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The influence of key enabling technologies on technological innovation

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Abstract

Key enabling technologies (KETs) have gained attention in science and policy due to their multidisciplinary nature and their ability to link distant knowledge fields, endowing them with a central role in recombinant innovation processes. However, it remains under-researched whether KETs generally have a higher influence on innovation processes than non-KETs. This study addresses the question by using propensity score matching and regression analysis. First, a balanced dataset is created through matching KET patents to non-KET patents that stem from a comparable context. Subsequently, it is analyzed whether KET patents are associated with higher forward citation frequencies than non-KETs. The results show that KETs receive more citations on average, but it appears that this effect is driven by a few very impactful patents. The results further show that not all KETs exert a measurable impact on forward citations and highlight the heterogeneities between the individual KETs. These findings call for a more critical assessment of the KET concept and for nuanced approaches in research and policy.

Keywords
Key enabling technologies, general purpose technologies, recombinant novelty, technological impact, patent citations, propensity score matching

JEL Classifications
O30; O31; O33; C21

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1. Introduction

More than a decade ago, the European Commission (EC) grouped six broad technology fields under the label of Key Enabling Technologies (KETs), with the aim of strengthening the European Union's (EU) policy focus on strategic technologies. The main reasoning was to promote the EU's industrial competitiveness and re-industrialization, and to tackle the grand societal challenges (GSCs) (European Commission 2009b, 2009a, 2012). While KETs lack a clear conceptualization, their popularity is rooted in the features accompanying their general breadth and multi-disciplinarity: KETs are enabling technologies and play an important role in recombinant innovation processes. This is because they can enable innovation both vertically, in downstream sectors/technology fields, and horizontally, across sectors/technology fields (Corradini and de Propris 2017; Teece 2018).

As previous studies in the young branch of literature on KETs have shown, the presence of KETs can positively affect innovation processes by extending knowledge recombination opportunities through their enabling nature (Antonietti and Montresor 2021; Wessendorf and Grashof 2023). Despite their strong potential to impact various processes related to the generation of technological innovation, such as regional diversification or the generation of radical innovation (e.g., Montresor and Quatraro 2017; Antonietti and Montresor 2021; Wessendorf and Grashof 2023), the question whether KETs are generally more impactful than non-KETs is under-researched. The current study is a first endeavor to approach this gap, as insights on the impact of KETs on innovation processes will help to address KETs more precisely in future studies. Considering KETs' origin at the policy level, better understanding KETs' will also have important policy implications.

It is hypothesized that the special properties of KETs render them more impactful than other technologies. The term 'impact' here refers to the contribution and relevance of KETs to subsequent technological innovation. Particularly the wide applicability, the capability to combine distant knowledge elements with another (bridging function), and their potential for complementary innovation, should enable them to easily influence innovation activities and to become central building blocks of innovations. Furthermore, KETs are differentiated into science- and engineering-based fields, as suggested by Wanzenböck, Neuländtner and Scherngell (2020), and it is hypothesized that the impact on innovation differs between these two groups.

The present study proxies knowledge by patents and measures their technological impact by citations in subsequent patents (forward citations), as common in the literature (e.g., Jaffe, Trajtenberg and Henderson 1993; Trajtenberg, Henderson and Jaffe 1997; Castaldi, Frenken and Los 2015). Germany serves as the focal country because it is strong in KETs (Butter et al. 2014). The study draws on a rich dataset combined from six different data sources. To ameliorate the comparison between the groups of KETs and non-KETs, a propensity score matching (PSM) is conducted, matching patents from both groups that originated in comparable contexts (e.g., firm size, industry class, regional economic strength). Finally, regression models are calculated to test the hypotheses.

The findings indicate that a smaller proportion of KET patents receives citations within seven years of publication in comparison to non-KETs. However, the cited KETs have the potential to receive more forward citations than the cited non-KETs, indicating a higher possible impact. At the disaggregate KET level (i.e., the level of the individual KETs) this result is only observed for photonics and industrial biotechnology, while the results are heterogeneous across the individual KETs. By delivering initial insights on the question whether KETs have a greater impact on technological innovation than non-KETs, this study particularly contributes to the discussion on the relevance of KETs and provides important implications for further research on KETs' effects and for innovation policy involving KETs. In particular, the results call for granular, KET-specific approaches.

The remainder of this paper is structured as follows. Section 2 provides the theoretical background and the hypotheses, before Section 3 presents the methodological approach and introduces the variables of interest. In Section 4 the results are reported, before they are discussed in Section 5. Section 6 concludes.

2. Theoretical Background

It is commonly acknowledged that (technological) innovation is a main driver of economic growth (e.g., Rosenberg 2004). During the cumulative innovation process, different bits of knowledge are recombined in new ways, reconfiguring already existing knowledge relationships, eventually resulting in new ideas that possibly may become innovations (Schumpeter 1947; Weitzmann 1998; Fleming 2001; Arthur 2007). Certain technologies, namely General Purpose Technologies[1] (GPTs), possess the potential to boost economic growth through their special innovation-spawning role: they are dynamic, broadly applicable and pervasive across the economy, offer scope for their own improvement over time, and promote the emergence of innovational complementarities[2] (Bresnahan and Trajtenberg 1995). These features can facilitate the combination of different knowledge elements and, in particular, the improvement loops between GPTs and complementary technologies can drive recombinant innovation (Bresnahan and

[1] Famous examples of GPTs are the steam engine, and electricity (Bresnahan and Trajtenberg 1995; Lipsey, Bekar and Carlaw 1998). More recently, also semi-conductors (e.g., Bresnahan and Trajtenberg 1995), biotechnology (e.g., Lipsey, Bekar and Carlaw 1998), and artificial intelligence (e.g., Cockburn, Henderson and Stern 2019) have been considered as (young) GPTs in the literature.

[2] Innovational complementarities can be seen as a form of technological complementarities. As Teece (2018) highlights: Technological complementarity is given when the full potential of a technology can only be exploited with the help of a complementary counterpart. Complementarities can further be distinguished to be linked to a) technologies around a GPT, directly defining and supporting the GPT, and b) technologies enabled along the downstream path that are, however, not part of the GPT they are enabled by (Bekar, Carlaw and Lipsey 2018). Example for a): Computers are used to produce chips, these chips enable a variety of products - among those are computers themselves. Example for b): Electricity enables computers, computers enable for instance the internet (Bekar, Carlaw and Lipsey 2018).

Trajtenberg 1995). As a result, GPTs spread widely across the whole economy, unfolding their effects in various industries (Bresnahan and Trajtenberg 1995; Helpman and Trajtenberg 1996; Helpman 1998).

Over the past decade, a potential subset of GPTs has gained prominence in the academic literature and at the policy-level, summarized under the umbrella term of 'Key Enabling Technologies' (KETs). The following Sub-section 2.1 addresses the concept of KETs and the subsequent sub-section outlines the research gap and derives the hypotheses.

2.1. Conceptualizing KETs

The KET concept was first introduced in the policy sphere by the European Commission (EC) in 2009, from where it spread to academia. It encompasses the broad technology fields of advanced materials, advanced manufacturing technologies (AMTs), industrial biotechnology, micro- and nanoelectronics (including semi-conductors), nanotechnology, and photonics (European Commission 2009a, 2009b). In particular, the EC intended to increase the policy focus on KETs, to emphasize the foreseen role of KETs in tackling societal challenges (e.g., climate change, ageing, and other grand societal challenges), and to promote their development and application for the re-industrialization of Europe to secure its global competitiveness (European Commission 2009a, 2009b, 2012).

In parallel with the growing policy attention towards KETs, scholars began to study KETs at the academic level, and literature has been evolving since (e.g., Montresor and Quatraro 2017, 2019; Wanzenböck et al. 2020; Antonietti, Cattani, Gambarotto and Pedrini 2023). Unfortunately, no clear theoretical conceptualization[3] was provided in the initial documents by the EC (European Commission 2009a, 2009b), which created – still existing – conceptual challenges in the academic literature. However, KETs can be better understood through concepts as General Purpose Technologies (GPTs) and enabling technologies (e.g., Montresor and Quatraro 2017; Teece 2018). Enabling technologies are not clearly defined in the literature either, but they are widely applicable and characterized by potential innovational complementarities – thus meeting two of the three GPT core features (Teece 2018). Unlike GPTs, of which usually only a handful exists at the same time, many enabling technologies can exist simultaneously[4] (Teece 2018). Some of them might eventually become a GPT in the course of time (Teece 2018;

[3] Also previous studies emphasized the lack of a profound framework (e.g. Wanzenböck, Neuländtner and Scherngell 2020).

[4] No uniform definition of GPTs exists in the literature, but they are usually associated with the core features described above (Cantner and Vannuccini 2012). As highlighted by Cantner and Vannuccini (2012), there are two generations of GPT models: The first generation considers only one GPT at a time (e.g., Aghion 2008) while the second one allows for the co-existence of several GPTs (e.g., Carlaw and Lipsey 2006). In the present study I follow the broader approach of co-exiting GPTs. Nevertheless, it is important to be aware that GPTs are rare technologies, in contrast to enabling technologies (see Teece 2018).

Martinelli, Mina and Moggi 2021). The literature remains generally ambiguous whether KETs are GPTs or just share most core characteristics. Therefore, there are reasons to believe that they can be conceptualized as something between enabling technologies and GPTs.

In the present study, I follow the suggestion of Teece (2018) to view KETs at least as 'junior GPTs' and I further acknowledge that (at least some) KETs can partially be considered GPTs. Considering that semi-conductors are treated as a GPT (Bresnahan and Trajtenberg 1995), for example, at least parts of micro- and nanoelectronics (MNE) fall into the GPT category. Biotechnology, the parent field of industrial biotechnology (Aschhoff et al. 2010), is another recognized potential GPT (Lipsey, Bekar and Carlaw 1998). Also lasers, a subfield of photonics, are treated as a potential GPT in the literature (Lipsey et al. 1998). Furthermore, Lipsey et al. (1998) and Shea, Grinde and Elmslie (2011) propose that nanotechnology is also a GPT[5]. Given these heterogeneities concerning their GPT status, this article argues that it is important to analyze the six KETs individually. Thereby their conceptualization can be advanced through differentiating their impact and potential, while such an approach also facilitates the development of a precise theoretical framework of the KET concept.

Furthermore, both GPTs and KETs are not final products but function as core building blocks of innovations (Bresnahan and Trajtenberg 1995; Montresor and Quatraro 2017). KETs are very generic and horizontal in nature, as they "*are multidisciplinary, cutting across many technology areas with a trend towards convergence and integration*" (European Commission 2009b, p. 1). Therefore, they are mainly defined by i) their very wide applicability across various fields, which again raises ii) their potential to induce complementary innovation (horizontally across sectors and technology fields, or vertically in downstream sectors and technology fields) (Teece 2018). Thus, besides the horizontal dimension (and like GPTs; see Bresnahan and Trajtenberg 1995), innovational complementarities in particular give KETs an additional vertical dimension (Corradini and de Propris 2017).

2.2. KETs' impact on innovation

Overall, their special properties endow KETs with a powerful role in driving potential recombinant innovation, as previous studies also have also shown (Wessendorf, Kopka and Fornahl 2021; Montresor, Orsatti and Quatraro 2022; Wessendorf and Grashof 2023; Wessendorf, Kopka and Fornahl 2024). From the technological perspective, KETs act as bridging platforms (Corradini and de Propris 2017): due to their wide applicability, KET knowledge can be combined with knowledge from various technology domains. In this sense, KETs can be considered as 'platforms'

[5] Since the diffusion and adoption of GPTs across the economy takes time, it can be difficult to identify young GPTs. (e.g., Jovanovic & Rousseau 2008; Teece 2018). From this an ambiguous view on KETs results: As indicated with the examples above, some scholars consider single KETs as GPTs. Further scholars see KETs as *young* GPTs (e.g., Antonietti et al. 2022; Montresor & Quatraro 2017; Aschhoff et al. 2010). Others take a more reserved view by treating KETs as *potential* GPTs (e.g., Martinelli et al. 2021; Antonietti & Montresor 2021).

that provide knowledge interfaces to which different knowledge can easily connect (Corradini and de Propris 2017).

Thus, KETs can function as a broker between knowledge fields that are otherwise very distant from each other. This opens up more opportunities for the recombination of knowledge elements, generally facilitating the recombinant process and ultimately enabling innovation (Antonietti and Montresor 2021; Montresor et al. 2022; Wessendorf and Grashof 2023; Wessendorf et al. 2024). While there are still many white spots in the literature, some (regional) economic effects of KETs have recently been investigated. Studies on the innovation-spawning role of KETs refer to their local impact, for instance by pointing out that their embeddedness in the regional knowledge base affects the regional innovation output (Wessendorf et al. 2024). However, to the best of my knowledge, one fundamental aspect of KETs has not explicitly been addressed yet, namely whether knowledge in KETs generally has a greater impact on subsequent innovation processes than knowledge in technologies that are not classified as KETs.

The existing literature indicates that KET knowledge should indeed have a positive impact on innovation because it facilitates recombinant innovation processes (Montresor and Quatraro 2017; Wessendorf and Grashof 2023). Thus, KET knowledge influences innovation processes, which is a prerequisite for the effects measured at the regional or organizational level in previous studies. It is likely that KETs diffuse and unfold their impact also via self-reinforcing loops. The diffusion of KETs should enlarge the scope of their impact and, as Bresnahan (2010) and Martinelli et al. (2021) highlight, technological diffusion can be driven by complementary innovations[6]. KETs might trigger complementary innovation that leads to their own diffusion, which again triggers complementary innovation and thereby also strengthens the impact of KETs. This potential relation gives reason to assume a strong impact of KETs. However, while previous studies investigated the impact of KETs in different (regional) context, the effects of KETs have not yet been contrasted to the effects of non-KETs. This step is important, as it fosters a better understanding which role the particular technological nature of KETs plays, in addition to the already identified geographical and organizational aspects which facilitate the influence of KETs on innovation-related processes.

To gain fundamental insights on the group of KETs and in order to address them more accurately in future analyses and concepts, this study raises the exploratory question whether the designated KETs' impact on innovation differs from technologies not classified as KETs. The question is mainly rooted in two aspects: first, innovational complementarities are at the core of KETs (Montresor and Quatraro 2017; Teece 2018; John, Wesseling, Worrell and Hekkert 2022) and potentially contribute to KETs' impact via involving them in innovation processes. Second, as described in Section 2.1, KETs are at least potential GPTs and the latter diffuse widely across the economy, bearing great potential for innovation, economic development, and an economy-wide impact. KETs are not necessarily as widespread as GPTs (Teece 2018), but should have the

[6] Especially by *"changing the potential application of known techniques"* (Martinelli, Mina and Moggi 2021, p. 184)

potential for a wide scope of their influence on innovation processes. Thus, I assume that KETs, compared to other technologies, are more prone to exert an impact on knowledge generation processes than non-KETs. A common way to measure the impact of technologies are patent citations (e.g., Jaffe et al. 1993; Trajtenberg et al. 1997; Castaldi et al. 2015), and as a proxy for the relevance of patents forward citations[7] are a suitable measure. Accordingly, I propose the following hypothesis.

H1: KET patents are associated with a higher citation frequency than non-KET patents.

