t-5}$					-0.00002 (0.001)
$Count_{IndBio,r,t-5}XDegree_{IndBio,r,t-5}$					0.0003 (0.0003)
$Count_{IndBio,r,t-5}XBetweeness_{IndBio,r,t-5}$					0.0005 (0.0004)
$Count_{IndBio,r,t-5}Connectedness_{ndBio,r,t-5}$					-0.001 (0.001)
$Count_{Nanotech,r,t-5}XDegree_{Nanotech,r,t-5}$					-0.008^{**} (0.003)
$Count_{Nanotech,r,t-5}XBetweeness_{Nanotech,r,t-5}$					0.007^{*} (0.004)
$Count_{Nanotech,r,t-5}XConnectedness_{Nanotech,r,t-5}$					-0.007 (0.006)
Observations	2,841	2,841	2,841	2,841	2,841
R^2	0.791	0.793	0.804	0.805	0.811
Adjusted r^2	0.791	0.792	0.803	0.804	0.808
F statistic	$10{,}743.290^{***}$	$10{,}829.330^{***}$	$11{,}580.870^{***}$	$11{,}643.370^{***}$	$11{,}970.860^{***}$
Note:					$^{*}p<0.10$, $^{**}p<0.05$, $^{***}p<0.01$

Table Appendix D: Detailed results of the analysis. Results for each network indicator and each KET. Source: Authors' own computations. (Knowledge complexity = *Complexity,* total number of regional patents = *Pat,* size of the techspace = *TechSpace Size*, number of KET patents = *Count*, degree centralization = *Degree*, betweenness centralization = *Betweenness,* techspace connectedness = *Connectedness,* advanced materials = *AdvMat*, micro- and nanoelectronics = *MNE*, advanced manufacturing technology = *AMT*, industrial biotechnology = *IndBio*, nanotechnology = *Nanotech*, photonics = *photonics,* region = *r*, focal time period = *t,* previous time period = *t-5*)