In general, KETs are technologies at the intersection of science and industry: they are – to varying degrees – science-based and industry-oriented, highly R&D driven, and provide important application interfaces (European Commission 2009b; Aschhoff et al. 2010; Wanzenböck et al. 2020; Antonietti and Montresor 2021). While there exists no clear categorization of KETs in the literature yet, industrial biotechnology and nanotechnology can roughly be grouped as more science-driven technologies, while AMTs, advanced materials, and photonics are more application- and engineering-based KETs (e.g., Aschhoff et al. 2010; Wanzenböck et al. 2020). Regarding the sixth KET, micro- and nanoelectronics (MNE), also including semi-conductors, the literature is rather equivocal. Whereas some studies highlight the science-based nature of semi-conductors (Pavitt 1984; Ponds, van Oort and Frenken 2010), Wanzenböck et al. (2020) view MNE to be rather engineering-based. Previous studies that consider the six single KETs find differences between their individual effects (e.g., Montresor and Quatraro 2017; Wanzenböck et al. 2020; Wessendorf and Grashof 2023). Particularly the engineering-based KETs advanced materials and AMTs are described to exhibit the most pronounced KET properties (e.g., Aschhoff et al. 2010; Montresor and Quatraro 2017). Consequently, they may diffuse and unfold an impact more rapidly. Additionally, science-based KETs build more on codified knowledge, while engineering-based KETs build more on tacit knowledge (European Commission 2015; Wanzenböck et al. 2020). While codified knowledge is easier to transmit across geographic distances, tacit knowledge is more geographically 'sticky' (von Hippel 1994) and its transfer works mainly through personal interaction and face-to-face encounters (Polanyi 1966; Nelson and Winter 1982; Maskell and Malmberg 1999; Gertler 2003). Thus, relevant tacit knowledge can be harder to access and replicate through other actors or organizations external to those applying the knowledge. At the same time, the application-driven nature of engineering-based KETs may mean more practical problem-solving approaches and a more direct industrial applicability of new solutions, leading to a faster adoption. This may not only support their diffusion but also accelerate innovation cycles. Furthermore, tacit knowledge is an important prerequisite for the emergence of radical innovation (Mascitelli 2000). Even though radical innovation occurs seldomly (Verhoeven, Bakker and Veugelers 2016; Grashof, Hesse and Fornahl 2019), it is highly impactful (Knuepling, Wessendorf and Basilico 2022), in the sense of being destructive but also creating new

[7] Forward citations represent a patent's frequency of being cited by subsequent patents.

markets and business models. Moreover, it has been shown that engineering-based KETs can drive the emergence of radical innovation, due to their ability to combine distant knowledge (Wessendorf and Grashof 2023). All in all, given the aspects explained above, engineering-based KETs might show a greater measurable impact, compared to science-based KETs. Accordingly, I suggest the following hypothesis:

H2: The difference in forward citations between patents in engineering-based KETs and non-KETs is greater than the difference in forward citations between science-based KETs and non-KETs.

In the following section, the methodological strategy to analyze the hypotheses is introduced.

3. Data and Methods

3.1. Data

To assess the assumptions on the diffusion of KETs, the present study uses patent data, matched with organization-level and regional-level data. I consider patent applications to the European Patent Office (EPO) from applicants located in Germany (German applicant address). The dataset is constructed with data from six major data sources and contains information on the patent applications including information on the applicant and the region where the applicant is located. First, I retrieve regionalized patent data from the OECD Regpat database as well as patent data from the OECD Patent Quality Indicators database (both August 2023 version). Then I enrich the dataset with data on the applicant organizations retrieved from two databases of Bureau van Dijk (BvD), namely Orbis IP and Orbis[8]. As it is common to consider the patent family level instead of single patent applications (e.g., Kopka and Fornahl 2024), I additionally join the patent family IDs (*docdb_family_id*) on the dataset. The family IDs were obtained from PATSTAT (2020 version), the patent database by the EPO, using the patents' *application ID*. Finally, I query regional data from the German *Regionaldatenbank*[9] for the regions where patent applicants are located and merge them on the dataset (via the applicant's region ID). After omitting all observations with missing values, the final dataset comprises 4,244 applicants from Germany and 36,886 patent families, among these 3,331 (9%) assigned to KETs. Table 1 presents information about the patent families considered, whereas the variables of interest are introduced in the following section.

[8] I use the *application ID* to retrieve the applicants' *BvD ID*, with which I then query data on the organizational level in Orbis and Orbis IP.

[9] The regional database by the German federal and state statistical offices (www.regionalstatistik.de)

Table 1: KET-specific counts and shares of patent families in the dataset.

Technologies	Patent families	Share in all patent fam.
Non-KETs	33,535	91%
All KETs (aggreg. level)	3,331	9%
AMTs	1,476	4%
Photonics	985	3%
Industrial Biotechnology	667	2%
Adv. Materials	349	1%
Nanotechnology	100	0.3%
MNE	73	0.2%
All	**36,886**	**100%**

3.2. Variables

To analyze the research question, I first perform a propensity score matching (as described in the following Section 3.3 and Appendix 2) in which KET patents are paired with non-KET patents that originated in comparable contexts. This procedure ensures the comparability between KET patents and non-KET patents in the analysis of forward citations. In the next step, I compare the influence of patents of these two groups on subsequent innovation and calculate negative binomial regression models with clustered standard errors. In the following subsection the variables for the matching and for the analysis of the diffusion of KETs are retrieved from the dataset described above, or created based on it.

3.2.1 Patent level variables

As patent citations are commonly used in the literature to proxy technological impact (e.g., Jaffe et al. 1993; Trajtenberg et al. 1997; Castaldi et al. 2015), I use forward citations to capture the impact of KETs and non-KETs. I investigate whether KET patents receive more citations than non-KET patents within seven years of publication[10]. The citation count of each patent application (based applications to the EPO) is the focal variable and is directly retrieved from the OECD Patent Quality Indicators database[11]. For the analysis the patent citations are aggregated at the patent family level (*agg_cits7*) and the variable is log-transformed *(log_agg_cits7)*. Prior to the transformation, a constant of 1 is added to the citation count, in order to handle patents with 0 citations. As the PATSTAT 2020 version is used to query the patent family IDs and because the data quality tends to drop towards the end of the period covered by the PATSTAT database, I select patents with priority application years 2009 and 2010. Due to the

[10] The publication usually takes place 18 months after the application (Squicciarini, Dernis and Criscuolo 2013).

[11] Including self-citations, because they can be even more valuable than citations by others (Hall, Jaffe and Trajtenberg 2005; Squicciarini, Dernis and Criscuolo 2013).

seven-year time lag between publication and forward citation count, this approach ensures a more reliable citation count compared to counting citations of patents filed later.

3.2.2. Technology level variables and identifying KET patents

Following previous studies (e.g., Wessendorf et al. 2024), KET patents are identified via codes[12] of the international patent classification (IPC) assigned to the patents, as provided by van de Velde et al. (2012). Due to their broad and horizontal nature, the individual KETs share some 'natural overlaps' (Larsen et al. 2011; van de Velde et al. 2012; Butter et al. 2014). To account for this, KET patents are identified at a very fine-grained level by using full-digit IPC codes (e.g., Wessendorf and Grashof 2023). If a patent lists one IPC code assigned to a KET, this patent is considered a KET patent (one patent can be assigned to multiple KETs). Binary variables are constructed that indicate whether a patent is a KET-patent (1) or not (0): once at the aggregate level (*isKET*) and also for every individual KET (*is[abbrev. KET name]*)[13]. Non-KET patents are patents that cannot be assigned to any of the six KETs. Furthermore, each patent is assigned to one broader technology field classified by Schmoch (2008).

3.2.3. Organizational level variables

To proxy collaborations and knowledge exchange, I consider the average applicant share of the patents in each patent family[14] (*av_app_share*). Since an organization's age can affect its innovation behavior (Huergo and Jaumandreu 2004), I calculate the age of each applicant organization's at the time of priority application (*org_age*), based on the organization-level data from Orbis. Also an organization's size can affect R&D investments, R&D success, and thus an organization's innovation and patenting behavior (e.g., Acs and Audretsch 1990; Arant et al. 2019). To include the applicant organizations' sizes in the analysis, I consider the size class of the organization as provided by Orbis, based on the number of employees, operating revenue and assets (*size_class*). This variable is ordinal scaled with four ranks ('small', 'medium', 'large', 'very large')[15]. Furthermore, I use the number of publications of the applicant organization[16] as a proxy for the organizations' innovativeness and their experience in

[12] The full list of codes is provided in Appendix 8.
[13] *isKET* = KET (aggregate level), *isAMT* = Advanced Manufacturing Technologies (AMT), *isAM* = (Advanced Materials), *isIB* = (Industrial Biotechnology), *isMNE* = (Micro- and Nanoelectronics, including semi-conductors), *isNT* = (Nanotechnology), *isPT* = (Photonics)
[14] *av_app_share* is computed as the sum of the applicant shares of all applications within one patent family, divided by the number of applications in the patent family.
[15] Size classification in Orbis, according to the user guide (organizations need to meet at least one of the following criteria):
Very large: Operating revenue >= 100 mil. EUR, employees >= 1000, total assets: 200 mil. EUR / *Large:* Operating revenue >= 10 mil. EUR, employees >= 150, total assets: 20 mil. EUR, not very large / *Medium:* Operating revenue >= 1 mil. EUR, employees >= 15, total assets: 2 mil. EUR, not (very) large / *Small companies:* not included in any of the above categories
[16] As Orbis only provides the count of an organization's publications from 2015 on, I create a proxy by using the organizations' mean publication number of the five-year period 2015-2019.

applying for patents (*pubs_org*). In addition, I include 4-digit NACE[17] codes[18] to assign the patents' applicant organizations to economics sectors (*NACE*).

Additionally, since external knowledge can play an important role in recombinant innovation processes (e.g., Miguelez and Moreno 2018; Hesse and Fornahl 2020), I consider whether an organization's ownership structure displays direct international ties in the patent application year. A binary variable[19] (*struct_mn*) indicates whether this is the case (1) or whether it is unclear (0). Even though the variable does not contain comprehensive information on multinational enterprises, it is a is good proxy to include at least a parts of them as such.

3.2.4. Regional variables

Based on the applicants' addresses, all patents are regionalized at the level of 141 German labor market regions (LMR), as defined by Kosfeld and Werner (2012). LMRs are functionally defined and larger than NUTS3- but smaller than NUTS2-regions. They consider commuter traffic and thus account for the fact that human capital, in which knowledge is embedded, often is attracted to the location of work from a wider geographic area that exceeds the administrative boundaries of the municipality where the occupation is located (Kosfeld and Werner 2012). At the LMR level I compute the average annual population density (*popdens*) for the time period 2008-2011[20] to proxy agglomeration economies and knowledge spillovers. To consider the regional absorptive capacity (Cohen and Levinthal 1990) and regional human capital in general that may have affected the generation of the patents in the dataset, I use the number of employees with an academic degree and calculate the logged average for each LMR in the time period 2008-2011 (*log_acad_empl*).

3.2.5. Variables' summary statistics

Prior to the next step, all observations with missing values in any of the variables are removed. The descriptive statistics of the relevant variables, including a brief description, are reported in Appendix 1. In summary, the dataset is very heterogeneous.

[17] NACE = Nomenclature générale des activités économiques dans les Communautés Européennes“ (Statistical Classification of Economic Activities in the European Community)
[18] NACE rev. 2
[19] It would have been desirable to instead include a dummy variable in the analysis that indicates whether an organization is a multinational enterprise or not. Unfortunately, the Orbis database contains only the most up-to-date ownership information (from 2024) and regarding ownership information, only shareholder data is available for 2009 and 2010. Thus, I simply assess direct shareholders and subsidiaries (as far as possible) and complement the available information by data on the global ultimate owners (GUOs) of the patent applicants. In the first step, I analyze which applicant organizations had shareholders that were located in foreign countries in 2009 or 2010. In the second step, I retrieve a list of subsidiaries (as of 2024) for the applicants and identify all foreign subsidiaries, of which an applicant of my dataset was a shareholder in 2009 or 2010. This way, at least a part of companies with multinational activities can be identified. Finally, I retrieve a list of the applicants' GUOs from Orbis (as of 2024). With the help of data on mergers and acquisitions (M&A) I filter for those applicants that have a foreign GUO that has not been subject to any M&A transaction since the focal time period of 2009/2010.
[20] By choosing the time period 2008-2011, I consider one year before and one year after the focal period to reduce the risk of data distortion by outlier values in the focal period.

The patents in the dataset tend to be from regions with academics, while for example the population density and the organization's age vary on a broad range.

3.3. Methodological strategy

Before assessing whether there is a difference in the citation frequency between KET patents and non-KET patents, I conduct a propensity score matching (PSM), which is a common method to estimate treatment effects by enabling causal inference without requiring too many underlying assumptions (Ho, Imai, King and Stuart 2007; Abadie and Imbens 2016; Leusin 2022; Cantner, Grashof, Grebel and Zhang 2023). I consider KET patents to be 'treated' patents and non-KET patents as the control group, thus matching KET patents to non-KET patents that emerged in a comparable context. While this procedure leads – disadvantageously – to information losses[21], it – very advantageously – creates a balanced dataset for the further analysis (Rosenbaum and Rubin 1983; Leusin 2022; Cantner et al. 2023). In the PSM, I consider the binary KET variables for the assignment to the treatment and control groups and the following covariates, introduced in Section 3.2: *av_app_share, org_age, size_class, pubs_org, NACE, struct_mn, pop_dens, log_acad_empl* and *schmoch*. Depending on the individual variable, I either choose a direct match or a match via the nearest neighbor algorithm. Further details and background information on the PSM is provided in Appendix 2.

As the control group is much larger than the treatment group, I set the matching ratio to 1:2 for KETs at the aggregate level, meaning that one KET patent is matched to up to two control patents[22]. In the second step of the analysis, I split the treatment group of KETs into six subgroups of the individual KETs. Only subgroups that account for at least 1% of the number of control patents are included in the analysis (arbitrary threshold). As the number of patents in nanotechnology and in MNE is below this threshold[23], both are excluded from the analysis. Since the four remaining KET subgroups are much smaller than the aggregate KET treatment group, the matching ratio[24] here is set to 1:5. Appendix 3 shows the sample sizes and Appendix 4 reports the statistics of the treatment groups and the control group before and after the matching for both parts of the analysis (aggregate and individual KET level), indicating a strong balance improvement.

To further assess the quality of the matching and to control whether statistically significant differences exist between the samples after the matching, I compare the variances through running an F-test on the pre-matching and post-matching samples,

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[21] Information (patents, in the present case) too distant from their counterfactuals are not considered (e.g., Leusin 2022).

[22] A robustness check is performed with matching ratios 1:1 and 1:5, the results show consistency in the balance after the matching.

[23] Micro- and Nanoelectronics (MNE):73 observations, Nanotechnology: 100 observations

[24] A robustness check is performed with matching ratios 1:1 and 1:10 for individual KETs and 1:1 and 1:5 for aggregate KETs. The results show consistency in the balance after the matching.

for each variable that is matched via nearest neighbor matching. The F-tests indicate a strong balance improvement and are reported in detail in Appendix 5.

To gain a more detailed view of citation patterns of the KET group and the non-KET group, for each group the patents are allocated in deciles that are created based on the group-specific citation counts. For this, the datasets resulting from the PSM are used. Since KETs can be matched to multiple non-KETs, the mean of the logged citation counts is computed for the non-KET patents in each matched group. The non-KET deciles then are created based on the mean values of non-KETs, which also serve as the basis for a further comparison between KETs and non-KETs. Two indicators are employed for the analysis: For each decile, a) the average logged citation count per group is computed and b) the maximum logged citation counts per group is considered.

Finally, a series of negative binomial regression models with clustered standard errors is calculated. The negative binomial approach is chosen because the dependent variable exhibits overdispersion. The standard errors are clustered at the patent family level (*docdb_family_id*), since a single patent can occur multiple times in the dataset, for instance when it has more than one applicant and the applicants are located in different regions or belong to a different size class. As it is common that many patents do not receive citations (Squicciarini, Dernis and Criscuolo 2013), only patents that are cited are considered in the regression analysis. The number of citations (*agg_cits7*) serves as the dependent variable while in each model one of the KET dummies is employed as explanatory variable (*isKET_dum, isAMT_dum, etc.*). Additionally, the models control for the following variables introduced above (mostly logged): *log_popdens, log_acad_empl, log_org_age*[25], *size_class, log_pubs_org, log_av_app_share,* and *struct_mn*. The results are presented and discussed in the following section. For each model the variance inflation factor (VIF) is computed and the results raise no concern for multicollinearity issues. The descriptive statistics for each regression dataset are provided in Appendix 7.

4. Results

4.1. Descriptive statistics

Propensity score matching facilitated the comparison of citation counts between KET and non-KET patents by matching on the basis of criteria relevant to the generation of (KET) patents and by balancing the dataset (see Appendix 4). The descriptive statistics on the number of patent citations[26] provide an overview on the citation frequencies of KETs and non-KETs (see Table 2). Both groups display highly right-skewed distributions, as many patents receive few or no citations (the median of the

[25] To manage outliers, organizations older than 150 years (arbitrary threshold) are assigned an age of 151 years.
[26] Note that the logged number of forward citations is considered.

logged citation count is 0 for KET patents and non-KETs). The skewness is higher for KET patents (1.61) than for non-KETs (1.47), as also indicated by the higher mean (KETs: 0.54 non-KETs: 0.47) and the higher maximum (KETs: 4.94, non-KETs: 4.09). The variation is larger for KETs. The identical third quartile for KETs and non-KETs (0.69) indicates that the higher average citation count of KETs is due to fewer patents with higher counts. Furthermore, the mean values show that KETs receive more citations on average than non-KETs.

Table 2: Summary statistics of logged forward citation count per KET.

KET	Group	Min.	1st Qu.	Med.	Mean	3rd Qu.	Max.	SD	Skew-ness
KETs (agg. Level)	treatment	0	0	0	0.54	0.69	4.94	0.71	1.61
	control	0	0	0	0.47	0.69	4.09	0.65	1.47
AMTs	treatment	0	0	0	0.48	0.69	3.13	0.64	1.32
	control	0	0	0	0.46	0.69	4.45	0.65	1.59
Advanced Materials	treatment	0	0	0.69	0.61	1.1	3.43	0.66	1.06
	control	0	0.23	0.5	0.59	0.86	2.56	0.67	0.97
Industrial Biotech	treatment	0	0	0	0.55	0.69	4.94	0.85	2.15
	control	0	0	0	0.52	0.80	4.03	0.71	1.44
Photonics	treatment	0	0	0	0.59	1.1	4.09	0.75	1.52
	control	0	0	0	0.42	0.69	2.89	0.58	1.24

Also at the individual KET level, the summary statistics reveal very right-skewed distributions and a high variability that even exceeds the mean in most cases. No citations occur in the first half of observations, with the exception of advanced materials, where the control group counts a few citations at the first quartile and both groups have a median greater than 0 (higher for advanced materials). While the descriptives differ between the four analyzed KETs, they all have higher mean values than their control groups, likely due to their higher maximum forward citation counts. Surprisingly, AMTs differ from the remaining KETs as their control group has a higher citation maximum (although the mean citation count is slightly higher for AMTs than for the control group).

4.2. Decile-based analysis

In order to obtain more detailed observations than is possible at the quartile level, the analysis is further carried out at the level of citation-based deciles (to which the patents are assigned as described in Section 3.3[27]). Figures 1a-1c show the comparison of the mean citation count and the maximum citation count within each decile. Extending the insights from the previous sub-section (4.1), no citations are observed in the lowest deciles for any group and only non-KET patents are cited in the lower deciles (non-KETs receive citations 2-3 deciles earlier than KETs). In the upper deciles, KETs show higher citation counts than non-KETs, in most cases.

[27] Appendix 6 provides an additional way of decile creation, based on the citations of KETs in matched groups.

At the individual KET-level, the clearest difference between KETs and the non-KETs control group exists in the case of photonics. While patents in this KET receive no forward citations in the lower five deciles, the upper five deciles suggest that photonics patents are cited more frequently than non-KETs. Advanced materials display differences to non-KETs and the pattern is related to the pattern in photonics but the differences between advanced materials and the control group is less pronounced. Industrial biotechnology is characterized by rather small differences to non-KETs in the upper deciles, both regarding the maximum citation count and the mean citation count. As already indicated in the previous sub-section, AMTs are a special case: while their mean citation count is higher than for non-KETs in the top four deciles, the non-KET group accounts for the highest citation number in the tenth decile. Regarding other deciles in the upper half, AMTs are only (slightly) more impactful in deciles 6, 8, and 9.

The findings generally reveal that fewer KET patents receive citations than non-KET patents, while those that are cited tend to be cited more frequently. Thus, the next step of the analysis in the following subsection focuses on the question whether among the cited patents a KET-status influences the citation frequency.

Figure 1a: Mean logged citation count and maximum logged citation count across deciles for KETs at the aggregate level, compared to non-KETs.

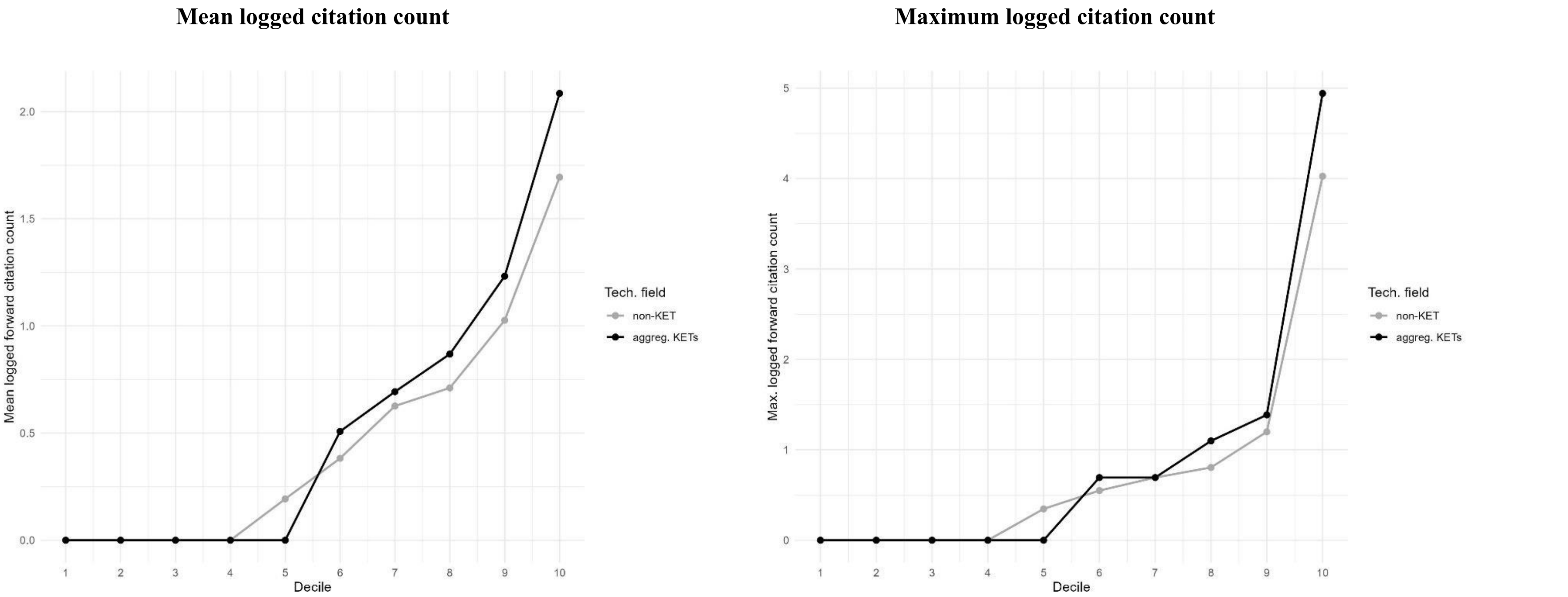


Figure 1b: Mean logged citation count across deciles per technology group.

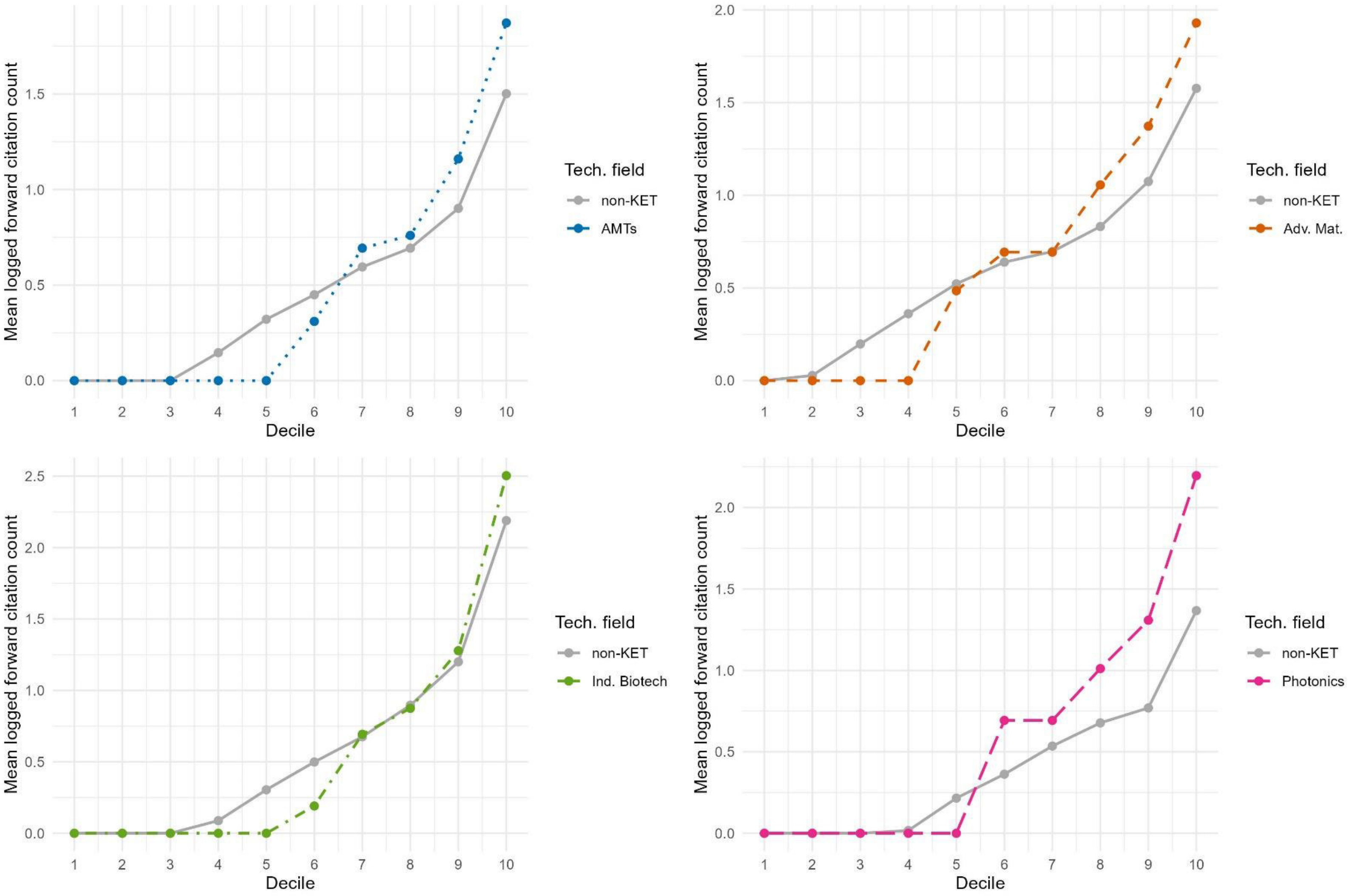
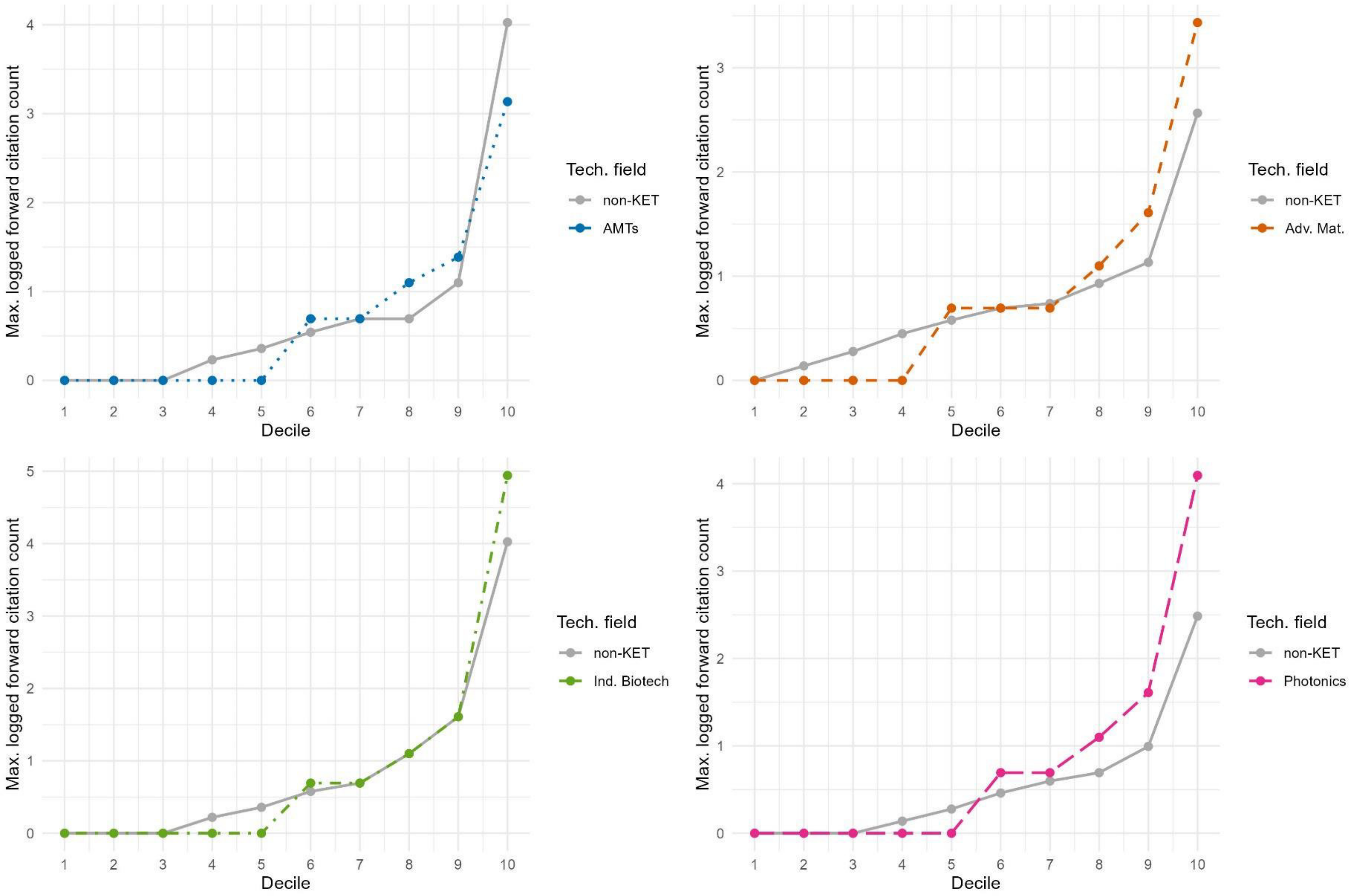


Figure 1c: Maximum logged citation count per decile and technology group



4.3. Regression analysis

In the next step, a series of negative binomial regression models with clustered standard errors is computed. The results show that, at the aggregate level, being a KET is associated with a statistically significant positive influence on the forward citation count. This aligns with the findings from the earlier descriptive analysis. Moreover, this effect seems to be particularly driven by photonics, where the KET status has a highly significant positive influence on forward citations. Additionally, also industrial biotechnology exhibits a statistically significant positive effect. In contrast, the KET status of advanced materials patents shows no influence on the citation frequency. While the descriptive overview (Section 4.1), surprisingly, suggested that AMTs are a special case (given their control group's maximum citation frequency is higher), the analysis now provides additional evidence regarding the particularity of this group. Here, AMTs are found to be associated with a statistically significant negative impact on forward citations, meaning that AMTs lead to fewer forward citations than their control group of non-KETs.

The control variables included in the regression do not have a consistent statistically significant impact across the different KETs. In many cases, their observed effects are outside the significance thresholds, but including them in the models increases the model fit (McFadden's-R^2). The variation in the effects of the control variables may stem from differences in sample sizes variations in the characteristics of the individual KETs.

Table 5: Results of negative binomial regression models (clustered standard errors in parentheses).

	Dependent variable: agg_cits7				
	(1)	(2)	(3)	(4)	(5)
isKET_dum	0.163*				
	(0.093)				
isAM_dum		-0.034			
		(0.149)			
isAMT_dum			-0.165*		
			(0.087)		
isIB_dum				0.471**	
				(0.238)	
isPT_dum					0.484***
					(0.120)
log_popdens	0.039	-0.048	0.062	-0.040	0.176**
	(0.052)	(0.089)	(0.072)	(0.093)	(0.075)
log_acad_lmr_avg	0.040	0.074	0.013	0.192	-0.064
	(0.051)	(0.111)	(0.057)	(0.127)	(0.070)
log_av_app_share	-0.088	0.491	-0.644**	0.191	0.507**
	(0.226)	(0.435)	(0.265)	(0.376)	(0.234)
log_org_age	-0.012	0.074	-0.067	0.073	0.074*
	(0.044)	(0.046)	(0.044)	(0.120)	(0.044)
log_mean_pub_nr	0.072***	0.006	0.027	0.030	0.063**
	(0.026)	(0.026)	(0.024)	(0.079)	(0.027)
struct_MN	-0.011	-0.077	0.034	-0.038	0.148
	(0.077)	(0.137)	(0.085)	(0.255)	(0.100)
size_class: medium	0.299	0.608	-0.034	-0.236	0.386
	(0.337)	(0.524)	(0.167)	(0.493)	(0.343)
size_class: small	-0.098	-0.115	-0.099	-0.268	0.347*
	(0.238)	(0.243)	(0.208)	(0.530)	(0.196)
size_class: very_large	-0.240	0.287	0.024	-0.891*	-0.077
	(0.224)	(0.220)	(0.137)	(0.507)	(0.143)
Constant	0.229	0.072	0.475	-0.247	-0.410
	(0.530)	(0.918)	(0.503)	(1.443)	(0.515)
McFadden's R^2	0.34	0.319	0.364	0.333	0.385
Observations	2,167	462	1,379	433	994
Log Likelihood	-4,783.140	-966.500	-2,914.551	-1,053.563	-1,997.857
theta	1.506*** (0.060)	2.214*** (0.230)	1.852*** (0.102)	1.168*** (0.092)	2.341*** (0.168)
Akaike Inf. Crit.	9,588.280	1,955.000	5,851.102	2,129.126	4,017.714
Note:					*p**p***p<0.01

5. Discussion

In the following, the results presented in Section 4 are discussed. While the expectations towards KETs are high, the results draw a mixed picture of their influence on subsequent innovation. In summary, the influence rather concentrates on fewer but more impactful patents. Moreover, the actual impact substantially varies across the individual KETs.

5.1. Aggregate KET level

At the aggregate level, KETs exhibit a higher mean citation count than the non-KETs control group, suggesting they play a more influential role in innovation processes than non-KETs. This finding is complementary to previous studies that focus on the innovation-spawning role of KETs (e.g., Montresor and Quatraro 2017; Wessendorf and Grashof 2023; Wessendorf et al. 2024), supporting H1 to a certain extent. However, a closer look reveals that in both groups of KETs and non-KETs normally not all patents generate a measurable impact, as proven by the number of patents with zero citations. While it is common for many patents to remain uncited (Squicciarini et al. 2013), interestingly even fewer KET patents are cited than non-KETs – indicating that fewer KET-based innovations are highly relevant in subsequent innovation processes. On the other hand, *if* KET-based innovations make an impact, it can be greater than the influence of non-KET innovations. When excluding patents with zero citations from the analysis, i.e. when only considering patents that influence innovation processes, the empirical results from the regression analysis suggest that KETs, at the aggregate level, are more influential than non-KETs. Given the results from the different steps of the analysis, in summary partial support for H1 is found and the findings highlight that KETs can play a special role in innovation processes.

KETs' multi-disciplinarity and cross-cutting nature (European Commission 2009a; Aschhoff et al. 2010) enable them to establish links between different technological fields, making KETs central elements in recombinant innovation processes. This bridging function (Corradini and de Propris 2017), combined with the broad applicability of KETs (European Commission 2009b, 2009a; Larsen et al. 2011), may explain the stronger influence of KET knowledge in the observed cases: as a 'bridge' or knowledge interface, and in line with its GPT-like nature, KET knowledge becomes a central element in innovation processes as a 'knowledge connector'. As such, it has the potential to appear in innovations more often than other (and less broadly defined) technologies, which is measured by the forward citations evaluated in the present analysis. Furthermore, KETs' innovational complementarities trigger downstream innovation (Bresnahan and Trajtenberg 1995; Teece 2018) that potentially cite the upstream KET patent. However, the results raise the questions why not the majority of KET patents has a higher impact than non-KET patents and whether the bridging function of KETs might not be so pronounced for all KETs and their subfields[1]. While the special properties of KETs can explain their positive effects on recombinant innovation (e.g., Montresor and Quatraro 2017; Montresor et al. 2022; Wessendorf and Grashof 2023), and likely are foundational elements of KETs' impact, they might also pose challenges. As outlined in Section 2, the innovation-spawning effect of KETs is partially rooted in their innovational complementarities. Consequently, the impact that KETs can unfold also depends on advancements in complementary technologies and the emergence of complementary innovation (Aschhoff et al. 2010). Thus, the fact that many KET patents remain uncited might not always be related to KETs themselves, but can be due to developments in other technology fields and application sectors instead. Advancements in KETs may not be able to be fully utilized and exploited when complementary technologies lack the necessary progress. Regarding KETs' bridging function, it is generally comparatively rare that very distant knowledge is getting linked during innovation processes (Verhoeven et al. 2016; Grashof et al. 2019). While KETs can support linking distant knowledge elements (Wessendorf and Grashof 2023), at the same time the opportunity to act as bridging technology may not be given that frequently. Another important obstacle is the so-called 'valley of death': as outlined by the EC, Europe is strong in KET knowledge but has difficulties with its commercialization (e.g. Aschhoff et al. 2010; Butter et al. 2015), which limits their impact as they cannot fully unfold their market potential (potentially hampering KETs diffusion and application, negatively impacting citations). Moreover, KETs are rather complex technologies and also products and value chains based on KETs are more complex (e.g., European Commission 2009a; van de Velde et al. 2012; Butter et al. 2014). In contradiction to KETs' wide applicability, this might make it more difficult for KET knowledge to become incorporated in innovation processes in some cases, thus weakening the advantage of a wide applicability and leading to fewer citations. It also needs to be noted that not receiving a citation does not exclude the presence of an impact. When KETs are the basis for downstream innovation but are not part of the innovation themselves (see complementarities described in Section 2), or when certain knowledge elements in KETs are widely spread and become 'common knowledge' (as in the case of some GPTs), they exert an impact but may not be referred to in patents. Moreover, as Bresnahan (2010) outlines, particularly for young GPTs the diffusion may be slow in the beginning. This might also apply to (some) KETs, given that they are young technologies at different life cycle stages, and could impede their impact. Whereas, undoubtfully, further research is necessary to test these assumptions, the aspects above may explain the findings of fewer KET patents receiving forward citations.

[1] Examples for subfields of KETs: Laser technologies are subfields of photonics, synthetic biotechnology is a subfield of biotechnology (within this subfield, for instance CRISPR-Cas9 is a component/tool), lightweight alloys are a subfield of advanced materials.

5.2. KETs at the individual level

At the level of the individual KETs[2], it applies to all analyzed KETs that fewer patents exert an impact than non-KET patents. The greater impact of KETs, observed in the regression analysis at the aggregate level, only holds for photonics and industrial biotechnology (at higher significance levels), which are both more impactful than their non-KET control groups. This makes them the main drivers of the overall KET effect and science- and more application-oriented KETs cannot be distinguished based on the results, contrary to the initial presumption. Moreover, the results do not even permit to clearly group photonics with the other application-driven KETs (advanced materials or AMTs). Since AMTs even are negatively associated with citation frequency and no statistically significant effect of advanced materials is found, the underlying assumption of H2 that KETs consistently outperform other technologies does not hold. Given these recognitions, H2 clearly must be rejected.

In comparison to AMTs and advanced materials, industrial biotechnology and photonics are more specialized, which could enhance their visibility when they have been adopted in industries and regions, resulting in higher citation frequencies. Additionally, given that both industrial biotechnology and photonics are related to fields identified as GPTs in the literature (Lipsey et al. 1998; Aschhoff et al. 2010), as described in Section 2.1, they could be at higher maturity level than AMTs and advanced materials, influencing innovation processes as more established technologies. Furthermore, industrial biotechnology, which is science-based and builds more on codified knowledge (Wanzenböck et al. 2020) may 'naturally' be more outstanding in terms of forward citations, since codified knowledge is easier to refer to and patent activities may be more common in the field. Considerung AMTs, their special role contradicts the initial overall assumptions of a strong innovation-driving effect. However, their highly heterogeneous nature (e.g., Aschhoff et al. 2010; van de Velde et al. 2012) may cause the mixed results. On the one hand, their mean citation count in the four upper deciles exceeds the mean of the non-KET control groups, while on the other hand, the maximum citation count in the 10th decile is observed for non-KETs and the regression analysis reveals a negative effect. While, undoubtfully, further investigations on the role of AMTs and potential barriers are necessary here, several aspects may be relevant. First, knowledge in application-oriented technologies often is exchanged more informally (Wanzenböck et al. 2020). Hence, depending on the subfield, patent activities may be less common. Second, firms may choose to not patent innovations, for instance in order to not disclose strategically relevant knowledge to competitors, or because the available resources make filing a patent application seem inefficient. Third, while the decile analysis shows that some AMTs patents are more impactful than non-KET patents, other patents might rather represent incremental innovation, relating to improvements in specific manufacturing contexts, thus attracting less general attention. The absence of a

[2] Four of the six KETs are included in the analysis, since nanotechnology and MNE are excluded due to a very low number of observations (see Section 3).

statistically significant effect in advanced materials could be due to similar aspects that are just not as pronounced as in the case of AMTs.

5.3. KETs as heterogeneous technology fields

Although the findings of the present study do not fully align with the proposed hypotheses, they are consistent with other studies in observing heterogeneous effects across the individual KETs (e.g., Montresor and Quatraro 2019; Wessendorf and Grashof 2023). Similar to previous research, the expected effects are found at the aggregate level but do not hold for all KETs when considering them separately. Antonietti et al. (2023) find, for instance, that KETs at the aggregate level increase the regional complexity of skills, tasks and occupations. At the disaggregate level, they only find effects of advanced materials and industrial biotechnology on the complexity of occupations though, and of AMTs and advanced materials on task and skill complexity. Wessendorf and Grashof (2023) observe, amongst others, a positive effect of KETs on radical innovation generation in firms, but at the disaggregate level this only holds for advanced materials, photonics, and (to a lesser extent) AMTs. Antonietti and Montresor (2021) show that, from the aggregate perspective, KETs can drive regional diversification. Regarding the individual KETs, only AMTs and advanced materials exhibit this effect. While the specific context and focus of these studies needs to be considered, it is important to note that they all derive their core assumptions from the horizontal and vertical enabling nature of KETs. Additionally, taking the results from previous studies into account, it is very context-specific for which of the KETs the expected enabling function under investigation is observed. Considering AMTs for example, the observed positive effect on regional diversification by Antonietti and Montresor (2021) may stem from cross-industry spillovers of this very broad KET. However, not all spillovers may lead to patent citations. Furthermore, process innovation in AMTs presumably is more difficult to patent/cite due to its tacit nature. While these findings and potential explanations highlight the importance for future research to consider the context in which KET patents are cited, it particularly reinforces the need for a granular approach to KETs. As emphasized in previous literature (Montresor and Quatraro 2017), KETs are at different stages of their life cycle, and the different subfields of individual KETs are probably at different technology readiness levels (TRLs), which potentially is another piece that contributes to the puzzle of observed differences in forward citations. Some KET-subfields might rather be in the emerging phase, being adopted slowly and not receiving many citations, while others are in the growth phase, rapidly diffusing and drawing attention towards them. While the results could also be owed to the broad and diverse nature of KETs, they raise the question whether it could be more effective to address sub-KETs instead of the complete individual KET-fields (for instance 'enzymes' or 'biochemicals' in the case of industrial biotechnology). In summary, the results of this study provide limited support for the idea of a high impact of KETs in general (European Commission 2009b, 2009a, 2012) and strongly call for a more granular investigation of KETs' impact.

5.4. Future research directions

While the heterogeneities in the results may be based on multifaceted underlying reasons, they highlight the need for further research with a more nuanced approach on the specific KETs, as previously advocated by other studies that also found differing effects of the individual KETs (e.g., Antonietti et al. 2023; Wessendorf et al. 2024). Why KETs are not always more impactful than non-KETs is beyond the scope of this study and raises several questions with opportunities for future research. While the link between the impact of KETs and their innovation-spawning role still needs to be explored in detail, it should particularly be investigated whether the special impact of KETs can emerge across the board of KETs or whether only certain subfields of the individual KETs drive the effects that are commonly associated with KETs. The latter may be one explanation for the heterogeneity in KETs' effects – not only in the context of this study, but also for heterogeneities outlined by other studies (e.g., Antonietti and Montresor 2021; Wessendorf and Grashof 2023; Wessendorf et al. 2024). Another interesting question for future research is whether a greater impact of certain KET patents rather is exerted horizontally, unfolding their bridging function (Corradini and de Propris 2017), or vertically, via innovational complementarities (Teece 2018). It also is essential to explore the influence of regional and firm-level characteristics on the relationship between KET status and forward citations, to find out whether factors at these level contribute to the diverse effects observed in this study.

As a comparison of the life cycle stages of different KETs still is a blind spot in the literature and an own study for itself, further research on the impact and diffusion of KETs would benefit from including life cycle aspects. While the differences between the individual aspects may partially be explained by life-cycle-related aspects, the question is whether this also applies to the subgroup of KETs, or whether the intra-KET differences (few impactful patents, many patents without citations) are rather explained by other factors. Additionally, to provide general insights on the influence of KETs, this study's approach is rather broad. Future research, however, should not only consider the origin of KET patents, but for in-depth insights the context in which KET patents are cited should be considered at the levels of organizations, industries, and regions.

6. Summary and Concluding Remarks

6.1. Summary

Despite the strong potential of KETs to influence a variety of innovation-related processes, it is under-researched whether KETs generally have a greater influence on innovation processes than non-KETs. In a first step towards closing this gap, the present study analyses whether KET patents have a greater influence on innovation processes than non-KET patents. Based on the special properties of the former, I assume that KETs are more impactful, while KET-specific differences are expected. Forward citations of patents are chosen as a proxy of the impact of patents and at the aggregate level, the results reveal indeed that KETs, on average, are more impactful than non-KETs. A closer look, however, shows that the impact is limited as actually fewer KET patents receive forward citations than non-KETs. Thus, the regression models employed in the analysis focus on the patents that receive citations, and show that patents comprising KET knowledge are associated with a higher forward citation frequency than non-KET patents. In other words, the impact of KETs is concentrated on a few but impactful patents: KETs do not always have a measurable or a strong impact compared to non-KETs, but if they exert any impact, they have the potential to be more influential than non-KETs. However, even though potentially greater, the influence of KETs on innovation appears to be more limited and specific than it is the case for non-KETs. While I follow Wanzenböck et al. (2020) to roughly categorize KETs in science-driven and engineering-based technologies, the results of the present study do not permit any indications for this categorization based on KETs' influence on innovation, contrary to my second hypothesis.

Overall, the difference in citation frequency between KETs and non-KETs, when examined at the aggregate level, suggests that KETs can indeed be more important in recombinant innovation processes than non-KETs, even though this does not apply to the majority of KET patents. Furthermore, the findings indicate the complexity of the group of KETs, as the results are heterogeneous and partly deviate from the literature-based assumptions. It appears that the innovation-driving function of KETs might not only depend on their GPT-features, but on context-specific aspects in combination with their special nature. Life-cycle related aspects, the availability of complementarities to utilize advances in KETs, knowledge characteristics and commercialization barriers could play a role and should be addressed in future studies.

6.2. Limitations and further opportunities for future research

Besides the aspects already indicated previously, further limitations of this study must be acknowledged that also offer opportunities for further research. First of all, the current approach does not allow to conclude on causal relationships. Second, the analysis is based on forward citations of patents. The use of patent data has its well-known limitations, as for instance not all innovations are patented, and not all patents are commercially utilized (Griliches 1990). Consequently, the effects of KETs might be underestimated, especially in fields where patenting is not common. Future research could be enriched by including alternative innovation indicators, and also alternative indicators to measure the impact of KET knowledge (e.g., by constructing knowledge spaces and employing indicators of social network analysis). Third, the matching approach limited the analysis of KETs to those KET patents that are, in selected aspects, comparable to non-KET patents. Many KET patents did not receive any match from the group of non-KET patents, which limits the generalizabilty of the findings. Thus, future research should also consider the origin of KET patents more closely and take into account that the special nature of KETs could potentially mean that KET patents originate in contexts that are not always comparable to non-KETs (making matching harder). Fourth, the generalizability is also limited by this study's focus on the single country of Germany. While Germany is strong in KETs (Butter et al. 2014), each country might have different priorities and knowledge in KETs. At least an EU-wide focus should be implemented in future studies. Fifth, due to data limitations, only patents that were applied within a two-year period were considered. Subsequent research should consider longer time periods, if possible. Sixth, further studies could benefit from identifying other enabling technologies as well as GPTs among the group of non-KETs, to reduce the risk of comparing KETs to KET-like technologies.

6.3. Contributions, implications and final remarks

Despite these limitations, this study extends the literature on KETs' effects by addressing their direct influence on innovation. First, while KETs are broad technology fields sharing similar core characteristics, the results particularly highlight their heterogeneity by showing that KETs' impacts are not uniform and concentrate on a few highly impactful innovations within the individual KET fields. Second, further questions are raised that are central to gain a preciser understanding of KETs and the mechanisms underlying their effects. Third, the results particularly highlight the need for a critical assessment in which contexts KETs unfold an impact. To address them precisely in future research and policy-making, it must be analyzed in which settings KETs are generally impactful or whether only a handful of innovations and specific subfields of the individual KETs drive the effects commonly attributed to them.

The findings also offer important policy implications. Policies and policy measures targeting KETs in the context of innovation, for instance in the form of investments in R&D, skills and infrastructure, must adopt a granular approach. While the results need further investigation to identify potential barriers for KETs' influence in different settings, it is advisable to address KETs at least at the specific KET-level, if not even at the level of KET-subfields, and in the specific context in which KETs are supposed to unfold an impact. Once the KET subfields that extert a particularly strong impact on innovation activities are identified, innovation policies should promote their further development. Also for firms, the results suggest the need to prioritize subfields of the individual KETs that demonstrate a stronger impact on innovation. To enhance their innovation potential, firms should assess which of these subfields align with their capabilities and markets to make targeted investments.

Given the diverse results on KETs from other studies and the present insights, one should not only focus on the core commonalities between KETs but equally consider their breadth and distinguishing aspects. Nevertheless, this study also highlights the potential impact KETs can have - even though their influence is not as striking as expected.

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Appendix

Appendix 1: Descriptive statistics of the relevant variables

Tables A1a through A1d report the descriptive statistics of the relevant variables. As is shown in the tables, the average population density (*popdens*) varies across a very wide range while the statistics suggest a few extreme outliers. Regarding the number of academic employees in the LMR where the patents in the dataset originated, the distribution has a slightly longer left tail, meaning there are some patents from regions with a comparatively low regional number of employees holding an academic degree, while the statistics show that the variation is generally moderate and most patents are rather from regions with more academics. As for the applicant share, it can be derived that some patent families on average have multiple applicants per patent. However, in at least 75% of the patent families in the dataset there is on average one applicant per patent (there can be different applicants within the family though). The mean number of publications *pubs_org* varies on a very wide range and is very right-skewed, with many organizations having few publications and few organizations achieving extreme values. The organization's age at the time of patent application also varies on a wide range (from 0 to 622 years), while one quarter of the organizations is at maximum 20 years old and half of the organizations 61 years or younger. The high maximum and the average that is slightly higher than the median suggest that a few outliers exist, which also increases the standard deviation. As the statistics for *struct_mn*, a binary variable, reveal, 30% of the organizations could be identified to have multinational ties in the application years 2009 and 2010. The citation counts *agg_cits7* and *log_agg_cits7* are very right-skewed with excess zeros, meaning many patents receive no citations at all, while some patents receive many citations. This is in line with the general pattern that usually many patents are not cited (Squicciarini et al. 2013). The log-transformation of *agg_cits7* leads to an improvement of the data quality for the analysis. The frequencies for the categorial variable *schmoch* are shown in Table A1b. All 35 technology fields by Schmoch (2008) are represented to varying extents. The observation frequency of the different expressions of *size_class* can be seen in Table A1c. Almost three quarters (74%) of the patents are applied for by very large organizations, followed by large organizations (13%). Medium sized-companies are only represented in 5% of the cases and small ones in 8%. Also the majority of NACE codes is represented. In summary, the dataset is very heterogeneous.

Table A1a: Summary statistics of numeric variables.

	Min.	1st Qu.	Med.	Mean	3rd Qu.	Max.	sd	Skew-ness
Popdens	39.0	1,764.5	4,912.7	4,435.6	6,690.4	11,075.4	2905.0	0.2
log_acad_empl	7.2	10.3	11.3	11.1	12.0	12.4	1.1	-0.4
org_age	0	20.0	61.0	73.1	124.0	622	55.1	0.6
pubs_org	1.0	5.3	17.7	127.4	175.6	875.8	203.1	1.8
av_app_share	0.1	1.0	1.0	0.96	1.0	1.0	0.1	-3.1
struct_mn	0	0	0	0.3	1.0	1.0	0.5	0.8
agg_cits7	0	0	0	1.2	1.0	194.0	3.5	18.2
log_agg_cits7	0	0	0	0.5	0.7	5.3	0.6	1.5

Table A1b: Frequencies of occurences of the 35 individual technology fields (as defined by Schmoch 2008)

Schmoch	Count	%	Schmoch	Count	%
1	3,605	9.3	19	1,201	3.1
2	455	1.2	20	707	1.8
3	389	1.0	21	726	1.9
4	583	1.5	22	28	0.1
5	171	0.4	23	1,239	3.2
6	991	2.5	24	539	1.4
7	130	0.3	25	1,425	3.7
8	793	2.0	26	1,688	4.3
9	468	1.2	27	2,305	5.9
10	2,004	5.1	28	655	1.7
11	224	0.6	29	1,618	4.2
12	729	1.9	30	1,100	2.8
13	2,124	5.5	31	2,246	5.8
14	1,307	3.4	32	3,456	8.9
15	585	1.5	33	800	2.1
16	762	2.0	34	1,038	2.7
17	1,123	2.9	35	1,594	4.1
18	172	0.4			

Table A1c: Observations of variable size_class.

size_class	Count	%
small	2,948	7.6
medium	2,017	5.2
large	5,067	13.0
very_large	28,948	74.3

Table A1d: Frequencies of 4-digit NACE codes in the main dataset.

NACE	Count	%
0111	5	0.01
0161	1	0.00
0600	5	0.01
0729	4	0.01
0811	16	0.04
0812	1	0.00
0891	1	0.00
1013	2	0.01
1039	1	0.00
1050	3	0.01
1062	1	0.00
1071	2	0.01
1072	3	0.01
1073	3	0.01
1080	2	0.01
1081	13	0.03
1082	8	0.02
1083	6	0.02
1084	1	0.00
1086	2	0.01
1089	17	0.04
1091	1	0.00
1100	1	0.00
1200	6	0.02
1310	4	0.01
1320	1	0.00
1330	7	0.02
1390	4	0.01
1391	5	0.01
1392	8	0.02
1393	3	0.01
1394	20	0.05
1395	15	0.04
1396	28	0.07
1399	10	0.03
1412	7	0.02
1431	1	0.00
1512	2	0.01
1520	33	0.08
1610	7	0.02
1621	5	0.01
1623	31	0.08
1624	1	0.00
1629	1	0.00

NACE	Count	%
1712	14	0.04
1720	1	0.00
1721	32	0.08
1722	4	0.01
1729	14	0.04
1812	241	0.62
1813	6	0.02
1814	2	0.01
1820	1	0.00
1920	4	0.01
2000	96	0.25
2011	9	0.02
2012	19	0.05
2013	90	0.23
2014	263	0.67
2015	10	0.03
2016	432	1.11
2017	1	0.00
2020	6	0.02
2030	87	0.22
2040	7	0.02
2041	439	1.13
2042	129	0.33
2050	3	0.01
2051	47	0.12
2052	10	0.03
2059	1619	4.15
2060	47	0.12
2100	97	0.25
2110	464	1.19
2120	305	0.78
2200	6	0.02
2211	126	0.32
2219	75	0.19
2220	25	0.06
2221	167	0.43
2222	90	0.23
2223	63	0.16
2229	247	0.63
2311	1	0.00
2312	6	0.02
2313	5	0.01
2314	8	0.02
2319	107	0.27
2320	15	0.04

NACE	Count	%
2332	8	0.02
2341	3	0.01
2342	4	0.01
2343	10	0.03
2344	33	0.08
2349	6	0.02
2351	4	0.01
2352	3	0.01
2361	27	0.07
2362	2	0.01
2363	1	0.00
2365	1	0.00
2369	16	0.04
2391	9	0.02
2399	25	0.06
2410	18	0.05
2420	22	0.06
2430	9	0.02
2432	12	0.03
2433	2	0.01
2434	4	0.01
2441	7	0.02
2442	50	0.13
2443	5	0.01
2444	6	0.02
2445	64	0.16
2450	5	0.01
2451	9	0.02
2452	9	0.02
2453	17	0.04
2454	4	0.01
2500	6	0.02
2510	4	0.01
2511	171	0.44
2512	54	0.14
2521	18	0.05
2529	3	0.01
2530	4	0.01
2540	68	0.17
2550	60	0.15
2561	19	0.05
2562	14	0.04
2571	26	0.07
2572	486	1.25
2573	288	0.74

NACE	Count	%
2590	3	0.01
2591	4	0.01
2592	8	0.02
2593	83	0.21
2594	45	0.12
2599	253	0.65
2610	9	0.02
2611	1252	3.21
2612	6	0.02
2620	79	0.20
2630	65	0.17
2640	98	0.25
2651	806	2.07
2660	628	1.61
2670	269	0.69
2710	4	0.01
2711	73	0.19
2712	236	0.61
2720	40	0.10
2730	1	0.00
2731	5	0.01
2732	84	0.22
2733	24	0.06
2740	408	1.05
2751	1417	3.64
2790	577	1.48
2800	131	0.34
2810	2	0.01
2811	112	0.29
2812	27	0.07
2813	191	0.49
2814	129	0.33
2815	661	1.70
2820	5	0.01
2821	17	0.04
2822	174	0.45
2823	10	0.03
2824	52	0.13
2825	85	0.22
2829	503	1.29
2830	204	0.52
2840	3	0.01
2841	218	0.56
2849	88	0.23
2890	11	0.03

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NACE	Count	%
2891	335	0.86
2892	200	0.51
2893	261	0.67
2894	168	0.43
2895	26	0.07
2896	52	0.13
2899	1000	2.57
2900	35	0.09
2910	1180	3.03
2920	46	0.12
2930	68	0.17
2931	302	0.77
2932	3937	10.10
3011	40	0.10
3012	1	0.00
3020	118	0.30
3030	640	1.64
3040	47	0.12
3092	9	0.02
3099	4	0.01
3101	48	0.12
3102	1	0.00
3103	4	0.01
3109	30	0.08
3200	1	0.00
3212	65	0.17
3220	1	0.00
3230	20	0.05
3240	13	0.03
3250	504	1.29
3291	14	0.04
3299	76	0.19
3300	3	0.01
3312	28	0.07
3320	333	0.85
3500	80	0.21
3511	38	0.10
3521	9	0.02
3522	2	0.01
3530	1	0.00
3700	3	0.01
3811	3	0.01
3820	2	0.01
3830	2	0.01
3832	1	0

NACE	Count	%
4100	1	0
4120	15	0.04
4211	4	0.01
4212	7	0.02
4213	1	0
4221	8	0.02
4311	1	0
4312	2	0.01
4321	18	0.05
4322	19	0.05
4329	7	0.02
4332	7	0.02
4333	6	0.02
4334	3	0.01
4339	1	0
4391	8	0.02
4399	15	0.04
4500	1	0
4510	7	0.02
4520	1	0
4530	21	0.05
4531	52	0.13
4532	75	0.19
4610	1	0
4611	1	0
4612	14	0.04
4613	6	0.02
4614	20	0.05
4615	5	0.01
4616	1	0
4618	32	0.08
4619	3	0.01
4621	2	0.01
4622	1	0
4623	2	0.01
4624	3	0.01
4636	8	0.02
4637	1	0
4640	3	0.01
4641	4	0.01
4642	3	0.01
4643	90	0.23
4644	4	0.01
4645	63	0.16
4646	438	1.12

NACE	Count	%
4647	8	0.02
4649	39	0.1
4651	97	0.25
4652	68	0.17
4660	8	0.02
4661	12	0.03
4662	20	0.05
4663	5	0.01
4664	1	0
4669	213	0.55
4670	7	0.02
4671	4	0.01
4672	13	0.03
4673	19	0.05
4674	96	0.25
4675	66	0.17
4676	3	0.01
4677	1	0
4690	34	0.09
4711	17	0.04
4719	17	0.04
4741	6	0.02
4742	18	0.05
4743	1	0
4752	25	0.06
4754	1	0
4762	1	0
4764	13	0.03
4765	2	0.01
4770	11	0.03
4774	21	0.05
4775	8	0.02
4778	3	0.01
4791	4	0.01
4799	5	0.01
4910	1	0
4920	2	0.01
4940	2	0.01
4941	2	0.01
5020	2	0.01
5210	2	0.01
5221	6	0.02
5223	16	0.04
5229	52	0.13
5320	54	0.14

NACE	Count	%
5621	1	0
5829	136	0.35
5912	6	0.02
6110	215	0.55
6120	2	0.01
6190	6	0.02
6200	76	0.19
6201	2378	6.1
6202	20	0.05
6203	2	0.01
6209	5	0.01
6312	4	0.01
6399	3	0.01
6420	353	0.91
6492	1	0
6530	3	0.01
6610	5	0.01
6619	503	1.29
6622	1	0
6810	3	0.01
6820	212	0.54
6830	1	0
6831	10	0.03
6832	25	0.06
6920	5	0.01
7010	1223	3.14
7022	31	0.08
7100	2	0.01
7110	2	0.01
7111	3	0.01
7112	1009	2.59
7120	36	0.09
7200	150	0.38
7210	1264	3.24
7211	444	1.14
7219	455	1.17
7220	1	0
7311	5	0.01
7410	1	0
7490	886	2.27
7730	6	0.02
7732	3	0.01
7739	10	0.03
7740	472	1.21
8110	1	0

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NACE	Count	%
8129	1	0
8211	2	0.01
8220	1	0
8230	1	0
8292	1	0
8299	459	1.18
8541	4	0.01
8542	72	0.18
8559	3	0.01
8610	50	0.13
8690	30	0.08
8810	20	0.05
9300	5	0.01
9499	31	0.08
9525	1	0
9601	1	0
9609	122	0.31

Appendix 2: Brief summary on the propensity score matching (PSM)

In the first step of a PSM, a treatment group (comprising units that received a certain treatment) and a control group (units that did not receive the treatment) are defined. Then a propensity score is computed for all observations. It indicates the probability of receiving the treatment, based on certain covariates that are considered in the analysis[3] (Rosenbaum and Rubin 1983). Even though the values between covariates may differ, they might have similar propensity scores, which facilitates their comparison (Abadie and Imbens 2016). Subsequently, treated units are matched to untreated units, while the aim is to match statistical twins (i.e., those units with a similar propensity score). As described in Section 3.3, I consider KET patents to be 'treated' patents and non-KET patents as the control group, thus matching KET patents to non-KET patents that emerged in a comparable context. On the one hand, this procedure leads to information losses. On the other hand, it balances the dataset for the subsequent steps (Rosenbaum and Rubin 1983; Leusin 2022; Cantner et al. 2023). Hence, a PSM comprises a trade-off between the amount of excluded observations and a sufficiently small distance between the treated and untreated units, in order to reduce bias in the subsequent analyses (Caliendo and Kopeinig 2008; Leusin 2022).

To perform the matching, I use the software R's MatchIt library (Ho, Imai, King and Stuart 2011). The binary KET variables are used for the assignment to the treatment group and the following variables, introduced in Section 3.2, are considered: *av_app_share, org_age, size_class, pubs_org, NACE, struct_mn, pop_dens, log_acad_empl* and *schmoch*. The propensity score is estimated with a glm model. While direct matches are assigned for *schmoch, nace, class_size, av_app_share,* and *struct_mn*, the nearest neighbor matching algorithm is applied for the remaining four covariates (e.g., Rosenbaum and Rubin 1983; Caliendo and Kopeinig 2008; Ho et al. 2011; Abadie and Imbens 2016), meaning that for these variables the matching is conducted based on the smallest distance on the propensity scores between treated and untreated units (Ho et al. 2011). The distance basically represents the difference between the matched units (e.g.,Leusin 2022). To ensure a certain degree of similarity and to obtain a good matching quality, I prevent the matching of too distant pairs by defining a caliper of 0.1. The caliper limits the number of standard deviations of the distance between the units in the matched pairs (Caliendo and Kopeinig 2008). Appendix 3 reports the sample sizes after the PSM and Appendix 4 provides the balance comparison before and after the matching for the four individual KETs under investigation and for KETs at the aggregate level.

[3] *"The propensity score is the conditional probability of assignment to a particular treatment given a vector of observed covariates"* (Rosenbaum and Rubin 1983, p. 41)

Appendix 3: Sample sizes after propensity score matching (PSM)

Table A3: Sample sizes after propensity score matching.

Variable	Sample	All	Matched	Unmatched	Percent matched
isKET	treated	3,623	1,872	1,751	52
	control	35,357	2,978	32,379	8
isAM	treated	385	197	188	51
	control	35,357	677	34,680	2
isAMT	treated	1,597	848	749	53
	control	35,357	2,379	32,978	7
isIB	treated	726	291	435	40
	control	35,357	696	34,661	2
isPT	treated	1,073	651	422	60
	control	35,357	1,674	33,683	5
isMNE	treated	78	*excluded from matching (due to small sample size of treatment groups)*		
	control	35,357			
isNT	treated	112			
	control	35,357			

Appendix 4: Balance overview before and after propensity score matching (PSM)

*Tab. A4a: Matching results for **KETs** at the aggregate level, including balance improvements.*

Variable	Sample	Means treated	Means control	Std. Mean Diff.	Std. Mean Diff. Balance improvement (%)	Var. Ratio	Var. Ratio Balance improvement (%)	Std. Pair Dist.
distance	unmatched	0.0963	0.0926	0.1992	99.8	1.0916	98.6	-
	matched	0.0958	0.0958	0.0005		0.9988		0.0023
popdens	unmatched	4848.5843	4393.2721	0.1532	96	1.0541	39.6	-
	matched	5312.9224	5357.5541	-0.0150		1.0323		0.0281
log_acad_empl	unmatched	11.1229	11.0712	0.0501	93.2	0.8704	97.0	-
	matched	11.2793	11.2955	-0.0157		1.0042		0.0489
org_age	unmatched	69.9429	73.4002	-0.058	64	1.1920	89.8	-
	matched	82.5139	83.9100	-0.0234		1.0180		0.0339
pubs_org	unmatched	125.6776	127.5918	-0.0096	73.3	0.9502	69.0	-
	matched	145.4607	140.5333	0.0248		1.0160		0.0406
av_app_share	unmatched	0.9159	0.9612	-0.2370	64.5	1.9570	100	-
	matched	0.9386	0.9386	0		1.0002		0
schmoch	unmatched	13.9244	20.5932	-0.7767	100	0.6269	100	-
	matched	13.5668	13.5668	0		1.0002		0
size_class: large	unmatched	0.1341	0.1296	0.0134	100	-	-	-
	matched	0.0796	0.0796	0		-		0
size_class: medium	unmatched	0.0729	0.0496	0.0896	100	-	-	-
	matched	0.0224	0.0224	0		-		0
size_class: small	unmatched	0.0916	0.0740	0.0612	100	-	-	-
	matched	0.0913	0.0913	0		-		0
size_class: very large	unmatched	0.7014	0.7469	-0.0995	100	-	-	-
	matched	0.8066	0.8066	0		-		0
NACE	unmatched	4249.3765	3927.8852	0.1416	100	1.351	99.9	-
	matched	4058.8541	4058.8541	0		1.0002		0
struct_mn	unmatched	0.2744	0.3198	-0.1019	100	-	-	-
	matched	0.3184	0.3184	0		-		0

*Tab. A4b: Matching results for **photonics**, including balance improvements.*

Variable	Sample	Means treated	Means control	Std. Mean Diff.	Std. Mean Diff. Balance improvement (%)	Var. Ratio	Var. Ratio Balance improvement (%)	Std. Pair Dist.
distance	unmatched	0.0333	0.0293	0.3925	99.8	0.8581	99.8	-
	matched	0.0329	0.0329	0.0007		0.9996		0.0032
popdens	unmatched	3944.4611	4393.2721	-0.1763	93.5	0.7730	85.2	-
	matched	4313.1376	4284.1197	0.0114		0.9625		0.0268
log_acad_empl	unmatched	11.2109	11.0712	0.1232	99.6	1.0499	70.4	-
	matched	11.3702	11.3697	0.0004		0.9857		0.0207
org_age	unmatched	66.1761	73.4002	-0.1412	74.2	0.8770	67.3	-
	matched	75.9098	77.4915	-0.0364		1.0438		0.0316
pubs_org	unmatched	121.0422	127.5918	-0.0303	-24.6	1.1248	84.6	-
	matched	113.5257	121.6891	-0.0378		0.9820		0.0313
av_app_share	unmatched	0.9055	1.0453	-0.2786	100	1.4718	99.9	-
	matched	0.2947	0.2947	0		1.0006		0
schmoch	unmatched	6.9879	20.5932	-1.7676	100	0.5038	99.9	-
	matched	7.6390	7.6390	0		1.0006		0
size_class: large	unmatched	0.1761	0.1296	0.1223	100	-	-	-
	matched	0.1290	0.1290	0		-		0
size_class: medium	unmatched	0.0643	0.0496	0.0600	100	-	-	-
	matched	0.0200	0.0200	0		-		0
size_class: small	unmatched	0.1249	0.0740	0.1540	100	-	-	-
	matched	0.1167	0.1167	0		-		0
size_class: very large	unmatched	0.6347	0.7469	-0.2330	100	-	-	-
	matched	0.7343	0.7343	0		-		0
NACE	unmatched	4114.4809	3927.8852	0.0863	100	1.2253	99.7	-
	matched	4103.3886	4103.3886	0		1.0006		0
struct_mn	unmatched	0.1594	0.3198	-0.4389	100	-	-	-
	matched	0.1736	0.1736	0		-		0

*Tab. A4c: Matching results for **advanced materials**, including balance improvements.*

Variable	Sample	Means treated	Means control	Std. Mean Diff.	Std. Mean Diff. Balance improvement (%)	Var. Ratio	Var. Ratio Balance improvement (%)	Std. Pair Dist.
distance	unmatched	0.0126	0.0108	0.3352	100	1.5816	99.3	-
	matched	0.0142	0.0142	-0.0001		1.0032		0.0006
popdens	unmatched	4951.2915	4393.2721	0.1739	97.1	1.2290	95.9	-
	matched	5992.6375	6009.0366	-0.0051		1.0085		0.0055
log_acad_empl	unmatched	10.9324	11.0712	-0.1448	95.4	0.7494	92.2	-
	matched	11.0709	11.0771	-0.0065		0.9796		0.0068
org_age	unmatched	76.0156	73.4002	0.0410	92.1	1.3616	94.7	-
	matched	93.5787	93.7841	-0.0032		1.0166		0.0168
pubs_org	unmatched	136.8291	127.5918	0.0431	97.5	1.1102	96.3	-
	matched	168.8868	169.1179	-0.0011		1.0038		0.0021
av_app_share	unmatched	0.9574	0.9612	-0.0259	100	1.1733	98.2	-
	matched	0.9822	0.9822	0		1.0028		0
schmoch	unmatched	20.3792	20.5932	-0.0303	100	0.4253	99.7	-
	matched	20.0964	20.0964	0		1.0028		0
size_class: large	unmatched	0.1584	0.1296	0.0791	100	-	-	-
	matched	0.0964	0.0964	0		-		0
size_class: medium	unmatched	0.0545	0.0496	0.0219	100	-	-	-
	matched	0.0203	0.0203	0		-		0
size_class: small	unmatched	0.0831	0.0740	0.0331	100	-	-	-
	matched	0.1015	0.1015	0		-		0
size_class: very large	unmatched	0.7039	0.7469	-0.0941	100	-	-	-
	matched	0.7817	0.7817	0		-		0
NACE	unmatched	3757.5039	3927.8852	-0.0753	100	1.3418	99.0	-
	matched	3772.8325	3722.8325	0		1.0028		0
struct_mn	unmatched	0.4130	0.3198	0.1892	100	-	-	-
	matched	0.4264	0.4264	0		-		0

Tab. A4d: Matching results for **AMTs**, including balance improvements.

Variable	Sample	Means treated	Means control	Std. Mean Diff.	Std. Mean Diff. Balance improvement (%)	Var. Ratio	Var. Ratio Balance improvement (%)	Std. Pair Dist.
distance	unmatched matched	0.0468 0.0470	0.0431 0.0470	0.2563 -0.0004	99.8	1.3971 1.007	99.8	- 0.0020
popdens	unmatched matched	4936.6604 5663.7126	4393.2721 5650.3475	0.1775 0.0044	97.5	1.1178 1.0076	93.2	- 0.0317
log_acad_empl	unmatched matched	11.0540 11.2758	11.0712 11.2644	-0.0164 0.0109	33.6	0.8947 1.0015	98.7	- 0.0533
org_age	unmatched matched	69.5210 84.0094	73.4002 84.2208	-0.0652 -0.0036	94.6	1.1871 0.9923	95.5	- 0.0224
pubs_org	unmatched matched	127.5253 147.2110	127.5918 148.4720	-0.0003 -0.0064	-1795.3	0.9230 0.9763	70.1	- 0.0241
av_app_share	unmatched matched	0.9309 0.9552	0.9612 0.9552	-0.1720 -0	100	1.6613 1.0005	99.9	- 0
schmoch	unmatched matched	16.8936 16.4410	20.5932 16.4410	-0.4690 -0	100	0.5292 1.0005	99.9	- 0
size_class: large	unmatched matched	0.1177 0.0660	0.1305 0.0660	-0.0367 0	100	- -	-	- 0
size_class: medium	unmatched matched	0.0720 0.0130	0.0509 0.0130	0.0868 0	100	- -	-	- 0
size_class: small	unmatched matched	0.0720 0.0625	0.0758 0.0625	-0.0077 0	100	- -	-	- 0
size_class: very large	unmatched matched	0.7383 0.8585	0.7428 0.8585	-0.0196 0	100	- -	-	- 0
NACE	unmatched matched	4133.0795 4012.7936	3950.2769 4127.7936	0.0939 -0	100	1.2525 1.0005	99.8	- 0
struct_mn	unmatched matched	0.3269 0.3974	0.3198 0.3974	0.0150 0	100	- -	-	- 0

*Tab. A4e: Matching results for **industrial biotechnology**, including balance improvements.*

Variable	Sample	Means treated	Means control	Std. Mean Diff.	Std. Mean Diff. Balance improvement (%)	Var. Ratio	Var. Ratio Balance improvement (%)	Std. Pair Dist.
distance	unmatched	0.0271	0.0280	0.4920	99.8	1.3358	99.5	-
	matched	0.0280	0.0305	0.0008		1.0014		0.0020
popdens	unmatched	5743.1279	4410.7761	0.4568	99.9	1.0419	64.9	-
	matched	6083.7823	6085.7619	-0.0007		0.9857		0.0170
log_acad_empl	unmatched	11.1718	11.0742	0.1156	93.3	0.6184	83.7	-
	matched	11.0889	11.0822	0.0077		0.9247		0.0333
org_age	unmatched	68.9394	73.1574	-0.0620	90.3	1.7333	98.0	-
	matched	82.9141	83.3488	-0.0158		1.0109		0.0199
pubs_org	unmatched	116.7598	127.6161	-0.0673	81.2	0.6245	99.2	-
	matched	134.6938	136.7311	-0.0127		1.0037		0.0190
av_app_share	unmatched	0.8716	1.0468	-0.3856	100	2.6137	99.9	-
	matched	0.8849	0.8849	0		1.0011		0
schmoch	unmatched	14.9573	20.0685	-1.9086	100	0.0742	100	-
	matched	14.9931	14.9931	-0		1.0011		0
size_class: large	unmatched	0.0964	0.1306	-0.1123	100	-	-	-
	matched	0.0687	0.0687	0		-		0
size_class: medium	unmatched	0.1185	0.0505	0.2131	100	-	-	-
	matched	0.0653	0.0653	0		-		0
size_class: small	unmatched	0.1047	0.0751	0.1003	100	-	-	-
	matched	0.1065	0.1065	0		-		0
size_class: very large	unmatched	0.6804	0.7438	-0.1425	100	-	-	-
	matched	0.7595	0.7595	0		-		0
NACE	unmatched	5278.3829	3932.7031	0.5482	100	1.5911	99.8	-
	matched	4755.9141	4755.9141	-0		1.0011		0
struct_mn	unmatched	0.2576	0.3167	-0.1352	100	-	-	-
	matched	0.2852	0. 2852	-0		-		0

Appendix 5: F-test results before and after matching

At the aggregate KET level, the results of the F-Tests show statistically significant differences for two covariates before the matching, while the differences between the covariates are no longer statistically significant after the matching in most cases. As desired, this indicates that the matching process has successfully balanced the treatment and control groups. Also, at the level of the individual KETs, the F-tests indicate strong balance improvement, as hardly any significant results occur after the matching, while statistically significant differences existed in many cases before the matching. The only exception is industrial biotechnology, where the result of the F-test *org_age* is statistically significant at the 0.05 significance level (p-value 0.014).

Tab. A5: F-test results for variables matched via nearest neighbor matching

Variable	p-value		F-value		num_df		den_df	
	before	after	before	after	before	after	before	after
KETs (aggregate level)								
pubs_org	0.040	0.419	1.53	1.035	35,356	2,977	3,622	1,871
popdens	0.031	0.446	0.949	0.969	35,356	2,977	3,622	1,871
org_age	$2.956 \cdot 10^{-13}$ ***	0.671	0.839	0.983	35,356	2,977	3,622	1,871
log_acad_empl	$3.464 \cdot 10^{-8}$ ***	0.427	1.149	0.968	35,356	2,977	3,622	1,871
Advanced Materials								
pubs_org	0.137	0.829	0.901	0.978	35,356	676	384	196
popdens	0.003 ***	0.360	0.814	0.903	35,356	676	384	196
org_age	$6.747 \cdot 10^{-6}$ ***	0.423	0.734	0.915	35,356	676	384	196
log_acad_empl	0.0002 ***	0.921	1.334	1.014	35,356	676	384	196
AMTs								
pubs_org	0.030 **	0.247	1.083	1.069	35,356	2,378	1,596	847
popdens	0.002 ***	0.389	0.895	0.953	35,356	2,378	1,596	847
org_age	$1.077 \cdot 10^{-6}$ ***	0.677	0.842	0.977	35,356	2,378	1,596	847
log_acad_empl	0.003 ***	0.489	1.118	0.959	35,356	2,378	1,596	847
Industrial Biotechnology								
pubs_org	$2.2 \cdot 10^{-16}$ ***	0.901	1.601	1.014	35,356	695	725	290
popdens	0.426	0.292	0.960	0.903	35,356	695	725	290
org_age	$2.2 \cdot 10^{-16}$ ***	0.014 **	0.577	0.787	35,356	695	725	290
log_acad_empl	$2.2 \cdot 10^{-16}$ ***	0.127	1.617	0.862	35,356	695	725	290
Photonics								
pubs_org	0.0060 ***	0.226	0.889	1.084	35,356	1,673	1,072	650
popdens	$1.795 \cdot 10^{-8}$ ***	0.267	1.294	1.076	35,356	1,673	1,072	650
org_age	0.0035 ***	0.374	1.140	1.061	35,356	1,673	1,072	650
log_acad_empl	0.257	0.322	0.953	0.938	35,356	1,673	1,072	650

Appendix 6: Decile-based analysis with alternative deciles

Here, KET patents are assigned to deciles based on their citation count and their matched control-patents are assigned to the same decile. Consequently, the mean citation count and the maximum citation count of KETs increases with each decile, as can be seen in Figures A5.1a through 5.2b.

In all cases, the analysis reveals a different behavior of KET patents and non-KETs patents. At the aggregate KET level (Figure A5.1a), the mean citation count of the non-KET control group stays relatively similar, except for the last decile. At the individual KET level, the variation stays within a rather small range for advanced materials and industrial biotech, while it is closer to the overall pattern for photonics and AMTs. With the exception of industrial biotechnology, in the last decile(s) the mean forward citation count slightly increases for non-KETs, but in no case does it even reach close to the mean citation count of KETs. On the other hand, KET patents from the lower deciles receive no citations, while their control groups receive citations throughout all deciles. Generally, these insights support this study's previous finding that *if* KETs have an impact, they have the potential to be more impactful than non-KETs. Furthermore, also these alternative results suggest that rather a handful of KET patents exerts a great impact on innovation. Moreover, the maximum forward citation count (Figures A5.2a and A5.2b) highlights that patents from the control groups tend to be cited more frequently when considering them in deciles based on KETs' forward citation frequencies. Only in the tenth decile KETs are more impactful in comparison. In summary, the alternative decile-based analysis suggests that KETs can have a stronger impact than non-KETs, but are not always more impactful. The results highlight that only being a KET is not sufficient to drive innovation in many cases. Further studies should explore the interactions of the KET status with regional and firm-level characteristics and their effect on the forward citation frequency of patents.

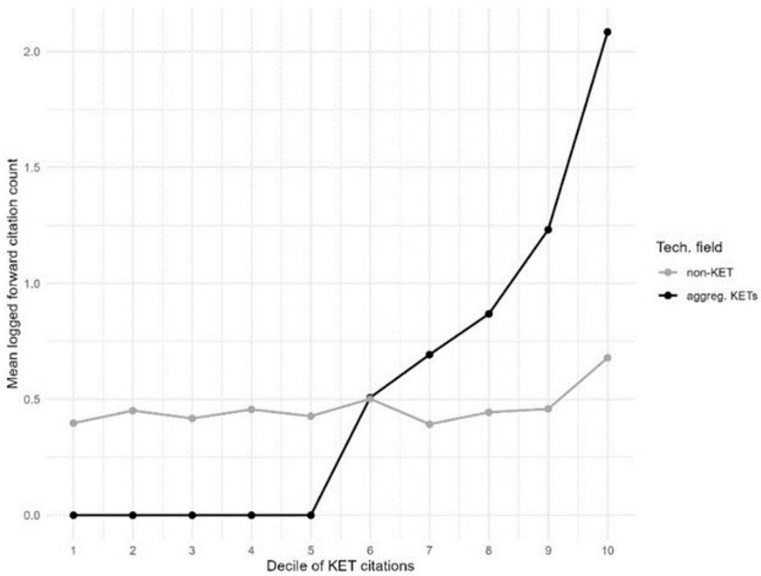


Figure A6.1a: Mean logged forward citation count across KET-based deciles

Figure A6.1b: Mean logged forward citation count across KET-based deciles (individual KETs)

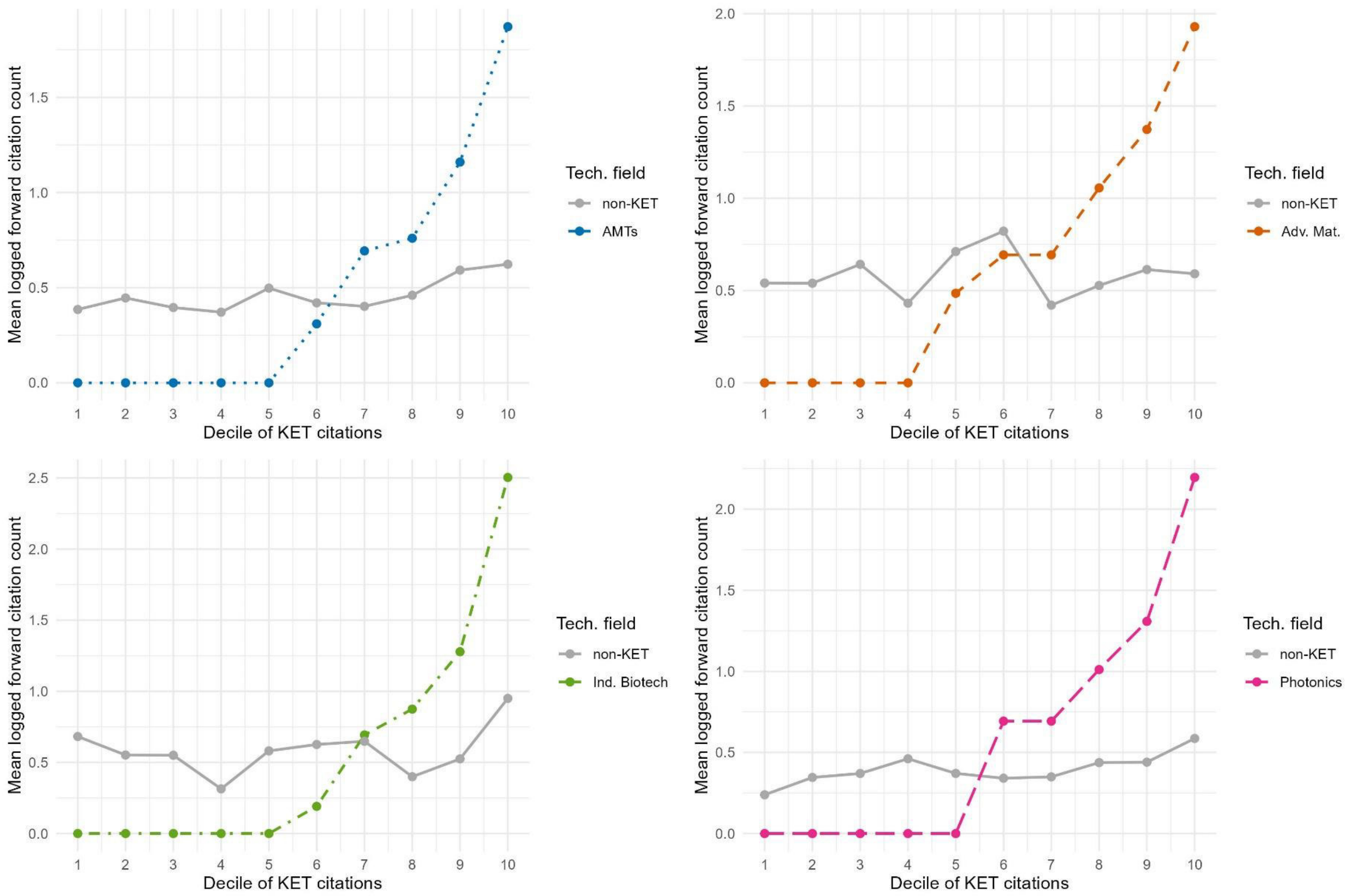


Figure A6.2a: Maximum logged forward citation count across KET-based deciles (individual KETs)

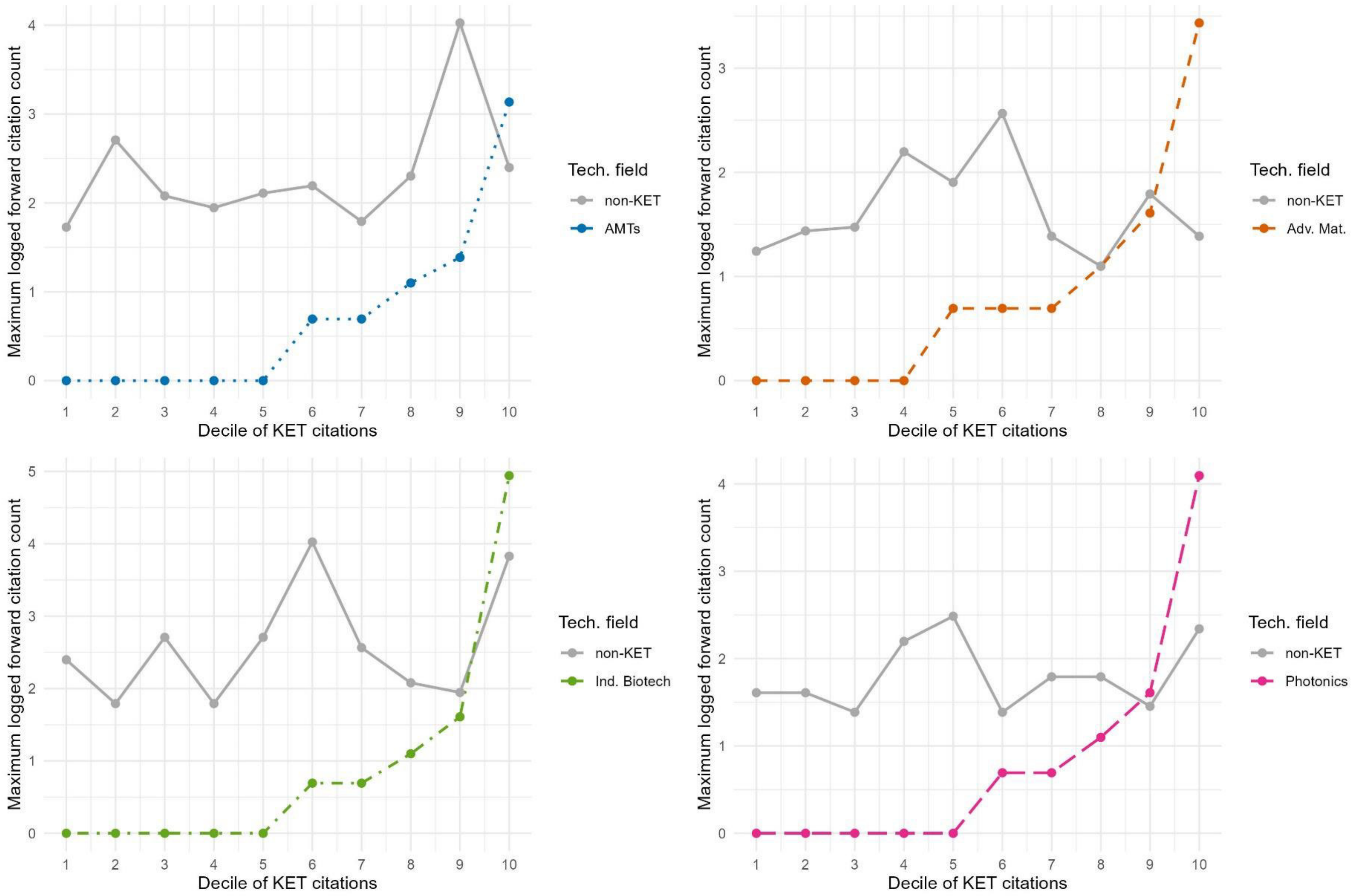
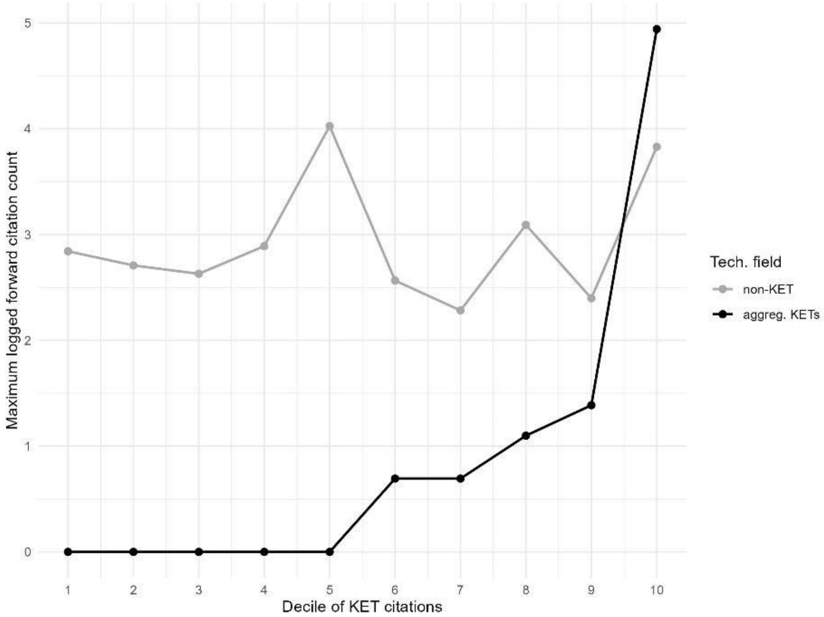


Figure A6.2b: Maximum logged forward citation count across KET-based deciles for KETs (aggregate level)



Appendix 7: Descriptive statistics of datasets used in the negative binomial regressions

KETs (aggregate level)

Table A7.1a: Descriptive statistics of KETs (aggregate level) regression dataset, count variables

	obs.	mean	sd	median	min	max
agg_cits7	4830	1.344	4.384	0.000	0.000	139.000
log_popdens	4830	8.340	0.873	8.741	3.970	9.312
log_acad_lmr_avg	4830	11.281	0.964	11.398	7.763	12.413
log_av_app_share	4830	-0.076	0.217	0.000	-0.693	0.000
log_org_age	4830	4.030	1.066	4.382	0.000	5.024
log_pubs_org	4830	3.274	2.084	2.874	0.000	6.775

Table A7.1b: Count of observations of factor levels, regression dataset for KETs (aggregate level).

	obs.	share in total obs.
isKET_dum: 1	1857	0.38
struct_MN: 1	1594	0.33
size_class: small	429	0.09
size_class: medium	96	0.02
size_class: large	362	0.07
size_class: very_large	3943	0.82

Table A7.1c: Frequency of observations in 2-digit NACE classes, KETs (aggregate level) regression dataset.

NACE	Frequency	Share	NACE	Frequency	Share
1	2	0	*45*	16	0.003
10	3	0.001	*46*	82	0.017
13	5	0.001	*47*	14	0.003
16	8	0.002	*53*	3	0.001
17	5	0.001	*62*	313	0.064
18	56	0.011	*64*	43	0.009
20	793	0.162	*66*	77	0.016
21	55	0.011	*68*	14	0.003
22	31	0.006	*70*	59	0.012
23	71	0.015	*71*	67	0.014
24	41	0.008	*72*	588	0.12
25	20	0.004	*74*	155	0.032
26	810	0.166	*77*	129	0.026
27	416	0.085	*82*	37	0.008
28	203	0.042	*85*	7	0.001
29	491	0.1	*86*	30	0.006
30	61	0.012	*88*	2	0
32	39	0.008	*93*	2	0
33	126	0.026	*94*	5	0.001
35	6	0.001	*96*	2	0
43	4	0.001			

Advanced materials

Table A7.2a: Descriptive statistics of advanced materials regression dataset, count variables.

	obs.	mean	sd	median	min	max
agg_cits7	871	1.452	3.006	1.000	0.000	48.000
log_popdens	871	8.507	0.846	8.808	4.617	9.312
log_acad_lmr_avg	871	11.125	0.860	10.912	8.226	12.413
log_av_app_share	871	-0.021	0.118	0.000	-0.693	0.000
log_org_age	871	4.215	1.034	4.905	1.099	5.024
log_pubs_org	871	3.458	2.084	2.451	0.000	6.582

Table A7.2b: Count of observations of factor levels, regression dataset for advanced materials.

	obs.	share in total obs
isAM_dum: 1	195	0.22
struct_MN: 1	391	0.45
size_class: small	100	0.11
size_class: medium	14	0.02
size_class: large	54	0.06
size_class: very_large	703	0.81

Table A7.2c: Frequency of observations in 2-digit NACE classes, advanced materials regression dataset.

NACE	Frequency	Share	NACE	Frequency	Share
16	10	0.011	*43*	4	0.005
17	2	0.002	*46*	4	0.005
18	16	0.018	*62*	54	0.061
20	358	0.405	*64*	6	0.007
22	25	0.028	*66*	64	0.072
23	39	0.044	*68*	10	0.011
24	14	0.016	*70*	15	0.017
25	2	0.002	*71*	13	0.015
26	24	0.027	*72*	64	0.072
27	18	0.02	*74*	36	0.041
28	18	0.02	*82*	12	0.014
29	48	0.054	*85*	4	0.005
30	24	0.027			

Advanced manufacturing technologies (AMTs)

Table A7.3a: Descriptive statistics of AMTs regression dataset, count variables.

	obs.	mean	sd	median	min	max
agg_cits7	3212	1.179	3.276	0.000	0.000	85.000
log_popdens	3212	8.464	0.809	8.808	4.345	9.312
log_acad_lmr_avg	3212	11.263	0.927	11.372	8.226	12.413
log_av_app_share	3212	-0.060	0.195	0.000	-0.693	0.000
log_org_age	3212	4.113	1.039	4.663	0.000	5.024
log_pubs_org	3212	3.423	2.008	2.874	0.000	6.775

Table A7.3b: Count of observations of factor levels, regression dataset for AMTs

	obs.	share in total obs
isAMT_dum: 1	839	0.26
struct_MN: 1	1349	0.42
size_class: small	191	0.06
size_class: medium	26	0.01
size_class: large	171	0.05
size_class: very_large	2824	0.88

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Table A7.3c: Frequency of observations in 2-digit NACE classes, AMTs regression dataset.

NACE	Frequency	Share	NACE	Frequency	Share
13	5	0.002	*45*	5	0.002
16	2	0.001	*46*	49	0.015
17	6	0.002	*53*	6	0.002
18	9	0.003	*62*	259	0.079
20	706	0.216	*64*	25	0.008
21	23	0.007	*66*	40	0.012
22	9	0.003	*68*	6	0.002
23	55	0.017	*70*	49	0.015
24	28	0.009	*71*	37	0.011
25	19	0.006	*72*	374	0.115
26	450	0.138	*74*	94	0.029
27	151	0.046	*77*	25	0.008
28	222	0.068	*82*	37	0.011
29	396	0.121	*85*	6	0.002
30	63	0.019	*93*	2	0.001
32	2	0.001	*94*	6	0.002
33	99	0.03			

Industrial biotechnology

Table A7.4a: Descriptive statistics of industrial biotechnology regression dataset, count variables.

	obs.	mean	sd	median	min	max
agg_cits7	981	1.794	7.019	0.000	0.000	139.000
log_popdens	981	8.557	0.859	9.031	3.970	9.312
log_acad_lmr_avg	981	11.086	0.752	10.747	8.598	12.413
log_av_app_share	981	-0.122	0.264	0.000	-0.693	0.000
log_org_age	981	4.037	1.160	4.605	0.000	5.024
log_pubs_org	981	3.326	1.939	2.815	0.000	6.604

Table A7.4b: Count of observations of factor levels, regression dataset for industrial biotechnology.

	obs.	share in total obs
isIB_dum: 1	287	0.29
struct_MN: 1	339	0.35
size_class: small	97	0.1
size_class: medium	39	0.04
size_class: large	64	0.07
size_class: very_large	781	0.8

Table A7.4c: Frequency of observations in 2-digit NACE classes, industrial biotechnology regression dataset.

NACE	Frequency	Share	NACE	Frequency	Share
1	2	0.002	***46***	74	0.074
10	6	0.006	***62***	22	0.022
13	2	0.002	***64***	13	0.013
18	6	0.006	***66***	16	0.016
20	248	0.248	***70***	2	0.002
21	56	0.056	***71***	3	0.003
22	2	0.002	***72***	255	0.255
23	2	0.002	***74***	52	0.052
24	11	0.011	***82***	6	0.006
26	122	0.122	***85***	2	0.002
28	22	0.022	***86***	34	0.034
29	20	0.02	***88***	2	0.002
32	7	0.007	***96***	2	0.002
35	12	0.012			

Photonics

Table A7.5a: Descriptive statistics of photonics regression dataset, count variables.

	obs.	mean	sd	median	min	max
agg_cits7	2319	1.116	3.039	0.000	0.000	59.000
log_popdens	2319	8.136	0.860	8.500	3.970	9.312
log_acad_lmr_avg	2319	11.358	1.051	11.853	8.564	12.413
log_av_app_share	2319	-0.073	0.213	0.000	-0.693	0.000
log_org_age	2319	4.039	0.974	4.382	0.000	5.024
log_pubs_org	2319	2.851	2.157	2.451	0.000	6.709

Table A7.5b: Count of observations of factor levels, regression dataset for photonics.

	obs.	share in total obs
isPT_dum: 1	645	0.28
struct_MN: 1	529	0.23
size_class: small	203	0.09
size_class: medium	38	0.02
size_class: large	257	0.11
size_class: very_large	1821	0.79

Table A7.5c: Frequency of observations in 2-digit NACE classes, photonics regression dataset.

NACE	Frequency	Share	NACE	Frequency	Share
18	62	0.027	46	4	0.002
20	127	0.054	47	15	0.006
22	12	0.005	62	215	0.092
23	20	0.009	64	30	0.013
25	11	0.005	66	9	0.004
26	498	0.213	68	4	0.002
27	347	0.148	70	18	0.008
28	39	0.017	71	45	0.019
29	286	0.122	72	188	0.08
30	21	0.009	74	114	0.049
32	48	0.021	77	139	0.059
33	67	0.029	82	4	0.002
45	16	0.007			

Appendix 8: Technology codes of the International Patent Classification (IPC) which were assigned to the European Key Enabling Technologies (KETs).

Tab A8: Full-digit IPC codes of KETs. (Source: van de Velde et al. 2012)

Nano-technology	Photonics	Industrial Biotechnology	Advanced Materials	Micro- and Nano-electronics (MNE)	Advanced Manufacturing Technologies (AMTs)		
B82Y	F21K	C02F 3/34	B32B 9	G01R 31/26	B01D 15	C04B 11/028	C21C 5/52
B81C	F21V	C07C 29	B32B 15	G01R 31/27	B01D 67	C04B 35/622	C21C 5/54
B82B	F21Y	C07D 475	B32B 17	G01R 31/28	B01J 10	C04B 35/624	C21C 5/56
	G01D 5/26	C07K 2	B32B 18	G01R 31/303	B01J 12	C04B 35/626	C21C 7
	G01D 5/58	C08B 3	B32B 19	G01R 31/304	B01J 13	C04B 35/653	C21D
	G01D 15/14	C08B 7	B32B 25	G01R 31/317	B01J 14	C04B 35/657	C22B 11
	G01G 23/32	C08H 1	B32B 27	G01R 31/327	B01J 15	C04B 37	C22B 21
	G01J	C08L 89	B82Y 30	G09G 3/14	B01J 16	C04B 38/02	C22B 26
	G01L 1/24	C09D 11	C01B 31	G09G 3/32	B01J 19/02	C04B 38/10	C22B 4
	G01L 3/08	C09D 189	C01D 15	H01F 1/40	B01J 19/08	C04B 40	C22B 59
	G01L 11/02	C09J 189	C01D 17	H01F 10/193	B01J 19/18	C04B 7/60	C22B 9
	G01L 23/06	C12M	C01F 13	H01G 9/028	B01J 19/20	C04B 9/20	C22C 1
	G01M 11	C12P	C01F 15	H01G 9/032	B01J 19/22	C07C 17/38	C22C 3
	G01P 3/36	C12Q	C01F 17	H01H 47/32	B01J 19/24	C07C 2/08	C22C 33
	G01P 3/38	C12S	C03C	H01H 57	B01J 19/26	C07C 2/46	C22C 35
	G01P 3/68	C07K 14/435	C04B 35	H01S 5	B01J 19/28	C07C 2/52	C22C 47
	G01P 5/26	C07K 14/47	C08F	H01L	B01J 20/30	C07C 2/58	C22F
	G01Q 20/02	C07K 14/705	C08J 5	H03B 5/32	B01J 21/20	C07C 2/80	C23C 14/56
	G01Q 30/02	C07K 16/18	C08L	H03C 3/22	B01J 23/90	C07C 201/16	C23C 16/54
	G01Q 60/06	C07K 16/28	C22C	H03F 3/04	B01J 23/92	C07C 209/82	C25B 9
	G01Q 60/18	C12N 15/09	C23C	H03F 3/06	B01J 23/94	C07C 213/10	C25B 15/02
	G01R 15/22	C12N 15/11	D21H 17	H03F 3/08	B01J 23/96	C07C 227/38	C25C
	G01R 15/24	C12N 15/12	G02B 1	H03F 3/10	B01J 25/04	C07C 231/22	C25D 1
	G01R 23/17	C12N 5/10	H01B 3	H03F 3/12	B01J 27/28	C07C 249/14	C30B 15/20
	G01R 31/308	C12P 21/08	H01F 1/0	H03F 3/14	B01J 27/30	C07C 253/32	C30B 35
	G01R 33/032	C12Q 1/68	H01F 1/12	H03F 3/16	B01J 27/32	C07C 263/18	C40B 60
	G01R 33/26	G01N 33/15	H01F 1/34	H03F 3/183	B01J 29/90	C07C 269/08	D01D 10
	G01S 7/481	G01N 33/50	H01F 1/42	H03F 3/21	B01J 31/40	C07C 273/14	D01D 11
	G01V 8	G01N 33/53	H01F 1/44	H03F 3/343	B01J 38	C07C 277/06	D01D 13
	G02B 5	G01N 33/68	H01L 51/30	H03F 3/387	B01J 39/26	C07C 29/74	D01F 9/133
	G02B 13/14	G01N 33/566	H01L 51/46	H03F 3/55	B01J 41/20	C07C 303/42	D01F 9/32
	G03B 42	C12N 1/19	H01L 51/54	H03K 17/72	B01J 47	C07C 315/06	D06B 23/20
	G03G 21/08	C12N 1/21		H05K 1	B01J 49	C07C 319/26	D21H 23/20
	G06E	C12N 1/15		B82Y 25	B01J 8/06	C07C 37/68	D21H 23/70
	G06F 3/042	C12N 15/00			B01J 8/14	C07C 4/04	D21H 23/74
	G06K 9/58	C12N 15/10			B01J 8/24	C07C 4/06	D21H 23/78
	G06K 9/74	C12P 21/02			B01J 10	C07C 4/16	D21H 27/22
	G06N 3/067				B01L	C07C 4/18	F24J 1

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Nano-technology	Photonics	Industrial Biotechnology	Advanced Materials	Micro- and Nano-electronics (MNE)	Advanced Manufacturing Technologies (AMTs)		
	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
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